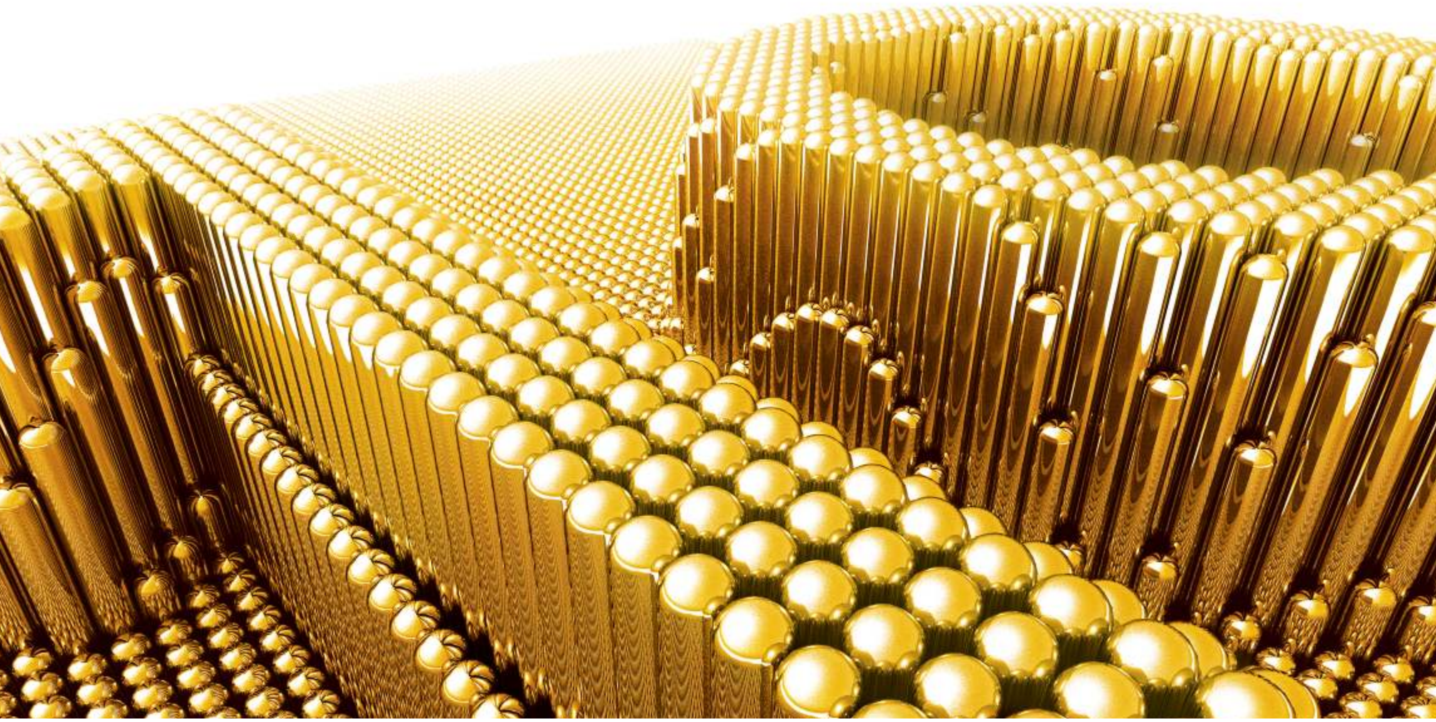
HALCON

the Power of Machine Vision

Solution Guide II-D

Classification



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More information about HALCON can be found at: `http://www.halcon.com/`

About This Manual

In a broad range of applications classification is suitable to find specific objects or detect defects in images. This Solution Guide leads you through the variety of approaches that are provided by HALCON.

After a short introduction to the general topic in section 1 on page 7, a first example is presented in section 2 on page 11 that gives an idea on how to apply a classification with HALCON.

Section 3 on page 15 then provides you with the basic theories related to the available approaches. Some hints how to select the suitable classification approach, a set of features that is used to define the class boundaries, and some samples that are used for the training of the classifier are given in section 4 on page 25.

Section 5 on page 29 describes how to generally apply a classification for various objects like pixels or regions based on various features like color, texture, or region features. Section 6 on page 59 shows how to apply classification for a pure pixel-based image segmentation and section 7 on page 83 provides a short introduction to the classification for optical character recognition (OCR). For the latter regions are classified by region features.

Finally, section 8 on page 103 provides some general tips that may be suitable when working with complex classification tasks.

The HDevelop example programs that are presented in this Solution Guide can be found in the specified subdirectories of the directory `%HALCONROOT%`.

Contents

Chapter 1

Introduction

What is classification?

Classifying an object means to assign an object to one of several available classes. When working with images, the objects usually are pixels or regions. Objects are described by features, which comprise, e.g., the color or texture for pixel objects, and the size or specific shape features for region objects. To assign an object to a specific class, the individual class boundaries have to be known. These are built in most cases by a training using the features of sample objects for which the classes are known. Then, when classifying an unknown object, the class with the largest correspondence between the feature values used for it's training and the feature values of the unknown object is returned.

What can you do with classification?

Classification is reasonable in all cases where objects have similarities, but within unknown variations. If you search for objects of a certain fixed shape, and the points of a found contour may not deviate from this shape more than a small defined distance, a template matching will be faster and easier to apply. But if the shapes of your objects are similar, but you can not define exactly what the similarities are and what distinguishes these objects from other objects in the image, you can show a classifier some samples of known objects (with a set of features that you roughly imagine to describe the characteristics of the object types) and let the classifier find the rules to distinguish between the object types. Classification can be used for a lot of different tasks. You can use classification, e.g., for

- image segmentation, i.e., you segment images into regions of similar color or texture,
- object recognition, i.e., you find objects of a specific type within a set of different object types,
- quality control, i.e., you decide if objects are good or bad,
- novelty detection, i.e., you detect changes or defects of objects, or
- optical character recognition (OCR).

What can HALCON do for you?

To solve the different requirements on classification, HALCON provides different types of classifiers. The most important HALCON classifiers are

- a classifier that uses neural nets, in particular multi-layer perceptrons (MLP, see section 3.4 on page 21),
- a classifier that is based on support-vector machines (SVM, see section 3.5 on page 23), and
- a classifier that is based on Gaussian mixture models (GMM, see section 3.3 on page 18).
- Furthermore, for image segmentation also some simple but fast classifiers are available. These comprise a classifier that segments two-channel images based on the corresponding 2D histogram (see section 6.2 on page 77), a hyperbox classifier, and a classifier that can be applied using either an Euclidean or a hyperbox metric (see section 3.2 on page 17 and section 6.3 on page 78).

For specific classification tasks, specific sets of HALCON operators are available. We distinguish between the three following basic tasks:

- You can apply a general classification. Here, arbitrary objects like pixels or regions are classified based on arbitrary features like color, texture, shape, or size. Section 5 on page 29 shows how to apply the suitable operators for MLP, SVM, and GMM classification.
- You can apply classification for image segmentation. Here, the classification is used to segment images into regions of different classes. For that, the individual pixels of an image are classified due to the features color or texture and all pixels belonging to the same class are combined in a region. Section 6 on page 59 shows how to apply the suitable operators for MLP, SVM, and GMM classification (section 6.1 on page 59) as well as for some simple but fast classifiers that segment the images using the 2D histogram of two image channels (section 6.2 on page 77) or that apply an Euclidean or hyperbox classification (section 6.3 on page 78).
- You can apply classification for OCR, i.e., individual regions are investigated due to region features and assigned to classes that typically (but not necessarily) represent individual characters or numbers. Section 7 on page 83 shows how to apply the suitable operators for MLP and SVM classification.

What are the basic steps of a classification with HALCON?

The basic proceeding for a classification with HALCON is as follows:

1. First, some sample objects, i.e., objects of known classes, are investigated. That is, a set of characteristic features is extracted from each sample object and stored in a so-called feature vector (explicitly by the user or implicitly by a specific operator).
2. The feature vectors of many sample objects are used to train a classifier. With the training, the classifier derives suitable boundaries between the classes.

3. Then, unknown objects, i.e., the objects to classify, are investigated with the help of the same set of features that was already used for the training samples. This step leads to feature vectors for the unknown objects.

4. Finally, the trained classifier uses the class boundaries that were derived during the training to decide for the new feature vectors to which classes they belong.

What information do you find in this solution guide?

This manual provides you with

- basic theoretical background for the provided classifiers (section 3 on page 15),
- tips for the decision making, in particular tips for the selection of a suitable classification approach, the selection of suitable features that describe the objects to classify, and the selection of suitable training samples (section 4 on page 25),
- guidance for the practical application of classification for general classification (section 5 on page 29), image segmentation (section 6 on page 59), and OCR (section 7 on page 83), and
- additional tips that may be useful when applying classification (section 8 on page 103). In particular, tips how to adjust the most critical parameters, tips how to use OCR for the classification of arbitrary regions, and tips how to visualize the feature space for 2D and 3D feature vectors are provided.

What do you have to consider before classifying?

Note that the decision which classifier to use for a specific application is a challenging task. There are no fixed rules which approach works better for which application, as the number of possible fields of applications is very large. At least, section 4.1 on page 25 provides some hints about the advantages and disadvantages of the individual approaches.

Additionally, if you have decided to use a specific classifier, it is not guaranteed that you get a satisfying result within a short time. Actually, in almost any case you have to apply a lot of tests with different parameters until you get the result you aimed at. Classification is very complex! So, plan enough time for your application.

Chapter 2

A First Example

This section shows a first example for a classification that classifies metal parts based on selected shape features. To follow the example actively, start the HDevelop program `solution_guide\classification\classify_metal_parts.hdev`; the steps described below start after the initialization of the application.

Step 1: Create classifier

First, a classifier is created. Here, we want to apply an MLP classification, so a classifier of type MLP is created with `create_class_mlp`. The returned handle `MLPHandle` is needed for all following classification steps.

```
create_class_mlp (6, 5, 3, 'softmax', 'normalization', 3, 42, MLPHandle)
```

Step 2: Add training samples to the classifier

Then, the training images, i.e., images that contain objects of known class, are investigated. Each image contains several metal parts that belong to the same class. The index of the class for a specific image is stored in the tuple `Classes`. In this case, nine images are available (see figure 2.1). The objects in the first three images belong to class `0`, the objects of the next three images belong to class `1`, and the last three images show objects of class 2.

```
FileNames := ['nuts_01','nuts_02','nuts_03','washers_01','washers_02', \
              'washers_03','retainers_01','retainers_02','retainers_03']
Classes := [0,0,0,1,1,1,2,2,2]
```

Now, each training image is processed by the two procedures `segment` and `add_samples`.

```
for J := 0 to |FileNames|-1 by 1
    read_image (Image, 'rings/'+FileNames[J])
    segment (Image, Objects)
    add_samples (Objects, MLPHandle, Classes[J])
endfor
```

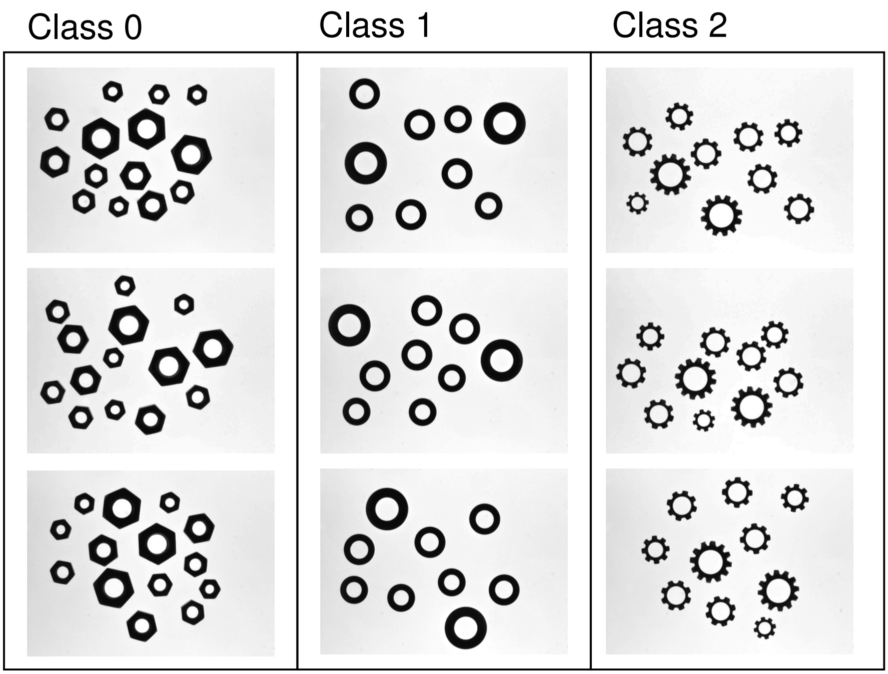

Figure 2.1: Training images.

The procedure `segment` segments and separates the objects that are contained in the image using a simple blob analysis (for blob analysis see Solution Guide I, chapter 4 on page 31).

```
procedure segment (Image, Regions)
bin_threshold (Image, Region)
connection (Region, ConnectedRegions)
fill_up (ConnectedRegions, Regions)
return ()
```

For each region, the procedure `add_samples` determines a feature vector using the procedure `get_features`. The feature vector and the known class index build the training sample, which is added to the classifier with the operator `add_sample_class_mlp`.

```
procedure add_samples (Regions, MLPHandle, Class)
count_obj (Regions, Number)
for J := 1 to Number by 1
    select_obj (Regions, Region, J)
    get_features (Region, Features)
    add_sample_class_mlp (MLPHandle, Features, Class)
endfor
return ()
```

The features extracted in the procedure `get_features` are region features, in particular the 'circularity', 'roundness', and the four moments (obtained by the operator moments_region_central_invar) of the region.

```
procedure get_features (Region, Features)
select_obj (Region, SingleRegion, 1)
circularity (SingleRegion, Circularity)
roundness (SingleRegion, Distance, Sigma, Roundness, Sides)
moments_region_central_invar (SingleRegion, PSI1, PSI2, PSI3, PSI4)
Features := [Circularity,Roundness,PSI1,PSI2,PSI3,PSI4]
return ()
```

Step 3: Train the classifier

After adding all available samples, the classifier is trained with train_class_mlp and the samples are removed from memory with clear_samples_class_mlp.

```
train_class_mlp (MLPHandle, 200, 1, 0.01, Error, ErrorLog)
clear_samples_class_mlp (MLPHandle)
```

Step 4: Classify new objects

Now, images with different unknown objects are investigated. The segmentation of the objects and the extraction of their feature vectors is realized by the same procedures that were used for the training images (segment and get_features). But this time, the class of a feature vector is not yet known and has to be determined by the classification. Thus, opposite to the procedure add_samples, within the procedure classify the extracted feature vector is used as input to the operator classify_class_mlp and not to add_sample_class_mlp. The result is the class index that is suited best for the feature vector extracted for the specific region.

```
for J := 1 to 4 by 1
    read_image (Image, 'rings/mixed_'+J$'02d')
    segment (Image, Objects)
    classify (Objects, MLPHandle, Classes)
    disp_obj_class (Objects, Classes)
endfor
```

```
procedure classify (Regions, MLPHandle, Classes)
count_obj (Regions, Number)
Classes := []
for J := 1 to Number by 1
    select_obj (Regions, Region, J)
    get_features (Region, Features)
    classify_class_mlp (MLPHandle, Features, 1, Class, Confidence)
    Classes := [Classes,Class]
endfor
return ()
```

For a visual check of the result, the procedure disp_obj_class displays each region with a specific color that depends on the class index (see figure 2.2).

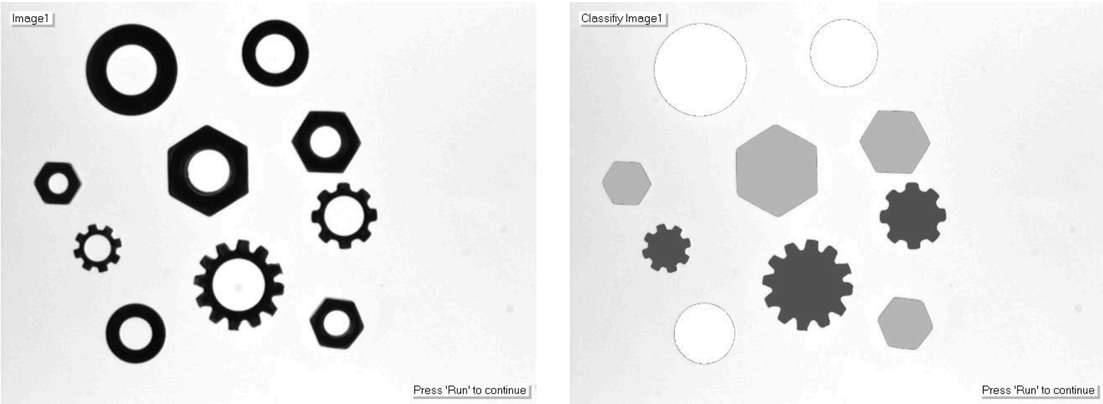

Figure 2.2: Classifying metal parts because of their shape: (left) image with metal parts, (right) metal parts classified into three classes (illustrated by different gray values).

```
procedure disp_obj_class (Regions, Classes)
count_obj (Regions, Number)
Colors := ['yellow', 'magenta', 'green']
for J := 1 to Number by 1
    select_obj (Regions, Region, J)
    dev_set_color (Colors[Classes[J-1]])
    dev_display (Region)
endfor
return ()
```

Step 5: Destroy the classifier

At the end of the program, the classifier is destroyed.

```
clear_class_mlp (MLPHandle)
```

Chapter 3

Classification: Theoretical Background

This section introduces you to the basics of classification (section 3.1) and the specific classifiers that can be applied with HALCON. In particular, the Euclidean and hyperbox classifiers (section 3.2), the classifier based on Gaussian mixture models (section 3.3), the classifier based on multi-layer perceptrons (neural nets, section 3.4), and the classifier based on support-vector machines (section 3.5) are introduced.

3.1 Classification in General

Generally, a classifier is used to assign an object to one of several available classes. For example, you have gray value images containing citrus fruits. You have extracted regions[1] from the images and each region represents a fruit. Now, you want to separate the oranges from the lemons. To distinguish the fruits, you can apply a classification. Then, the extracted regions of the fruits are your objects and the task of the classification is to decide for each region if it belongs to the class `'oranges'` or to the class `'lemons'`.

For the decision to which class a region belongs you need knowledge about the differences between the classes and the similarities within each individual class. This knowledge can be obtained by analyzing typical features of the objects to classify. Given the example with the citrus fruits (the actual program is described in more detail in section 8.3.1 on page 107), suitable features can be, e.g., the `'area'` (an orange is in most cases bigger than a lemon) and the shape, in particular the `'circularity'` of the regions (the outline of an orange is closer to a circle than that of a lemon). Figure 3.1 shows some oranges and lemons for which the regions are extracted and the region features `'area'` and `'circularity'` are calculated.

The features are arranged in an array that is called feature vector. The features of the feature vector span a so-called feature space, i.e., a vector space in which each feature is represented by an axis. Generally,

[1] How to extract regions from images is described, e.g., in Solution Guide I, chapter 4 on page 31

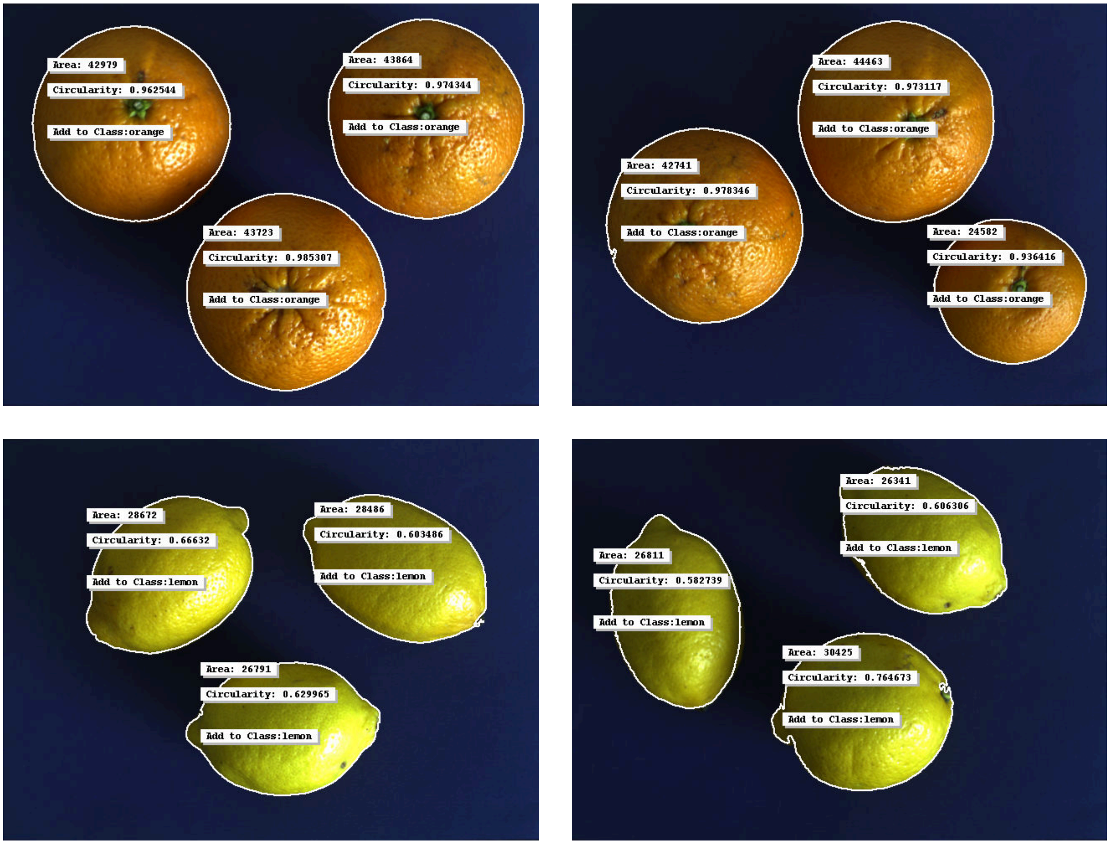

Figure 3.1: Region features of oranges and lemons are extracted and can be added as samples to the classifier.

a feature space can have any dimension, depending on the number of features contained in the feature vector. For visualization purpose, here a 2D feature space is shown. In practice, feature spaces of higher dimension are very common.

In figure 3.2 the feature vectors of the fruits shown in figure 3.1 are visualized in a 2D graph, for which one axis represents the `'area'` values and the other axis represents the `'circularity'` values. Although the regions vary in size and circularity, we can see that they are similar enough to build clusters. The goal of a classifier is to separate the clusters and to assign each feature vector to one of the clusters. Here, the oranges and lemons can be separated, e.g., by a straight line. All objects on the lower left side of the line are classified as lemons and all objects on the upper right side of the line are classified as oranges.

As we can see, the feature vector of a very small orange and that of a rather circular lemon are close to the separating line. With a little bit different data, e.g., if the small orange additionally would be less circular, the feature vectors may be classified incorrectly. To minimize errors, a lot of different samples and in many cases also additional features are needed. An additional feature for the citrus fruits may be, e.g., the gray value. Then, not a line but a plane is needed to separate the clusters. If color images

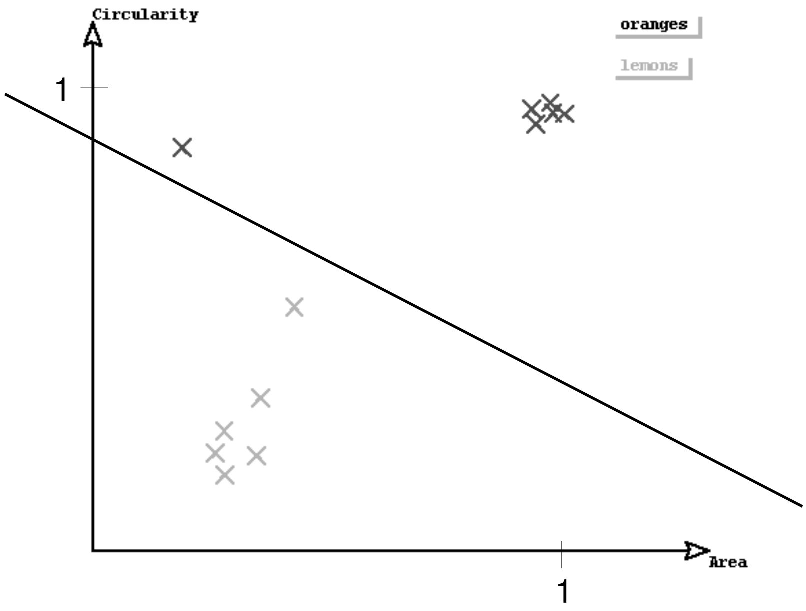

Figure 3.2: The normalized values for the 'area' and 'circularity' of the fruits span a feature space. The two classes can be separated by a line.

are available, you can combine the area and the circularity with the gray values of three channels. For feature vectors of more than three features, an n-dimensional plane, also called hyperplane, is needed.

Classifiers that use separating lines or hyperplanes are called linear classifiers. Other classifiers, i.e., non-linear classifiers, can separate clusters using arbitrary surfaces and may be able to separate clusters more conveniently in some cases.

Summarized, we need a suitable set of features and we have to select the classifier that is suited best for a specific classification application. To select the most appropriate approach, we have to know some basics about the available classifiers and the algorithms they use. In the following, we coarsely introduce you to the theories behind the Euclidean and hyperbox classifiers (section 3.2), the classifier based on Gaussian mixture models (section 3.3), the classifier based on multi-layer perceptrons (neural nets, section 3.4), and the classifier based on support-vector machines (section 3.5).

3.2 Euclidean and Hyperbox Classifiers

One of the simple classifiers is the Euclidean or minimum distance classifier. With HALCON, the Euclidean classification is available for image segmentation, i.e., the objects to classify are pixels and the feature vectors contain the gray values of the pixels. The dimension of the feature space depends on the number of channels used for the image segmentation. Geometrically interpreted, this classifier builds circles (in 2D) or n-dimensional hyperspheres (in nD) around the cluster centers to separate the clusters from each other. In section 6.3 on page 78 it is described how to apply the Euclidean classifier for image segmentation. With HALCON, the Euclidean metric is used only for image segmentation, not for the classification of general features or OCR. This is because the approach is stable only for feature vectors of low dimension.

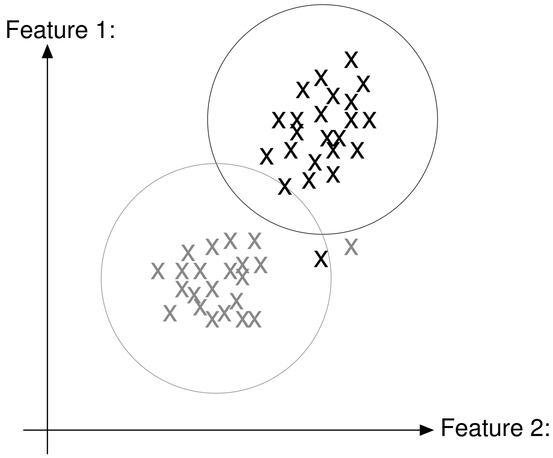

Figure 3.3: Euclidean classifier.

Whereas the Euclidean classifier uses n-dimensional spheres, the hyperbox approach uses axis-parallel cubes, so-called hyperboxes. This can be imagined as a threshold approach in multidimensional space. That is, for each class specific value ranges for each axis of the feature space are determined. If a feature vector lies within all the ranges of a specific class, it will be assigned to this class. The hyperboxes can overlap. For objects that are ambiguous, the hyperbox approach can be combined with another classification approach, e.g., an Euclidean classification or a maximum likelihood classification. Within HALCON, the Euclidean distance is used and additionally weighted with the variance of the feature vector. In section 6.3 on page 78 it is described how to apply the hyperbox classifier for image segmentation.

HALCON provides also operators for hyperbox classification of general features as well as for OCR, but these show almost no advantages but a lot of disadvantages compared to the MLP, SVM, and GMM approaches, and thus are not described further in this solution guide.

3.3 Gaussian Mixture Models (GMM)

The classification approaches described in section 3.2 on page 17 followed rather simple rules. The theory for the classification with Gaussian mixture models (GMM) is a bit more complex, so we have to deal with the theory of classification in more detail.

