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**Content-based
image retrieval
tools and techniques**

T. Jaworska

Instytut Badań Systemowych
Polska Akademia Nauk

Systems Research Institute
Polish Academy of Sciences



POLSKA AKADEMIA NAUK

Instytut Badań Systemowych

ul. Newelska 6

01-447 Warszawa

tel.: (+48) (22) 3810100

fax: (+48) (22) 3810105

Kierownik Zakładu zgłaszający pracę:
Prof. dr hab. inż. Janusz Kacprzyk

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Tatiana Jaworska

Content-Based
Image Retrieval
Tools and Techniques

In the beginning was an image.

To my mother
who inspired me
to develop intellectually

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4 Object Detection

4.1 Introduction

To acquire a region-based signature, a key step is to segment images. Reliable segmentation is especially critical for characterizing shapes within images. While there is no denying that achieving good segmentation is a major step toward image understanding, some of the issues plaguing current techniques are computational complexity, reliability of good segmentation, and acceptable segmentation quality assessment methods.

There are many different methods of image segmentation. One approach extracts a central object from a mono-chromatic background, for example, based on morphological operations by Chen et al. [120], or based on the curvature shape by Abbassi et al. [100], and by Sze [101]. The latter approach segments multi-object images, which is most challenging.

Based on the features described in Chapter 3, the objects from an image can also be extracted. For instance, the clustering of local feature vectors based on a histogram is a widely used method to segment images. Therefore, below we present some of the most standard algorithms and we conclude by showing our approach to image segmentation and describing the set of features which we selected to construct the feature vector for each segment.

4.2 Object Segmentation Based on Colour

4.2.1 *K-means Algorithm*

Definition 4.1. (*K-means*)

Let X be a data set (for example a raster image) such as $x_{mm} \in X$. We have an initial k means of partition $P = \{C_1, C_2, \dots, C_k\}$ of X , which satisfies the following conditions:

1.
$$\bigwedge_{x_{mn} \in X} \bigvee_{C_j \in P} x_{mn} \in C_j;$$
2.
$$\bigwedge_{x_{mn} \in X} x_{mn} \in C_j \Rightarrow x_{mn} \notin C_i \text{ where } i \neq j, \quad C_i, C_j \in P.$$

Intuitively, each data point is assigned to a cluster whose centroid is the nearest, for example, in the Euclidean distance terms. Therefore, the criterion that is used in order to achieve such an assignment is the following:

$$f(P, U) = \sum_{j=1}^c \sum_{m=1}^M \sum_{n=1}^N \|x_{mn} - v_{C_j}\|^2 \quad (4.1)$$

where: v_{C_j} - are cluster centroids C_j for $j = 1, \dots, c$, $U = \{v_{C_j}\}$ - the vector of all centroids.

We find the minimal value of function f for a given data set and the number of clusters k . The algorithm searches for the true cluster centres by iterating the following two steps:

1. Calculating the current partition based on the current clusters
2. Modifying the current clusters by minimizing the within-cluster sum of squares objective.

We applied the K -means algorithm for our RGB images, but the results were highly dissatisfying. The results are presented in Fig. 4.1 for two numbers of clusters.



Fig. 4.1 Example of application of the K -means algorithm to the image from Fig. 2.6.

4.2.2 Fuzzy C-means Algorithm

The fuzzy C-means (FCM) clustering [121] generalizes the hard K -means algorithm to allow points to partially belong to multiple clusters. In the case of image segmentation, an image X of size $M \times N$ and L grey levels is a data set. The degree to which each image point $x_{mn} \in X$ belongs to a cluster C_j is partially defined by a membership function $0 \leq \mu_{C_j}(x_{mn}) \leq 1$, where $j = 1, \dots, c$; $m = 1, \dots, M$ and $n = 1, \dots, N$. A membership function should be constructed in the following way:

$$\bigwedge_{x_{mn} \in X} \sum_j \mu_{C_j}(x_{mn}) = 1 \quad (4.2)$$

There are $M \times N$ such sums, and

$$\bigwedge_{x_{mn} \in X} \bigvee_{C_j \in P} \mu_{C_j}(x_{mn}) > 0 \quad (4.3)$$

Optimal fuzzy c-partitioning of X are taken as local minima of the objective function, denoted as f_X .

