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A Content-Based Fuzzy Image Database Based on The Fuzzy ARTMAP Architecture

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Abstract

A major design issue in content-based image retrieval system is the selection of the feature set. This study attacks the problem of finding a discriminative feature for each class, which is optimal in some sense. Fuzzy ARTMAP architecture is used to find this discriminative feature set. For this purpose, initially, a large variety of features are extracted from the regions of the pre-segmented images. Then, the feature set of each object class is learned using the Fuzzy Art Map Architecture, by identifying the weights of each feature for each object class. In the querying phase, trained set of feature weights of fuzzy ARTMAP's are used to find the label of each object class. This task is achieved by combining the regions in the images and computing the maximum membership value for the compound regions, which correspond to a possible object class. The query object is matched to each segment group in a fuzzy database using the membership values of segment groups.

1. Introduction

Content-based image retrieval (CBIR) systems become an attractive research area due to the demand created by the increasing size of the image and video resources. Instead of manually annotating the text-based keywords, images are indexed by their own visual content, such as color, texture, and shape. In Image processing literature, there is a wide range of descriptors for CBIR systems. Some of these descriptors have been standardized by the Moving Picture Experts Group (MPEG) [1].

Although MPEG-7 provides a variety of descriptors, selection of a set of descriptors for an image data is an open research issue in content-based image retrieval systems. For example, given an image, composed of a house and sky in the background, the house is best described by shape features, whereas the description of the sky, requires color and texture features [2].

In most of the image retrieval systems, the images in the database are compared to the query image with a common set of features, which are used to represent all the objects and/or classes in the database. For large number of classes, the power of separation of the image collection with the same set of features decreases, specially in large databases [3], [4]. As the number and the diversity of images in the database increase, the fixed feature set methods fail to give satisfactory results.

As an alternative approach, in a recent study, a CBIR system, which uses different set of features for each query class, is proposed in [5]. The 'best set of features' for each query class is estimated in a training module, Then, the similar objects are retrieved by using the best feature set for that query object, applied on the pre-segmented image database. The performance of this method is much better then the systems, which use any combinations of fixed features for all the objects. This result can be verified by analyzing a general C-class classification problem, where the images in a particular class may be similar to each other according to a set of color features, but not similar according to a set of shape features and the images in some other classes are similar to each other according to shape features and dissimilar according to color features. As a consequence, in an image retrieval system, if only one set of features is used, the performance of the system changes depending on the characteristics of the object class.

Applying fuzzy processing techniques to CBIR has been extensively studied in the literature. In [6], fuzzy logic is developed to interpret the overall color information of images. Nine colors that match human perceptual categories are chosen as features. In [7], a color histogram approach is proposed. A class of similarity distances is defined based on fuzzy logic operations. In [8], a fuzzy logic approach for region-based image retrieval is proposed. In the retrieval system, an image is represented by a set of segmented regions, each of which is characterized by a fuzzy feature set reflecting color, texture and shape properties. The resemblance of two images is then defined as the overall similarity between two families of fuzzy features.

In this study, rather then using the 'best set of features', we represent each object class by a different mixture of a large feature set and query that class with the corresponding weight vector. The weights of the mixture are obtained by training a fuzzy neural network architecture, called, fuzzy ARTMAP [9], which computes a membership value depending on the relevance of each feature for each object class.

In the fuzzy database querying, the system asks the questions like "Is this almost a bird?" or "Find me objects which consists of some tigers or some horses". The queries are defined using the membership values.

2. Formation Of The Feature Space By Fuzzy ARTMAP Training

In this section, a fuzzy feature space will be created by training the fuzzy ARTMAP architecture. For this purpose, firstly, the images in the database are segmented into regions using the N-cut segmentation algorithm of reference [10]. It is well known that this algorithm performs over-segmentation, which mostly yields objects or parts of the objects. The images in the database are stored as the output of this segmentation process for the further processing steps.