One of the basic theories when dealing with classification comprises the Bayes decision rule. Generally, the Bayes decision rule tells us to minimize the probability of erroneously classifying a feature vector by maximizing the probability for the feature vector x to belong to a class. This so-called 'a posteriori probability' should be maximized over all classes. Then, the Bayes decision rule partitions the feature space into mutually disjoint regions. The regions are separated by hypersurfaces, e.g., by points for 1D

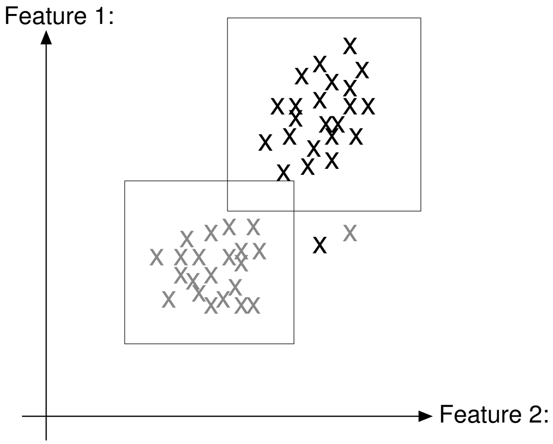

Figure 3.4: Hyperbox classifier.

data or by curves for 2D data. In particular, the hypersurfaces are defined by the points in which two neighboring classes are equally probable.

The Bayes decision rule can be expressed by

$$P(w_i|x) = \frac{P(x|w_i) \times P(w_i)}{P(x)}$$

with

- $P(w_i|x)$: a posteriori probability
- $P(x|w_i)$: a priori probability that the feature vector x occurs given that the class of the feature vector is w_i
- $P(w_i)$: Probability, that the class w_i occurs
- $P(x)$: Probability that the feature vector x occurs

For classification, the a posteriori probability should be maximized over all classes. Here, we coarsely show how to obtain the a posteriori probability for a feature vector x. First, we can remark that $P(x)$, i.e., the probability of the class, is a constant if x exists.

The first problem of the Bayes classifier is how to obtain $P(w_i)$, i.e., the probability of the occurrence of a class. Two strategies can be followed. First, you can estimate it from the used training set. This is recommended only if you have a training set that is representative not only with regard to the quality of the samples but also with regard to the frequency of the individual classes inside the set of samples. As this strategy is rather uncertain, a second strategy is recommended in most cases. There, it is assumed that each class has the same probability to occur, i.e., $P(w_i)$ is set to $1/m$ with m being the number of available classes.

The second problem of the Bayes classifier is how to obtain the a priori probability $P(x|w_i)$. In principle, a histogram over all feature vectors of the training set can be used. The apparent solution is to subdivide each dimension of the feature space into a number of bins. But as the number of bins grows exponentially with the dimension of the feature space, you face the so-called 'curse of dimensionality'. That is, to get a good approximation for $P(x|w_i)$, you need more memory than can be handled properly. With another solution, instead of keeping the size of a bin constant and varying the number of samples in the bin, the number of samples k for a class w_i is kept constant while varying the volume of the region in space around the feature vector x that contains the k samples $(v(x, w_i))$. The volume depends on the k nearest neighbors of the class w_i, so the solution is called k nearest-neighbor density estimation. It has the disadvantage that all training samples have to be stored with the classifier and the search for the k nearest neighbors is rather time-consuming. Because of that, it is seldom used in practice. A solution that can be used in practice assumes that $P(x|w_i)$ follows a certain distribution, e.g., a normal distribution. Then, you only have to estimate the two parameters of the normal distribution, i.e., the mean vector μ_i and the covariance matrix Σ_i. This can be achieved, e.g., by a maximum likelihood estimator.

In some cases, a single normal distribution is not sufficient, as there are large variations inside a class. The character `'a'`, e.g., can be represented by 'a' or '*a*', which have significantly different shapes. Nevertheless, both belong to the same character, i.e., to the same class. Inside a class with large variations, a mixture of l_i different densities exists. If these are again assumed to be normal distributed, we have a Gaussian mixture model. Classifying with a Gaussian mixture model means to estimate to which specific mixture density a sample belongs. This is done by the so-called expectation minimization algorithm.

Coarsely spoken, the GMM classifier uses probability density functions of the individual classes and expresses them as linear combinations of Gaussian distributions (see figure 3.5). Comparing the approach to the simple classification approaches described in section 3.2 on page 17, you can imagine the GMM to construct n-dimensional error (covariance) ellipsoids around the cluster centers (see figure 3.6).

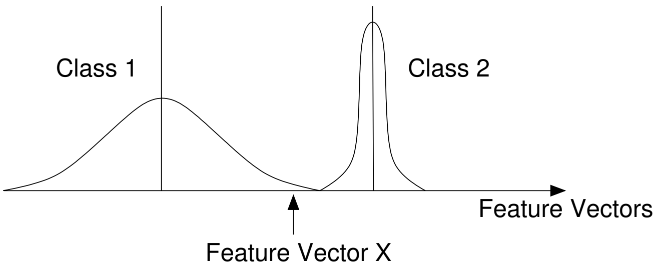

Figure 3.5: The variance of class 1 is significantly larger than that of class 2. In such a case, the distance to the Gauss error distribution curve is a better criteria for the class membership than the distance to the cluster center.

GMM are reliable only for low dimensional feature vectors (approximately up to 15 features), so HALCON provides GMM only for the classification of general features and image segmentation, but not for OCR. Typical Applications are image segmentation and novelty detection. Novelty detection is specific for GMM and means that feature vectors that do not belong to one of the trained classes can be rejected. Note that novelty detection can also be applied with SVM, but then a specific parameter has to be set and only two-class problems can be handled, i.e., a single class can be trained and the feature vectors that do not belong to that single class are rejected.

There are two general approaches for the construction of a classifier. First, you can estimate the a pos-

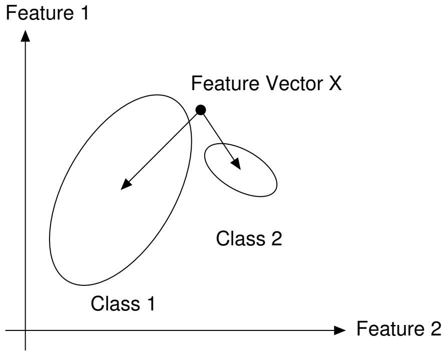

Figure 3.6: The feature vector X is nearer to the error ellipse of class 1 although the distance to the cluster center of class 1 is larger than the distance to the cluster center of class 2.

teriori probability from the a priori probabilities of the different classes (statistical approach), which we have introduced here for classification with the GMM classifier. Second, you can explicitly construct the separating hypersurfaces between the classes (geometrical approach). This can be realized in HALCON either with a neural net using multi-layer perceptrons (see section 3.4) or with support-vector machines (see section 3.5 on page 23).

3.4 Multi-Layer Perceptrons (MLP)

Neural nets directly determine the separating hyperplanes between the classes. The simplest surface to separate classes is a plane. If the classes are separated by hyperplanes, the classifier is called linear classifier, as we already learned in section 3.1 on page 15. For two classes the hyperplane actually separates the feature vectors of the two classes, i.e., the feature vectors that lie on one side of the plane are assigned to class 1 and the feature vectors that lie on the other side of the plane are assigned to class 2. In contrast to this, for more than two classes the planes are chosen such that the feature vectors of the correct class have the largest positive distance of all feature vectors from the plane.

A linear classifier can be built, e.g., using a neural net with a single layer like shown in figure 3.7 (a,b). There, so-called processing units (neurons) first compute the linear combinations of the feature vectors and the network weights and then apply a nonlinear activation function.

A classification with single-layer neural nets needs linearly separable classes, which is not sufficient in many classification applications. To get a classifier that can separate also classes that are not linearly separable, you can add more layers, so-called hidden layers, to the net. The obtained multi-layer neural net (see figure 3.7, c) then consists of an input layer, one or several hidden layers and an output layer. Note that one hidden layer is sufficient to approximate any separating hypersurface and any output function with values in [0,1] as long as the hidden layer has a sufficient number of processing units.

Within the neural net, the processing units of each layer (see figure 3.8 on page 23) compute the linear combination of the feature vector or of the results from a previous layer. That is, each processing unit first computes it’s activation as a linear combination of the input values:

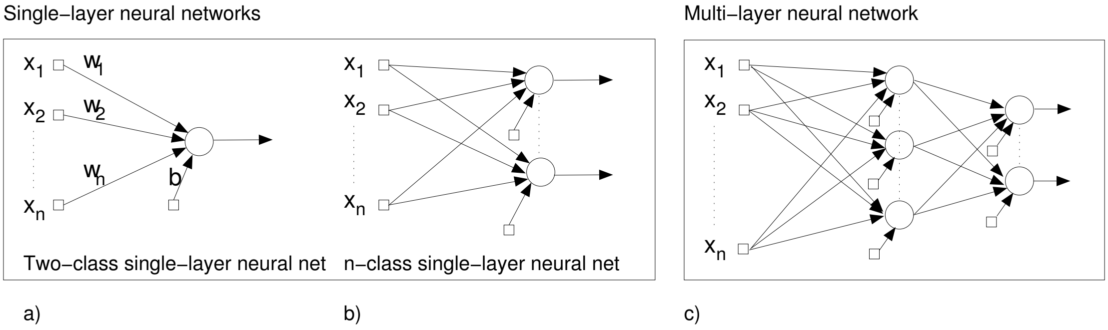

Figure 3.7: Neural networks: single-layered for (a) two classes and (b) n classes, (c) multi-layered: (from left to right) input layer, hidden layer, output layer.

$$a_j^{(l)} = \sum_{i=1}^{n_l} w_{ij}^{(l)} x_i^{(l-1)} + b_j^{(l)}$$

with

- x_i^0: feature vector
- $x_i^{(j)}$: result vector of layer l
- $w_{ji}^{(l)}$ and $b_j^{(l)}$: weights of layer l

Then the results are passed through a nonlinear activation function:

$$x_j^{(l)} = f(a_j^{(l)})$$

With HALCON, for the hidden units the activation function is the hyperbolic tangent function:

$$f(x) = tanh(x) = \frac{e^x - e^x}{e^x + e^x}$$

For the output function (when using the MLP for classification) the softmax activation function is used:

$$f(x) = \frac{e^{x_i}}{\Sigma_{j=1}^{n} e^{x_j}}$$

To derive the separating hypersurfaces for a classification using a multi-layer neural net, the network weights have to be adjusted. This is done by a training. That is, data with known output is inserted to the input layer and processed by the hidden units. The output is then compared to the expected output. If

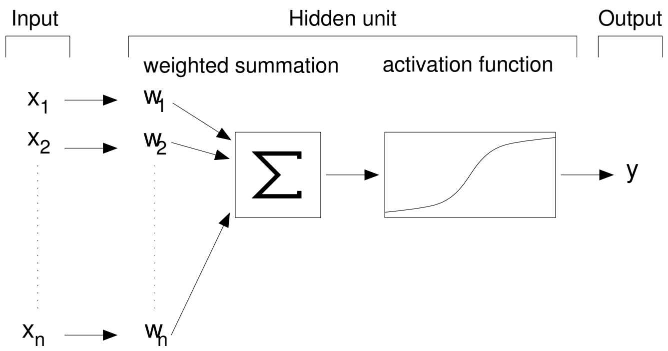

Figure 3.8: Processing unit of an MLP.

the output does not correspond to the expected output (within a certain error tolerance), the weights are incrementally adjusted so that the error is minimized. Note that the weight adjustment using HALCON is realized by a very stable numeric algorithm that leads to better results than obtained by the classical back propagation algorithm.

MLP works for classification of general features, image segmentation, and OCR. Note that MLP can be used also for least squares fitting (regression) and for classification problems with multiple independent logical attributes.

3.5 Support-Vector Machines (SVM)

Another classification approach that can handle classes that are not linearly separable uses support-vector machines (SVM). Here, no non-linear hypersurface is obtained, but the feature space is transformed into a space of higher dimension, so that the features become linearly separable. Then, the feature vectors can be classified with a linear classifier.

In figure 3.9, e.g., two classes in a 2D feature space are illustrated by black and white squares, respectively. In the 2D feature space, no line can be found that separates the classes. When adding a third dimension by deforming the plane built by `Feature1` and `Feature2`, the classes become separable by a plane.

To avoid the already mentioned curse of dimensionality (see section 3.3 on page 18) for SVM, not the features but a kernel is transformed. The challenging task is to find the suitable kernel to transform the feature space into a higher dimension so that the black squares in figure 3.9 go up and the white ones stay in their place (or at least stay in another value range of the axis for the additional dimension). Common kernels are, e.g., the inhomogeneous polynomial kernel or the Gaussian radial basis function kernel.

With SVM, the separating hypersurface for two classes is constructed such that the margin between the two classes becomes as large as possible. The margin is defined as the closest distance between the separating hyperplane and any training sample. That is, several possible separating hypersurfaces are tested and the surface with the largest margin is selected. The training samples from both classes that have exactly the closest distance to the hypersurface are called 'support vectors' (see figure 3.10 for two linearly separable classes).

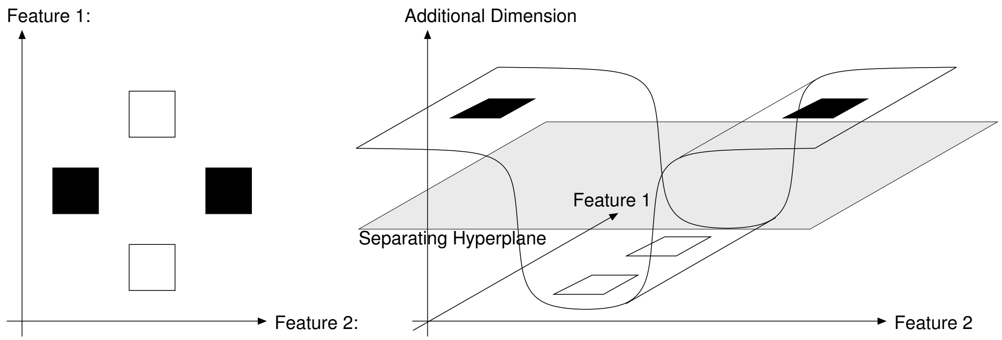

Figure 3.9: Separate two classes (black and white squares): (left) In the 2D feature space the classes can not be separated by a straight line, (right) by addition of a further dimension, the classes become linearly separable.

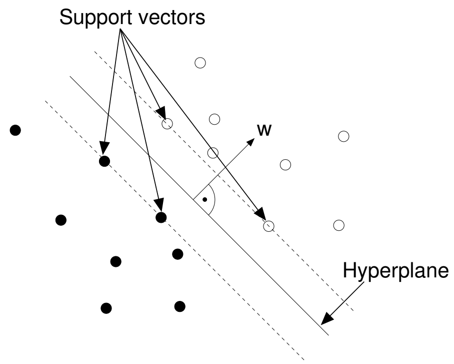

Figure 3.10: Support vectors are those feature vectors that have exactly the closest distance to the hyperplane.

By nature SVM can handle only two-class problems. Two approaches can be used to extend the SVM to a multi-class problem: With the first approach pairs of classes are built and for each pair a binary classifier is created. Then, the class that wins most of the comparisons is the best suited class. With the second approach, each class is compared to the rest of the training data and then, the class with the maximum distance to the hypersurface is selected (see also section 5.4.1 on page 46).

SVM works for classification of general features, image segmentation, and OCR.

Chapter 4

Decisions to Make

This section provides you with some hints how to select the suitable classification approach (section 4.1), the features that build the feature vectors (section 4.2), and a set of suitable training samples (section 4.3 on page 27). Note, that only some hints but no fixed rules can be given for almost all decisions that are related to classification, as the best suited approach, features, and samples depend strongly on the specific application.

4.1 Select the Suitable Classification Approach

In most cases, we recommend to use either the MLP, SVM, or GMM classifier for classification, as these three approaches are the most flexible ones. For image segmentation, they additionally can be sped up using a look-up table. But note that the so-called LUT-accelerated classification is suitable only for images with a maximum of three channels. Furthermore, the offline part of the classification is increasing and the storage requirements are relatively high. The advantages and disadvantages of the different approaches are as follows:

- The **MLP classifier** leads to good recognition rates and is fast at classification. In exchange, the training is not as fast as for the SVM classifier, especially when having large training sets. If the application is time critical but the training can be applied offline, the MLP approach is a good choice. A feature vector that does not match to one of the trained classes can be assigned to a rejection class for the image segmentation version. But in comparison to the GMM classifier, the rejection class may be influenced by outliers, so that an additional, explicit training of a rejection class is recommended. If you want to add additional training samples, you should not append a second training (although it is possible in principle), but repeat the training with both the old and the new training samples.
- Compared to the MLP classifier, the **SVM classifier** leads to slightly better recognition rates and is faster at training, especially for large training sets. Additionally, a training of new samples can be simply appended to a previous training (but note that a new training is always to be preferred). In exchange, the classification is not as fast as for the MLP classifier and the classifier needs much more memory capacity. A rejection class is not returned for the image segmentation version.

- The **GMM classifier** has the advantage that, controlled by the parameter settings, a feature vector that does not match to one of the trained classes can be reliably assigned to a rejection class. Additionally, you can apply a second training that is appended to the first training, e.g. in order to add new training samples (but note that a new training is always to be preferred). The disadvantage of the GMM classifier is that the recognition rates are not as good as the recognition rates obtained by the MLP or SVM classifiers. Further, the length of the feature vector is more restricted. It is recommended to have not more than 15 features for the GMM, whereas for MLP or SVM a feature vector of 500 features is still realistic. As the GMM classifier is suitable only for feature vectors of low dimension, no OCR approach is available.

- The **classifier based on a 2D histogram** is suitable for the pixel-based image segmentation of two-channel images. It provides a very fast alternative if a 2D feature vector is sufficient for the classification task.

- The **hyperbox and Euclidean classifiers** are suitable for feature vectors of low dimension, e.g., when applying a color classification for image segmentation. Especially for classes that are built by rather compact clusters, they are very fast. Compared to a LUT-accelerated classification using MLP, SVM, or GMM, the storage requirements are low and the feature space can easily be visualized. The hyperbox classifier, which is described here only for image segmentation, although it is provided by HALCON also for the general classification and OCR, may be used, e.g., in those very rare cases when only one sample is available for the training.

4.2 Select Suitable Features

The features that are suitable for a classification strongly depend on the specific application and the objects that have to be classified. Thus, no fixed rules for their selection can be provided. For each application, you have to individually decide which features describe the object best. Generally, the following features can be used for the different classification tasks:

- For a **general classification** all types of features, i.e., region features as well as color or texture, can be used to build the feature vectors. The feature vectors have to be explicitly built by feature values that are derived from a set of suitable operators.

- For **image segmentation**, the colors or textures of the pixels of a multi-channel image are used as features. Here, you do not have to explicitly extract the feature vectors as they are derived automatically by the corresponding image segmentation operators from the color or texture image.

- For **OCR**, a restricted set of region features is used to build the feature vectors. Here, you do not have to explicitly calculate the features but select the feature types that are implicitly and internally calculated by the corresponding OCR specific operators. The dimension of the resulting feature vector is equal or larger than the number of selected feature types, as some feature types lead to several feature values (see section 7.5 on page 98 for the list of available features).

If your objects are described best by texture, you can follow different approaches. You can, e.g., create a texture image by applying the operator `texture_laws` with different parameters and combining the thus obtained individual channels into a single image, e.g., using `compose6` for a texture image containing six channels. Another common approach is to use, e.g., the operator cooc_feature_image to calculate texture features like energy, correlation, homogeneity, and contrast. We refer to Solution Guide I, chapter 14 on page 189 for further information about texture.

If your objects are described best by region features, you can use any of the operators that are described in the Reference Manual in section Regions/Features. For OCR, the set of available region features is restricted to the set of features introduced in section 7.5 on page 98.

4.3 Select Suitable Training Samples

In section 1 on page 7 we learned that classification is reasonable in all cases where objects have similarities, but within undefined variations. To learn the similarities and variations, the classifier needs representative samples. That is, the samples should not only show the significant features of the objects to classify but should also show a large variety of allowed deviations. That is, if an object is described by a specific texture, small deviations from the texture that are caused, e.g., by noise, should be covered by the samples. Or if an object is described by a region having a specific size and orientation, the samples should contain several objects that deviate from both 'ideal' values within a certain tolerance. Otherwise, only objects that exactly fit to the 'ideal' object are found in the later classification. In other words, the classifier has no sufficient generalization ability.

Generally, for the training of a classifier a large amount of samples with a realistic set of variations for the calculated features should be provided for every available class. Otherwise, the result of the later classification may be unsatisfying as the unknown objects show deviations from the trained data that were not considered during the training. Nevertheless, if for any reason no sufficient number of samples can be provided, some tricks can be applied:

- One trick is to generate artificial samples by copying the few available samples and slightly modifying them. The modifications depend on the object to classify and the features used to find the class boundaries. When working with texture images, e.g., noise can be added to slightly modify the copies of the samples. Or given the example with the objects of a specific size and orientation, you can modify copies of the samples by, e.g., slightly changing their size using an erosion or dilation. And you can change their orientation by rotating the image by different, but small angles. Ideally, you create several copies and modify them so that several deviations in all allowed directions are covered.

- A second trick can be applied if the number of samples is unequally distributed for the different classes. For example, you want to apply classification for quality inspection and you have a large amount of samples for the good objects, but only a few samples for each of several error classes. Then, you can split the classification task into two classification tasks. In the first instance, you merge all error classes into one class, i.e., you have reduced the multi-class problem to a two-class problem. You have now a class with good objects and the rejection class contains all erroneous objects, which in the sum are represented by a larger number of samples. Then, if the type of error attached to the rejected objects is of interest, you apply a second classification, this time without the lot of good examples. That is, you only use the samples of the different error classes for the training and classify the objects that were rejected during the first classification into one of these error classes.

Chapter 5

Classification of General Features

This section shows how to apply the different classifiers to general features, i.e., arbitrary objects like pixels or regions are classified due to arbitrary features like color, texture, shape, or size. In contrast to the image segmentation approach described in section 6 on page 59, which classifies only pixels, or the OCR approach in section 7 on page 83, which classifies regions with focus on optical character recognition, here pixels as well as regions can be classified.

The general proceeding for a classification of arbitrary features, i.e., the sequence of operators used for the individual approaches is similar for the MLP, SVM, and GMM classification. In section 5.1 the general proceeding is illustrated by an example that checks the quality of halogen bulbs using shape features. In section 5.2 the steps of a classification and the involved operators are listed for a brief overview. The parameters used for the operators are in many cases specific for the individual approaches because of the different underlying algorithms (see section 3 on page 15 for the theoretical background). They are introduced in more detail in section 5.3 for MLP, section 5.4 for SVM, and section 5.5 for GMM.

5.1 General Proceeding

The general proceeding is similar for MLP, SVM, and GMM classification (see figure 5.1). In all cases, a classifier with specific properties is created. Then, known objects are investigated, i.e., you extract the features of objects for which the classes are known and add the feature vectors together with the corresponding known class ID to the classifier. With a training, the classifier then derives the rules for the classification, i.e., it decides how to separate the classes from each other. To investigate unknown objects, i.e., to classify them, you extract the same set of features for them that was used for the training and classify the feature vectors with the trained classifier. Finally, you clear the classifier from memory.

In the following, we illustrate the general proceeding with the example `solution_guide\classification\classify_halogen_bulbs.hdev`. Here, halogen bulbs are classified into good, bad, and not existent halogen bulbs (see figure 5.2). For that, the regions representing the insulation of the halogen bulbs are investigated. The classification is applied with the SVM approach. The operator names for the MLP and GMM classification differ only in their ending. That is, if you want to apply

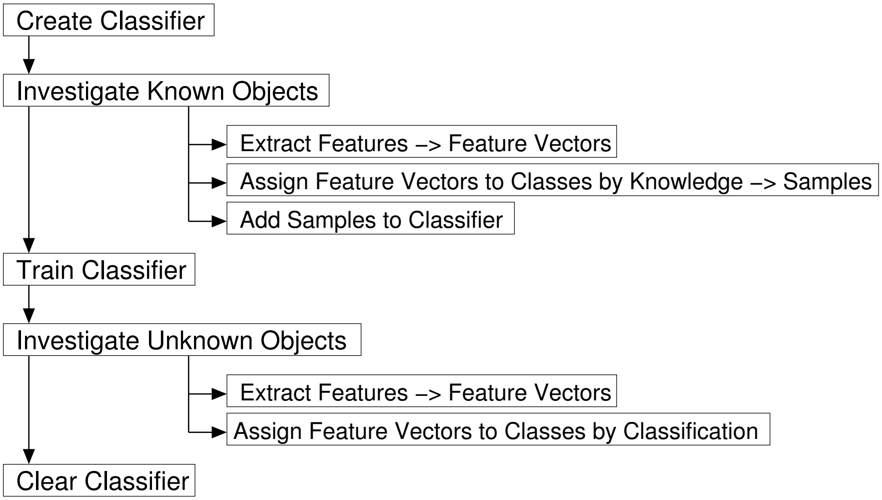

Figure 5.1: The basic steps of a general classification.

an MLP or a GMM classification, you mainly have to replace the 'svm' by 'mlp' or 'gmm' in the specific operator names and adjust different parameters. The parameters and their selection are described in section 6.1.3 for MLP, section 6.1.4 for SVM, and section 6.1.5 for GMM.

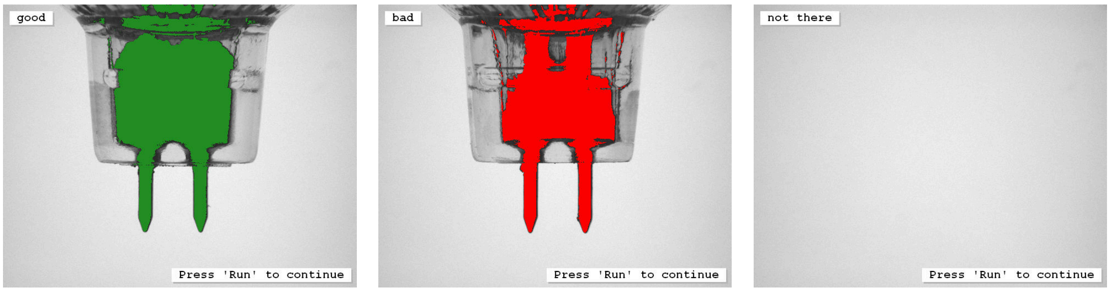

Figure 5.2: Classifying halogen bulbs into (from left to right): good, bad, and not existent halogen bulbs.

The program starts with the assignment of the available classes. The halogen bulbs can be classified into the classes `'good'` (halogen bulb with sufficient insulation), `'bad'` (halogen bulb with insufficient insulation), or `'none'` (no halogen bulb can be found in the image).

```
ClassNames := ['good','bad','none']
```

As the first step of the actual classification, an SVM classifier is created with the operator `create_class_svm`. The returned handle of the classifier `SVMHandle` is needed for all classification specific operators that are applied in the following.

```
Nu := [0.05]
KernelParam := [0.02]
create_class_svm (7, 'rbf', KernelParam, Nu, |ClassNames|, 'one-versus-one', \
                  'principal_components', 5, SVMHandle)
```

As each classification application is unique, the classifier has to be trained for the current application. That is, the rules for the classification have to be derived from a set of samples. In case of the SVM approach, e.g., the training determines the optimal support vectors that separate the classes from each other (see section 3.5 on page 23).

A sample is an object for which the class membership is known. Generally, each kind of object can be classified with the general classification approach as long as it can be described by a set of features or respectively the feature's values. Common objects for image processing are regions, pixels, or a combination of both. For the example with the halogen bulbs, the objects that have to be trained and classified are the regions that represent insulations of halogen bulbs. For each known object, the feature vector, which consists of values that are derived from the extracted region, and the corresponding (known) class name build the training sample. For each class a representative set of training samples must be provided to achieve suitable class boundaries. In the example, the samples are added within the procedure `add_samples_to_svm`.

Within the procedure, for each class the corresponding images are obtained. Note that different methods can be used to assign the class memberships for the objects of an image. In the example described in section 2 on page 11, a tuple was used to assign the class name for each image. There, the sequence of the images and the sequence of the elements in the tuple had to correspond. Here, the images of each class are stored in a directory that is named like the class. Thus, the procedure `add_samples_to_svm` uses the directory names to assign the feature vectors to the classes. For example, the images containing the good halogen bulbs are stored in the directory `'good'`. Then, for each class, all images are read from the corresponding directory.

Now, for each image the region of the halogen bulb's insulation is extracted by the operator `threshold`, the features of the region are extracted inside the procedure `calculate_features`, and the feature vector is added together with the corresponding class ID to the classifier using the operator `add_sample_class_svm`.

```
procedure add_samples_to_svm (ClassNames, SVMHandle, WindowHandle, ReadPath):::
for ClassNumber := 0 to |ClassNames|-1 by 1
    list_files (ReadPath + ClassNames[ClassNumber], 'files', Files)
    Selection := regexp_select(Files, '.*[.]png')
    for Index := 0 to |Selection|-1 by 1
        read_image (Image, Selection[Index])
        threshold (Image, Region, 0, 40)
        calculate_features (Region, Features)
        add_sample_class_svm (SVMHandle, Features, ClassNumber)
    endfor
endfor
return ()
```

The feature vectors that are used to train the classifier and those that are classified for new objects must consist of the same set of features. In the example program, the features are calculated inside the procedure `calculate_features` and comprise

- the 'area' of the region,
- the 'compactness' of the region,
- the four geometric moments ('PSI1', 'PSI2', 'PSI3', and 'PSI4') of the region, which are invariant to translation and general linear transformations, and
- the 'convexity' of the region.

