Reducing the Semantic Gap of the MRI Image Retrieval Systems Using a Fuzzy Rule Based Technique

Abolfazl Lakdashti, M. Shahram Moin, and Kambiz Badie

Abstract

The main problem in content–based medical image retrieval system is semantic gap, where the meaning that the user has in mind for an image is at a higher semantic level than the features on which the database operates. To overcome the shortcomings in the current content–based medical image retrieval systems and to provide a mechanism to better understand the images semantics, a fuzzy rule based method is proposed which determines which of the image features are more important than the other ones, by making a proper weight vector for the distance measure. For instance, for a given query image, large weights could be assigned to shape features, whilst texture features could be almost ignored by taking small weights. For the training purpose, an algorithm is provided by which the system adjusts its fuzzy rule parameters by gathering the trainers opinions on which and how much the image pairs are relevant. For further improving the performance of the system, a feature space dimensionality reduction method is also proposed. To ensure that this method will increase the precision of the system, we monitored the precision parameter in its training. Our experimentation on IRMA medical image data set shows that the proposed method outperforms two of the most popular image retrieval methods, i.e. a classification based method and a feature weighting technique, and could be used to reduce the semantic gap in the image retrieval systems.

Keywords: Image retrieval, Medical images, Rule base.

1. Introduction

Content-based image retrieval (CBIR) refers to the retrieval of images from a database that are similar to a query image, using measures of information derived from the images themselves, rather than relying on the accompanying text or annotation [1]. To facilitate CBIR, the contents of the images need to be characterized by quantitative features. The features of the query image are compared with the features of each image in the database, and images having high similarity with respect to the query image are retrieved and displayed [1], [2]. One problem of CBIR has always been the semantic gap. Semantic gap is a wide gap between the subjective users interpretation of image similarity in a given context and that of the objective similarity model used by the image retrieval system. Therefore semantic information of the image is not utilized enough during retrieval. CBIR of medical images is a useful tool, and could provide radiologists with assistance in the form of a display of relevant past cases with proven pathology, along with the associated clinical, diagnostic, and other information [3], [4].

In [5] a solution is proposed to provide efficient retrieval of medical imaging. Depending on the user, the same image can be described through different views. In essence, an image can be described on the basis of either low-level properties, such as texture or color; contextual data, such as date of acquisition or author; or semantic content, such as real-world objects and relations. Their approach consists of providing a multispaced description model capable of integrating different facets (or views) of the medical image. Visual retrieval solutions are recommended and are appropriate for noncomputer-science users. They demonstrate how spatial precision of medical image content and ambiguities can be resolved. An implementation called Medical Image Management System (MIMS) has been realized.

In [6], the authors presented an intelligent content–based image retrieval system called I-Browse, which integrates both iconic and semantic content for histological image analysis. The I-Browse system combines low-level image processing technology with high-level semantic analysis of medical image content through different processing modules in their proposed system architecture. Similarity measures are proposed and their performance is evaluated. Furthermore, as a by product of semantic analysis, I-Browse allows textual annotations to be generated for unknown images. As an image browser, apart from retrieving images by image
example, it also supports query by natural language.

A CBIR framework for diverse collection of medical images of different imaging modalities, anatomic regions with different orientations and biological systems has been proposed in [7]. Organization of images in such a database (DB) is well defined with predefined semantic categories. Their proposed framework consists of machine learning methods for image prefiltering, similarity matching using statistical distance measures, and a relevance feedback (RF) scheme. To narrow down the semantic gap and to increase the retrieval efficiency, the authors investigated both supervised and unsupervised learning techniques to associate low-level global image features (e.g., color, texture, and edge) in the projected PCA-based eigen space with their high-level semantic and visual categories. Specially, they explored the use of a probabilistic multiclass support vector machine (SVM) and fuzzy c-mean (FCM) clustering for categorization [8] and prefiltering images to reduce the search space. A category-specific statistical similarity matching has been proposed in a finer level on the prefiltered images. To incorporate a better perception subjectivity, an RF scheme has also been added to update the query parameters dynamically and adjust the proposed matching functions.

A method for medical image retrieval based on color-texture correlogram and GTI model for endoscopic images has been proposed in [9]. First, the authors defined a new image feature called color-texture correlogram which is the extension of color correlogram. The texture image extracted by texture spectrum algorithm is combined with color feature vector, and then they calculate the spatial correlation of color-texture feature vector. In order to obviate the expensive computation, they used another way to calculate the pixels’ correlation to reduce its time complexity. Similarity measure is the key technology in image retrieval, and GTI model is used in medical image retrieval for similarity measure, and the technique of relevance feedback is used in the algorithm to enhance the effectiveness of retrieval. For more information on recent works about content based medical image retrieval approaches, please refer to [10-18].

Using fuzzy logic for image retrieval can improve the performance of the CBIR systems. A method of color-image retrieval based on fuzzy correlation has been reported in [19], in which a-cut relations in fuzzy set theory are applied to define color match and height match of color peaks for synthesizing fuzzy correlation of two color histograms, and RGB space is partitioned into six sub-regions in the experiment for the regional color comparisons. In [20], the authors proposed a methodology for semantic indexing and retrieval of images, based on techniques of image segmentation and classification combined with fuzzy reasoning. In the proposed knowledge-assisted analysis architecture a segmentation algorithm firstly generates a set of over-segmented regions. Then, a region classification process is employed to assign semantic labels using a