Initially, a crisp feature space is formed by selecting a large variety of features from the MPEG7 descriptors. Dominant Color (4 features), Color Structure (32 features), Scalable Color (16 features), Edge Direction Histogram (80 features) and Region-based Shape (35 features) are chosen from reference [1]. The features are normalized to analogue [0-1] scale and concatenated to form the feature vectors, which are then fed to the fuzzy ARTMAP architecture.

ARTMAP is a class of Neural Network architectures that perform incremental supervised learning of recognition categories and multi-dimensional maps in response to input vectors presented in arbitrary order. ARTMAP was initially proposed to classify input patterns represented as binary values. Carpenter et al. [9] refined the model by redefining ART dynamics in terms of fuzzy set theory operations. Fuzzy ARTMAP learns to classify inputs represented with a fuzzy set of features where each feature is a value in [0,1] scale indicating the extent to which that feature is present.

The fuzzy ARTMAP system includes a pair of Adaptive Resonance Theory modules (ART_a and ART_b) that create stable recognition categories in response to arbitrary sequences of input patterns (Figure-1). Input features are the feature vectors of the input class. Target prediction is the corresponding label of each input class. Map field module maps the input features to the corresponding target predictions. Such a mapping can be performed by finding the appropriate weight vector (w_j) for each input feature class.

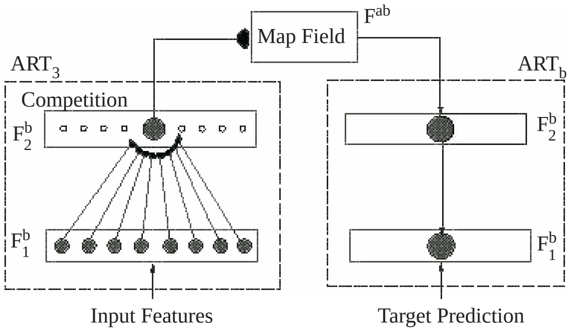

Figure 1. Fuzzy ARTMAP architecture.

Fuzzy ARTMAP [9] is trained by the hand-labeled objects of pre-defined classes. For this purpose, a training set is formed, by entering the objects from each class. The details of the training algorithm of fuzzy ARTMAP are given in [9]. The main point is to find the weight vector ($\underline{w}_j$) for each training object group j. The weight vector shows the relevance of each feature for a particular training class. In the labeling phase, this vector is used to identify the unknown object.

The same fuzzy ARTMAP architecture is used for two different phases of training. In the first phase, the whole objects, which are selected by the user in a rectangular area are trained, whereas in the second one, the segments of the selected object which are obtained from the output of the N-cut segmentation algorithm are trained.

The fuzzy ARTMAP architecture, used for training the whole object, receives a feature vector, which is formed by concatenation of color, texture and shape features. In this study, we used dominant color, color structure, scalable color, edge direction histogram and region-based shape of MPEG-7 features. The input to the fuzzy ARTMAP architecture, for the sub regions excludes the region based shape feature, since the shape is not a characteristic feature of the sub regions of the objects. Figure-2 shows the input and output of the trained fuzzy ARTMAP architectures.

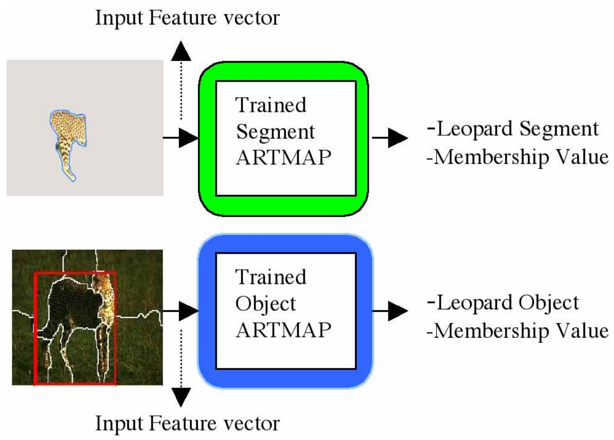

Figure 2. The Input and Output of trained Fuzzy ARTMAP.

