The problem of classification in Content-Based Image Retrieval systems

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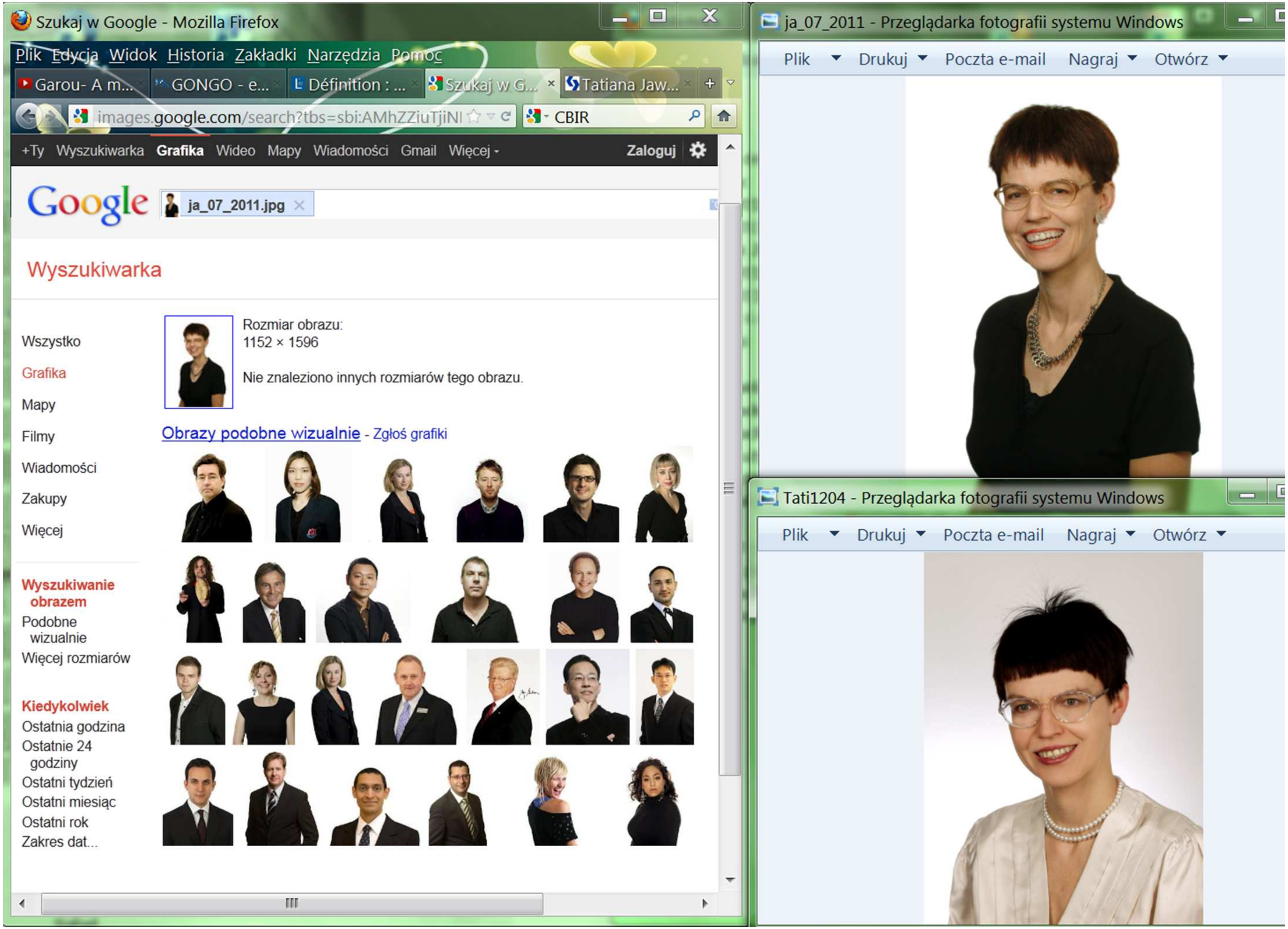
Presentation plan

- Overview of the main idea of the Content-Based Image Retrieval (CBIR) system
- Representation of Graphical Data
- Spatial relationship of graphical objects
- Overview of classification methods
- Fuzzy rule-rased classifiers
- Classification results
- Use of Classified Objects in CBIR
- Construction of search engine
- Challenging tasks
- References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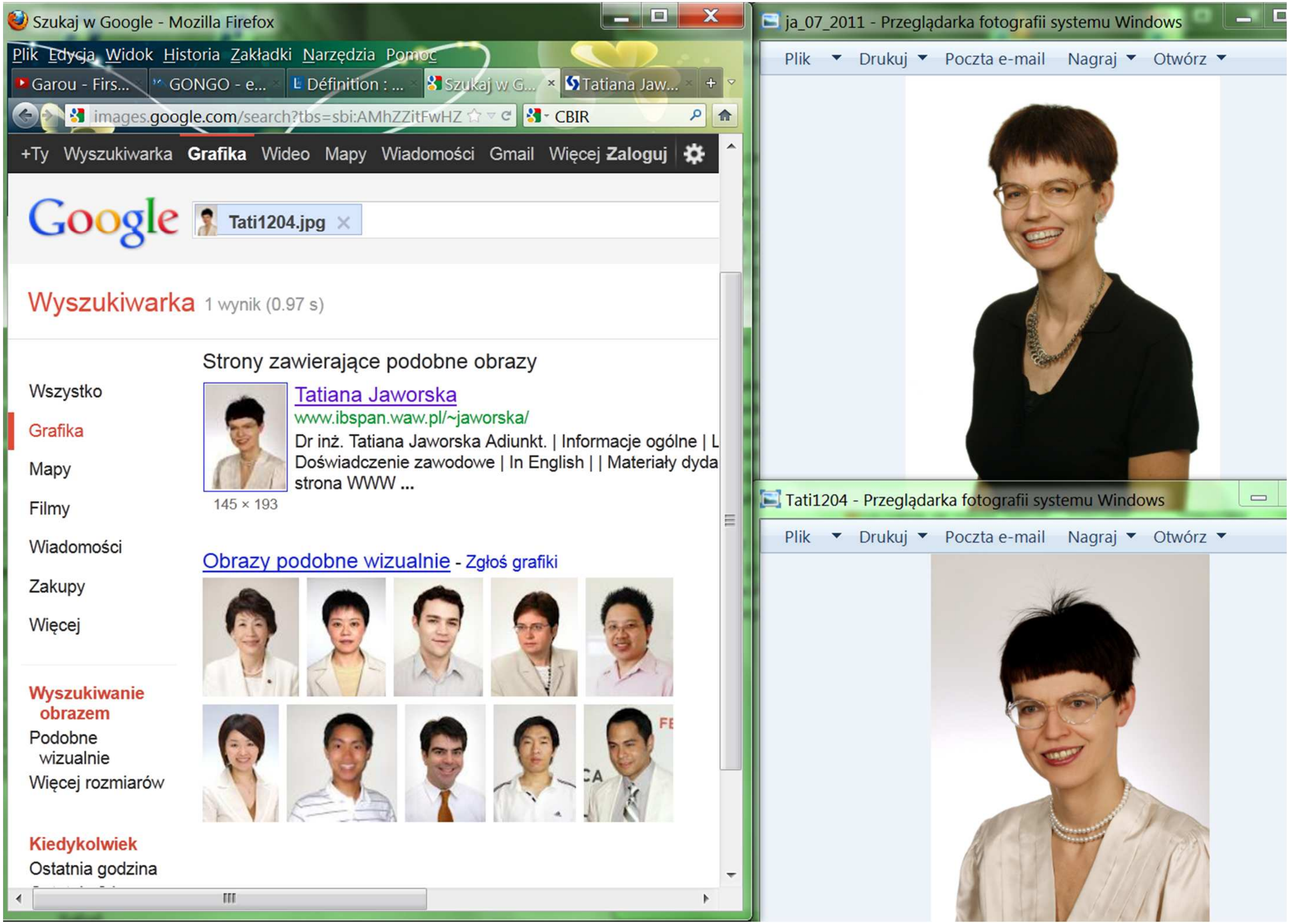

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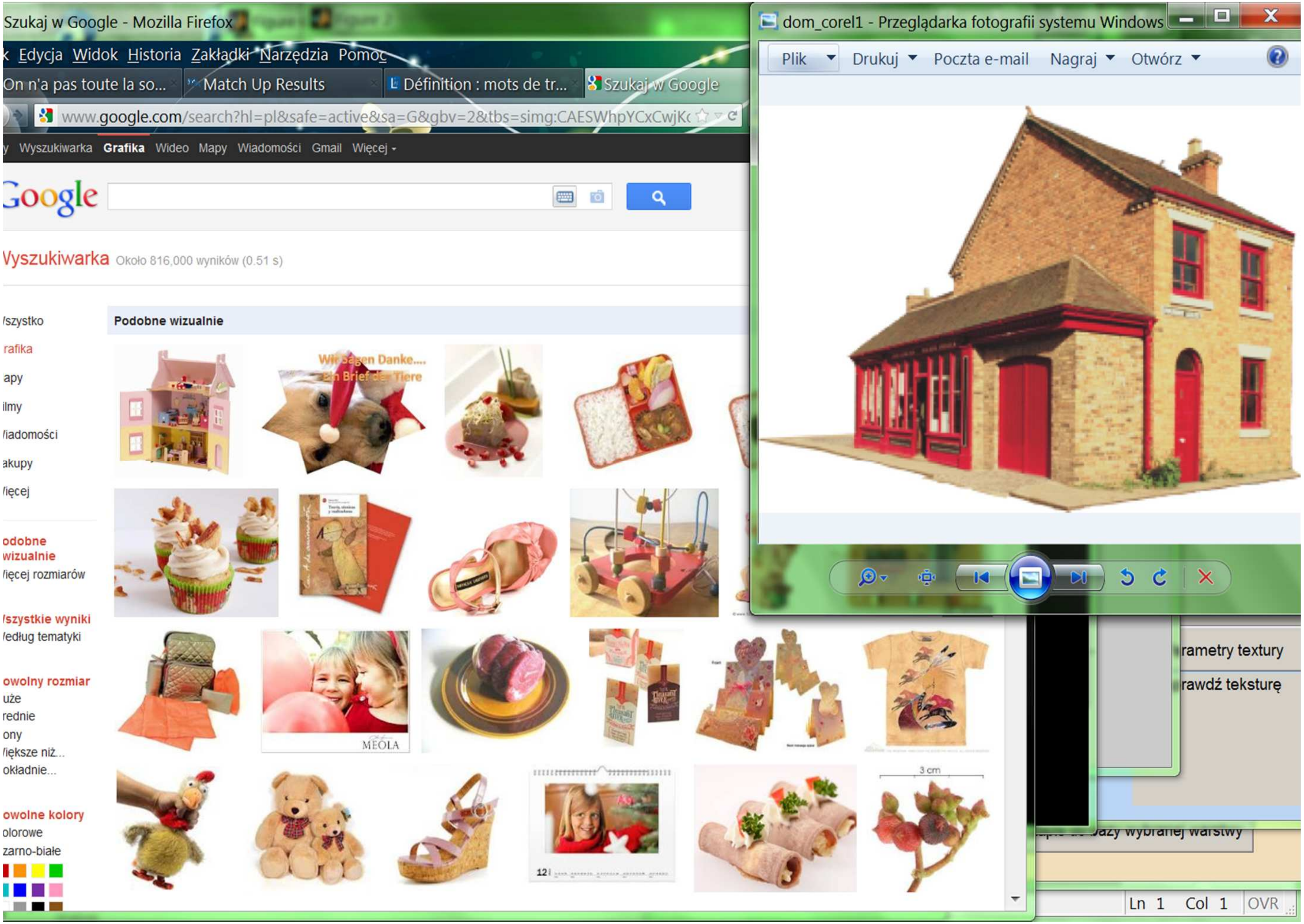