$$\min_p \{f_X(P, U)\}$$

The objective function has to incorporate fuzzy membership degrees into the clusters and an additional parameter q , introduced as a weight exponent in the fuzzy membership. Hence, we receive the following objective function:

$$f_X(P, U) = \sum_{j=1}^c \sum_{m=1}^M \sum_{n=1}^N [\mu_{C_j}(x_{mn})]^q (x_{mn} - v_{C_j})^2 \quad (4.4)$$

where:

$U = \{v_{C_j}\}$ - the vector of all centroids, where $j = 1, \dots, c$,

P - is a set of fuzzy partitions of the points x_{mn} between C_j ,

$q > 1$ - the fuzzy membership degree.

We assume the Euclidean metrics and function (4.4) to be positive. The larger q results in smaller membership values μ_{C_j} and thus, the fuzzier clusters. In the limit $q \rightarrow 1$, the membership functions μ_{C_j} converge to 1, which implies a crisp partitioning. Like hard K -means, the fuzzy C-means clustering tries to find a good partition $\{C_j\}$, minimizing function $f_X(P, U)$. Additionally, the fuzzy algorithm needs to search for membership functions μ_{C_j} that minimize $f_X(P, U)$. In order to accomplish both objectives, a necessary condition for the local minimum of f_X has

to be obtained from $f_X(P, U)$. Basically, the partial derivatives of $f_X(P, U)$ have to be equal to 0.

$$\frac{\partial f_X(P, U)}{\partial \mu_{C_j}} = q[\mu_{C_j}(x_{mn})]^{q-1} \sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_j})^2 = 0 \quad \text{for each } j \quad (4.5)$$

$$\frac{\partial f_X(P, U)}{\partial v_{C_j}} = \sum_{j=1}^c \sum_{m=1}^M \sum_{n=1}^N [\mu_{C_j}(x_{mn})]^q 2(x_{mn} - v_{C_j}) = 0 \quad (4.6)$$

Hence, we calculate v_{C_j} for each j , where $1 \leq j \leq c$:

$$v_{C_j} = \frac{\sum_{m=1}^M \sum_{n=1}^N \mu_{C_j}(x_{mn})^q x_{mn}}{\sum_{m=1}^M \sum_{n=1}^N \mu_{C_j}(x_{mn})^q} \quad (4.7)$$

Next, comparing two derivatives (4.5) and (4.6) for $j \neq i$, we obtain:

$$q[\mu_{C_j}(x_{mn})]^{q-1} \sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_j})^2 = q[\mu_{C_i}(x_{mn})]^{q-1} \sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_i})^2 \quad (4.8)$$

$$\mu_{C_j}(x_{mn}) = \mu_{C_i}(x_{mn}) \left[\frac{\sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_i})^2}{\sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_j})^2} \right]^{\frac{1}{q-1}} \quad (4.9)$$

From condition (4.2) we obtain:

$$\mu_{C_j}(x_{mn}) = \frac{1}{\sum_{j=1}^c \left[\frac{\sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_j})^2}{\sum_{m=1}^M \sum_{n=1}^N (x_{mn} - v_{C_j})^2} \right]^{\frac{1}{q-1}}} \quad (4.10)$$

Based on the equations (4.7) and (4.10), we can specify the FCM algorithm which updates the centroids and the membership functions iteratively, until the termination criterion is satisfied, as follows:

Step 1: Randomly initialize centroids $V = \{v_{C_1}, v_{C_2}, \dots, v_{C_c}\}$.

Step 2: Make $V \leftarrow V^{st}$.

Step 3: Calculate the membership functions from (4.10).

Step 4: Update centroids v_{C_j} in V according to (4.7).

Step 5: Calculate the distance between the old and new centroids

$$E = \sum_{i=1}^c (v_{C_i}^{st} - v_{C_i})^2.$$

Step 6: If $E > \varepsilon$ then go to Step 2.

Step 7: If $E \leq \varepsilon$ then output the final result.

In 1990 Bezdek proved the convergence of the FCM algorithm for $q > 1$ [122].

