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Classifying content-based Images using Self Organizing Map Neural Networks Based on Nonlinear Features

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ABSTRACT

Classifying similar images is one of the most interesting and essential image processing operations. Presented methods have some disadvantages like: low accuracy in analysis step and low speed in feature extraction process. In this paper, a new method for image classification is proposed in which similarity weight is revised by means of information in related and unrelated images. Based on researchers' idea, most of real world similarity measurement systems are nonlinear. Thus, traditional linear methods are not capable of recognizing nonlinear relationship and correlation in such systems. Undoubtedly, Self Organizing Map neural networks are strongest networks for data mining and nonlinear analysis of sophisticated spaces purposes. In our proposed method, we obtain images with the most similarity measure by extracting features of our target image and comparing them with the features of other images. We took advantage of NLPCA algorithm for feature extraction which is a nonlinear algorithm that has the ability to recognize the smallest variations even in noisy images. Finally, we compare the run time and efficiency of our proposed method with previous proposed methods.

Keywords - **Self Organizing Maps (SOM); Nonlinear dimensionality reduction; recognizing content-based images; Artificial neural networks; feature vector; machine learning; Support Vector Machine; clustering.**

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I. INTRODUCTION

In recent years, the computer technology growth, the importance of multimedia information and huge digital archives has attracted many researchers attention to create appropriate tools for image retrieval. From first of 1990, content-based image retrieval was the main field in most researches. Image retrieval systems operate in two steps: in first step, visual features of database images are extracted automatically. In the second step, after receiving user's desired image (target image), its low-level features are extracted and then the database begins the search process to find the most similar image to it. In content-based image retrieval systems, the user intends to find semantic similarity in images whereas most of common databases perform search operation based on low-level features closed to user's desired image and this kind of search might not be acceptable by the users to gain their desired result. This shows that low-level features are not sufficient to represent semantic features of images. On the other hand, people's aims are different and different users may infer differently from an image [1]. To overcome these limitations, we set images in to related and unrelated ranges by means of image histograms. That means network training is done by predictions and image histogram estimation. Extracted features of images are kept in low-level visual features database [2-4]. The subsystem performs the search operation on the target image, extracts the proper features of it and calculates the similarity between feature vector of the target image and the feature vectors of database images. Then the system matches the target image with the closest image in database. These images are presented to the user via graphical user interface and the interaction between the user and the system continues till the user gains his target images. This process is called "related feedback" and is used for short time learning. In this paper, a new method for related feedback is proposed in which similarity function is revised by means of information in related and unrelated images. In proposed our method NLPCA is used for weight modification by using a new hierarchical technique and the weight of each feature is set based on the score of the related images in the retrieval process and there is no need for user comments in this range.

- **Review of short time learning method**

These methods are divided in to two categories called "the algorithms based on machine learning" and "the algorithms based on query vector and similarity function". Methods based on machine learning are divided in to two groups: "supervised" and "unsupervised". Supervised learning methods contain methods like: support vector machines [5-7], Bayes classification [8], neural networks [9] and decision tree. Low-level features are usually used for learning high-level concepts. SVM is used in short time learning for discriminating data in to one and two groups [10].

Unsupervised learning methods cluster the images of the database automatically and without user's interference. Image clustering is an unsupervised method and it aims to classify images so that outside cluster similarity will be high and inside cluster similarity will be low. K-means clustering methods are a kind of unsupervised learning methods.

- **A method to improve similarity function**

In this work, a method to improve similarity function is proposed based on related and unrelated image information. It should be mentioned that in the proposed system low-level features of database images are extracted. To do so, we presume that there are *N* images in image database $X=\{X_1,X_2,\ldots,X_N\}$ and we have feature vector F_i corresponding to the image X_i that contains low-level features of the image. Thus, feature database contains *N* feature vectors $F=\{F_1,F_2,\ldots,F_N\}$. The feature vector F_i is the combination of several conflict feature vectors. As an example, suppose that *k* kinds of different features are extracted and then concatenated together as a feature vector (feature *k* contains L_k feature components $k=\{1,2,\ldots,K\}$ and $F_i=[f_i^1,f_i^2,\ldots,f_i^k]$ is the feature vector in which f_i^k denotes to the feature of the type *k* , $k=\{1,2,\ldots,K\}$). In the similarity function improvement methods, the similarity function is calculated as the following relationship.

