Developments in Fuzzy Sets,
Intuitionistic Fuzzy Sets,
Generalized Nets and Related Topics.
Volume I: Foundations

Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics Volume II: Applications

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Aspects of intuitionistic fuzzy sets and possibility theory in graphical object classification 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 our researches is to provide effective and efficient means for the interpretation of graphical object classification. 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 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 [21] and its related possibility theory [22] have 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 [23]. 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 Atanassov's intuituinistic fuzzy sets and possibility theory 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, misclassification of graphical objects and imperfect knowledge.

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 top 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 the 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 pro-

vide distinct information on image content, so this model provides access from different levels as a multi-layer representation.
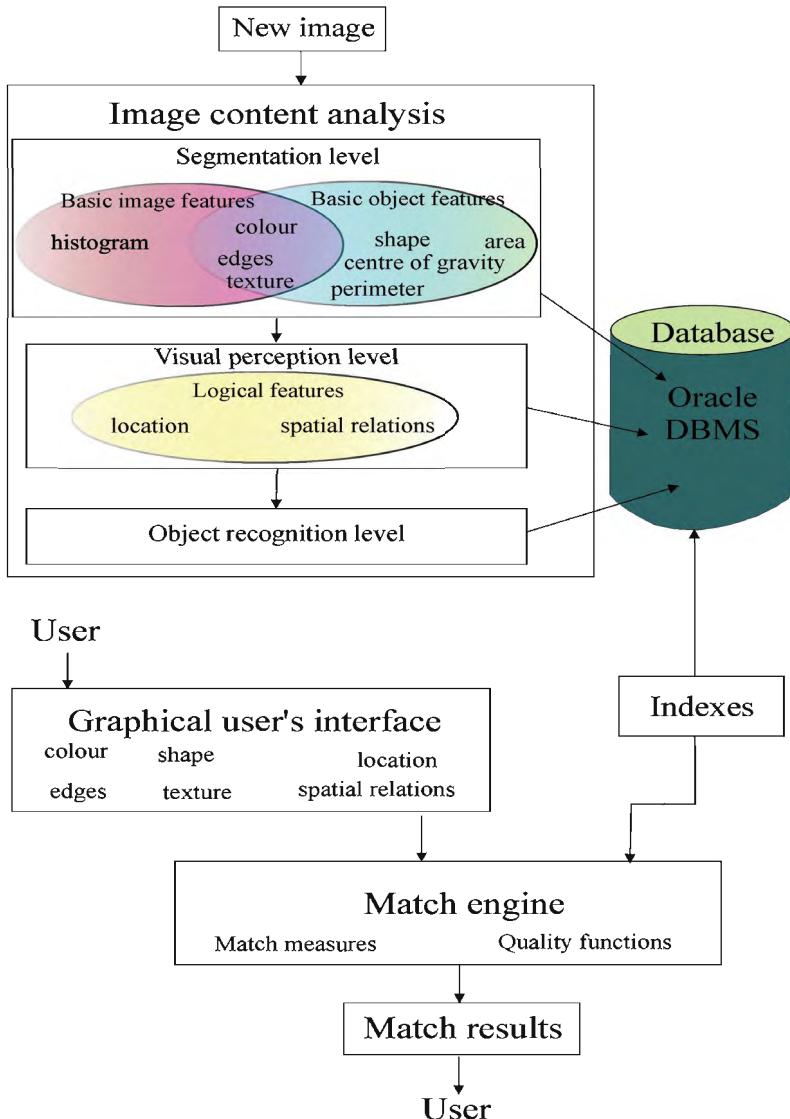

Figure 1: Block diagram of our content-based image retrieval system

Each new image added to our CBIR system, as well as the graphical 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]. The information obtained from the image content analysis is stored in the database.

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 [11];
4. the graphical user's interface (GUI), also applied in Matlab. 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 [11].
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.

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 Atanassov's intuitionistic fuzzy sets and possibility theory.

The bottom part of figure 1 is dedicated to users - the GUI block – and presents the on-line functionality of the system – the match engine and match results blocks.

