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FACE IMAGE RETRIEVAL USING LWT-PCA WITH DIFFERENT CLASSIFIERS

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Abstract: — **In This paper, the face images retrieved system based on Lifting wavelet transforms with principal component analysis (PCA). These techniques are implemented and their performances are investigated using frontal facial images from the ORL database. The retrieval accuracy compare with different distance methods like Euclidean distance and Manhattan distance. Lifting wavelet Transform(LWT) is effective representing in image features and is suitable in Face image retrieval, it still encounters problems especially in implementation. e.g. Floating point operation and decomposition speed. We use the advantages of lifting scheme, a spatial approach for constructing wavelet filters, which provides feasible alternative for problems facing its classical counterpart. Lifting scheme has such intriguing properties as convenient construction, simple structure, integer-to-integer transform, low computational complexity as well as flexible adaptivity, revealing its potentials in Face image retrieval. Lifting wavelet transform with PCA gives less computation and high retrieval rate.**

Keywords: Lifting Wavelet Transform, Principal Component Analysis,Euclidean distance,Manhattan distance, and ORL database.

1. INTRODUCTION

The main aim of face image retrieval is to retrieve face images, which are similar to a specific query face images can be used for many applications, such as photo management, visual surveillance, criminal face identification and searching specific faces from the internet etc. The retrieval task contains two types of target images.one is the face images with the same identity of the query face. The other is the face images which have appearance similar to the query face.

Lifting scheme, a novel approach for constructing the so-called second-generation wavelet, provides feasible alternative for problems facing the classical first generation wavelet in image applications. Constructed entirely in spatial domain and based on the theory of different wavelet filter banks with perfect reconstruction, lifting scheme can easily build up a gradually improved multi-resolution analysis through iterative primal lifting and dual lifting. It turns out that lifting scheme outperforms the classical especially in effective implementation, such as convenient construction, in-place computation, lower computational complexity and simple inverse transform etc. We can also build wavelets with more vanishing moments and more smoothness, contributing to its flexible adaptivity and non-linearity.

In existing there are many methods to retrieve the face images some of those are color face image retrieval, histogram face image retrieval, semantic feature extraction, discrete cosine transform, LDA, and wavelet. But had some disadvantages those techniques like In color feature extraction we cannot able to retrieve the similar images with different color, The Discrete Cosine Transform (DCT) we can handle only in frequency_domain, we cannot handle in spatial domain and when we use the shape based face image retrieval detecting the edges of the images and segmentation the images is difficult. The lifting scheme has many advantages over the previous approaches.

Principal Component Analysis (PCA) method is widely used for dimensionality reduction and recorded a great performance in face image retrieval. PCA based approaches typically include two phases training and classification. In the training phase, an Eigen space is established from the training samples using PCA method and the training face images mapped it for classification.

In this paper we use lifting schemes to decompose grey scale images into multilevel scale and wavelet coefficients, then image feature extraction and similarity match by means of Euclidian distance and Manhattan distance methods.

2. GENERAL STRUCTURE OF PROPOSED FACE RETRIEVAL SYSTEM

Fig.2.1 shows the basic block diagram of Face image retrieval system. Our Proposed method compares the performance of face image retrieval using LWT-PCA with similarity matching by using Euclidian distance method.

We compared two methods; in first method all train images decomposed using discrete wavelet transform. After DWT, we are taking only low frequency components (LL) of the image for further dimensionality reduction by using PCA. Then the final feature vectors of all the train images are stored in the database. Same process is done for query image. Finally first 5 similar face images are retrieved by using Euclidian distance method.