$$d(F_i,F_j) = w_n^1 \sum_l^{L_1} h_l^1 \left(\frac{f_{i,l}^1 - f_{j,l}^1}{f_{i,l}^1 - f_{j,l}^1} \right)^2 + \ldots + w_n^K \sum_l^{L_K} h_l^K \left(\frac{f_{i,l}^K - f_{j,l}^K}{f_{i,l}^K - f_{j,l}^K} \right)^2$$

(1)

Where F_i, F_j and *d* denote to the feature vectors of the two images *i* and *j* and the dissimilarity criterion between these two feature vectors, respectively. $F_{i,1}^k$ is the *i*-th component of the feature of type *k* extracted from the *i*-th image and L_k is the length of the feature vector of type *k*. w_n^k denotes to the normalized weight related to the feature of type *k* and h_1^k is the weight belonging to component 1 of the feature of type *k*. In the similarity function improvement methods, the weights are set according to the related and unrelated images. In the first step of the retrieval operation, after extracting the features of the target image, the weights corresponding to each of the features (*w*) and feature components (*h*) are considered as 1. In our work, we use the information from the related image set for correcting the weights of the features (*w*) and to modify the weights of the feature components (*h*), we use both of related and unrelated image sets.

- **The proposed method for correcting the weights of the features (w)**

For correcting the weights, image retrieval is performed based on each feature. Then the score of the images which are known as the related images is calculated for each extracted feature. After that, the weight of each feature in image is considered as the sum grades in the images for that feature. Suppose in one stage of retrieval, image set $Q^+=\{X_1^+,X_2^+,\ldots,X_m^+\}$ is selected as the related images. To determine the weight of each feature in the next stage, the database images are sorted based on each feature in query. Then the grade of each image of Q^+ set based on each feature is specified in retrieval stage and the weight of each of feature types is computed as follows.

$$w^k = \frac{1}{\sum_{i=1}^{m} rank^k(X_i^+)}, \quad w_n^k = \frac{w^k}{\sum_{k=[1,2,\ldots,K]} w^k} \qquad (2)$$

Where $rank^k(X_i^+)$ denotes to the grade of the image X_i^+ in the retrieval list based on the feature type *k* and the normalized weight w_n^k related to that feature.

- **Image feature extraction using nonlinear discriminant analysis**

We consider the set $X = [x_1, x_2, \cdots, x_N]$ as a sample of *c* class $\{\omega_1, \omega_2, \cdots, \omega_C\}$ when $x_i \in R_n$. Subspace learning methods try to find transition function Φ so that transition from *n*-dimensional space to *d*-dimensional space ($d \ll n$) is possible by minimizing or maximizing the target function and the transition function Φ is equal to $y_i = \Phi^T x_i$ when $yi \in Rd$. This transition function minimizes the space dimensionality for between-class scatter matrix and maximizes it for within-class scatter matrix. The structure of between-class scatter and within-class scatter matrixes is defined by the following formulas.

$$S_b^L = \sum_{ci=1}^{c} \sum_{cj=1}^{c} (\bar{xc}_i - \bar{xc}_j) W_{cicj} (\bar{xc}_i - \bar{xc}_j)^T \qquad (3)$$

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$$s_w^L = \sum_{c=1}^{c} \sum_{xi,xj \in w0}^{1} (x_i - x_j) W_{ij}^{(c)} (x_i - x_j)^T \quad (4)$$

That $\overline{xc}_i$ shows the mean of vector w_{c_i} . The weight $w_{ij}^{(C)}$ for the pair data x_i and x_j within class c is defined as follows.

$$W_{cicj} = \begin{cases} \exp\left(-\frac{\left\| \overline{x}c_i - \overline{x}c_j \right\|^2}{2\sigma^2}\right) \\ 0 \end{cases}$$

(5)

$$W_{ij}^{(c)} = \begin{cases} \exp\left(-\frac{\left\| xc - xc_j \right\|^2}{2\sigma^2}\right) \\ 0 \end{cases}$$

(6)

Also σ is determined experimentally.

