International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:2, No:7, 2008

A Fast Adaptive Content-based Retrieval System of Satellite Images Database using Relevance Feedback

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Abstract**—**In this paper, we present a system for content-based retrieval of large database of classified satellite images, based on user's relevance feedback (RF).Through our proposed system, we divide each satellite image scene into small subimages, which stored in the database. The modified radial basis functions neural network has important role in clustering the subimages of database according to the Euclidean distance between the query feature vector and the other subimages feature vectors. The advantage of using RF technique in such queries is demonstrated by analyzing the database retrieval results.

Keywords**—**content-based image retrieval, large database of image, RBF neural net, relevance feedback

I. Introduction

CONTENT-based image retrieval (CBIR) has become one of the most active research areas in the past few years. Generally, primitive visual features, representing color, shape, and texture extracted form an image to represent its content. Similar images can be retrieved from a collection of images, based on primitive features either single or combination. Successful content-based image retrieval systems require the integration of various techniques, in the field of image processing, and information retrieval. In this paper, we propose a human-computer interactive system to CBIR based on relevance feedback. In our system, we build a large database of remotely sensed data, which consists of Landsat TM classified (i.e. segmented) satellite images scenes that cover different areas in Egypt and show land use / land cover.

We are concerned with using relevance feedback based on modified radial basis function (RBF), for retrieval of large database of satellite images. In section (2) we give a brief introduction of Landsat TM images, a description of the database and the preprocessing steps applied to it. The proposed system description and algorithm are given in section (3). The classification results are shown in section (4), and finally conclusions are given in section (5).

II. Preprocessing Data & Database construction

A. Preprocessing Data

Since the previous decades, several methods of satellite image classification used, such methods include supervised, and unsupervised approaches. Supervised techniques perform better in the classification, while unsupervised techniques; require no priori knowledge of the input data

The study area data used through our proposed system is Landsat-7 TM [1] satellite images of different regions of Egypt, acquired on 6 May 1998, and 21June 2001. Training of the classification model was take place by dividing the Landsat-7 TM images scenes into small subimages of 128-by-128 pixels.

The output of the classification preprocessing stage is 128-by-128 pixel classified subimages of remotely sensed data, which sorted and indexed in a large database of images. The question here is how to retrieve these kinds of data? Taking into account, preserving the spatial information, and saving subimages projection that associated with each subimage, and giving the subimages their values.

Our proposed system gives the answer of this question that we build content-based image retrieval database (CBIR) [15-18] system based on user relevance feedback to fine-tune the retrieval results or change the key region if the direction of the system does not satisfy the user.

The preprocessing stage starts with subimage segmentation, and extracts the subimages' feature vectors. For satellite images, the segmentation operation is known as 'classification', since in this process, pixel labeling will take place, to produce several classes of information, according to the classification application [2]. In our proposed system, we are interested in taking our research application as 'land cover \ land use' application [3,10,11,12,13]. Therefore, we choose the subimages' suitable band combination to be bands (1,4,7), and classify subimages for land cover\land use. Information extracted from the subimages in terms of classified (i.e. segmented) subimages with land cover categories that group similar labeled pixels into regions. The other applications' subimages such as soil types, urban studies, are also stored in the database, therefore, the user should choose the application needed, and through this paper, we will see how user information is very important for the performance of the system.

Maximum likelihood (ML) is one of the most popular techniques used for satellite images supervised classification. In our proposed system, backpropagation supervised artificial neural networks (BP)[4-9] classification technique applied to achieve best classification results as possible as we can. A comparison of the classification accuracies between both techniques took place as in table (4).

The used data is Landsat -7 TM images for different regions in Egypt. The classification problem involves the identification of seven land cover types. Each scene is rectified and consists of seven band, we choose the suitable band combination that reflect the desired land cover types such as water, vegetation and urban in our proposed system, the choice of band combinations according to the needed application will described in details latter.

B. Database Construction

The subimages feature vectors is extracted for each subimage regions, which based, for example, on color, shape, mean, variance, location of the subimage four corners. These extracted feature vector has been stored and indexed in the database in a way that helps the retrieval stage , this is done by attaching to each subimage some indicators that help to decide if the subimage is classified to its right cluster correctly or not

III. Content-Based Image Retrieval

A. Query Stage

A query initiated by the selection of the region of interest from a key image. This identifies the object or the scene's element, which should be present in the retrieved subimages. The system selects a preliminary set of images by minimizing the Euclidian distance measure from the region's feature vector to those of potentially similar regions and that the feature dimensionality is N.

