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Content-based image retrieval tools and techniques

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Content-Based Image Retrieval Tools and Techniques

In the beginning was an image.

To my mother
who inspired me
to develop intellectually

Contents

5 Object Recognition

5.1 Introduction

Object recognition is a process of identifying a specific object contained in an image. The goal of object recognition is to detect objects in images using different models and identify these selected objects by classifying them. Additionally, of interest is how these objects are located relative to each other in the image.

As we have mentioned above, in the first stage of CBIR construction we are interested in the recognition of objects segmented in the pre-processing. At present, there are tendencies to use different methods to separate foreground objects from the monolithic background, beginning from separate colour and texture regions, as it was presented by Li and Shapiro in [132], through the use of wavelets [133] to morphological operations [120].

In the case of more complicated images, there is a need to recognize the foreground objects, sometimes overlapped by others which are found against puzzling, multi-object background, as we can see in Fig. 2.6. Obviously, such images are more challenging and the recognition process forces us to use different methods to obtain proper classification.

The semantic approach to images, and particularly object recognition, requires image/object classification. Moreover, extracting semantically coherent regions/objects is in itself very challenging. Probabilistic representations can potentially provide an alternative to the above-mentioned methods, allowing for rich descriptions with limited parametrization.

5.2 Object Classification

Image classification has often been treated as a pre-processing step for speeding-up image retrieval in large databases and improving accuracy. This problem is crucial for multimedia information retrieval in general, and for image retrieval in particular. Usually, the classification problem can be defined as follows:

Definition 5.1. (Object classification)

Let Ω be a complete set of objects which we want to automatically recognize. Then we want to define a division into k separate classes $c_1,\dots,c_k$. It means that there must be a division function Θ, such as:

$$\Theta\colon \Omega \rightarrow L = \{1,\dots, k\} \tag{5.1}$$

which assigns each object from the set Ω to a particular class. We do not know the assignment rules, the only thing we know is the Ω subset that we call the learning or training subset.

There are a number of standard classification methods in use, such as: k-NN [134], SVM [135], Naïve Bayes (NB) classifier [136], neural network [137], and others [138]. Having surveyed these methods, we started our classification from the simplest algorithm, namely, the similarity to the pattern which compares the features of a classified object with the set of pattern features which define classes.

Object classification is so important in the context of CBIR because it is used for several purposes, for example [139]:

1. to compare whole images. Specifically, an algorithm which describes a spatial object location needs classified objects.
2. to help the user form a query in the GUI. The user forms a query choosing graphical objects semantically collected in groups.
3. to compare image objects coming from the same class as a stage in the image retrieval process.

Generally, the classical classification algorithms have been adapted to image recognition. While supervised classification is more systematic, the availability of comprehensive training data is often scarce. In particular, the veracity of "ground truth" in image data itself is a subjective question.

5.2.1 Object Similarity/Dissimilarity Metrics

Definition 5.2. (Metrics Properties)

Generally, when we analyse a metric space we assume by default that four basic conditions are satisfied:

- Non-negativity: $d(x,y) \geq 0$;

- Identity: $d(x,y) = 0 <=> x=y$;
- Symmetry: $d(x,y) = d(y,x)$; (5.2)
- Triangle inequality: $d(x,y) + d(y,z) \geq d(x,z)$ for any points x,y,z of the set.

These conditions express our common notions of distance. For example, the distance between distinct points is positive and the distance from point A to B is equal to the distance from B to A.

We may also need to find the distance between two vectors, namely, feature vectors. Then, in a normed vector space $(X, ||\cdot||)$ we can define a metric on X by

$$d(x,y) = ||x-y|| \tag{5.3}$$

A metric defined in such a way is translation invariant and homogeneous. The most widely used similarity measure is the Euclidean measure. It can be applied to measure the distance between two points or between two feature vectors.

Object similarity can be seen as a region-based similarity (compare sect. 3.8), where each object is described by its own feature vector.

The simplest approach to object similarity/dissimilarity is the comparison of feature vectors of two objects. In the context of object recognition, we are more interested in object classification than in plain object comparison. However, the most common approach is the comparison of two object feature vectors $\mathbf{x}$ and $\mathbf{y}$ using, for instance, the Euclidean (5.1) or Minkowski (5.3) metric. In fact, each feature in a vector is compared individually and then combined. This is a strong hypothesis whose main advantage is allowing parallel processing of all the features and simplifying the comparison operations by reducing the dimensionality of the comparison to be carried out.

This hypothesis can be best verified for the features of the same nature, i.e. when the distributions of values are of the same nature. In reality, it is difficult to build a global distance or similarity measure in a unitary space. In fact, the first step to do so is the normalization of the ranges of all features to [0,1]. As a final step, the n-dimensional vector is summarized into a scalar in order to sort the images of the database and find the more similar ones.

Many measures exist for quantitative variables, mostly constructed in an additive way after counting the differences for each variable separately. The basic metrics useful for our purpose are presented in Table 5.1:

Table 5.1 Dissimilarity Metrics for Quantitative Data in $\mathbb{R}^m$.

Metric name	Dissimilarity $d(\mathbf{x},\mathbf{y})$	No.
Euclidean	$\sqrt{(\mathbf{x}-\mathbf{y})^T(\mathbf{x}-\mathbf{y})}$	(5.1)

Weighted Euclidean	$\sqrt{(\mathbf{x}-\mathbf{y})^T \mathrm{diag}(w_i^2)(\mathbf{x}-\mathbf{y})}$	(5.2)
Minkowski	$\sqrt[\frac{1}{p}]{\sum_{i=1}^{m} \lvert x_i - y_i \rvert^p}, \quad p \geq 1, \; p \neq 2$	(5.3)
Mahalanobis	$\sqrt{(\mathbf{x}-\mathbf{y})^T C^{-1}(\mathbf{x}-\mathbf{y})}$ C is covariance matrix	(5.4)
City block	$\sum_{i=1}^{m} \lvert x_i - y_i \rvert$	(5.5)
Max norm	$\max_i \lvert x_i - y_i \rvert$	(5.6)

5.2.2 Decision Trees

In the construction of decision trees [140] a measure of discrimination is used in order to rank attributes and select the best one. The construction of a decision tree is equivalent to a restriction of the whole set of attributes which describes the data to a set of pertinent attributes. Each vertex of a binary tree is associated with an attribute [141].

