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Incremental Classification of Images by Human Assisted Fuzzy Similarity Analysis

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Abstract—**This paper proposes a computational scheme for incremental classification of images, based on human assisted fuzzy similarity analysis. First of all, two main parameters from each image are extracted in the form of a *center-of-gravity* and a *generalized volume* of the image model. .Then their differences for each pair of images are taken as respective features *F1* and *F2,* which serve *as* inputs of the fuzzy inference system for similarity analysis. This system uses special *asymmetrical* Gaussian membership functions that are later tuned by using a predefined list of *human decisions* (similarities). The list includes fixed number of available pairs of images and the objective is to minimize the discrepancy between the human and the computer similarity decision.**

The proposed incremental classification scheme uses an initial list of *Core Images* to compare the new sequentially coming images with the core images. With a predetermined threshold, some images are judged as members of the *existing class* in the Core and other form new members that create a *new class* in the Image Base.

The flexibility and applicability of the proposed human assisted incremental classification is illustrated on an example for classification of *16* flower images and the results are discussed in the paper.

I. Introduction

Clustering and classification problems [1,2] that usually are dealing with a large number of objects use different kinds of similarity analysis of these objects in order to obtain the solution. A typical example is the similarity analysis, performed over a large amount of different images, which is important step in the computational procedure for classification of pictorial information. Similarity analysis and classification of pictorial information is a very specific area of activity, where in most case the human expert is superior to the available computerized systems. Among the different reasons for such situation are the complexity and the subjective nature (vagueness) of the problem itself, as well as the variety of the possible criteria that could be used for the similarity analysis. Despite such difficulties, finding a "good", reasonable solution to the problem of similarity evaluation is a key factor for a subsequent plausible classification that leads to many successful applications. Among them are such as automated visual search through a large amount of image information, its proper sorting and classification for the purpose of different kinds of decision making and (technical or medical) diagnosis.

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In this paper we present a computational scheme for incremental type of human assisted classification of images. Here a fuzzy inference procedure for similarity analysis is used, which can learn the human expert experience in order to properly adjust the decision process. The incremental nature of the proposed computation scheme leads to creating a growing type of *image base*, which in fact accumulates past knowledge about the similarity and decision making.

All the details as well as an example for classification of *16* flower images are given in the sequel of the paper.

II. Incremental Classification Scheme Based on Fuzzy Similarity Analysis

The block diagram of the proposed incremental classification scheme is presented in Fig. 3.1., which is a further development of our previous ideas for similarity analysis, discussed in [7,8].

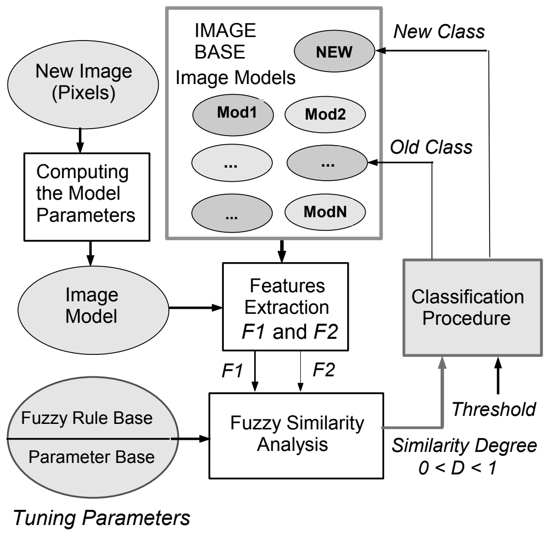

Fig. 2.1. Block Diagram of the proposed Incremental Classification scheme, based on Fuzzy Similarity Analysis.

The procedure starts with a small number of known *core images* which form the initial size of the *Image Base*. During classification, the similarity degree of each new (unknown) image is computed against all currently existing *core images* in the *Image Base*. As a result, depending on the preliminary given *threshold Th* for classification, the new image could join an *existing class* (core image) in the current Image Base or could be classified as "different image" thus forming a *new class* and thus *enlarging* the Image Base. In such way, the proposed classification is an incremental procedure, allowing the Image Base to gradually grow, when a new image with a low similarity to all currently existing core images is discovered.

