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Some aspects of intuitionistic fuzzy sets and possibility theory as an approach to graphical object semantics for CBIR

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Abstract

This article introduces the imprecision approach to high–level graphical object interpretation. It presents a step towards soft computing which supports the implementation of a content-based image retrieval (CBIR) system dealing with graphical object classification. Some crucial aspects of CBIR are presented here to illustrate the problems that we are now struggling with. The main motivation of these researches is to provide effective and efficient means for the semantic interpretation of graphical objects. The paper shows how the traditional feature vector method extends to match graphical objects, difficult to classify, by applying intuitionistic fuzzy sets and possibility theory. We consider the cases where both classification of objects and their retrieval are modelled with the aid of fuzzy set extensions.

Keywords: content-based image retrieval system, graphical object, image indexing, image classification, intuitionistic fuzzy sets, possibility theory.

1 Introduction

In recent years, the availability of image resources on the WWW has increased tremendously. This has created a demand for effective and flexible techniques for automatic image retrieval, coupled with the fact that a lot of graphical information is available in an imperfect form only. Indeed, information is likely to be imprecise, vague, uncertain, incomplete, inconsistent, etc. For this reason, attempts to perform the Content-Based Image Retrieval (CBIR) in an efficient way, that is based on shape, colour, texture and spatial relations, have been made for many years. Nevertheless, the CBIR system, for a number of reasons, has yet to reach maturity. A major problem in this area is computer perception. In other words, there remains a considerable gap between image retrieval based on low-level features, such as shape, colour, texture [12], [14], [19] and spatial relations, and image retrieval based on high-level semantic concepts, for example, houses, windows, roofs, flowers, etc [5], [7],[15]. This problem emerges especially as challenging when image databases are exceptionally large.

Given the above context, it comes as no surprise that fast retrieval in databases has recently been an active research area. The effectiveness of the retrieval process from the start has been a motivation to develop more advanced, semantically richer system models. One of the numerous problems which CBIR system authors struggle with is the ability to deal with information imperfection. Here, we will focus on this issue, briefly introducing some other, related aspects of the main subject.

In the literature, the fuzzy set theory [22] its related possibility theory [24] has been used as the underlying mathematical framework for enhanced approaches to integrate imperfection at the level of alphanumeric data in, what is usually called a "fuzzy" database [25]. However, we propose a fuzzy approach to graphical data in the CBIR structure. This problem has turned out specially challenging with graphical information gradually becoming predominant in modern databases [9], [13]. Application of the interval-valued fuzzy sets and Atanassov's intuituinistic fuzzy sets seems to be justified in terms of improvement of the effectiveness of graphical object classification for image retrieval. We are aware that some problems remain and in this paper we will discuss a few of them, for example, feature selection for object classification.

This paper is organized as follows. Section 2 presents the main concept of the CBIR system describing its principal elements. Section 3 quotes the definitions of Atanassov's intuituinistic fuzzy sets. In Section 4 some indexing and classification mechanisms are introduced. In Section 5 numerical results are demonstrated and discussed in terms of using fuzzy sets for image retrieval, while Section 6 analyses possibility theory for graphical object classification. Section 7 concludes the presented methods.

2 CBIR Concept Overview

In content-based image retrieval, representation and description of the content of an image is a central issue. Among different structural levels, object level is considered the key linking the lower feature level and the higher semantic one [1]. In order to be effective in terms of the presentation and choice of images, the system has to be capable of finding the graphical objects that a particular image is composed of.

Figure 1 shows the block diagram of our CBIR system. As can be seen, the left part of the diagram illustrates the image content analysis block of our system. In this approach we use a multi-layer description model [8]. The description for a higher layer could be generated from the description of the lower layer, and establishing the image model is synchronized with the procedure for progressive understanding of image contents. These different layers could provide distinct information on image content, so this model provides access from different levels as a multi-layer representation.

Each new image added to our CBIR system, as well as the user's query, must be preprocessed, as shown in the segmentation level frame of the image content analysis block (top, Fig. 1). All graphical objects, such as houses, trees, a beach, the sky etc., must be segmented and extracted from the background at the stage of preprocessing. Although colour images are downloaded from the Internet (in the JPEG format), their preprocessing is unsupervised. Similarly, an object extraction from the image background must be done in a way enabling unsupervised storage of these objects in the DB.