3. Object Labelling With Fuzzy ARTMAP

An algorithm is developed to extract and label the objects in the images, where the groups of segments are compared to the query objects using the mixture weights of the trained fuzzy ARTMAP architectures. The input to the algorithm are the

i) pre-segmented images of the unlabelled database images,

ii) weight vectors for each object class, (GetLabelFuzzyARTMAPObject returns the label and membership of the input object) and

iii) weight vectors for each sub-regions (GetLabelFuzzyARTMAPObjectParts returns the label of the input segment).

The Output of the algorithm is

i) the object labels, l_j ,

ii) membership values, m_j for each object and

iii) rectangular coordinates, c_j of each object in the image.

In order to find and label the segment groups, which correspond to the query object, the algorithm in Table-1 is developed:

Table 1. Segment Grouping and Database Labeling Algorithm.

Step 1: For each of the pre-segmented image of the unlabelled database images, repeat (if all images are processed go to Step 9)
Step2: For each of the N-Cut segment of the selected unlabelled image, repeat (if all segments are processed go to Step 4)
Step3: Find label of each selected N-Cut segment by using 'GetLabelFuzzyARTMAPObjectParts' method. Go to Step 2.
Step 4: For each of the neighbour segments of the selected image, repeat (if all neighbour segments are processed go to Step 6)
Step 5: If the neighbour segments have the same label, then combine these segments. Go to Step 4.
Step 6: For each of the combined segment group, repeat (if all combined segment groups are processed go to Step 1)
Step 7: Find label of each combined segment group by using 'GetLabelFuzzyARTMAPObject' method.
Step 8: If the label of the combined segment group and the label of its segments are the same then save Labels (l_j) , memberships (m_j) and rectangular coordinates (c_j) of the combined segment group for the selected image. Go to Step 6.
Step 9: Stop.

The output of the labeling algorithm is a set of labeled segment groups and their membership degrees obtained from fuzzy ARTMAP architecture. Figure-3 shows the processing sequence of the algorithm with an example image.

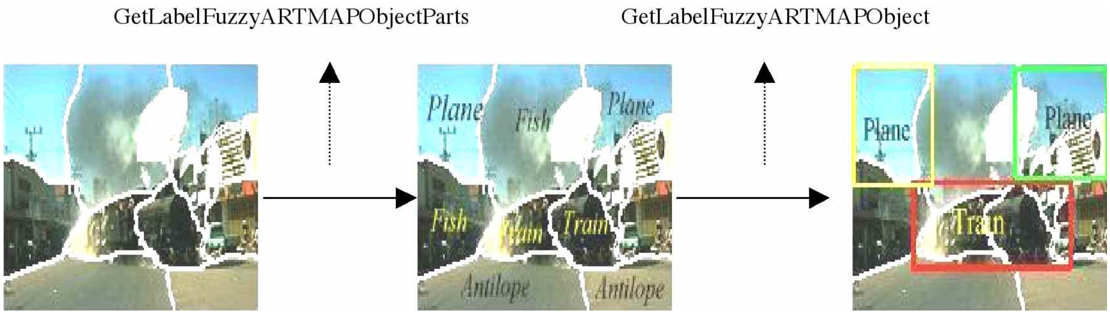

Figure 3. Processing sequence of the labeling algorithm with an example image.

The output of the segment grouping and database labeling algorithm provides us a set of labeled segment groups and their membership values. In the querying process, these labelled segment groups and their membership values will be used.

4. Fuzzy Database Querying

Suppose in the training phase, the system learned a set of objects and their corresponding membership values. If we have a large image database, which is automatically segmented by N-Cut algorithm, it is not possible to obtain reliable results by using crisp parameters to search for an object among these segments. Fuzziness is needed in such a search, because descriptions of image contents usually involve inexact and subjective concepts and also users can identify their queries better with linguistic variables rather than numbers.