The use of linear principal component analysis encounters the problem of the large size of the feature vector and the error of Eigen matrix in returning the original value of the matrix. To solve this problem we utilize nonlinear principal component analysis. This algorithm chooses all the linear and nonlinear points and leads to high speed and accuracy in selecting the components. The linear transforms have weak performance in discriminating the data whose classes are not intuitively separable. NLPCA is used to decrease the correlation in the data exactly like PCA. In fact, PCA specifies linear correlation between features while NLPCA specifies linear and nonlinear correlations between features without considering the nonlinear nature of the data. In NLPCA method a neural network is trained to determine nonlinear mapping. NLPCA is a nonlinear generalized version of PCA. Up to now, most of the generalizations of PCA were based on one type of learning [11,12]. While using each type of linear or nonlinear PCA, it is important to discriminate between their applications in dimensionality reduction. In the first set of applications we must describe a subspace with high capability. It is not necessary to have unique features and the only need is to define mean square error for the data.

Implementing the hierarchical NLPCA algorithm has two main properties like scalability and stability. The first property refers to the responding capability for the increase in overload .As an example the scalability refers to the ability of a system in increasing the total performance while inserting resources (like dimensionality). The second property refers to the i-th specification of n features containing i solutions for m features so that m ~= n. Then we rich to balance and we will be able to retrieve the original matrix.
Fig. 1. Compares the features of PCA and NLPCA together in 5 levels.

- **Self-Organizing Map learning algorithm**

Self-Organizing Map learning algorithm is a type of unsupervised learning methods. Originally, an unsupervised learning algorithm can be specified by the first grade equations. These equations illustrate how network weights will be agreed by spend of time or repeating the discrete case. According to weights agreement, a similarity measure is used for guiding the learning process and we usually will face some kinds of correlation, clustering or competing behaviors in this case. Generally, Self Organizing Map learning algorithm is based on the selection of the winner neuron and the movement of this neuron and some of its neighbors toward the input data. This algorithm can be summarized as the next steps.

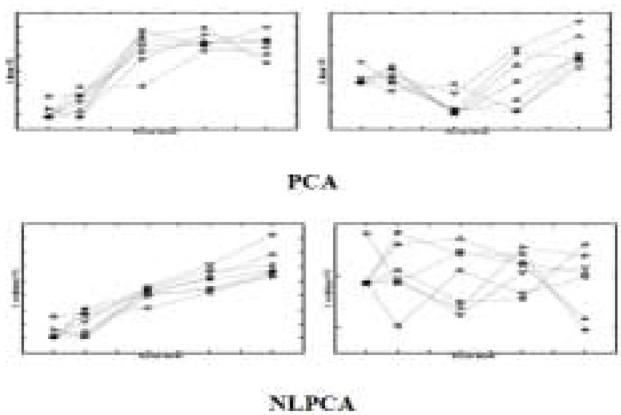

Fig1 .Comparison between the features of PCA and NLPCA in 5 levels .

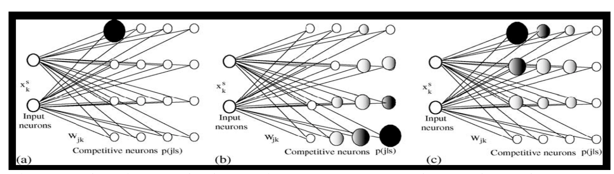

Fig2 Selection of the winner neuron through reference patterns.

- **First step**

In this step, the weight of each neuron is initialized based on nonlinear features. Then an input pattern $X = (x_1, x_2, ..., x_d)$ is applied to the network.

- **Determining the winner neuron**

In this step, the winner neuron is specified based on the network similarity measure. We can make use of different similarity measures in self organizing maps but the most popular measure that is used in these networks is Euclidean distance. The equation of Euclidean distance is as follows.

$$\| X - W \| = \left(\sum_{i=1}^{d} (X_i - w_i)^2 \right)^{1/2} \quad (7)$$

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Now the input is compared with all the elements exist in the network. The winner neuron is the neuron with the minimum distance through all the reference patterns. So, the winner neuron is the reference vectors.

$$\|X - m_c\| = \min_i \{\|X - m_r\|\} \quad (8)$$

A sample of the selection of the winner neuron through the reference patterns is represented in figure. 2.