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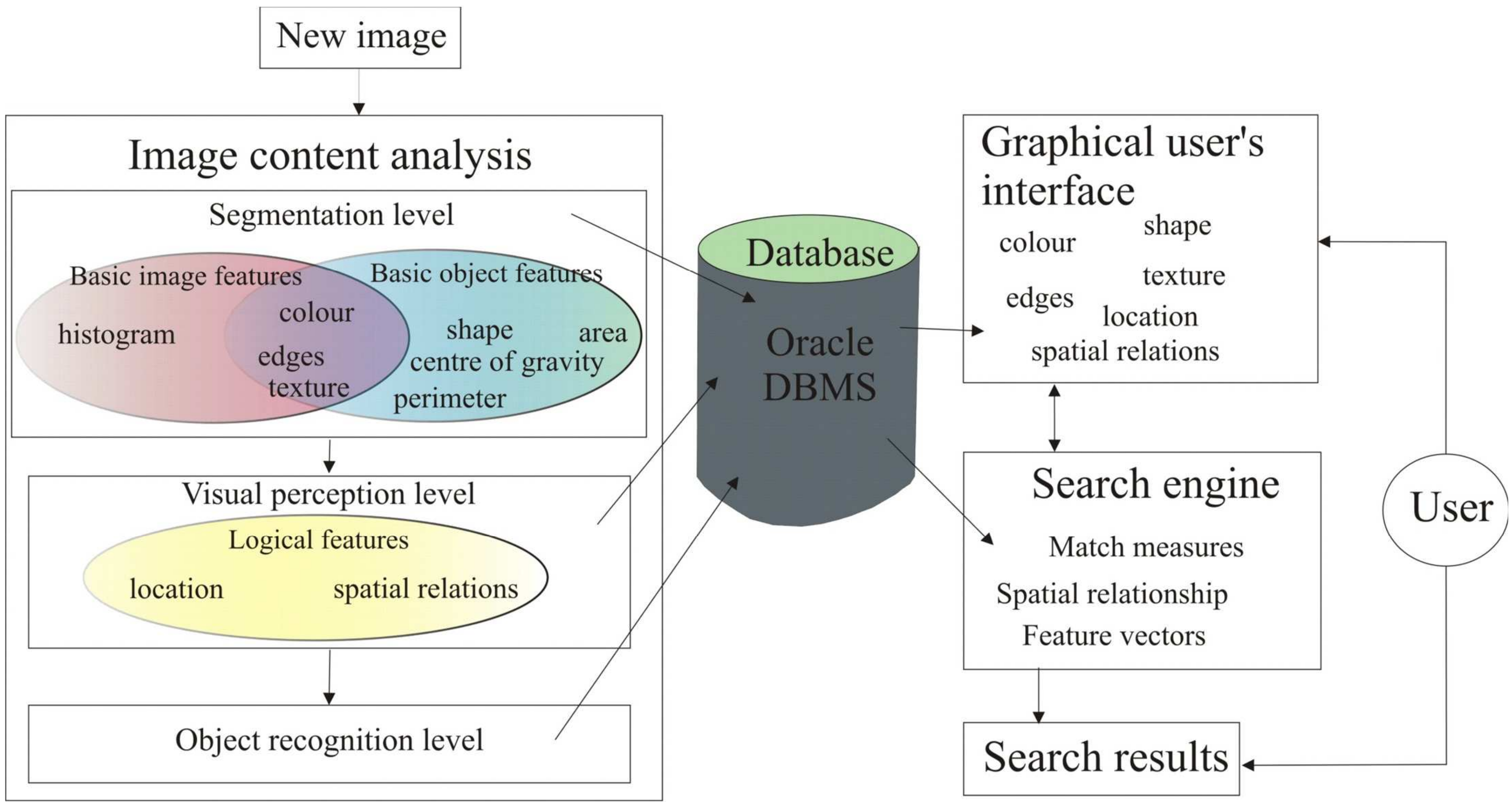
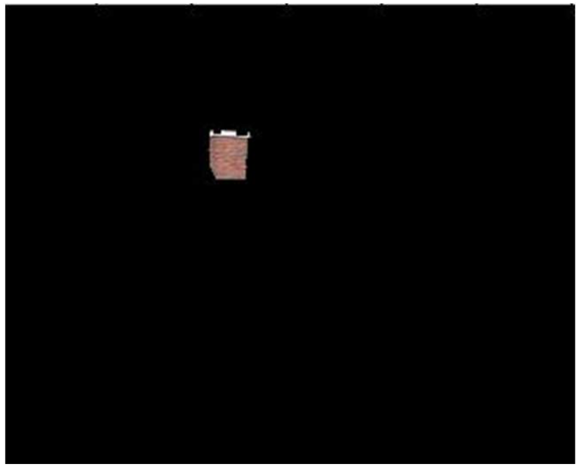
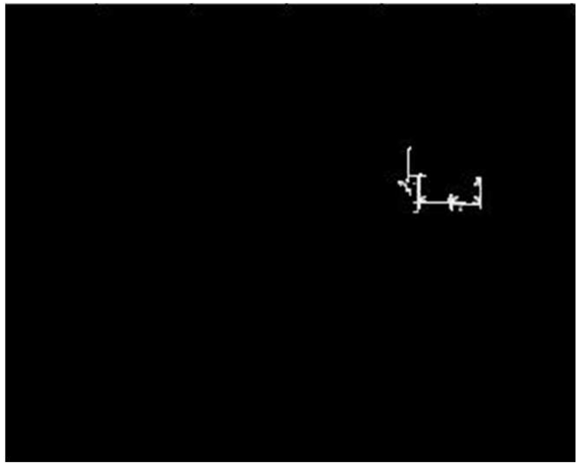
General scheme

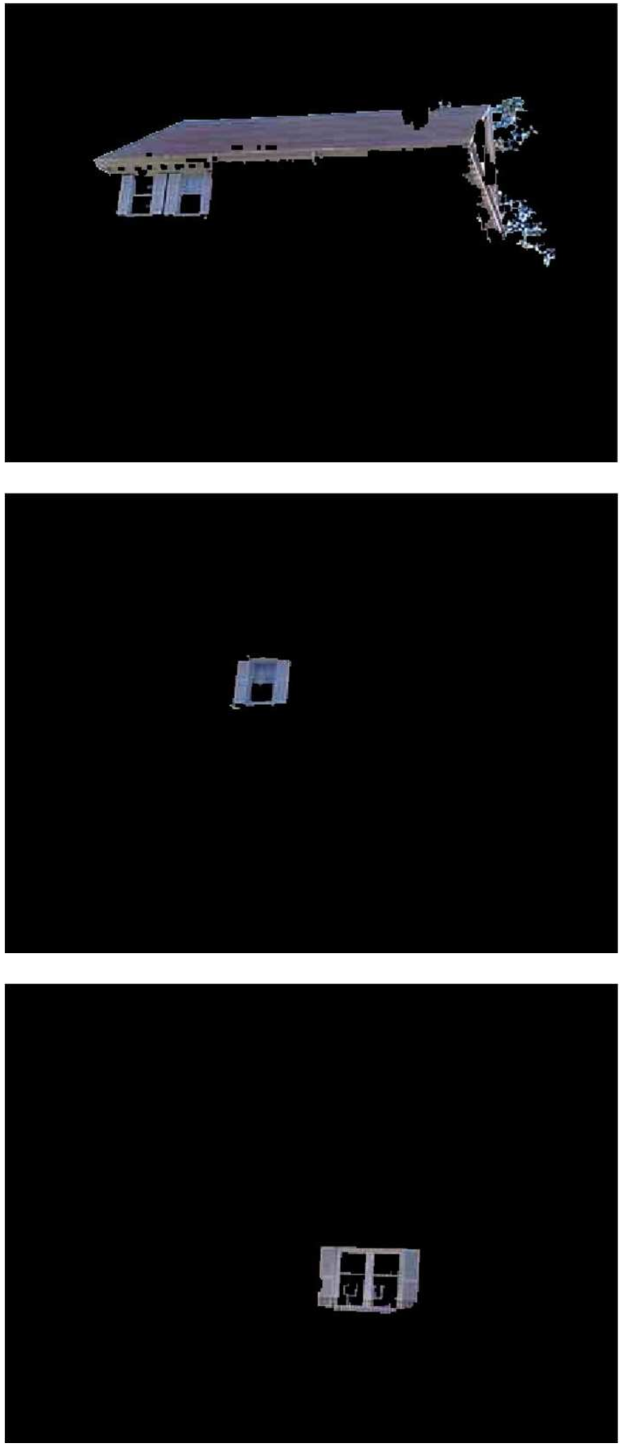


Object extraction





Object extraction



Representation of graphical data

- Feature vector consists of low-level features
  - average colour k_{av}
  - texture parameters T_p
  - area A
  - centroid $\{x_c, y_c\}$
  - eccentricity e,
  - orientation α
  - bounding box $\{bb_1(x,y), \ldots, bb_s(x,y)\}$
  - Euler number E
  - *…….*
- Shape descriptors
  - First and second moments of inertia $m_{11},\ldots,m_{22}$
  - 10 first moments of Zernike Z_{pq}

Zernike polynomials

Zernike moments are a set of complex polynomials $\{V_{pq}(x,y)\}$ which form a complete orthogonal set over the unit disk of $x^2 + y^2 \leq 1$. In polar coordinates the polynomials take on the following form :

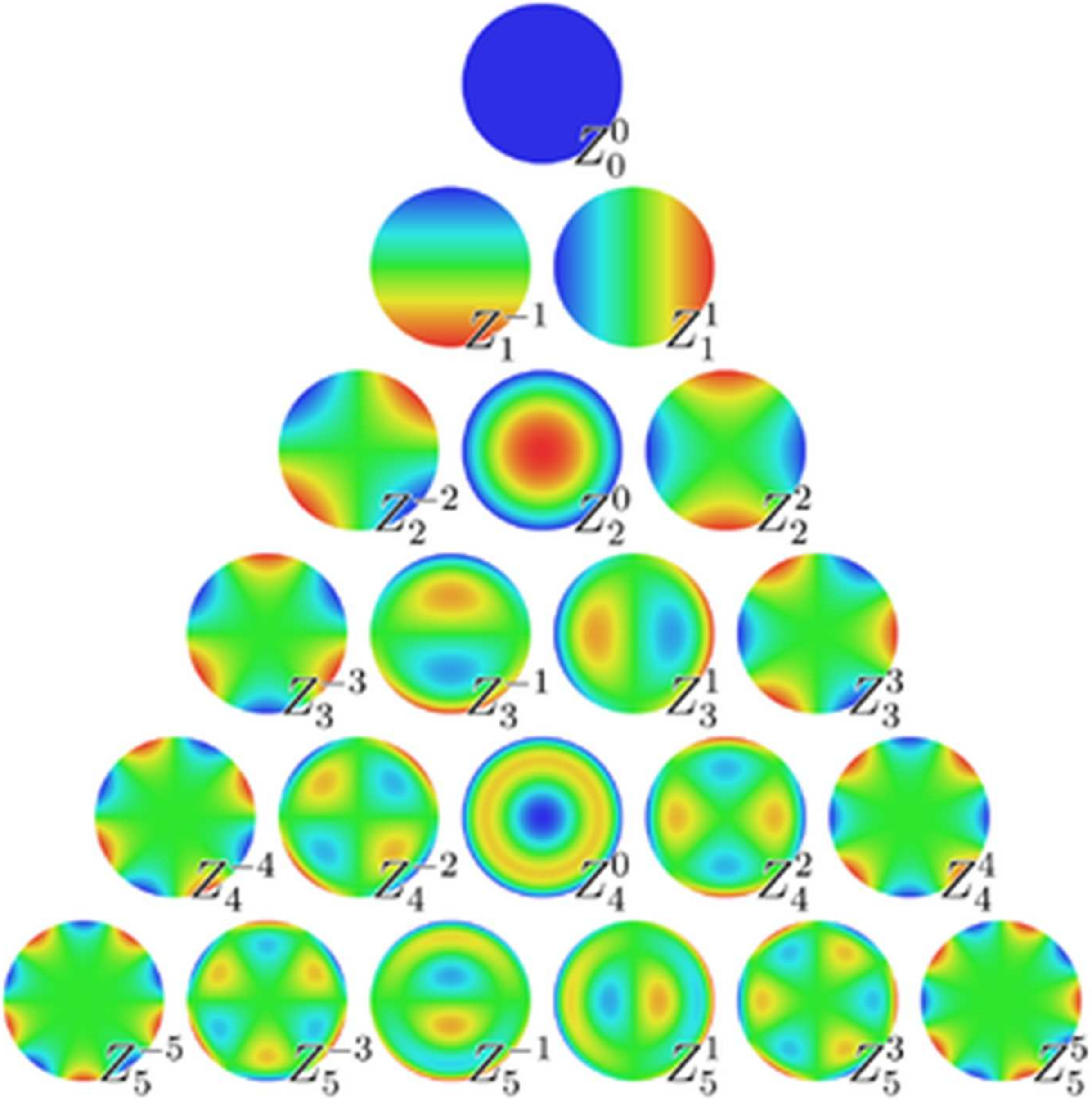
$$V_{pq}(r,\theta) = R_{pq}(r)e^{jq\theta}$$