From Fig. 2.1. it is seen that the raw data (pixels) from each image are used to derive a simple *Image Model* that contains two parameters (discussed in the next Section). Then for each pair of images to be compared, two respective features *F1* and *F2* are calculated and used as inputs of the block for fuzzy similarity analysis. Finally the similarity degree *D* is used for the incremental classification procedure. All computational details are given in Sections III and IV of the paper.

III. Image Models Parameters and Features Extraction for Similarity Analysis

Quite often the first step before the actual similarity analysis and classification of the images is to reduce the large amount of the "raw pixel" (RGB) information contained in the original images. This step is called *Information Compression* and has been discussed previously in the literature [4-8].

From a computational viewpoint the information compression could be considered as a *transformation* of the original large data set: $\mathbf{x}_i = [x_{i1}, x_{i2}, ..., x_{iK}], i = 1,2,...,M$, consisting of *M* pixel data in the *K=3* dimensional input space (RGB). This *information compression* procedure can be perform by using different unsupervised competitive learning algorithms, such as clustering algorithms [1,2], the Self-Organizing (*Kohonen*) Maps [3], the *Neural-Gas* Algorithm [4] and other competitive learning algorithms [5,6]. The common point here is that all these algorithms try to find the most appropriate positions the *N* neurons (clusters) in the *K*-dimensional parameter space so that to resemble as much as possible the density distribution of the original data in the space.

Such compression is worth for a very large number of data and have been used in our previous works as in [7,8]. However, for *small* to *medium* number of data (in the approximate range of about *200-300,000* pixels or less), the *direct computation* of all "raw data" could be a preferable option. Further on in this paper we use such the *direct* computation method for calculating the Image Model parameters.

We propose here the use of the following two Image Model parameters P1 and P2 that cane be calculated directly from the "raw pixel data" as follows:

1) *The Center-of-Gravity*: $\mathrm{P1} = \mathbf{CG} = [CG_1, CG_2, ..., CG_K]$ of the *K = 3* dimensional data is a vector, with its three components for R, G and B computed as follows:

$$CG_j = \sum_{i=1}^{M} x_{ij} \Big/ M, \; j = 1,2,...,K \tag{1}$$

2) The *Generalized Volume* P2 = *VOL* of the Image Model:

$$P2 = VOL = 2\sqrt{\sum_{j=1}^{K} R_j^2} \tag{2}$$

where

$$R_j = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(x_{ij} - CG_j)^2}, \; j = 1,2,...,K \tag{3}$$

It is seen from above equations that the volume P2 is a kind of measure of the *size* of the 3-dimensional oval (ellipsoid) of the *pixel cloud* for this image.

According to the block diagram in Fig. 2.1. the next step is the extract the features *F1* and *F2* from a given pair of images *(A,B)* that are further used as *Inputs* of the *fuzzy similarity* analysis. They are computed in a very simple way as follows:
1) The Feature *F1* is the Center-of-Gravity Distance *CGD* between Image *A* and Image *B*:

$$F1 \equiv CGD_{AB} = \sqrt{\sum_{j=1}^{K} [CG_j^A - CG_j^B]^2} \tag{4}$$

2) The Feature *F2* is called Volume Difference *VLD* between Image *A* and Image *B*:

$$F2 \equiv VLD_{AB} = |VOL_A - VOL_B| \tag{5}$$

IV. Basic Structure of the Fuzzy Rule Based Similarity Analysis

The next computation step, as seen from the block diagram in Fig. 2.1., is the *Fuzzy Similarity* Analysis. It is basically a standard *fuzzy inference* procedure, which consists of the following three main computation steps:

1) *Fuzzyfication*;
2) *Fuzzy Inference* (with *Product Operation*) and
3) *Defuzzification* (*Weighted Average*).

As for the membership functions, we use here a smooth type *Asymmetrical Gaussian* functions with *different* width parameters σ_L and σ_R for the left and the right part respectively. There are two main reasons for such choice. The first one is that the smooth Gaussian functions can better represent the nonlinearity in the fuzzy decision. The second one is that by selecting different width parameters we are able to keep a "good" enough and *constant* overlapping level between any pair of *neighboring* membership functions. Thus more plausible results could be obtained and additionally, a reduction of the number of tuning parameters in the next optimization task.