### Table 1. The notations of variables in the paper.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>Number of images in the database</td>
</tr>
<tr>
<td>$f_{i}^{c}$</td>
<td>$i^{th}$ feature element of the query image, $0 \leq i \leq M$</td>
</tr>
<tr>
<td>$F^{c}$</td>
<td>$M \times 1$ feature vector of the query image</td>
</tr>
<tr>
<td>$w_{i}$</td>
<td>Weight of the $i^{th}$ feature element, $0 \leq i \leq M$</td>
</tr>
<tr>
<td>$A_{j}$</td>
<td>Trapezoidal shaped fuzzy set of the $i^{th}$ dimension for the $j^{th}$ rule at the premise part</td>
</tr>
<tr>
<td>$N_{r}$</td>
<td>Number of fuzzy rules</td>
</tr>
<tr>
<td>$w_{i}^{j}$</td>
<td>Defuzzified version of the $i^{th}$ fuzzy set of the consequent part of the $j^{th}$ rule</td>
</tr>
<tr>
<td>$W$</td>
<td>$M \times 1$ weight vector</td>
</tr>
<tr>
<td>$s(.)$</td>
<td>A function for converting similarity score vector $S$ to the appropriate weight vector $W$ based on the trainers intension</td>
</tr>
<tr>
<td>$g(.)$</td>
<td>A function for converting distance values to the similarity scores</td>
</tr>
<tr>
<td>$Z$</td>
<td>$A N \times M$ matrix of feature element differences between a certain query image and all the database images</td>
</tr>
<tr>
<td>$Y$</td>
<td>$A M \times M$ matrix of all Euclidian distances</td>
</tr>
<tr>
<td>$C^{j}$</td>
<td>The $j^{th}$ cluster produced by the clustering module</td>
</tr>
<tr>
<td>$f_{min}$</td>
<td>The minimum value of the $i^{th}$ feature element of all points in the $j^{th}$ cluster</td>
</tr>
<tr>
<td>$f_{max}$</td>
<td>The maximum value of the $i^{th}$ feature element of all points in the $j^{th}$ cluster</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{i}^{t}$</td>
<td>$i^{th}$ feature element of the $t^{th}$ target image, $1 \leq t \leq N$</td>
</tr>
<tr>
<td>$F^{t}$</td>
<td>$M \times N$ matrix of feature vectors of all the target images</td>
</tr>
<tr>
<td>$D_{ij}$</td>
<td>Weighted Euclidian distance between a pair of query and target images</td>
</tr>
<tr>
<td>$A_{j}$</td>
<td>Trapezoidal shaped fuzzy set of the $i^{th}$ dimension for the $j^{th}$ rule at the consequent part</td>
</tr>
<tr>
<td>$N_{r}$</td>
<td>Number of fuzzy rules</td>
</tr>
<tr>
<td>$\mu_{j}$</td>
<td>Degree of match for the premise part of the $j^{th}$ rule</td>
</tr>
<tr>
<td>$\hat{w}_{i}$</td>
<td>Inferred weight value for the $i^{th}$ dimension</td>
</tr>
<tr>
<td>$S$</td>
<td>$N \times 1$ score vector of elements assigned to each of $N$ images in the training set for a certain query</td>
</tr>
<tr>
<td>$P$</td>
<td>The average precision of the returned images for all query images</td>
</tr>
<tr>
<td>$s(.)$</td>
<td>The criterion for evaluating a certain clustering</td>
</tr>
<tr>
<td>$X$</td>
<td>$A M \times 1$ vector of summation of feature differences weighted by the scores</td>
</tr>
<tr>
<td>$i_{k}$</td>
<td>$A N \times 1$ vector of elements $1$</td>
</tr>
<tr>
<td>$P_{k}$</td>
<td>$k^{th}$ parameter of the $i^{th}$ fuzzy set of the $j^{th}$ rule $1 \leq k \leq 4, 1 \leq i \leq M, 1 \leq j \leq N$</td>
</tr>
</tbody>
</table>
confidence degree and simultaneously merge regions based on their semantic similarity. This information comprises the assertional component of a fuzzy knowledge base which is used for the refinement of mistakenly classified regions and also for the extraction of rich implicit knowledge used for global image classification. This knowledge about images is stored in a semantic repository permitting image retrieval and ranking.

In [21], a new framework called fuzzy relevance feedback in interactive content-based image retrieval (CBIR) systems has been introduced. The authors proposed a fuzzy relevance feedback approach which enables the user to make a fuzzy judgment. It integrates the user’s fuzzy interpretation of visual content into the notion of relevance feedback. An efficient learning approach has been proposed using a fuzzy radial basis function (FRBF) network. The network is constructed based on the user’s feedbacks. The underlying network parameters are optimized by adopting a gradient-descent training strategy due to its computational efficiency. For other recent works on using fuzzy logic in image retrieval systems, please refer to [22-25].

In this paper, we try to model the operation of an expert based on the input-output data he or she use in retrieval of the images, using fuzzy rules created by an automatic process. This method is called IRFuM, which stands for Image Retrieval via Fuzzy Modeling. Fuzzy modeling is widely used for modeling a control process to build stable controllers. For some of the most popular methods please refer to [26-30]. Modeling the human operation can be done by many other techniques, but fuzzy modeling simplifies analysis and design of the system, since fuzzy rules are able to simulate our inference system. The main idea behind our solution can be discussed as follows. When an expert looks at a query image (in query–by–image retrievals), some portions and/or features of the query image become more important than the other parts or features. For example, when he looks at an image of a bird behind which a background of blue sky exists, he concentrates on the bird but not on the blue regions and therefore, he ignores the blue sky backgrounds in the database images. We propose a fuzzy model that upon receiving a query image, it assigns different weights for image regions and features during the retrieval process. The system learns these weights from the expert user’s input–output data. This can reduce the semantic gap in CBIR systems, as our experiments confirm this fact.

Some parts of our proposed method are reported distinctly in [31], [32]. In [33], [34], we proposed two other approaches in semantic based image retrieval using fuzzy modeling. The main difference between our proposed approach here and those approaches is in estimation of FE weights.

The remainder of this paper is organized as follows. In section 2, we present our method for reducing the semantic gap in image retrieval systems. The details of the proposed fuzzy modeling and fuzzy system are described in this section. Section 3 is dedicated to the experiments and results and finally, section 4 concludes the paper.

Notations. The notations of the variables used in the paper are presented in Table 1.

2. Fuzzy–Based modeling of human operation

Fuzzy modeling is an efficient way for modeling the human behavior to solve a problem, since, it directly maps the human inference system to the fuzzy If–Then rules, where each rule has a meaningful explanation in our sense. In the case of other learning algorithms, including hidden Markov model (HMM) and artificial neural networks (ANN), such a direct mapping cannot be found and hence, analyzing the system is somewhat complicated. “If–Then” rules can be made explicitly by the expert itself, or implicitly from input–output data gathered from his operation. In complex problems, determination of fuzzy rules directly by expert is impossible, and hence, the rule–base should be derived indirectly from the gathered data using a training algorithm. In this section, we first describe the operation of the designed fuzzy system and then give the details of the training algorithm.

