Human-Guided Fuzzy Decision for Image Similarity Analysis and Classification Based on Information Compression

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This paper introduces an original unsupervised learning algorithm for information compression that is further used in the proposed fuzzy inference procedure for discovering similarities between different images for the purpose of their classification. Two features extracted from each compressed information model are used in the paper to represent the location of the compressed model in the three-dimensional red-green-blue (RGB) space and its size (volume). A method for tuning the fuzzy inference procedure is proposed in the paper that uses a predefined human preference in the form of a given list of similar images with their approximate similarity levels. Thus the whole computation scheme is a kind of human-guided similarity analysis. The choice of the optimization algorithm and the selection of the optimization criterion are among the important problems, discussed in the paper. The final goal is to achieve a plausible "human-like" decision for similarity, when processing large number of images and other pictorial information. The whole proposed computation scheme for similarity analysis and classification is illustrated on a test example of flower images followed by detailed discussions.

1. INTRODUCTION

Recently a strong attention has been paid to the problem of similarity analysis. This is a problem with a large potential for many practical applications when complex data sets or large number of pictorial information has to be distinguished, grouped and sorted appropriately, based on some kind of similarity measure.

In this paper we are dealing with the problem of rough, approximate similarity analysis of image information[1] in the typical human-like aspect of this meaning. It means that we are not interested in finding specific objects within the image or in finding the shape and contours of such objects. What is the main point of interest here is to evaluate the *similarity* between a given pair of images using a numerical value within the range [0, 1]. It is convenient to measure the similarity

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by the inverse parameter called *difference degree* (or *dissimilarity degree*). Then a difference degree of 0 has the meaning of "equal images" whereas difference degree of 1 refers to "completely different" images.

Such kind of similarity analysis is important in many fields of decision making for analyzing large number of *unstructured images*, such as landscapes, flowers, or specific images obtained from machine, or medical examination procedures for the purpose of diagnosing faults and diseases.

Evaluation of the similarity between different images is a typical *fuzzy task* that involves some difficult to measure (vague) factors, such as overall *impression* or sometimes personal *feeling* of the human expert. It is therefore obvious that the results from the similarity analysis and classification, defined in this way, would differ from one to another human decision maker.

It is natural to employ a fuzzy inference system for performing the similarity analysis, which constitutes the main part of the classification process. Because of the vagueness of the generic problem of similarity, it is also obvious that the fuzzy classifier cannot be constructed by totally unsupervised learning, but rather by a kind of *partial supervised learning,* which takes in to accounts certain (preliminary known) *human decisions* and opinions. Furthermore, we refer to such approach as *human-guided* similarity analysis.

The rest of the paper is organized as follows. Section 2 briefly describes the proposed computation scheme for similarity analysis and classification of images. Section 3 presents an algorithm for information compression that is used for extraction of two proposed features in Section 5, whereas Section 4 presents example of 20 test images for the further analysis. Sections 6 and 7 describe in details the fuzzy inference procedure used for similarity analysis and the proposed method of its optimization with some simulation results. Discussions and conclusions are drawn in Section 8.

2. THE PROPOSED SCHEME FOR SIMILARITY ANALYSIS AND CLASSIFICATION

In the classical formulation of the classification and pattern recognition, the problem is viewed as off-line classification of preliminary given set of data (patterns) with fixed size. Then the task is to classify every single data (pattern) from the given set as belonging to one or another class. In the case of similarity analysis and classification of images, we have some differences, namely that each image is represented by a large number of pixels in the three-dimensional RGB space. Then we have to classify and analyze on similarity the *whole data set* rather than some individual data points (pixels). This makes the approach to this problem somewhat different.

In this paper we propose a *two-stage* computational procedure that starts with information compression algorithm, which reduces the original large data set in to a smaller number of neurons. Furthermore, we use this small subset of neurons, called compressed information model (CIM), for evaluating the characteristics of each image. Two main features are extracted from each CIM, namely the center-of-gravity of the image and its *WAS*. In the second stage of the computation scheme, a fuzzy inference procedure is performed that uses the extracted features as two inputs. The fuzzy decision about similarity between a given pair of images is produced in numerical way, as the difference degree between these images, defined in the range [0,1].

To produce plausible results from the similarity analysis, we also propose in this paper a special *human-guided* optimization scheme, in which the optimization criterion is constructed by using existing human preferences (or experience) on similarity. Finally, the optimization process minimizes the discrepancy between the human and computer fuzzy decision for similarity. All the details about the entire computational scheme including the illustrations are given in the sequel of the paper.