An illustrative example of the proposed asymmetrical type Gaussian membership functions is given in Fig. 4.1. with three different predetermined overlapping levels. It has been found empirically that the left and the right width for a given membership function with a center at *C* can be calculated as follows:

$$\sigma_L = R(C - CL); \quad \sigma_R = R(CR - C) \tag{6}$$

Here *R* is the user-defined *overlapping ratio* and *CL* and

CR are the *centers* of the *left* and *right* membership function, respectively.

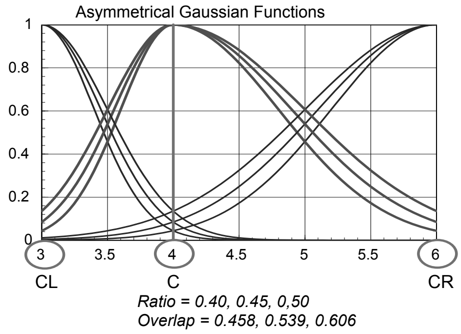

Fig. 4.1. The assumed Asymmetrical Gaussian Membership Functions .

Further on we use *5* membership functions for the features *F1* and *F2*, with the following linguistic labels:

VS = Very Small; *SM = Small*; *MD = Medium*; *BG = Big* and *VB = Very Big*;

Then the Fuzzy Rule Base (FRB) for the Fuzzy Inference procedure consists of *25* fuzzy rules, as shown in Fig. 4.2.

D Fuzzy Difference between two Images

F2 (Volume Difference) \ F1 (Center-of-Graviy Distance)	VS	SM	MD	BG	VB
VB	U5	U6	U7	U8	U9
BG	U4	U5	U6	U7	U8
MD	U3	U4	U5	U6	U7
SM	U2	U3	U4	U5	U6
VS	U1	U2	U3	U4	U5

Fig. 4.2. The Fuzzy Rule Base used for the Similarity Analysis.

Each fuzzy rule has its crisp numerical output (*Singleton*) that is selected among the available full set of *9* singletons $U_1,U_2,...,U_9$, with $U_1< U_2<...< U_9$ .These singletons represent the *Difference Degree* (or *Dissimilarity Degree*) $0.0 \le D \le 1.0$ for the features *F1* and *F2* computed for a given pair of Images (*A,B*).

The proposed *Fuzzy Rule Base* $D = \mathbf{F}(F1, F2)$ in Fig. 4.2. is constructed by using basic *human logic* and understanding about similarity between pairs of images. .

The numerical values of all 9 *singletons* have been fixed in this paper, as follows:

$$U_1=0.0;\quad U_2=0.125;\quad U_3=0.250;\\ U_4=0.375;\ U_5=0.500;\ U_6=0.625;\\ U_7=0.750;\ U_8=0.875;\ U_9=1.0 \tag{7}$$

As an example, the crisp output of the Fuzzy Rule *No. 14* (*i = 14*) from Fig. 4.2. will be :

$$\text{IF}(P1 \text{ is MD AND } P2 \text{ is BG})\text{THEN}\\ u_{14}=U6=0.625 \tag{8}$$

It is clear from Fig. 4.2. that all fuzzy rules have their individual *Singletons*: $u_i \in [U_1,U_2,...,U_9],\ i=1,2,...,L$.

The standard weighted-average method for *Defuzzification* is used for computing the *Dissimilarity* Degrees *D* between a given pair of images, as follows:

$$D = \sum_{i=1}^{L} u_i v_i \Big/ \sum_{i=1}^{L} v_i \tag{9}$$

Here $0 \le v_i \le 1,\ i=1,2,...,L$ is the *Firing* (*Activation*) *Degree* of the *i*-th fuzzy rule and *L = 25* is the total number of the fuzzy rules.

The above proposed incremental classification scheme, based on fuzzy similarity is illustrated here on an example of *16* images of different flowers, as shown in Fig. 5.1.

Fig. 5.1. An example of *16* Images of flowers, used for similarity analysis and Incremental Classification.

As seen from this figure, some images look very *similar*, while others are quite *different*, if taking into account the variety of colors and the overall (vague) human evaluation.

First, the BMP files with the original images have been preprocessed in order to obtain the respective *3*-dimensional “raw data”, which contain the *pixel values* (the *3*-dimensional matrices: *R-G-B*) for each image, within the range of *0-255*.

Each image has a resolution of *256 x 196*, which makes $M = 49{,}152$ pixels for further direct processing. The pixels form a kind of *cloud* in the RGB space, as depicted for a visual comparison of two images in Fig. 5.2.