Our proposed model requires an offline training phase for which we propose a complete training algorithm for reduction of feature space dimensionality, determining the number of fuzzy rules, and adjusting the fuzzy set parameters. This training algorithm leads to a fuzzy system whose we describe the operation at run–time in the following sub–section.
A. Fuzzy System for Image Retrieval: Run–Time Operation

The overall structure of the proposed fuzzy system is depicted in Fig. 1. When an image is given to the system, it first extracts the image’s predefined features. The resulting feature vector is used as an input to the fuzzy inference module which creates M weights \( w_1, w_2, \ldots, w_M \), where \( M \) denotes the dimension of the feature space and \( \sum_{i=1}^{M} w_i = 1 \). These weights along with the features of the query image are used for computing the distance measure as follows:

\[
D^q = \sum_{j=1}^{M} w_j | f_j^q - f_j^t |
\]

in which \( f_j^q \) and \( f_j^t \) denote the \( j \)th FE of query and target images, respectively. We assume that the FEs are normalized to lie between 0 and 1. \(| | \) measures the absolute value of its operand. \( f_j^q \)'s are stored for each database image as shown in Fig. 1.

Note that we could assign a single weight to a group of FEs instead of individually assigning different weights. For example, it is possible to assign a single weight to all shape FEs, a single weight to all texture FEs, etc. This is appropriate when the training set is small. However, the more weight values are used, the more precise system is resulted. Hence, the proposed system has the flexibility in assigning weight values for a group of FEs or individually to each FE. Here from, we assume that each FE takes a separate weight value. However, extension to the case of assigning a single weight to a group of FEs is straightforward.

The fuzzy rule base contains If–Then rules of the following form:

**Table 2. Scores of similarity for different situations.**

<table>
<thead>
<tr>
<th>Score</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Completely similar</td>
</tr>
<tr>
<td>4</td>
<td>Very similar</td>
</tr>
<tr>
<td>3</td>
<td>Similar</td>
</tr>
<tr>
<td>2</td>
<td>Somewhat similar</td>
</tr>
<tr>
<td>1</td>
<td>Not similar but relevant in some sense</td>
</tr>
<tr>
<td>0</td>
<td>Not similar and not relevant</td>
</tr>
</tbody>
</table>

Rule 1: if \( f_1^q \) is \( A_1^N \) and \( f_2^q \) is \( A_2^N \) and \( \ldots \) \( f_M^q \) is \( A_M^N \), then \( w_1 = B_1 \) and \( w_2 = B_2 \) and \( \ldots \) \( w_M = B_M \).

Rule 2: if \( f_1^q \) is \( A_1^S \) and \( f_2^q \) is \( A_2^S \) and \( \ldots \) \( f_M^q \) is \( A_M^S \), then \( w_1 = B_1^S \) and \( w_2 = B_2^S \) and \( \ldots \) \( w_M = B_M^S \).

\( \vdots \)

Rule \( N_r \): if \( f_1^q \) is \( A_1^{N_r} \), \( f_2^q \) is \( A_2^{N_r} \), and \( \ldots \) \( f_M^q \) is \( A_M^{N_r} \), then \( w_1 = B_1^{N_r} \) and \( w_2 = B_2^{N_r} \) and \( \ldots \) \( w_M = B_M^{N_r} \).

In which \( A_i \) and \( B_i \) are trapezoidal–shaped fuzzy sets and \( N_r \) denotes the number of rules. Given the input feature vector \( F^q = [ f_1^q, f_2^q, \ldots, f_M^q ]^T \), the fuzzy inference module in Fig. 1 performs the following steps:

1) Calculate the degree of match, \( \mu_i \), in the premises for the \( j \)th rule, \( 1 \leq j \leq N_r \), as:

\[
\mu_i = \prod_{j=1}^{M} A_i^j(f_j^q) \tag{2}
\]

where \( A_i^j(\cdot) \) calculates the membership value of its operand.

2) Defuzzify \( B_i \)'s in the consequents using any defuzzification such as taking the center of gravity:

\[
w_j = \sum_{j=1}^{N_r} \mu_i^j w_j^i / \sum_{j=1}^{N_r} \mu_i^j \tag{3}
\]

3) Calculate the inferred weight values, by taking the weighted average of \( w \) with respect to

\[
\hat{w}_j = \sum_{j=1}^{N_r} \mu_i^j w_j^i / \sum_{j=1}^{N_r} \mu_i^j \tag{4}
\]

These \( \hat{w}_j \) s along with feature vector \( f^q \) are used for calculation of distances \( D^q \) of the query image from target images in the image database using Eq. (1). Then, the system returns images with distance \( D^q \) less than a pre-defined threshold \( T \).

B. Training the Fuzzy System: Off–line Phase

In making a fuzzy model, four steps should be considered:

1) Designing the format of fuzzy rules.
2) Determining the relevant inputs.
3) Determining the number of rules.
4) Calculating the parameters.

To generate the input–output dataset, a subset of \( N \) images has been used among them \( N_q \) query images have been selected randomly. An expert looks at each query image and gives an score from 0 to 5 to each database image indicating how much it is similar to the query image. Table 2 shows the scores for different situations. Using these scores, we make a function \( F : N^N \rightarrow R^M \), \( F(S) = W \), in which \( S = [s_1, s_2, \ldots, s_N]^T \)

\( N \) denotes score vector of length \( N \) for each query and \( W = [w_1, w_2, \ldots, w_M]^T \) is the weight vector, which is the resulted data. Calculation of the function \( F \) from the training data is discussed in section 2-B.2. Extracted features of the query image (input data) along with these weights (output data) are used for training the fuzzy system.