For this purpose, we apply two-stage segmentation, enabling us to extract accurately the desired objects from the image. In the first stage, the image is divided into separate RGB colour components which are next divided into layers according to three light levels. In the second stage, individual graphical objects are extracted from each layer. Next, the low-level features are determined for each object, understood as a fragment of the entire image. These features include: colour, area, centroid, eccentricity, orientation, texture parameters, moments of inertia, etc. The segmentation algorithm and object extraction algorithm, as well as the texture parameter-finding algorithm are presented in detail in an article by Jaworska [10].

In general, the system consists of 5 main blocks (fig. 1):

1. the image preprocessing block (responsible for image segmentation), applied in Matlab;
2. the Oracle Database, storing information about whole images, their segments (here referred to as image objects), segment attributes and object location;
3. the indexing module responsible for the image indexing procedure;
4. the graphical user's interface (GUI), also applied in Matlab.
5. the match engine responsible for image matching and retrieval. In this paper we would like to focus on the advanced mechanism, dealing with imprecision implemented in this engine.

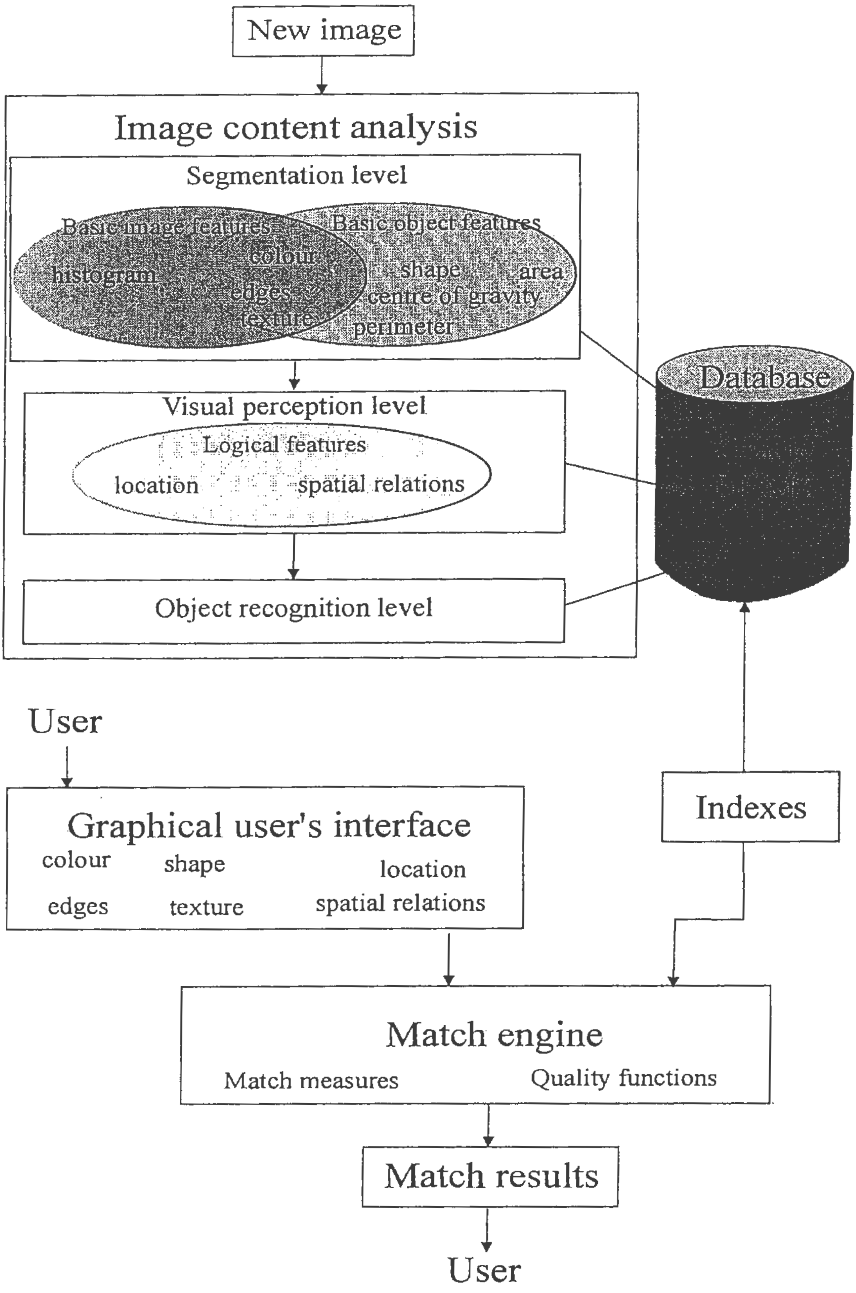

Figure 1. Block diagram of our content-based image retrieval system

The information obtained from the image content analysis is stored in the database. In the diagram the indexes block is kept apart as an important element of the system, which prepares information to the matching engine.