From the more formal point of view, a decision tree represents a function that takes as input a vector of attribute values and returns a single output value as a 'decision'. We consider a list of attributes of our objects $\{x_1, x_2, \ldots, x_r\}$ and classes $C = \{c_1, \ldots, c_k\}$. A learning subset contains examples associated with both values of the attributes and a class [140].

Inductive learning regarding a given domain is based on a set of examples. Each example is a case already solved or completely known. It is associated with a pair [description, class] where the description is a set of pairs [attribute, value] which, in turn is the available knowledge. The class of the example is the decision (or category, or solution...) associated with the given description. Such a set of examples is called a training set. Samples considered as examples can be taken from a database, with their attributes and classes as descriptors of each case. The aim of the inductive process is to find a general rule to determine the relation between values of attributes and classes in C. The inductive method is based here on a decision tree from the learning subset.

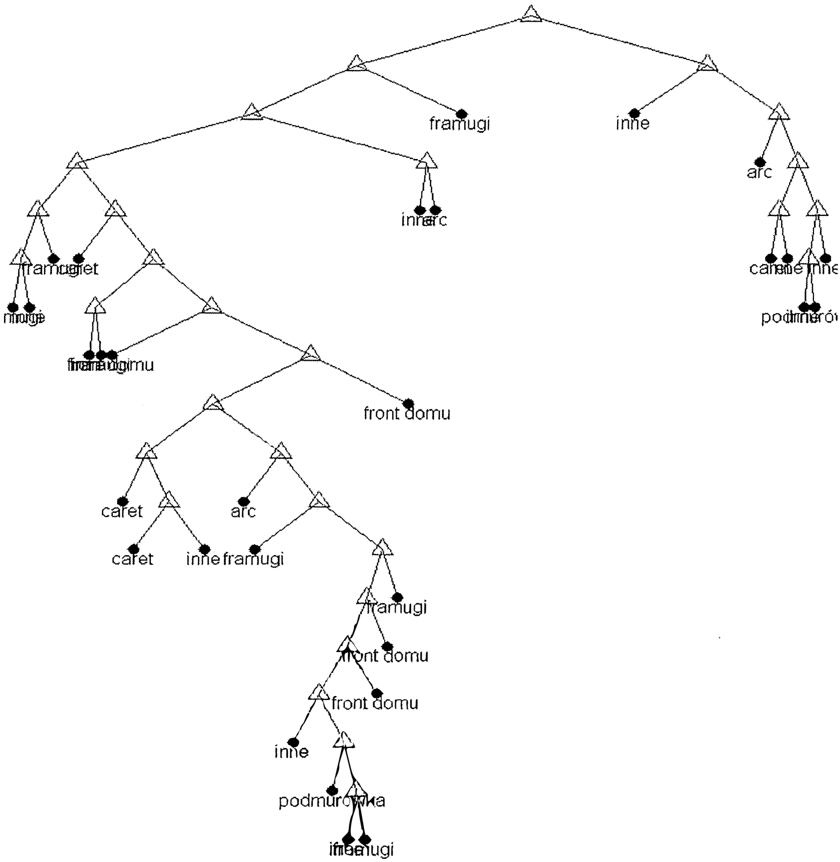

Fig. 5.1 Example of a decision tree pruned to the 7^{th} level. We omitted the feature values in nodes for the clarity of the figure.

The decision tree construction methods are based on the hypothesis that the value for the class is equally distributed. Thus, we have to balance the number of objects of each class by randomly selecting a subset of the whole development dataset because the process of tree construction is very sensitive to the lack of representation of certain important attributes of the minority class or imbalanced classes.

Each attribute x_j can be either symbolic, numerical, or fuzzy. In our case, attributes are numerical: real and complex. Hence, there exist many constructions depending on attribute types and class assigned methods, i.e. many kinds of decision trees (DT) [142], [143], [144]: symbolic DT, binary DT [145], fuzzy DT [146], etc.

5.2.3 Naïve Bayes (NB) classifier

Naïve Bayes (NB) is a simple technique for constructing classifiers: models that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set. It is not a single algorithm for training such classifiers, but a family of algorithms based on a common principle: all NB classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. An NB classifier considers each of these features to contribute independently to the probability, regardless of any possible correlations between them.

An advantage of the NB is the fact that it only requires a small amount of training data to estimate the parameters necessary for classification. For some types of probability models, NB classifiers can be trained very efficiently in a supervised learning setting [136].

In many practical applications, including image processing, parameter estimation for NB models uses the method of maximum likelihood; in other words, one can work with the Naïve Bayes model without accepting Bayesian probability or using any Bayesian methods.

Generally, the NB is a conditional probability model: given a problem instance to be classified, represented by a vector $\mathbf{x} = (x_1, \ldots, x_n)$ representing some n features (independent variables); it assigns to this instance probabilities:

$$p(C_m \mid x_1, \ldots, x_n)\,, \tag{5.7}$$

for each of M possible classes. Using Bayes' theorem, the conditional probability can be decomposed as:

$$p(C_m \mid \mathbf{x}) = \frac{p(C_m)p(\mathbf{x}|C_m)}{p(\mathbf{x})} \tag{5.8}$$

In practice, there is interest only in the numerator of that fraction, because the denominator does not depend on C and the values of the features are given, so that the denominator is effectively constant. From the definition of conditional probability we know that:

$$p(C_m \mid x_1, \ldots, x_n) = p(C_m)p(x_1, \ldots, x_n \mid C_m) \tag{5.9}$$

Assuming conditional independence of each feature:

$$p(C_m \mid x_1, \ldots, x_n) \propto p(C_m)\, p(x_1 \mid C_m)\, p(x_2 \mid C_m)\, p(x_3 \mid C_m) \ldots \qquad (5.10)$$

$$\propto p(C_m) \prod_{i=1}^{n} p(x_i \mid C_m)$$

Based on this assumption, a classification can be constructed where the function that assigns a class label $\hat{y} = C_m$ for some m looks as follows:

$$\hat{y} = \arg\max_{m \in \{1,\ldots,M\}} p\,(C_m) \prod_{i=1}^{n} p(x_i \mid C_m) \qquad (5.11)$$

Despite the fact that the far-reaching independence assumptions are often inaccurate, the Naïve Bayes classifier has several properties that make it surprisingly useful in practice [147]. In particular, the decoupling of the class conditional feature distributions means that each distribution can be independently estimated as a one-dimensional distribution. This helps to alleviate problems deriving from the *curse of dimensionality*, namely high-dimensional space of data sets which scale exponentially with the increase of the feature number [148].