4.2.3 Mean Shift

Mean shift is a procedure for locating the maxima of a density function given discrete data sampled from that function [123]. It is useful in detecting the modes of this density [123]. This is an iterative method, and we start with an initial estimate. Let a kernel function be given. This function determines the weight of nearby points for re-estimation of the mean. Typically, the Gaussian kernel of the distance to the current estimate is used, $[K(x_i - x)] = e^{(-e^{|x_i - x|})}$. The weighted mean of the density determined in the window by K is:

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x)x_i}{\sum_{x_i \in N(x)} K(x_i - x)} \quad (4.11)$$

where $N(x)$ is the neighbourhood of x , a set of points for which $K(x) \neq 0$.

The mean-shift algorithm now sets $x \leftarrow m(x)$, and repeats the estimation until converges.

4.2.4 The Colour Approach to the Hybrid Semantic System

The first stage in our work was the survey and selection of an appropriate algorithm which would separate, based on low-level features, the graphical segments from images to offer them later to the user. The above-mentioned algorithms described colour distribution in the whole image, which means that they do not serve our purpose best.

Next, we began with two well-known clustering algorithms: the K -means clustering [124], [125], and developed later, the fuzzy C -means clustering algorithm (FCM) [122]. In our case, we found clusters in the 3D colour space

RGB. The search for data sets, which is conducted by those algorithms, is based on the distance from the cluster centroid which evaluates the accuracy of a partition. It means that each datum belongs to exactly one cluster of the partition.

We expected that clustering would isolate different image elements according to colours. Unfortunately, the results were dissatisfying. After examining point distribution in the colour space, it turned out that points created one tight set located very close to a diagonal, similar for nearly all the images we analyzed. In Fig. 4.2 such a shape (red point cloud) is exemplified only in the RGB space, omitting point distribution (x, y) in the image.

Consequently, when we used the K -means algorithm, we obtained segmentation whose only criterion was the brightness of pixels because the centroids were located approximately on the diagonal.

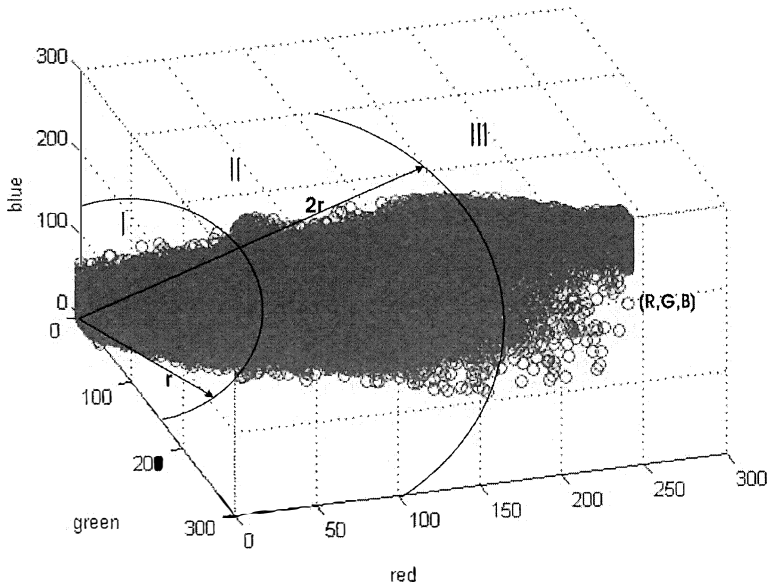


Fig. 4.2 The way of labelling the set of pixels. Regions I, II, III show pixel brightness and the biggest value of the triple (R,G,B) determines its colour.

These results forced us to work out a new algorithm which uses colour information about a single point to a greater extent. With the aim of labelling a pixel we found the biggest value from the triple (R,G,B) and we defined it as a cluster colour. In this way, we obtained three segments – red, green and blue. Additionally, points with equal values of RGB were labelled as grey. Tentatively, it was accepted, but for better results each colour was divided into three shades as three regions (I, II, III) which determine point brightness. The idea of segmentation is illustrated in Fig. 4.2. The radius r of the dividing sphere was counted in the Euclidean measure, namely:

$$r = \frac{\sqrt{R_{\max}^2 + G_{\max}^2 + B_{\max}^2}}{3}. \quad (4.1)$$

Generally, $R_{\max} = G_{\max} = B_{\max} \leq 255$ because full saturation of colours is rare. Moreover, we added three segments: black, grey and white for pixels, where $R=G=B$ or was not exactly equal according to their region (I, II, III). We assumed that 'not exactly equal' meant that $|R - G| < \sigma$ and $|R - B| < \sigma$, where $10 < \sigma < 15$. Having done this, we obtained images segmented into 12 clusters. We called this algorithm 'colour one'.