The next element of the system is the matching engine, which uses indexes based on the multi-layer description model and object patterns to search for "the best matching images". Research on models which extend the flexibility of matching methods to obtain semantically profound retrieval, similar to human image understanding, leads us to experiments with interval-valued fuzzy sets and Atanassov's intuitionistic fuzzy sets.

The bottom part of figure 1 is dedicated to users and presents the on-line functionality of the system. Its first element is the GUI block. In comparison to the previous systems, ours has been developed in order to give the user the possibility to design their image which later becomes a query for the system. If users have a vague target image in mind, the program offers them tools for composing their imaginary scenery.

In 2001 a set of MPEG-7 descriptors was introduced. These descriptors are more complicated, as they encompass colour descriptors (colour layout, colour structure, dominant colour and scalable colour), texture descriptors (edge histogram and homogeneous texture) and shape descriptors (contour and region) [27], [28]. The MPEG-7 has been accepted as standard and is used in some applications. Unfortunately, it neglects important criteria for the assessment of image similarity, such as spatial information and spatial relationships. Additionally, the MPEG-7 approach is inflexible and complex, and as such non extendable to the fuzzy methods. Hence, the fast changing experimental systems rarely use this standard.

3 Basic Concepts of Extended Fuzzy Sets

Definition 1

A fuzzy set A over a universe of discourse U is defined by means of a membership function μ_A which associates with each element x of U a membership grade $\mu_A(u) \in [0,1]$ [22].

In what follows, a fuzzy set A over a universe of discourse U is denoted by

$$A = \{(x, \mu_A(x) \mid x \in U)\}. \qquad (1)$$

Two important concepts of *core* and *support* are related to a fuzzy set A:

$$core(A) = \{x \mid x \in U \wedge \mu_A(x) = 1\}$$

and

$$support(A) = \{x \mid x \in U \wedge \mu_A(x) > 0\}.$$

In the literature various extensions of the concept of a fuzzy set have been proposed: interval-valued fuzzy sets (IVFSs), Atanassov's intuitionistic fuzzy sets (A-IFSs) and twofold fuzzy sets (TFSs). Fuzzy sets, as originally defined by Zadeh in [ref nr], are sometimes called 'regular' in order to distinguish them from these extensions.

Definition 2

An interval-valued fuzzy set (IVFS) A over a universe of discourse U [2] is defined by two functions

$$\mu_A^l, \mu_A^u : U \rightarrow [0,1] \tag{2}$$

such that

$$0 \leq \mu_A^l(x), \mu_A^u(x) \leq 1, \quad \forall x \in U \tag{3}$$

and is denoted by

$$A = \{< x, \mu_A^l(x), \mu_A^u(x) > | \, x \in U\} \tag{4}$$

The constraint (3) reflects that μ_A^l and μ_A^u are respectively interpreted as a lower and upper bound on the actual degree of membership of x in A. Thus, a range of possible membership grades, determined by the interval defined by the lower and upper bound membership grades, is associated with each element of the universe of discourse. This allows for more flexibility in the modelling of the extent to which an element belongs (or does not belong) to the set. Considering the special case where $\mu_A^l = \mu_A^u$, it follows clearly that interval-valued fuzzy sets are a generalization of regular fuzzy sets.

Definition 3

Atanassov's intuitionistic fuzzy set (A-IFS) A over a universe of discourse U [20], [23] is defined by two functions

$$\mu_A, \nu_A : U \rightarrow [0,1] \tag{5}$$

such that

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1, \quad \forall x \in U \tag{6}$$

and is denoted by

$$A = \{< x, \mu_A(x), \nu_A(x) > | \, x \in U\} . \tag{7}$$

For each $x \in U$ the numbers $\mu_A(x)$ and $\nu_A(x)$, respectively, represent the degree of membership and the degree of non-membership of x in A. The A-IFS graphical interpretation is presented in figure 2. The constraint (6) reflects the consistency condition. For each value $x \in U$, the difference

$$h_A(x) = 1 - \mu_A(x) - \nu_A(x) \tag{8}$$

is referred to as the hesitation margin. If for $x \in U$, $h_A(x) = 0$, then there is no hesitation about x being an element of A or not, which implies that $\nu_A(x) = 1 - \mu_A(x)$. On the other hand, if for $x \in U$, $h_A(x) = 1$, then there is full hesitation as $\mu_A(x) = 0$. In all other cases, the consistency condition guarantees that $h_A(x) \in]0,1[$, which reflects partial hesitation.