5.2.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a non-probabilistic binary linear classifier introduced by Cortes and Vapnik [135] in 1995. An SVM model is a representation of samples as points in a space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible [149]. New examples are then mapped into the same space and predicted to belong to a category based on whichever side of the gap they fall on.

The SVM constructs a hyperplane or a set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification. Intuitively, good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (the so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

For easy visualization, the case of a 2D input space can be considered. Data are linearly separable and there are many different hyperplanes that can perform separately (Fig. 5.2). Actually, for $\mathbf{x} \in \mathbb{R}^2$, the separation is performed by 'planes' $w_1 x_1 + w_2 x_2 + b = 0$, which is the decision boundary.

There are many functions that can be used to find the optimal separating function without knowing us the underlying probability distribution. In the case of a classification of linearly separable data, the idea is as follows: among all the hyperplanes that minimize the training error (i.e, empirical risk) find the one with the largest margin M.

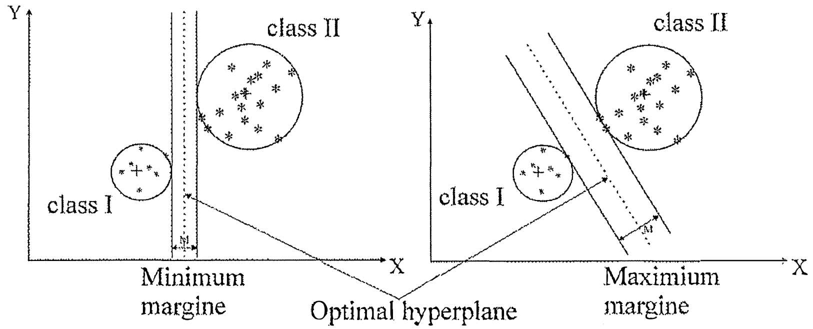

Fig. 5.2 The optimal hyperplane and margins M for an SVM trained with samples from two classes. The samples on the margin are called support vectors.

By using given training examples, during the learning stage, the SVM finds parameters $\mathbf{w} = [w_1\ w_2\ \dots\ w_n]^{\mathrm{T}}$ and b of a discriminant or decision function $d(\mathbf{x},\mathbf{w}, b)$:

$$d(\mathbf{x},\mathbf{w},b) = \mathbf{w}^T\mathbf{x} + b = \sum_{i=1}^{n} w_i x_i + b\,, \tag{5.12}$$

where: $\mathbf{x}, \mathbf{w} \in \mathbb{R}^n$, and the scalar b is called a bias. The dashed separation lines in Fig. 5.2 represent the line that follows from $d(\mathbf{x},\mathbf{w}, b) = 0$.

We can notice that the hyperplane is in the canonical form with respect to training data $\mathbf{x} \in \mathbf{X}$. If

$$\min_{x_j \in X} \left|\mathbf{w}^T\mathbf{x} + b\right| = 1 \tag{5.13}$$

and if the canonical hyperplane has a maximum margin M then this hyperplane is located in the middle of M. From the geometric properties the margin can be described as $M = \dfrac{2}{\|\mathbf{w}\|}$ where: $\|\mathbf{w}\| = \sqrt{\mathbf{w}^T\mathbf{w}} = \sqrt{\sum_i w_i^2}$. If $\|\mathbf{w}\|$ is minimal, M is a maximum.

SVMs belong to a family of generalized linear classifiers. Their special property is that they simultaneously minimize the empirical classification error and maximize the geometric margin; hence they are also known as maximum margin classifiers.

5.2.5 Fuzzy Rule-Based Classifier (FRBC)

The Fuzzy Rule-Based Classifier FRBC uses fuzzy sets for reasoning and has been introduced by Ishibuchi [150].

Definition 5.3. (Fuzzy Rule-Based Classifier -Ishibuchi [150])

Let us consider an M-class classification problem in an n-dimensional normalized hyper-cube $[0,1]^n$. For this instance, fuzzy rules of the following type are used:

$$\text{Rule } R_q: \quad \text{If } x_1 \text{ is } A_{q1} \text{ and ... and } x_n \text{ is } A_{qn} \text{ then Class } L_q \text{ with } CF_q, \tag{5.14}$$

where R_q is the label of the q^{th} fuzzy rule, $\mathbf{x} = (x_1, ..., x_n)$ is an n-dimensional feature vector, A_{qi} is an antecedent fuzzy set (i = 1,...,n), L_q is a class label, CF_q is a real number in the unit interval [0,1] which represents a rule weight. The rule weight can be specified in a heuristic manner or it can be adjusted, e.g., by a learning algorithm introduced by Ishibuchi et al. [151], [152].

The n-dimensional vector $A_q = (A_{q1}, ..., A_{qn})$ is used to represent the antecedent part of the fuzzy rule R_q in (5.14) in a concise manner.

A set of fuzzy rules S of the type shown in (5.14) forms a fuzzy rule-based classifier. When an n-dimensional vector $\mathbf{x}_p = (x_{p1},...,x_{pn})$ is presented to S, first the *compatibility grade* of $\mathbf{x}_p$ with the antecedent part A_q of each fuzzy rule R_q in S is calculated as the product operator

$$\mu_{A_q}(\mathbf{x}_p) = \mu_{A_{q1}}(\mathbf{x}_{p1}) \times ... \times \mu_{A_{qn}}(\mathbf{x}_{pn}) \quad \text{for } R_q \in S \tag{5.15}$$

where $\mu_{A_{qi}}(.)$ is the membership function of A_{qi}. Then a single winner rule $R_{w(\mathbf{x}_p)}$ is identified for $\mathbf{x}_p$ as follows:

$$w(\mathbf{x}_p) = \underset{q}{\operatorname{argmax}}\{CF_q \times \mu_{A_q}(\mathbf{x}_p) \mid R_q \in S\}, \tag{5.16}$$

where $w(\mathbf{x}_p)$ denotes the rule index of the winner rule for $\mathbf{x}_p$.