Note that feature vectors have to consist of real values. As some of the calculated features are described by integer values, e.g., the feature 'area', which corresponds to the number of pixels contained in a region, the feature vector is transformed into a tuple of real values before it is added to the classifier.

```
procedure calculate_features (Region, Features)
area_center (Region, Area, Row, Column)
compactness (Region, Compactness)
moments_region_central_invar (Region, PSI1, PSI2, PSI3, PSI4)
convexity (Region, Convexity)
Features := real([Area,Compactness,PSI1,PSI2,PSI3,PSI4,Convexity])
return ()
```

After adding all samples to the classifier with the procedure add_samples_to_svm, the actual training is applied with the operator train_class_svm. In this step, the classifier derives it's classification rules.

```
train_class_svm (SVMHandle, 0.001, 'default')
```

These classification rules are applied now inside the procedure classify_regions_with_svm to halogen bulbs of unknown classes. The procedure works similar as the procedure for adding the training samples. But now, the images that contain the unknown types of halogen bulbs are read, no class information is available, and instead of adding samples to the classifier, the operator classify_class_svm is applied to classify the unknown feature vectors with the derived classification rules.

```
procedure classify_regions_with_svm (SVMHandle, Colors, ClassNames,
                                     ReadPath):::
list_files (ReadPath, ['files','recursive'], Files)
Selection := regexp_select(Files, '.*[.]png')
read_image (Image, Selection[0])
for Index := 0 to |Selection|-1 by 1
    read_image (Image, Selection[Index])
    threshold (Image, Region, 0, 40)
    calculate_features (Region, Features)
    classify_class_svm (SVMHandle, Features, 1, Class)
endfor
return ()
```

At the end of the program the handle of the classifier is destroyed with clear_class_svm to clear it from memory.

```
clear_class_svm (SVMHandle)
```

The example shows the application of operators that are essential for a classification. Further operators are provided that can be used, e.g., to separate the training from the classification. That is, you run a program that applies the training offline, save the trained classifier to file with `write_class_svm`, and in another program you read the classifier from file again with `read_class_svm` to classify your data in an online process. When closing the training program, the samples are not stored automatically. To store them to file for later access you apply the operator `write_samples_class_svm`. A later access using `read_samples_class_svm` may be necessary, e.g., if you want to repeat the training with additional training samples. If you do not separate the training and the classification process, you can save memory by clearing the samples manually from memory before applying the classification (if you do not need the samples anymore). This is done with `clear_samples_class_svm`.

The following sections provide you with a list of involved operators (section 5.2) and go deeper into the specific parameter adjustment needed for MLP (section 5.3), SVM (section 5.4), and GMM (section 5.5).

5.2 Involved Operators (Overview)

This section gives a brief overview on the operators that are provided for a general MLP, SVM, and GMM classification. First, the operators for the basic steps of a classification are introduced in section 5.2.1. Then, some advanced operators are introduced in section 5.2.2.

5.2.1 Basic Steps

Summarizing the information obtained in section 5.1 on page 29, the classification consists of the following basic steps and operators, which are applied in the same order as listed here:

1. Create a classifier. Here, some important properties of the classifier are defined. The returned handle is needed in all later classification steps. Each classification step modifies this handle.
   - `create_class_mlp`
   - `create_class_svm`
   - `create_class_gmm`
2. Predefine the sequence in which the classes are defined and later accessed, i.e., define the correspondences between the class IDs and the class names. This step may as well be applied before the creation of the classifier.
3. Get feature vectors for sample objects of known class IDs. The operators that are suitable to obtain the features depend strongly on the specific application and thus are not part of this overview.
4. Successively add samples, i.e., feature vectors and their corresponding class IDs to the classifier.
   - `add_sample_class_mlp`
   - `add_sample_class_svm`
   - `add_sample_class_gmm`
5. Train the classifier. Here, the boundaries between the classes are derived from the training samples.

- train_class_mlp
- train_class_svm
- train_class_gmm

6. Store the used samples to file and access them in a later step (optionally).

   - write_samples_class_mlp and read_samples_class_mlp
   - write_samples_class_svm and read_samples_class_svm
   - write_samples_class_gmm and read_samples_class_gmm

7. Store the trained classifier to file and read it from file again or, if the offline and online part is not separated, clear the samples manually from memory.

   - write_class_mlp (default file extension: .gmc) and read_class_mlp or clear_samples_class_mlp
   - write_class_svm (default file extension: .gsc) and read_class_svm or clear_samples_class_svm
   - write_class_gmm (default file extension: .ggc) and read_class_gmm or clear_samples_class_gmm

8. Get feature vectors for objects of unknown class. These feature vectors have to contain the same features (in the same order) that were used to define the training samples.

9. Classify the new feature vectors. That is, insert the new feature vector to one of the following operators and get the corresponding class ID.

   - classify_class_mlp
   - classify_class_svm
   - classify_class_gmm

10. Clear the classifier from memory.

    - clear_class_mlp or clear_all_class_mlp
    - clear_class_svm or clear_all_class_svm
    - clear_class_gmm or clear_all_class_gmm

Besides the basic steps of a classification, some additional steps and operators can be applied if suitable. These advanced operators are listed in the following section.

5.2.2 Advanced Steps

Especially if the training and classification do not lead to a satisfying result, it is helpful to access some information that is implicitly contained in the model. Available steps to query information are:

- Access an individual sample from the training data. This is suitable, e.g., to check the correctness of it's class assignment. The sample had to be stored previously by the operator add_sample_class_mlp, add_sample_class_svm, or add_sample_class_gmm, respectively.

  - get_sample_class_mlp
  - get_sample_class_svm
  - get_sample_class_gmm

- Get the number of samples that are stored in the training data. The obtained number is needed, e.g., to access the individual samples or respectively to know how much individual samples you can access.
  - get_sample_num_class_mlp
  - get_sample_num_class_svm
  - get_sample_num_class_gmm

- Get information about the information content of the preprocessed feature vectors. This information is reasonable, if the parameter `Preprocessing` was set to `'principal_components'` or `'canonical_variates'` during the creation of the classifier. Then, you can check if the information that is contained in the preprocessed feature vector still contains significant data or if a different preprocessing parameter, e.g., `'normalization'`, is to be preferred.
  - get_prep_info_class_mlp
  - get_prep_info_class_svm
  - get_prep_info_class_gmm

- Get the parameter values that were set during the creation of the classifier. This is suitable if the offline training and the online classification were separated and the information about the training part is not available anymore.
  - get_params_class_mlp
  - get_params_class_svm
  - get_params_class_gmm

Furthermore, there are operators that are available only for specific classifiers:

- For MLP and GMM you can evaluate the probabilities of a feature vector to belong to a specific class. That is, you can determine the probabilities for each available class and not only for the most probable classes. If only the most probable classes are of interest, no explicit evaluation is necessary, as these probabilities are returned also when classifying the feature vector.
  - evaluate_class_mlp
  - evaluate_class_gmm

- For SVM you can reduce the number of support vectors returned by the offline training to speed up the following online classification.
  - reduce_class_svm

- Additionally, for SVM the number or index of the support vectors can be determined after the training. This is suitable for the visualization of the support vectors and for diagnostic reasons.

- get_support_vector_num_class
- get_support_vector_class

The following sections introduce the individual parameters for the basic operators and provide tips for their adjustment.

5.3 Parameter Setting for MLP

This section goes deeper into the parameter adjustment for an MLP classification. We recommend to first adjust the parameters so that the classification result is satisfying. The most important parameter that has to be adjusted to get the MLP classifier work optimally is

- NumHidden (create_class_mlp).

If the classification generally works, you can start to tune the speed. The most important parameters to enhance the speed are

- Preprocessing / NumComponents (create_class_mlp) and
- MaxIterations (train_class_mlp).

In the following, we introduce the parameters of the basic MLP operators. The focus is on the parameters for which the setting is not immediately obvious or for which it is not immediately obvious how they influence the classification. These are mainly the parameters needed for the creation and training of the classifier. Further information about these operators as well as the usage of the operators with obvious parameter settings can be found in the Reference Manual entries for the individual operators.

5.3.1 Adjusting create_class_mlp

An MLP classifier is created with the operator create_class_mlp. There, several properties of the classifier are defined that are important for the following classification steps. The returned handle is needed (and modified) in all following steps. The following parameters can be adjusted:

Parameter NumInput

The input parameter NumInput specifies the dimension of the feature vectors used for the training as well as for the classification. Opposite to the GMM classifier (see section 5.5 on page 50), a number of 500 features is still realistic.

Parameter NumHidden

The input parameter NumHidden defines the number of units of the hidden layer of the multi-layer neural net (see section 3.4 on page 21) and significantly influences the result of the classification and thus should be adjusted very carefully. It's value should be in a similar value range as NumInput and NumOutput. Smaller values lead to a less complex separating hyperplane, but in many cases nevertheless may lead to good results. With a very large value for NumHidden, you run the risk of overfitting (see figure 5.3). That is, the classifier uses unimportant details like noise to build the class boundaries. That way, the classifier works very well for the training data, but fails for unknown feature vectors that do not contain the same unimportant details. In other words, overfitting means that the classifier looses it's generalization ability.

To adjust NumHidden, it is recommended to apply tests with independent test data, e.g., using the cross validation introduced in section 8.1 on page 103. Note that the example hdevelop\Classification\Neural-Nets\class_overlap.hdev provides further hints about the influence of different values for NumHidden.

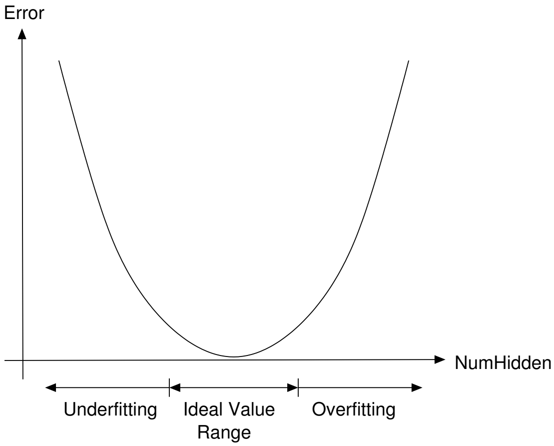

Figure 5.3: The value of NumHidden should be adjusted carefully to avoid under- or overfitting (note that the illustrated curve is idealized and in practice would be less straight).

Parameter NumOutput

The input parameter NumOutput specifies the number of classes.

Parameter OutputFunction

The input parameter OutputFunction describes the functions used by the output unit of the neural net. Available values are 'softmax', 'logistic', and 'linear'. In almost all classification applications, OutputFunction should be set to 'softmax'. The value 'logistic' can be used for classification problems with multiple independent logical attributes as output, but this kind of classification problems is very rare in practice. The value 'linear' is used for least squares fitting (regression) and not for classification. Thus, you can ignore it here.

Parameters Preprocessing/NumComponents

The input parameter Preprocessing defines the type of preprocessing applied to the feature vector for the training as well as later for the classification or evaluation. A preprocessing of the feature vector can be used to speed up the training as well as the classification. Sometimes, even the recognition rate can be enhanced.

Available values are 'none', 'normalization', 'principal_components', and 'canonical_variates'. In most cases, the preprocessing should be set to 'normalization' as it enhances the speed without loosing relevant information compared to using no preprocessing ('none'). The feature vectors are normalized by subtracting the mean of the training vectors and dividing the result by the standard deviation of the individual components of the training vectors. Hence, the transformed feature vectors have a mean of 0 and a standard deviation of 1. The normalization does not change the length of the feature vector.

If speed is important and your data is expected to be highly correlated, you can reduce the dimension of the feature vector using a principal component analysis ('principal_components'). There, the feature vectors are normalized and additionally transformed such that the covariance matrix becomes a diagonal matrix. Thus, the amount of data can be reduced without losing a large amount of information.

If you know that your classes are linearly separable, you can also use canonical variates ('canonical_variates'). This approach is known also as linear discriminant analysis. There, the transformation of the normalized feature vectors decorrelates the training vectors on average over all classes. At the same time, the transformation maximally separates the mean values of the individual classes. This approach combines the advantages of a principal component analysis with an optimized separability of the classes after the data reduction. But note that the parameter 'canonical_variates' is recommended only for linearly separable classes. For MLP, 'canonical_variates' can only be used if OutputFunction is set to 'softmax'.

Figure 5.4 and figure 5.5 illustrate how 'principal_components' and 'canonical_variates', dependent on the distribution of the feature vectors, can reduce the feature vectors to a lower number of components by transforming the feature space and projecting the feature vectors to one of the principal axes.

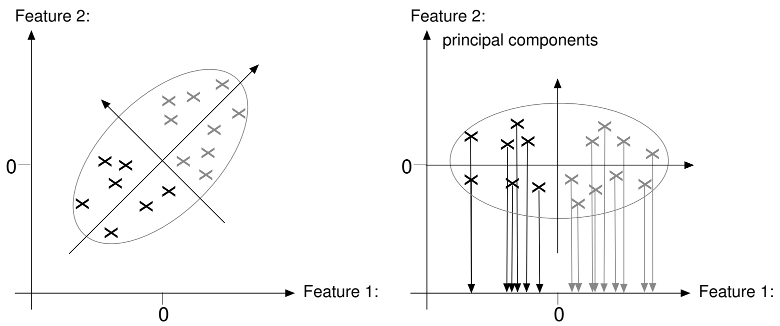

Figure 5.4: After transforming the feature space via principal component analysis, the illustrated linearly separable classes can be separated using only one feature.

The input parameter NumComponents defines the number of components to which the feature vector is reduced if a preprocessing is selected that reduces the dimension of the feature vector. In particular,

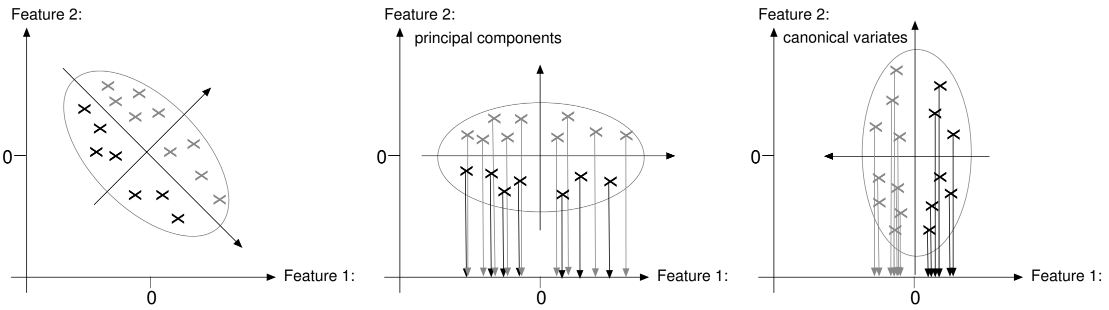

Figure 5.5: Here, after transforming the feature space via principal component analysis, the illustrated linearly separable classes still need two features to be separated. After transforming the feature space using canonical variates they can be separated by a single feature.

NumComponents has to be adjusted only if Preprocessing is set to 'principal_components' or 'canonical_variates'.

If Preprocessing is set to 'principal_components' or 'canonical_variates' you can use the operator get_prep_info_class_mlp to check if the content of the transformed feature vectors still contain significant data. Furthermore, you can use the operator to determine the optimum number of components. Then, you first create a test classifier with, e.g., NumComponents set to NumInput, generate and add the training samples to the classifier, and then apply get_prep_info_class_mlp. The output parameter CumInformationCont is a tuple containing numbers between 0 and 1. These numbers describe the amount of the original data that is covered by the transformed data. That is, if you want to have at least 90% of the original data covered by the transformed data, you search for the first value that is larger than 0.9 and use the corresponding index number of the tuple CumInformationCont as value for a new NumComponents. Then, you destroy the test classifier and create a new classifier for the final training (this time NumComponents is set to the new value). Note that it is suitable to store the samples into a file during the test training (write_samples_class_mlp) so that you do not have to successively add the training samples again but simply read in the sample file using read_samples_class_mlp.

Parameter RandSeed

The weights of the MLP (see section 3.4 on page 21) are initialized by a random number. For the sake of reproducibility the seed value for this random number is stored in the input parameter RandSeed.

Parameter MLPHandle

The output parameter of create_class_mlp is the MLPHandle, which is needed for all following classification specific operators.

5.3.2 Adjusting add_sample_class_mlp

A single sample is added to the MLP classifier using add_sample_class_mlp. For the training, several samples have to be added by successively calling add_sample_class_mlp with different samples. The following parameters can be adjusted:

Parameter MLPHandle

The input and output parameter MLPHandle is the handle of the classifier that was created with create_class_mlp and to which the samples subsequently were added with add_sample_class_mlp. After applying add_sample_class_mlp for all available samples, the handle is prepared for the actual training of the classifier.

Parameter Features

The input parameter Features contains the feature vector of a sample to be added to the classifier with add_sample_class_mlp. This feature vector is a tuple of values. Each value describes a specific numeric feature. Note that the feature vector must consist of real numbers. If you have integer numbers, you have to transform them into real numbers. Otherwise, an error message is raised.

Parameter Target

The input parameter Target describes the target vector, i.e., you assign the corresponding class ID to the feature vector.

If OutputFunction is set to 'softmax', the target vector is a tuple that contains exactly one element with the value 1 and several elements with the value 0. The size of the vector corresponds to the number of available classes specified by NumOutput inside create_class_mlp. The index of the element with the value 1 defines the class the feature vector Features belongs to. Alternatively, a single integer containing the class number (counted from 0) can be specified.

For OutputFunction set to 'logistic', the target vector consists of values that are either 0 or 1. Each 1 shows that the corresponding feature is present.

If OutputFunction is set to 'linear', the target vector can contain arbitrary real numbers. As this parameter value is used for least squares fitting (regression) and not for classification, it is not explained further.

5.3.3 Adjusting train_class_mlp

The training of the MLP classifier is applied with train_class_mlp. Training the MLP means to determine the optimum values of the MLP weights (see section 3.4 on page 21). For this, a sufficient number of training samples is necessary. Training is performed by a complex nonlinear optimization process that minimizes the discrepancy of the MLP output and the target vectors that were defined with add_sample_class_mlp. The following parameters can be adjusted:

Parameter MLPHandle

The input and output parameter MLPHandle is the handle of the classifier that was created with create_class_mlp and for which samples were stored either by adding them via add_sample_class_mlp or by reading them in with read_samples_class_mlp. After applying train_class_mlp, the handle is prepared for the actual classification of unknown data. That is, it then contains information about how to separate the classes.

Parameters MaxIterations / WeightTolerance / ErrorTolerance

The input parameters MaxIterations, WeightTolerance, and ErrorTolerance control the nonlinear optimization algorithm. MaxIterations specifies the number of iterations of the optimization algorithm. The optimization is terminated if the weight change is smaller than WeightTolerance and the change of the error is smaller than ErrorTolerance. In any case, the optimization is terminated after at most MaxIterations iterations. For the latter, values between 100 and 200 are sufficient in most cases. The default value is 200. By reducing this value, the speed of the training can be enhanced. For the parameters WeightTolerance and ErrorTolerance the default values do not have to be changed in most cases.

Parameter Error

The output parameter Error returns the error of the MLP with the optimal weights on the training samples.

Parameter ErrorLog

The output parameter ErrorLog returns the error value as a function of the number of iterations. This function can be used to decide if a second training with the same training samples but a different value for RandSeed should be applied, which is the case if the function runs into a local minimum.

5.3.4 Adjusting evaluate_class_mlp

The operator evaluate_class_mlp can be used to evaluate the probabilities for a feature vector to belong to each of the available classes. If only the probabilities for the two classes to which the feature vector most likely belongs are searched for, no evaluation is necessary, as these probabilities are returned also for the final classification of the feature vector. The following parameters can be adjusted:

Parameter MLPHandle

The input parameter MLPHandle is the handle of the classifier that was previously trained with the operator train_class_mlp.

Parameter Features

The input parameter Features contains the feature vector that is evaluated. The feature vector must consist of the same features as the feature vectors used for the training samples within add_sample_class_mlp.

Parameter Result

The output parameter Result returns the result of the evaluation. This result has different meanings, dependent on the OutputFunction that was set with create_class_mlp. If OutputFunction was set to 'softmax', which should be the case for most classification applications, the returned tuple consists of probability values. Each value describes the probability of the given feature vector to belong to the corresponding class. If OutputFunction was set to 'logistic', the elements of the returned tuple represent the presences of the respective independent attributes.

5.3.5 Adjusting classify_class_mlp

The operator classify_class_mlp classifies a feature vector according to the class boundaries that were derived during the training. It can only be called if OutputFunction was set to 'softmax' in create_class_mlp. The following parameters can be adjusted:

Parameter MLPHandle

The input parameter MLPHandle describes the handle that was created with create_class_mlp, to which samples were added with add_sample_class_mlp, and that was trained with train_class_mlp. The handle contains all the information that the classifier needs to assign an unknown feature vector to one of the available classes.

Parameter Features

The input parameter Features contains the feature vector of the object that is to be classified. The feature vector must consist of the same features as the feature vectors used for the training samples within add_sample_class_mlp.

Parameter Num

The input parameter Num specifies the number of best classes to be searched for. Generally, Num is set to 1 if only the class with the best probability is searched for, and to 2 if the second best class is also of interest, e.g., because the classes overlap.

Parameter Class

The output parameter Class returns the result of classifying the feature vector with the trained MLP classifier, i.e., a tuple containing Num elements. That is, if Num is set to 1, a single value is returned that corresponds to the class with the highest probability. If Num is set to 2, the first element contains the class with the highest probability and the second element contains the second best class.

Parameter Confidence

The output parameter Confidence outputs the confidence of the classification. Note that in comparison to the probabilities returned for a GMM classification, here the returned values can be influenced by outliers, which is caused by the specific way an MLP is calculated. For example, the confidence may be high for a feature vector that is far from the rest of the training samples of the specific class but significantly on the same side of the separating hypersurface. On the other side, the confidence can be low for objects that are significantly within the cluster of training samples of a specific class but near to the separating hypersurface as two classes overlap at this part of the cluster (see figure 5.6).

5.3.6 Adjusting clear_class_mlp

Parameter MLPHandle

To destroy the classifier, the operator clear_class_mlp is applied only with the input parameter MLPHandle. If several MLP classifiers were created, you can also destroy them all in one step using the operator clear_all_class_mlp. Then, no parameter has to be set.

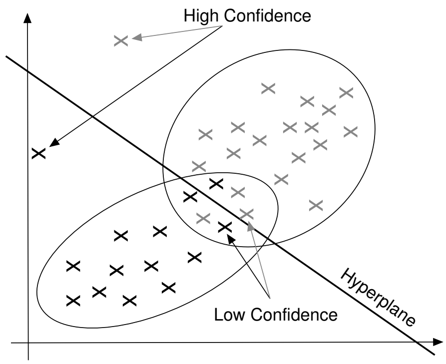

Figure 5.6: The confidence calculated for an MLP classification can be unexpected for outliers. That is, feature vectors that are far away from their class centers can be classified with high confidence or those that are near to the class centers but inside an overlapping area between two classes can be classified with low confidence.

5.4 Parameter Setting for SVM

This section goes deeper into the parameter adjustment for an SVM classification. We recommend to first adjust the parameters so that the classification result is satisfying. The most important parameters that have to be adjusted to get the SVM classifier work optimally are:

- `Nu` (`create_class_svm`)
- `KernelParam` (`create_class_svm`)

If the classification generally works, you can start to tune the speed. The most important parameters to enhance the speed are:

- `Preprocessing` (`create_class_svm`):

  A combination of `KernelType` set to `'rbf'` and the `Preprocessing` set to `'principal_components'` speeds up the SVM significantly (even faster than MLP), as the features are reduced and thus the dimension for the support vectors are reduced as well.

- `MaxError` (`reduce_class_svm`)

In the following, we introduce the parameters of the basic SVM operators. The focus is on the parameters for which the setting is not immediately obvious or for which it is not immediately obvious how they influence the classification. These are mainly the parameters needed for the creation and training of the classifier. Further information about these operators as well as the usage of the operators with obvious parameter settings are provided in the Reference Manual entries for the individual operators.

5.4.1 Adjusting create_class_svm

An SVM classifier is created with the operator create_class_svm. There, several properties of the classifier are defined that are important for the following classification steps. The returned handle is needed (and modified) in all following steps. For the operator, the following parameters can be adjusted:

Parameter NumFeatures

The input parameter NumFeatures specifies the dimension of the feature vectors used for the training as well as for the classification. Opposite to the GMM classifier (see section 5.5 on page 50), a number of 500 features is still realistic.

Parameters KernelType / KernelParam

In section 3.5 on page 23 we saw for an SVM classification that the feature space is transformed into a higher feature space by a kernel to get linearly separable classes. The input parameter KernelType defines how the feature space is mapped into this higher dimension. The mapping that is suitable and recommended in most cases uses a kernel that is based on the Gauss error distribution curve and is called Gaussian radial basis function kernel ('rbf').

If KernelType is set to 'rbf', the input parameter KernelParam is used to adjust the γ of the error curve (see figure 5.7) and should be adjusted very carefully. If the value for γ is very high, the number of support vectors increases, which results on one hand in an overfitting, i.e., the generalization ability of the classifier is lost (for overfitting see also the description of NumHidden in section 5.3.1 on page 36) and on the other hand the speed is reduced. On the other side, with a very low value for γ, an underfitting occurs, i.e., the number of support vectors is not sufficient to obtain a satisfying classification result.

It is recommended to start with a small γ and then progressively increase it. Generally, it is recommended to simultaneously search for a suitable Nu-γ pair, as these together define how complex the separating hypersurface becomes. The search can be applied, e.g., using the cross validation that is described in section 8.1 on page 103.

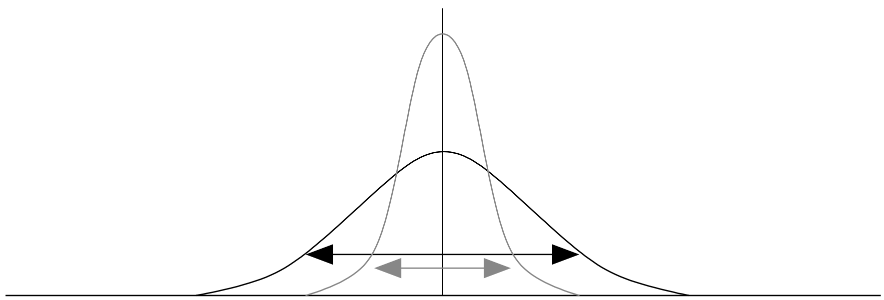

Figure 5.7: γ describes the amount of influence of a support vector upon it's surrounding.

Besides 'rbf', you can also select a linear or polynomial kernel for KernelType, but these kernels should be used only in very special cases (see below).

The linear kernel (KernelType set to 'linear') transforms the feature space using a dot product. The linear kernel should be used only if the classes are expected to be linearly separable. If a linear kernel is selected, the parameter KernelParam has no meaning and can be ignored.

The polynomial kernels (KernelType set to 'polynomial_homogeneous' or 'polynomial_inhomogeneous') in very rare cases can be used if the classification with 'rbf' was not successful, but in most cases, 'rbf' leads to a better result. If a polynomial kernel is selected, the parameter KernelParam describes the degree 'd' of the polynom. Note that a degree higher than 10 might result in numerical problems.

Parameter Nu

For classes that are not linearly separable, data from different classes may overlap. The input parameter Nu regularizes the separation of the classes, i.e., with Nu, the upper bound for training errors within the overlapping areas between the classes is adjusted (see figure 5.8) and at the same time the lower bound for the number of support vectors is determined. Nu should be adjusted very carefully. It's value must be a real number between 0 and 1. As a rule of thumb, it should be set to the expected error ratio of the specific data set, e.g., to 0.05 when expecting a maximum training error of 5%. The training error occurs because of, e.g., overlapping classes. Note that a very large Nu results in a large data set and thus reduces the speed significantly. Additionally, with a very large Nu the training may be aborted and an error handling message is raised. Then, Nu has to be chosen smaller. On the other hand, a very small Nu leads to instable numerics, i.e., many feature vectors would be classified incorrectly.

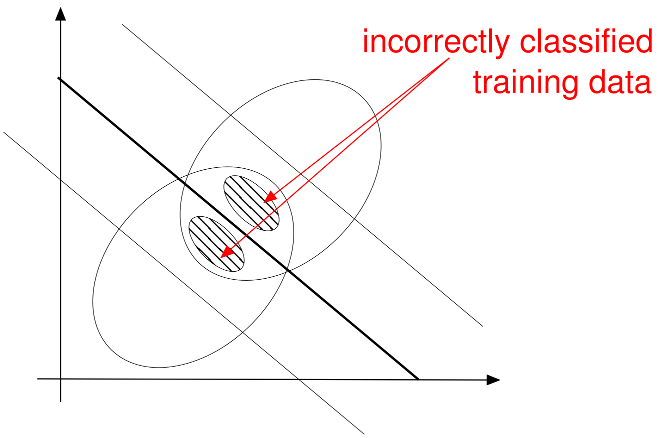

Figure 5.8: The parameter Nu determines the amount of the incorrectly classified training data within the overlap between two classes.