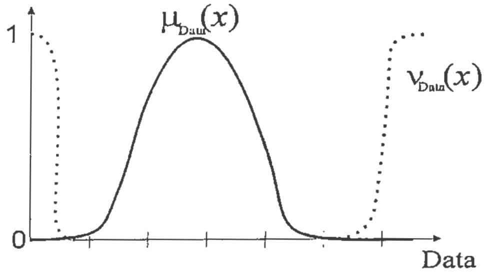

Figure 2. Graphical representation of Atanassov's intuitionistic fuzzy set.

Thus, as in the case of interval-valued fuzzy sets in Atanassov's intuitionistic fuzzy sets there are also two grades associated with each element of the universe. Compared to interval-valued fuzzy sets, the semantics of these grades is however different. The grade $\mu_A(x)$ of x in A is interpreted as a membership grade, which is the same as the original interpretation of membership grades in fuzzy sets. The grade $\nu_A(x)$ of x in A is interpreted as a non-membership grade. Hereby, it is explicitly demonstrated that membership and non-membership do not necessarily complement each other, in other words they do not need to sum up to 1, as it is illustrated in fig. 2.

4 Methods of Image Indexing and Classification

Since the early 90's the effectiveness of classifiers has considerably improved which is strongly connected with fast development of machine learning methods, for example, nearest neighbour classifiers [26], Bayesian classifiers, decision trees or support vector machines.

In the case of image analysis we have tried to achieve categories strictly connected with the human perception of images. Before image set can be represented by the classifier, some form of representation must be chosen. Feature selection is a key task for the proper classification [21]. For graphical objects low-level features are as important as shape descriptors and object locations (mutually and in the whole image). If not enough features are used there is the possibility of confusing features that have a high information gain whereas using many features is troublesome due to space and computing time limitations.

4.1 Data Representation for Objects

Each object, selected according to the algorithm presented in detail in [11], is described by some low-level features, also called attributes. The attributes describing each object include: average colour k_{av}, texture parameters T_p, area A, convex area A_c, filled area A_f, centroid $\{x_c, y_c\}$, eccentricity e, orientation α, moments of inertia m_{11}, bounding box $\{b_1(x,y), ..., b_s(x,y)\}$ (s – number of vertices), major axis length m_{long}, minor axis length m_{short}, solidity s and Euler number E. These attributes are presented in the example window of the interface (Fig. 3) for a selected object. Let F be a set of attributes where $F = \{k_{av}, T_p, A, A_c, ..., E\}$. For ease of notation we will use $F = \{f_1, f_2, \ldots, f_r\}$, where r – number of attributes. For an object, we construct a feature vector O containing the above-mentioned features - attributes:

$$O = \begin{bmatrix} O(k_{av}) \\ O(T_p) \\ O(A) \\ \vdots \\ O(E) \end{bmatrix} = \begin{bmatrix} O(f_1) \\ O(f_2) \\ O(f_3) \\ \vdots \\ O(f_r) \end{bmatrix}. \tag{9}$$

This feature vector is further used for object classification.

The average colour is a complex feature. It means that values of the red, green and blue components are summed up for all the pixels belonging to an object, and divided by the number of object pixels:

$$k_{av} = \{r_{av}, g_{av}, b_{av}\} = \left\{ \frac{\sum_{m=1}^{n} r_m}{n}, \frac{\sum_{m=1}^{n} g_m}{n}, \frac{\sum_{m=1}^{n} b_m}{n} \right\}. \tag{10}$$

The next complex feature attributed to objects is texture. Texture parameters are found in the wavelet domain (the Haar wavelets are used). The algorithm details are also given in [10]. The use of this algorithm results in obtaining two ranges for the horizontal object dimension h and two others for the vertical one v:

$$T_p = \begin{Bmatrix} h_{\min_{1,2}}; h_{\max_{1,2}} \\ v_{\min_{1,2}}; v_{\max_{1,2}} \end{Bmatrix}. \tag{11}$$