Given that region r_k from image p_k is chosen as the key, then the best match in the initial query will be region r_m is chosen from p_m if

$$D(r_k, p_k, r_m, p_m) = \min(D(r_k, p_k, r_i, p_j) \forall i = \{0....M\} and j = \{0...P\} \tag{1}$$

and where

$$D(r_1, p_1, r_2, p_2) = \sqrt{\sum_{i=0}^{N} (f(r_1, p_1) - f(r_2, p_2))^2} \tag{2}$$

Since each region has feature vector consisting of elements of $\{f_0,\ldots,f_N\}$.A radial basis function neural network (RBF)[14] is used to cluster this data. Centroids of RBF are determined in the initialization. The number of clusters varies according to the volume of the input data but with t training examples, it usually returns between $t/3 and t/2$ clusters. According to the locality of the feature vectors for the user's classified examples they are classified as relevant (positive examples) or irrelevant (negative examples).then to get the next group of subimages, feature vectors of all regions in all subimages in the database are compared to the vectors describing the node centroids. Assume that there are C clusters each with $\{c_0,\ldots\ldots,c_Q\}$, the Euclidian distance between a given region's feature vector and each of these clusters is calculated as in equation(2) and the cluster C_{min} with minimum distance found. The user identifies a variable threshold $\boldsymbol{\theta}$ of the cluster radius.

The iterative refinement continues until the user is satisfied with the resulting subimages. If, at any stage, the user is unhappy with the direction of the system, then, the user can take a new key region that added to the dataset. This has been found to avoid the local minima in the class training.

Each image group can be viewed as a node in a feedback neural network characterized by its centroid and its variance i.e. there exist a transformation such that every feature vector can be expressed in terms of the centroid and variance of all the image groups. The radial basis function (RBF)[14] is such a nonlinear transform that provides a set of functions, which constitute a basis for the input feature vector. This transform can be modified such that, each component represents the membership function of an subimage to a group.

Let x be an arbitrary image feature vector, c_i the centroid of the i^{th} cluster feature space and N number of image clusters. The modified RBF transform maps x to F(x) according to the equation

$$[F(x)]_i = \exp\{\frac{-1}{2\sigma_i^2}\|x - c_i\|^2\} \tag{3}$$

where $[F(x)]_i$ is the i^{th} component of F(x) and σ_i^2 is the variance of the i^{th} cluster.

RBF transform represents the membership function of each image to a group. The proposed system transforms each subimage region feature vector x to F(x) by applying the modified RBF transform utilizing the feedback information in the form F(x), the weights in the network are updated using a correlation matrix.

In order to embed relevance feedback information into the system, the weights $\{w_{ij}|\ 1\le i,j\le N\}$ which contain the relationship between group I, and group j are updated, using the correlation matrix M_k

$$M_k = \begin{bmatrix} w_{11} & w_{12} & \cdots\cdots & w_{1N} \\ w_{21} & w_{22} & \cdots\cdots & w_{2N} \\ . & . & & \\ . & . & & \\ . & . & & \\ . & . & & \\ . & . & & \\ w_{N1} & w_{N2} & & w_{NN} \end{bmatrix} \tag{4}$$

In addition, k is the current iteration .suppose for a given iteration n+m images are displayed, and the user marks n images as being relevant, so the rest m images are considered as irrelevant to the query

Let q be the query feature vector, $\{p_i|1\le i\le n\}$ the set of positive feedback vectors and $\{n_i|\ 1\le i\le m\}$ the set of negative feedback vectors .the correlation matrix is updated as follow:

$$M_k = M_{k-1} + \sum_{i=1}^{n} F(q)F(p_i)^T - \sum_{i=1}^{m} F(q)F(n_i)^T \tag{5}$$

where M_{k-1}represent the previous estimate of the weight matrix M_k is the updated weight matrix based on the relevance feedback provided by the user, and F(x) is the membership function of the feature vectors.

Computing correlation as in equation (5), the weights between positive clusters are increased and the weights between negative clusters are decreased.

The system correlation matrix saves updates, and correlates the subimage groups to make the system learn progressively with each new session and become less dependent on the initial settings

The cluster splitting and merging process eventually breaks the feature space into semantically related clusters. For non-neighboring clusters that contain semantically related subimages, the correlation weights between those clusters of subimages are large in value. Thus, the correlation matrix is used to guide the system search process for retrieval, such that rather than searching nearby clusters, the system allowed to jump across clusters of subimages to search for semantically related clusters.