The center-of-gravities *COG* of all *16* Images from Fig. 5.1 are computed by (1) and shown in the 3-dimensional RGB space in Fig. 5.3. As seen from this figure, some of them are quite close (obviously corresponding to similar images) while others are far from each other (possibly for different images).

The next Fig. 5.4. shows the image model volumes *VOL* for all 16 images from Fig. 5.1. As seen there is a big difference between some images, which provides valuable information for the next classification procedure.

The above two figures Fig. 5.3. and Fig. 5.4. show the complexity of the problem for similarity analysis, which is obviously difficult to be solved if using only each of the features *F1* or *F2* separately.

Fig. 5.5. is a two-dimensional plot of the features *F1* and *F2* for all *120* pairs of images. It is helpful for approximate estimation of the *ranges* [*min,max*] of the features *F1* and *F2*. These ranges are utilized to fix the *borders* for *the initial positions* of the asymmetrical membership functions, as shown in Fig. 5.5. The computed 3-D response surface of the initial fuzzy inference system is shown in Fig. 5.6.

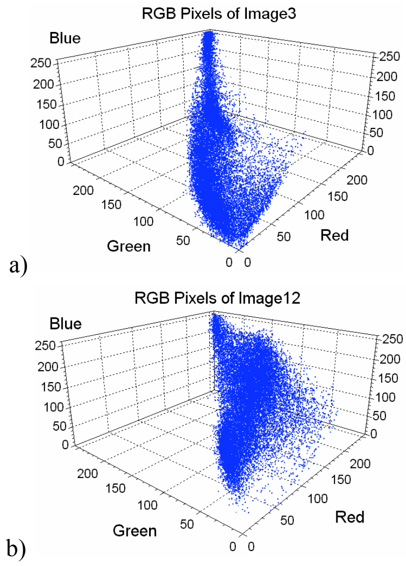

Fig. 5.2. 3-Dimenainal plot of the Raw Data (RGB Pixels) of *Image3* and *Image12* from Fig. 5.1.They form different “clouds of data” in the space.

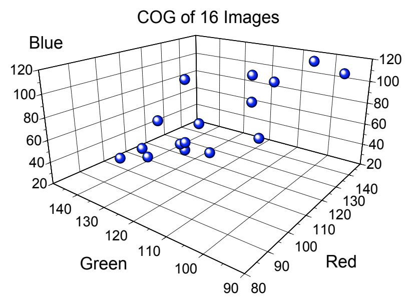

Fig. 5.3. Center-of-Gravities COG, computed by (1) for all 16 Images.

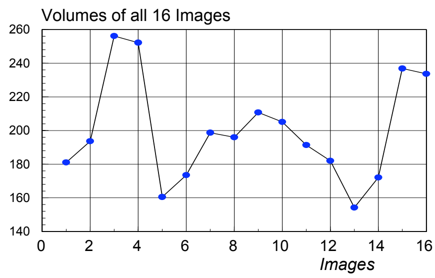

Fig. 5.4. The Generalized Volumes *VOL* of all *16* Images from Fig. 5.1.

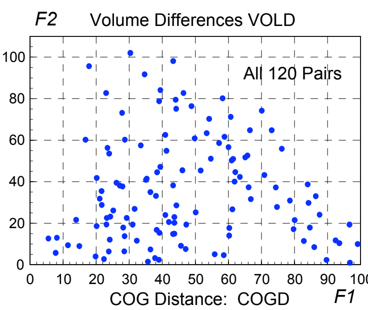

Fig. 5.5. Locations of the Features (*F1,F2)* for all 120 pairs of Images.

a)

b)

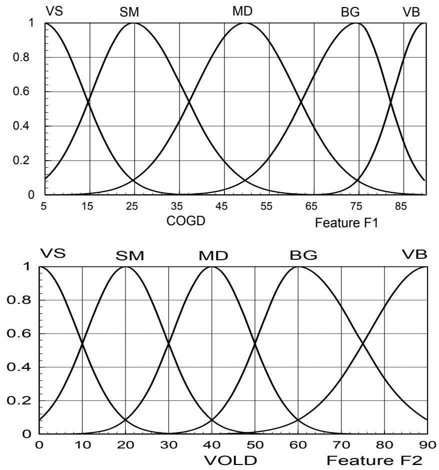

Fig. 5.6. Initial positions of the membership functions for *F1* and *F2*.