3. UNSUPERVISED LEARNING ALGORITHM FOR INFORMATION COMPRESSION

The first step before the actual similarity analysis and classification of the images is to find a way to decrease the large amount of the "raw pixel information" contained in the original images. Furthermore, we call this computation step an *information compression*. From a computational viewpoint, the information compression could be considered as a *transformation* of the original large data set: $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{iK}], i = 1, 2, \ldots, M$, consisting of M data in the K-dimensional input space in to a respective neural model consisting of N neurons in the same space. Here $N \ll M$. and $CR = M/N$ is the so-called compression ratio.

The *information compression* of the original large data set (pixels or process data) can be perform by using different unsupervised competitive learning algorithms, such as clustering algorithms,[2,3,4] the self-organizing (*Kohonen*) maps,[2,5] the neural-gas,[5–7] and other versions of competitive algorithms[8–11] etc. The common point here is that all these algorithms try to find the most appropriate positions of the preliminary fixed number of N neurons (clusters) in the K-dimensional data space so that to resemble as much as possible the density distribution of the original data in the same space.

The essential part of any unsupervised learning algorithm is the so-called *updating rule* for the neuron centers $\mathbf{c}_i, i = 1, 2, \ldots, N$ in the K-dimensional space. The algorithm is performed for a preliminary fixed number of T iterations ($t = 0, 1, 2, \ldots, T$) as follows:

$$\mathbf{c}_i(t) = \mathbf{c}_i(t-1) + \Delta\mathbf{c}_i(t), i = 1, 2, \ldots, N. \tag{1}$$

Here the computation of the update $\Delta\mathbf{c}_i(t)$ varies depending on the type of the unsupervised algorithm.

The neural-gas learning algorithm[5,7] used in this paper, is a *special* version of the basic competitive unsupervised learning, where the amount of the update is computed as:

$$\Delta\mathbf{c}_i(t) = R(t)H_s(t, r_i)[\mathbf{x}_s - \mathbf{c}_i(t-1)], i = 1, 2, \ldots, N; s = 1, 2, \ldots, M \tag{2}$$

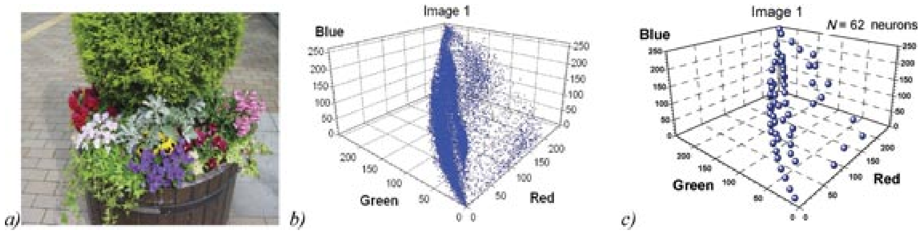

Figure 1. Example of (a) image, (b) raw data (RGB pixels), and (c) compressed information model (CIM).

Here $R(t)$, $0 \leq R(t) \leq 1$, $t = 0, 1, 2, \ldots, T$ is a monotonically decreasing *learning rate,* which guarantees the convergence and stability of the learning process:

$$R(t) = R_0 \exp(-t/T_C), t = 0, 1, \ldots, T \tag{3}$$

The so-called *neighborhood function* in (2) $0 \leq H_s(t, r_i) \leq 1$ also decreases exponentially with the iterations. It computes the dynamically changing (decreasing) *activity area* for each neuron during the iterations, as follows:

$$H_s(t, r_i) = \exp[-(r_i - 1)/B(t)], t = 0, 1, \ldots, T;$$

$$s = 1, 2, \ldots, M; i = 1, 2, \ldots, N \tag{4}$$

where

$$B(t) = \exp(-t/T_W), t = 0, 1, \ldots, T \tag{5}$$

Here $r_i \in [1, 2, \ldots, N]$ is an integer number for the so called *ranking position* of the i-th neuron ($i = 1, 2, \ldots, N$) to the s-th data point ($s = 1, 2, \ldots M$). This ranking position is defined according to the distance between the i-th neuron and the s-th data point. The closest neuron (in a sense of a minimal *Euclidean* distance) is called "winning neuron" and gets ranking $r = 1$. The second closest neuron gets $r = 2$ and so on.