- **Determining neighbor neurons**

After determining the winner neuron, a set of neighbor neurons of the winner neuron whose values should be altered are specified. Generally, modifying the values related to the neighbor neurons is performed in two ways [13]. In the first case, a definite neighborhood radius is selected around the winner cell. In this method all the neurons in the network that has a definite distance from the winner neuron, move toward the input with a constant coefficient. This coefficient has the maximum value in the winner neuron and going away from the winner neuron decreases its value.

- **Weights modification**

Finally, the weights pertaining to the winner neuron and its neighbors must be modified based on network's input. These modifications are done by the relationship 9.

$$m_r(t+1) = m_r(t) + \alpha(t) \cdot h_{cr}(t)[x(t) - m_r(t)] \quad (9)$$

where $x(t)$ is the input vector in time t and $m_r(t)$ is the *r*-th reference pattern in time t and $\alpha(t)$ denotes to learning rate in time and $h_{cr}(t)$ is the neighborhood function which can be defined based on kernel function by the equation 10.

$$h_{cr}(t) = \exp\left(-\frac{\|k_c - k_r\|^2}{2\sigma(t)^2}\right).$$

(10)

Where $k_c, k_r \in \Re^d$ denotes to the winner neuron and its reference neighbor patterns and is the radius of the kernel function in time t. The result of these issues is the modification of weights and the movement of these neurons toward the training sample. $\alpha(t)$ Is the parameter used for controlling the convergence of the algorithm and is dependent to the number of iterations. In order to rich the stability in the network $0 < \alpha(t) < 1$ and its decrease based on the time *t* is steady. Unsupervised training is more complex than supervised training and thus it requires more time to learn training patterns [14].

- **The Proposed method**

The block diagram of our proposed algorithm is presented in figure. 3.

We first extract robust image features by means of NLPCA and then we calculate the weights of the input matrix by means of relationship 2. After that we assign the weight matrix to the SOM neural network and this network begins classifying the input matrixes.

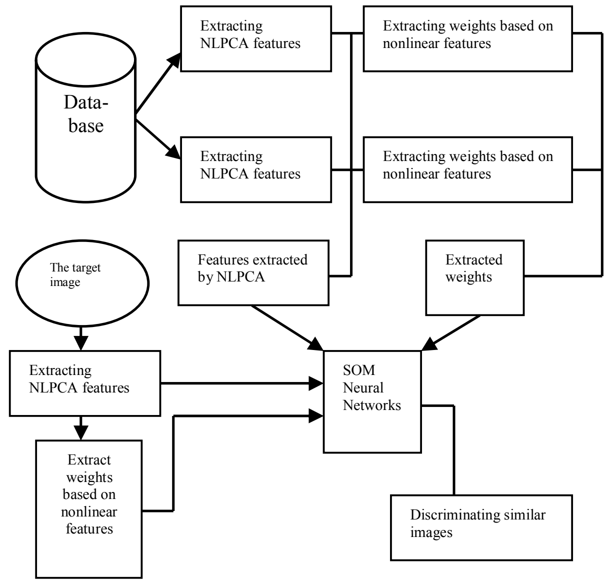

Fig3. The block diagram of our proposed algorithm.

- **experimental result**

We evaluated our proposed method on the public COREL database which contains more than 17000 images.
Table 1. Shows the results of our implementation with KNN [15] and simple SOM [16] algorithms. These results are achieved by experimenting our method on different images. As it can be seen, our method has decomposed images with a very low error rate.
Our proposed algorithm has higher speed and accuracy. The reason of the time difference is that we extracted a small feature matrix based on NLPCA algorithm. But in simple SOM algorithm we have to train the total set of features to extract a proper pattern.

II. HEADINGS

The **headings** and **subheadings**, starting with "**1. Introduction**", appear in upper and lower case letters and should be **set in bold and aligned flush left**. All headings from the Introduction to Acknowledgements are numbered sequentially using 1, 2, 3, etc. Subheadings are numbered 1.1, 1.2, etc. If a subsection must be further divided, the numbers 1.1.1, 1.1.2, etc.