The output of the segment grouping algorithm provides us a very convenient infrastructure to construct a fuzzy database. The proposed system uses fuzzy object-oriented database modeling FOOD proposed in [11]. For each fuzzy attribute, a fuzzy domain and a similarity matrix are defined. Similarity matrices represent the relation within the fuzzy attributes. Fuzziness may occur at three different levels in this fuzzy object-oriented database model, the attribute level, the object/class level and the class/super class level. In this study, we are specifically interested in the fuzziness at attribute and object/class level. For each of the query segment group, the inclusion degree of this segment group to the training classes is calculated by using membership values. The segment is identified as the class whose inclusion degree is the greatest.

Let us explain the fuzzy query with an example. Suppose the system trained 3 objects, which are "plane", "horse" and "leopard", and the N-Cut segmented images in Figure-4 will be searched for these objects. The following fuzzy linguistic variables are proposed:

Almost = [0.85, 1.0], Some = [0.7, 0.85], A little = [0.55, 0.7], Few = [0.40, 0.55]. After applying segment grouping and database labelling algorithm, the membership values are computed as shown in Table 2.

Table 2. Images and Corresponding Membership Values.

	PLANE MEMBERSHIP	HORSE MEMBERSHIP	LEOPARD MEMBERSHIP
Image 1	0.923769	0.412534	0.635566
Image 2	0.856751	0.589010	0.706071
Image 3	0.845345	0.742654	0.947400
Image 4	0.839860	0.742057	0.935919
Image 5	0.814194	0.900858	0.846719
Image 6	0.678255	0.892642	0.787659

By using "Images and Corresponding Membership Values" Table, and fuzzy linguistic variables, almost, some, a little, and few, we obtain Table 3, which is called Image Fuzzy Linguistic Variable Table.

Table 3. Image Fuzzy Linguistic Variable Table.

	PLANE MEMBERSHIP	**HORSE MEMBERSHIP**	**LEOPARD MEMBERSHIP**
Image 1	AlmostPlane(AP)	FewHorse (FH)	AlittleLeopar (LL)
Image 2	AlmostPlane (AP)	AlittleHorse (LH)	SomeLeopar (SL)
Image 3	SomePlane (SP)	SomeHorse (SH)	AlmostLeopar (AL)
Image 4	SomePlane (SP)	SomeHorse (SH)	AlmostLeopar (AL)
Image 5	SomePlane (SP)	AlmostHorse (AH)	SomeLeopar (SL)
Image 6	AlittlePlane (LP)	AlmostHorse (AH)	SomeLeopar (SL)

For "almost" and "some" fuzzy linguistic variables, fuzzy representations of the images in the database become:

Fuzzy Rep. of Image 1 = {AlmostPlane} = {AP}

Fuzzy Rep. of Image 2 = {AlmostPlane,SomeLeopar} = {AP,SL}

Fuzzy Rep. of Image 3 = {SomePlane,SomeHorse,AlmostLeopar} = {SP,SH,AL}

Fuzzy Rep. of Image 4 = { SomePlane,SomeHorse,AlmostLeopar } = {SP,SH,AL}

Fuzzy Rep. of Image 5 = { SomePlane,AlmostHorse,SomeLeopar } = {SP,AH,SL}

Fuzzy Rep. of Image 6 = { AlmostHorse,SomeLeopar } = {AH,SL}

In this particular example, there are 3 object classes and 4 linguistic variables for each query object class. As a result, a 12x12 similarity matrix is constructed by considering the similarities of the objects and the linguistic variables. This matrix is given in Table 4. The user can change the similarity degrees, according to the application domain.

Table 4. Similarity Matrix.