2D Zernike moments with p^{th} order with repetition q for the intensity function $f(x,y)$ of the image are described as:

$$Z_{pq} = \frac{p+1}{\pi} \iint_{x^2+y^2 \leqslant 1} V_{pq}^*(x,y) f(x,y) \, dx \, dy$$

where $V_{pq}^*(x,y) = V_{p,-q}(x,y)$

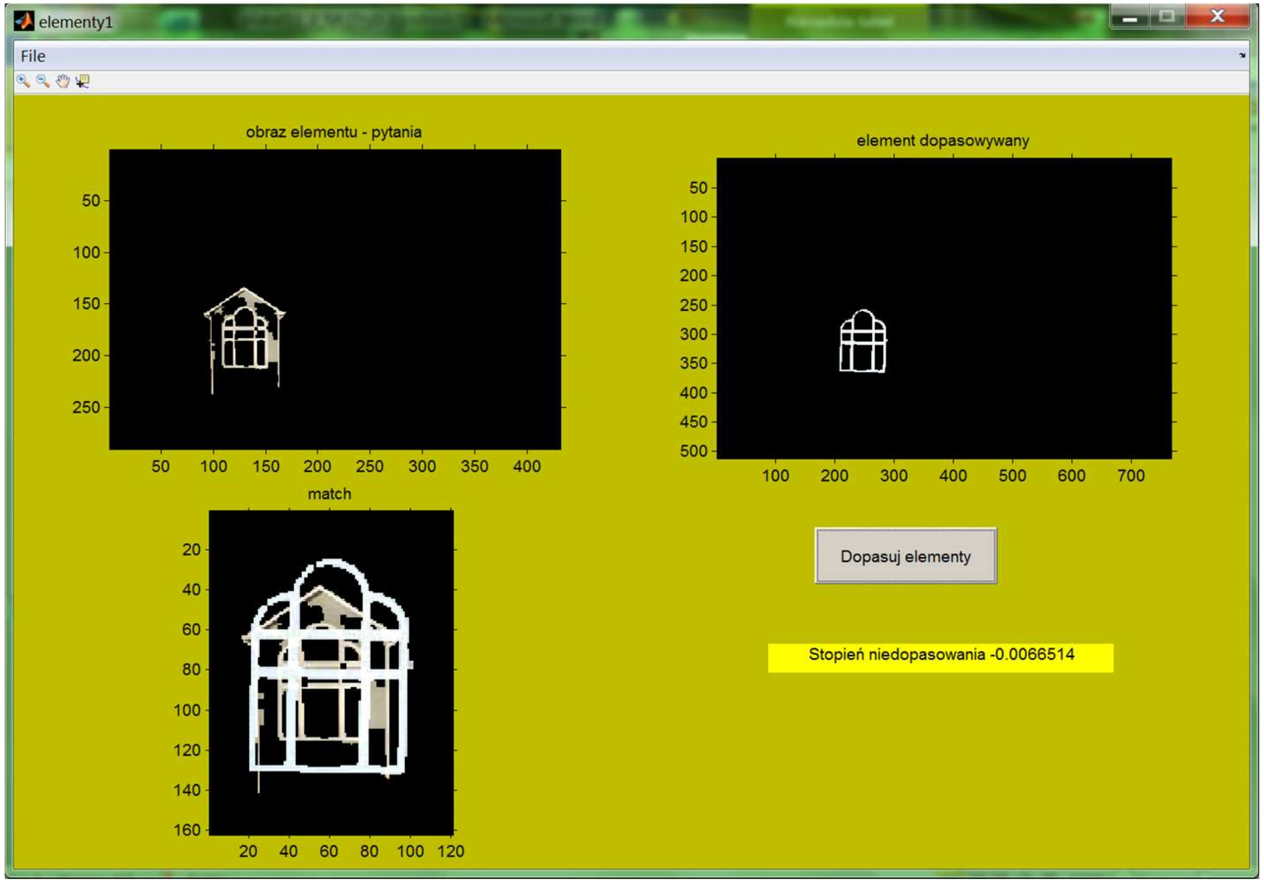
Zernike functions



Characteristic features of Zernike moments

1. The above-defined Zernike moments are invariant only to rotation.
2. The translation invariance is achieved by the location of the original image centroid in the centre of the coordinates.
3. The scale invariance is obtained by normalizing Z_{00} by the total number of image pixels.

An example of two matched objects based on the minimal Euclidean distance for the first 10 Zernike moments.



Feature vector

- Let F be a set of features where $F = \{k_{av}, T_p, A, A_c, \ldots, E\}$ consists of attributes listed above.
- For ease of notation, we will use $F = \{f_1, f_2, \ldots, f_n\}$, where n – number of features.
- Therefore, for an object, we construct a feature vector **X** containing the object features:

$$\mathbf{x} = \{x_1, x_2, \ldots, x_n\},$$

Pattern library

- The pattern library contains information about pattern types, shape descriptors, object location and allowable parameter values for an object. We define a model feature vector P_O for each graphical element. We assume weights $\boldsymbol{\mu}_P$ characteristic of a particular type of element which satisfy:

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

- Patterns can be counted in a different way. The simplest method is a calculation of the average value of the most similar feature vector. Another one is to use the k-means algorithm, but not to cluster all the vectors, but only to find a centroid of cluster, which guarantees the nearest distance from vectors belonging to one pattern. More sophisticated methods can also be used.

Spatial relationship of graphical objects 1

For the comparison of the spatial features of two images an image I_i is interpreted as a set of n objects composing it: $Ii = \{o_{i1}, o_{i2}, \dots, o_{in}\}$

Each object o_{ij} is characterized by a unique identifier and a set of features. 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.). For convenience, we number the classes of the objects and thus L_k's are just numbers.

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

Spatial relationship of graphical objects 2

Let us assume that there are, in total, M classes of the objects recognized in the database, denoted as labels L_1, L_2, …, L_M. Then, by the signature of an image I_i we mean the following vector:

$$\text{Signature}\ (I_i) = [\text{nobc}_{i1}, \text{nobc}_{i2}, \ldots, \text{nobc}_{iM}]$$

where: nobc_{ik} denotes the number of o_{ij} objects of class L_k present in the representation of an image I_i.

Additionally, for an image I_i we consider a representation of spatial relationships of the image objects. The o_{ij} objects' mutual spatial relationship is calculated based on the principal component analysis (PCA) .

Spatial relationship of graphical objects 3

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

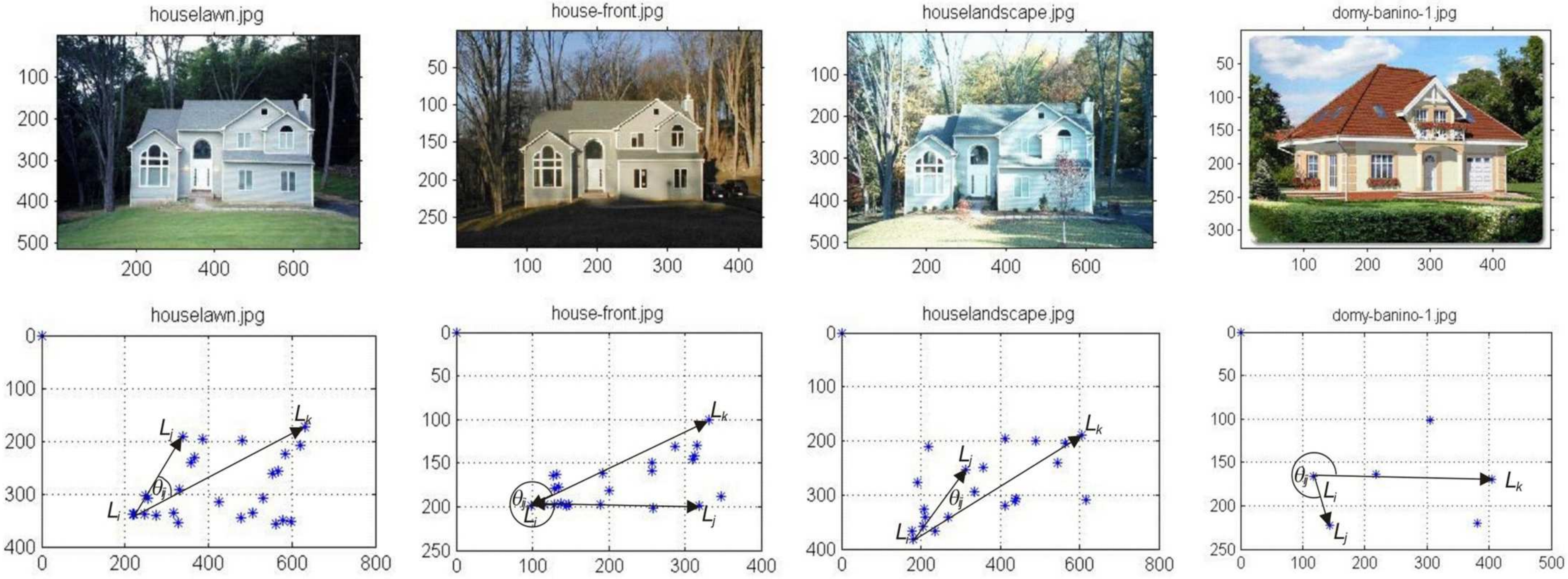
$$\text{dist}\ (C_p, C_q) = \max\ \{\text{dist}\ (C_i, C_j)\ \forall i,j \in \{1,2,\ldots,k\} \text{ and } L_i \neq L_j\}$$

where: dist(•) is the Euclidean distance between two centroids.

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.

Determination of angle relative to the reference direction

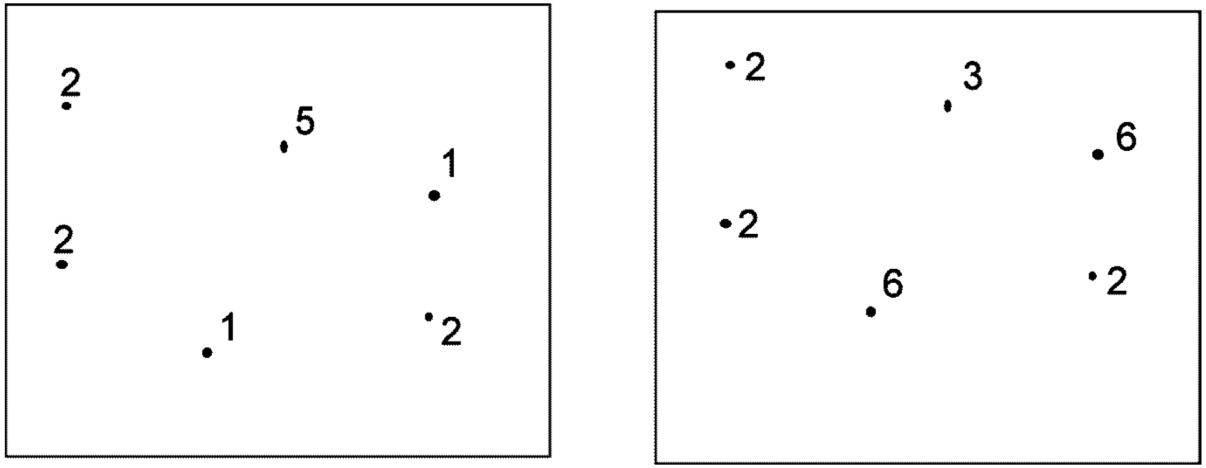
We received triples (L_i , L_j, θ_{ij}) where the mutual location of two objects in the image is described in relation to the line of reference. Thus, there are $T = m(m\text{-}1)/2$ numbers of triples, generated to logically represent the image consisting of m objects.



Principal component analysis (PCA)

- O is a set of observations for three variables. We construct a matrix of observations $O_{3\times N}$, where each triple is one observation.
- PCA is a procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance.
- In our case we use 3 first principal components.