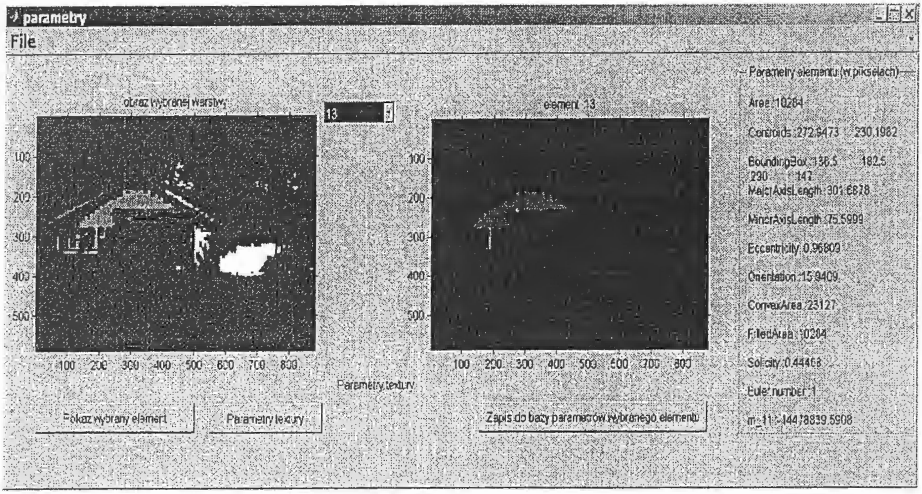

Figure 3. (Left) One colour layer from which the object was extracted. (Centre) An image of a separate object (element 13). (Right) Object attributes.

4.2 Pattern Library

The pattern library contains information about pattern types, shape descriptors, object location and allowable parameter values for an object [11]. We define a model feature vector P_k for each graphical element. We assume weights μ_P characteristic of a particular type of element which satisfy:

$$\mu_{P_k}(f_i) \in [0,1] \tag{12}$$

where: $1 \le i \le r$, k – number of patterns. These weights for each pattern component should be assigned in terms of the best distinguishability of patterns.

First, each graphically extracted object is classified into a particular category from the pattern library. For this purpose, in the simplest case, we use an L_m metric, where the distance between vectors O and P_k in an r-dimensional feature space is defined as follows:

$$d(O,P_k) = \left[\sum_{i=1}^{r} \mu_{P_k}(f_i) \left| O(f_i) - P_k(f_i) \right|^m \right]^{1/m} \tag{13}$$

where: k – pattern number, $1 \le i \le r$, m is the order of the metric. For $m = 1$ and for $m = 2$, it becomes the Manhattan and the Euclidean distance, respectively.

In the fuzzy set description our weights μ_P correspond to a membership function. Then, for the most important attributes of a graphical object we can assume $\mu_p(f_i) \approx 1$. For instance, if we compare objects with a similar shape we use the number of vertices s as one of the attributes. First, objects with the same number of vertices s (or s - 1) of bounding boxes are presumed the most similar to each other. If the differences in vertices are greater, the weight decreases down to 0, $\mu_p(b_i) \geq 0$ in the bounding boxes case, and it means that object shapes are not similar.

5 Classification Results

The first step in our task was defining patterns P_k for each graphical object category. We chose patterns for door and glass pane models distinguished from other objects, as an example. For this experiment, we used thirty-five known graphical objects, previously extracted from some images. There were nine doors with object ID = [4,5,7,9,13,15,20,28,35] and nine panes with object ID = [3,6,14,16,17,27,29,30,34], respectively.

From the above-mentioned method, we used the classification tree for data for 8 features of an object. These features are: eccentricity, moments of inertia, solidity, minor axis length, major axis length, orientation and average colour RGB components.