Fig. 4.2 presents the colour space of the image shown in Fig. 2., divided into 12 clusters, using the above-described algorithm. In Fig. 4.3 a) we can see that the image is divided into objects with dominant colours so each main RGB layer is visible separately. For better illustration, we present in Fig. 4.3 b) objects segmented from Fig. 2. in their average colours. Average colour k_{av} is understood as an average value of each colour component summed up separately for each object $k_{av} = \{r_{av}, g_{av}, b_{av}\}$.

Fig. 4.3 c) illustrates the red layer divided into three brightness regions. Segmented elements are visible in Fig. 4.3 d), e) and f). There can be 50 to 500 elements separated from an image depending on image size. The smallest are neglected in further analysis, for instance in classification.



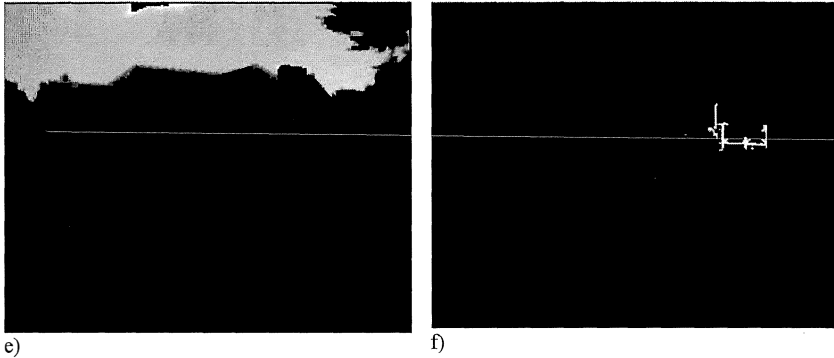


Fig. 4.3 a) 12 cluster segmentation of Fig. 2. obtained by using the 'colour' algorithm, b) segmented objects presented in their average colours, c) the red layer consisted of three brightness regions, d), e) and f) extracted objects in natural colour: chimney, sky and railing, respectively.

The additional advantage of our approach is the fact that it is very fast because it uses only operations of comparison for each pixel, with no multiplication or square, as it is necessary for the K -means algorithm. As a result, our color algorithm is tenfold faster than the K -means algorithm. Moreover, it should be pointed out that the bigger the image, the greater the difference between the calculation time of both algorithms.

4.3 Object Segmentation Based on Texture

In the case of textured objects the LBP operator, introduced by Ojala et al. in 2002 [65], can be applied to object segmentation (see subsect. 3.3.1). Fig. 4.4 presents a texture mosaic composed of five textures from outdoor scenes, such as those frequently encountered in satellite images.

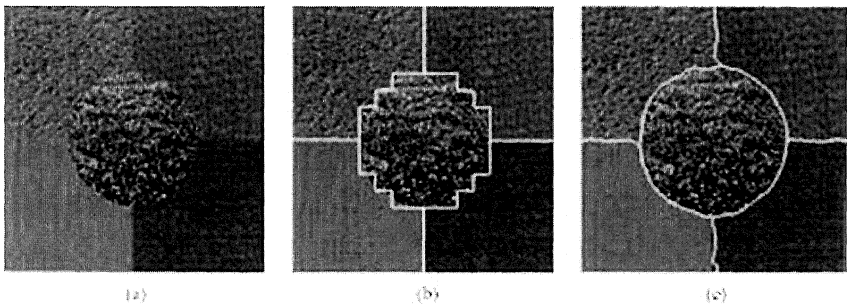


Fig. 4.4 Texture mosaic segmentation based on LBP [65].

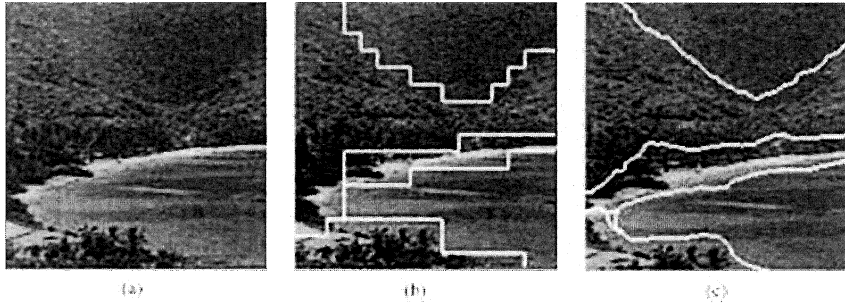


Fig. 4.5 Natural scene segmentation based on the texture according to the LBP [65].