Comparison between two images based on spatial relationships

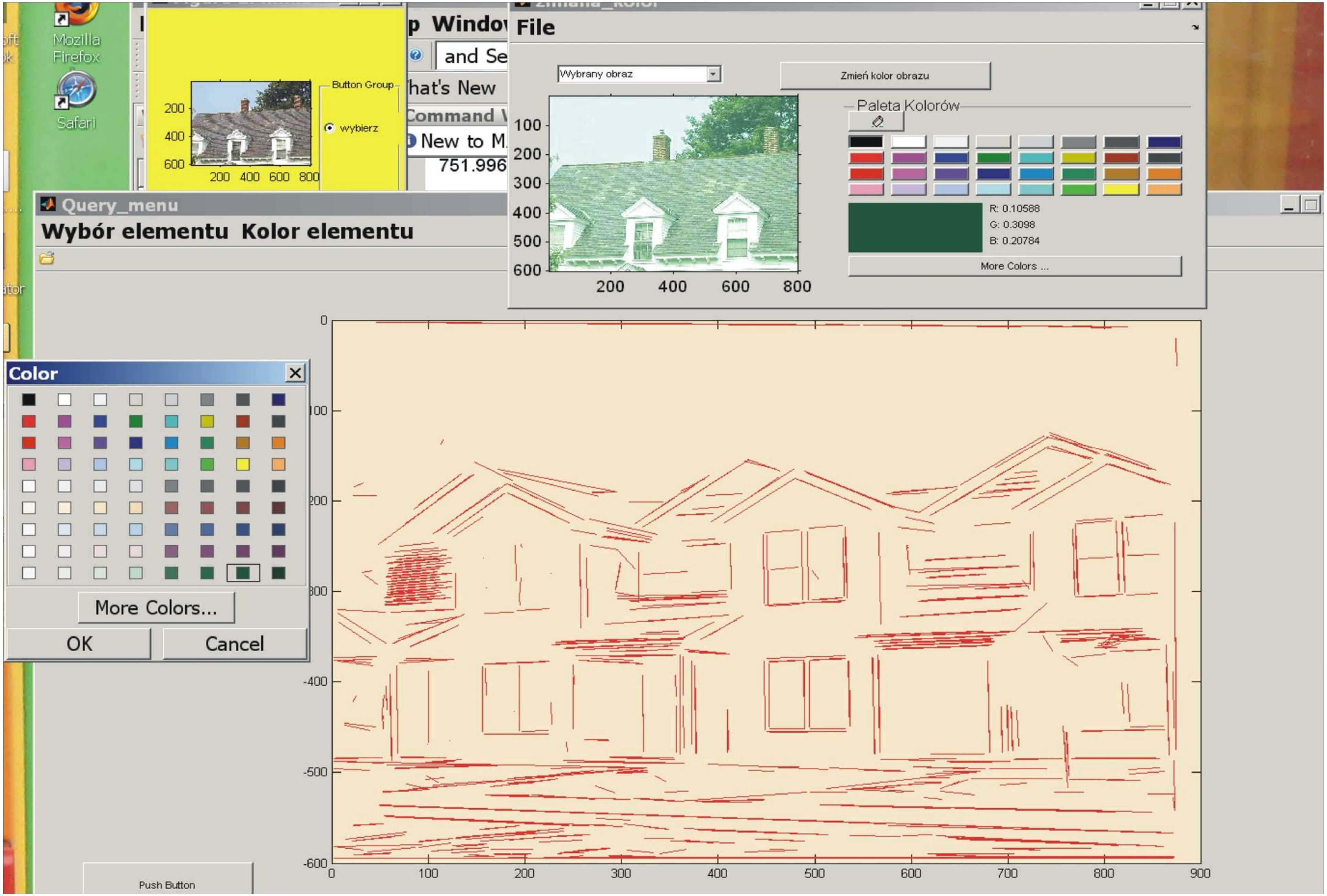


a) b)

a) PCA = [-0,001786 -0,003713 0,999992]

b) PCA = [0,000206   0,003988 0,999992]

Query menu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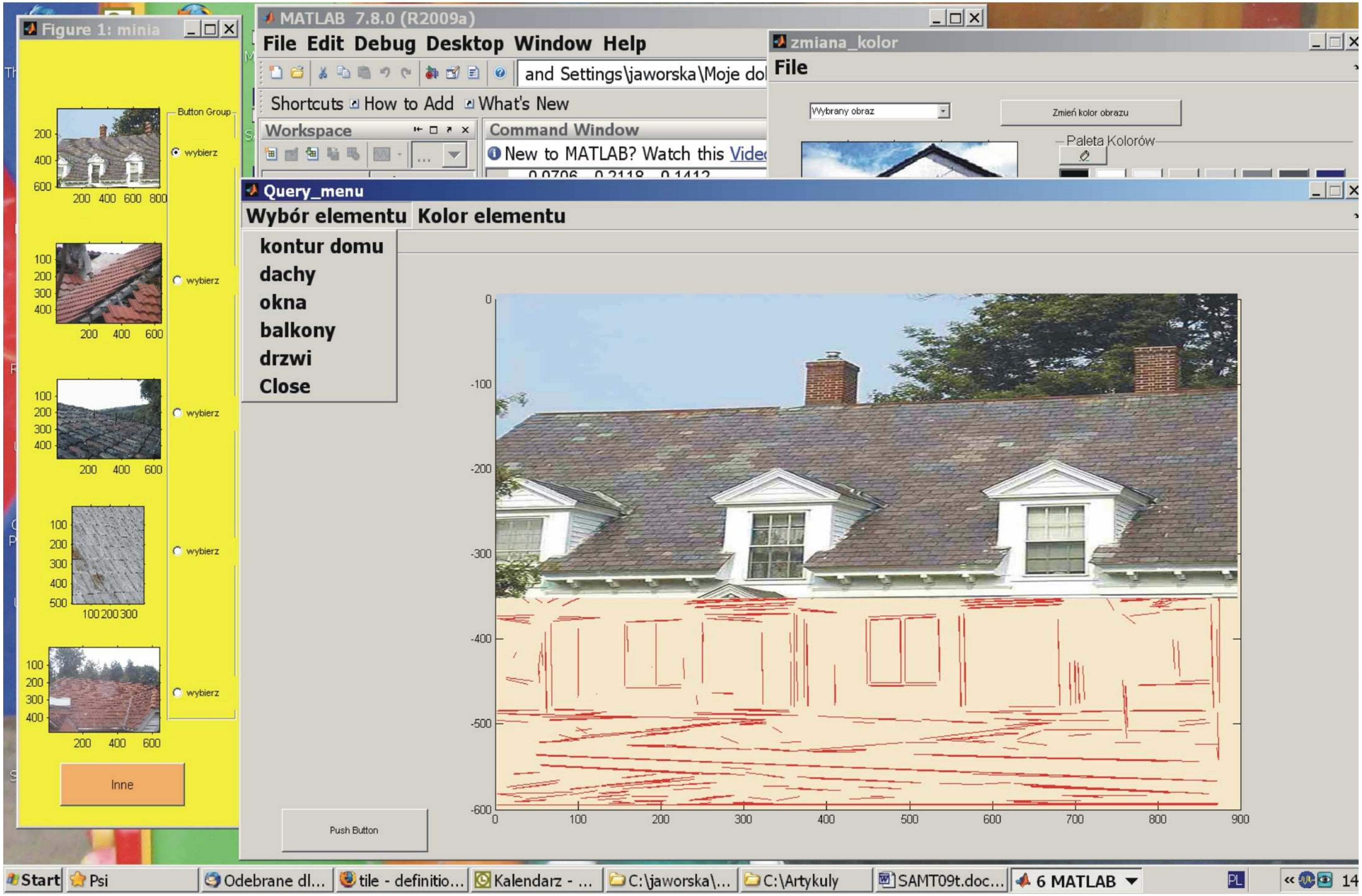
Graphical query by example – user's menu

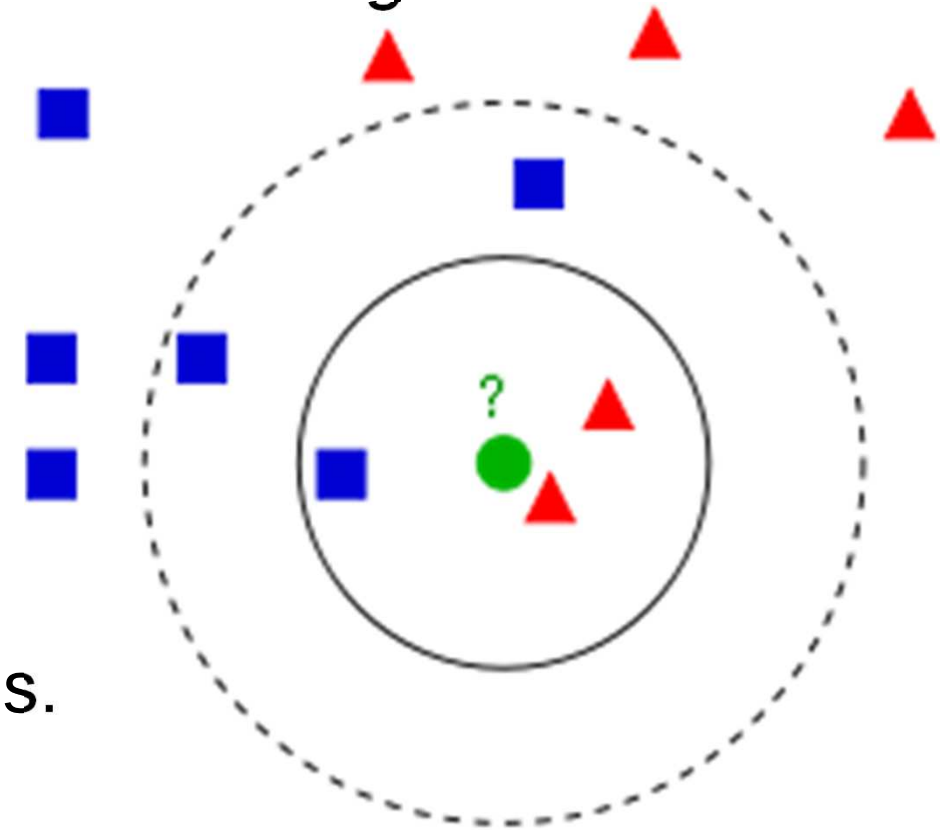


Classification methods

- k-Nearest-Neighbours
- Naive Bayes
- Support Vector Machine
- Neural network
- Decision tree
- ⋮
- Fuzzy rule-based classifiers

k-Nearest-Neighbours

A very simple classifier can be based on a nearest-neighbour approach. The training examples are vectors in a multidimensional feature space, each with a class label. We find the closest objects from the training set to an object being classified.



Example:
The test sample
(green circle)
should be classified:
for k=3 to red triangles,
but for k=5 to blue squares.

Naive Bayes

A naive Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature, given the class variable.

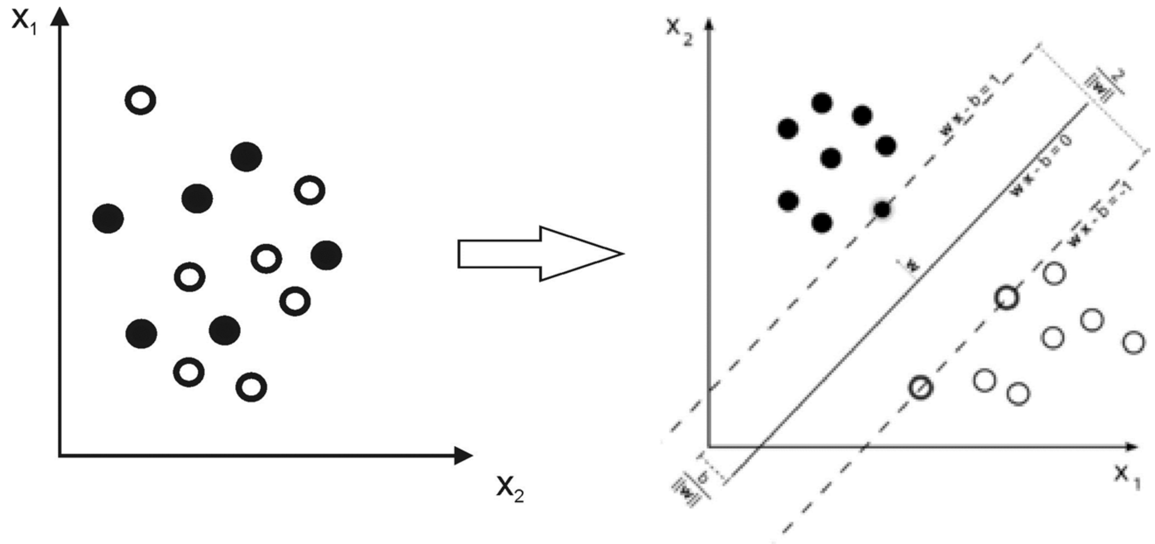
Depending on the precise nature of the probability model, naive Bayes classifiers can be trained very efficiently in a supervised learning setting.