The vector $\mathbf{x}_p$ is classified by the single winner rule $R_{w(\mathbf{x}_p)}$ belonging to the respective class. If there is no fuzzy rule with a positive *compatibility grade* of $\mathbf{x}_p$ (i.e., if $\mathbf{x}_p$ is not covered by any fuzzy rules in FC), the classification of $\mathbf{x}_p$ is rejected. The classification of $\mathbf{x}_p$ is also rejected if multiple fuzzy rules with different consequent classes have the same maximum value on the right-hand side of (5.16). In this case, $\mathbf{x}_p$ is on the classification boundary between different classes. We use the single winner-based fuzzy reasoning method in (5.16) for pattern classification.

An ideal theoretical example of a simple three-class, two-dimensional pattern classification problem with 20 patterns from each class is considered by Ishibuchi and Nojima [150]. There three linguistic values (*small*, *medium* and *large*) are used as antecedent fuzzy sets for each of the two attributes, and 3×3 fuzzy rules are generated.

FC: fuzzy rule-based classifier with nine fuzzy rules [150]

R_1: If x_1 is *small* and x_2 is *small* then Class2 with 1.0,
R_2: If x_1 is *small* and x_2 is *medium* then Class2 with 1.0,
R_3: If x_1 is *small* and x_2 is *large* then Class1 with 1.0,
R_4: If x_1 is *medium* and x_2 is *small* then Class2 with 1.0,
R_5: If x_1 is *medium* and x_2 is *medium* then Class2 with 1.0,
R_6: If x_1 is *medium* and x_2 is *large* then Class1 with 1.0,
R_7: If x_1 is *large* and x_2 is *small* then Class3 with 1.0,
R_8: If x_1 is *large* and x_2 is *medium* then Class3 with 1.0,
R_9: If x_1 is *large* and x_2 is *large* then Class3 with 1.0.

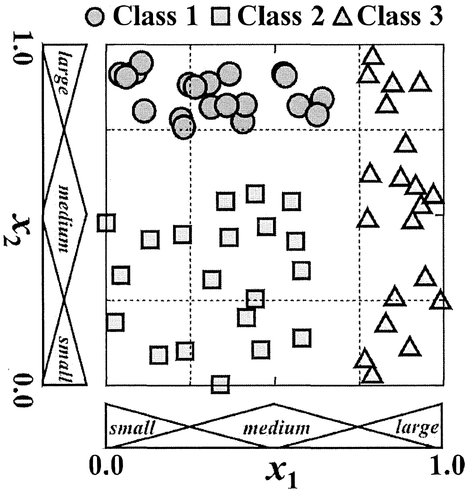

Fig. 5.3 An ideal example of a fuzzy rule-based classifier *FC* followed by Ishibuchi and Nojima [150].

5.3 Object Classification for the Hybrid Semantic System

For the Hybrid Semantic System we have to classify objects in order to:

1. use particular classes as patterns. We store these data in DB to use them in CBIR algorithms.
2. specify a spatial object location in our system. In our system spatial object location in an image is used as the global feature. The object's mutual spatial relationship is calculated based on the algorithm adopted from the concept of principal component analysis (PCA), proposed by Chang and Wu [14] and later modified by Guru and Punitha [15], to determine the first principal component vectors (PCVs) (details in sect. 5.5).

3. to help the user ask a query in GUI. The user chooses for a query graphical objects semantically collected in groups.
4. compare image objects coming from the same class as a stage in the image retrieval process (see details in sect. 9.9).

Thus, the feature vector **y** (cf. (4.4)) is used for object classification. So far, four classifiers on two levels have been implemented in this system. At the first level, we have implemented three classifiers, namely similarity to pattern, decision tree and Naïve Bayes. We have known that there is no universal classifier or even special dedicated classifier for such a challenging problem as image recognition. In the light of all of the above, we decided to apply four classifiers, each based on a different mechanism to decrease classification errors.

Additionally, a fuzzy rule-based classifier (FRBC) [153], [154] is used in order to identify the most ambiguous objects. According to Ishibuchi, this classifier decides which of the three classes a new element belongs to. These three classes are taken from the three above-listed classifiers.

We are aware of the fact that there can always exist some elements which are misclassified, but their number has been significantly minimised by means of a two-level classification.

We have to classify objects in order to use them in a spatial object location algorithm and to offer the user a classified group of objects.

5.3.1 Similarity to pattern

The basic approach to classification is the comparison of an object feature vector **y** to the previously prepared patterns P_k for each class. Patterns can be created in different ways. The simplest method is the calculation of the average value of each vector component. The designed classes/ patterns should attribute objects in accordance with human perception to M semantic classes. The subsets of the most representative objects are used to define particular class are also used as learning subsets. In order to compare the object vector with a pattern we apply the Euclidean metric, where p=2 and Minkowski metric, where p=3:

$$d(\mathbf{y},P_k)=\sqrt[p]{\sum_{i=1}^{r}\xi_{P_k}(y_i)\left|\mathbf{y}(y_i)-P_k(y_i)\right|^p} \tag{5.17}$$

where: k – pattern or class number, $1 \le i \le r$. All pattern vectors are normalized. A new object is classified to a class for which d is the minimum [155], [42].

We also assume weights $\xi_k(i)$ for all pattern features where: i is the number of feature, $1 \le i \le r$. Weights for real features are the coefficients of variation

$$\xi_{P_k} = \frac{\sigma(i)}{\bar{x}(i)} \in [0,1] \tag{5.18}$$

in order to reflect the dispersion of each feature in the subset selected as a pattern (where σ – standard deviation and $\bar{x}$ – mean value for each feature). However, Zernike's moments are complex features, hence to obtain the real weight we apply the formula [139].

$$\xi(i) = \sqrt{\frac{\sigma_{\mathbf{Re}}^2 + \sigma_{\mathbf{Im}}^2}{\bar{x}_{\mathbf{Re}}^2 + \bar{x}_{\mathbf{Im}}^2}} \tag{5.19}$$

where standard deviations and means are calculated separately for real and imaginary parts of complex moments.

For all predefined classes we have created a class (pattern) library (also stored in the DB (see Chapter 6)) which contains information about pattern types, feature weights and objects belonging to learning subsets [11].