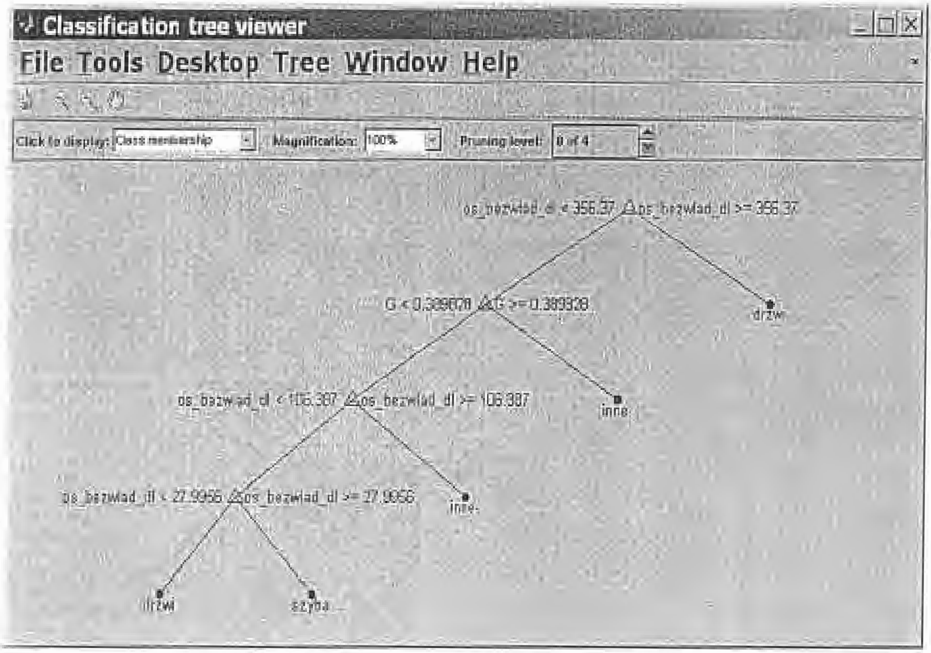

Figure 4. Classification tree for data for 8 features without any modifications.

As we can see in fig. 4 the main distinguishing parameter is the major axis length. We had to normalize all data to [0,1] to be able to compute distances of vectors from the particular pattern. The ratio of the minor axis length to the major axis length is also a feature similar to the original data, but after applying it we obtain the simpler classification tree (fig. 5).

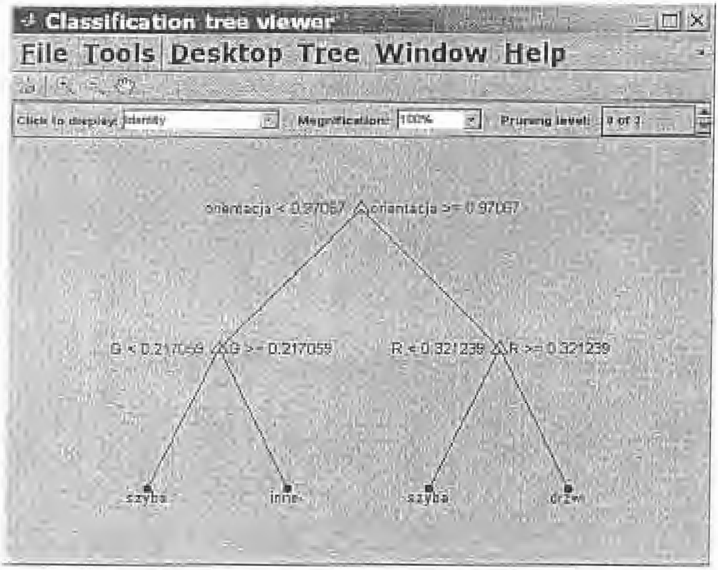

Figure 5. Classification tree with ratio of minor to major axes.

Table 1: Patterns for the door and glass pane models based on the most distinguishable features.

Features	Pattern_door	Weight μ_P	Pattern_pane	Weight μ_P
eccentricity	0,93	0,1	0,85	0,1
moments of inertia	average	0,01	average	0,01
solidity	0,8	0,3	0,9	0,19
minor axis length /major axis length	0,427	0,1	0,5	0,1
orientation	0,99	0,46	0,99	0,3
average colour component R	0,33	0,01	0,15	0,1
average colour component G	0,217	0,01	0,22	0,1
average colour component B	0,33	0,01	0,12	0,1

After some numerical experiments we chose two patterns, respectively, for the door and glass pane models based on the most distinguishable features (as it is shown in Table 1).

Figure 6 illustrates the appropriateness of our decision. There are distances d (computed based on eq. (13) but without weights μ_P) for each object in its ID order. The figure presents overlapped distances for door and pane patterns on each other (see the legend). The majority of smallest d corresponds with the ID object numbers for pattern_door and pattern_pane, respectively.

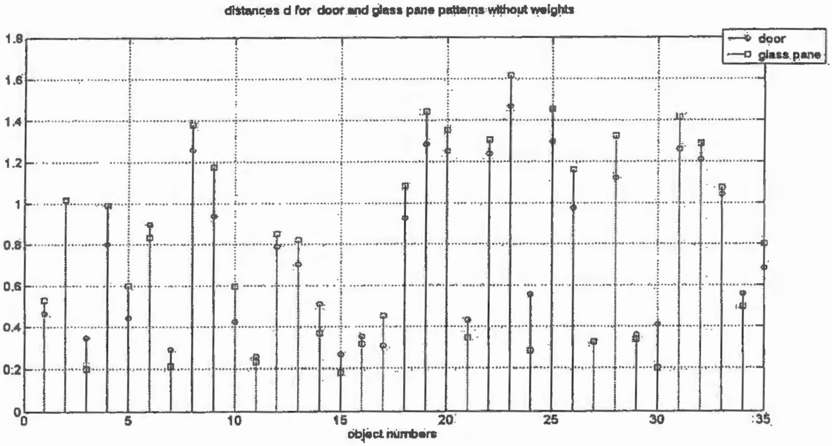

Figure 6. Distances d for all graphical objects computed for pattern_door and pattern_pane, respectively without wights.