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 $\mu_A(u) \in [0,1]$ [21].
In what follows, a fuzzy set A over a universe of discourse U is denoted by
$$A = \{(x, \mu_A(x) \,|\, x \in U)\}. \tag{1}$$
Two important concepts of *core* and *support* are related to a fuzzy set A:
$$core(A) = \{x \,|\, x \in U \wedge \mu_A(x) = 1\}$$
and
$$support\,(A) = \{x \,|\, x \in U \wedge \mu_A(x) > 0\}.$$

Definition 2
Atanassov's intuitionistic fuzzy set (A-IFS) A over a universe of discourse U [2] is defined by two functions:
$$\mu_A, v_A : U \to [0,1] \tag{5}$$
such that
$$0 \le \mu_A(x) + v_A(x) \le 1, \quad \forall x \in U \tag{6}$$
and is denoted by
$$A = \{< x, \mu_A(x), v_A(x) > \,|\, x \in U\}. \tag{7}$$
For each $x \in U$ the numbers $\mu_A(x)$ and $v_A(x)$, respectively, represent the degree of membership and the degree of non-membership of x in A. The constraint (6) reflects the consistency condition. For each value $x \in U$, the difference
$$h_A(x) = 1 - \mu_A(x) - v_A(x) \tag{8}$$
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 $v_A(x) = 1 - \mu_A(x)$. 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.
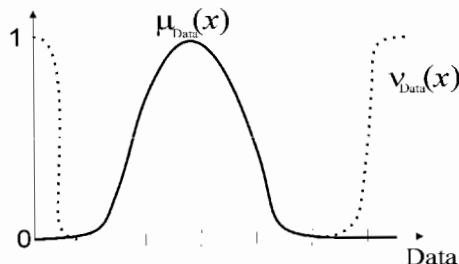

Figure 2: Graphical representation of Atanassov's intuitionistic fuzzy set

Thus, as in Atanassov's intuitionistic fuzzy sets there are two grades associated with each element of the universe. 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 $v_A(x)$ 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 [24], 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 [20]. For graphical objects low-level features are as important as shape descriptors and object locations (mutually and in the whole image). If not enough number of features is we can receive confusing results whereas using many features is troublesome due to space and computing time limitations.

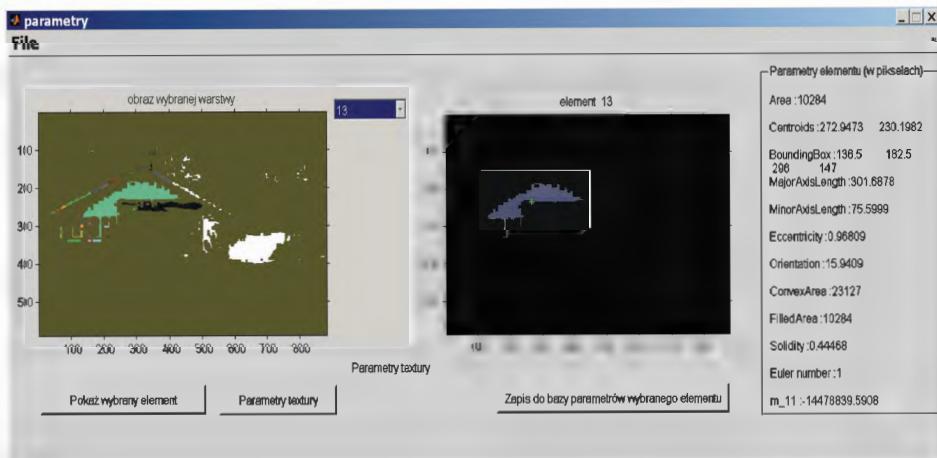## 4.1 Data representation for objects

Figure 3: (Left) One colour layer from which the object was extracted (centre) an image of a separate object (element 13) (right) object features

Each graphical object, selected according to the algorithm presented in detail in [10], is described by some low-level features such as: 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 $\{b_1(x,y), ..., b_w(x,y)\}$ (w – number of vertices), major axis length m_{long}, minor axis length m_{short}, solidity s and Euler number E. These features are presented in the example window of the interface (Fig. 3) for a selected object. Let F be a set of features where $F = \{k_{av}, T_p, A, A_c, ..., E\}$. For ease of notation we will use $F = \{f_1, f_2, ..., f_r\}$, where r – number of features. For an object, we construct a feature vector O containing the above-mentioned features:

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

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:

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

The next complex feature attributed to objects is texture. Texture parameters are found in the wavelet domain. The 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:

$$T_p = \left\{ \begin{array}{l} h_{\min_{1,2}}; h_{\max_{1,2}} \\ v_{\min_{1,2}}; v_{\max_{1,2}} \end{array} \right\}. \tag{11}$$

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 type of graphical element. We assume weights μ_P characteristic for each model which satisfy:

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

where: $1 \leq i \leq r$, 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 Euclidean metric, where the distance between vectors O and P_k in an r-dimensional feature space is defined as follows:

$$d(O, P_k) = \left[\sum_{i=1}^{r} \mu_{P_k}(f_i) \left| O(f_i) - P_k(f_i) \right|^2 \right]^{1/2} \qquad (13)$$

where: k – pattern number, $1 \leq i \leq r$. In the fuzzy set description our weights μ_P correspond to a membership function. Then, for the most important features of a graphical object we can assume $\mu_p(f_i) \approx 1$.

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 35 known graphical objects, previously extracted from some images. There were 9 doors with object ID = [4,5,7,9,13,15,20,28,35] and 9 panes with object ID = [3,6,14,16,17,27, 29,30,34], respectively.

From the methods mentioned in Sec. 4, 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.

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 containing the original data, but after applying this axes ratio and 6 features enumerated above, we obtain a simpler classification tree (fig. 5).

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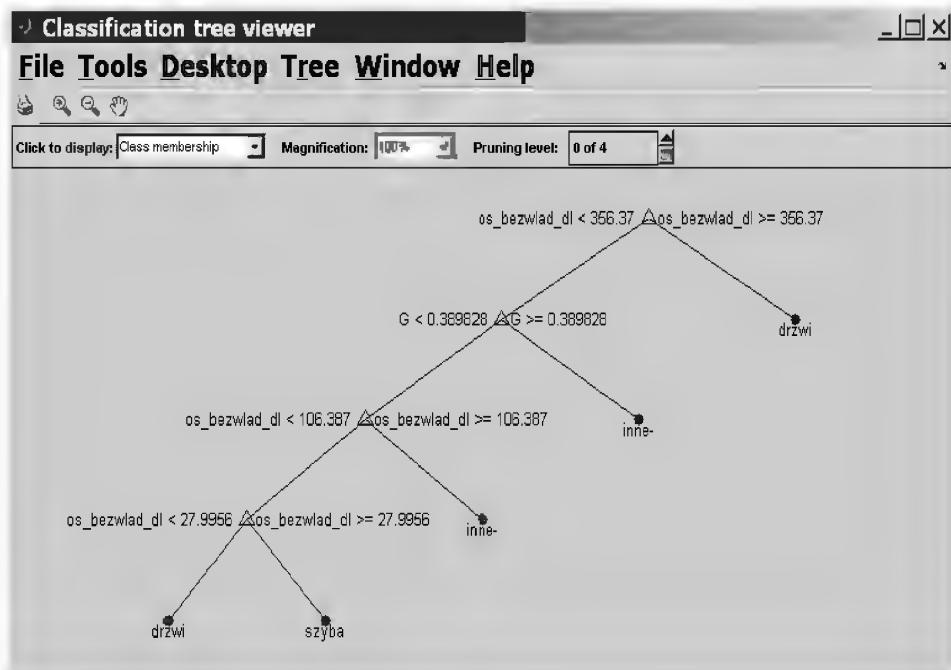
Figure 4: Classification tree for data for 8 features without any modifications
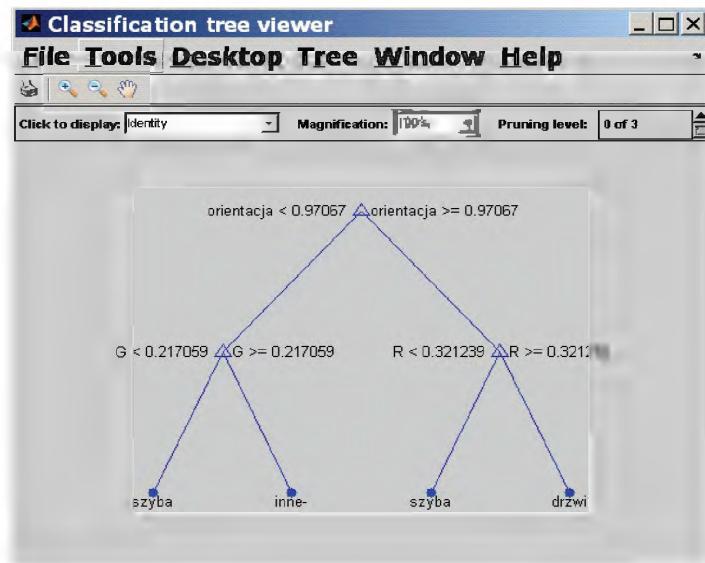