To select a suitable value for Nu, it is recommended to start with a small value and then progressively increase it. Generally, it is recommended to simultaneously search for a suitable Nu-γ pair, as these together define how complex the separating hypersurface becomes. The search can be applied, i.e., using the cross validation that is described in section 8.1 on page 103.

Parameter NumClasses

The input parameter NumClasses specifies the number of classes.

Parameter Mode

As we saw in section 3.5 on page 23, SVM can handle only two-class problems. With the input parameter Mode you define if your application is a two-class problem or if you want to extent the SVM to a multi-class problem.

Having a two-class problem, you have training data for a single class and decide during the classification if a feature vector belongs to the trained class or not. That is, the hyperplane lies around the training data and implicitly separates the training data from a rejection class. This Mode is called 'novelty-detection' and can only be applied if KernelType is set to 'rbf'.

If you want to extent the SVM to a multi-class problem, you have to divide the decision into binary sub-cases. There, you have two possibilities. Either, you set Mode to 'one-versus-one' or you set it to 'one-versus-all'.

When using the mode 'one-versus-one', for each pair of classes a binary classifier is created and the class that wins most comparisons is selected. Here, n classes result in n(n-1)/2 classifiers. This approach is fast but suitable only for a small number of classes (approximately up to 10).

For 'one-versus-all', each class is compared to the rest of the training data and the class with the maximum distance to the hypersurface is selected. Here, the number of needed binary classifiers corresponds to the number of classes. This approach is not as fast as 'one-versus-one', but can and should be used for a higher number of classes.

Parameters Preprocessing / NumComponents

The input parameter Preprocessing defines the type of preprocessing applied to the feature vector for the training as well as later for the classification or evaluation. A preprocessing of the feature vector can be used to speed up the training as well as the classification. Sometimes, even the recognition rate can be enhanced.

Available values are 'none', 'normalization', 'principal_components', and 'canonical_variates'. In most cases, the preprocessing should be set to 'normalization' as it enhances the speed without loosing relevant information compared to using no preprocessing ('none'). The values 'principal_components' and in rare cases 'canonical_variates' can be used to enhance the speed. As the preprocessing types are the same as used for an MLP classification, we refer to section 5.3.1 on page 38 for further information.

The input parameter NumComponents defines the number of components to which the feature vector is reduced if a preprocessing is selected that reduces the dimension of the feature vector. In particular, NumComponents has to be adjusted only if Preprocessing is set to 'principal_components' or 'canonical_variates'. If Preprocessing is set to 'principal_components' or 'canonical_variates' you can use the operator get_prep_info_class_svm to determine the optimum number of components as described in section 5.3.1 on page 38.

Parameter SVMHandle

The output parameter of create_class_svm is the SVMHandle, which is needed for all following classification specific operators.

5.4.2 Adjusting add_sample_class_svm

A single sample is added to the SVM classifier using add_sample_class_svm. For the training, several samples have to be added by successively calling add_sample_class_svm with different samples. The following parameters can be adjusted:

Parameter SVMHandle

The input and output parameter SVMHandle is the handle of the classifier that was created with create_class_svm and to which the samples subsequently are added with add_sample_class_svm. After applying add_sample_class_svm for all available samples, the handle is prepared for the actual training of the classifier.

Parameter Features

The input parameter Features contains the feature vector of a sample to be added to the classifier with add_sample_class_svm. This feature vector is a tuple of values. Each value describes a specific numeric feature. Note that the feature vector must consist of real numbers. If you have integer numbers, you have to transform them into real numbers. Otherwise, an error message is raised.

Parameter Class

The input parameter Class contains the ID of the class the feature vector belongs to. The ID is an integer number between 0 and 'Number of Classes -1'. If you created a tuple with class names, the class ID is the index of the corresponding class name in the tuple.

5.4.3 Adjusting train_class_svm

The training of the SVM classifier is applied with train_class_svm. The following parameters can be adjusted:

Parameter SVMHandle

The input and output parameter SVMHandle is the handle of the classifier that was created with create_class_svm and for which samples were stored either by adding them via add_sample_class_svm or by reading them in with read_samples_class_svm. After applying train_class_svm, the handle is prepared for the actual classification of unknown data. That is, it then contains information about how to separate the classes.

Parameter Epsilon

Training the SVM means to gradually optimize the function that determines the class boundaries. This optimization stops if the gradient of the function falls below a certain threshold. This threshold is set with the input parameter Epsilon. In most cases it should be set to the default value, which is 0.001. With a too small threshold, the optimization becomes slower without leading to a better recognition rate. With a too large threshold, the optimization stops before the optimum is found, i.e., the recognition rate may be not satisfying.

There are two cases, in which changing the value of Epsilon might be reasonable. First, when having a very small Nu and a small or unbalanced set of training data, it may be suitable to set Epsilon smaller than the default value to enhance the resulting recognition rate. Second, when applying a cross validation to search for a suitable Nu-γ pair (see section 8.1 on page 103), it is recommended to select a larger value for Epsilon during the search. Thus, the cross validation is sped up without significantly changing the parameters for the optimal kernel. Having found the optimal Nu-γ pair, the final training is applied again with the small (default) value.

Parameter TrainMode

The input parameter TrainMode determines the mode for the training. We recommend to use the mode 'default' in most cases. There, the whole set of available samples is trained in one step. Appending a new set of samples to a previously applied training is possible with the mode 'add_sv_to_train_set'. This mode has some advantages that are listed in the Reference Manual entry for train_class_svm, but you have to be aware that only the support vectors that resulted from the previously applied training are reused. The samples of the previously applied training are ignored. This most likely leads to a different hypersurface than obtained with a training that uses all available training samples in one step. The risk of obtaining a hypersurface that is not suitable for all available samples is illustrated in figure 5.9.

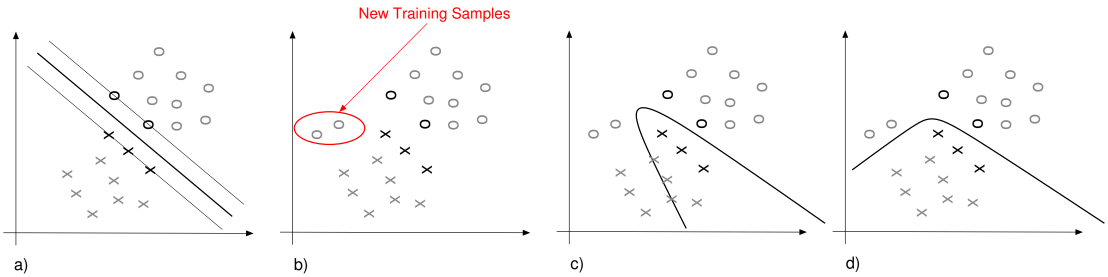

Figure 5.9: Risk of appending a second training: a) training samples of the first training and the obtained hypersurface, b) new samples added for a second training, c) hypersurface obtained by a second training using the new samples with the support vectors obtained by the first training, d) hypersurface obtained by a new training that uses all available samples.

5.4.4 Adjusting reduce_class_svm

The operator reduce_class_svm can be used to reduce the number of support vectors that were returned by the training. This is suitable to speed up the online classification. The following parameters can be adjusted:

Parameter SVMHandle

The input parameter SVMHandle is the handle of the classifier that was created with create_class_svm, to which training samples were added with add_sample_class_svm, and which was trained with train_class_svm. reduce_class_svm does not modify the handle but creates a copy of it (SVMHandleReduced) and modifies the copy.

Parameters Method / MinRemainingSV / MaxError

The input parameter Method defines the method used to reduce the number of support vectors. Momentarily, only the method 'bottom_up' is available. There, the number of support vectors is reduced by iteratively merging the support vectors until either the minimum number of support vectors that is set with MinRemainingSV is reached, or until the accumulated maximum error exceeds the threshold that is set with MaxError.

Note that the approximation of the original support vectors by a reduced number of support vectors reduces also the complexity of the hypersurface and thus can lead to a poor classification rate. A common approach is to start with a small value for MaxError, e.g, 0.0001, and to increase it step by step. To control the reduction ratio, the number of remaining support vectors is checked by get_support_vector_num_class and the classification rate is checked by classifying a separate test data with classify_class_svm.

Parameter SVMHandleReduced

The output parameter SVMHandleReduced returns the copied and modified handle of a classifier that has the same parameterization as the original handle but a different support vector expansion. Additionally, it does not contain the training samples that are stored with the original handle.

5.4.5 Adjusting classify_class_svm

The operator classify_class_svm is used to decide to which of the trained classes an unknown feature vector belongs. The following parameters can be adjusted:

Parameter SVMHandle

The input parameter SVMHandle describes the handle that was created with create_class_svm, to which samples were added with add_sample_class_svm, and that was trained with train_class_svm. The handle contains all the information that the classifier needs to assign an unknown feature vector to one of the available classes.

Parameter Features

The input parameter Features contains the feature vector of the object that is to be classified. The feature vector must consist of the same features as the feature vectors used for the training samples within add_sample_class_svm.

Parameter Num

The input parameter Num specifies the number of best classes to be searched for. Generally, Num is set to 1 if only the class with the best probability is searched for, and to 2 if the second best class is also of interest, e.g., because the classes overlap. If Mode was set to 'novelty-detection' in create_class_svm, Num must be set to 1.

Parameter Class

The output parameter Class returns the result of classifying the feature vector with the trained SVM classifier. This result depends on the Mode that was selected in create_class_svm. If Mode was set to 'one-versus-one', it contains the classes ordered by the number of votes of the sub-classifiers. That is, the first element of the returned tuple is the class with the most votes, the second is the class with the second most votes etc. If Mode was set to 'one-versus-all', it contains the classes ordered by the value of each sub-classifier. That is, the first element of the returned tuple is the class with the highest value, the second element is the class with the second best value. If Mode was set to 'novelty-detection', a single value is returned (Num must be set to 1). In particular, the value is 1 if the feature vector belongs to the trained class and 0 if the feature vector belongs to the rejection class.

5.4.6 Adjusting clear_class_svm

To destroy the classifier, the operator clear_class_svm is applied only with the input parameter SVMHandle. If several SVM classifiers were created, you can also destroy them all in one step using the operator clear_all_class_svm. Then, no parameter has to be set.

5.5 Parameter Setting for GMM

This section goes deeper into the parameter adjustment for a GMM classification. We recommend to first adjust the parameters so that the classification result is satisfying. The most important parameters that have to be adjusted to get the GMM classifier work optimally are:

- NumDim (create_class_gmm)
- NumCenters (create_class_gmm)
- CovarType (create_class_gmm)
- ClassPriors (train_class_gmm)

If the classification generally works, you can start to tune the speed. The most important parameters to enhance the speed are:

- CovarType (create_class_gmm)
- Preprocessing / NumComponents (create_class_gmm)

In the following, we introduce the parameters of the basic GMM operators. The focus is on the parameters for which the setting is not immediately obvious or for which it is not immediately obvious how they influence the classification. These are mainly the parameters needed for the creation and training of the classifier. Further information about these operators as well as the usage of the operators with obvious parameter settings are provided in the Reference Manual entries for the individual operators.

5.5.1 Adjusting create_class_gmm

A GMM classifier is created with the operator create_class_gmm. There, several properties of the classifier are defined that are important for the following classification steps. The returned handle is needed (and modified) in all following steps. The following parameters can be adjusted:

Parameter NumDim

The input parameter NumDim specifies the dimension of the feature vectors used for the training as well as for the classification.

Note that GMM works optimally only for a limited number of features! If the result of the classification is not satisfying, maybe you have used too much features as input. As a rule of thumb, a number of 15 features should not be exceeded (although some applications work also for larger feature vectors). If your application needs significantly more features, in many cases an MLP or SVM classification is to be preferred.

Parameter NumClasses

The input parameter NumClasses specifies the number of classes.

Parameter NumCenters

As we learned in section 3.3 on page 18 a GMM class can consist of different Gaussian centers (see also figure 5.10). The input parameter NumCenters defines the number of Gaussian centers per class. You can specify this number in different ways. That is, you can either specify a single number of centers, then each class has exactly this number of class centers. Or you can specify the allowed lower and upper bound for the number of centers. This can be done either with a single range for all classes or with a range for each class individually. From these bounds, the optimum of centers is determined with the help of the Minimum Message Length Criterion (MML). In most cases, it is recommended to specify a range for all classes and to start with a high value as upper bound and the expected number of centers as lower bound. If the classification is successful, you can try to reduce the range to enhance the speed.

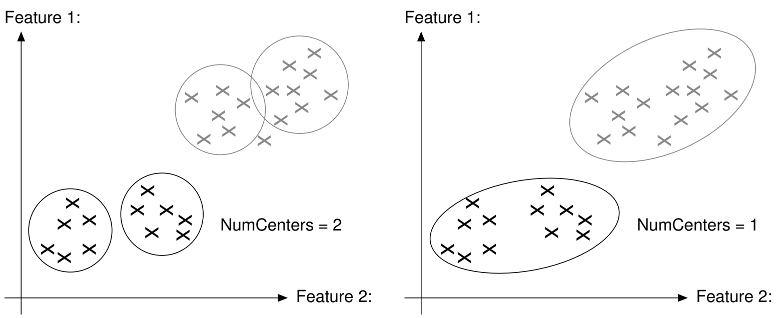

Figure 5.10: Number of Gaussian centers of a class: (left) 2 and (right) 1.

Note that if the training is canceled with the error message 3335 ('Internal error while training the GMM'), most probably the value for NumCenters is not optimal.

Parameter CovarType

The input parameter CovarType defines the type of the covariance matrix used to calculate the probabilities. With this, you can further constrain the MML, which is used to determine the optimum of centers. Three types of covariance matrices are available. If you use the default, 'spherical', the covariance matrix is a scalar multiple of the identity matrix. With the value 'diag' a diagonal matrix is obtained and with 'full' the covariance matrix is positive definite (see figure 5.11). Note that the flexibility of the centers but also the complexity of the calculations increases from 'spherical' over 'diag' to 'full'. That is, you have to decide whether you want to increase the flexibility of the classifier or if you want to increase the speed.

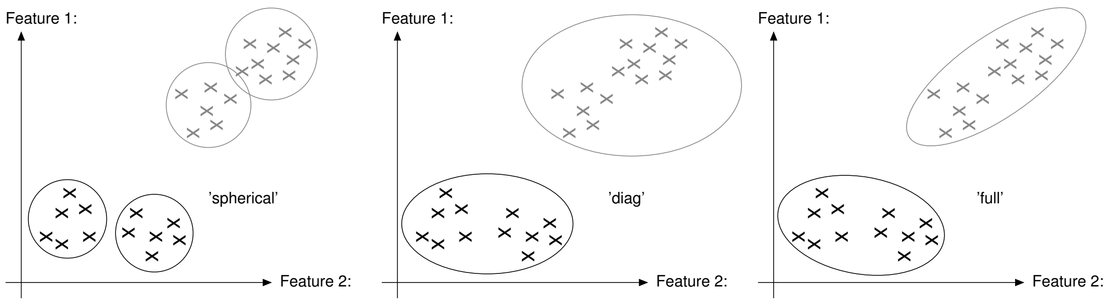

Figure 5.11: The covariance type set to (from left to right) 'spherical', 'diag', and 'full'.

Parameters Preprocessing / NumComponents

The input parameter Preprocessing defines the type of preprocessing applied to the feature vector for the training as well as later for the classification or evaluation. A preprocessing of the feature vector can be used to speed up the training as well as the classification. Sometimes, even the recognition rate can be enhanced.

Available values are 'none', 'normalization', 'principal_components', and 'canonical_variates'. In most cases, Preprocessing should be set to 'normalization' as it enhances the speed without loosing relevant information compared to using no preprocessing ('none'). The values 'principal_components' and in rare cases 'canonical_variates' can be used to enhance the speed. As the preprocessing types are the same as used for an MLP classification, we refer to section 5.3.1 on page 38 for further information.

The input parameter NumComponents defines the number of components to which the feature vector is reduced if a preprocessing is selected that reduces the dimension of the feature vector. In particular, NumComponents has to be adjusted only if Preprocessing is set to 'principal_components' or 'canonical_variates'. If Preprocessing is set to 'principal_components' or 'canonical_variates' you can use the operator get_prep_info_class_gmm to determine the optimum number of components as described in section 5.3.1 on page 38.

Parameter RandSeed

The coordinates of the centers are initialized by a random number. For the sake of reproducibility the seed value for this random number is stored in the input parameter RandSeed.

Parameter GMMHandle

The output parameter of create_class_gmm is the GMMHandle, which is needed for all following classification specific operators.

5.5.2 Adjusting add_sample_class_gmm

A single sample is added to the GMM classifier using add_sample_class_gmm. For the training, several samples have to be added by successively calling add_sample_class_gmm with different samples. The following parameters can be adjusted:

Parameter GMMHandle

The input and output parameter GMMHandle is the handle of the classifier that was created with create_class_gmm and to which the samples subsequently were added with add_sample_class_gmm. After applying add_sample_class_gmm for all available samples, the handle is prepared for the actual training of the classifier.

Parameter Features

The input parameter Features contains the feature vector of a sample to be added to the classifier with add_sample_class_gmm. This feature vector is a tuple of values. Each value describes a specific numeric feature. Note that the feature vector must consist of real numbers. If you have integer numbers, you have to transform them into real numbers. Otherwise, an error message is raised.

Parameter ClassID

The input parameter ClassID contains the ID of the class the feature vector belongs to. The ID is an integer number between 0 and 'Number of Classes -1'. If you created a tuple with class names, the class ID is the index of the corresponding class name in the tuple.

Parameter Randomize

The input parameter Randomize defines the standard deviation of the Gaussian noise that is added to the training data. This value is needed mainly for originally integer feature values. There, the modeled Gaussians may be aligned along axis directions and thus lead to an unusually high number of centers returned by train_class_gmm (see figure 5.12). This effect can be prevented by setting Randomize to a value larger than 0. According to experience, a value between 1.5 and 2 in most cases leads to a satisfying result. If the feature vector has been created from integer data by scaling, Randomize must be scaled with the same scale factor that was used to scale the original data.

5.5.3 Adjusting train_class_gmm

The training of the GMM classifier is applied with train_class_gmm. The following parameters can be adjusted:

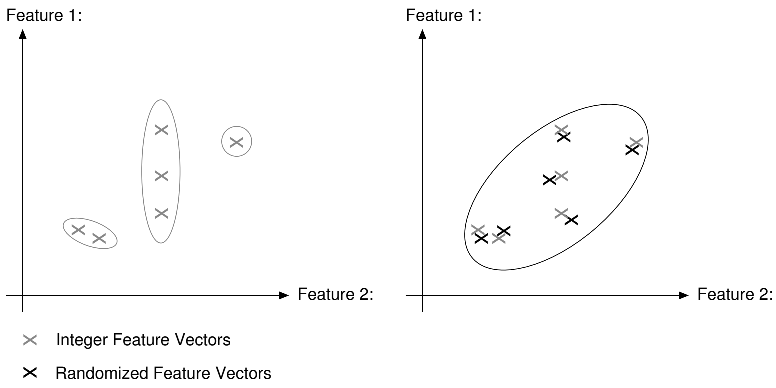

Figure 5.12: Adding noise to integer values: (left) the integer feature vectors lead to many classes, whereas for the (right) randomized feature vectors one class is obtained.

Parameter `GMMHandle`

The input and output parameter `GMMHandle` is the handle of the classifier that was created with `create_class_gmm` and for which samples were stored either by adding them via `add_sample_class_gmm` or by reading them in with `read_samples_class_gmm`. After applying `train_class_gmm`, the handle is prepared for the actual classification of unknown data. That is, it then contains information about how to separate the classes.

Parameters `MaxIter` / `Threshold`

The input parameter `MaxIter` defines the maximum number of iterations used for the expectation minimization algorithm. The input parameter `Threshold` defines the threshold for the relative change of the error for the expectation minimization algorithm to terminate. By reducing the number of iterations, the speed can be optimized for specific applications. But note that in most cases, the parameters `MaxIter` and `Threshold` should be used with the default values.

Parameter `ClassPriors`

The input parameter `ClassPriors` is used to select the mode for determining the probability of the occurrence of a class (see also section 3.3 on page 18). That is, `ClassPriors` determines if a weighting of the classes is used that is derived from the proportion of the corresponding sample data used for the training (`ClassPriors` set to `'training'`) or if all classes have the same weight (`ClassPriors` set to `'uniform'`), i.e., the weight is `1/NumClasses` for all classes (see figure 5.13). By default, the mode `'training'` is selected, i.e., the probability of the occurrence of a class is derived from the frequency of the class in the training set. If your training data is not representative for the frequency of the individual classes, you should use `'uniform'` instead.

Parameter `Regularize`

The input parameter `Regularize` is used to prevent the covariance matrix from a collapse which can occur for linearly dependent data. Here, we recommend to use the default value, which is `0.0001`.

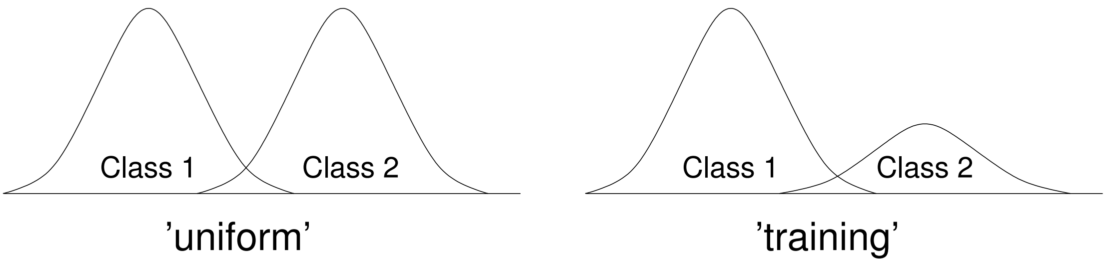

Figure 5.13: Probability of the occurrence of a class set to (left) 'uniform' and (right) 'training'.

Parameter `Centers`

The output parameter `Centers` returns the number of found centers per class.

Parameter `Iter`

The output parameter `Iter` returns the number of iterations that were executed for the expectation minimization algorithm for each class.

5.5.4 Adjusting `evaluate_class_gmm`

The operator `evaluate_class_gmm` can be used to evaluate the probabilities for a feature vector to belong to each of the available classes. If only the probabilities for the most probable classes are searched for, no evaluation is necessary, as these probabilities are returned also for the final classification of the feature vector. The following parameters can be adjusted:

Parameter `GMMHandle`

The input parameter `GMMHandle` is the handle of the classifier that was previously trained with the operator `train_class_gmm`.

Parameter `Features`

The input parameter `Features` contains the feature vector that is evaluated. The feature vector must consist of the same features as the feature vectors used for the training samples within `add_sample_class_gmm`.

Parameter `ClassProb`

The output parameter `ClassProb` returns the a-posteriori probabilities of the given feature vector to belong to each of the classes.

Parameter `Density`

The output parameter `Density` returns the probability density of the feature vector.

Parameter KSigmaProb

The output parameter KSigmaProb describes the probability that another sample lies farther away from the mean. This value can be used for novelty detection. Then, all feature vectors with a KSigmaProb value below a certain k-sigma probability, e.g., 0.0001, can be rejected.

5.5.5 Adjusting classify_class_gmm

The operator classify_class_gmm is used to decide to which of the trained classes an unknown feature vector belongs. The following parameters can be adjusted:

Parameter GMMHandle

The input parameter GMMHandle describes the handle that was created with create_class_gmm, to which samples were added with add_sample_class_gmm, and that was trained with train_class_gmm. The handle contains all the information that the classifier needs to assign an unknown feature vector to one of the available classes.

Parameter Features

The input parameter Features contains the feature vector of the object that is to be classified. The feature vector must consist of the same features as the feature vectors used for the training samples within add_sample_class_gmm.

Parameter Num

The input parameter Num specifies the number of best classes to be searched for. Generally, Num is set to 1 if only the class with the best probability is searched for, and to 2 if the second best class is also of interest, e.g., because the classes overlap.

Parameter ClassID

The output parameter ClassID returns the result of classifying the feature vector with the trained GMM classifier, i.e., a tuple containing Num elements. That is, if Num is set to 1, a single value is returned that corresponds to the class with the highest probability. If Num is set to 2, the first element contains the class with the highest probability and the second element contains the second best class.

The following parameters output the probabilities of the classes. In comparison to the confidence value returned for an MLP classification (see section 5.3.5 on page 42), the returned values are rather reliable.

Parameter ClassProb

The output parameter ClassProb returns the a-posteriori probabilities of the given feature vector to belong to each of the classes. In contrast to the ClassProb returned by evaluate_class_gmm, the probability is further normalized.

Parameter Density

The output parameter Density returns the probability density of the feature vector.

Parameter KSigmaProb

The output parameter KSigmaProb describes the probability that another sample lies farther away from the mean. This value can be used for novelty detection. Then, all feature vectors with a KSigmaProb value below a certain k-sigma probability, e.g., 0.0001, can be rejected.

5.5.6 Adjusting clear_class_gmm

To destroy the classifier, the operator clear_class_gmm is applied only with the input parameter GMMHandle. If several GMM classifiers were created, you can also destroy them all in one step using the operator clear_all_class_gmm. Then, no parameter has to be set.

Chapter 6

Classification for Image Segmentation

If classification is used to find objects in an image, the individual pixels of an image are classified according to the features 'color' or 'texture' and all pixels belonging to the same class are combined in a region representing the desired object. That is, the image is segmented into regions of different classes.

For image segmentation, the pixels of an image are classified according to a set of available classes, which are defined by the training samples. The training samples are image regions of known classes. The features used for the training of the classes as well as for the classification are color or texture. Such a pixel-based classification can be realized by several approaches in HALCON. These are MLP, SVM, and GMM classifiers (see section 6.1) and some simple but fast classifiers that use a 2D histogram to segment two-channel images (see section 6.2 on page 77) or that apply a hyperbox or Euclidean classification for multi-channel images (see section 6.3 on page 78).

6.1 Proceeding for MLP, SVM, and GMM

The set of operators used for image segmentation with MLP, SVM, and GMM in parts corresponds to the set of operators used for the general classification described in section 5 on page 29. Operators that are specific for image segmentation are the operators that add the training samples to the classifier and the operators used for the actual classification. These are used instead of the corresponding general operators.

In section 6.1.1, the general proceeding for image segmentation is illustrated by different examples that on the one hand show how to segment different citrus fruits from the background using color and on the other hand show how to apply novelty detection for a regular mesh using texture. In section 6.1.2 the steps of an image segmentation and the involved operators are listed for a brief overview. The parameters of the operators that are specific for image segmentation are introduced in more detail in section 6.1.3 for MLP, section 6.1.4 for SVM, and section 6.1.5 for GMM.

Finally, section 6.1.6 shows how to speed up an image segmentation for images with a maximum of three image channels by applying a classification that is based on look-up tables (LUT). Here, the trained classifier is used to create a look-up table that stores every possible response of the MLP, SVM, or GMM, respectively. Using the LUT-accelerated classifier instead of the original trained classifier, the class of every image point can be taken directly from the LUT instead of being calculated expensively. But note that for a LUT-accelerated classification also additional memory is needed and the runtime for the offline part is increasing.

6.1.1 General Proceeding

Figure 6.1 shows the general proceeding for image segmentation. The main difference to the general classification approach is that on the one hand the objects to classify are restricted to pixels and on the other hand the features are not explicitly extracted but automatically derived from the different channels of a color or texture image. Thus, you do not have to apply a feature extraction for the training and once again for the classification, but simply apply a training using some sample regions of multi-channel images and then you can immediately use the trained classifier to segment images into regions of the trained color or texture classes.

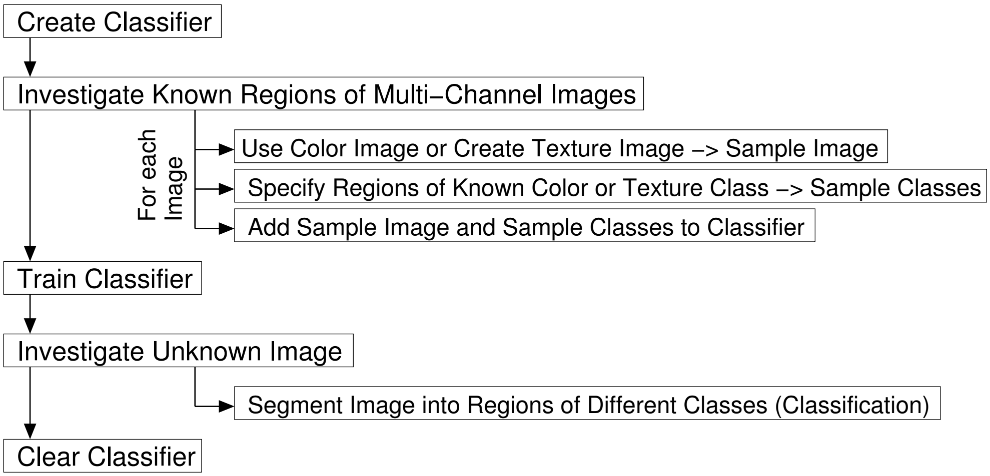

Figure 6.1: The basic steps of image segmentation.