Later this operator was applied to segment natural scenes as we see in Fig. 4.5.

Acharyya and Kundu [126] applied an orthogonal and linear phase M -band wavelet transform to decompose an image into $M \times M$ channels. Various combinations of these bandpass sections were taken to obtain different scales and orientations in the frequency plane. Texture features are obtained by subjecting each bandpass section to a nonlinear transformation and computing the measure of energy in a window around each pixel of the filtered texture images. Unsupervised texture segmentation was obtained by a simple K -means clustering.

Another attempt at automatic texture segmentation, i.e. without any a priori knowledge of either the type of textures or the number of textures in the image was taken by Faizal et al. [89]. As it has been mentioned in subsect. 3.3. B the method used a modified discrete wavelet frame (DWF) decomposition to extract important features from an image before a mean shift algorithm is used together with a fuzzy C-means (FCM) clustering to cluster or segment the image into different texture regions. The proposed algorithm has the advantage of high accuracy while low computational costs.

4.4 Object Segmentation Based on Shape

The idea behind the Curvature Scale Space (CSS) representation [100] is that the contour can be represented by set of points where the contour curvature changes, as well as curvature fragments between these points. For each point in the contour, it is possible to compute the curvature of the contour at that point, based on the neighboring points; a point whose two closest neighbours have different curvature values is considered a curvature change. In fact, not all curvature changes are needed to compute the CSS representation, but only those where the curvature goes from a positive to a negative value or vice-versa. When it happens, the curvature values have to go necessarily through zero and therefore these changes are called zero-crossings of the curvature, as illustrated in Fig. 4.6. As for the average curvature between two of these zero-crossings, it basically corresponds to

the angle difference between the tangents to the contour at these two points divided by the arc length joining these two points.

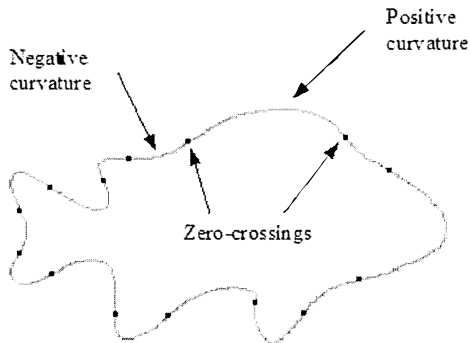


Fig. 4.6 Zero-crossings of the curvature.

A different approach was represented by Latecki and Lakämper [127] who described shape as line segments for silhouette presentation. To reduce the influence of digitization noise, as well as segmentation errors, the shapes are simplified to a set of segments and their length function normalized with respect to the total length of the whole contour.

Goh and Chan presented a part-based shape descriptor that incorporates both the description of the general shape form of each subpart, as well as the local boundary perturbation (boundary texture) [128]. A shape is decomposed into subparts along segmented sections of the extracted shape axes and each part is described by two 1-D histograms derived from the local gradient vector field. The shape part descriptor, associated with each subpart of an object, is a saliency measure which weighs its visual significance based on the proportion of the overall shape region to the subpart.

The shape description is used in most applications, for examples, archeological ones. In this case, decoration patterns are described by Xu and Liu [129] as a closed contour set. The contour of a 2D object is a simple closed curve and the area enclosed by the curve is topologically homeomorphic to a disk. It has also been assumed that the centroid of the curve has been moved to the origin of the 2D coordinate system. A contour L is described by the function $z(t) = (x(t), y(t))$, $0 \leq t < 1$ which is the arc-length parameterization.

4.5 Object Segmentation Based on Local Features

Mutch and Lowe [130] modified the model of Serre, Wolf, and Poggio [131] by applying Gabor filters at all positions and scales; then feature complexity and

position/scale invariance were built up by alternating template matching and max pooling operations. Images were reduced to feature vectors, which were then classified by an SVM. Features are computed hierarchically in five layers: an initial image layer and four subsequent layers, each built from the previous by alternating template matching and max pooling operations (see Fig. 4.7).