The *initial learning rate* R_0 and the *steepness* parameters T_C and T_W have to be set prior to the learning. In the further simulation, we use the following settings for information compression: $T = 500$; $R_0 = 0.16$ and $T_C = T_W = T/5$. Figure 1 illustrates the information compression of the original three-dimensional RGB pixel data of one test image by preliminary fixed number of $N = 62$ neurons.

4. TEST EXAMPLE FOR SIMILARITY ANALYSIS OF IMAGES

For a better understanding of the whole idea of the proposed computation scheme for similarity analysis and classification, we display in Figure 2 a test example of 20 different flower images.

It is easy to discover in a human-like way several groups of close similarities between all these 20 images in Figure 2, such as: *Image* 1 and *Image* 2; *Image* 3

Figure 2. Images of 20 flowers used for similarity analysis.

and *Image* 4; *Image* 5 and *Image* 6; *Image* 7 and *Image* 8; *Image* 17 and *Image* 18; and *Image* 19 and *Image* 20. At the same time, it is also easy to notice some pairs of *quite different* images, such as *Image* 7 and *Image* 9; *Image* 11 and *Image* 17; *Image* 15 and *Image* 19 and possibly others. As mentioned in the previous section, the human-like similarity analysis is realized in a vague way, by roughly estimating the variety of the colors and their distribution within each image, followed by a comparison between every two given images.

For the further simulations and similarity analysis of the above 20 images, they have been first compressed by the algorithm from Section 3 into respective CIMs with $N = 30$ neurons.

5. FEATURE SELECTION FOR FUZZY SIMILARITY ANALYSIS

As seen from Figure 1 in Section 2, to evaluate the similarity between a given pair of operation modes, based on their compressed models (CIMs), we have to evaluate two important *features* $F1$ and $F2$ that characterize in an easy-to-understand numerical way the relation (similarity) between each pair of modes. For this purpose, we propose here to extract the following two distinct *parameters* $P1$ and $P2$ that characterize the *location* and the *size* of each operation mode in the K-dimensional input space. They are further called: $P1$—*center-of-gravity* (**CG**) and $P2$—*weighted average size WAS* of the given operation mode.

(1) The *Center-of-Gravity* $\mathbf{CG} = [CG_1, CG_2, \ldots, CG_K]$ of a K-dimensional operation mode is a *vector* that is computed directly from the respective CIM as follows:

$$CG_j = \sum_{i=1}^{N} c_{ij} g_i \bigg/ \sum_{i=1}^{N} g_i, \; j = 1, 2, \ldots, K \tag{6}$$

Here $c_{ij}, j = 1, 2, \ldots, K$ denotes the *center* (coordinates) of the i-th neuron in the K-dimensional input space and $0 < g_i \leq 1, i = 1, 2, \ldots, N$ are the *normalized weights* of the neurons:

$$g_i = m_i/M; i = 1, 2, \ldots, N \tag{7}$$

$m_i \leq M, i = 1, 2, \ldots, N$ is the number of all data points: $\mathbf{x}_s, s = 1, 2, \ldots, m_i$, for which the i-th neuron is a *winning neuron* (i.e., the neuron with the shortest *Euclidean* distance to all of these data points). Obviously, the following equation holds: $\sum_{i=1}^{N} m_i = M$ and therefore$\sum_{i=1}^{N} g_i = 1$.

(2) The *WAS* of the operation mode (and its respective CIM) is a *scalar* value, which takes in to account the normalized weights of all neurons and the Euclidean distance ED_{pq}between all pairs of neurons, $\{p, q\}, p = 1, 2, \ldots, N;$

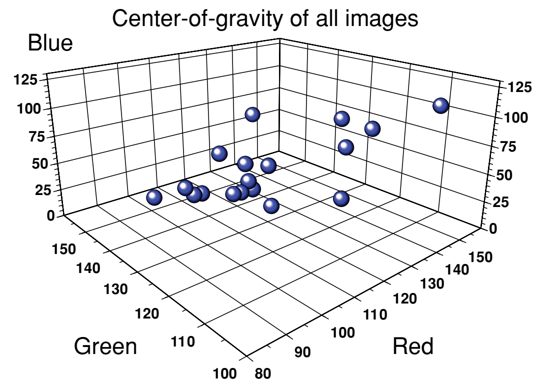

Figure 3. Center-of-Gravities **CG** for all 20 images from Figure 2.