In many practical applications, parameter estimation for naive Bayes models uses the method of maximum likelihood; in other words, one can work with the naive Bayes model without believing in Bayesian probability. In spite of their oversimplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations.

Support Vector Machine

A support vector machine constructs a set of hyper-planes in a high-dimensional space, which can be used for classification. Intuitively, a good separation is achieved by the hyper-plane that has the largest distance (functional margin) to the nearest training data point of any class.

However, it is often the case that the data are far from linear and the datasets are inseparable. Then kernels are used to map non-linearly the input data to a high-dimensional space (feature space). The new mapping is then linearly separable.

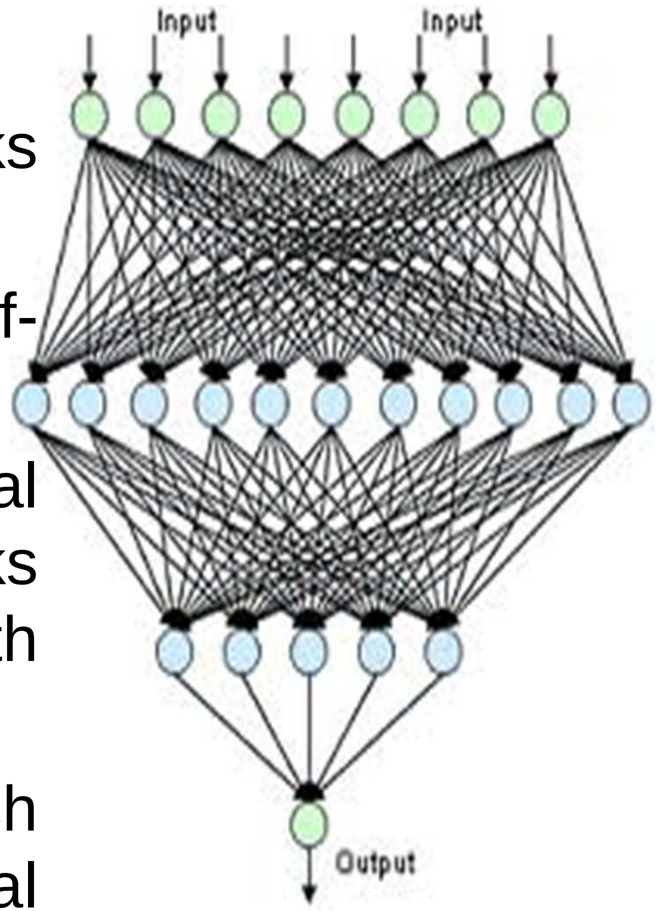


Neural network

The term neural network was traditionally used to refer to a network or circuit of biological neurons.

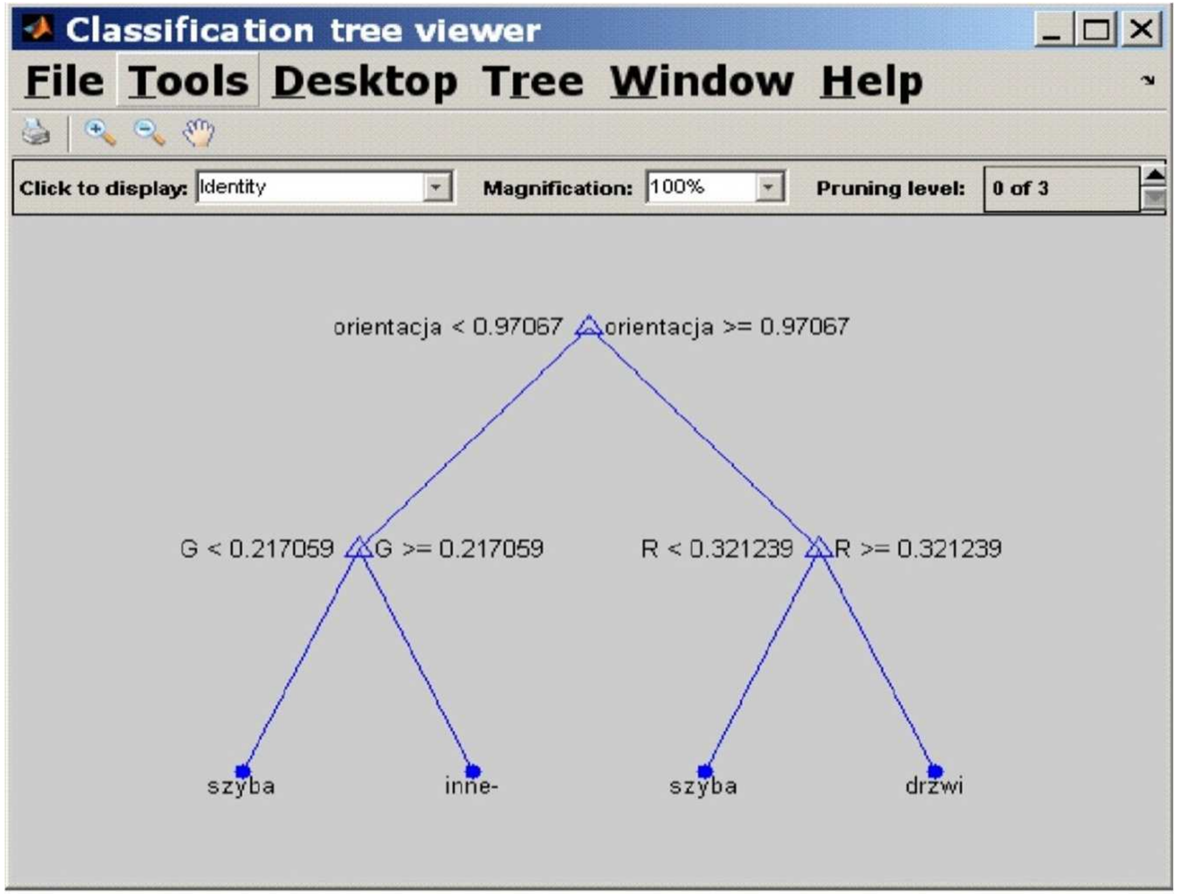
The advantage of neural networks lies in the following theoretical aspects.

1. Neural networks are data driven self-adaptive methods.
2. They are universal functional approximators in that neural networks can approximate any function with arbitrary accuracy.
3. They are nonlinear models, which makes them flexible in modelling real world complex relationships.



Decision tree

Decision tree methods have also been widely used for some classification problems. The algorithms that are used for constructing these trees usually work top-down by choosing a variable at each step that is the next best variable to use in splitting the set of items.



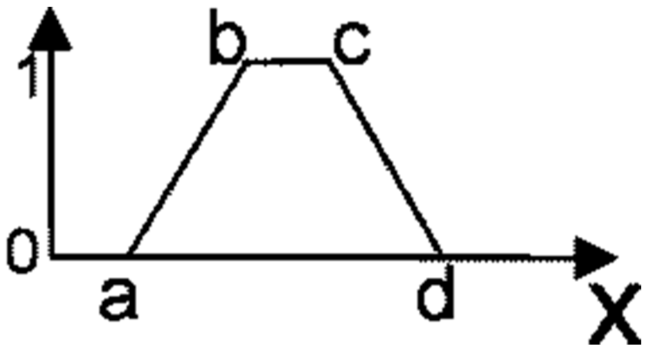
Fuzzy set

According to Zadeh, a fuzzy set F in U is uniquely specified by its membership function μ_F: $U \rightarrow [0,1]$. Thus, the fuzzy set is described as follows:

$$F = \{(u, \mu_F(u)) | u \in U\}$$

For our purpose, we use a trapezoidal membership function which is defined by four parameters a,b,c,d:

$$\text{trap mf}(u; a, b, c, d) = \begin{cases} 0, & u < a \\ (u-a)/(b-a), & a \le u \le b \\ 1, & b \le u \le c \\ (d-u)/(d-c), & c \le u \le d \\ 0, & d < u \end{cases}$$



Fuzzy rule-based classifiers 1

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

Rule R_q : If x_1 is A_{q1} and ... and x_n is A_{qn} then Class C_q with CF_q,

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 ($i = 1,...,n$), C_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 way. We use the n-dimensional vector $\boldsymbol{A}_q = (A_{q1}, ..., A_{qn})$ to represent the antecedent part of the fuzzy rule R_q in the above formula in a concise manner.

Fuzzy rule-based classifiers 2

A set of fuzzy rules S of the type shown in the Rule R_q 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 $\boldsymbol{A}_q$ of each fuzzy rule R_q in S is calculated by the product operator as:

$$\mu_{A_q}(\mathbf{x}_{\boldsymbol{p}}) = \mu_{A_{q1}}(\mathbf{x}_{\boldsymbol{p1}}) \times ... \times \mu_{A_{qn}}(\mathbf{x}_{\boldsymbol{pn}}) \text{ for } R_q \in S,$$

where $\mu_{A_{qi}}(.)$ shows the membership function of A_{qi}.

Then a single winner rule $R_{w(\mathbf{x}_p)}$ is identified for $\mathbf{x}_p$ as follows:

$$w(\mathbf{x}_{\boldsymbol{p}}) = \arg\max_q \{CF_q \times \mu_{A_q}(\mathbf{x}_{\boldsymbol{p}}) \mid R_q \in S\}$$

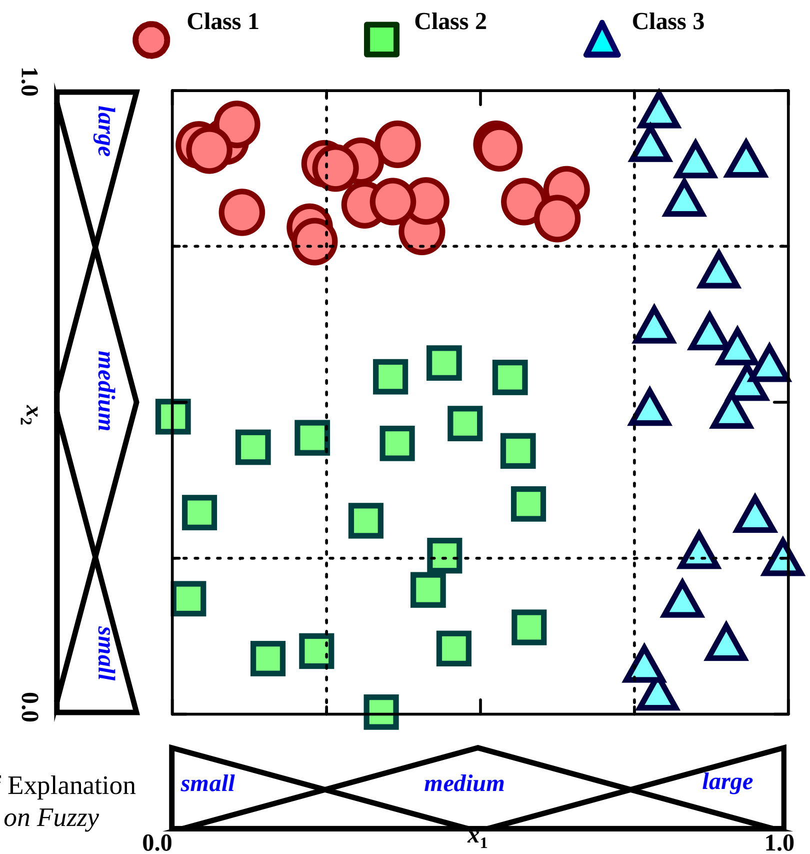
where $w(\mathbf{x}_p)$ denotes the rule index of the winner rule for $\mathbf{x}_p$.

The vector $\mathbf{x}_p$ is classified by the single winner rule $R_{w(\mathbf{x}_p)}$ belonging to the respective class. We use the single winner-based fuzzy reasoning method for pattern classification.

Fuzzy rule-based classifier proposed by Ishibuchi

An ideal theoretical example of a simple three-class, two-dimensional pattern classification problem with 20 patterns from each class is considered by H. Ishibuchi and Y. Nojima.

In this example three linguistic values (*small*, *medium* and *large*) were used as antecedent fuzzy sets for each of the two attributes and 3×3 fuzzy rules were generated.