Fig. 2 shows a high–level block diagram of our proposed algorithm for training the fuzzy system. This training is an off–line task which is done once in the life cycle of the system. However, this task can be done in a periodic manner in long–time periods for updating the system parameters. First, we proceed with reduction of
feature space dimensionality (Section 2-B.1). Then, the training weight values are computed from the similarity scores (section 2-B.2). After this, we determine the number of rules and a fuzzy partition of the input space (this section). Then, the parameters of the consequence and premise parts of fuzzy rules are computed (section 2-B.3). Finally, we use the computed premise fuzzy rules parameters as an initial guess for their fine adjustment (section 2-B.4). In general, it seems that one cannot separate the tasks of dimensionality reduction from that of determining the number of fuzzy rules nor separate the task of determining the number of fuzzy rules from adjusting the fuzzy set parameters; these are mutually related. However, we are able to separate these steps by using our method. This is a great advantage of the new method. In principle, the algorithm for the identification is of the iterative type.

Generally, to design a fuzzy system, one first pay attention to rule premises and find an optimal partition based on a certain criterion. In this paper, we propose a different approach. We first pay attention to the consequences of the rules and then find a partition concerning the premises. Also, we do not take an ordinary fuzzy partition of the input space, since this could increase, the number of rules exponentially with the number of FEs. We use the fuzzy c–means (FCM) method, to determine the number of fuzzy rules; by clustering the output data (computed weights).

The number of rules is equal the number of extracted fuzzy clusters in weights space. Number of clusters is determined using the criterion \( S(c) \) defined as

\[
S(c) = \sum_{j=1}^{c} \sum_{i=1}^{n} \left( \| w_j - v_i \|_2^2 - \| v_i - \bar{W} \|_2^2 \right),
\]

where

- \( n \) : number of data to be clustered;
- \( c \) : number of clusters, \( c \geq 2 \);
- \( w_j \) : jth weight vector;
- \( \bar{W} \) : average of data: \( w_1, w_2, \ldots, w_n \);
- \( v_i \) : vector expressing the center of ith cluster;
- \( \| \cdot \|_2 \) : norm.

The number of clusters, \( c \), is determined so that \( S(c) \) reaches a minimum as \( c \) increases: it is supposed to be a local minimum as usual. As it can be seen in Eq. (5), the first term of the right-hand side is the variance of the data in a cluster and the second term is that of the clusters themselves. Therefore the optimal clustering is considered to minimize the variance in each cluster and to maximize the variance between the clusters. Now we show an algorithm for extraction of the number optimum clusters by FCM and \( S(c) \):

1. Reduce the feature space dimensionality (Section 2-B.1);
2. Calculate matrix (Section 2-B.2);
3. Set the number of clusters: \( c := 1 \);
4. \( S(1) := + \infty \);
5. do
6. \( c := c+1 \);
7. Make fuzzy clustering using the FCM algorithm;
8. Compute the clustering performance criterion: \( S(c) \); (Eq. 5);
9. while \( S(c) \) become greater than \( S(c-1) \)
10. Find the parameters of the fuzzy sets at the consequence part (Section 2-B.3);
11. Find the parameters of the fuzzy sets at the premise part (Section 2-B.3);
12. Adjust the parameters of the fuzzy sets at the premise part (Section 2-B.4);
13. End do
14. \( S(f) := \| \cdot \|_2 \) ; % Set of all remained FEs
15. \( S_r := \emptyset \) ; % Set of all selected FEs
16. \( \text{P max} := - \infty \) ; % Maximum average precision
17. \( \text{P max,prev} := - \infty \) ; % \( \text{P max} \) of the previous stage
18. \( \text{P}(0) = - \infty \) ;
19. do
20. while all elements of \( R_f \) be selected
21. \( \text{Add} \) f max to \( S_f \);
22. Remove currently selected FE from \( S_f \);
23. while \( R_f \neq \emptyset \)
24. Choose next FE from \( R_f \);
25. Add the selected FE to \( S_f \);
26. Compute the average precision \( p \) (Eq. 9);
27. \( \text{P}(0) = - \infty \) ;
28. do
29. Compute the distance of each test query image
30. % feature vector from that of each test database
31. image using only FEs from \( S_f \);
32. Compute the average precision \( p \) (Eq. 9);
33. if \( \text{P} > \text{P max} \)
34. \( \text{P max} := \text{P} ; \)
35. \( \text{f max} := \text{Currently Selected FE} ; \)
36. end % (of if)
37. if \( \text{p} < \text{P max,prev} \)
38. Remove currently selected FE from \( R_f \);
39. Remove currently selected FE from \( S_f \);
40. while all elements of \( R_f \) be selected
41. \( \text{Add} \) f max to \( S_f \);
42. Remove currently selected FE from \( S_f \);
43. while \( R_f \neq \emptyset \)
44. Choose next FE from \( R_f \);
45. Add the selected FE to \( S_f \);
46. Compute the distance of each test query image
47. % feature vector from that of each test database
48. image using only FEs from \( S_f \);
49. Compute the average precision \( p \) (Eq. 9);
50. \( \text{P}(0) = - \infty \) ;
51. do
52. while all elements of \( R_f \) be selected
53. \( \text{Add} \) f max to \( S_f \);
54. Remove currently selected FE from \( S_f \);
55. while \( R_f \neq \emptyset \)
56. \( \text{Choose} \) next FE from \( R_f \);
57. \( \text{Add} \) the selected FE to \( S_f \);
58. Compute the distance of each test query image
59. % feature vector from that of each test database
60. image using only FEs from \( S_f \);
61. Compute the average precision \( p \) (Eq. 9);
62. \( \text{P}(0) = - \infty \) ;
63. do
64. while all elements of \( R_f \) be selected
65. \( \text{Add} \) f max to \( S_f \);
66. Remove currently selected FE from \( S_f \);
67. while \( R_f \neq \emptyset \)
amongst the total set of FEs; we increase the number of FEs one by one, evaluating a criterion. Our algorithm checks at most \(M(M - 1)/2\) subsets to find optimal subset of FEs.