Only for doors ID = [7,15] and for glass panes ID = [17,27] we can notice misclassification. Hence, subsequently, we added weights μ_P for both patterns, respectively, and obtained distances d for each object according eq. (13). The results are presented in fig. 7 for pattern_door and in fig. 8 for pattern_ pane, respectively. Doors and panes in our experiment were varied, for instance, the panes came from windows as well as doors, which means that not all objects classified as doors or panes gained the minimal values of d in comparison with other objects. But the weight introduction improved the classification when we compare patterns between themselves for each object separately. We can see it in fig. 7 and fig. 8, respectively. It is worth noticing that for the above-mentioned doors and panes the distances for patterns P_{door} and P_{pane} with weights received better values. For example, $d(7,P_{door}) = 0.065$ whereas $d(7,P_{pane}) = 0.067$ or $d(15,P_{door}) = 0.051$ whereas $d(15,P_{pane}) = 0.057$, and $d(27,P_{door}) = 0.113$ whereas $d(27,P_{pane}) = 0.104$. This is a right tendency in the case when we have many patterns and we classify a new object.

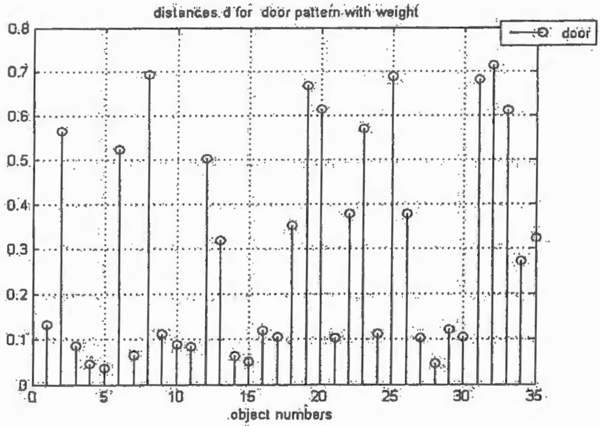

Figure 7. Distances d for pattern_door with weight $\mu_{P_{door}}$.

However, in reality, while misclassifications occur, the relationship is more complicated. The example for this is object ID = 17 which is a glass pane but distances values for the considered patterns are equal to $d(17,P_{door}) = 0.1$ and $d(17,P_{pane}) = 0.166$, respectively.

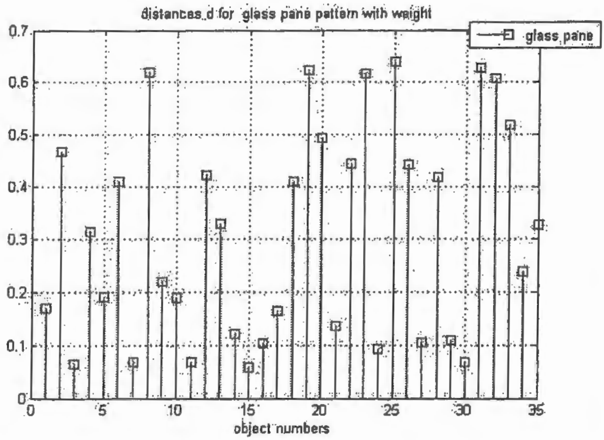

Figure 8. Distances d for pattern_pane with weight $\mu_{P_{pane}}$.

6 Possibility theory for the best graphical object classification

We can assume that we have such imbalanced and misclassified data for which it is very problematic to achieve high accuracy by simply classifying some examples as negative. Many attempts have been made to address the imbalanced data problem. Some methods try to receive more balanced, relevant and irrelevant training data via up-sampling and down-sampling [6]. Unfortunately, in the case of overlapping classes or a lesser number of classes than required even the balance received in an artificial way does not solve the problem.

As it has been shown in fig. 6, the commonly used methods of feature selection (using the positive features only) may lead to misclassification of irrelevant objects. It may be even worse for the imbalanced data with dominating irrelevant objects.

Hence, we suggest the application of intuitionistic fuzzy sets for the graphical object classification. For our example, when we look at fig. 6, it is easy to see that for some objects problem will become spatially complicated when we introduce $k > 2$ patterns.