Besides the classical image segmentation, the operators for SVM and GMM can be used also for novelty detection. Then, for SVM only one class is trained and the classification returns the pixels that significantly deviate from the class. For GMM, one or more classes can be trained and the classification rejects the pixels that significantly deviate from any of the classes. That is, the 'novelties' (or defects, respectively) within an image are those pixels that are not assigned to one of the trained classes. The following examples demonstrate how to apply classical image segmentation and novelty detection.

6.1.1.1 Image Segmentation

The example `solution_guide\classification\segment_citrus_fruits.hdev` shows how to segment an image to separate lemons and oranges from their background. The lemons and oranges were already introduced in section 3 on page 15. There, a general classification with shape features was proposed to distinguish the lemons from the oranges. The corresponding example can be found in section 8.3.1 on page 107. Here, the lemons and oranges are separated from the background using their color, i.e., the feature vectors are built by the gray values of three image channels. The classification is applied with the MLP approach. The operator names for the GMM or SVM classification differ only in their ending. That is, if you want to apply a GMM or an SVM classification, you mainly have to replace 'mlp' by 'gmm' or 'svm' in the specific operator names and adjust different parameters. The parameters of the operators that correspond to the general classification and their selection are described in section 5.3 for MLP, section 5.4 for SVM, and section 5.5 for GMM. The parameters of the operators that are specific for image segmentation and their selection are described in section 6.1.3 for MLP, section 6.1.4 for SVM, and section 6.1.5 for GMM.

The program starts with the creation of an MLP classifier. Following the instructions given in section 5.3.1 on page 36 the parameter `NumInput` is set to `3` as the images consist of three channels, which leads to three features for the feature vectors, the parameter `NumHidden` is set to `3` so that it is in a similar value range as `NumInput` and `NumOutput`, and `NumOutput` is set to `3` as three classes are used: one for the oranges, one for the lemons, and one for the background. `OutputFunction` must be set to `'softmax'` for image segmentation. `Preprocessing` is set to `'normalization'`, so `NumComponents` can be ignored. The operator returns the handle of the new classifier that is needed for the following steps.

```
create_class_mlp (3, 3, 3, 'softmax', 'normalization', 10, 42, MLPHandle)
```

Now, an image containing oranges is read and a region for the class `'orange'` and one for the class `'background'` are created (see figure 6.2, left). As no lemon is contained in the image, an empty region is created by `gen_empty_region`. All three regions are concatenated to a tuple with `concat_obj` and are then added together with the input image and the handle of the classifier to the classifier with `add_samples_image_class_mlp`.

```
read_image (Image, 'color/citrus_fruits_01')
gen_rectangle1 (OrangeRegion, 100, 130, 230, 200)
gen_rectangle1 (BackgroundRegion, 30, 20, 50, 50)
gen_empty_region (EmptyRegion)
gen_empty_obj (TrainingRegions1)
concat_obj (TrainingRegions1, OrangeRegion, TrainingRegions1)
concat_obj (TrainingRegions1, EmptyRegion, TrainingRegions1)
concat_obj (TrainingRegions1, BackgroundRegion, TrainingRegions1)
add_samples_image_class_mlp (Image, TrainingRegions1, MLPHandle)
```

A second image is read that contains lemons. Now, a region for the class `'lemons'` and one for the class `'background'` are generated (see figure 6.2, right) and are concatenated together with an empty region to a tuple of regions. The sequence of the contained regions is the same as for the image with the oranges, i.e., the first element contains the region for oranges (in this case an empty region), the second element contains the region for lemons, and the third element contains the region for the background. Then, the operator `add_samples_image_class_mlp` is called again to extent the samples that are already added to the classifier.

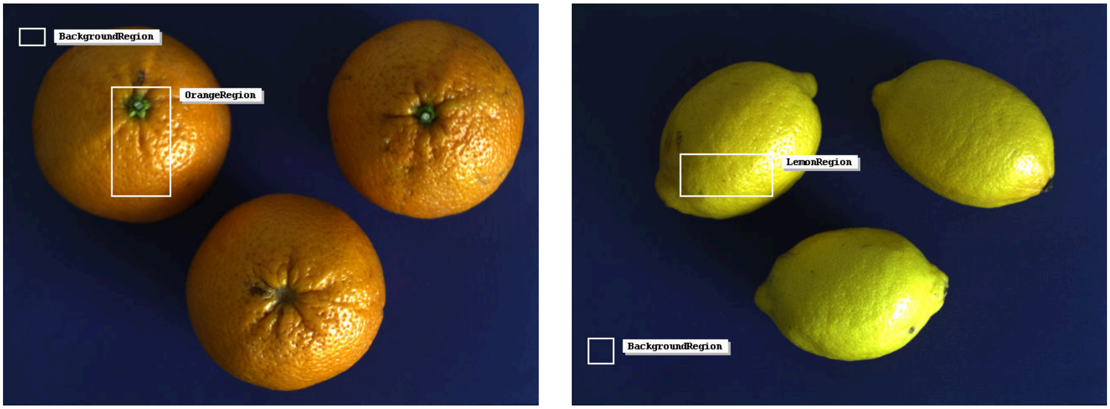

Figure 6.2: Regions from two images are used as training regions.

```
read_image (Image, 'color/citrus_fruits_03')
gen_rectangle1 (LemonRegion, 180, 130, 230, 240)
gen_rectangle1 (BackgroundRegion, 400, 20, 430, 50)
gen_empty_obj (TrainingRegions2)
concat_obj (TrainingRegions2, EmptyRegion, TrainingRegions2)
concat_obj (TrainingRegions2, LemonRegion, TrainingRegions2)
concat_obj (TrainingRegions2, BackgroundRegion, TrainingRegions2)
add_samples_image_class_mlp (Image, TrainingRegions2, MLPHandle)
```

After adding all training regions, the classifier is trained.

```
train_class_mlp (MLPHandle, 200, 1, 0.01, Error, ErrorLog)
```

Now, a set of images is read and segmented according to the rules that the classifier derived from the training. The result is a region for each class.

```
for i := 1 to 15 by 1
    read_image (Image, 'color/citrus_fruits_'+ i$'.2d')
    classify_image_class_mlp (Image, ClassRegions, MLPHandle, 0.5)
    select_obj (ClassRegions, ClassOranges, 1)
    select_obj (ClassRegions, ClassLemons, 2)
    select_obj (ClassRegions, ClassBackground, 3)
    dev_set_draw ('fill')
    dev_display (Image)
    dev_set_color ('slate blue')
    dev_display (ClassBackground)
    dev_set_color ('goldenrod')
    dev_display (ClassOranges)
    dev_set_color ('yellow')
    dev_display (ClassLemons)
```

The result of the segmentation is visualized by three different colors. Note that the colors applied in the example and the colors used for the representation in figure 6.3 vary because different colors are suited for print purposes and for the presentation on a screen. Note further, that the erroneously classified pixels have their reason in the overlapping classes that occur because of gray shadings that affected both types of fruits.

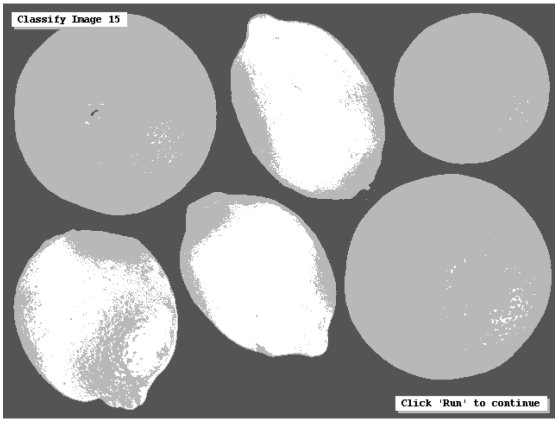

Figure 6.3: Segmentation of the image into the classes (dim gray) `'background'`, (gray) `'oranges'`, and (white) `'lemons'`. Erroneously classified pixels at the border of the lemons occur, because the shadows at the border of both fruit types have the same color.

For a better result, the illumination could have been adjusted more carefully to avoid shadings and reflections of the fruits. Additionally, many more samples would have been needed for a 'real' application. Note that this example mainly aims to demonstrate the general proceeding of an image segmentation. But even with the few erroneously classified pixels, a class decision can be found for each fruit. For that, we apply a post processing. That is, for each fruit class we use morphological operators to close small gaps, apply the operator `connection` to separate connected components, and then select those shapes from the connected components that exceed a specific size. Additionally, holes inside the regions are filled up with `fill_up` and the shapes of the regions are transformed to their convex hulls with `shape_trans`. The result is shown in figure 6.4. At the end of the program, the classifier is cleared.

```
    closing_circle (ClassOranges, RegionClosingOranges, 3.5)
    connection (RegionClosingOranges, ConnectedRegionsOranges)
    select_shape (ConnectedRegionsOranges, SelectedRegionsOranges, 'area', \
                  'and', 20000, 99999)
    fill_up (SelectedRegionsOranges, RegionFillUpOranges)
    shape_trans (RegionFillUpOranges, RegionFillUpOranges, 'convex')
    closing_circle (ClassLemons, RegionClosingLemons, 3.5)
    connection (RegionClosingLemons, ConnectedRegionsLemons)
    select_shape (ConnectedRegionsLemons, SelectedRegionsLemons, 'area', \
                  'and', 15000, 99999)
    fill_up (SelectedRegionsLemons, RegionFillUpLemons)
    shape_trans (RegionFillUpLemons, RegionFillUpLemons, 'convex')
    dev_display (Image)
    dev_set_draw ('margin')
    dev_set_color ('goldenrod')
    dev_display (RegionFillUpOranges)
    dev_set_color ('yellow')
    dev_display (RegionFillUpLemons)
endfor
clear_class_mlp (MLPHandle)
```

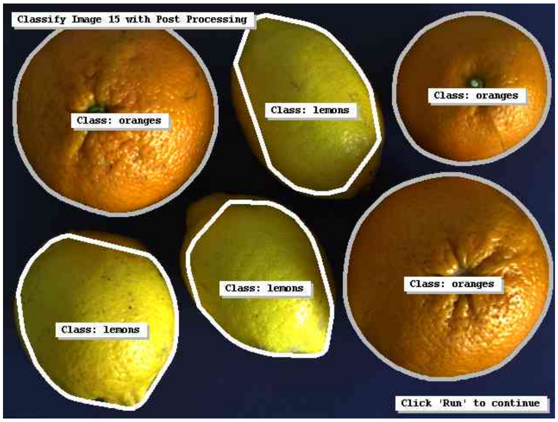

Figure 6.4: Segmentation result after postprocessing.

For the images at hand, alternatively also a general classification using shape features can be applied like described in section 8.3.1 on page 107.

6.1.1.2 Novelty Detection with SVM

The example program `hdevelop\Segmentation\Classification\novelty_detection_svm.hdev` shows how to apply a novelty detection with SVM. For a novelty detection with SVM, a single class is trained and the classification is used to find all regions of an image that do not belong to this class.

The program trains the texture of a regular plastic mesh. Before creating a classifier, a rectangle is generated that is used later as region of interest. This region of interest is necessary, because the images of the plastic mesh to be inspected do not contain an integer number of mesh cells. Thus, if the original image would have been trained and classified, the texture filters that are applied to create a multi-channel texture image would probably return artifacts at the image borders.

```
gen_rectangle1 (Rectangle, 10, 10, Height/2-11, Width/2-11)
```

The SVM classifier is created with `create_class_svm`. With SVM, novelty detection is a two-class problem (see also section 5.4.1 on page 46) and the classifier must be explicitly set to `'novelty-detection'` using the parameter `Mode`. Additionally, the `KernelType` must be set to `'rbf'`.

```
create_class_svm (5, 'rbf', 0.01, 0.0005, 1, 'novelty-detection', \
                  'normalization', 5, SVMHandle)
```

Then, all training images, i.e., images containing a good mesh, are read in a loop and scaled down by a factor of two. This is done, so that the textures can be optimally filtered with a filter size of 5x5 when creating a multi-channel texture image within the procedure `gen_texture_image`. Theoretically, also the original size could be used with a filter size of 10x10, but this would need too much time and the accuracy for the smaller image is sufficient for the application. The procedure `gen_texture_image` creates a multi-channel texture image for each image. This is then passed together with the region of interest to the operator `add_samples_image_class_svm` to add the sample region to the classifier.

```
for J := 1 to 5 by 1
    read_image (Image, 'plastic_mesh/plastic_mesh_'+J$'02')
    zoom_image_factor (Image, ImageZoomed, 0.5, 0.5, 'constant')
    disp_message (WindowHandle, 'Adding training samples...', 'window', -1, \
                  -1, 'black', 'true')
    gen_texture_image (ImageZoomed, ImageTexture)
    add_samples_image_class_svm (ImageTexture, Rectangle, SVMHandle)
endfor
```

The procedure `gen_texture_image` creates the multi-channel image by applying the texture filter `texture_laws` to the zoomed image with varying parameters and combining the differently filtered images to one image using `compose5`. The result is additionally smoothed before the procedure returns the final texture image.

```
texture_laws (Image, ImageEL, 'el', 5, 5)
texture_laws (Image, ImageLE, 'le', 5, 5)
texture_laws (Image, ImageES, 'es', 1, 5)
texture_laws (Image, ImageSE, 'se', 1, 5)
texture_laws (Image, ImageEE, 'ee', 2, 5)
compose5 (ImageEL, ImageLE, ImageES, ImageSE, ImageEE, ImageLaws)
smooth_image (ImageLaws, ImageTexture, 'gauss', 5)
```

After adding all training regions to the classifier, the classifier is trained with `train_class_svm`. To speed up the classification, the resulting support vectors are reduced with `reduce_class_svm`, which leads to the new classifier `SVMHandleReduced`. Note, that this operator is specific for SVM.

```
train_class_svm (SVMHandle, 0.001, 'default')
reduce_class_svm (SVMHandle, 'bottom_up', 2, 0.001, SVMHandleReduced)
```

Now, the novelty detection is applied to several images. That is, each image is transformed to a multi-channel texture image like described for the training part. This time, as `classify_class_svm` needs only the image and not a region as input, the image is additionally reduced to the domain of the region of interest. The reduced image is then passed to the operator `classify_class_svm` for novelty detection. The output parameter `ClassRegions` (here called `Errors`) returns all pixels of the image that do not belong to the trained texture. With a set of morphological operators and a blob analysis it is checked if connected components that exceed a certain size exist, i.e., if the image contains significant 'novelties'.

```
for J := 1 to 14 by 1
    read_image (Image, 'plastic_mesh/plastic_mesh_'+J$'02')
    zoom_image_factor (Image, ImageZoomed, 0.5, 0.5, 'constant')
    gen_texture_image (ImageZoomed, ImageTexture)
    reduce_domain (ImageTexture, Rectangle, ImageTextureReduced)
    classify_image_class_svm (ImageTextureReduced, Errors, SVMHandleReduced)
    opening_circle (Errors, ErrorsOpening, 3.5)
    closing_circle (ErrorsOpening, ErrorsClosing, 10.5)
    connection (ErrorsClosing, ErrorsConnected)
    select_shape (ErrorsConnected, FinalErrors, 'area', 'and', 300, 1000000)
    count_obj (FinalErrors, NumErrors)
    if (NumErrors > 0)
        disp_message (WindowHandle, 'Mesh not OK', 'window', -1, -1, \
                      'black', 'true')
    else
        disp_message (WindowHandle, 'Mesh OK', 'window', -1, -1, 'black', \
                      'true')
    endif
endfor
```

At the end of the novelty detection the classifiers are cleared from memory.

```
clear_class_svm (SVMHandle)
clear_class_svm (SVMHandleReduced)
```

6.1.1.3 Novelty Detection with GMM

The example program `hdevelop\Segmentation\Classification\novelty_detection_gmm.hdev` shows how to apply a novelty detection with GMM. Generally, the example does the same as `hdevelop\Segmentation\Classification\novelty_detection_svm.hdev` did. That is, the same images are used and the results are rather similar (see figure 6.5). The significant differences between novelty detection with GMM and with SVM concern the parameter settings when creating the classifier and the output returned when classifying an image.

When creating the classifier for GMM, in contrast to SVM, no explicit parameter for novelty detection is needed. Here, simply a classifier for a single class (`NumClasses` set to `1`) is created.

```
create_class_gmm (5, 1, [1,5], 'spherical', 'normalization', 5, 42, \
                  GMMHandle)
```

When classifying an image, the output parameter ClassRegions (here called Correct) of the operator classify_image_class_gmm, in contrast to the novelty detection with SVM, does not return a region built by erroneous pixels but a region that is built by pixels that belong to the trained texture class. To obtain the erroneous region, the difference between the input region and the returned region has to be calculated using difference.

```
classify_image_class_gmm (ImageTextureReduced, Correct, GMMHandle, \
                          0.001)
difference (Rectangle, Correct, Errors)
```

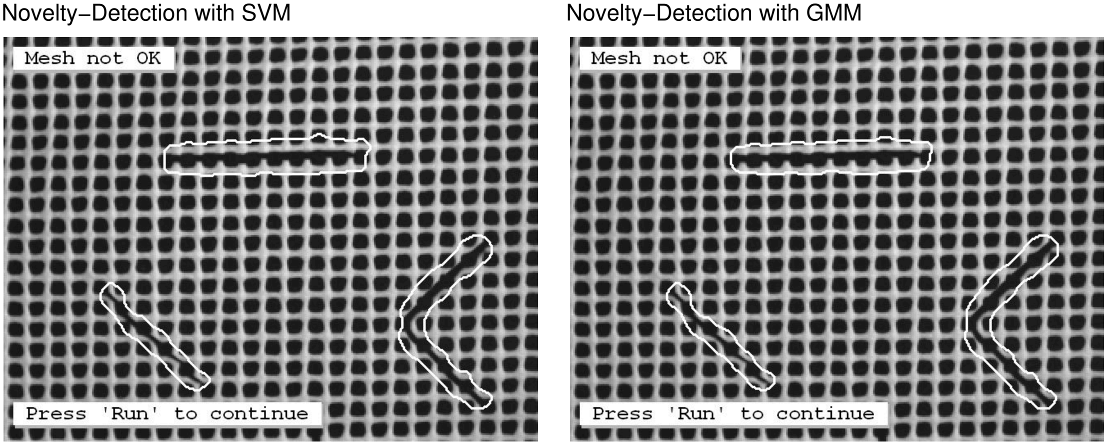

Figure 6.5: Novelty detection is used to extract parts of an image or region that do not fit to a trained pattern and can be applied with SVM or GMM.

Both significant differences occur because the GMM classifier by default returns only those regions that precisely belong to the trained classes (within a specified threshold) and thus automatically rejects all other pixels. For SVM, parts that do not belong to a class can only be determined for two-class problems, i.e., when explicitly setting the Mode to 'novelty-detection'. Otherwise, SVM assigns all pixels to the available classes, even if some pixels do not significantly match any of them. When explicitly setting a parameter for novelty detection, it is obvious that the returned region should show the requested novelties. For GMM, no specific parameter has to be set, i.e., the novelty detection is realized by applying a regular image segmentation. Thus, the returned region shows the parts of the image that match the trained class. Note that for the GMM classifier novelty detection is not restricted to a two-class problem and image segmentation, but can be applied also for multi-class problems and general classification (see section 5.5.5 on page 56).

6.1.2 Involved Operators (Overview)

This section gives a brief overview on the operators that are provided for MLP, SVM, and GMM classification for image segmentation. In particular, first the operators for the basic steps and then the advanced operators used for an image segmentation are introduced.

6.1.2.1 Basic Operators

Summarizing the information obtained in section 6.1.1 on page 60, the image segmentation consists of the following basic steps and operators, which are applied in the same order as listed here. Note that the steps are similar to the steps applied for a general classification (see section 5.2.1 on page 33), mainly the step for adding the samples and the step for the actual classification vary.

1. Create a classifier. Here, some important properties of the classifier are defined. The returned handle is needed in all later classification steps. Each classification step modifies this handle. This step corresponds to the proceeding of the general classification.
    - create_class_mlp
    - create_class_svm
    - create_class_gmm
2. Predefine the sequence in which the classes are defined and later accessed, i.e., define the correspondences between the class IDs and the class names, respectively define the colors that visualize the different classes. This step may as well be applied before the creation of the classifier.
3. Add samples, i.e., a region for each class to the classifier. In contrast to the general classification, a single operator call can be used to add all sample regions at once. The sequence of the added regions define the classes, i.e., the first region is class 0, the second is class 1 etc. Having several images for the training, the operator can be called multiple times, then the sample regions for the classes must be defined in the same sequence. If one of the classes is not represented in an image, an empty region has to be assigned. This step significantly differs from the proceeding of the general classification.
    - add_samples_image_class_mlp
    - add_samples_image_class_svm
    - add_samples_image_class_gmm
4. Train the classifier, i.e., use the added samples to obtain the boundaries between the classes. This step corresponds to the proceeding of the general classification.
    - train_class_mlp
    - train_class_svm
    - train_class_gmm
5. Store the used samples to file and access them in a later step (optionally). This step corresponds to the proceeding of the general classification.

- write_samples_class_mlp and read_samples_class_mlp
- write_samples_class_svm and read_samples_class_svm
- write_samples_class_gmm and read_samples_class_gmm

6. Store the trained classifier to file and read it from file again or, if the offline and online part is not separated, clear the samples manually from memory. This step corresponds to the proceeding of the general classification.

   - write_class_mlp (default file extension: .gmc) and read_class_mlp or clear_samples_class_mlp
   - write_class_svm (default file extension: .gsc) and read_class_svm or clear_samples_class_svm
   - write_class_gmm (default file extension: .ggc) and read_class_gmm or clear_samples_class_gmm

7. Segment the image by classification. That is, insert a new image and use one of the following operators to segment the image into regions of different classes. This step significantly differs from the proceeding of the general classification.

   - classify_image_class_mlp
   - classify_image_class_svm
   - classify_image_class_gmm

8. Clear the classifier from memory. This step corresponds to the proceeding of the general classification.

   - clear_class_mlp or clear_all_class_mlp
   - clear_class_svm or clear_all_class_svm
   - clear_class_gmm or clear_all_class_gmm

Besides the basic steps of a classification, some additional steps and operators can be applied if suitable. These advanced operators are similar for image segmentation and general classification.

6.1.2.2 Advanced Operators

Especially if the training and classification do not lead to a satisfying result, it is helpful to access some information that is implicitly contained in the model. Available steps to query information are:

- Access an individual sample from the training data. This is suitable, e.g., to check the correctness of it's class assignment. The sample had to be stored previously by the operator add_samples_image_class_mlp, add_samples_image_class_svm, or add_samples_image_class_gmm, respectively.

  – get_sample_class_mlp
  – get_sample_class_svm

  - get_sample_class_gmm

- Get the number of samples that are stored in the training data. The obtained number is needed, e.g., to access the individual samples or respectively to know how much individual samples you can access.
  - get_sample_num_class_mlp
  - get_sample_num_class_svm
  - get_sample_num_class_gmm

- Get information about the information content of the preprocessed feature vectors. This information is reasonable, if the parameter `Preprocessing` was set to `'principal_components'` or `'canonical_variates'` during the creation of the classifier. Then, you can check if the information that is contained in the preprocessed feature vector still contains significant data or if a different preprocessing parameter, e.g., `'normalization'`, is to be preferred.
  - get_prep_info_class_mlp
  - get_prep_info_class_svm
  - get_prep_info_class_gmm

- Get the parameter values that were set during the creation of the classifier. This is suitable if the offline training and the online classification were separated and the information about the training part is not available anymore.
  - get_params_class_mlp
  - get_params_class_svm
  - get_params_class_gmm

Furthermore, there are operators that are available only for specific classifiers. In particular,

- For SVM you can reduce the number of support vectors returned by the offline training to speed up the following online classification.
  - reduce_class_svm

- Additionally, for SVM the number or index of the support vectors can be determined after the training. This is suitable for the visualization of the support vectors and thus for diagnostic reasons.
  - get_support_vector_num_class
  - get_support_vector_class

If you want to speed up an image segmentation for images with a maximum of three image channels, you can apply a classification that is based on look-up tables (LUT, see also section 6.1.6 on page 74). Then, the proceeding differs from the basic image segmentation as follows:

- After creating a classifier, adding samples to it and training it, the result of the training is stored in a LUT-accelerated classifier.

  - create_class_lut_mlp
  - create_class_lut_svm
  - create_class_lut_gmm

- For the actual image segmentation, instead of classify_image_class_mlp, classify_image_class_svm, or classify_image_class_gmm, respectively, the LUT-accelerated classifier is applied.

  - classify_image_class_lut

- At the end of the classification, besides the originally created and trained classifier also the LUT-accelerated classifier is destroyed.

  - clear_class_lut

6.1.3 Parameter Setting for MLP

Most rules for the parameter setting for an image segmentation using MLP classification correspond to the rules for the general classification with MLP (see section 5.3 on page 36). As the most important operators and parameters to adjust are listed and described there, here only the parameter settings for the operators that are specific for image segmentation are described. These are the operators that add the training samples, i.e., sample regions, to the classifier and those that segment the unknown image.

6.1.3.1 Adjusting add_samples_image_class_mlp

For image segmentation with MLP, sample regions are added to the classifier with add_samples_image_class_mlp. In contrast to the samples used for a general classification, here, no feature vectors have to be generated explicitly but are implicitly given by the gray values of each pixel of the respective input region in all channels of the input image. The dimension of the feature vectors depends on the number of channels of the image containing the sample regions. The quality of the samples is very important for the quality of the classification. Section 4.3 on page 27 provides hints how to select a set of suitable samples. For the operator add_samples_image_class_mlp, the following parameters have to be set:

- Image: The image that contains the sample regions
- ClassRegions: The tuple containing the training regions. Here, one region per class is defined. The number of classes corresponds to the number of regions, and thus, the label of an individual class corresponds to the position of the training region in the tuple, i.e., it's index.
- MLPHandle: The handle of the classifier that was created with create_class_gmm

The operator returns the modified handle of the classifier (MLPHandle).

6.1.3.2 Adjusting classify_image_class_mlp

With the operator classify_image_class_mlp a new image is segmented into regions of the classes that were trained with train_class_mlp using the samples that were added with add_samples_image_class_mlp. The following parameters have to be set:

- Image: The image that has to be segmented into the classes that were trained with train_class_gmm.
- MLPHandle: The handle of the classifier that was created with create_class_mlp, to which samples were added with add_samples_image_class_mlp, and that was trained with train_class_mlp.
- RejectionThreshold: The threshold on the probability measure returned by the classification. All pixels having a probability below RejectionThreshold are not assigned to any class.

The operator returns a tuple of regions in ClassRegions. This tuple contains one region for each class. The sequence of the classes corresponds to the sequence used for the training regions that were added to the classifier with add_samples_image_class_mlp.

In contrast to the general classification using classify_class_mlp described in section 5.3.5 on page 42, no confidence for the classification but a rejection class is returned. This rejection class depends on the selected rejection threshold. Note that the returned rejection class has not the same quality than the rejection class returned for a GMM classification, as the MLP classification is typically influenced by outliers (see section 5.3.5 on page 42). Thus, for MLP the explicit training of a rejection class is recommended.

6.1.4 Parameter Setting for SVM

Most rules for the parameter setting for an image segmentation using SVM classification correspond to the rules for the general classification with SVM (see section 5.4 on page 43). As the most important operators and parameters to adjust are listed and described there, here only the parameter settings for the operators that are specific for image segmentation are described. These are the operators that add the training samples, i.e., sample regions, to the classifier and those that segment the unknown image.

6.1.4.1 Adjusting add_samples_image_class_svm

For image segmentation with SVM, sample regions are added to the classifier with add_samples_image_class_svm. In contrast to the samples used for a general classification, here, no feature vectors have to be generated explicitly but are implicitly given by the gray values of each pixel of the respective input region in all channels of the input image. The dimension of the feature vectors depends on the number of channels of the image containing the sample regions. The quality of the samples is very important for the quality of the classification. Section 4.3 on page 27 provides hints how to select a set of suitable samples. For the operator add_samples_image_class_svm, the following parameters have to be set:

- Image: The image that contains the sample regions
- ClassRegions: The tuple containing the training regions. Here, one region per class is defined. The number of classes corresponds to the number of regions, and thus, the label of an individual class corresponds to the position of the training region in the tuple, i.e., it's index.
- SVMHandle: The handle of the classifier that was created with create_class_svm

The operator returns the modified handle of the classifier (SVMHandle).