We decided to classify separately objects with and without texture to reduce the misclassification between these two groups. This division diminishes the number of classification errors resulting from the fact that the patterns for non-textured objects give smaller values *d* because eight texture components are equal to 0.

The methods used to find a similarity/dissimilarity among images or objects are insufficient because an assignment to a particular class aggregates some information, hence these metrics are not distinctive enough.

5.3.2 Decision Tree – Example of Implementation

As it was carefully explained in subsect 5.2.2 the construction of decision trees differs from finding similarities with a measure of discrimination ranks attributes and select the best one. We construct our trees using the Matlab function ClassificationTree.fit (training_set,classes).

In order to avoid high error rates resulting from as many as 40 classes we use the hierarchical method. The more general division is created by dividing the whole data set into five clusters applying *k*-means clustering. The most numerous classes of each cluster constituting a meta-class are assigned to five decision trees, which results in 8 classes for each one.

The second stage of the method, after constructing the trees, is the classification of a new object on the basis of its values of the feature vector. This stage is also realized by the Matlab function predict(tree,X_new).

5.3.3 FRBC – Example of Implementation

In multi-class systems, such as ours, an FRBC can be used as a second level classifier which has a decisive role in the ambiguous classification at the first level. It means that when an object has not been classified unequivocally to the same class by similarity to pattern metrics, decision trees, NB classifiers at the first stage, the FRBC is applied and it decides definitely about the object class.

The theoretical method presented by Ishibuchi does not answer the question how to construct membership functions for the crisp, real data, especially those corresponding to linguistic values. Hamilton and Stashuk [156] gave a suggestion for the construction of membership functions based on the standardized residual analysis but they applied it to continuous data.

However, we solved this problem calculating the mean value $\bar{x}$ and standard deviation σ for the elements of each of the three classes suggested by the classfiers of the first level. The membership function of each class is constructed as a trapezoidal function (see Fig. 5.4), where points b and c are in the $\pm\sigma/2$ distance from the mean value $\bar{x}$, and the basis points a and d are $\pm\sigma$ distant from the mean value [51].

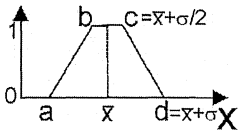

Fig. 5.4 Exemplification of a membership function calculated on the basis of statistical class parameters.

Then, we divide the ranges of features x_1 and x_2 into three equal intervals. Next, we compare the mean value of a particular class to correspondent intervals. The effect is visible in Fig. 5.5 for the horizontal and vertical axes.

Table 5.2 Classification boundaries for a fuzzy rule-based classifier.

x_2	*Large*	$S_1L_2 \rightarrow R_3$	$M_1L_2 \rightarrow R_6$	$L_1L_2 \rightarrow R_9$
	Medium	$S_1M_2 \rightarrow R_2$	$M_1M_2 \rightarrow R_5$	$L_1M_2 \rightarrow R_8$
	Small	$S_1S_2 \rightarrow R_1$	$M_1S_2 \rightarrow R_4$	$L_1S_2 \rightarrow R_7$
		Small	*Medium*	*Large*
	x_1			

In each case, the fuzzy rule-based classifier is constructed automatically by matching the membership function related to the proper linguistic value, resulting in the right class for each rule. Table 5.2 resembles the arrangement of rules to feature ranges. The classifier FC_2 corresponds to the example seen in Fig. 5.5:

FC_2: fuzzy rule-based classifier with nine fuzzy rules

R_1: If x_1 is *small* and x_2 is *small* then non-defined with 1.0,

R_2: If x_1 is *small* and x_2 is *medium* then balcony with 1.0,

R_3: If x_1 is *small* and x_2 is *large* then arc with 1.0,
R_4: If x_1 is *medium* and x_2 is *small* then non-defined with 1.0,
R_5: If x_1 is *medium* and x_2 is *medium* then balcony with 1.0,
R_6: If x_1 is *medium* and x_2 is *large* then non-defined with 1.0,
R_7: If x_1 is *large* and x_2 is *small* then pillar with 1.0,
R_8: If x_1 is *large* and x_2 is *medium* then non-defined with 1.0,
R_9: If x_1 is *large* and x_2 is *large* then non-defined with 1.0.

The winner is the rule for which the product operator is maximum (cf. (5.15)), as follows:

$$\mu_{R_3}(\mathbf{x}_p) = \mu_{small}(\mathbf{x}_1) \times \mu_{large}(\mathbf{x}_2) = \mu_{small}(8.6383) \times \mu_{large}(0.1506) = 1 \times 1 = 1$$

The fuzzy rule-based classifier is stable, irrespective of attribute selection. Hence, we treat it as a "decisive voice" in the case of differences between similarity to pattern metrics, decision tree and NB classifications.

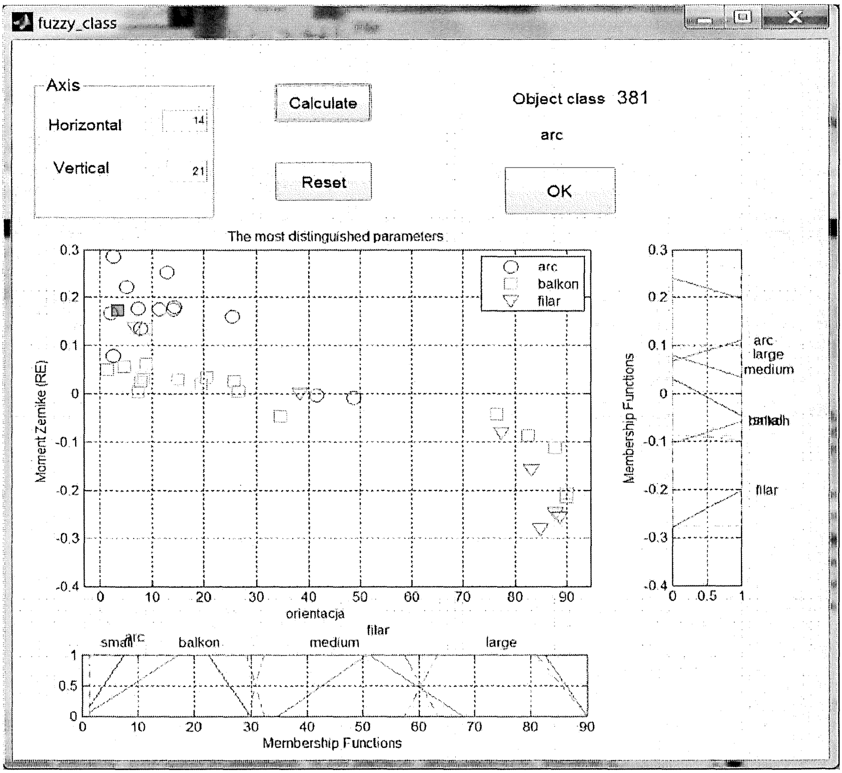

Fig. 5.5 Classification example [51]. The new element marked by the full green square is recognized as an arc among classes: arc, pillar and balcony. Membership functions are represented by

solid colour lines and linguistic intervals are drawn in dashed lines. In this case, x_1 is orientation and x_2 the real part of Zernike's moment.