μ s	**AP**	**SP**	**LP**	**FP**	**AH**	**SH**	**LH**	**FH**	**AL**	**SL**	**LL**	**FL**
AP	1	0.85	0.70	0.55	0.3	0.25	0.20	0.15	0.30	0.25	0.20	0.15
SP	0.85	1	0.85	0.55	0.25	0.3	0.25	0.20	0.25	0.3	0.25	0.20
LP	0.70	0.85	1	0.85	0.20	0.25	0.3	0.25	0.20	0.25	0.3	0.25
FP	0.55	0.70	0.85	1	0.15	0.20	0.25	0.3	0.15	0.20	0.25	0.30
AH	0.3	0.25	0.20	0.15	1	0.85	0.70	0.55	0.50	0.45	0.40	0.35
SH	0.25	0.3	0.25	0.20	0.85	1	0.85	0.55	0.45	0.50	0.45	0.40
LH	0.20	0.25	0.3	0.25	0.70	0.85	1	0.85	0.40	0.45	0.50	0.45
FH	0.15	0.20	0.25	0.3	0.55	0.70	0.85	1	0.35	0.40	0.45	0.50
AL	0.3	0.25	0.20	0.15	0.50	0.45	0.40	0.35	1	0.85	0.70	0.55
SL	0.25	0.3	0.25	0.20	0.45	0.50	0.45	0.40	0.85	1	0.85	0.55
LL	0.20	0.25	0.3	0.25	0.40	0.45	0.50	0.45	0.70	0.85	1	0.9
FL	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.70	0.85	1

For a query "Find me objects which are almost horse," firstly, Image Fuzzy Linguistic Variable Table and Similarity Matrix in Table 4 are constructed. Then, the following inclusion formula in FOOD modeling [11] calculates the inclusion (INC) degree of each image:

$$\text{INCLUSION} = \text{Avg}[\text{Max}(\mu\text{s}(\text{x}_{ij}, \text{y}_k))] \;,$$

where μs denote the similarity values in Table 4, x_{ij} denote the jthfuzzy representation of the ith image in the database and y_k denote the kth fuzzy representation of the query. Inclusion degrees of each image for the "almost horse" query are calculated as:

INC(Image 1) = Avg(Max(μs(AP,AH)) = Avg(0.3) = 0.3

INC(Image 2) = Avg(Max(μs(AP,AH), μs(SL,AH)) = Avg(Max(0.3,0.45)) = 0.45

INC(Image 1) = Avg(Max(μs(AP,AH)) = Avg(0.3) = 0.3

INC(Image 4) = Avg(Max(0.25,0.85,0.50)) = 0.85

INC(Image 5) = Avg(Max(0.25,1.00,0.45)) = 1.00

INC(Image 6) = Avg(Max(1.00,0.45)) = 1.00

The final step for the query processing is to sort the inclusion values for matching the objects and output the ones that are greater than a threshold value. If the threshold is chosen as 0.85, Image-5 and Image-6 of Figure-4 are retrieved.

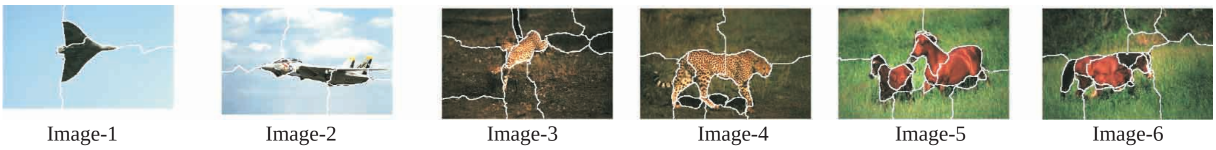

Figure 4. N-Cut segmented images used in fuzzy querying.

Figure-5 shows the segments found by Segment Grouping and database labelling algorithm and their corresponding inclusion values for the query "Find me objects, which are almost horse."