### Figure 4. Fuzzy cluster in the input space.

First, we begin with a CBIR system with one input. In this case, we compute the \(L\) distance measure of each test query image feature vector from that of database images. This distance measure is defined as follows:

\[
D_{CBIR}^L = \sum_{i=1}^{M} |f_i - f_q|
\]  

(6)

We assume that the FEs are normalized to lie between 0 and 1. These distances should be converted to similarity scores. Any decreasing function \(g(D)\) with the following constraints can be chosen:

\[
g(0) = 5 \\
g(1) = 0
\]

(7)

We use the following empirical function:

\[
g(D) = 5(1-D)
\]

(8)

After finding the similarity scores, the average precision, \(P\), for all test query images for each number of retrieved images \(N_r=1,\ldots,N\) is computed as:

\[
P = \frac{1}{NN_q} \sum_{i=1}^{N_q} \sum_{j=1}^{N_q} Pr_{i,j}
\]  

(9)

where \(P_{i,j}\) indicates the precision value of the \(i\)th query image after retrieving \(j\) images. The precision is defined as:

\[
\text{Precision: } P_{i,j} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}}
\]

(10)

We select one of the FEs which maximizes \(P\). Then we add another FE to our CBIR system. We select the second FE again for maximizing the value of \(P\). We continue the above process until the value of \(P\) starts to decrease. In each step, we check whether the computed \(P\) for the newly added FE is less than the precision value computed at the previous iteration, \(P_{i,j}^{\text{max}}\). If so, current FE is removed, since processing this FE at next steps cannot increase the precision.

This procedure ensures that the precision of final CBIR system using the selected FEs is not less than that of the CBIR system using all FEs. Moreover, using smaller feature vectors reduces the memory requirements of the image retrieval system and speeds up the retrieval process. Note that the proposed algorithm should be executed only once.

### Figure 5. Making fuzzy sets from clusters

### Figure 6. Fuzzy sets used in the fuzzy rules.

### Figure 7. Two fuzzy clusters induced from one output cluster.

2) Calculation of Optimal Weights for Training: In this section, we present our approach for determining the function \(F\), defined in Section 2-B.1 This function is
used to calculate weight vector W from score vector S. This problem can be stated as follows: Find \(w, s\) such that the following squared error minimizes:

\[
E = \sum_{s=1}^{N} \left[ D^{w,s} - g^{-1}(s) \right]^2
\]

Subject to: \(\sum_{i=1}^{N} w_i = 1 \tag{11}\)

where \(D^{w,s}\) denotes the weighted distance between the query image and \(i^{th}\) target image defined by Eq. (1). \(g^{-1}\) represents the inverse function defined in Eq. (8). Incorporating the above constraint in the optimization procedure by using the Lagrange multiplier method, we obtain:

\[
w = Y^{-1}(X - i_j Y^{-1} X - 1) \tag{12}\]

in which \(W\) is a \(M \times 1\) vector of elements \(w_{1i}\), the weight of \(j^{th}\) FE for the query image. \(X\) is a \(M \times 1\) vector of elements 1 and \(X\) is a \(M \times 1\) vector defined as:

\[
Y = Z^T \times g^{-1}(s) \tag{13}\]

The proof of Eq. (12) is given in Appendix. Finally, the function \(F\) is defined as \(F(S) = W\).

3) Determining the Premise and Consequent Fuzzy Set Parameters: As a result of fuzzy clustering, every output \(w_i\) is associated with the grade of membership belonging to \(a\) fuzzy cluster \(B_i\). Notice that we now have the following data associated with the grade of the membership of \(w_i\) in \(B_k^\delta\) (1 \(\leq k \leq N, 1 \leq j \leq M\).

\[
\text{a) vertical, b) horizontal, c) diagonal down/right, d) diagonal down/left, e) non-orientation}
\]

Figure 8. Five types of pattern orientations [35].

We can induce a fuzzy cluster \(A\) in the input space as shown in Fig. 4. By making the projection of the cluster \(A\) onto the axes of the coordinates \(x_1\) and \(x_2\), we obtain the fuzzy sets \(A_1\) and \(A_2\) as shown in Fig. 5. As is easily seen, we have at this stage the following equation:

\[
A_i(f^i_j) = A_2(f^2_j) = B_i(w^i_j) = B_j(w^j_i) \tag{16}\]

where \(B\) is the output cluster.

To calculate the trapezoidal–shaped fuzzy set parameters, we propose the following equations:

\[
p^i_{j} = \min \{f^i_j | A(F^i) = \max \{A(F^i) | F^i \in C^i\}\}, \tag{17}\]

\[
p^j_{k} = \max \{f^j_k | A(F^j) = \max \{A(F^j) | F^j \in C^j\}\}, \tag{17}\]

\[
p^i_{j} = f^i_{j\min} - A^i_j(f^i_{j\min}) \frac{P_{2,1}^i - f^i_{j\min}}{1 - A^i_j(f^i_{j\min})} \tag{17}\]

\[
p^j_{k} = f^j_{k\max} - A^j_k(f^j_{k\max}) \frac{P_{3,1}^j - f^j_{k\max}}{1 - A^j_k(f^j_{k\max})} \tag{17}\]

where

\[
f^i_{j\min} = \min \{f^i_j | F^i \in C^j\}, \tag{17}\]

\[
f^j_{k\max} = \max \{f^j_k | F^j \in C^i\}. \tag{17}\]

The parameter \(p^i_{j}\) denotes the \(k^{th}\) parameter of the \(i^{th}\) fuzzy set in the \(j^{th}\) rule depicted in Fig. 6. In Eq. (17) \(C^i\) denotes the \(j^{th}\) cluster, and \(f^i_j\) is the \(j^{th}\) element of the vector \(F^i\). \(p^i_{j}\) and \(p^j_{k}\) are determined as the end points for which the membership value of corresponding fuzzy cluster maximizes. \(p^i_{j}\) is the intersection of the line between membership values of \(p^i_{j}\) and the member point with minimum value by the line \(l_0 = 0\). \(p^j_{k}\) is computed in the same way. Note that this is an initial guess for the parameters \(p^i_{j}\), whose the value will be adjusted using an adjusting algorithm described in section 2-B.4. Eq. (17) is written for premise fuzzy set parameters, however, it can be used in the same way to find consequent fuzzy set parameters replacing \(f^i_j\) by \(w^i_j\) and other parameters appropriately. Fig. 5 shows an example of determining these parameters for a case of 2–D feature space. In this figure, each point indicates a query image. These points constitute a fuzzy cluster and the parameters of related fuzzy sets are obtained using Eq. (17).