Section (4) shows the system results, the RBF schematic diagram, and the system flowchart. Training of the system is done off-line; the used algorithm is given in the next section

B. *The Algorithm*

1- Layer stacking and rectifying the images
2- Choose the suitable band for the application (in our case we choose layers that reflect Land cover/Land use Bands 7,4,1)
3- Divide each image scene into subimages with 128-by128 pixels, and R =band7, G=band4, B=band1
4- Classify subimages to get segmented subimages
5- Extract the feature vector from each subimage' region
6- Build database to store classified (segmented) images
7- Compute the Euclidean Distance between the feature vector of the query subimage' key region, and the stored feature vectors of the subimages regions in the database to get preliminary candidate cluster of subimages that contain all the subimages with regions of minimum Euclidean distance values as initialization
8- Calculate redial basis functions neural network centroids
9- Use the modified radial basis function transform that maps the feature vector X to F(X) as follows

$$[F(x)]_i = \exp\left\{\frac{-1}{2\sigma_i^{2}}\|x - C_i\|^2\right\}$$

where σ^2 is variance of the i^{th} cluster, C_i is the i^{th} cluster feature space, $[F(x)]_i$ is the i^{th} component of F(x), RBF transform represent the membership function of each image to a group

10- update the RBF weights by updating the correlation matrix M_k
11- Take the user's feedback to mark images as relevant or irrelevant then update the subimage groups by merging and splitting groups, and update the correlation matrix too.
12- Fine-tune the system results by reclustering the database images, if user is not satisfied with the system's results direction, another key region can be chosen.

IV. Results

TABLE I
LEARNING SCHEDULE FOR BACK-PROPAGATION NEURAL NETWORK
(with 14 hidden units)

Learning schedule for back-propagation neural network (with 14 hidden units)			
Learn count	10000	30000	50000
Learning Rate	0.3	0.15	0.0375
Momentum	0.4	0.2	0.05
No. of inputs and No. of Outputs	3 and 7	3 and 7	3 and 7
No. of hidden layers	1	1	1
Total Error	0.89	0.35	0.01

TABLE II
BACKPROPAGATION NEURAL NETWORK CLASSIFICATION RESULTS

Neural Network Classified Classes								
ground categories	water	old agriculture	New agriculture	sand	mixed grass	roads	urban	total
Water1	159	9	0	2	0	0	0	170
Agriculture2	2	395	0	1	0	0	0	398
Agriculture1	0	0	147	0	0	5	0	152
Wet land	5	0	0	450	9	0	0	464
Sand	0	0	5	7	100	0	0	112
Reclaimed land	0	0	3	0	0	263	30	296
Urban	0	0	0	0	0	78	97	175
Total	166	404	155	460	109	346	127	1767

TABLE III
CONFIDENCE ACCURACY FOR BACKPROPAGATION NEURAL NETWORK CLASSIFICATION

Run Simulations	classification rate	train set average	std. Dev.	classification rate	test set average	std. Dev.
1	0.915	0.922	0.001	0.893	0.895	0.004
2	0.913			0.888		
3	0.92			0.89		
4	0.918			0.89		
5	0.918			0.892		
6	0.92			0.892		
7	0.921			0.89		
8	0.92			0.892		
9	0.925			0.894		
10	0.922			0.895		
11	0.922			0.899		
confidence interval of simulations 9%	0.919454545	0.922	0.998	0.892272727	0.895	0.903

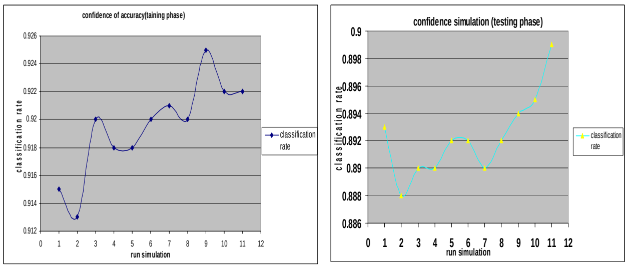

Fig. 1 confidence accuracy a) training, b) testing phases

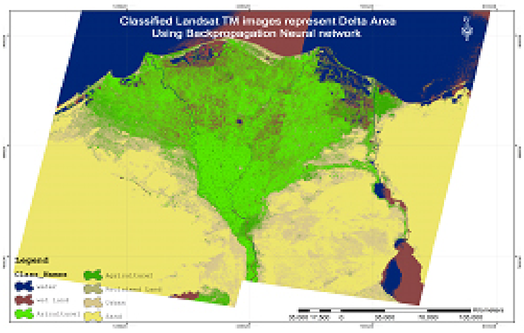

Fig. 2 Backpropagation classification results for the Nile Delta of Egypt as an example of supervised classification results

TABLE IV
COMPARISON BETWEEN THE USED SUPERVISED CLASSIFIERS' ACCURACIES

classification accuracies achieved with different classifier	
classifier used	Accuracy %
Maximum Likelihood	82.9
Neural Network (backpropagation)	85.1