$q = 1, 2, \ldots, N$, as shown in the next two Equations 8 and 9:

$$WAS = \sum_{p=1}^{N-1} \sum_{q=p+1}^{N} ED_{pq} w_{pq} \Bigg/ \sum_{p=1}^{N-1} \sum_{q=p+1}^{N} w_{pq}. \tag{8}$$

where

$$w_{pq} = g_p \times g_q, \; p = 1, 2, \ldots, N; q = 1, 2, \ldots, N \tag{9}$$

Figure 3 shows the locations of the centers-of-gravity **CG,** computed by (6) and (7) for all 20 images. It is seen from this figures that **CG** of many images are quite close to each other in the three-dimensional RGB input space, which could result later in a wrong classification.

Similarly, Figure 4 shows the weighted averages sizes *WAS* of all 20 images, computed by (8) and (9). It also can be noticed here that some sizes are quite similar, which could also lead to wrong classification.

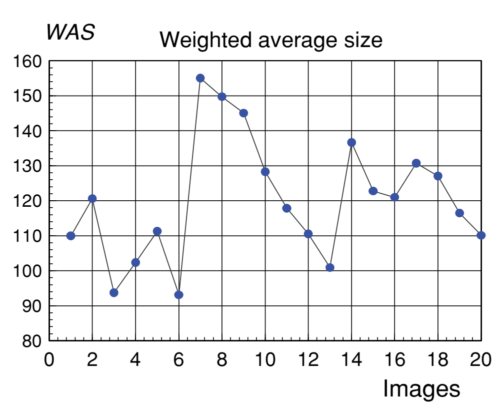

Figure 4. Weighted average size for all 20 images from Figure 2.

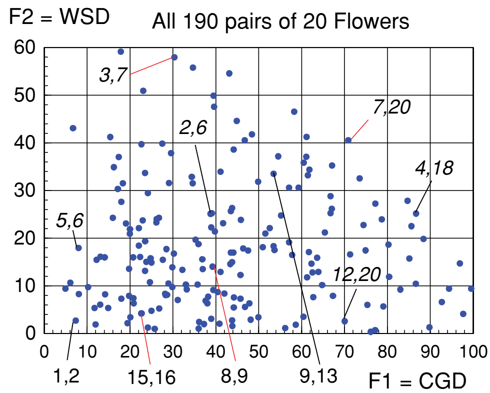

Figure 5. The features $F1$ and $F2$ for all pairs of images from Figure 2.

The above two parameters $P1 = \mathbf{CG}$ and $P2 = WAS$ carry important information that can be used for selection of the two *features* $F1$ and $F2$ used as inputs of the Fuzzy Inference procedure for similarity analysis from Figure 1.

We propose here an easy way to extract the features $F1$ and $F2$ as follows:

– The feature $F1$ is a *scalar* value, computed as the *distance CGD* between the centers-of-gravities **CG** of a given pair $\{A, B\}$ of operation modes:

$$F1 = CGD_{AB} = \sqrt{\sum_{j=1}^{K} \left[CG_j^A - CG_j^B\right]^2} \tag{10}$$

– Similarly the feature $F2$ is a *scalar* value computed as the *difference WSD* between the *WASs* of the same pair $\{A, B\}$ of operation modes, namely:

$$F2 = WSD_{AB} = |WAS_A - WAS_B| \tag{11}$$

The above two features can be computed for all pairs of images from Figure 2, which makes $20 \times 19/2 = 190$ combinations. The plot of these combinations in the two-dimensional space $F1 - F2$ is given in Figure 5.

The labels of some pairs (such as: 1, 2 and 9, 13) are shown in these figures for a better understanding of the physical meaning of these two features and their relation to the similarity. For example, the similar images, such as 1, 2; 5, 6; 8, 9; and 15, 16 have relatively small values for $F1$ and $F2$, compared with the different images, such as 9, 13, which have large values for $F1$ and $F2$ or at least one of them is large). This general tendency is further used for creating the logic of the Fuzzy Rule Base that is used in the Fuzzy Inference procedure, described in the next section.

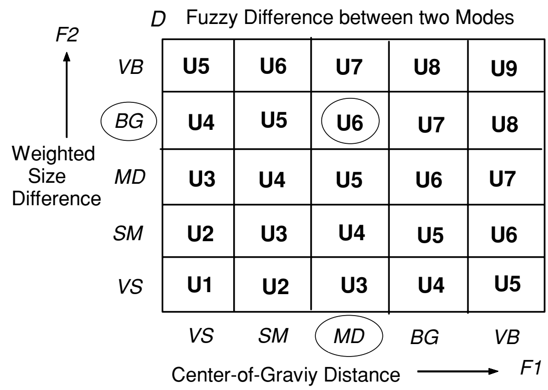

Figure 6. The Fuzzy Rule Base used for fuzzy similarity analysis.