Now, this cluster gives a fuzzy rule: if \(f^i_j\) is \(A_i\) and \(f^j_k\) is \(A_j\), then \(w_i\) is \(B_i\) and \(w_j\) is \(B_j\).

Remark 1: Although the output cluster \(B\) is convex, the input cluster \(A\) corresponding to \(B\) might not be convex. In this case we approximate the input cluster with a convex fuzzy set. Finally, we approximate this convex fuzzy set and \(B\) as well, with a fuzzy set of trapezoidal type as shown in Fig. 6, which is used in the fuzzy model.

Remark 2: the next problem is that we might have more than two fuzzy clusters, \(A_i\) and \(A_j\) in the input space which corresponds to the same fuzzy cluster \(B\) in the output space. In this case we carefully form two convex fuzzy clusters as illustrated in Fig. 7. We obtain the following two rules with the same consequent:
As one can easily find, a fuzzy partition of the input space is obtained as a direct result of fuzzy clustering. Here, we propose the following algorithm:

1) For each cluster
   - Compute average precision $P_1$ from Eq. (9).
   - Find the optimum sub-clustering of the cluster using Eq. (5).
   - Compute average precision $P_2$ from Eq. (9) for these newly computed clusters.
   - If $P_2 > P_1$, split the cluster to these new optimal sub-clusters.
2) End.

4) Adjusting the Premise Fuzzy Set Parameters: In this section, we determine at the stage of parameter identification the values of parameters in this model. The parameters are concerned with membership functions. We propose an algorithm for adjusting the fuzzy set parameters by approximating a convex fuzzy set with a trapezoidal fuzzy set (Fig. 6). As a result, we can drive a qualitative model from a fuzzy model with these parameters, which it is better to improve the parameters in order to use a fuzzy model for simulation. So we adjust the parameters as we do in the ordinary parameter identification. This process leads to better precisions for image retrieval task. Our proposed algorithm can be stated as follows:

1) Set the value $a$ of adjustment.
2) Assume that the $k$-th parameter of the $i$-th fuzzy set in the $j$-th fuzzy rule is $p_{i,j}^k$ (Fig. 6).
3) For each fuzzy rule $j$
   - For each fuzzy set $i$ in the premise of fuzzy rule $j$ – For each parameter $k (k = 1, 2, 3, 4)$
     * Compute $\tilde{p} = p_{i,j}^k + a$ and $\bar{p} = p_{i,j}^k - a$
     * If $k = 1, 2, 3$, and $\tilde{p} > p_{i,j}^k$, then $\tilde{p} = p_{i,j}^k$
     * If $k = 2, 3, 4$, and $\bar{p} < p_{i,j}^k$, then $\bar{p} = p_{i,j}^k$
     * Choose the parameter which shows the best performance in Eq. (9) among $\{\tilde{p}, p_{i,j}^k, \bar{p}\}$ and replace $p_{i,j}^k$ with it.
     * If $\tilde{p}$ or $\bar{p}$ is chosen then while the performance $p$ increases, change $p_{i,j}^k$ in the same direction by a until $P$ decreases or $p_{i,j}^k$ reaches to its neighbor parameter.
4) End.

In experimental, we have used 2% of the width of the universe of discourse as the value of $a (a = 2\%)$.

Note that we do not adjust the parameters in the consequents of the rules. This algorithm reaches to a local maximum of precision parameter $P$. This local maximum is sufficient for most of the situations.

3. Experimental Results

In this section, we provide our experimental results on making a fuzzy system for semantic-based image retrieval. Our target database involves 10004 images from the IRMA database and classified them into 28 classes. The IRMA collection compiles anonymous radiographs, which have been arbitrarily selected from routine at the Department of Diagnostic Radiology, Aachen University of Technology (RWTH), Aachen, Germany.
The imagery represents different ages, genders, view positions and pathologies. Therefore, image quality varies significantly. All images were downscaled to fit into a 512 * 512 bounding box maintaining the original aspect ratio. Our training database contains 2000 images out of these 10004 images. We assigned similarity scores to 200 query images selected randomly from this training set. We used a rule of thumb for determining the size of training set as follows:

Use about 100 images per each class (in our experiments: 2000 images). This is an empirically rule which is proved to provide sufficient training data in our experiments. For example, if we have 100 million images containing 100 classes, only 10000 images are sufficient for training the system (i.e., about %0.01 of total images.)

A. Low Level Features

Pattern orientation histogram (POH) method is a new non-edge based image retrieval technique based on the pattern orientations in spatial domain [35]. POH represents distribution of five types of patterns from each image and produces 80 bins histogram. Patterns are classified into five categories based on their orientation:

- vertical
- horizontal
- diagonal down/left
- diagonal Down/right
- non-orientation

In this method, first, each image is divided into 4 * 4 (16) non-overlapping and equal-sized partitions called image-block. Thus, we obtain 16 equal-sized image-blocks from original image. Then, each image-block is segmented into some sub-blocks and pattern orientations are extracted from each sub-block. Pattern orientations are detected using signal energy rate of sub-blocks. Then, local pattern histograms for each of these image-blocks are computed. As a result, local pattern histograms are obtained for each image. Therefore, with 16 image-blocks in original image and five bins for each image-block, we obtain a histogram containing 80 bins. Then, histogram bin values are normalized into the interval [0,1]. The normalized histogram is quantized with 3 bits per bin. Extracted feature vector can be used in similarity image retrieval systems.

B. Results of Running Feature Selection Algorithm

After running our algorithm, 28 FEs among 80 FEs are selected. One of the most popular approaches in reduction of feature space dimensionality is to use the principle component analysis (PCA) approach. We used this approach of feature space dimensionality reduction for the comparison purpose.