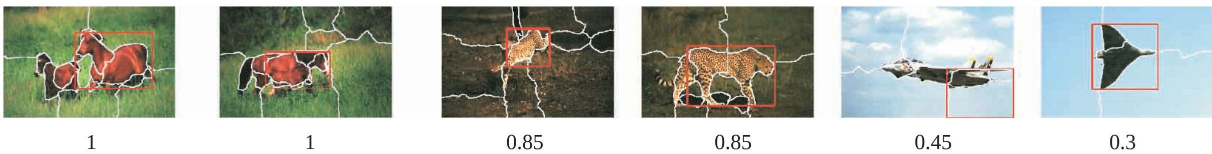

Figure 5. Segment groups and corresponding inclusion degrees.

5. Experimental Results

The proposed content-based fuzzy image retrieval system is developed in C++ Builder and tested over a subset of Corel Draw image database. 10 object classes, namely, *Antelope, Bear, Cheetah, Horse, Fish, Fox, Penguin, Plane, Sun Set, and Train,* are selected from the images of Corel Draw. In order to form the training set, 30 images are selected for each object class, from Corel Draw image database. Test set for the queries are formed by randomly selecting additional 30 images for each class from the same data set. Total of 600 images for the training and test stages are segmented using the N-cut segmentation algorithm, yielding 3154 and 2605 unlabelled regions for the training and test data, respectively.

In the first set of experiments, the performance of fuzzy ARTMAP is tested using the training data. The whole objects are selected by the user, as sub-images with rectangular areas from the training images. The fuzzy ARTMAP is trained with the whole objects. Then, the fuzzy ARTMAP is trained with 2129 regions of these 300 training objects. Note that, only the regions, which are the segments of the training objects, are used. After the training, the same set is used to validate the fuzzy ARTMAP labeling. The validation results are given in Table 5.

Table 5. Validation results of Fuzzy ARTMAP Neural Network architecture.

	# of Correctly Recognized	# of Incorrectly Recognized
300 Training Objects	**294**	**6**
2129 Training Regions	**1661**	**468**

The recognition rate of fuzzy ARTMAP for the whole objects is 98%. This shows the power of fuzzy ARTMAP architecture. On the other hand, the recognition rate of fuzzy ARTMAP for object parts is reduced to 78%. This result is expected due to irregularities in the object parts, which do not always share the same characteristics to resemble the objects, preventing the fuzzy ARTMAP architecture to train the object parts belonging to the same object, properly.

Second set of experiments test the performance of the proposed segment grouping and database labeling algorithm. The same set of objects are used as in the previous experiment. The segment grouping and database labeling algorithm is applied to each image in the test set. Table-6 and Table-7 give the recognition rates of the proposed method in the training and test objects, respectively.

The recall values are calculated as 91% for the training data and 83% for the test data, indicating that the proposed system effectively finds the relevant objects at the output. On the other hand, precision values are 65% and 54% for the training and test data, respectively. Therefore, the proposed system finds irrelevant images along with the relevant ones. This result can be explained with the sample image in Figure-3 where, yellow and green rectangles are falsely labelled as "plane" object. This is due to the fact that, most plane objects used in training, includes "sky" as background which misleads our system.

After the labeling process, queries like "Show me all images containing almost plane objects" are performed. Figure-6 shows a sample query result and the related membership values.

Table 6. Recognition rates of Proposed Method with trained dataset.

Object Name	# of Correctly Labeled	# of Incorrectly Labeled	Total # of Labeled
Antelope	27	21	48
Bear	27	19	46
Cheetah	28	7	35
Horse	26	9	35
Fish	25	14	39
Fox	27	13	40
Penguin	29	17	46
Plane	30	18	48
Sun Set	27	11	38
Train	26	19	45
TOTAL	**272**	**148**	**420**

0.9996 0.9986 0.9985 0.9979 0.9964

Figure 6. First 5 query results and corresponding membership values for the query object "almost plane".