Figure 5: Classification tree with ratio of minor to major axes

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

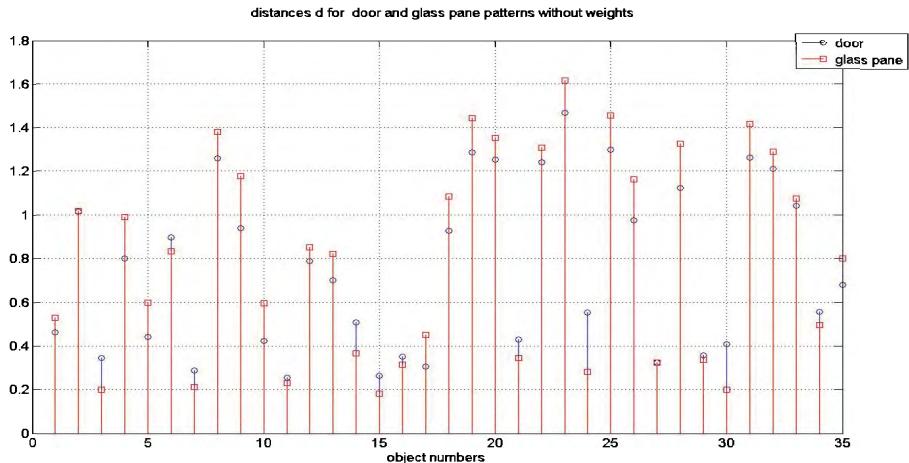| Features	Pattern door	Weight $\mu_{P_{door}}$	Pattern pane	Weight $\mu_{P_{pane}}$
eccentricity	0.93	0.1	0.85	0.1
moments of inertia	average	0.01	average	0.01
solidity	0.8	0.3	0.9	0.19
minor axis length /major axis length	0.427	0.1	0.5	0.1
orientation	0.99	0.46	0.99	0.3
average colour component R	0.33	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

Figure 6: Distances *d* for all graphical objects computed for pattern_door and pattern_pane, respectively without weights

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 overlapping distances for door and pane patterns (see the legend). The majority of smallest *d* corresponds with the object numbers IDs for pattern_door and pattern_pane, respectively.

Only for doors ID = [7,15] and for glass panes ID = [17,27] misclassification can be noticed. Hence, subsequently, we added weights μ_P for both patterns, respectively, and obtained distances *d* for each object according to 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 to each other 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.
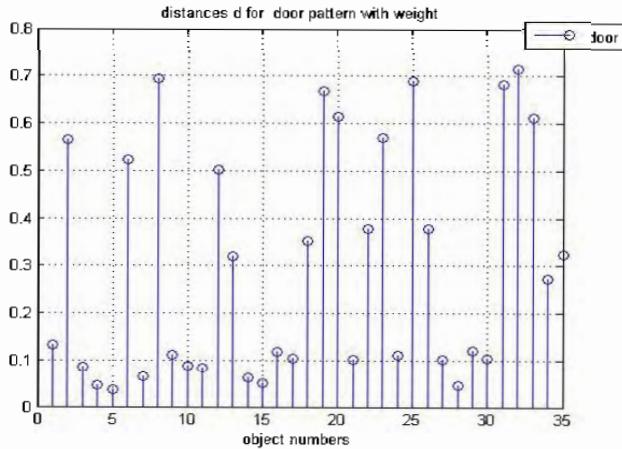

Figure 7: Distances d for pattern_door with weight $\mu_{P_{door}}$

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

6 Possibility theory for the best graphical object classification

We can assume that we have such imbalanced and misclassified data that it is very problematic to achieve high accuracy by simply classifying some examples as negative. However, many attempts have been made to address the imbalanced data problem. Some methods try to receive more balanced, relevant and