6.1.4.2 Adjusting classify_image_class_svm

With the operator classify_image_class_svm a new image is segmented into regions of the classes that were trained with train_class_svm using the samples that were added with add_samples_image_class_svm. The following parameters have to be set:

- Image: The image that has to be segmented into the classes that were trained with train_class_svm.
- SVMHandle: The handle of the classifier that was created with create_class_svm, to which samples were added with add_samples_image_class_svm, and that was trained with train_class_svm.

The operator returns a tuple of regions in ClassRegions. This tuple contains one region for each class. The sequence of the classes corresponds to the sequence used for the training regions that were added to the classifier with add_samples_image_class_svm.

6.1.5 Parameter Setting for GMM

Most rules for the parameter setting for an image segmentation using GMM classification correspond to the rules for the general classification with GMM (see section 5.5 on page 50). As the most important operators and parameters to adjust are listed and described there, here only the parameter settings for the operators that are specific for image segmentation are described. These are the operators that add the training samples, i.e., sample regions, to the classifier and those that segment the unknown image.

6.1.5.1 Adjusting add_samples_image_class_gmm

For image segmentation with GMM, sample regions are added to the classifier with add_samples_image_class_gmm. In contrast to the samples used for a general classification, here, no feature vectors have to be generated explicitly but are implicitly given by the gray values of each pixel of the respective input region in all channels of the input image. The dimension of the feature vectors depends on the number of channels of the image containing the sample regions. The quality of the samples is very important for the quality of the classification. Section 4.3 on page 27 provides hints how to select a set of suitable samples. For the operator add_samples_image_class_gmm, the following parameters have to be set:

- Image: The image that contains the sample regions
- ClassRegions: The tuple containing the training regions. Here, one region per class is defined. The number of classes corresponds to the number of regions, and thus, the label of an individual class corresponds to the position of the training region in the tuple, i.e., it's index.
- GMMHandle: The handle of the classifier that was created with create_class_gmm
- Randomize: The parameter that handles undesired effects that may occur for originally integer feature values (see also section 5.5.2 on page 53).

The operator returns the modified handle of the classifier (GMMHandle).

6.1.5.2 Adjusting classify_image_class_gmm

With the operator classify_image_class_gmm a new image is segmented into regions of the classes that were trained with train_class_gmm using the samples that were added with add_samples_image_class_gmm. The following parameters have to be set:

- Image: The image that has to be segmented into the classes that were trained with train_class_gmm.
- GMMHandle: The handle of the classifier that was created with create_class_gmm, to which samples were added with add_samples_image_class_gmm, and that was trained with train_class_gmm.
- RejectionThreshold: The threshold on the K-sigma probability (KSigmaProb) measure returned by the classification (see also section 5.5.5 on page 56). All pixels having a probability below RejectionThreshold are not assigned to any class.

The operator returns a tuple of regions in ClassRegions. This tuple contains one region for each class. The sequence of the classes corresponds to the sequence used for the training regions that were added to the classifier with add_samples_image_class_gmm.

In contrast to the general classification using classify_class_gmm described in section 5.5.5 on page 56, no probabilities for the classes but a rejection class is returned. This rejection class depends on the selected rejection threshold.

6.1.6 Classification Based on Look-Up Tables

A significant speed up for the image segmentation can be obtained by applying a classification that is based on look-up tables (LUT). That is, you store the content of a trained classifier in a LUT und use the LUT-accelerated classifier instead of the original classifier for the classification. The proceeding is as follows:

First, you create an MLP, SVM, or GMM classifier, add samples to it, and apply the training as described for the basic image segmentation in the previous sections.

Then, the LUT-accelerated classifier is created using the operator create_class_lut_mlp, create_class_lut_svm, or create_class_lut_gmm, respectively. Here, you insert the handle of the trained classifier and adjust some parameters. In particular, you can adjust the parameters 'bit_depth', 'class_selection' and for MLP and GMM also 'rejection_threshold':

- 'bit_depth' describes the number of bits used from the pixels. It controls the storage requirement of the LUT-accelerated classifier and the runtime needed for the LUT-accelerated classification. A byte image usually has got 8 bit. If the bit depth is set to a value of 7 or 6, the storage requirement can be reduced. But note that a bit depth that is smaller than the bit depth of the image can lead to a lower accuracy of the classification.
- 'class_selection' can be used to control the accuracy and the runtime needed for the creation of the LUT-accelerated classifier. A higher accuracy slows down the runtime and a lower accuracy leads to a speed-up. The value of 'class_selection' is ignored if the bit depth of the LUT is maximal.
- 'rejection_threshold' corresponds to the rejection threshold that is described for the basic image segmentation in section 6.1.3.2 for MLP and section 6.1.5.2 for GMM.

For the actual image segmentation, the operator classify_image_class_lut is applied instead of the operator classify_image_class_mlp, classify_image_class_svm, or classify_image_class_gmm, respectively. Note that the number of channels of the image that has to be classified must correspond to the value specified for the dimension of the feature space when creating the original classifier, i.e., the value of NumInput in create_class_mlp, NumFeatures in create_class_svm, or NumDim in create_class_gmm.

As soon as a classifier is not needed anymore, it is destroyed to free the memory. In most cases, the original trained classifier can be destroyed as soon as the LUT-accelerated classifier has been created. But note that if you need it for further applications, you should store it to file before destroying it (see section 6.1.2.1 on page 68). To destroy the original trained classifier you apply clear_class_mlp, clear_class_svm, or clear_class_gmm, respectively, as described for the basic image segmentation. The LUT-accelerated classifier cannot be stored to file, as it needs a lot of memory and thus, it is more suitable to create it again from the reused original classifier when starting a new application. When it is not needed anymore, it is destroyed using clear_class_lut.

The HDevelop example program hdevelop\Applications\Color-Inspection\classify_fuses_gmm_based_lut.hdev uses a LUT-accelerated classifier that is based on a trained GMM classifier to segment fuses of different color (see figure 6.6).

First, the ROIs that serve as training samples for different color classes are selected and concatenated into the tuple Classes. Then, a GMM classifier is created, the training samples are added, and the classifier is trained. Until now, the proceeding is the same as for the image segmentation that was described in the previous sections.

```
create_class_gmm (3, 5, 1, 'full', 'none', 3, 42, GMMHandle)
add_samples_image_class_gmm (Image, Classes, GMMHandle, 0)
train_class_gmm (GMMHandle, 100, 0.001, 'training', 0.001, Centers, Iter)
```

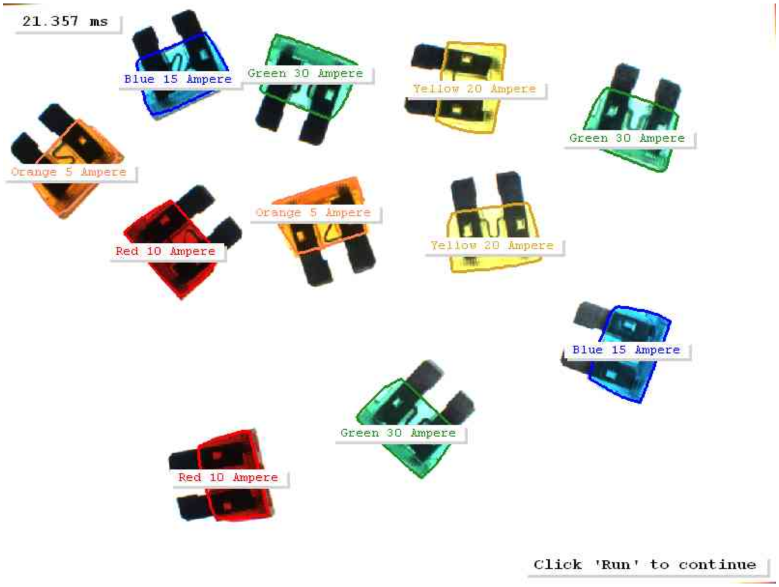

Figure 6.6: Fuses of different color are segmented using a LUT-accelerated GMM classifier.

In contrast to the basic image segmentation, the training result, i.e., the classifier, is then stored in a LUT-accelerated classifier using create_class_lut_gmm. The original classifier is not needed anymore and is therefore destroyed.

```
create_class_lut_gmm (GMMHandle, ['bit_depth','rejection_threshold'], [6, \
                      0.03], ClassLUTHandle)
clear_class_gmm (GMMHandle)
```

Now, for each image that has to be classified, the operator classify_image_class_lut is applied to segment the images based on the LUT of the new classifier. At the end of the program, the LUT-accelerated classifier is destroyed as well.

```
for Img := 0 to 3 by 1
    read_image (Image, ImageRootName + Img)
    classify_image_class_lut (Image, ClassRegions, ClassLUTHandle)
endfor
clear_class_lut (ClassLUTHandle)
```

The HDevelop example program hdevelop\Segmentation\Classification\classify_image_class_lut.hdev compares the runtime needed by MLP, SVM, and GMM classification using the basic image segmentation on the one hand and the LUT-accelerated classification on the other hand. It exemplarily shows that the online part of the LUT-accelerated classification is significantly faster than that of the basic image segmentation. **But note that it needs also additional memory and the runtime for the offline part is increasing.** Because of that the LUT-accelerated classification is restricted to feature spaces with a maximum of three dimensions. Figure 6.7 shows the interdependencies between the number of classes, the bit depth, and the required memory for a three-channel image. Furthermore, depending on the selected bit depth of the look-up table, the accuracy of the classification may be decreasing. Summarized, if a three-channel image has to be segmented, a speed-up of the online part is required, and the runtime for the offline part is not critical, LUT-accelerated classification is a good extension to the basic image segmentation.

Number of classes	Bit depth	Needed memory
256	3 x 8 Bit	32 MB
1	3 x 8 Bit	2 MB
10	3 x 6 Bit	0,125 MB

Figure 6.7: Memory needed for a LUT-accelerated classifier for three-channel images with different numbers of classes and different bit depths.

6.2 Proceeding for a Two-Channel Image Segmentation

For two-channel images a simple and very fast pixel classification can be applied using the operator `class_2dim_sup`. As we already learned, a class is defined as a well-defined part of the feature space and the dimension of the feature space depends on the number of features used for the classification. In case of a two-channel image and a pure pixel based classification, the classification is based only on the two gray values that are assigned to each pixel position and thus the two-dimensional feature space can be visualized in a 2D graph or in a 2D image, respectively. There, for each position of the image or a specific image region the gray value of the first image `ImageCol` is used as column coordinate and the gray value of the second image `ImageRow` is used as row coordinate (see figure 6.8, left). A class is defined by the feature space of a manually specified image region.

The general proceeding using `class_2dim_sup` for a two-channel image segmentation is as follows: you first specify a class by a region in the two-channel image that is typical for the class. Then, you apply the operator `histo_2dim`, which needs the two channels and the specified image region as input and returns the two-dimensional histogram, i.e., an image in which the position of a pixel is built by the combination of the gray values of the two channels and it's gray value is defined by the frequency of the specific gray value combination. To extract the essential region of the feature space, a threshold is applied. Now, the result can be preprocessed for generalization purposes (see figure 6.8, right), e.g., by a morphological operation like `closing_circle`. For the actual classification, the feature space region and the two channels of the image that has to be classified are used as input for the operator `class_2dim_sup`. The returned region `RegionClass2Dim` consists of all pixels in the classified two-channel image, for which the gray value distribution is similar to the gray value distribution of the training region, i.e., for which the position in the feature space lies inside the preprocessed feature space region that defines the class.

The example `hdevelop\Segmentation\Classification\class_2dim_sup.hdev` shows the proceeding for the segmentation of a two-channel image that contains several capacitors. First the color image is decomposed into it's three channels, so that two of them can be accessed for the classification. Then, a sample region for one of the capacitors is defined and used as input for `histo_2dim`, which together with `threshold` and `closing_circle` is used to derive a generalized feature space region. Fi-

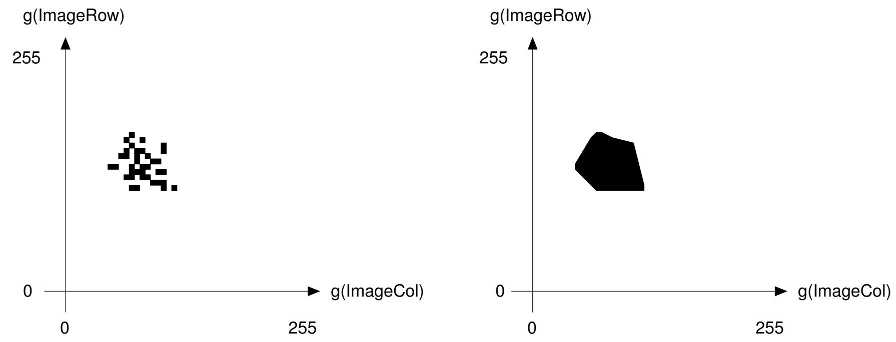

Figure 6.8: Positions of the 2D feature space for a supervised classification: (left) gray values of the two images in a 2D graph, (right) feature space region (class) after generalization.

nally, the two channels of the image and the trained feature space region are used by `class_2dim_sup` to get the region with all pixels that correspond to the trained feature space.

```
read_image (Image, 'ic')
decompose3 (Image, Red, Green, Blue)
gen_rectangle1 (Pattern, 362, 276, 371, 298)
histo_2dim (Pattern, Red, Blue, Histo2Dim)
threshold (Histo2Dim, Features, 1, 255)
closing_circle (Features, FeaturesClosed, 11.5)
class_2dim_sup (Red, Blue, FeaturesClosed, RegionClass2Dim)
```

This image segmentation approach is very fast. To select the two channels of a multi-channel image that should be used for the classification, different approaches exist. For color images, i.e., three-channel 'rgb' images, you can, e.g., apply a color transformation using `trans_from_rgb` to transform the 'rgb' image into a, e.g., 'hsi' image. This image contains one channel for the 'hue', one for the 'saturation', and one for the 'intensity' of the pixels. When using the 'hue' and 'saturation' channels for the classification, you obtain a classifier that is invariant to illumination changes (see also Solution Guide I, chapter 13 on page 173 for color transformations). For arbitrary multi-channel images you can also transform your image by a principal component analysis using the operator `principal_comp`. Then, the first two channels of the returned image are the channels with the largest information content and thus are predestinated to be input to the two-channel image segmentation.

6.3 Proceeding for Euclidean and Hyperbox Classification

For the simple image segmentation of multi-channel images, two operators are available: `class_ndim_box` and `class_ndim_norm`. The first one is used for a hyperbox classification and the second one can be applied either using a hyperbox or an Euclidean metric (for hyperbox and Euclidean classification see section 3.2 on page 17). Note that both operators can be applied following the general idea of hyperbox classification, but their implementations differ significantly.

From a user's point of view the key difference between `learn_ndim_box` and `learn_ndim_norm` is that for `learn_ndim_box` the rejection class affects the classification process itself. Here, a hyperplane is generated that separates the classes 'Foreground' and 'Background', so that no points in feature space are classified incorrectly. For learn_ndim_norm, however, an overlap between the classes 'Foreground' and 'Background' is allowed. This has it's effect on the return value Quality. The larger the overlap, the smaller the value. Note that the operator class_ndim_norm is very efficient. Compared, e.g., to the classic image segmentation using GMM (section 6.1.5 on page 73), it is significantly faster (approximately by factor 3). Compared to a LUT-accelerated classification it has the advantage that the storage requirements are low and the feature space can be easily visualized. Thus, if the classes are build by compact clusters, it is a good alternative.

6.3.0.1 Classification with class_ndim_box

The image segmentation using a hyperbox classification is applied as follows. Similar to the complex classification approaches using MLP, SVM, and GMM, you first create a classifier. For a hyperbox classification, it is created with create_class_box. Then, you specify a foreground and a background region to use them as input for the training with learn_ndim_box. The gray value combinations of each pixel of the region Foreground represent the pattern to be trained and those of the region Background define gray value combinations that have to be rejected.

Each pixel is trained once during the training process. For pixels of the region Foreground the class 0 is used, while for pixels of the region Background 1 is used. Pixels are trained by alternating pixels from Foreground with pixels from Background. If one region is smaller than the other, pixels are taken cyclically from the smaller region until the larger region is exhausted. The operator learn_ndim_box later accepts only pixels that can be classified into class 0. Note that all channels must be of the same type.

The actual classification of the image, i.e., the segmentation of the image into parts belonging to the class and parts to be rejected, is realized with class_ndim_box. At the end, you destroy the classifier with close_class_box.

No parameters need to be adjusted for this approach. The only influence you have on the classification process is a suitable selection of the training regions Foreground and Background.

The example hdevelop\Segmentation\Classification\class_ndim_box.hdev shows how to apply a hyperbox classification for image segmentation. The image is read, a classifier is created, the foreground and background regions are defined and used for a training, the image is segmented, and finally, the classifier is cleared from memory. The result of the image segmentation is shown in figure 6.9.

```
read_image (Image, 'ic')
create_class_box (ClassifHandle)
gen_rectangle1 (foreground, 360, 198, 369, 226)
gen_rectangle1 (reject, 150, 336, 337, 504)
learn_ndim_box (foreground, reject, Image, ClassifHandle)
class_ndim_box (Image, Regions, ClassifHandle)
close_class_box (ClassifHandle)
```


6.3.0.2 Classification with class_ndim_norm

Opposite to the approach with class_ndim_box, when segmenting an image using class_ndim_norm, you do not explicitly create and destroy a classifier, but immediately apply the training using

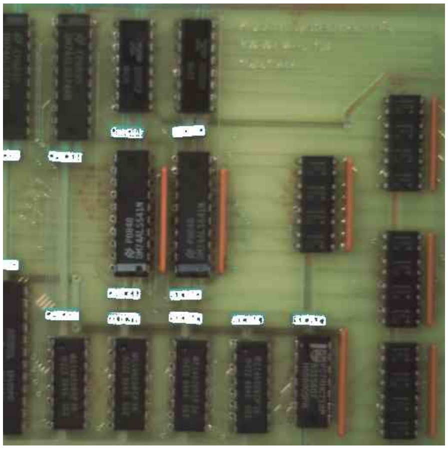

Figure 6.9: Result of image segmentation using class_ndim_box (returned regions marked in white).

learn_ndim_norm. Instead of storing the training results in a classifier and using the classifier as input for the classification, the training returns explicit information about the centers and radii of the clusters related to the trained patterns and this information is used as input for the classification, which is applied with class_ndim_norm. You can choose between a classification using hyperboxes and a classification using hyperspheres (Euclidean classification).

With learn_ndim_norm you generate the classification clusters from the region Foreground. The region Background can be used to define a rejection class, but in contrast to learn_ndim_box may also be empty (an empty region can be created by gen_empty_region). Note that the rejection class does not influence the clustering, but can be used to detect problems that might occur because of overlapping classes.

To choose between the two available clustering approaches, the parameter Metric is used. It can be either set to 'euclid', which uses a minimum distance algorithm (n-dimensional hyperspheres) or to 'maximum', which uses n-dimensional hyperboxes to built the clusters. Metric must be set to the same value for the training as well as for the classification. The Euclidean metric usually yields the better results but needs more run time.

The parameter Distance describes the minimum distance between two cluster centers and thus determines the maximum value allowed for the output parameter Radius. Note that the cluster centers depend on the sequence used to add the training samples (pixels). Thus, it is recommended to select a small value for Distance. Then, the (small) hyperboxes or hyperspheres can approximate the feature space well. But simultaneously, the runtime during classification increases.

The ratio of the number of pixels in a cluster to the total number of pixels (in percent) must be larger than the value of the parameter MinNumberPercent, otherwise the cluster is not returned. MinNumberPercent serves to eliminate outliers in the training set. If it is chosen too large many clusters are suppressed.

As result of the operator, the parameter Radius returns the minimum distance between two cluster centers, i.e., radii for hyperspheres or half edge lengths for hyperboxes, and Center returns the coordinates of the cluster centers. Furthermore, the parameter Quality returns the quality of the clustering, i.e., a measure of overlap between the rejection class and the classifier classes. Values larger than 0 denote the corresponding ratio of overlap. If no rejection region is given, it's value is set to 1. The regions in `Background` do not influence the clustering. They are merely used to check the results that can be expected.

When classifying a multi-channel image with `class_ndim_norm`, you set the same metric (`Metric`) used also for the training and set the parameter `SingleMultiple` to `'single'` if one region has to be generated or to `'multiple'` if multiple regions have to be generated for each cluster. Additionally, `Radius` and `Center`, which were returned by `learn_ndim_norm`, are inserted. The result of `class_ndim_norm` is returned in `Regions`, which either contains a single region or a tuple of regions, depending on the value of `SingleMultiple`.

The example `hdevelop\Segmentation\Classification\class_ndim_norm.hdev` shows how to apply an image segmentation with `class_ndim_norm`. The image is read and within the image a region for the class to be trained and an empty region for the rejection class are generated and used as input for the training with `learn_ndim_norm`. The classification is then applied with `class_ndim_norm`. The result of the image segmentation is shown in figure 6.10.

```
read_image (Image, 'ic')
gen_rectangle1 (Region, 360, 198, 369, 226)
gen_empty_region (EmptyRegion)
learn_ndim_norm (Region, EmptyRegion, Image, 'euclid', 10, 0.01, Radius, \
                 Center, Quality)
class_ndim_norm (Image, Regions, 'euclid', 'multiple', Radius, Center)
```

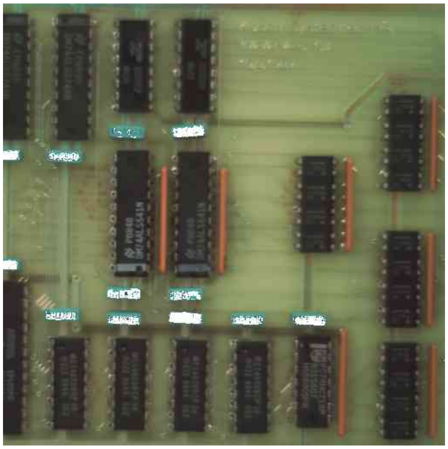

Figure 6.10: Result of image segmentation using class_ndim_norm (returned regions marked in white).

Chapter 7

Classification for Optical Character Recognition (OCR)

If classification is used for optical character recognition (OCR), individual regions are first extracted from the image by a segmentation and then, with the help of some region features, assigned to classes that typically (but not necessarily) represent individual characters or numbers. Approaches that are suitable for this feature based OCR comprise the MLP and the SVM classifiers. A hyperbox classifier is also provided, but is not recommended anymore.

In section 7.1 the general proceeding for OCR is illustrated by an example that trains and reads the characters `'A'` to `'G'`. In section 7.2 the steps of OCR and the involved operators are listed for a brief overview. The parameters used for the basic OCR operators are introduced in section 7.3 for MLP and section 7.4 for SVM. Section 7.5 finally lists all features that are available for OCR.

7.1 General Proceeding

Figure 7.1 shows the general proceeding for OCR. Typically, the proceeding is divided into an offline and an online process. The offline process comprises the training of the font, i.e., regions that represent characters or numbers (in the following just called 'characters') are extracted and stored together with the corresponding character names in training files. The content of a training file optionally can be accessed again. The access is needed for different reasons. First, they can be used to find errors that occurred during the training, which is needed on one hand for your general quality assurance and on the other hand for the correspondence with your HALCON support team (if needed), and second, you can reuse the contained information for the case that you want to apply a similar application in the future.

Now, the training files are used to train the font. To access the font in the later online process, the classifier is written into a font file before the classifier is cleared from memory.

If you want to read a font that is rather common and you want to use the MLP approach, you can also use one of the pretrained fonts provided by HALCON (see Solution Guide I, chapter 12 on page 155 for illustrations of the provided fonts). The pretrained fonts are stored in the subdirectory `ocr` of the folder where you installed HALCON. Then, you can skip the offline training process. For the SVM approach, no pretrained fonts are available.

In the online process, the font file is read so that the classifier can be accessed again. Then, the regions of unknown characters are extracted, most suitably by the same method that was used within the offline training process, and classified, i.e., the characters are read. At the end, the classifier is cleared from memory again.

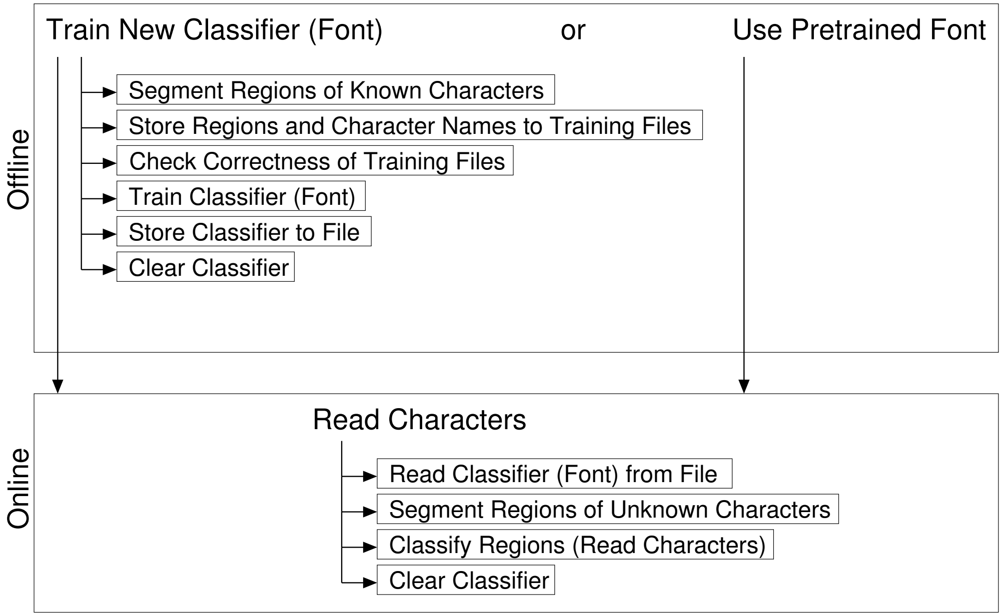

Figure 7.1: The basic steps of OCR.

In the following, we illustrate the general proceeding for OCR classification with the examples `solution_guide\classification\train_characters_ocr.hdev` and `solution_guide\classification\classify_characters_ocr.hdev`. These exemplarily show how the characters `'A'`, `'B'`, `'C'`, `'D'`, `'E'`, `'F'`, and `'G'` are first trained (see figure 7.2) and then read (see figure 7.3) with an SVM based OCR classification. Note that the number of classes as well as the number of training samples is very small as the example is used only to demonstrate the general proceeding. Typically, a larger number of classes is trained with OCR and a lot of samples and probably a different set of features are needed to get a robust classification.

The examples use SVM based OCR classification. For MLP the general proceeding and the operators are similar. Then, you mainly have to replace `'svm'` by `'mlp'` in the specific operator names and adjust different parameters. The specific parameters are explained in more detail in section 7.3 on page 90 for MLP and section 7.4 on page 94 for SVM.

The program `solution_guide\classification\train_characters_ocr.hdev` starts with the creation of an SVM based OCR classifier using the operator `create_ocr_class_svm`. Here, the most important parameters are adjusted. The width and height of a normalized character is defined (the reason for this is explained in more detail in section 7.3.1 on page 90) and the mode for the interpolation

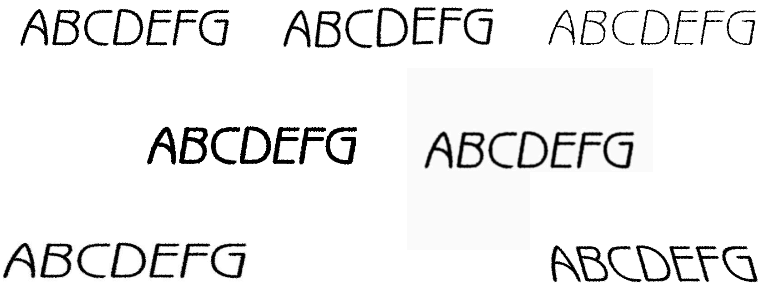

Figure 7.2: Training images for the characters `'A'`, `'B'`, `'C'`, `'D'`, `'E'`, `'F'`, and `'G'`.

that is used to scale the characters to the average character size is set. Further, the features that should be calculated to get the feature vector are selected. OCR can be applied for a broad set of features, which is listed in section 7.5 on page 98. The default features are `'ratio'` and `'pixel_invar'`. Here, the default does not lead to a satisfying result, so we use the features `'convexity'`, `'num_holes'`, `'projection_horizontal'`, and `'projection_vertical'` instead. Now, the names of the available classes (the characters A to G) are assigned, which were previously stored in the tuple `ClassNames`. Furthermore, some SVM specific parameters are adjusted that are described in more detail for the general classification in section 5.4 on page 43. The output of `create_ocr_class_svm` is the handle of the classifier (`OCRHandle`), which is needed for the following classification steps.

```
ClassNames := ['A', 'B', 'C', 'D', 'E', 'F', 'G']
create_ocr_class_svm (8, 10, 'constant', ['convexity', 'num_holes', \
                      'projection_horizontal', 'projection_vertical'], \
                      ClassNames, 'rbf', 0.02, 0.05, 'one-versus-one', \
                      'normalization', 10, OCRHandle)
```

For the training of the characters, the training images are read and the regions of the characters are extracted via a blob analysis within the procedure `get_regions`. Alternatively you can use also a combination of the operators `segment_characters` and `select_characters` to extract regions.