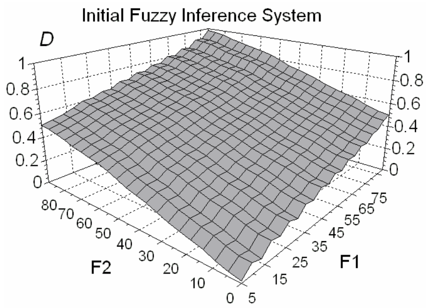

Fig. 5.7. The response surface of the initial fuzzy decision system.

V. THE HUMAN ASSISTED FUZZY SIMILARITY ANALYSIS

It is obvious that plausible "human-like" results from the Fuzzy similarity analysis could be obtained only by proper tuning of the membership functions in Fig. 5.6., as well as the singleton parameters in (7). Therefore, in order to make the computer-based similarity analysis closer to the human decision, we have chosen a set of *14* pairs of images, for which an appropriate *human decision* is available, s shown in Fig. 6.1. All the human decisions are arranged in *four* groups (*4* rough levels): ***0.1***; ***0.3***; ***0.5*** and ***0.7***, as will be shown later in Fig. 6.4.

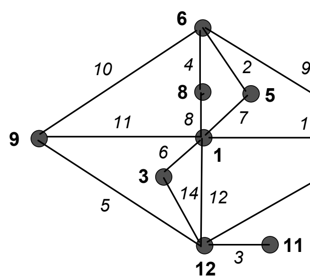

Fig. 6.1. Graph structure of all images. The selected pairs for human decision are shown as arcs between the respective nodes (images).

It is clear that the human decisions are *subjective* ones, as is also the choice of the *number* of selected pairs. Therefore all these parameters affect the results from the computer system for similarity analysis.

By using the above assumed *14* human decisions, an appropriate tuning of the Fuzzy Inference System has to be performed in order to minimize the *Discrepancy* (the error) between the *human based* and the *computer based* decision for similarity. This discrepancy is calculated here in a simple way, as the *mean* of the absolute differences between all *14* decisions.

In principal, any multi-variable optimization procedure could be applied for tuning the fuzzy inference system. In this paper we have used a modified version of the popular Particle Swarm Optimization (PSO) algorithm with *Inertia Weight* [9]. This algorithm optimizes the *intermediate* locations of the membership functions, i.e. the variables *SM*, *MD* and *BG* for the features *F1* and *F2*. This is in fact a *6*-dimensional optimization with special implemented constrains: *SM* < *MD* < *BG*. Because of space limitations, further details are omitted in this paper.

The optimized membership functions are shown in Fig. 6.2. and the resulted 3-D *nonlinear* response function is shown in Fig. 6.3.

a)

b)

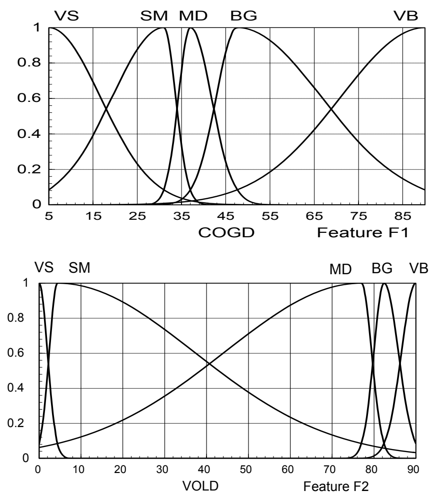

Fig. 6.2. The optimized Membership Functions for *F1* and *F2*.

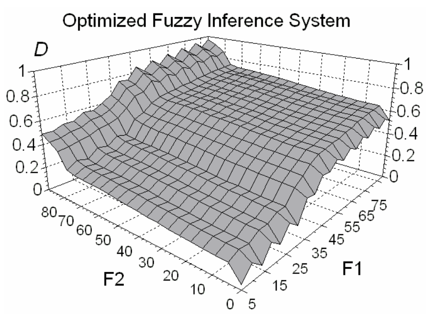

Fig. 6.3. The optimized Nonlinear Response Surface of the Fuzzy Decision.

The results of the similarity analysis and the Discrepancy before and after the optimization are shown in Fig. 6.4.