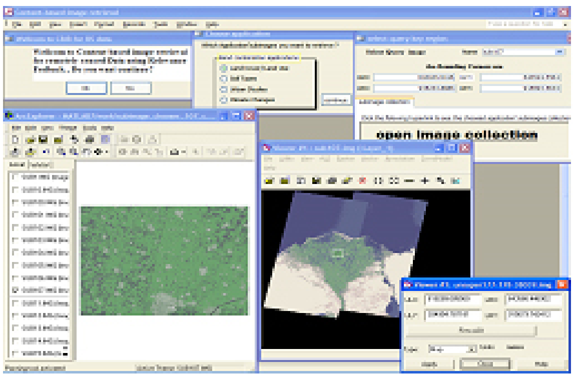

Fig. 3 A snapshot of the system in the query image chooser stage

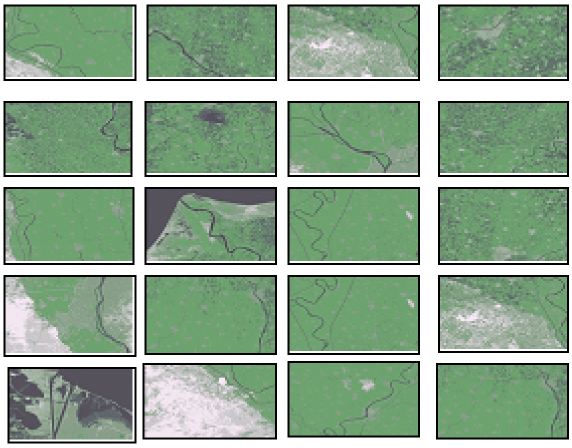

Fig. 4 the final results of the system that shows the top best 20 retrieved subimages

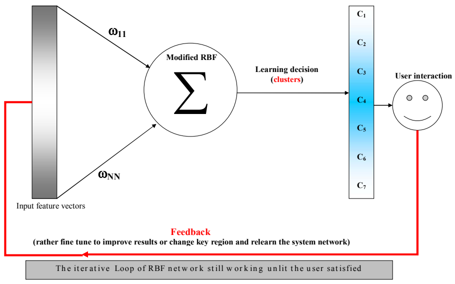

Fig. 5 the RBF neural net schematic

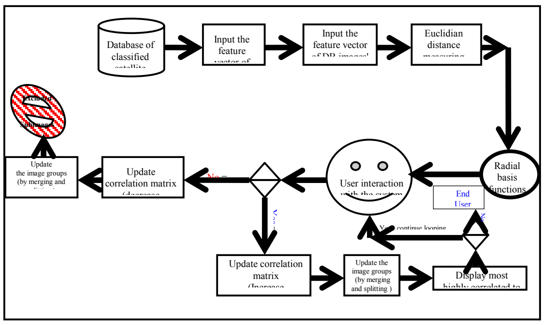

Fig. 6 Fast Adaptive Retrieval System Diagram

V. Conclusion

In this paper, we propose a content-based retrieval of large database of satellite images. We suggest the use of modified RBF transform for clustering because of its varied values of the variance σ_i^2

We note also, that σ_i^2 should be tuned so that the Gaussian functions are not too peaked or too flat. The appropriate value of σ_i^2 is very sensitive to the number and the distribution of RBF centers.

In addition, σ_i^2 not only affects the learning time but also it makes gradual changes in weights, therefore, learning becomes stable and there are no abrupt changes.

On the other hand, the correlation matrix served in the proposed system as a memory of the acquired information. The user interaction gives the system the semantic meanings and relationships between images in our large database of satellite images and makes our proposed system is fast, adaptive the system can adapt it self by merging and splitting subimages clusters after the system's learning and training processes take place, retrieval process is done fastly, in time order of $O(N^2)$, where N is the number of subimage clusters.

In our proposed system, the user should assign a value to the threshold variable θ that the cluster radius should not exceed

To build, analyze, design the system in this stage, and the user interface of our proposed system, we use Matlab7® image processing, image acquisition, toolboxes, Erdas Imagine®, ERSI ArcExplorer®, and Microsoft Access®

We propose as the next paper that will be concentrating on the results of this paper, to analyze the retrieved images data using GIS-based system. In this next paper, we suggest to use the retrieval results as input to that second part of the system. We also suggest using GIS to build Geodatabase containing the geospatial analysis information yielding from previous retrieval stage, and use GIS capabilities to build a GIS model.

ACKNOWLEDGMENT

We would like to acknowledge the support by Groundwater Sector of the Ministry of Water Resources & Irrigation of Egypt, Especially for Prof. Dr. Fattma A. Attia Head groundwater Sector we would like express our deepest gratitude and appreciation for her support.

Also, we would like to acknowledge and express our deepest gratitude and appreciation to both of Prof. Dr. Laila F. Abd El Aal and Prof. Dr. Samia A. Mashli their sincere help and continues support and guidance.

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