In the program, the first region is added together with it's class name (which is obtained from the tuple `ClassName`) to a new training file with `write_ocr_trainf`. All following regions and their corresponding class names are appended to this training file with `append_ocr_trainf`.

```
for i := 1 to 7 by 1
    read_image (Image, 'ocr/chars_training_'+ i$'.2d')
    get_regions (Image, SortedRegions)
    count_obj (SortedRegions, NumberObjects)
    for j := 1 to NumberObjects by 1
        select_obj (SortedRegions, ObjectSelected, j)
        if (i=1 and j=1)
            write_ocr_trainf (ObjectSelected, Image, ClassNames[j-1], \
                              'train_characters_ocr.trf')
        else
            append_ocr_trainf (ObjectSelected, Image, ClassNames[j-1], \
                               'train_characters_ocr.trf')
        endif
    endfor
endfor
```

After all samples were added to the training file, the operator `read_ocr_trainf` is applied to check if the training samples and the corresponding class names were correctly assigned within the training file. In a short for-loop, the individual characters and their corresponding class names are visualized. Note that the index for iconic objects (`Characters`) starts with `1` and that of numeric objects (`CharacterNames`) with `0`.

```
read_ocr_trainf (Characters, 'train_characters_ocr.trf', CharacterNames)
count_obj (Characters, NumberCharacters)
for i := 1 to NumberCharacters by 1
    select_obj (Characters, CharacterSelected, i)
    dev_display (CharacterSelected)
    disp_message (WindowHandle, CharacterNames[i-1], 'window', 10, 10, \
                  'black', 'true')
endfor
```

Then, the OCR classifier is trained with `trainf_ocr_class_svm`, which needs the training file as input. For SVM, the number of support vectors obtained from the training can be reduced to enhance the speed of the later classification. This is done with `reduce_ocr_class_svm`. The resulting handle is stored in a font file with `write_ocr_class_svm` for later access. For MLP the handle obtained directly by the training would be stored.

```
trainf_ocr_class_svm (OCRHandle, 'train_characters_ocr.trf', 0.001, \
                      'default')
reduce_ocr_class_svm (OCRHandle, 'bottom_up', 2, 0.001, OCRHandleReduced)
write_ocr_class_svm (OCRHandleReduced, 'font_characters_ocr')
```

At the end of the training program, both classifiers are cleared from memory using the operator `clear_all_ocr_class_svm`.

```
clear_all_ocr_class_svm ()
```

Now, the example program `solution_guide\classification\classify_characters_ocr.hdev` is used to read unknown characters of the same font type used for the training.

A font is read from file with read_ocr_class_svm. Then, the images with unknown characters are read, and the regions that most probably represent characters are extracted. If possible, the method to extract the regions should be the same for the offline and online process. Of course this advice can only be followed if the methods used in the offline process are known, i.e., it can not be followed when using pretrained fonts.

The extracted regions are then classified, i.e., the characters are read. In the example, we read all regions simultaneously with do_ocr_multi_class_svm. Alternatively, you can also read the regions individually with do_ocr_single_class_svm. Then, not only the best class for each region is returned, but also the second best (and third best etc.) class can be obtained, which might be suitable when having overlapping classing. But if only the best class is of interest, do_ocr_multi_class_svm is faster and therefore recommended. Finally, the classifier is cleared from memory with clear_ocr_class_svm.

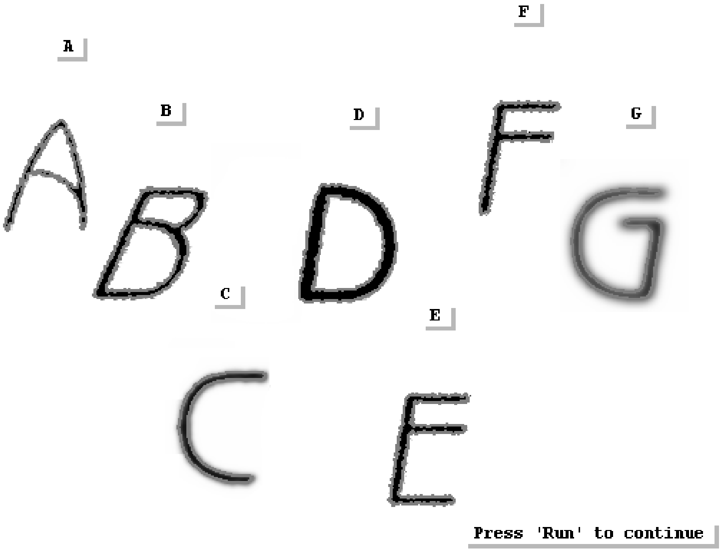

Figure 7.3: Classifying the characters 'A', 'B', 'C', 'D', 'E', 'F', and 'G' with OCR.

```
read_ocr_class_svm ('font_characters_ocr', OCRHandle)
for i := 1 to 3 by 1
    read_image (Image, 'ocr/chars_'+ i$'.2d')
    get_regions (Image, SortedRegions)
    do_ocr_multi_class_svm (SortedRegions, Image, OCRHandle, Classes)
    area_center (SortedRegions, AreaCenter, Row, Column)
    count_obj (SortedRegions, NumberObjects)
    for j := 1 to NumberObjects by 1
        disp_message (WindowHandle, Classes[j-1], 'window', \
                      Row[j-1]-100, Column[j-1], 'black', 'true')
    endfor
endfor
clear_ocr_class_svm (OCRHandle)
```

7.2 Involved Operators (Overview)

This section gives a brief overview on the operators that are provided for OCR. In particular, first the operators for the basic steps and then the advanced operators used for OCR are introduced.

7.2.0.3 Basic Operators

The basic steps apply the following operators in the following sequence.

1. Create an OCR classifier using `create_ocr_class_mlp` or `create_ocr_class_svm`. There, important parameters have to be adjusted.

2. Extract the regions that represent the characters that have to be trained.

3. Store the samples, i.e., the training regions and the corresponding class names to a training file. This can be done in different ways. Either

   - store all samples at once using `write_ocr_trainf`. Then the regions as well as the corresponding class names have to be available in a tuple. Or
   - successively add the individual regions (characters) and their corresponding class names to the training file using `append_ocr_trainf`.
   - Write characters into a training file with `write_ocr_trainf_image`. That is, regions, representing characters, including their gray values (region and pixel) and the corresponding class name are written into a file. An arbitrary number of regions within one image is supported. In contrast to `write_ocr_trainf` one image per character is passed. The domain of this image defines the pixels which belong to the character. The file format can be defined by the parameter 'ocr_trainf_version' of the operator `set_system`.

   Additionally, several training files can be concatenated with `concat_ocr_trainf`.

4. Read the training characters from the training file and convert them into images with `read_ocr_trainf` to check the correctness of the training file content.

5. Train the OCR classifier with `trainf_ocr_class_mlp` or `trainf_ocr_class_svm`.

6. Write the OCR classifier to a font file with `write_ocr_class_mlp` (default file extension: .omc) or `write_ocr_class_svm` (default file extension: .osc).

7. Read the OCR classifier from the font file with `read_ocr_class_mlp` or `read_ocr_class_svm`.

8. Extract the regions of the characters that have to be classified according to the trained font.

9. Classify the regions of the characters to be classified. Here, you have different possibilities:

   - Classify multiple characters with an OCR classifier with `do_ocr_multi_class_mlp` or `do_ocr_multi_class_svm`.

- Classify a single character with an OCR classifier with do_ocr_single_class_mlp or do_ocr_single_class_svm.

10. Clear the classifiers, i.e., either

- clear a specific OCR classifier with clear_ocr_class_mlp or clear_ocr_class_svm,
- or clear all OCR classifiers of a specific type with clear_all_ocr_class_mlp or clear_all_ocr_class_svm.

7.2.0.4 Advanced Operators

Besides the basic steps of an OCR classification, some additional steps and operators can be applied if suitable. In particular, you can

- compute the features of a character with get_features_ocr_class_mlp or get_features_ocr_class_svm,
- return the parameters of an OCR classifier with get_params_ocr_class_mlp or get_params_ocr_class_svm,
- compute the information content of the preprocessed feature vectors of an OCR classifier with get_prep_info_ocr_class_mlp or get_prep_info_ocr_class_svm (if Preprocessing was set to 'principal_components' or 'canonical_variates'),
- query which characters are stored in a training file with read_ocr_trainf_names,
- read training specific characters from files and convert them to images with read_ocr_trainf_select, or
- classify a related group of characters with an OCR classifier with do_ocr_word_mlp or do_ocr_word_svm. This is an alternative to do_ocr_multi_class_mlp or do_ocr_multi_class_svm and is suitable when searching for specific words or regular expressions that are specified in a lexicon that was created was with create_lexicon or imported with import_lexicon.

Besides these operators, some operators are provided that are available only for SVM:

- To enhance the speed, the trained SVM based OCR classifier can be approximated with a reduced number of support vectors applying reduce_ocr_class_svm after the training.
- The number of support vectors that are stored within the SVM based OCR classifier is returned with get_support_vector_num_ocr_class_svm.
- The index of a support vector from a trained SVM based OCR classifier is returned with get_support_vector_ocr_class_svm.

In the following, the parameters for the basic operators are introduced and tips for their adjustment are provided.

7.3 Parameter Setting for MLP

The following sections introduce you to the parameters that have to be set for the basic operators needed for an MLP based classification for OCR.

7.3.1 Adjusting create_ocr_class_mlp

An MLP classifier for OCR is created using create_ocr_class_mlp. Here, most of the important parameters have to be set.

Parameter WidthCharacter / HeightCharacter

Like for the general classification described in section 5 on page 29, OCR uses a set of features to classify regions into classes, which in this case correspond to specific characters and numbers. Some of the features that can be used for OCR are gray value features for which the number of returned features varies dependent on the region's size. As a classifier requires a constant number of features, i.e., the dimension of the feature vector has to be the same for all training samples and all regions to be classified, the region of a character has to be transformed (scaled) to a standard size. This size is determined by `WidthCharacter` and `HeightCharacter`. In most applications, sizes between 6x8 and 10x14 should be used. As a rule of thumb, the values may be small if only few characters have to be distinguished but large when classifying characters with complex shapes (e.g., Japanese signs).

Parameter Interpolation

The input parameter `Interpolation` is needed to control the transformation of the region to the size specified with `WidthCharacter` and `HeightCharacter`. Generally, when transforming a region, transformed points will lie between discrete pixel coordinates. To assign each point to it's final pixel coordinate and additionally to avoid aliasing, which typically occurs for scaled regions, an appropriate interpolation scheme is needed. Three types of interpolation with different quality and speed properties are provided by HALCON and can be selected for the parameter `Interpolation`:

- `'none'`

  If `'none'` is selected, a nearest-neighbor interpolation is applied. There, the gray value is determined from the nearest pixel's gray value. This interpolation scheme is very fast but may lead to a low interpolation quality.

- `'constant'`

  If `'constant'` is selected, a bilinear interpolation is applied. There, the gray value is determined from the four nearest pixels through bilinear interpolation. If the transformation contains a scaling with a scale factor smaller than `1`, a kind of mean filter is used to prevent aliasing effects. This interpolation scheme is of medium speed and quality.

- `'weighted'`

  If `'weighted'` is selected, again a bilinear interpolation is applied, but now, aliasing effects for a scaling with a scale factor smaller than `1` are prevented by a kind of Gaussian filter instead of a mean filter. This interpolation scheme is slow but leads to the best quality.

The interpolation should be chosen such that no aliasing effects occur in the transformation. For most applications, `Interpolation` should be set to `'constant'`.

Parameter Features

The input parameter `Features` specifies the features that are used for the classification. `Features` can contain a tuple of several feature names. Each of these feature names results in one or more features to be calculated for the classifier. That is, the length of the tuple in `Features` is similar or smaller than the dimension of the final feature vector. In section 7.5 on page 98 all features that are available for OCR are listed. To classify characters, in most cases the `'default'` setting can be used. Then, the features `'ratio'` and `'pixel_invar'` are selected. Note that the selection of the features significantly influences the quality of the classification.

Parameter Characters

The input parameter `Characters` contains a tuple with the names of the characters that will be trained. Each name must be passed as a string. The number of elements in the tuple determines the number of available classes.

Parameter NumHidden

The input parameter `NumHidden` follows the same rules as provided for the corresponding operator used to create an MLP classifier for a general classification (see section 5.3.1 on page 36).

Parameters Preprocessing / NumComponents

The parameters `Preprocessing` and `NumComponents` follow the same rules as provided for the corresponding operator used to create an MLP classifier for a general classification (see section 5.3.1 on page 36). The only exception is that for the OCR classification the features are already approximately normalized. Thus, `Preprocessing` can typically be set to `'none'`.

If `Preprocessing` is set to `'principal_components'` or `'canonical_variates'` you can use the operator `get_prep_info_ocr_class_mlp` to determine the optimum number of components as described for the general classification in section 5.3.1 on page 38.

Parameter RandSeed

The parameter `RandSeed` follows the same rules as provided for the corresponding operator used to create an MLP classifier for a general classification (see section 5.3.1 on page 36).

Parameter OCRHandle

The output parameter `OCRHandle` is the handle of the classifier that is needed and modified throughout the following classification steps.

7.3.2 Adjusting write_ocr_trainf / append_ocr_trainf

After creating a classifier and segmenting the regions for the characters of known classes, i.e., character names, the samples must be stored to a training file. Here, the same operators are used for MLP and SVM classifiers.

Different operators are provided for storing training samples to file. You can either store all samples to file in one step by inserting a tuple containing all regions and a tuple containing all corresponding class names to the operator write_ocr_trainf. Or you can successively append single training samples to the training file using append_ocr_trainf. If you choose the latter, be aware that the training file is extended every time you run the program, i.e., it is not created anew. So, if you want to successively add samples, it is recommended to use write_ocr_trainf for the first sample and append_ocr_trainf for all following samples. The operators are applied as follows:

- Store training samples to a new training file:

  When storing all training samples simultaneously into a file using write_ocr_trainf, you have to assign a tuple of regions that represent characters to the parameter Character. The image that contains the regions must be set in Image so that knowledge about the gray values within the regions is available. In Class a tuple of class names that correspond to the regions with the same tuple index must be inserted. Finally, you specify the name and path of the stored training file in FileName.

- Append training samples to a training file:

  When successively storing individual training samples into a file using append_ocr_trainf, the same parameters as for write_ocr_trainf have to be set. But in contrast to the operator write_ocr_trainf the characters are appended to an existing file using the same training file format. If the file does not exist, a new file is generated.

If no file extension is specified in FileName the extension '.trf' is appended to the file name. The version of the file format used for writing data can be defined by the parameter 'ocr_trainf_version' of the operator set_system.

If you have several training files that you want to combine, you can concatenate them with the operator concat_ocr_trainf.

7.3.3 Adjusting trainf_ocr_class_mlp

trainf_ocr_class_mlp trains the OCR classifier OCRHandle with the training characters stored in the OCR training file given by TrainingFile. The remaining parameters MaxIterations, WeightTolerance, ErrorTolerance, Error, and ErrorLog have the same meaning as introduced for the training of an MLP classifier for a general classification (see section 5.3.3 on page 40).

7.3.4 Adjusting do_ocr_multi_class_mlp

With do_ocr_multi_class_mlp multiple characters can be classified in a single call. Typically, this is faster than successively applying do_ocr_single_class_mlp, which classifies single characters, in a loop. However, do_ocr_multi_class_mlp can only return the best class of each character. If the second best class is needed, e.g., because the classes significantly overlap (see section 5.3.5 on page 42 for the possible outliers related to the confidence values of MLP classifications), do_ocr_single_class_mlp should be used instead. The following parameters have to be set for do_ocr_multi_class_mlp:

Parameter Character

The input parameter Character contains a tuple of regions that have to be classified.

Parameter Image

The input parameter Image contains the image that provides the gray value information for the regions that have to be classified.

Parameter OCRHandle

The input parameter OCRHandle is the handle of the classifier that was trained with trainf_ocr_class_mlp.

Parameter Class

The output parameter Class returns the result of the classification, i.e., a tuple of character names that correspond to the input regions that were given in the tuple Character.

Parameter Confidence

The output parameter Confidence returns the confidence value for the classification. Note, that for the confidence of MLP classifications, outliers are possible as described for the general classification in section 5.3.5 on page 42.

7.3.5 Adjusting do_ocr_single_class_mlp

Instead of using do_ocr_multi_class_mlp to add all samples in a single call, do_ocr_single_class_mlp can be used to successively add samples. Then, besides the best class for a region, also the second best (and third best etc.) class can be obtained. This may be suitable, if the class membership of a region is uncertain because of, e.g., overlapping classes. If only the best class for each region is searched for, do_ocr_multi_class_mlp is faster and therefore recommended.

Parameter Character

The input parameter Character contains a single region that has to be classified.

Parameter Image

The input parameter Image contains the image that provides the gray value information for the region that has to be classified.

Parameter OCRHandle

The input parameter OCRHandle is the handle of the classifier that was trained with trainf_ocr_class_mlp.

Parameter Num

The input parameter Num specifies the number of best classes to be searched for. Generally, Num is set to 1 if only the class with the best probability is searched for, and to 2 if the second best class is also of interest, e.g., because the classes overlap.

Parameter Class

The output parameter Class returns the result of the classification, i.e., the Num best character names that correspond to the input region that was specified in Character.

Parameter Confidence

The output parameter Confidence returns the Num best confidence values for the classification. Note, that for the confidence of MLP classifications, outliers are possible as described for the general classification in section 5.3.5 on page 42.

7.3.6 Adjusting clear_ocr_class_mlp

To destroy the classifier, the operator clear_ocr_class_mlp is applied only with the input parameter OCRHandle. If several MLP classifiers were created, you can also destroy them all in one step using the operator clear_all_ocr_class_mlp. Then, no parameter has to be set.

7.4 Parameter Setting for SVM

The following sections introduce you to the parameters that have to be set for the basic operators needed for an SVM based classification for OCR.

7.4.1 Adjusting create_ocr_class_svm

An SVM classifier for OCR is created using create_ocr_class_mlp. Here, most of the important parameters have to be set.

Parameters WidthCharacter / HeightCharacter

Like for the general classification described in section 5 on page 29, OCR uses a set of features to classify regions into classes, which in this case correspond to specific characters and numbers. Some of the features that can be used for OCR are gray value features for which the number of returned features varies dependent on the region's size. As a classifier requires a constant number of features, i.e., the dimension of the feature vector has to be the same for all training samples and all regions to be classified, the region of a character has to be transformed (scaled) to a standard size. This size is determined by `WidthCharacter` and `HeightCharacter`. In most applications, sizes between 6x8 and 10x14 should be used.

Parameter `Interpolation`

The input parameter `Interpolation` is needed to control the transformation of the region to the size specified with `WidthCharacter` and `HeightCharacter`. Generally, when transforming a region, transformed points will lie between discrete pixel coordinates. To assign each point to it's final pixel coordinate and additionally to avoid aliasing, which typically occurs for scaled regions, an appropriate interpolation scheme is needed. The three types of interpolation that are provided by HALCON are `'none'`, `'constant'`, and `'weighted'`. The properties of the individual interpolation schemes were already introduced for the creation of an MLP based OCR classifier in section 7.3.1 on page 90. For most applications, `Interpolation` should be set to `'constant'`.

Parameter `Features`

The input parameter `Features` specifies the features that are used for the classification. `Features` can contain a tuple of several feature names. Each of these feature names results in one or more features to be calculated for the classifier. That is, the length of the tuple in `Features` is similar or smaller than the dimension of the final feature vector. In section 7.5 on page 98 all features that are available for OCR are listed. To classify characters, in most cases the `'default'` setting can be used. Then, the features `'ratio'` and `'pixel_invar'` are selected. Note that the selection of the features significantly influences the quality of the classification.

Parameter `Characters`

The input parameter `Characters` contains a tuple with the names of the characters that will be trained. Each name must be passed as a string. The number of elements in the tuple determines the number of available classes.

Parameters `KernelType`, `KernelParam`

The input parameters `KernelType` and `KernelParam` follow the same rules as provided for the corresponding operator used to create an SVM classifier for a general classification (see section 5.4.1 on page 44).

Parameter `Nu`

The input parameter `Nu` follows the same rules as provided for the corresponding operator used to create an SVM classifier for a general classification (see section 5.4.1 on page 44).

Parameter `Mode`

The input parameter `Mode` follows the same rules as provided for the corresponding operator used to create an SVM classifier for a general classification (see section 5.4.1 on page 44).

Parameters Preprocessing / NumComponents

The parameters Preprocessing and NumComponents follow the same rules as provided for the corresponding operator used to create a classifier for a general classification (see section 5.3.1 on page 36). For the sake of numerical stability, Preprocessing can typically be set to 'normalization'. In order to speed up classification time, 'principal_components' or 'canonical_variates' can be used, as the number of input features can be significantly reduced without deterioration of the recognition rate.

If Preprocessing is set to 'principal_components' or 'canonical_variates' you can use the operator get_prep_info_ocr_class_svm to determine the optimum number of components as described for the general classification in section 5.3.1 on page 38.

Parameter OCRHandle

The output parameter OCRHandle is the handle of the classifier that is needed and modified throughout the following classification steps.

7.4.2 Adjusting write_ocr_trainf / append_ocr_trainf

The proceeding to store the training samples into a training file is the same for MLP based and SVM based OCR classification. See section 7.3.2 on page 92 for details.

7.4.3 Adjusting trainf_ocr_class_svm

trainf_ocr_class_svm trains the OCR classifier OCRHandle with the training characters stored in the OCR training file given by TrainingFile. The remaining parameters Epsilon and TrainMode have the same meaning as introduced for the training of an SVM classifier for a general classification (see section 5.4.3 on page 47).

7.4.4 Adjusting do_ocr_multi_class_svm

With do_ocr_multi_class_svm multiple characters can be classified in a single call. Typically, this is faster than successively applying do_ocr_single_class_svm, which classifies single characters, in a loop. However, do_ocr_multi_class_svm can only return the best class of each character. If the second best class is of interest, do_ocr_single_class_mlp should be used instead. The following parameters have to be set for do_ocr_multi_class_svm:

Parameter Character

The input parameter Character contains a tuple of regions that have to be classified.

Parameter Image

The input parameter Image contains the image that provides the gray value information for the regions that have to be classified.

Parameter OCRHandle

The input parameter OCRHandle is the handle of the classifier that was trained with trainf_ocr_class_svm.

Parameter Class

The output parameter Class returns the result of the classification, i.e., a tuple of character names that correspond to the input regions that were given in the tuple Character.

7.4.5 Adjusting do_ocr_single_class_svm

Instead of using do_ocr_multi_class_svm to add all samples in a single call, do_ocr_single_class_svm can be used to successively add samples. Then, besides the best class for a region, also the second best (and third best etc.) class can be obtained. If only the best class for each region is searched for, do_ocr_multi_class_mlp is faster and therefore recommended.

Parameter Character

The input parameter Character contains a single region that has to be classified.

Parameter Image

The input parameter Image contains the image that provides the gray value information for the region that has to be classified.

Parameter OCRHandle

The input parameter OCRHandle is the handle of the classifier that was trained with trainf_ocr_class_svm.

Parameter Num

The input parameter Num specifies the number of best classes to be searched for. Generally, Num is set to 1 if only the class with the best probability is searched for, and to 2 if the second best class is also of interest.

Parameter Class

The output parameter Class returns the result of the classification, i.e., the Num best character names that correspond to the input region that was specified in Character.

7.4.6 Adjusting clear_ocr_class_svm

To destroy the classifier, the operator clear_ocr_class_svm is applied only with the input parameter OCRHandle. If several SVM classifiers were created, you can also destroy them all in one step using the operator clear_all_ocr_class_svm. Then, no parameter has to be set.

7.5 OCR Features

The features that determine the feature vector for an OCR specific classification are selected via the parameter Feature in the operator create_ocr_class_mlp or create_ocr_class_svm, respectively. Note that some of the features lead to more than one feature value, i.e., the dimension of the feature vector can be larger than the number of selected feature types. The following feature types can be set individually or in combinations:

Feature 'anisometry'

Anisometry of the character. If R_a and R_b are the two radii of an ellipse that has the "same orientation" and the "same side relation" as the input region, the anisometry is defined as:

anisometry $= \frac{R_a}{R_b}$

Feature 'chord_histo'

Frequency of the runs per row. The number of returned features depends on the height of the pattern.

Feature 'compactness'

Compactness of the character. If L is the length of the contour and F the area of the region, the compactness is defined as:

OCR Feature compactness $= \frac{L^2}{4\pi F}$

The compactness of a circle is 1. If the region is long or has holes, the compactness is larger than 1. The compactness responds to the run of the contour (roughness) and to holes.

Feature 'convexity'

Convexity of the character. If F_c is the area of the convex hull and F_o the original area of the region, the convexity is defined as:

convexity $= \frac{F_o}{F_c}$

The convexity is 1 if the region is convex (e.g., rectangle, circle etc.). If there are indentations or holes, the convexity is smaller than 1.

Feature 'cooc'

Values of the binary co-occurrence matrices. A binary co-occurrence matrix describes how often the values 0 (outside the region) and 1 (inside the region) are located next to each other in a certain direction (0, 45, 90, 135 degrees). This numbers are stored in the co-occurrence matrix at the locations (0,0), (0,1), (1,0), and (1,1). Due to the symmetric nature of the co-occurrence matrix, each matrix contains two independent entries, e.g., (0,0) and (0,1). These two entries are taken from each of the four matrices. The feature type 'cooc' returns eight features.

Feature 'foreground'

Fraction of pixels in the foreground.

Feature 'foreground_grid_16'

Fraction of pixels in the foreground in a 4x4 grid within the smallest enclosing rectangle of the character. The feature type 'foreground_grid_16' returns 16 features.

Feature 'foreground_grid_9'

Fraction of pixels in the foreground in a 3x3 grid within the smallest enclosing rectangle of the character. The feature type 'foreground_grid_9' returns nine features.

Feature 'gradient_8dir'

Gradients are computed on the character image. The gradient directions are discretized into 8 directions. The amplitude image is decomposed into 8 channels according to these discretized directions. 25 samples on a 5x5 grid are extracted from each channel. These samples are used as features (200 features).

Feature 'height'

Height of the character before scaling the character to the standard size (not scale-invariant).

Feature 'moments_central'

Normalized central moments of the character. The feature type 'moments_central' is invariant under other affine transformations, e.g., rotation or stretching, and returns the four features psi1, psi2, psi3, and psi4.

Feature 'moments_gray_plane'

Normalized gray value moments and the angle of the gray value plane. This incorporates the gray value center of gravity $({}^g\overline{r};{}^g\,\overline{c})$ together with the parameters α and β, which describe the orientation of the plane which approximates the gray values. The feature type 'moments_gray_plane' returns four features.

Feature 'moments_region_2nd_invar'

Normalized 2nd moments of the character. The feature type 'moments_region_2nd_invar' returns the three features μ_{11}, μ_{20}, and μ_{02}.

Feature 'moments_region_2nd_rel_invar'

Normalized 2nd relative moments of the character. The feature type 'moments_region_2nd_rel_invar' returns the two features phi1 and phi2.

Feature 'moments_region_3rd_invar'

Normalized 3rd moments of the character. The feature type 'moments_region_3rd_invar' returns the four features μ_{21}, μ_{12}, μ_{03}, and μ_{30}.

Feature 'num_connect'

Number of connected components.

Feature 'num_holes'

Number of holes.

Feature 'num_runs'

Number of runs in the region normalized by the area.

Feature 'phi'

Sine and cosine of the orientation of an ellipse that has the “same orientation” and the “same side relation” as the input region. The feature type 'phi' returns two features.

Feature 'pixel'

Gray values of the character. The number of returned features depends on the height and width of the pattern.

Feature 'pixel_binary'

Region of the character as a binary image. The number of returned features depends on the height and width of the pattern.

Feature 'pixel_invar'

Gray values of the character with maximum scaling of the gray values. The number of returned features depends on the height and width of the pattern.

Feature 'projection_horizontal'

Horizontal projection of the gray values, i.e., the mean values in the horizontal direction of the gray values of the input image. The number of returned features depends on the height of the pattern.

Feature 'projection_horizontal_invar'

Maximally scaled horizontal projection of the gray values. The number of returned features depends on the height of the pattern.

Feature 'projection_vertical'

Vertical projection of the gray values, i.e., the mean values in the vertical direction of the gray values of the input image. The number of returned features depends on the width of the pattern.