Ishibuchi H. and Nojima Y. (2011) Toward Quantitative Definition of Explanation Ability of fuzzy rule-based classifiers, *IEEE InternationalConference on Fuzzy Systems*, June 27-39, 2011,Taipai, Taiwan, 549-556.

Fuzzy rule-based classifier with 9 fuzzy rules

S_1:

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.

R_3	R_6	R_9
R_2	R_5	R_8
R_1	R_4	R_7

Classification results

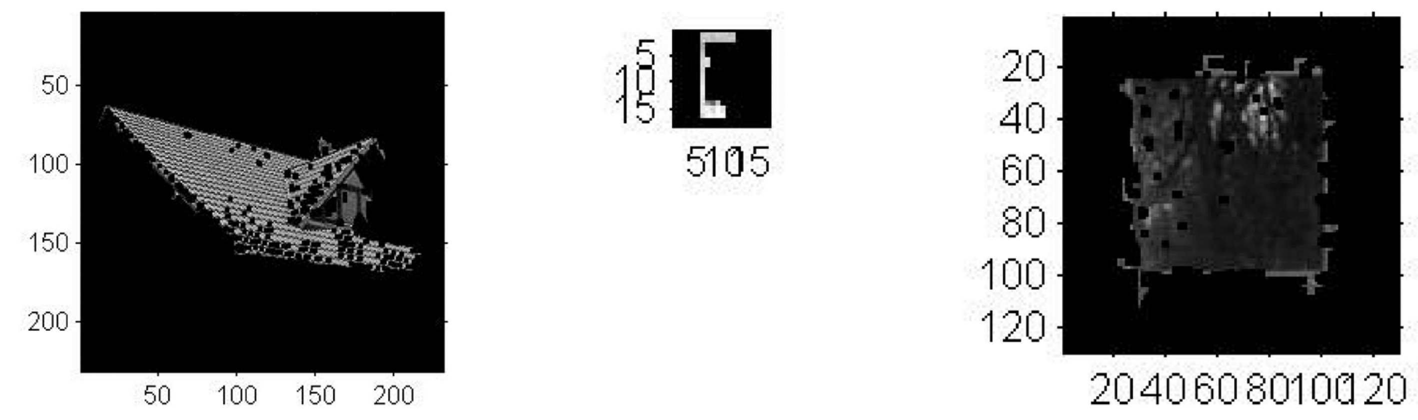
Based on the data collected in our CBIR system (n = 32 features for each graphical object), we have analysed the most distinguished features to present our experimental results.

We have chosen three classes from graphical objects in the training subset:

a) class1 - roof,

b) class2 - window frame,

c) class3 - window pane



a) b) c)

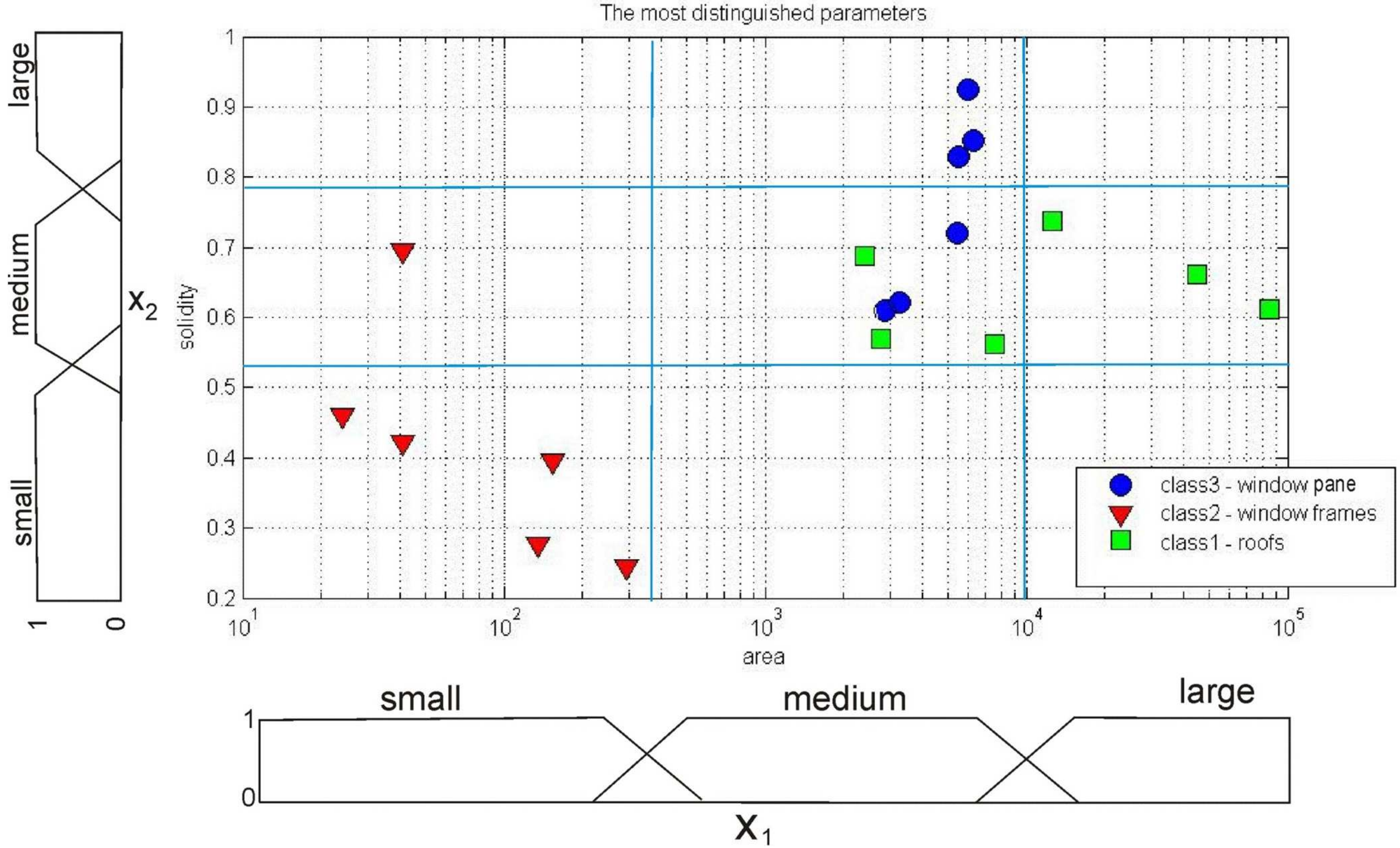
Results for fuzzy rule-based classifier with 9 fuzzy rules

For our fuzzy rule-based classifier we have classified data from a training subset according to the fuzzy rule-based classifier S_{r1}. with the 9 fuzzy rules constructed as follow:

S_{r1}: fuzzy rule-based classifier with 9 fuzzy rules

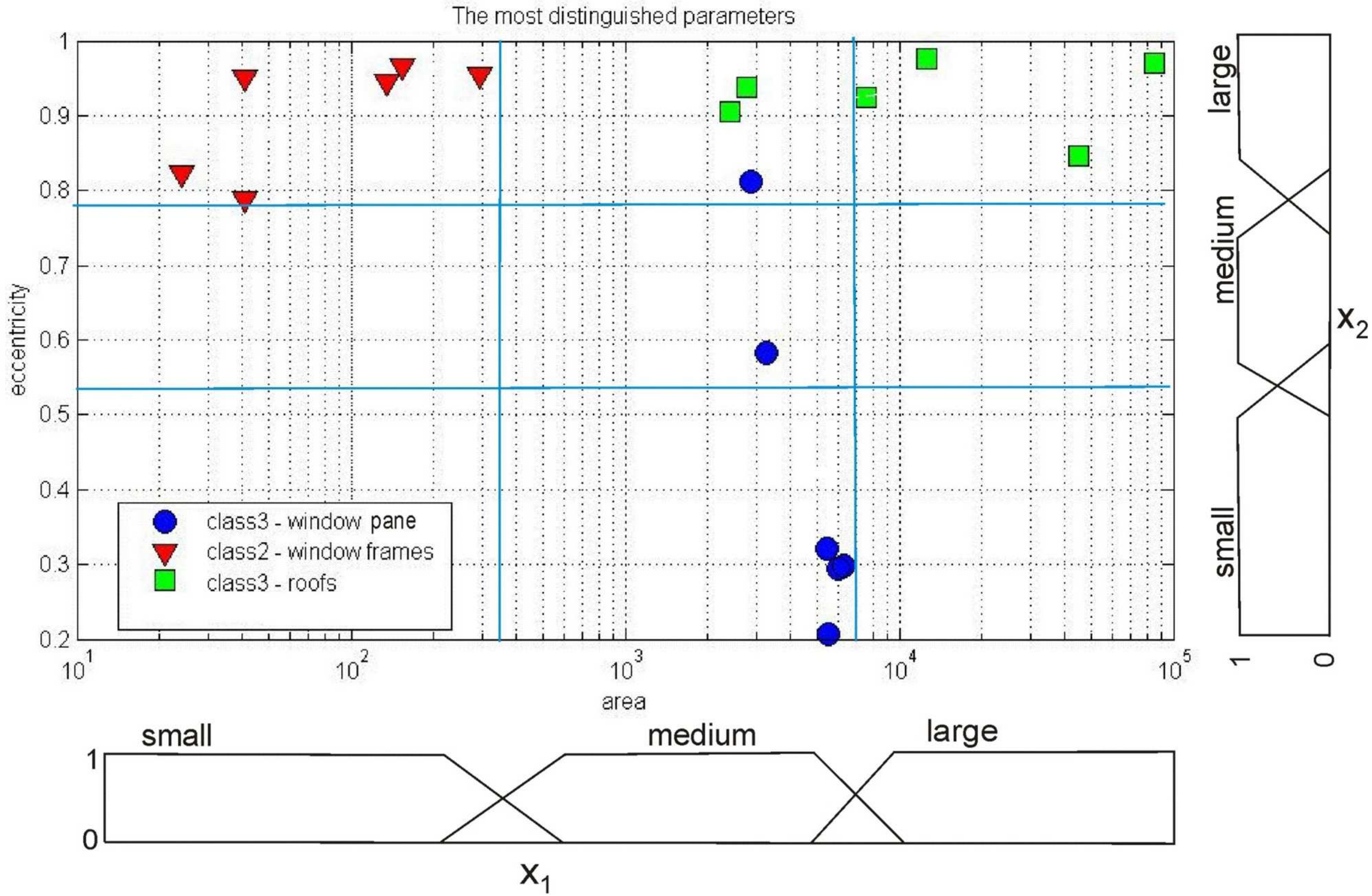
R_1: If x_1 is *small* and x_2 is *small* then Class2 with 1.0,
R_2: If x_1 is *small* and x_2 is *medium* then Class2 with 1.0,
R_3: If x_1 is *small* and x_2 is *large* then Class2 with 1.0,
R_4: If x_1 is *medium* and x_2 is *small* then Class3 with 1.0,
R_5: If x_1 is *medium* and x_2 is *medium*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