6. FUZZY RULE BASED PROCEDURE FOR SIMILARITY ANALYSIS

Once the features $F1$ and $F2$ are computed for a given pair $\{$A,B$\}$ if images are used as inputs in the fuzzy rule based decision procedure for similarity analysis. Thus the Fuzzy Rule Based Procedure becomes a two-input/one output fuzzy system, as follows: $D = \mathbf{F}(F1, F2)$. Here $0.0 \leq D \leq 1.0$ is the *difference degree* (or *dissimilarity degree*). A difference degree $D = 0$ means*s*that the operation modes A and B are *identical* (equal) and difference degree D =1 means that A and B are *completely different modes*.

As well known[2] the fuzzy decision procedure consists of the following three main computation steps, as follows:

1. *Fuzzyfication* (with triangular Membership Functions);
2. *Fuzzy Inference* (with Product Operation) and
3. *Defiuzzification* (Weighted Mean Average).

For the next simulations in the paper, we assume *five triangular membership functions* that characterize linguistically the two inputs (features), namely $F1$ and $F2$. They are used in the *fuzzification step* and have the following linguistic meaning: VS = very small; SM = small; MD = medium; BG = Big and VB = very big.

The Fuzzy Rule Base for the Fuzzy Inference procedure is shown in Figure 6. It consists of 25 fuzzy rules R_i, $i = 1, 2, \ldots, 25$ with respective *singleton* outputs: $u_i \in [U_1, U_2, \ldots, U_9]$, $i = 1, 2, \ldots, 25$. The structure of the fuzzy rule base has been generated by using a general *human logic, understanding*, and *experience* from comparison and evaluation of images. In this respect, the detailed analysis of the plot in Figure 5 is helpful in generating the fuzzy rules.

As seen from Figure 6, the singleton values of the fuzzy rules are predetermined into 9 levels $U_1, U_2, \ldots, U_9$ to follow a meaningful (human-like) logic of the fuzzy rule base, which would lead to plausible results from the fuzzy similarity analysis. For the same reason, the *generic* singleton values $U_1, U_2, \ldots, U_9$ should be arranged in a monotonously *increasing* order, as follows:

$$0 \leq U1 < U2 < \cdots < U9 \leq 1 \tag{12}$$

From a viewpoint of fuzzy theory, the above fuzzy rule base in Figure 6 corresponds to a modified *zero-order* Takagi–Sugeno fuzzy model with some constraints for the singletons values, according to (12), to keep the model interpretability. For the initial simulations of similarity in this paper we have used the following values of the generic singletons:

$$U_1 = 0.0; U_2 = 0.125; U_3 = 0.250;$$

$$U_4 = 0.375; U_5 = 0.500; U_6 = 0.625;$$

$$U_7 = 0.750; U_8 = 0.875; U_9 = 1.0 \tag{13}$$

For example, the *crisp* output of the Fuzzy Rule R_{14} ($i = 14$), marked by circles in Figure 6 is, as follows: R_{14} : IF (F1 is *MD* AND $F2$ is *BG*) THEN $u_{14} = U_6 = 0.625$

The well common weighted average method is used for the *Defuzzification* step, as follows:

$$D = \sum_{i=1}^{L} u_i v_i \Big/ \sum_{i=1}^{L} v_i \tag{14}$$

Here $0 \leq v_i \leq 1, i = 1, 2, \ldots, L$ is the *firing* (*activation*) *degree* of the i-th fuzzy rule and L =25 is the total number of the fuzzy rules. As already mentioned above, all fuzzy rules have their individual crisp values (*singletons*): $u_i \in [U_1, U_2, \ldots, U_9]$, $i = 1, 2, \ldots, L$, according to the notations of the Fuzzy Rule Base in Figure 6.

In the initial simulations for similarity analysis, we have used the following arrangement for triangular membership functions for feature $F1$ and $F2$, respectively, as shown in Figure 7. The centers (locations) of all five membership functions have been selected intuitively (obviously in a nonoptimal way) within the overall range for $F1 : [F1_{\min}, F1_{\max}]$ and for $F2$:$[F2_{\min}, F2_{\max}]$, that can be understood from the plot in Figure 5. The response surface of the initial Fuzzy Rule Base from Figure 8 is depicted in Figure 8.