Feature 'projection_vertical_invar'

Maximally scaled vertical projection of the gray values. The number of returned features depends on the width of the pattern.

Feature 'ratio'

Aspect ratio of the character.

Feature 'width'

Width of the character before scaling the character to the standard size (not scale-invariant).

Feature 'zoom_factor'

Difference in size between the character and the values of PatternWidth and PatternHeight (not scale-invariant).

Further information about the individual features and their calculation can be accessed via the Reference Manual entries for `create_ocr_class_mlp` or `create_ocr_class_svm`, respectively.

Chapter 8

General Tips

This sections provides you with some additional tips that may help you to optimize your classification application. In particular, a method for optimizing the most critical parameters is introduced in section 8.1, the classification of general region features with the OCR specific classification operators is described in section 8.2, and means to visualize the feature space for low dimensional feature vectors (2D and 3D) are given in section 8.3.

8.1 Optimize Critical Parameters with a Test Application

To optimize the most critical parameters for a classification, different parameter values should be tested with the available training data. To optimize the generalization ability of a classifier, the parameter optimization should be combined with a cross validation. There, the training data is divided into typically five sub sets and the training is performed rotative with four of the five sub sets and tested with the fifth sub set (see figure 8.1). Take care, that the training data is uniformly distributed in the sub sets. That is, if for one class only five samples are available, each sub set should contain one of it, and if for another class hundred samples are available, each sub set should contain twenty of them. Note that a cross validation needs a lot of time as it is reasonable mainly for a very large set of training data, i.e., for applications that are challenging because of the many variations inside the classes and the overlaps between the classes.

The actual test application can be applied as follows:

- You first split up the training data into five uniformly distributed data sets.
- Then, you create a loop over the different parameter values that are to be tested, e.g., over different values for `NumHidden` in case of an MLP classification. When adjusting two parameters simultaneously, e.g., the `Nu`-`KernelParam` pair for SVM, you have to nest two loops into each other.
- Within the (inner) loop, the cross validation is applied, i.e., each sub set of the training data is once classified with a classifier that is trained by the other four sub sets using the tested parameters. The sum of the correctly classified samples of the test data set is stored so that later the sum of correct classifications can be assigned to the corresponding tested parameter values.

Figure 8.1: Cross validation: The training data is divided into 5 sub sets. Each set is used once as test data (black) that is classified by a classifier trained by the training data of the other 4 sub sets (gray).

- After testing all parameter values, you select the best result, i.e., the parameter values that led to the largest number of correctly classified test samples within the test application are used for the actual classification application.

For the cross validation, a number of five sub sets is sufficient. When increasing this number, no advantage is obtained, but the training is slowed down significantly. The parameters for which such a test application is reasonable mainly comprise `NumCenters` for GMM (then, the parameter `CovarType` should be set to `'full'`), `NumHidden` for MLP, and the `Nu`-`KernelParam` pair for SVM.

8.2 Classify General Regions using OCR

Sometimes it may be convenient to use the operators provided for OCR also for the classification of general objects. This is possible as long as the objects can be described by the features that are provided for OCR (see section 7.5 on page 98). Note that many of the provided features are not rotation invariant. That is, if your objects have different orientations in the images, you have to apply an alignment before applying the classification. The example `solution_guide\classification\classify_metal_parts_ocr.hdev` shows how to use OCR to classify the metal parts that were already classified with a general classification in the example program `solution_guide\classification\classify_metal_parts.hdev` in section 2 on page 11.

The program starts with the creation of an OCR classifier using `create_ocr_class_mlp`. There, the approximated dimensions of the regions that represent the objects are specified by the parameters `WidthCharacter` and `HeightCharacter`. The parameter `Features` is set to `'moments_central'`. In contrast to the general classification, no feature vectors have to be explicitly calculated and stored. This may enhance the speed of the training as well as of the actual classification, and by the way needs less programming effort. The parameter `Characters` contains a tuple of strings that defines the available class names, in this case the classes 'circle', 'hexagon', and 'polygon' are available. In solution_guide\classification\classify_metal_parts.hdev the classes were addressed simply by their index, i.e., 0, 1, and 2. There, the assignment of names for each class would have been possible, too, but then an additional tuple with names must have been assigned and the correspondence between the class index and the class name must have been made explicit.

```
create_ocr_class_mlp (110, 110, 'constant', 'moments_central', ['circle', \
                     'hexagon','polygon'], 10, 'normalization', 10, 42, \
                      OCRHandle)
```

Now, the input images, which are the same as already illustrated in figure 2.1 on page 12, and the class names for the objects of each image are defined (FileNames and ClassNamesImage).

```
FileNames := ['nuts_01','nuts_02','nuts_03','washers_01','washers_02', \
              'washers_03','retainers_01','retainers_02','retainers_03']
ClassNamesImage := ['hexagon','hexagon','hexagon','circle','circle', \
                    'circle','polygon','polygon','polygon']
```

Then, the individual training regions of the objects are extracted from the training images. The procedure to segment the regions is the same as used for solution_guide\classification\classify_metal_parts.hdev in section 2 on page 11. The first region and it's corresponding class name is stored into an OCR training file using write_ocr_trainf. All following regions and their class names are stored into the same training file by appending them via append_ocr_trainf.

```
for J := 0 to |FileNames|-1 by 1
    read_image (Image, 'rings/'+FileNames[J])
    segment (Image, Objects)
    count_obj (Objects, NumberObjects)
    for k := 1 to NumberObjects by 1
        select_obj (Objects, ObjectSelected, k)
        if (J=0 and k=1)
            write_ocr_trainf (ObjectSelected, Image, ClassNamesImage[J], \
                              'train_metal_parts_ocr.trf')
        else
            append_ocr_trainf (ObjectSelected, Image, ClassNamesImage[J], \
                               'train_metal_parts_ocr.trf')
        endif
    endfor
endfor
```

After adding all training samples to the training file, the training file is used by trainf_ocr_class_mlp to train the 'font', which here consists of three different shapes.

```
trainf_ocr_class_mlp (OCRHandle, 'train_metal_parts_ocr.trf', 200, 1, 0.01, \
                      Error1, ErrorLog1)
```

The images with the objects to classify are read in a loop and for each image the regions that represent the objects are extracted using the same procedure that was used for the training. Now, each region is classified using do_ocr_single_class_mlp. Dependent on the classification result, the regions are visualized by different colors (see figure 8.2).

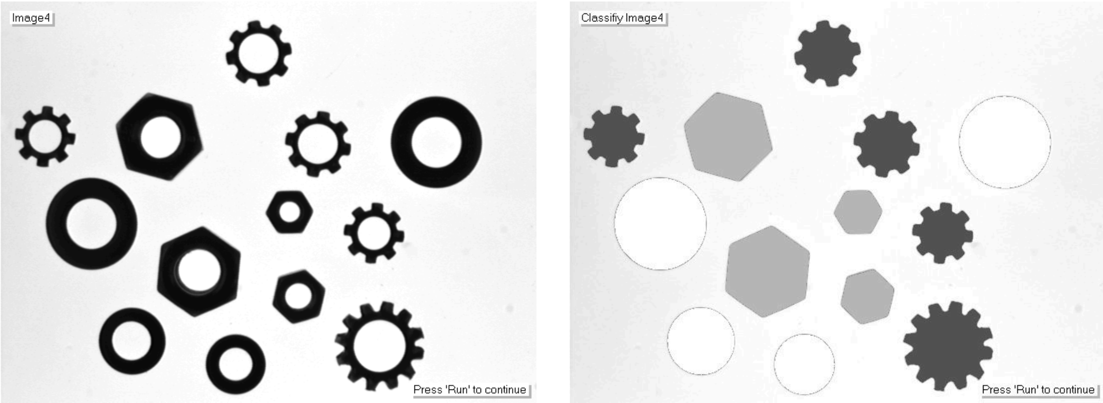

Figure 8.2: Classifying metal parts because of their shape using the OCR specific classification operators: (left) image with metal parts, (right) metal parts classified into three classes (illustrated by different gray values).

```
for J := 1 to 4 by 1
    read_image (Image, 'rings/mixed_'+J$'02d')
    segment (Image, Objects)
    for k := 1 to NumberObjects by 1
        select_obj (Objects, ObjectSelected, k)
        do_ocr_single_class_mlp (ObjectSelected, Image, OCRHandle, 1, Class, \
                                 Confidence)
        if (Class='circle')
            dev_set_color ('blue')
        endif
        if (Class='hexagon')
            dev_set_color ('coral')
        endif
        if (Class='polygon')
            dev_set_color ('green')
        endif
        dev_display (ObjectSelected)
    endfor
endfor
```

At the end of the program, the classifier is cleared from memory using clear_ocr_class_mlp.

```
clear_ocr_class_mlp (OCRHandle)
```

8.3 Visualize the Feature Space (2D and 3D)

Sometimes, it may be suitable to have a look at the feature space, e.g., to check if the selected features build clearly separable clusters. If not, another set of features should be preferred or further features should be added. A reasonable visualization is possible only for the 2D (section 8.3.1) and 3D feature space (section 8.3.2), i.e., feature vectors or parts of feature vectors that contain only two to three features.

8.3.1 Visualize the 2D Feature Space

In section 3 on page 15, the example solution_guide\classification\classify_citrus_fruits.hdev was coarsely introduced to explain what a feature space is. The example classifies citrus fruits into the classes 'oranges' and 'lemons' and visualizes the 2D feature space for the training samples. This feature space is built by the two shape features 'area' and 'circularity'. In the following, we summarize the steps of the example with the focus on how to visualize the 2D feature space.

At the beginning of the program, the names of the classes are defined and a GMM classifier is created. Then, inside a for-loop the training images are read, the regions of the contained fruits are segmented from the red channel of the color image (inside the procedure get_regions) and the features 'area' and 'circularity' are calculated for each region (inside the procedure get_features). The values for the area of the regions are integer values. As the feature vector has to consist of real values, the feature vector is converted into a tuple of real values before it is added to the classifier together with the corresponding known class ID.

```
ClassName := ['orange', 'lemon']
create_class_gmm (2, 2, 1, 'spherical', 'normalization', 10, 42, GMMHandle)
for i := 1 to 4 by 1
    read_image (Image, 'color/citrus_fruits_'+ i$'.2d')
    get_regions (Image, SelectedRegions)
    count_obj (SelectedRegions, NumberObjects)
    for j := 1 to NumberObjects by 1
        select_obj (SelectedRegions, ObjectSelected, j)
        get_features (ObjectSelected, WindowHandle, Circularity, Area, \
                      RowRegionCenter, ColumnRegionCenter)
        FeaturesArea := [FeaturesArea, Area]
        FeaturesCircularity := [FeaturesCircularity, Circularity]
        FeatureVector := real([Circularity, Area])
        if (i<=2)
            add_sample_class_gmm (GMMHandle, FeatureVector, 0, 0)
        else
            add_sample_class_gmm (GMMHandle, FeatureVector, 1, 0)
        endif
    endfor
endfor
```

Now, the feature space for the oranges (dim gray) and lemons (light gray) of the training samples is visualized by the procedure visualize_2D_feature_space (see figure 8.3).

```
visualize_2D_feature_space (Cross, Height, Width, WindowHandle, \
                            FeaturesArea[0:5], FeaturesCircularity[0:5], \
                            'dim gray', 18)
visualize_2D_feature_space (Cross, Height, Width, WindowHandle, \
                            FeaturesArea[6:11], FeaturesCircularity[6:11], \
                            'light gray', 18)
```

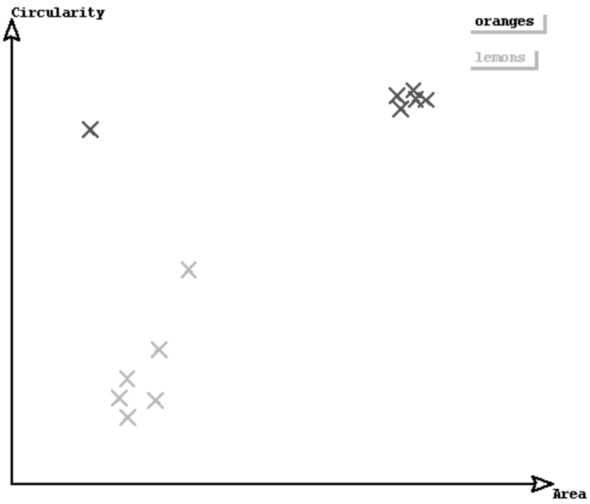

Figure 8.3: The feature space for the oranges (black) and lemons (gray) of the training samples.

Inside the procedure, first a 2D graph is created, i.e., depending on the width and height of the window, the origin of the 2D graph is defined in image coordinates (`OriginOfGraph`), each axis of the graph is visualized by an arrow (`disp_arrow`), and each axis is labeled with the name of the corresponding feature (`set_tposition`, `write_string`).

```
procedure visualize_2D_feature_space (Cross, Height, Width, WindowID,
                                      FeaturesA, FeaturesC,
                                      ColorFeatureVector, CrossSize):::
dev_set_color ('black')
OriginOfGraph := [(Height-0.1*Height), (0.1*Width)]
disp_arrow (WindowID, OriginOfGraph[0], OriginOfGraph[1], OriginOfGraph[0], \
            (Width-0.2*Width), 2)
disp_arrow (WindowID, OriginOfGraph[0], OriginOfGraph[1], (0.1*Height), \
            OriginOfGraph[1], 2)
set_tposition (WindowID, OriginOfGraph[0], (Width-0.2*Width))
write_string (WindowID, 'Area')
set_tposition (WindowID, 0.07*Height, OriginOfGraph[1])
write_string (WindowID, 'Circularity')
```

Then, the procedure determines the relations between the image coordinates and the feature values. For that, the extent of the graph is defined on one hand in pixels for the image coordinate system (ExtentOfGraph) and on the other hand in feature value units (RangeC, RangeA). Inside the image coordinate system, the extent is the same for both axes and depends on the window height. For the feature values, the extent is defined for each feature axis individually so that it covers the whole range of the corresponding feature values that is expected for the given set of feature vectors. That is, for each feature, the extent corresponds to the approximated difference between the expected maximum and minimum feature value. Having the extent of the graph in image coordinates as well as the individual value ranges for the features, the scaling factor for each axis between feature values and the image coordinate system is known (ScaleC, ScaleA).

```
ExtentOfGraph := Height-0.3*Height
RangeC := 0.5
RangeA := 24000
ScaleC := ExtentOfGraph/RangeC
ScaleA := ExtentOfGraph/RangeA
```

In addition to the scaling, a translation of the feature vectors is needed. Otherwise, the points representing the feature vectors would be outside of the window. Here, the feature vectors are moved such that the position that is built by the expected minimum feature values corresponds to the origin of the 2D graph in image coordinates. The feature values at the origin are then described by MinC and MinA.

```
MinC := 0.5
MinA := 20000
```

In figure 8.4 the relations between the image coordinates and the feature values are illustrated.

Knowing the relations between the feature values and the image coordinate system, the procedure calculates the image coordinates for each individual feature vector (RowFeature, ColumnFeature). For that, the distance of each feature value to the origin of the 2D graph is calculated (in feature value units) and multiplied with the scaling factor. The obtained distance in pixels (DiffC, DiffA) then simply is subtracted from respectively added to the corresponding image coordinates of the graph's origin (OriginOfGraph[0], OriginOfGraph[1]). The resulting image coordinates are visualized by a cross contour that is created with the operator gen_cross_contour_xld and displayed with dev_display.

```
NumberFeatureVectors := |FeaturesA|
for i := 0 to NumberFeatureVectors-1 by 1
    DiffC := ScaleC*(FeaturesC[i]-MinC)
    DiffA := ScaleA*(FeaturesA[i]-MinA)
    RowFeature := OriginOfGraph[0]-DiffC
    ColumnFeature := OriginOfGraph[1]+DiffA
    gen_cross_contour_xld (Cross, RowFeature, ColumnFeature, CrossSize, \
                           0.785398)
    dev_display (Cross)
endfor
return ()
```

After visualizing the feature space for the training samples with the procedure visualize_2D_feature_space, the training and classification is applied by the proceeding described in more detail in the sections of section 5 on page 29.

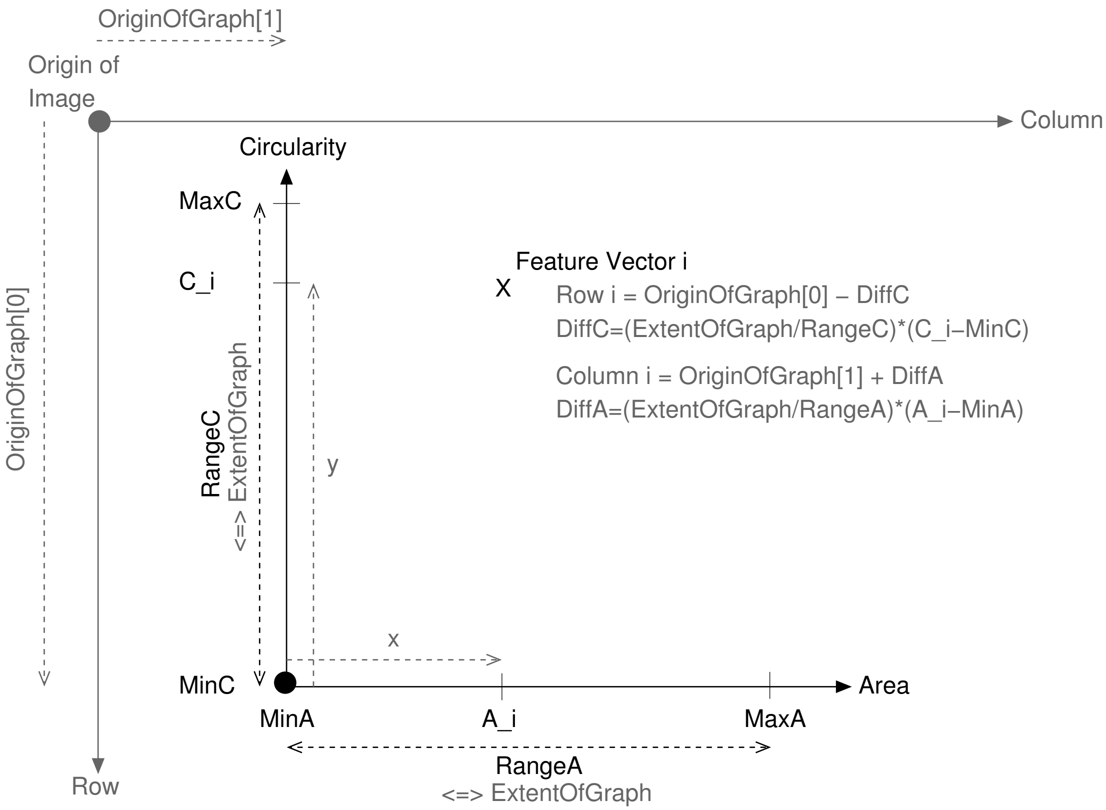

Figure 8.4: Relations between image coordinates (gray) and feature values (black).

```
train_class_gmm (GMMHandle, 100, 0.001, 'training', 0.0001, Centers, Iter)
for i := 1 to 15 by 1
    read_image (Image, 'color/citrus_fruits_'+ i$'.2d')
    get_regions (Image, SelectedRegions)
    count_obj (SelectedRegions, NumberObjects)
    for j := 1 to NumberObjects by 1
        select_obj (SelectedRegions, ObjectSelected, j)
        get_features (ObjectSelected, WindowHandle, Circularity, Area, \
                      RowRegionCenter, ColumnRegionCenter)
        FeaturesArea := [FeaturesArea, Area]
        FeaturesCircularity := [FeaturesCircularity, Circularity]
        FeatureVector := real([Circularity, Area])
        classify_class_gmm (GMMHandle, FeatureVector, 1, ClassID, ClassProb, \
                            Density, KSigmaProb)
    endfor
endfor
clear_class_gmm (GMMHandle)
```

8.3.2 Visualize the 3D Feature Space

The example `solution_guide\classification\visualize_3d_feature_space.hdev` shows how to visualize a 3D feature space for the pixels of two regions that contain differently texturized patterns. The feature vector for each pixel is built by three gray values.

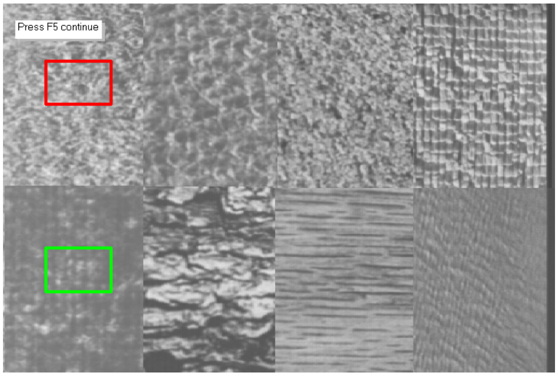

Figure 8.5: The two texture classes that have to be classified are marked by rectangles.

First, the feature vectors, i.e., the three gray values for each pixel have to be derived. For that, a texture image is created by applying different texture filters (`texture_laws`), which are combined with a linear smoothing (`mean_image`), to the original image. As we do not exactly know which laws filters are suited best to separate the specific texture classes from each other, we construct six differently filtered images and combine them to a six channel image (`compose6`).

```
set_system ('clip_region', 'false')
read_image (Image, 'combine')
get_part (WindowHandle, Row1, Column1, Row2, Column2)
texture_laws (Image, ImageTexture1, 'ee', 5, 7)
texture_laws (Image, ImageTexture2, 'ss', 2, 7)
texture_laws (Image, ImageTexture3, 'rr', 0, 7)
texture_laws (Image, ImageTexture4, 'ww', 0, 7)
texture_laws (Image, ImageTexture5, 'le', 7, 7)
texture_laws (Image, ImageTexture6, 'el', 7, 7)
mean_image (ImageTexture1, ImageMean1, 41, 41)
mean_image (ImageTexture2, ImageMean2, 41, 41)
mean_image (ImageTexture3, ImageMean3, 41, 41)
mean_image (ImageTexture4, ImageMean4, 41, 41)
mean_image (ImageTexture5, ImageMean5, 41, 41)
mean_image (ImageTexture6, ImageMean6, 41, 41)
compose6 (ImageMean1, ImageMean2, ImageMean3, ImageMean4, ImageMean5, \
          ImageMean6, TextureImage)
```

To get uncorrelated images, i.e., to discard data with little information, and to save storage, the six-channel image is transformed by a principal component analysis. The resulting transformed image is then input to the procedure `gen_sample_tuples`.

Tips

```
principal_comp (TextureImage, PCAImage, InfoPerComp)
gen_sample_tuples (PCAImage, Rectangles, Sample1, Sample2, Sample3)
```

Within the procedure, the first three images of the transformed texture image, i.e, the three channels with the largest information content, are accessed via `access_channel`. Then, inside the image, for the two texture classes rectangles are generated (see figure 8.5 on page 111) and all pixel coordinates within these rectangles are determined and stored in the tuples `RowsSample` and `ColsSample`. For each pixel the gray values of the first three channels of the transformed texture image are determined and stored in the tuples `Sample1`, `Sample2`, and `Sample3`.

```
procedure gen_sample_tuples (PCAImage, Rectangles, Sample1, Sample2,
                             Sample3):::
gen_empty_obj (ClassSamples)
Sample1 := []
Sample2 := []
Sample3 := []
gen_empty_obj (Rectangles)
access_channel (PCAImage, Image1, 1)
access_channel (PCAImage, Image2, 2)
access_channel (PCAImage, Image3, 3)
ClassNum := 0
I := 0
for Row := 80 to 340 by 260
    for Col := 40 to 460 by 460
        gen_rectangle1 (ClassSample, Row, Col, Row+60, Col+60)
        concat_obj (Rectangles, ClassSample, Rectangles)
        RowsSample := []
        ColsSample := []
        for RSample := Row to Row+60 by 1
            for CSample := Col to Col+60 by 1
                RowsSample := [RowsSample,RSample]
                ColsSample := [ColsSample,CSample]
            endfor
        endfor
        get_grayval (Image1, RowsSample, ColsSample, Grayvals1)
        get_grayval (Image2, RowsSample, ColsSample, Grayvals2)
        get_grayval (Image3, RowsSample, ColsSample, Grayvals3)
        Sample1 := [Grayvals1,Sample1]
        Sample2 := [Grayvals2,Sample2]
        Sample3 := [Grayvals3,Sample3]
    endfor
endfor
return ()
```

The feature vectors that are built by the gray values of the three channels are now displayed by the procedure `visualize_3d`. To show the feature space from different views, it is by default rotated in discrete steps around the y axis (`RotY`). Furthermore, the view can be changed by dragging the mouse. Then, dependent on the position of the mouse pointer in the graphics window, the feature space is additionally rotated around the x and z axes.

```
for j := 0 to 360 by 1
    dev_set_check ('~give_error')
    get_mposition (WindowHandle, Row, Column, Button)
    dev_set_check ('give_error')
    if (Button # [])
        RotX := fmod(Row,360)
        RotZ := fmod(Column, 360)
    else
        RotX := 75
        RotZ := 45
    endif
    RotY := j
    visualize_3d (WindowHandle, Sample1, Sample2, Sample3, RotX, RotY, \
                  RotZ)
endfor
```

Within the procedure visualize_3d, similar to the visualization of 2D feature vectors described in section 8.3.1 on page 107, the minimum and maximum values for the three feature axes are determined. Then, the maximum value range of the features is determined and is used to define the scale factor for the visualization. In contrast to the example used for the visualization of 2D feature vectors, the same scale factor is used here for all feature axes. This is because all features are of the same type (gray values), and thus the ranges are in the same order of magnitude.

```
Min1 := min(Sample1)
Max1 := max(Sample1)
Min2 := min(Sample2)
Max2 := max(Sample2)
Min3 := min(Sample3)
Max3 := max(Sample3)
MaxFeatureRange := max([Max1-Min1,Max2-Min2,Max3-Min3])
Scale := 1./MaxFeatureRange
```

After defining a value for the virtual z axis, a homogeneous transformation matrix is generated and transformed so that the feature space of interest fits completely into the image and can be visualized under the view specified before calling the procedure. The homogeneous transformation matrix is built using the operators hom_mat3d_translate, hom_mat3d_scale, and hom_mat3d_rotate. The actual transformation of the feature vectors with the created transformation matrix is applied with affine_trans_point_3d. To project the 3D points into the 2D image, the operator project_3d_point is used. Here, camera parameters are needed. These are defined as follows: the focal length is set to 0.1 to simulate a candid camera. The distortion coefficient κ is set to 0, because no distortions caused by the lens have to be modeled. The two scale factors correspond to the horizontal and vertical distance between two cells of the sensor, and the image center point as well as the width and height of the image are derived from the image size.

```
DistZ := 7
hom_mat3d_identity (HomMat3DIdentity)
hom_mat3d_translate (HomMat3DIdentity, -(Min1+Max1)/2, -(Min2+Max2)/2, \
                     -(Min3+Max3)/2+DistZ, HomMat3DTranslate)
hom_mat3d_scale (HomMat3DTranslate, Scale, Scale, Scale, 0, 0, DistZ, \
                 HomMat3DScale)
hom_mat3d_rotate (HomMat3DScale, rad(RotX), 'x', 0, 0, DistZ, \
                  HomMat3DRotateX)
hom_mat3d_rotate (HomMat3DRotateX, rad(RotY), 'y', 0, 0, DistZ, \
                  HomMat3DRotateY)
hom_mat3d_rotate (HomMat3DRotateY, rad(RotZ), 'z', 0, 0, DistZ, \
                  HomMat3DRotateZ)
affine_trans_point_3d (HomMat3DRotateZ, Sample1, Sample2, Sample3, Qx, Qy, \
                       Qz)
CamParam := [0.1,0,0.00005,0.00005,360,240,720,480]
project_3d_point (Qx, Qy, Qz, CamParam, Row, Column)
```

The result of the projection is a row and column coordinate for each feature vector. At this position, a region point is generated and displayed (see figure 8.6).

```
gen_region_points (Region, Row, Column)
set_part (WindowHandle, 0, 0, 479, 719)
set_system ('flush_graphic', 'false')
clear_window (WindowHandle)
disp_obj (Region, WindowHandle)
set_system ('flush_graphic', 'true')
```

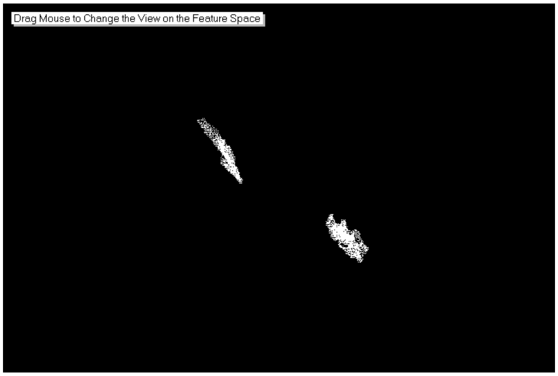

Figure 8.6: The feature space shows two clearly separated clusters for the two texture classes.

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