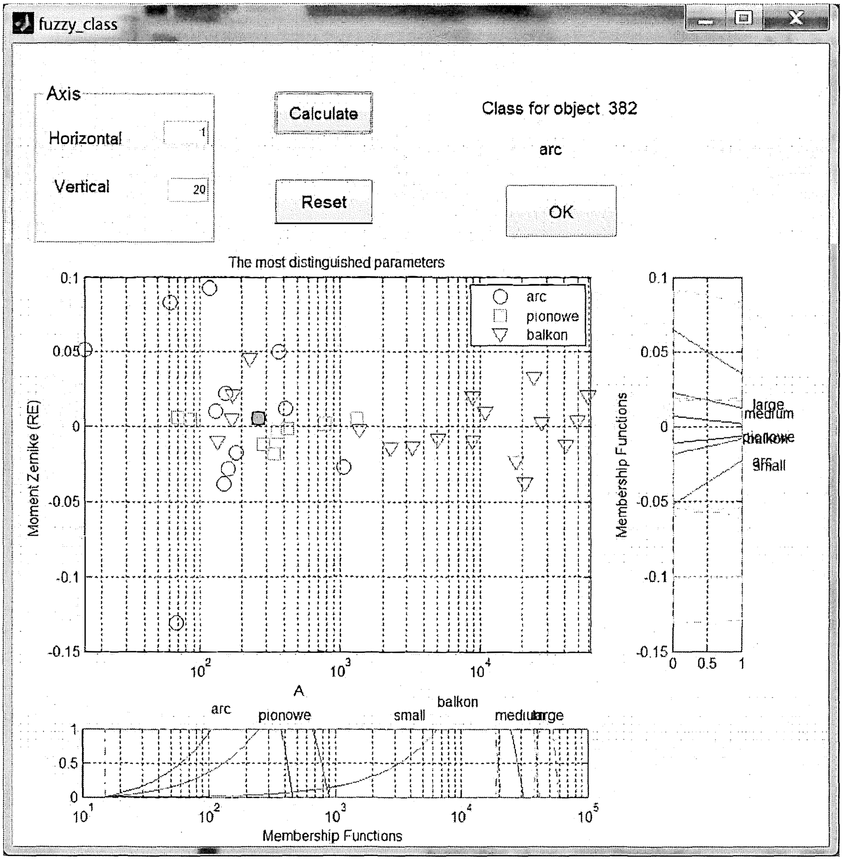

Fig. 5.6 Classification example **[51]**. The new element marked by the full green square is recognized as an arc among classes: arc, pillar and balcony. Membership functions are represented by solid colour lines and linguistic intervals are drawn in dashed lines. In this case, x_1 is area and x_2 the real part of Zernike's moment.

5.4 Convolutional Neural Networks

The recently developed method for the classification of large image collections appears to be the deep learning based on convolutional neural networks (CNN). Generally, neural networks (NNs) have been used for image classification since 80s, for instance, the Hopfield NN.

Deep neural networks (DNN) and convolutional neural networks (CNN), first introduced in 2006, are artificial neural networks (ANN) with multiple hidden layers of units between the input and output layers and which can model complex non-linear relationships.

Because ConvNets are designed to process data that come in the form of multiple arrays, they at once have been applied to a colour image composed of three 2D arrays containing pixel intensities in the three colour channels [157].

One very efficient property of convolutional layers is that they are easily organisable. We can 'feed' the output of one convolutional layer into another. With each layer, the network can detect higher-level, more abstract features.

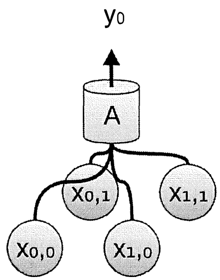

Fig. 5.7 The simplest 2D segment of a CNN. For each patch of samples - neurons $x_{[0,1]}$ (for pixels in image), A computes features [158].

The output in terms of inputs can be presented as:

$$y_{0,0} = \mathrm{A}\begin{pmatrix} x_{0,0} & x_{1,0} \\ x_{0,1} & x_{1,1} \end{pmatrix} \tag{5.20}$$

in the simplest case which can be seen in Fig. 5.7, and more generally, as:

$$y_{n,m} = \mathrm{A}\begin{pmatrix} x_{n,m}, & x_{n+1,m}, & \ldots, \\ x_{n,m+1}, & x_{n+1,m+1}, & \\ \ldots, & \ldots, & \ldots, \end{pmatrix} \tag{5.21}$$

The architecture of a typical ConvNet (see Fig. 5.10) is structured as a series of stages. The first few stages are composed of two types of layers: convolutional layers and pooling layers, as Fig. 5.8 depicts. Convolutional layers are often interweaved with pooling layers. In particular, there is a kind of layer called a max-pooling layer that is extremely popular. A max-pooling layer takes the maximum of features over small units of a previous layer. The output tells us if a feature was present in a region of the previous layer, but not precisely where. Max-pooling layers are a kind of a 'zoom-out'. They allow later convolutional layers to work on larger sections of the data, because a small patch after the pooling layer corresponds to a much larger patch before it.