7. OPTIMIZATION OF THE PROCEDURE FOR FUZZY SIMILARITY ANALYSIS

Now, with the initial tunings of parameters in the fuzzy inference procedure (namely the singletons as in (13) and the membership functions, as in Figure 7.), we are able to compute the similarities between each given image from the list of 20 images and all the remaining 19 images. The results are sorted and shown in Table 1. Here $N1$, $N2$, and $N3$ denote the ranking list of the first "most similar"

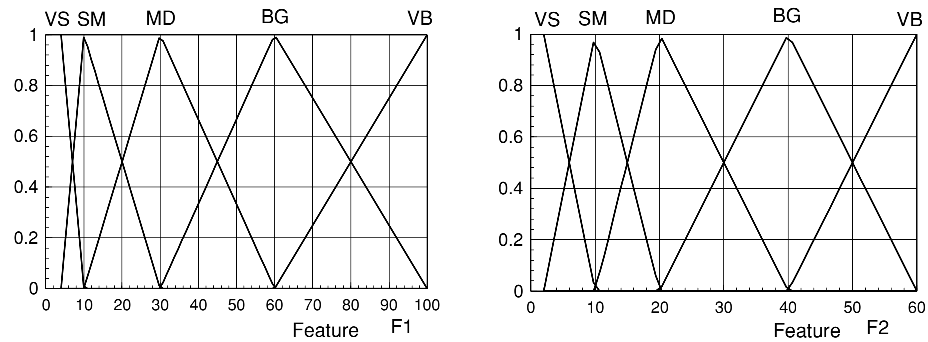

Figure 7. Initial positions of the membership functions for the features $F1$ and $F2$.

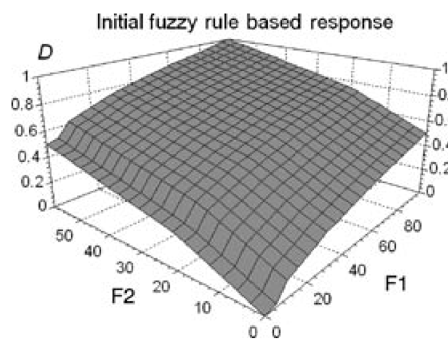

Figure 8. Response surface of the initial Fuzzy Rule Base from Figure 6 before optimization.

images to the given image and $D1$, $D2$, and $D3$ are their respective difference degrees, computed by (14).

From the above Table I it can be noticed that some of the computed similarity decisions represent a *contradiction* with the human decision (preference), if we have a look at the images in Figure 2. These contradictions are marked by *asterisk* in the column $N1$ from Table I and there could be several reasons for such contradictory results. One reason is in the *specific thinking* way of the human expert, who is able to take more facts (parameters) into consideration during the image comparison. These "hidden" parameters are not included into the relatively simple calculation of the assumed by us features $F1$ and $F2$ from (10) and (11).

We have some "degrees of freedom" to correct this problem by appropriate tuning (optimizing) all parameters in the fuzzy inference procedure. These are the parameters (*locations*) of the triangle membership functions and the *singletons* (consequents of the fuzzy rules). If successful optimization of these parameters is performed (according to a given optimization criterion), then we can expect correct (plausible) similarity analysis and classification.

There are two problems in connection with the optimization, namely: (1) construction of the *optimization criterion* with respective constraints and (2) selection

Table I. Results from the similarity analysis before optimization.

	Initial similarity analysis					
	No. 1		No. 2		No. 3	
Image	N1	D1	N2	D2	N2	D3
1	2	0.177	4	0.221	12	0.325
2	1	0.177	11	0.233	16	0.324
3	6*	0.227	4	0.339	13	0.342
4	1*	0.221	13	0.285	3	0.339
5	12*	0.159	13	0.248	16	0.255
6	13	0.187	3	0.227	5	0.308
7	8	0.229	12	0.451	14	0.451
8	7	0.229	14	0.392	9	0.464
9	17*	0.276	18	0.264	14	0.303
10	16*	0.138	11	0.265	15	0.294
11	16*	0.209	2	0.233	12	0.253
12	5	0.159	16	0.219	11	0.253
13	6	0.187	5	0.248	12	0.284
14	9*	0.303	17	0.340	10	0.342
15	16	0.255	10	0.294	19	0.303
16	10*	0.138	11	0.209	12	0.219
17	18	0.102	9	0.276	14	0.340
18	17	0.102	9	0.284	15	0.342
19	20	0.201	15	0.303	17	0.374
20	19	0.201	15	0.380	18	0.415

of the *optimization method* (algorithm) to be used. As for the selection of the "best" optimization method, this is not a topic of interest in this paper, so we will concentrate on the first problem, namely the selection of the optimization criterion DIS.-(dissimilarity). It should evaluate in a numerical way the overall discrepancy between the *human decision* (human preference) and the results from the computer-based similarity. Then the optimization method is aimed at minimizing the discrepancy by tuning the parameters of the fuzzy inference procedure.