Image layer - the image is converted to grayscale and the shorter edge is scaled down to 140 pixels while maintaining the aspect ratio. Next an image pyramid of 10 scales is created, each a factor of $2^{1/4}$ smaller than the last (using bicubic interpolation).

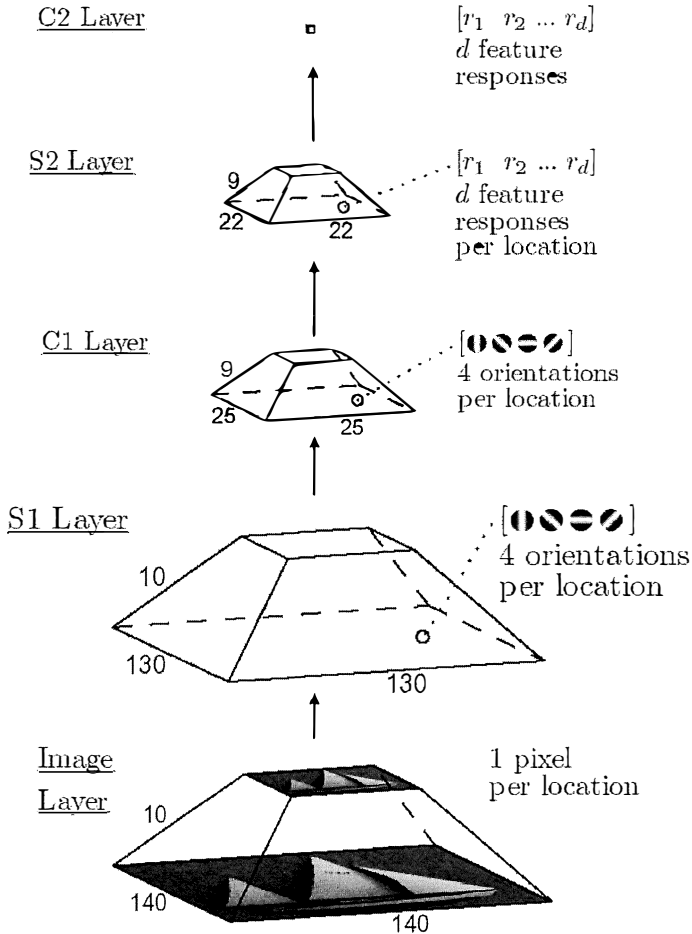


Fig. 4.7 Feature computation in the base model. Each layer has units covering three spatial dimensions ($x/y/scale$), and at each 3D location, an additional dimension of feature type. The image layer has only one type of pixels, layers S1 and C1 have 4 types, and the upper layers have d (many) types per location. Each layer is computed from the previous one by applying template matching or max pooling filters [130].

Gabor filter (S1) layer - is computed from the image layer by centering 2D Gabor filters with 4 orientations at each possible position and scale (compare Fig. 3.5).

Local invariance (C1) layer - pools nearby S1 units (of the same orientation) to create position and scale invariance over larger local regions, and as a result can also subsample S1 to reduce the number of 10×10 units across in position and 2 units deep in scale.

Intermediate feature (S2) layer. At every position and scale in the C1 layer, authors performed template matches between the patch of C1 units centred at that position/scale and each of d prototype patches. These prototype patches represent the intermediate-level features of the model.

Global invariance (C2) layer. Finally a d -dimensional vector was created, each element of which is the maximum response (anywhere in the image) to one of the model's d prototype patches. At this point, all position and scale information has been removed, i.e. we have a "bag of features".

4.6 Image Data Representation for the Hybrid Semantic System

Having described the methods for obtaining the most basic features, we can present in detail all low-level features which characterize segments in our DB (compare Fig. 3.16 in subject. 3.4.4.).