Then we can use, the apparently distant from our discussion possibility theory and introduce Baldwin's model developed by Baldwin [3], [4] and Szmidt [16], [17], [18] which so far has been employed only for votings. The basic representation of uncertainty in the Baldwin's model contains necessity n and possibility p. Following these authors we can cite equality of the parameters for Baldwin's model and IFS model (Table 2).

Table 2: Equality of the parameters for Baldwin's model and IFS model.

	Baldwin's model	IFS model
Voting for	n	μ
Voting against	$1-p$	ν
Abstaining	$p-n$	h

In the case of graphical object classification, we propose to use the notions *necessity* and *possibility* to a support the estimation of an object assignment to a particular class. As it was explained in Section 4, the assignment of object x into k-class is based on distances $d(O(x),P_k) \in [0,1]$ between an object feature vector and patterns.

We can assume that the necessity for an object to belong to a class is represented by the differences values d. An object is attributed into this class for which value d is the smallest. For a given object x, its distances from a particular patterns P_k we can denote as a distribution of possibility

$$p(x,P_k) = 1 - d(x,P_k), \tag{14}$$

then the possibility that x belongs to class P_k is equal to $p(x,P_k)$. Therefore, necessity that x belongs to class P_k is given in the form:

$$n(x,P_k) = \max_j (1-d_j) - \max_{j \neq k} p(x,P_j) \tag{15}$$

where $1 \le j,k \le n$. This formula means that we subtract the value of $d(x,P_k)$ from the maximum value of other ds without the distance for k-pattern, which is presented in fig. 9 (the case for x_k).

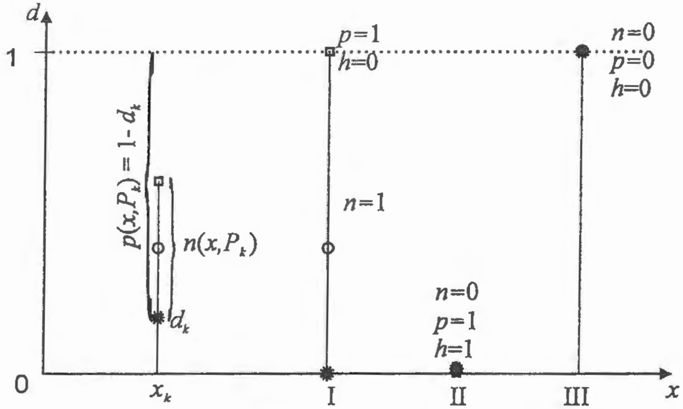

Figure 9. The interpretation of the degree of necessity, possibility and hesitation for the distances of object feature vector from a particular pattern.

Under the above assumptions, we can consider the extremal cases:

I. If $d_k = 0$ and $d_j = 1$ then $p(x,P_k) = 1$ and $n(x,P_k) = 1$, respectively. Thus, the degree of hesitation $h(x,P_k) = p(x,P_k) - n(x,P_k) = 0$.

II. If $d_k = 0$ and $d_j = 0$ then $p(x,P_k) = 1$ and $n(x,P_k) = 0$, respectively. Thus, the degree of hesitation $h(x,P_k) = 1$.

III. If $d_k = 1$ and $d_j = 1$ then $p(x,P_k) = 0$ and $n(x,P_k) = 0$, respectively. Thus, the degree of hesitation $h(x,P_k) = 0$. In this particular case we can infer there should be a new more class should be introduced.

IV. This approach seems to be useful in any cases of problem with assigning a new object to particular class introduced distinguishing the objects more precisely.

7 Conclusions

The construction of a CBIR system requires combining some systems: an image processing module for automatic segmentation, a database to store the generated information about images and their segments, and a module for image classification with predefined patterns. Having built these elements of the system, we faced the problem of image retrieval. We attempt to deal with it by introducing an intuitionistic fuzzy set as well as constructing and describing an object pattern library. Object patterns are used for optimum object distinction and identification.

The application of intuitionistic fuzzy sets in general, gives the opportunity of the introduction of another degree of freedom (non-memberships) into a set description. Such a generalization gives us an additional possibility to represent imperfect knowledge which leads to describing many real problems in a more adequate way.

To classify a new graphical object, we used already known method of comparison object feature vector with patterns. However, we suggest the application of possibility theory and introduce Baldwin's model with its notions of necessity, possibility and IFSn for imbalanced and uncertain data. This approach seems to be important for unsupervised analysis of large image databases.

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