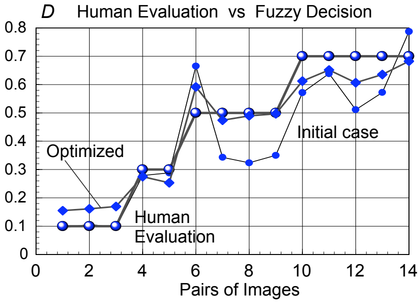

Fig. 6.4. Results from optimization of the computer-based similarity analysis by using a predetermined set of *14* human decisions from Fig. 6.1.

The mean *Discrepancy* level has decreased from *0.0921*in the initial (non-tuned) case to *0.0499* after optimization. The improvement can be visually noticed in Fig. 6.4.

VI. Results from the Incremental Classification

As seen from Fig. 2.1 in Section II, before performing the incremental classification, we assume that an *initial* Image Base with a small number of *Core Images* exists, in order to make the further comparisons with the new coming images.

It is natural to expect that the initial choice of the number and the list of the core images would affect the results from the online classification of the newly submitted images. The predefined *threshold Th* from Fig. 2.1. also affects the results from the classification.

At each step of the classification procedure, one new image *q* (different from the list of core images) is submitted for evaluation. Then the *so called minimal dissimilarity* $D^p_{\min}$ is calculated by (9) between the new image *q* and a certain core image *p* from the Image Base. If $D^p_{\min} \le Th$, a decision is made that the new image *q belongs* to the class *p* in the Image Base. Otherwise, image *q* creates a *new class* thus enlarging the Image Base by one new member.

Results from the proposed online incremental classification procedure is shown in Table 1 by using four different sets of *core images*, as seen in the table.

Table 1. 4 Examples of Online Incremental Image Classification

Step	Core: 1, 9	Core: 5, 9	Core: 1, 3	Core 1, 3, 9
1	2 **1**	1 **1**	2 **1**	2 **1**
2	3 **3**	2 **1**	4 **3**	4 **3**
3	4 **3**	3 **3**	5 **5**	5 **5**
4	5 **5**	4 **3**	6 **5**	6 **5**
5	6 **5**	6 **5**	7 **7**	7 **9**
6	7 **9**	7 **9**	8 **7**	8 **5**
7	8 **5**	8 **5**	9 **7**	10 **9**
8	10 **9**	10 **9**	10 **7**	11 **9**
9	11 **9**	11 **9**	11 **11**	12 **9**
10	12 **9**	12 **9**	12 **11**	13 **5**
11	13 **5**	13 **5**	13 **5**	14 **1**
12	14 **1**	14 **1**	14 **1**	15 **9**
13	15 **9**	15 **9**	15 **7**	16 **3**
14	16 **3**	16 **3**	16 **3**	-

A threshold *Th = 0.3* is assumed for all classifications. For each assumed set of *core images*, all the remaining images (from the whole group of *16* images in Fig. 5.1.) are considered as *new* images and submitted sequentially *one-by-one*, as seen from Table 1. The *bold numbers* in each column of the table show the class, to which the new image (the left number) belongs. During classification, the following *new classes* have been added in all *4* examples:

- for *Core* {**1, 9**} – new classes are: **3** and **5;**
- for *Core* {**5, 9**} – new classes are: **1** and **3;**
- for *Core* {**1, 3**} – new classes are: **6, 7** and **11;**
- for *Core* {**1, 3,9**} – new classes is **5;**

VII. Discussions and Conclusions

An incremental semi-unsupervised classification scheme for images is proposed in this paper. It uses a human expert experience for initial tuning of the fuzzy similarity system, before the actual incremental classification. The scheme is applicable for gradual incremental knowledge acquisition from large (unconstrained) number of images.

An important feature of the system is that its performance resembles closely the decision making of a particular human expert, used for its tuning. Therefore the tuned system could be regarded as a *decision making agent* for similarity analysis and classification. Then, a multi-agent system for a "*team decision making*" could be a possible option for further development of the proposed idea. .

There are some problems to be solved in future for improvement of this classification system. One is, for example, to find a good way for selecting of the most appropriate *initial core images* in the Image Base. Other problem is to find an appropriate algorithm for *pruning* and *periodically refreshing* (re-tuning) of the Image Base, based on the additional available information.

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