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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.
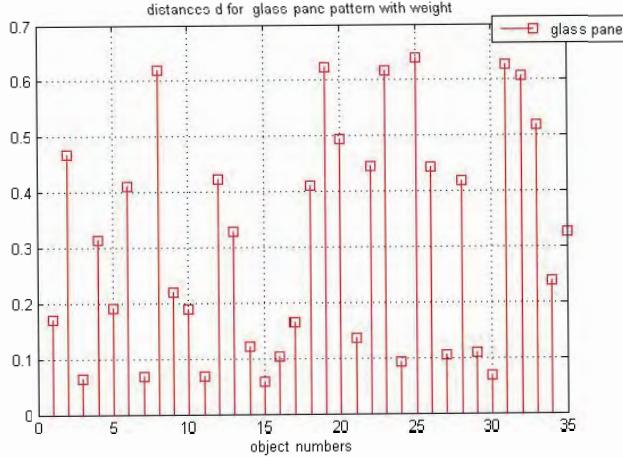

Figure 8: Distances d for pattern_pane with weight $\mu_{P_{pane}}$

As it has been shown in fig. 6, the commonly used methods of feature selection (using the positive features only) may lead to object misclassification. It may be even worse for the imbalanced data with dominating irrelevant objects. That is why, we suggest the application of intuitionistic fuzzy sets for the graphical object classification. For our task, when we look at fig. 6, it is easy to see that for some objects the classification problem will become especially 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 Baldwin's model contains terms necessity n and possibility p. Following these authors we can cite equality of the parameters for Baldwin's model and the 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 Sec. 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 of values d. An object is attributed into this class for which value d is the smallest. For a given object x, its distances from particular patterns P_k can be denoted 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, the 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 $1 \leq j,k \leq n$. This formula means that we subtract the smallest 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).
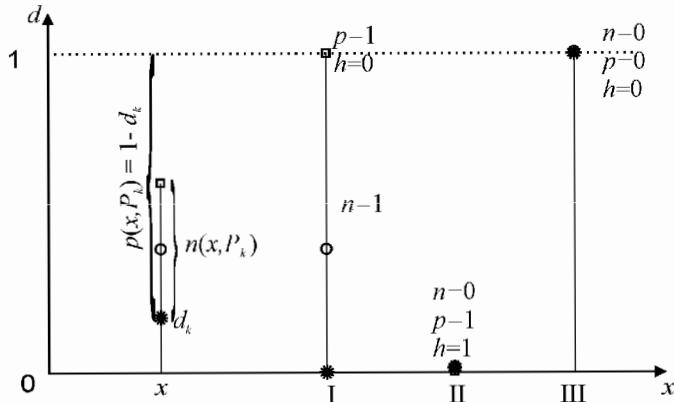

Figure 9: The interpretation of the degree of necessity, possibility and hesitation for the distances of an object feature vector from a particular pattern

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 class introduced distinguishing the objects more precisely.

This approach seems to be useful with respect to problems with assigning a new object to particular class or small distinguishability of some graphical objects.

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 to introduce 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 an already known method of comparing the object feature vector with patterns. However, we suggest the application of the possibility theory, and introduce Baldwin's model with its notions of necessity, possibility, and IFS for imbalanced and uncertain data. This approach seems to be important for unsupervised analysis of large image databases.

References

[1] Amsaleg L., Gros P., Berrani S-A. (2004) Robust Object Recognition in Images and the Related Database Problems. *Multimedia Tools and Applications*, 23, 1, Springer Netherlands, 221-235.

[2] Atanassov K. (1986) Intuitionistic fuzzy sets, *Fuzzy Sets and Systems* 20, 87-96

[3] Baldwin J. F. (1992) The Management of Fuzzy and Probabilistic Uncertainties for Knowledge Based Systems, in *Encyclopaedia of AI* (ed. S. A. Shapiro), John Wiley, 577-594.

[4] Baldwin J. F., Lawry J., Martin T. P., (1995) A Mass Assignment Theory of the Probability of Fuzzy Events, *ITRC Report 229*, University of Bristol, UK.

[5] Bamidele, A., Stentiford, F. W., Morphett, J. (2004). An attention-based approach to content-based image retrieval, *BT Technology Journal*, Vol. 22, No. 3, 151-160.