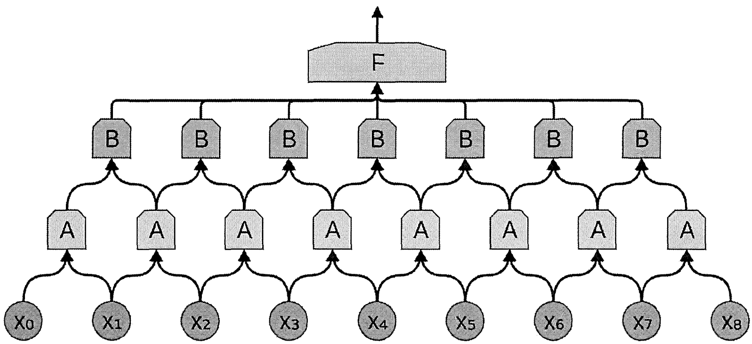

Fig. 5.8 *A* - convolutional layer, *B* - pooling layer.

Units in a convolutional layer are organized in feature maps, within which each unit is connected to local patches in the feature maps of the previous layer through a set of weights called a filter bank. The result of this local weighted sum is then passed through a non-linearity, such as a rectified linear unit (ReLU) – which is shown in Fig. 5.10. The introduction of a ReLU in 2012 by A. Krizhevsky et al. [159] was a breakthrough in applying CNN to computer vision. ReLU is a layer of neurons that uses the non-saturating activation function, for example hyperbolic tangent: $f(x) = \tanh(x)$, $f(x) = |\tanh(x)|$, or the sigmoidal function: $f(x) = (1+e^{-x})^{-1}$. The advantage of these functions is their fast action without a significant loss of general accuracy. Krizhevsky et al. used GPUs to train very large image collections with lots of image categories (for instance, ImageNet, compare sect. 7.2).

All units in a feature map share the same filter bank. Different feature maps in a layer use different filter banks. The reason for this architecture is twofold:

- first, in array data, such as images, local groups of values are often highly correlated, forming distinctive local motifs that are easily detected;
- second, the local statistics of images and other signals are invariant to location.

Mathematically, the filtering operation performed by a feature map is a discrete convolution, hence the name.

Although the role of the convolutional layer is to detect local conjunctions of features from the previous layer, the role of the pooling layer is to merge semantically similar features into one. Because of the relative positions of the features forming a motif, reliably detecting the motif can be done by the coarse-graining position of each feature, Fig. 5.9. A typical pooling unit computes the maximum of a local patch of units in one feature map (or in a few feature maps).

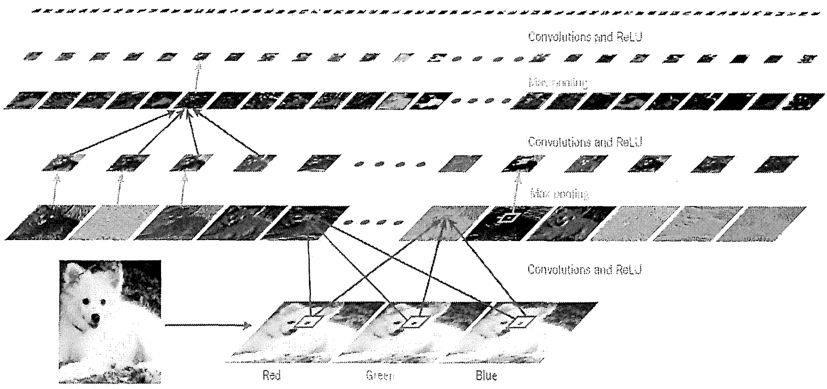

Fig. 5.9 The three colour components RGB (red, green, blue) (bottom right) of the image of a dog are the inputs to a typical convolutional network. Information flows bottom up, with lower-level features acting as oriented edge detectors, and a score is computed for each image class in output [157]. The outputs of each layer (horizontally) are the inputs to the next layer. Each rectangular image is a feature map corresponding to the output for one of the learned features, detected in each of the image positions.

Neighbouring pooling units take input from patches that are shifted by more than one row or column, thereby reducing the dimension of the representation and creating an invariance to small shifts and distortions. Two or three stages of convolution, non-linearity and pooling are stacked, followed by more convolutional and fully-connected (FC) layers. Back-propagating gradients through a ConvNet is as simple as through a regular, deep network, allowing all the weights in all the filter banks to be trained.

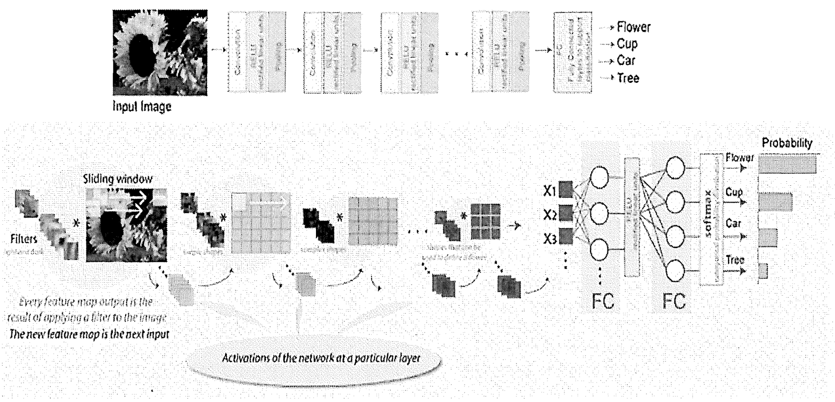

Fig. 5.10 General scheme of the deep learning classification process. The top flow presents a CNN training to perform an image classification task where the output of each convolved image is used as the input to the next layer. The bottom scheme shows the proper classification process (FC – Fully Connected layer) [160].

Now CNNs are used to classify the biggest image collections where many layers of information processing stages in hierarchical architectures are exploited for pattern classification and for feature or representation learning. The deep learning as such lies in the intersections of several research areas, including neural networks, graphical modelling, optimization, pattern recognition, and signal processing, etc. [40].

5.5 Spatial Relationship of Graphical Objects for the Hybrid Semantic System

It is easy for the user to recognize visually spatial object location but the system supports full automatic identification based on rules for location of graphical elements, which is a challenging task. In the light of global features presented in sect. 3.8, the spatial object relationship has not been mentioned, but from the human perception it is an important issue. For example, a question arises: if two images consisting of a set of these same objects, but are organized in another location, for instance, in a mirror symmetry are similar or not.

Let us assume that we analyse a house image. Then, for instance, an object which is categorized as a window cannot be located over an object which is categorized as a chimney. For this example, rules of location mean that all architectural objects must be inside the bounding box of a house. For the image of a Caribbean beach, an object which is categorized as a palm cannot grow in the middle of the sea, and so on.