The font size for **heading is 11 points bold face** and **subsections with 10 points and not bold.** Do not underline any of the headings, or add dashes, colons, etc.

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III. Indentations and Equations

The first paragraph under each heading or subheading should be flush left, and subsequent paragraphs should have a five-space indentation. A colon is inserted before an equation is presented, but there is no punctuation following the equation. All equations are numbered and referred to in the text solely by a number enclosed in a round bracket (i.e., (3) reads as "equation 3"). Ensure that any miscellaneous numbering system you use in your paper cannot be confused with a reference [4] or an equation (3) designation.

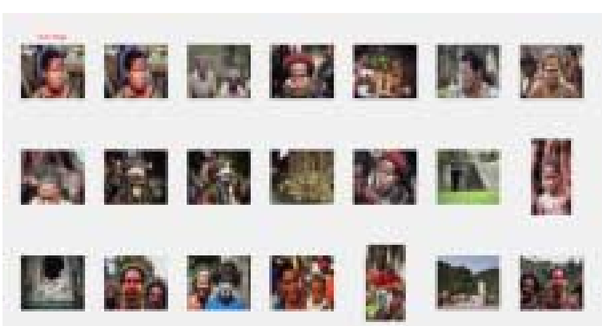
IV. Figures and Tables

To ensure a high-quality product, diagrams and lettering MUST be either computer-drafted or drawn using India ink. Figure captions appear below the figure, are flush left, and are in lower case letters. When referring to a figure in the body of the text, the abbreviation "Fig." is used. Figures should be numbered in the order they appear in the text.

Table captions appear centered above the table in upper and lower case letters. When referring to a table in the text, no abbreviation is used and "Table" is capitalized.

CONCLUSION

In improving the query vector, usually the related and unrelated images are used to modify the query vector and the weights of feature components are revised according to the interaction with user. This is done by NLPCA algorithm without any need for the user interference. After computing this weight and achieving the feature matrix, we begin to classify images. In this type of classification there is no need to calculate the weights of images and classification is performed faster. The proposed algorithm is compared with the algorithms such as SOM and KNN and it is shown that this approach outperforms these algorithms in terms of speed and accuracy.



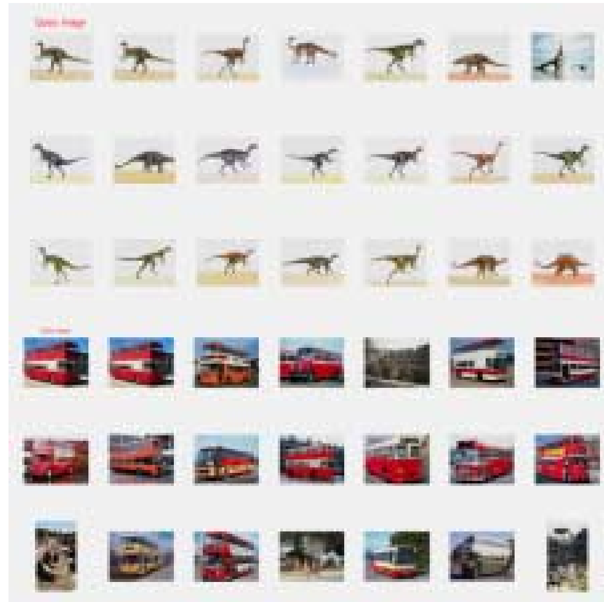


Fig4 . The results of our proposed method on the COREL database.

TABLE I. COMPARISON BETWEEN PROPOSED METHOD AND OTHER METHODS.

Algorithm	***Computational accuracy***	***Computational time***
SOMNLPCA	97.60%	325S
KNN[17]	76.85%	385S
SOM[18]	88.50%	512S

TABLE2 Confusion Matrix

CLASS	CLASS1	CLASS2	CLASS3	CLASS4	CLASS5
CLASS1	%98/3	%1.7	%0	%0	%0
CLASS2	%1.2	%97.8	%0	%0	%0
CLASS3	%1.1	%1.4	%97.5	%0	%0
CLASS4	%0	%0	%0	%99.1	%0.9
CLASS5	%0	%1.2	%0	%0	%97.2

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