[6] Chawla N., Bowyer K., *et al.* (2002) Smote: synthetic minority over-sampling technique, Artificial Intelligence Research, Vol 16, 321-357.

[7] Chow, T., Rahman, M., Wu, S. (2006). Content-based image retrieval by using tree-structured features and multi-layer self-organizing map, *Pattern Analysis and Applications,* Vol. 9, No 1, Springer-Verlag, London, 1-20.

[8] Deb S. (2004) Multimedia Systems and Content-Based Image Retrieval, IDEA Group Publishing, Melbourne.

[9] Flickner, M., Sawhney, H., et al. (1995). Query by Image and Video Content: The QBIC System, *IEEE Computer*, Vol. 28, No. 9, 23-32.

[10] Jaworska T. (2007). Object extraction as a basic process for content-based image retrieval (CBIR) system. *Opto-Electronics Review*, Vol.15, No. 4, 184-195

[11] Jaworska T. (2009). Multi-criteria object indexing and graphical user query as an aspect of content-based image retrieval system, In Borzemski L., Grzech A., Świątek J., Wilimowska Z., (eds), *Information Systems Architecture and Technology*, Wyd. Pol. Wrocławskiej, Wrocław, 103-112.

[12] Mokhtarian, F., Abbasi, S., Kittler J. (1996). Robust and Efficient Shape Indexing through Curvature Scale Space, *Proc. British Machine Vision Conference*, 53-62.

[13] Niblack W., Flickner M. et al. (1993) The QBIC Project: Querying Images by Content Using Colour, Texture and Shape, *SPIE* **1908,** 173 - 187.

[14] Ogle V., Stonebraker M. (1995) CHABOT: Retrieval from a Relational Database of Images, *IEEE Computer* **28**, No. 9, 40-48

[15] Stanchev, P. (2003) Using Image Mining for Image Retrieval, In *Proceeding of IASTED Conference, Cancun, Mexico*, 214-218.

[16] Szmidt E., Baldwin J. (2005) Assigning the parameters for Intuitionistic Fuzzy Sets, *Notes on IFSs*, Vol. 11, No. 6, 1-12.

[17] Szmidt E., Baldwin J. (2006) Intuitionistic fuzzy sets functions, mass assignment theory, possibility theory and histograms, *Proc. of IEEE WCCI*, Vancouver Canada, 234-243.

[18] Szmidt E., Kacprzyk J. (2008) Intuitionistic fuzzy sets – a prospective tool for text categorization. In K. Atanassov, J. Kacprzyk, *et al.* (eds.)

Developments in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics. Vol. 2, EXIT, 281-300.

[19] Tan, K-L., Ooi, B. Ch., Yee, Ch. Y. (2001). An Evaluation of Color-Spatial Retrieval Techniques for Large Image Databases, *Multimedia Tools and Applications*, Vol. 14, Springer Netherlands, 55-78.

[20] Visa S., Ralescu A. (2004) Experiments in guided class rebalanced based on class structure. 15th *Midwest Artificial Intelligence and Cognitive Science Conference*, Dayton, USA, 8-14.

[21] Zadeh L.A. (1965) Fuzzy Sets, Information and Control, Vol. 8, No 3, 338-353.

[22] Zadeh L.A. (1978) Fuzzy Sets as a basis for a theory of possibility, *Fuzzy Sets and Systems*, Vol. 1, 3-28.

[23] Zadrożny S., De Tré G., Kacprzyk J. (2008) On some approaches to possibilistic bipolar data modelling in databases. In K. Atanassov, J. Kacprzyk, *et al.* (eds.) *Advances in Fuzzy Sets, Intuitionistic Fuzzy Sets, Generalized Nets and Related Topics*. Vol. 2, EXIT, 197-219.

[24] Zhang J., Mani J. (2003) KNN approach to unbalanced data distributions: A case study involving information extraction. *Proc. of the ICML-2003 Workshop: Learning with Imbalanced Data Sets II*, 42-48

The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.

It may be viewed as a result of fruitful discussions held during the Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) organized in Warsaw on October 16, 2009 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Centre for Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT – Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bistrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, and the University of Westminster, Harrow, UK:

http://www.ibspan.waw.pl/ifs2009

The Eighth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2009) has been meant to commence a new series of scientific events primarily focused on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Moreover, other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems are discussed.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.