C. Computed Parameters of Fuzzy Sets at Premise and Consequent Parts of the Fuzzy Rules

Fig. 9 shows 3-D plots of computed parameters of fuzzy sets at premise and consequent parts of fuzzy rules. These parameters are resulted from parameter adjusting algorithm described in section 2-B.4. Parts a–d (e–h) show parameters \( p_i \) of premise (consequent) parts for each fuzzy rule and each selected FEs. As it can be seen, in consequent plots which show the results of cluster splitting phase described in Remark 2 of section 2-B.3, some parameter values are equal. Note that some \( p_i \) and \( p_r \) values lie outside the range [0,1]. This does not affect the operation of the system, since they show vertical, horizontal, diagonal down/left, diagonal Down/right and non-orientation (Fig. 8). In this method, first, each image is divided into 4 * 4 (16) non-overlapping and equal-sized partitions called image-block. Thus, we obtain 16 equal-sized image-blocks from original image. Then, each image-block is segmented into some sub-blocks and pattern orientations are extracted from each sub-block. Pattern orientations are detected using signal energy rate of sub-blocks. Then, local pattern histograms for each of these image-blocks are computed. As a result, local pattern histograms are obtained for each image. Therefore, with 16 image-blocks in original image and five bins for each image-block, we obtain a histogram containing 80 bins. Then, histogram bin values are normalized into the interval [0,1]. The normalized histogram is quantized with 3 bits per bin. Extracted feature vector can be used in similarity image retrieval systems.
membership values of more than 0 for input values of 0 and 1.

Fig. 10 denotes a plot of parameter $P$ from Eq. (9) computed for each iteration of the parameter adjusting algorithm (section 2-B.4). As it can be seen, the adjusting algorithm has an important impact on the precision of the system. The system begins with the average precision around 0.118 and reaches to a value around 0.123 at the end of parameter adjusting loop. This is a local maximum value computed in our adjusting algorithm. However, one can provide an algorithm for finding the global maximum, but with an unacceptable computation order. In our experiment, an abrupt change is occurred around iteration 4000. This shows that the corresponding parameters have considerable effect on the precision of the system. Hence, if one can determine these parameters in advance, by only adjusting them he can achieve acceptable precision with a little fraction of time versus running the algorithm for adjustment of all parameters.

Fig. 11 shows some of the rules created in the training phase. In our experiments, 46 fuzzy rules are made and the fuzzy set parameters are adjusted using the proposed algorithm described in Section 2-B.4.

D. Results of Image Retrieval System

a) Experimentation 1: Fig. 12 shows the retrieval results for a sample query image using simple CBIR method (i.e., using the mentioned features and a simple Euclidean distance measure), a typical classification based image retrieval systems, the MARS method [36], and our proposed image retrieval system based on fuzzy modeling using 28 selected FEs. To have a reasonable comparison, we used the same training set for making the weight matrix of the MARS method. Thus, we don't make relevance feedback, and use the training set instead. In this figure, the first 48 images retrieved are shown for comparison.

Fig. 12-(a) shows the retrieval results for the CBIR. In this method, the $L^1$ distance measure is used for determination of the distance between image feature vectors, and, images with less distance values are retrieved first. The errors of system due to semantic gap are evident in this figure, since only a few relevant images are returned.

Fig. 12-(b) depicts the first 48 images retrieved using a typical classification method. In this method, the same training set and the same number of classes are used for the classification. The minimum distance measure is used for decision rule and then images are labeled by the predefined labels. We tried to make similar conditions for fuzzy modeling and image classification to be enabled to compare these methods. We emphasis on this fact that fuzzy modeling is a semantic layer over a CBIR layer and it can be made independent of its CBIR layer properties such as the features. Note that we have not compared fuzzy modeling with the image classification methods reported in the literature, since they use their own low level features and have their own training method. Comparing our method with their method cannot lead to valid results, since the difference between image retrieval results may be arisen from the low level features used in each method, and not from the semantic approach imposed. In this example, a wrong class for the query image is determined and as a result, a bunch of irrelevant images is returned.

In Fig. 12-(c), the returned images for the MARS method are shown. As it can be seen, by weighting the features, more relevant images are returned.

Finally, Fig. 12-(d) shows the retrieval results for our proposed fuzzy modeling system. As it can be seen, more relevant images are returned in our system which shows the reduction of semantic gap in it. Obviously, using fuzzy modeling leads to retrieval of more relevant images. However, some irrelevant images are observed which is due to using low level features. One can decrease these errors by using more sophisticated feature elements. Note that the proposed method can be used beside other semantic based image retrieval systems to achieve a system with higher semantic capabilities.

b) Experimentation 2: Fig. 13 shows another example for retrieval of images in different systems. In this example, the classification method successfully determined the relevant class for the query image. But the error of classification resulted in return of some irrelevant images. That is, the error of classification method inherits by the image retrieval system. The total 48 returned images by our method is relevant in this case which shows the superiority of the proposed solution. The superiority of the proposed algorithm in this and pervious experiments is due to solving the proper optimization problem in our method. In the MARS method, the irrelevant images are omitted in the computations, since they have zero scores and thereby have no effect in the computations. But, in our method, the relevant and irrelevant images both affect the weight vector.

c) Experimentation 3: The results of the third experimentation are shown in Fig. 14. In this case, our method determined a wrong weight matrix for the query image. This is due to lack of appropriate rules in the rule base. However, by using a larger training set, we can reduce such errors. The MARS method here is more successful than the other ones.

d) Precision–recall plots: Fig. 15 shows the precision recall plots for some selected query images. The recall criterion is defined as follows:
Figure 12. Results of Experimentation 1: Retrieval results for different methods; (a) CBIR; (b) Classification; (c) MARS; (d) Fuzzy modeling using 28 FEs. (Images order: row–wise from left to right, i.e. first row is first retrieved, then second row and so on.)
Figure 13. Results of Experimentation 2: Retrieval results for different methods; (a) CBIR; (b) Classification; (c) MARS; (d) Fuzzy modeling using 28 FEs. (Images order: row–wise from left to right, i.e. first row is first retrieved, then second row and so on.)
Figure 14. Results of Experimentation 3: Retrieval results for different methods; (a) CBIR; (b) Classification; (c) MARS; (d) Fuzzy modeling using 28 FEs. (Images order: row-wise from left to right, i.e. first row is first retrieved, then second row and so on.)
Fig. 15. Precision–Recall plots for different types of images; - - (green) CBIR using all FEs, ... (red) Classification, -.- (blue) MARS, — (black) Fuzzy modeling using 28 FEs, — (cyan) Ideal.