An easy way to construct the criterion DIS is to define a finite list of pairs of images $\{A, B\}$ for which the similarity could be evaluated by the human in a firm way, within the range [0.1]. Then the criterion DIS is just summation of the absolute differences *DELTA* between the human and computer evaluation for all given pairs of images. It is clear that the number of pairs, included into the criterion plays important role in the final optimization results. Table II serves as one example how the criterion DIS can be created by using 9 pairs of images that are easy to me evaluated on similarity. Pairs 1,2,3,and 4 in Table II correspond to "very similar" images and therefore the proposed human evaluation is 0.1, whereas the last 3 pairs, numbered as 6,7, and 9 represent the opposite case of "quite different" images with proposed difference degree 0.9. When the computation scheme for similarity analysis is performed with the initial parameters of the fuzzy inference, according to (13) and Figure 7, then the criterion is DIS = 1.743.

Table II. Construction of the optimization criterion DIS and results after optimization.

Pair *no*.	Image *A*	Image *B*	Human evaluation	Computer evaluation	Difference *DELTA*
1	1	2	0.10	0.0629	0.037
2	3	4	0.10	0.1451	0.046
3	5	6	0.10	0.1276	0.028
4	7	8	0.10	0.0866	0.013
5	9	10	0.10	0.2872	0.187
6	1	9	0.90	0.9052	0.005
7	1	7	0.90	0.9024	0.002
8	11	14	0.90	0.5546	0.345

As optimization algorithm, we use here a relatively simple (random search) optimization, which is performed as a *two-stage* procedure for tuning the fuzzy inference parameters, as follows:

- Stage 1 optimizes the three intermediate locations (SM, MD, and BG) of the membership functions for both inputs $F1$ and $F2$, which makes $3 + 3 = 6$ optimization parameters. Here, to achieve meaningful results, at each iteration the following constraint for the intermediate membership functions should be satisfied: SM $<$ MD $<$ BG;
- Stage 2 optimizes the singleton values: $U_1, U_2, \ldots, U_9$, taking into account the constraints (12). This makes in total 7 optimization parameters: $U_2, U_3, \ldots, U_8$ since the singletons U_1 and U_9 are fixed in advance.

The two stages were performed once in a consequence: Stage 1 → Stage 2 with 20,000 iteration steps for each stage. As a result the optimization criterion DIS was decreased from the initial value of 1.743 to 0.876 (after Stage 1) and furthermore to 0.662 (after Stage 2).

The new locations of the membership functions for features $F1$ and $F2$, after Stage 1 of the optimization, are shown in Figure 9. Similarly, Figure 10 shows the modified singleton values $U_1, U_2, \ldots, U_9$ after Stage 2 of the optimization. Finally, Figure 11 displays the optimized fuzzy rule based response surface.

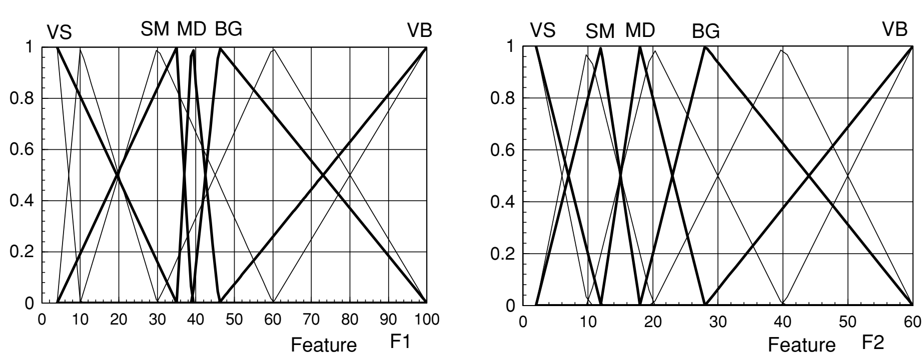

Figure 9. The optimized positions of the membership functions, shown in bold lines.