In the system designed by Jaworska [42], spatial object location in an image is used as the global feature. For this purpose, the mutual position of all objects is checked. Moreover, object location reduces the differences between high-level semantic concepts perceived by humans and low-level features interpreted by computers.

An image I_i is interpreted as a set of n objects o_{ij} composing it:

$$I_i = \{o_{i1}, o_{i2}, \ldots, o_{in}\}. \tag{5.22}$$

Each object o_{ij} is characterized by a unique identifier and a set of features discussed earlier (cf. subsect. 4.6). This set of features includes a centroid $C_{ij} = (x_{ij}, y_{ij})$ and a label L_{ij} indicating the class of an object o_{ij} (such as window, door, etc.), identified in the process described in section 5.3. Let us assume that there are, in total, M classes of the objects recognized in the database. For convenience, the classes of the objects are numbered and thus L_k's are just IDs of classes.

Formally, let I be an image consisting of n objects and k be the number of different classes of these objects, $k \leq M$, because usually there are some objects of the same type in the image, for example, there can be four windows in a house.

Now, let C_p and C_q be two object centroids with $L_p < L_q$, located at the maximum distance from each other in the image, i.e.,

$$\text{dist}\,(C_p, C_q) = \max\,\{\text{dist}\,(C_i, C_j)\ \ \forall i,j \in \{1,2,\ldots,k\}\ \text{ and }\ L_i \neq L_j\} \qquad (5.23)$$

where: dist(•) is the Euclidean distance between two centroids (see Fig. 5.11 middle subplots). The line joining the most distant centroids is the line of reference and its direction from centroid C_p to C_q is the direction of reference for computed angles θ_{ij} between other centroids. This way of computing angles makes the method invariant to image rotation.

Thus, the mutual location of two objects in the image is described in relation to the line of reference by triples (L_i, L_j, θ_{ij}) (see Fig. 5.11 middle subplots). Hence, there are $T = m\,(m\text{-}1)/2$ numbers of triples, generated to logically represent an image consisting of m objects. Let S be a set of all triples, then we apply the concept of principal component analysis (PCA) proposed by Chang and Wu [161] and later modified by Guru and Punitha [162] to determine the first principal component vectors (PCVs).

First, a matrix of observations $X_{3\times N}$ where each triple is one observation is constructed based on a set of observations S. Next, the mean value u of each variable is calculated, and the deviation from the mean vector **u** is subtracted in order to generate matrix **B=X-u1**, where **1** - vector of all 1s. In the next step, the covariance matrix $\mathbf{C}_{3\times 3}$ is found from the outer product of matrix **B** by itself as:

$$\mathbf{C} = \mathbb{E}\,[\mathbf{B}\otimes\mathbf{B}] = \mathbb{E}\,[\mathbf{B}\,\mathbf{B}^*] = 1/N\,[\mathbf{B}\,\mathbf{B}^*]. \qquad (5.24)$$

where: $\mathbb{E}$ is the expected value operator, ⊗ is the outer product operator, and * is the conjugate transpose operator. Eventually, eigenvectors, which diagonalise the covariance matrix **C,** are found as follows:

$$\mathrm{V}^{-1}\,\mathbf{C}\,\mathrm{V} = \mathbf{D} \qquad (5.25)$$

where: **D** is the diagonal matrix of the eigenvalues of **C**. Vectors V are our three principal components.

For further analysis we use the first nine coefficients of the PCV which are the 'spatial components' of the representation of an image I_i, and are denoted PCV_i.

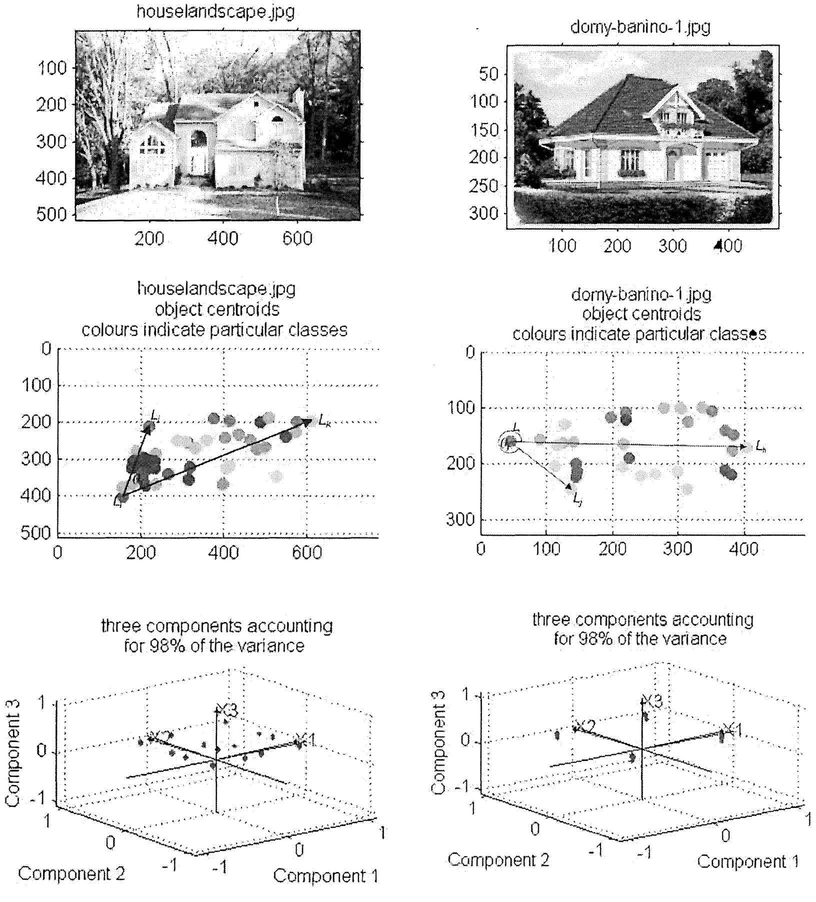

Fig. 5.11 The main stages of the PCV applied to determine the unique object spatial location in an image [52].

Fig. 5.11 presents the most important stages in the determination of spatial object location: from the presentation of the original image (top), through the object centroid locations (colours indicate particular classes) (middle subplot), to the 3D subplot of the principal components (bottom).

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