Recall = \frac{\text{Number of relevant images retrieved}}{\text{Total number of retrieved images}} \quad (19)

In these plots, the dashed (green) lines indicate the precision recall values for the simple CBIR method in which all FEs are used for retrieval and the weights for all FEs are set to equal values. The dotted (red) lines represent the performance indices for the classification method. The dashed-dotted (blue) lines show the performance indices for the MARS method, and the solid (black) lines represent our proposed method using 28 selected FEs obtained using the proposed fuzzy system. Finally, cyan squares represent the ideal case. From these plots, some important points are concluded:

- Comparing CBIR with classification method, we can conclude that in most cases the classification method overcomes the CBIR method. However, in some cases such as Fig. 15-(a), (b) and (e), the situation is reverse. These are the cases in which the correct class is not recognized for the given query.

- Comparing classification with MARS method, one can realize that MARS is more successful than the classification method in most cases which shows the success of the idea of weighting the feature elements.

- The proposed fuzzy system overcomes all methods based on the precision and recall values for most of these query images. Specially, the weakness of the MARS method with respect to our method is due to omission of the irrelevant images in its computations. However, as mentioned before, our method uses both relevant and irrelevant images in computation of the weight vector. However, in some cases such as Fig. 15–(i), our method is failed.

The content of Tables 3 and 4 consists of the precision and recall values of the same query images in Fig. 15 for the first 11, 21, ..., and 61 retrieved images in each method. Each row contains the results for simple CBIR method (CBIR), the classification system (Class), the MARS method, our proposed fuzzy system (Fuzzy), and the ideal system (Ideal). Based on the content of these tables, one can conclude the superiority of the proposed fuzzy system over other methods.

Fig. 16 shows the average precision–recall values assured for 50 different query images. The average precision–recall values of the ideal system are also depicted in this figure. Since, the number of relevant images differs for different query images and for any query image, most of the images are irrelevant, retrieving all images results in precision values of less than one in ideal case. It is shown that, our proposed fuzzy system results in better average precision–recall values compared to other approaches. However, the distance to the ideal system is
still far which is due to the fact that we yet use the low level features as the basis for comparing images in our system. For improving the performance of the proposed system, these solutions can be advantageous:

1) Using more sophisticated image features by which the relevant and irrelevant points become far from each other.

2) Using bigger training set for making the fuzzy rules.

Table 3. Precisions computed at different number of retrieved images for each method.

<table>
<thead>
<tr>
<th></th>
<th>11</th>
<th>21</th>
<th>31</th>
<th>41</th>
<th>51</th>
<th>61</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) CBIR</td>
<td>0.091</td>
<td>0.092</td>
<td>0.605</td>
<td>0.073</td>
<td>0.059</td>
<td>0.049</td>
</tr>
<tr>
<td>(a) Class</td>
<td>0.091</td>
<td>0.0476</td>
<td>0.032</td>
<td>0.024</td>
<td>0.02</td>
<td>0.0164</td>
</tr>
<tr>
<td>(a) MARS</td>
<td>0.364</td>
<td>0.2857</td>
<td>0.194</td>
<td>0.146</td>
<td>0.118</td>
<td>0.0894</td>
</tr>
<tr>
<td>(a) IRFuM</td>
<td>0.546</td>
<td>0.2857</td>
<td>0.226</td>
<td>1.1707</td>
<td>0.177</td>
<td>0.1475</td>
</tr>
</tbody>
</table>

4. Conclusion

We proposed and designed a fuzzy system for reduction of semantic gap in the content-based image retrieval systems. Our main contribution was on designing the fuzzy modeling itself, the structure for semantic-based image retrieval via a fuzzy system, and the training algorithms for making different parts of the fuzzy system. We developed a method for converting scores of similarity between query and target images to output data needed in the training phase. Our experiments on a dataset of 10004 images from the IRMA database show that using fuzzy system for adjusting weights for FEs in the distance measure can improve the precision–recall performance of the CBIR system. Moreover, we have shown that our system overcomes a typical classification problem.
tion–based image retrieval system and a feature weighting method from the precision–recall point of view.

**Appendix**

Derivation of optimal weights from similarity scores by using the Lagrange multiplier method, this constrained minimization problem can be converted to minimization of

\[
J = \sum_{i=1}^{N} \left[ \sum_{n=1}^{M} w_{in} |f_i^n - f_{w_i}^n| - g^{-1}(s_i) \right]^2 + \lambda \left( \sum_{i=1}^{N} w_i - 1 \right)
\]

(20)

where \( \lambda \) must be chosen to satisfy Eq. (12). In Eq. (20) \( g^{-1} \) is a function for converting scores to distances and is defined as the inverse function defined in Eq. (8) and equals to:

\[
g^{-1}(s) = \frac{1}{5} (5 - s)
\]

(21)

in our experiments. Let \( \partial J / \partial w_i = 0 \), we obtain

\[
2 \sum_{i=1}^{N} \left[ f_i^n - f_{w_i}^n \right] g^{-1}(s_i) - \sum_{i=1}^{N} w_i \left[ f_i^n - f_{w_i}^n \right] = \lambda
\]

(22)

Using Eqs. (13)–(15), Eq. (22) reduces to

\[
X - Y \times W = - \frac{2}{3} I_{M}
\]

(23)

Multiplying both sides of Eq. (23) by \( i_{w_i} Y^{-1} \) and by considering that \( i_{w_i} Y = \sum_{w_i} w_i = 1 \), we get

\[
i_{w_i} Y^{-1} X = - \frac{2}{3} i_{w_i} Y^{-1} i_{w_i}
\]

(24)

Solving Eq. (24) for \( \lambda \) and substituting the results in Eq. (23), we obtain

\[
X - Y W = - \left( \frac{i_{w_i} Y^{-1} X}{i_{w_i} Y^{-1} i_{w_i}} \right) u
\]

(25)

Eq. (12) is calculated by multiplying both sides of Eq. (25) by \( Y^{-1} \) and solving the equation for \( W \).

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A. Lakdashti et al.: Reducing the Semantic Gap of the MRI Image Retrieval Systems Using a Fuzzy Rule Based Technique


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