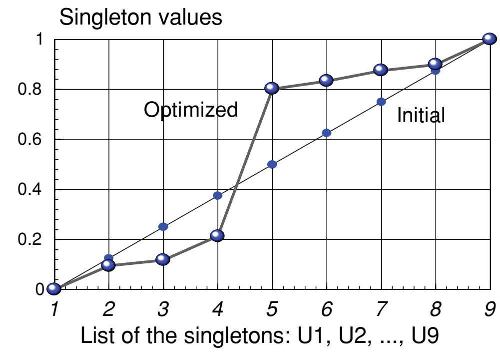

Figure 10. The optimized singletons, shown in bold line.

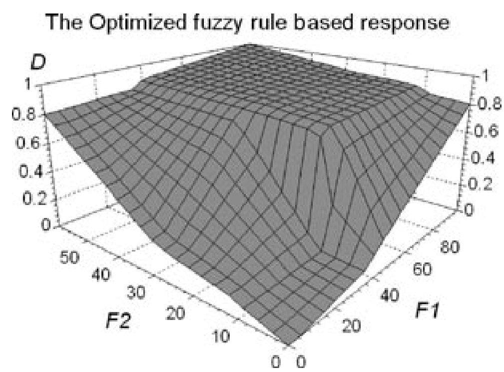

Figure 11. The optimized response surface of the fuzzy inference procedure.

The final classification results are shown in Table III. It is seen from this table that most of the arguable (conflict) cases, shown as asterisks in Table I, have been corrected. There are still some contradictory results from this similarity analysis. They can be resolved by gathering information about some additional *correct cases* of human similarity evaluation and adding them as new members of the optimization criterion DIS from Table II.

It is worth noting that the proposed optimization procedure is from the type of *human-guided* optimization, and as a final result it produces solutions (similarity evaluations) that are most closed to the similarity evaluation *manner* of the specific human expert. Although theoretically such optimization cold be regarded as “subjective” and not exact solution to the problem, at the same time it is a powerful tool to adjust the computer results in accordance to a specific “thinking way” or “decision making” of the human.

Table III. Results from the similarity analysis after optimization.

	Optimized similarity analysis					
	No. 1		No. 2		No. 3	
Image	N1	D1	N2	D2	N2	D3
1	**4**	0.067	**2**	0.096	**11**	0.110
2	**11**	0.068	**1**	0.096	**16**	0.198
3	**6**	0.065	**4**	0.102	**13**	0.103
4	**1**	0.067	**3**	0.102	**13**	0.104
5	**12***	0.036	**16**	0.076	**11**	0.084
6	**3**	0.065	**13**	0.078	**4**	0.112
7	**8**	0.066	**14**	0.350	**10**	0.451
8	**7**	0.066	**14**	0.251	**10**	0.514
9	**17***	0.083	**18**	0.089	**10**	0.127
10	**16***	0.084	**11**	0.084	**15**	0.089
11	**16***	0.057	**2**	0.068	**5**	0.084
12	**5**	0.036	**16**	0.069	**11**	0.085
13	**6**	0.078	**12**	0.090	**5**	0.092
14	**10**	0.103	**8**	0.137	**8**	0.251
15	**16**	0.076	**10**	0.089	**18**	0.103
16	**11**	0.057	**12**	0.069	**5**	0.076
17	**18**	0.031	**9**	0.083	**15**	0.115
18	**17**	0.031	**9**	0.089	**15**	0.103
19	**20**	0.061	**18**	0.112	**15**	0.113
20	**19**	0.061	**15**	0.249	**18**	0.271

8. DISCUSSIONS AND CONCLUSIONS

The main originality of the proposed scheme for similarity analysis and classification is that it is a *human-guided* fuzzy decision, in which the specific human experience and preference is taken in to account and included in to the optimization criterion. This criterion is furthermore used for tuning the parameters of the membership functions and the singletons of the fuzzy inference procedure so that to achieve the best possible matching between the computer results and human preferences.

There are several directions to improve the current state of this research. One is to investigate other optimization criteria that take into account some other aspects of the human evaluation for similarity, to implement them numerically in to the optimization scheme. Important research direction is also to investigate and propose a good, effective method for this multivariate and constrained optimization.

Another area of investigation that could lead to a significant improvement of the proposed scheme for similarity is to extract some different, more complex features from the compressed images that can reveal different parameters of the CIM, such as shape or density of the three-dimensional RGB data cloud. It is supposed that the usage of such more complex features could lead a better and more plausible similarity analysis.

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