Three-class problem for two features

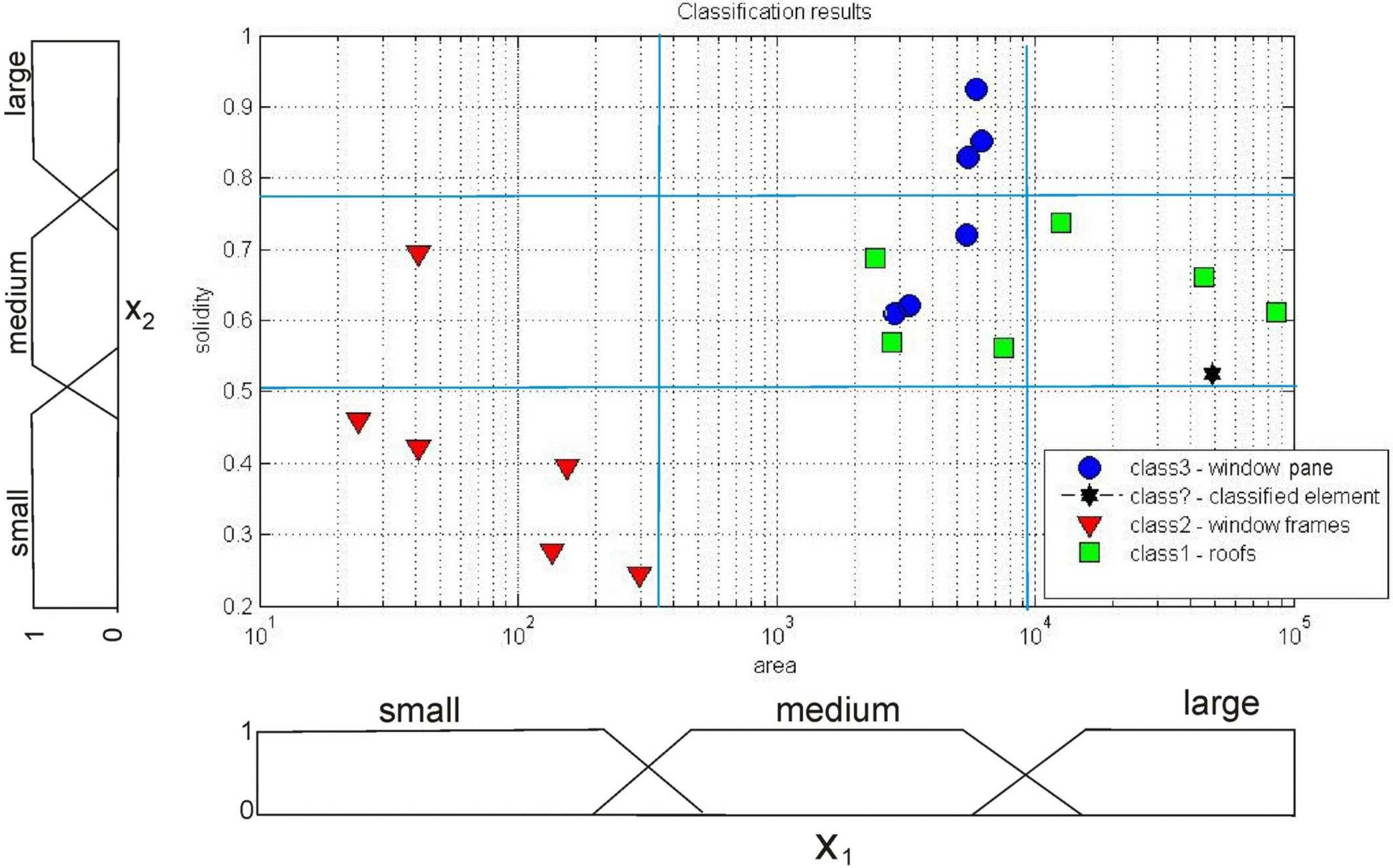


x_1 – area and x_2 – solidity

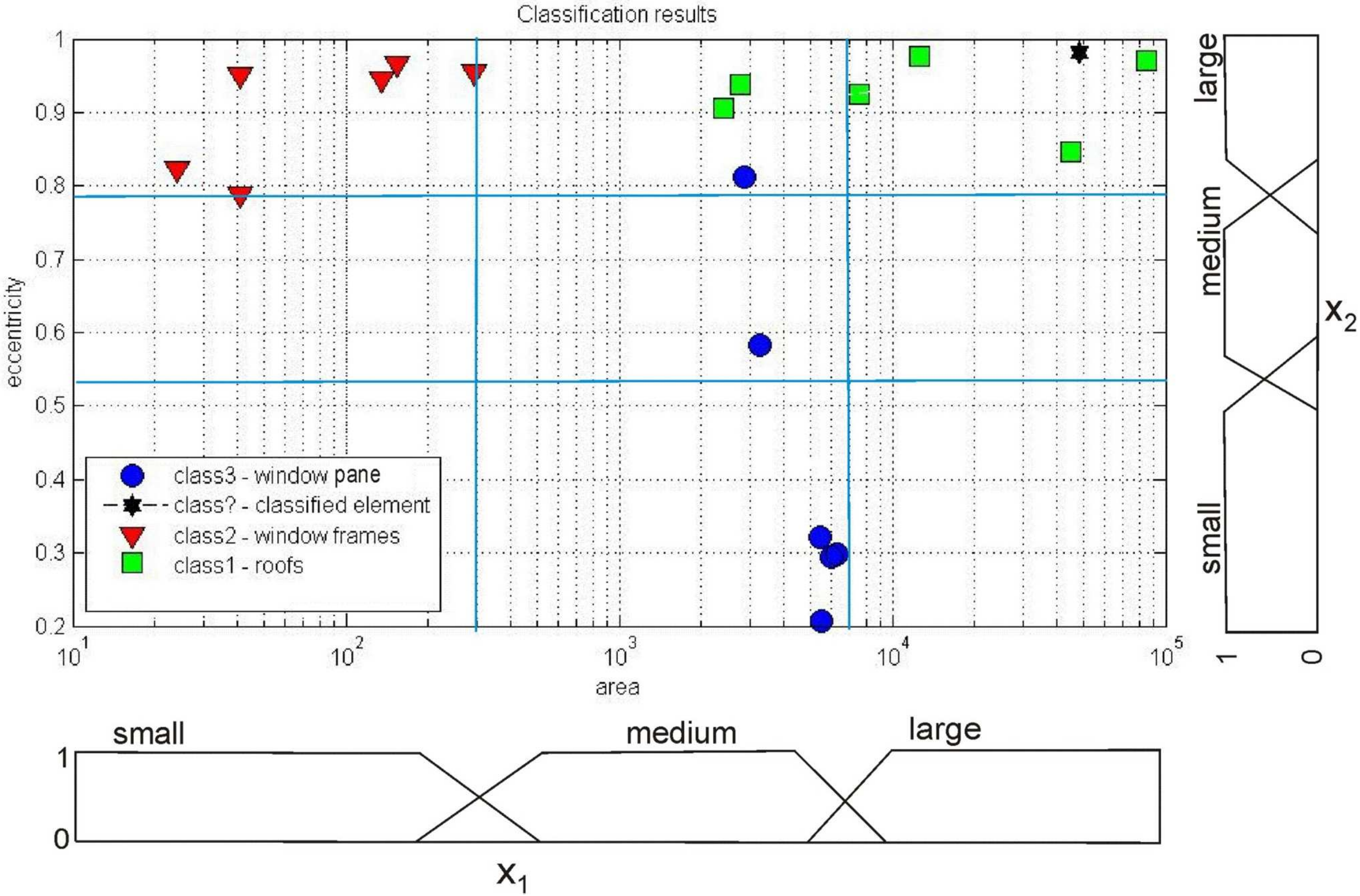
Three-class problem for two features



x_1 – area and x_2 – eccentricity



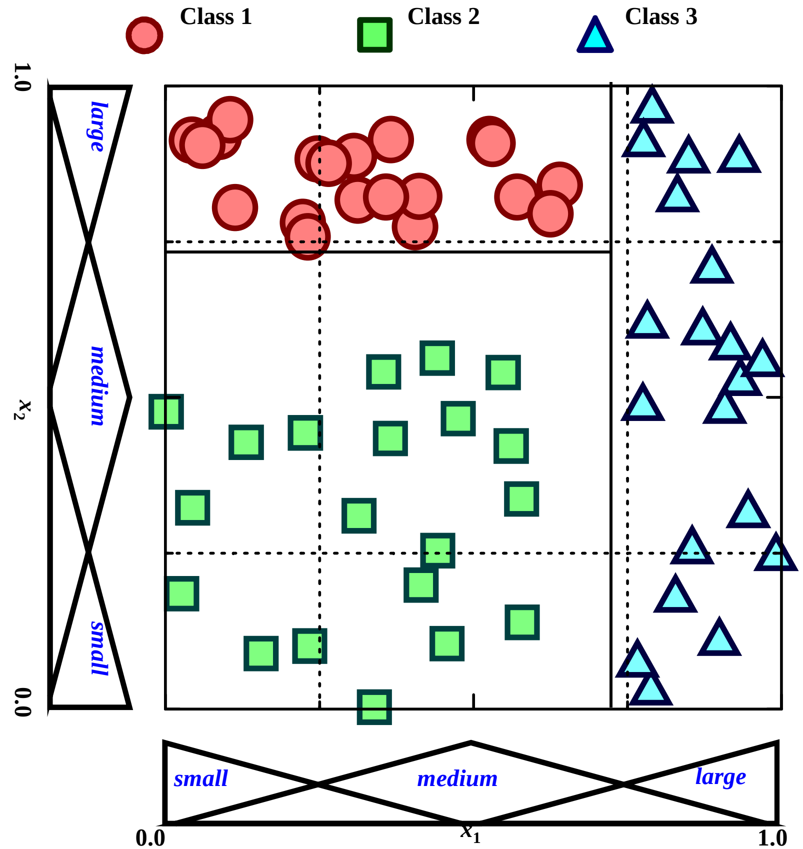
The black asterisk is a classified element for the fuzzy rule classifier with 9 rules.



The black asterisk is a classified element for the fuzzy rule classifier with 9 rules.

Fuzzy rule-based classifier with 3 fuzzy rules

If the negation of *large* (i.e., *not large*) is used in the antecedent part, the number of fuzzy rules in S_2 can be described as (Ishibuchi and Nojima (2011)):



S_2: fuzzy rule-based classifier with three fuzzy rules

R_{1245}: If x_1 is *not large* and x_2 is *not large* then Class2 with 1.0,
R_{36}: If x_1 is *not large* and x_2 is *large* then Class1 with 1.0,
R_{789}: If x_1 is *large* then Class3 with 1.0,

where the membership function of *not large* is defined as

$$\mu_{\text{not large}}(x) = 1 - \mu_{\text{large}}(x) \quad \text{for} \quad 0 \le x \le 1$$

Fuzzy rule-based classifier with 3 fuzzy rules

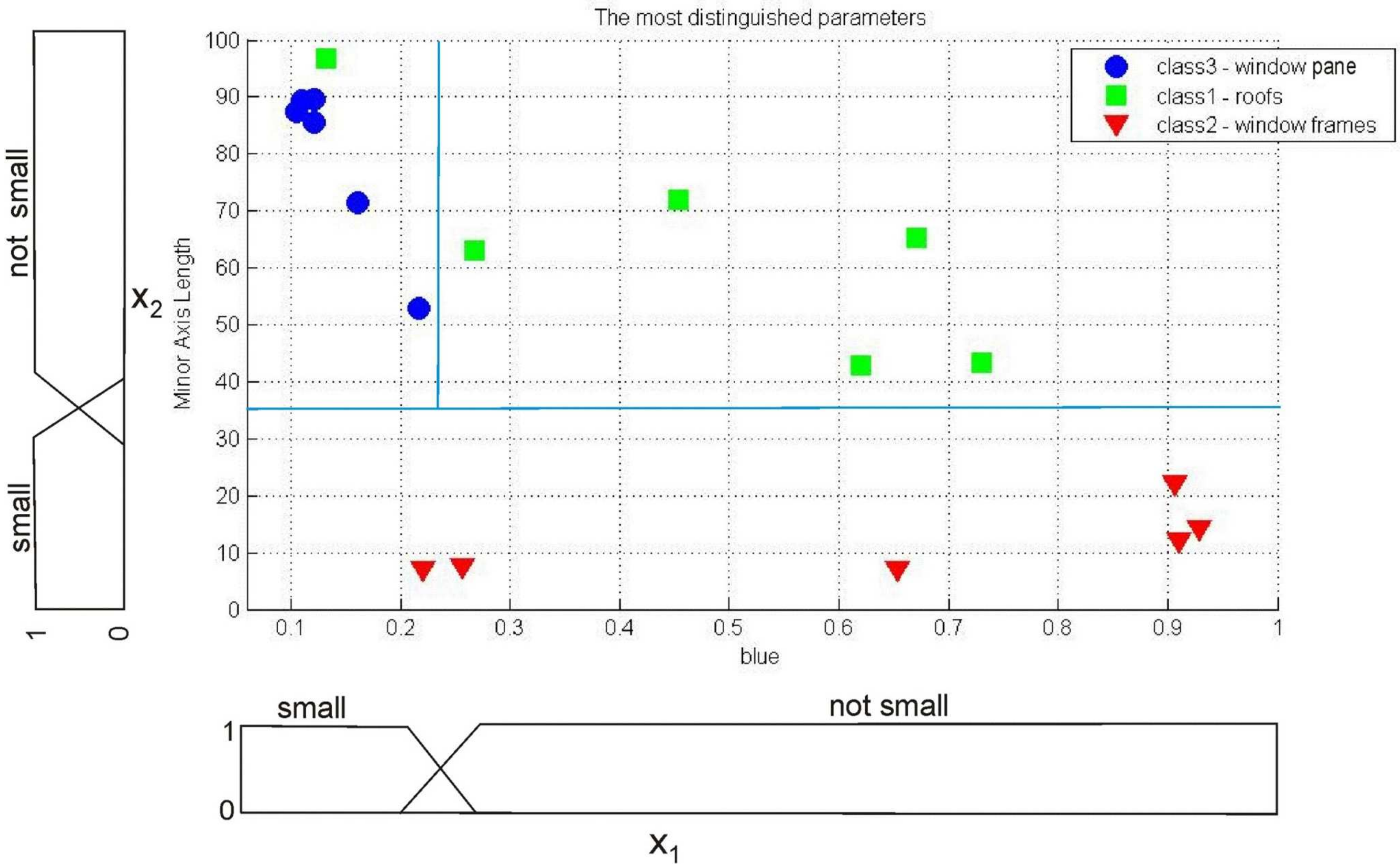
For our purpose, we use the negation of *small* (i.e., *not small*) in the antecedent part, where:

$\boldsymbol{S_{r2}}$**:**
R_{23}: If x_1 is *small* and x_2 is *not small* then Class3 with 1.0,
R_{5689}: If x_1 is *not small* and x_2 is *not small* then Class1 with 1.0,
R_{147}: If x_2 is *small* then Class2 with 1.0,

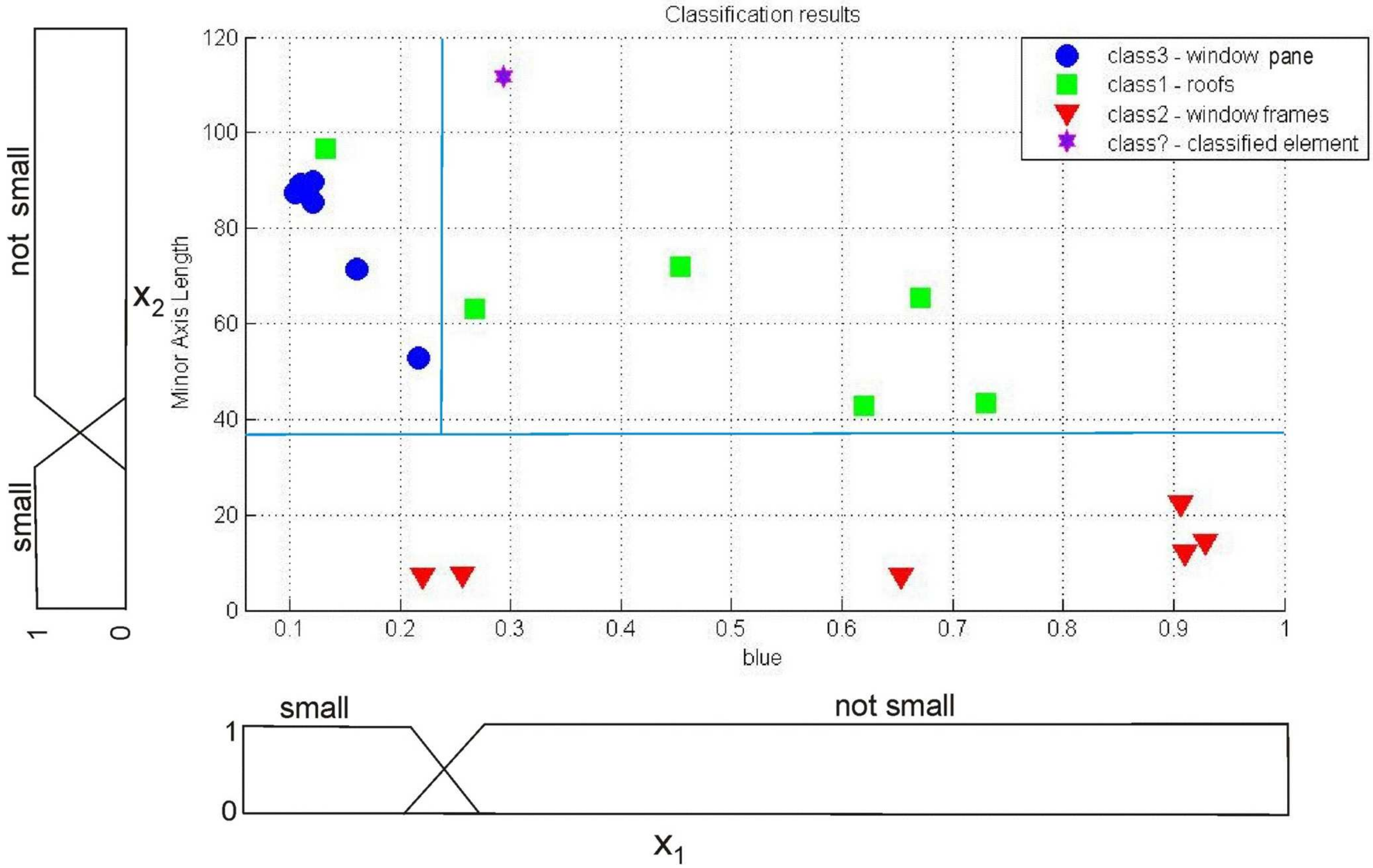
where the membership function of *not small* is defined as:

$$\mu_{\textit{not small}}(x) = 1 - \mu_{\textit{small}}(x) \quad \text{for} \quad 0 \le x \le 1$$

Three-class problem for two features



x_1 – blue and x_2 – minor axis length



The magenta asterisk is a classified element
for the fuzzy rule classifier with 3 rules.

Construction of search engine 1

Let a query be an image I_q, such as $I_q = \{o_{q1}, o_{q2},\ldots, o_{qn}\}$. An image in the database will be denoted as $I_b = \{o_{b1}, o_{b2},\ldots, o_{bm}\}$. In order to answer the query, represented by I_q, we compare it with each image I_b in the database in the following way.

To begin with, we determine the first similarity measure $\mathrm{sim}_{\mathrm{sgn}}$ between I_q and I_b

$$\mathrm{sim}_{\mathrm{sgn}}\,(I_q,I_b) = d_H\,(\mathrm{nobc}_q, \mathrm{nobc}_b)$$

computing the distance between two vectors of their signatures, analogically to the calculation of the frequency of occurrence for terms in text documents:

$$\mathrm{TF}\left(o_i^b, nobc_j^b\right) = \begin{cases} 0 & , n_{ij} = 0 \\ \dfrac{n_{ij}}{\sum_{k=0}^{m} n_{kj}} & , n_{ij} > 0 \end{cases}$$

Construction of search engine 2

If the above similarity is smaller than the threshold (a parameter of the query), then image I_b is rejected, i.e., not considered further in the process of answering query I_q.

Otherwise, we proceed to the next step and we find the spatial similarity $\mathrm{sim}_{\mathrm{PCV}}$ of images I_q and I_b computing the Euclidean distance between their PCVs as:

$$\mathrm{sim}_{\mathrm{PCV}}(I_q, I_b) = 1 - \sqrt{\sum_{i=1}^{3} (PCV_{bi} - PCV_{qi})^2}$$

Construction of search engine 3

If the similarity is smaller than the threshold, then image I_b is rejected, i.e., not considered further in the process of answering query I_q. Otherwise, we proceed to the final step, namely, we compare the similarity of the objects representing both images I_q and I_b. For each object o_{qi} present in the representation of the query I_q, we find the most similar object o_{bj} of the same class, i.e., $L_{qi} = L_{bj}$.

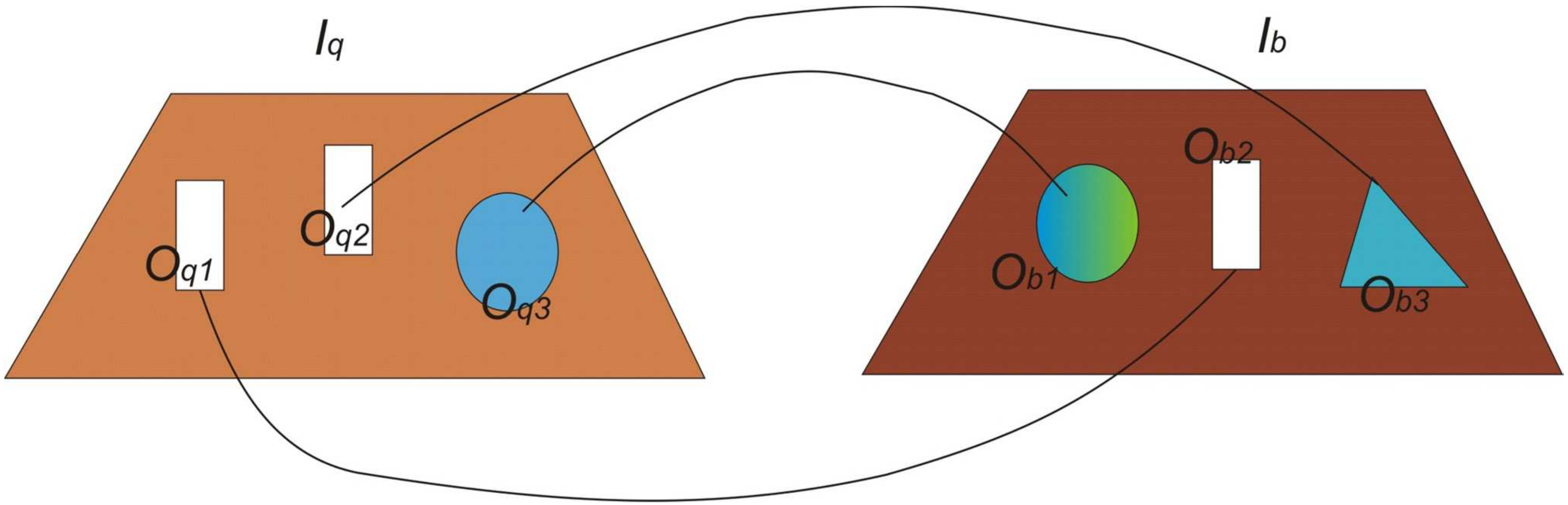
If there is no object o_{bj} of the class L_{qi}, then $\mathrm{sim}_{\mathrm{ob}}(o_{qi}, o_b)$ is equal to 0. Otherwise, similarity $\mathrm{sim}_{\mathrm{ob}}(o_{qi}, o_b)$ between objects of the same class is computed as follows:

$$\mathrm{sim}_{\mathrm{ob}}(o_{qi}, o_{bj}) = 1 - \sqrt{\sum_l (Fo_{qil} - Fo_{bjl})^2}$$

where l indexes the set of features F_O used to represent an object.

Pair matching with elimination

When we find highly similar objects, for instance, $sim_{ob} > 0.9$, we eliminate these two objects from the following process of comparison.



This process is realized according to the Hungarian algorithm for the assignment problem implemented by Munkres.

Construction of search engine 4

Thus, we obtain the vector of similarities between the query I_q and an image I_b.

$$\mathrm{sim}(I_q, I_b) = \begin{bmatrix} \mathrm{sim}_{\mathrm{ob}}(o_{q1}, o_{b1}) \\ \vdots \\ \mathrm{sim}_{\mathrm{ob}}(o_{qn}, o_{bn}) \end{bmatrix}$$

where n is the number of objects present in the representation of I_q.

In order to compare images I_b with the query I_q, we compute the sum of $\mathrm{sim}_{\mathrm{ob}}(o_{qi}, o_{bi})$ and then use the natural order of the numbers. Thus, the image I_b is listed as the first in the answer to the query I_q, for which the sum of similarities is the highest.

Use of classified objects in CBIR

1. Use particular patterns to define classes. We store these data in the DB to use them in CBIR algorithms;
2. Classified objects are used in the above-mentioned concept of a spatial object location in an image
3. Classified objects help the user ask a query in GUI. The user chooses for a query graphical objects semantically collected in groups;
4. Finally, the image objects coming from the same class are applied to the search engine as a stage in the image retrieval process.

Conclusions

- The ability of a fuzzy set and fuzzy rule-based classifiers to classify graphical objects in our CBIR system has been confirmed.
- An example of classification based on nine and three fuzzy rules according to the data character has been shown.
- In order to exemplify the proposed method the most distinguished coordinates from a feature vector have been chosen
- The preliminary results obtained so far using the simplest configuration are quite promising
- The classification method discussed here is to be used in our search engine

Proponowane zagadnienia

- Opracowanie reguł ułatwiających klasyfikację obiektów
  - Porównywanie wielowymiarowych wzorców
- Przetestowanie różnych miar podobieństwa
- Identyfikacja obiektów na podstawie klasy wzorców
- Opracowanie ontologii wspomagającej rozpoznawanie obrazu

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