As we specified it in subject. 4.2.3 after segmentation each object is assigned its:

- **Average colour** k_{av} , is the values of the red, green and blue components summed up for all the pixels belonging to an object, and divided into the number of object pixels:

$$k_{av} = \{r_{av}, g_{av}, b_{av}\} = \left\{ \frac{\sum_{i=1}^n r_i}{n}, \frac{\sum_{i=1}^n g_i}{n}, \frac{\sum_{i=1}^n b_i}{n} \right\} \quad (4.2)$$

- **Texture** T_p divided into eight parameters: two ranges for the minimal and maximal horizontal texture components h and two others for the vertical one v .

$$T_p = \begin{bmatrix} h_{\min 1,2} ; h_{\max 1,2} \\ v_{\min 1,2} ; v_{\max 1,2} \end{bmatrix} \quad (4.3)$$

- **Area** A calculated as a sum of pixels constituting an object.
- **Convex area** A_c is the number of pixels in the smallest convex polygon that can contain the object.

- **Bounding box** is the smallest rectangle containing the object. $b_i(x,y)$, $i=1,\dots,4$ are the coordinates of the rectangle corners.
- **Major axis length** m_{long} and **minor axis length** m_{short} are the lengths measured in pixels of the major and minor axes of the ellipse, respectively. The Fig. 4.8 illustrates the axes and orientation α of the ellipse.
- **Orientation** of the ellipse is the angle α between the horizontal dotted line and the major axis.
- **Centroid** $C(x_c, y_c)$ is the mass centre of the object.
- **Eccentricity** e is the ratio of the distance between the foci of the ellipse and its major axis length. The eccentricity of the ellipse has the same second moment as the object.
- **Euler number** E is equal to the number of objects in the region minus the number of holes in those objects.
- **Inertia moments** $\mu_{00} - \mu_{11}$ defined as (3.31).
- **Zernike moments** $Z_{00} - Z_{33}$ defined as (3.32).
- **Solidity** s is the ratio of the area to the convex area $s=A/A_c$.

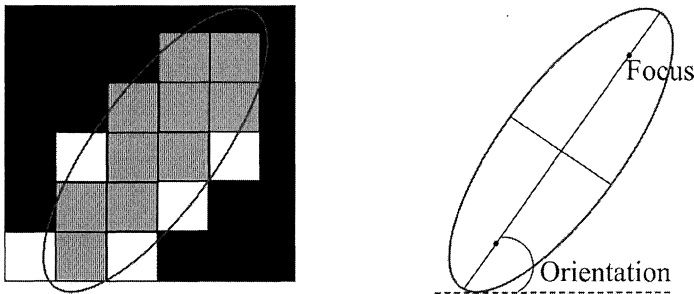


Fig. 4.8 The left side shows an image region and its corresponding ellipse. The right side shows the same ellipse with the solid lines as the axes, the dots on the major axis as foci and the orientation which is the angle α between the horizontal dotted line and the major axis.

All features, as well as extracted images of graphical objects, are stored in the DB (see Chapter 6).

Generally, the data structure used in pattern recognition especially image recognition systems in particular are of two types: object data vectors and relational data.

Object data is the asset of numerical vectors as $\mathbf{Y} = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n\}$, where \mathbf{y}_i is a feature vector in the p -dimensional measurement space Ω_Y . An i^{th} object, $i=1, 2, \dots, n$, has vector \mathbf{y}_i as its numerical representation, where $\mathbf{y}_{ij} = \{f_{i1}, f_{i2}, \dots, f_{iq}\}$, where q – the number of features/attributes. Relational data is a set of n^2 numerical relationships $\{r_{ij}\}$ between pairs of objects o_{ij} . In other words, r_{ij} represents the extent to which i^{th} and j^{th} objects are related in the sense of some relationship ρ , for instance, binary. If the objects that are pairwise related by ρ are called $P = \{p_1, p_2, \dots, p_n\}$, then $\rho: P \times P \rightarrow \mathbb{R}$.

In the context of our feature selection, we construct a feature vector \mathbf{y} containing the set of features, where: $\mathbf{y}=\{f_1, f_2, \dots, f_q\}=\{k_{av}, T_p, A, A_c, \dots, E\}$ for each object o_i , in our particular case $q=45$:

$$\mathbf{y} = \begin{bmatrix} y(k_{av}) \\ y(T_p) \\ y(A) \\ \vdots \\ y(E) \end{bmatrix} = \begin{bmatrix} y(f_1) \\ y(f_2) \\ y(f_3) \\ \vdots \\ y(f_q) \end{bmatrix} \quad (4.4)$$

This feature vector is further used for object classification (see Chapter 5 Sect. 3) and image retrieval (see Chapter 9 Sect. 9).

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