Table 7. Recognition rates of Proposed Method with test dataset.

Object Name	# of Correctly Labeled	# of Incorrectly Labeled	Total # of Labeled
Antelope	23	25	48
Bear	23	24	47
Cheetah	26	13	39
Horse	25	15	40
Fish	22	18	40
Fox	24	24	48
Penguin	25	20	45
Plane	28	24	52
Sun Set	27	17	44
Train	25	24	49
TOTAL	**248**	**204**	**452**

6. Conclusion And Future Work

In this study, a content-based image retrieval system, using a different feature set for each query class is developed. The feature set for each class is formed among a large group of features by a learning scheme. For this purpose, Fuzzy ARTMAP architecture is utilized to learn the relevance of each feature for each query class by identifying the weight vectors for features. The weight vector for features is, then, used to label the database, which is then used for querying.

Fuzzy ARTMAP is a very powerful classifier regarding some of its key characteristics. Firstly, fuzzy ARTMAP makes salient feature detection in the form of expectations for each class. A large variety of features extracted with different computational methods are used in combination and their relative importance to discriminate different classes, are detected by the fuzzy ARTMAP architecture. Secondly, with the fuzzy ARTMAP architecture, images can be grouped under proper classes even if their feature vectors are dissimilar. Such property cannot be achieved by classical distance-based similarity measuring CBIR systems.

In the proposed system, the user can query the database by using fuzzy linguistic variables. The extensions to improve the membership assignment and efficiency of fuzzy similarity matching are an ongoing research topic.

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References

[1] L. Cieplinski, W. Kim, J.-R. Ohm, M. Pickering, and A.Yamada, "MPEG-7 Visual part of eXperimentation Model Version 12.0",12/06/2001

[2] Zoran Stejic,Eduardo M. Iyoda,Yasufumi Takama, Kaoru Hirota, "Content-based Image Retrieval Through Local Similarity Patterns Defined by Interactive Genetic Algorithm.", GECCO-2001, San Francisco, USA, pp. 390-397,July 2001

[3] Berchtold,C. Bohm,D. Keim, and H. Kriegel, "A cost Model for nearest neighbor search in high-dimensional data space", In Proc. ACM Symp. On Principles of Database Systems,pages 78-86, Tuscon, Arizona,1997

[4] K.V. Ravi Kant, Divyakant Agrawal, Amr El Abbadi, Ambuj Singh, " Dimensionality Reduction for Similarity Searching In Dynamic Databases.", Computer Vision and Image Understanding: CVIU, 1998

[5] M. Uysal, F. Y. Vural, "Selection of The Best Representative Feature And Membership Assignment For Content-Based Fuzzy Image Database",CIVR-2003, Illinois.

[6] S. Kulkami, B. Verma, P. Sharma, and H. Selvaraj, "Content-Based Image Retrieval Using a Neuro-Fuzzy Technique", Proc. IEEE Int. Conf. Neural Networks, pp. 846-850,1999

[7] C. Vertan and N. Boujemaa, "Embedding Fuzzy Logic in Content-Based Image Retrieval", NAFIPS '00, pp. 85-89, July 2000

[8] Y. Chen, J. Z. Wang, "A Region-based Fuzzy Feature Matching Approach to Content-Based Image Retrieval", IEEE Transactions and Pattern Analysis and Machine Intelligence, Vol. 24, No. 9 September 2002.

[9] Gail A. Carpenter, Stephen Grossberg, Natalya Markuzon, John H. Reynolds and David B. Rosen, "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps", IEEE Transactions on Neural Networks, Vol. 3, No :5, September 1992.

[10] Jianbo Shi, Jitendra Malik, "Normalized Cuts and Image Segmentation", IEEE Transactions and Pattern Analysis and Machine Intelligence,1997.

[11] A. Yazici and R. George, Fuzzy Database Modeling, Physica-Verlag, 1999