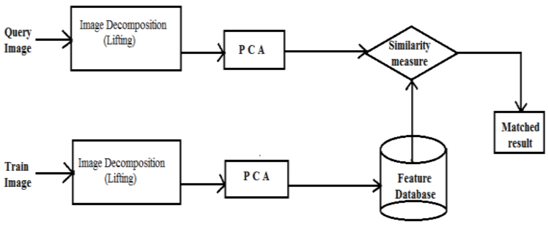

Fig 2.1 Block diagram of our Proposed System

3. LIFTING WAVELETS TRANSFORM

Any Discrete Wavelets Transform with Finite filters can be decomposed into a finite sequence of simple filtering steps, which are called the lifting steps. Fig.4.1 shows the forward wavelet transform using lifting scheme. This decomposition related to a factorization of the polyphase matrix of wavelet or sub band filters into elementary matrices is described as follows. The polyphase representation of a discrete-time filter h(z) is defined as

$$h(z) = he(z^2)+z^{-1}ho(z^2) \qquad \textbf{(3.1)}$$

Where he denotes the even coefficients, and ho denotes the odd coefficients.

$$h_e(z) = \sum_k h_{2k} z^{-k}$$
$$h_o(z) = \sum_k h_{2k+1} z^{-k} \qquad \textbf{(3.2)}$$

The low pass filter h(z) and High pass filter g(z) can thus be represented by their poly phase matrix

$$P(z) = \begin{bmatrix} h_e(z) & g_e(z) \\ h_o(z) & g_o(z) \end{bmatrix} \text{ and } \tilde{P}(z)$$

can also be defined for the analysis filter analogously.

The filters he (z), ho (z), g_e (z) and g_o (z), along with their analysis counterparts, are Laurent polynomials. As the set of all Laurent polynomials exhibits a commutative ring structure, within which polynomial division with remainder is possible, long division between Laurent polynomials is not a unique operation. The Euclidean algorithm can be used to decompose P (z) Ṗ (z) as

$$P(z) = \prod_{i=1}^{m} \begin{bmatrix} 1 & s_i(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ t_i(z) & 1 \end{bmatrix} \begin{bmatrix} k & 0 \\ 0 & 1/k \end{bmatrix}$$

$$\check{P}(z) = \prod_{i=1}^{m} \begin{bmatrix} 1 & 0 \\ -s_i(z^{-1} & 1 \end{bmatrix} \begin{bmatrix} 1 & -t_i(z^{-1}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1/K & 0 \\ 0 & K \end{bmatrix} \qquad \textbf{(3.3)}$$

As this factorization is not unique, several pairs of {si(z)} and {ti(z)} filters are admissible However, in case of DWT implementation, all possible choices are equivalent.

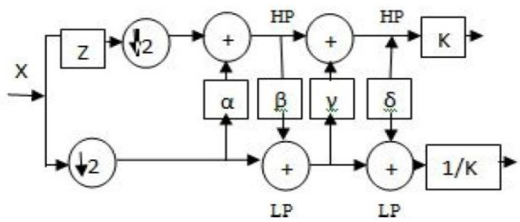

Fig 3.1 Block diagram of the forward wavelet transform using lifting scheme

4. PRINCIPLE COMPONENT ANALYSIS

Principal component analysis is classical method used in statistical pattern recognition and signal processing for dimensionality reduction and feature extraction. Every test image can be transformed to low dimensional feature vector to be projected onto the eigen face space which was obtained from the training set. This feature vector can then be compared with the set of feature vectors obtained from the training set. The face classifier can use different distance measures such as Euclidean distance or cosine distance. The PCA algorithm
Can be detailed as follows
Let the training set of face images be $\Gamma_1, \Gamma_2 \ldots \Gamma M$ then the average of the set is defined by

$$\mathbf{\Psi=1/M} \sum_{n=1}^{M} \mathbf{\Gamma_n} \qquad \textbf{(4.1)}$$

Each face differs from the average by the vector

$$\Phi i = \Gamma_i - \Psi \qquad \textbf{(4.2)}$$

This set of very large vectors is then subject to PCA, which seeks a set of *M* orthonormal
Matrix C can be defined as

$$C = 1/M \sum_{n=1}^{M} \Phi_n \Phi_n^T = A A^T \qquad \textbf{(4.3)}$$

The Vectors, Um, which best describes the distribution of the data. Then the covariance Where the matrix A =[$\Phi_1 \Phi_2 \ldots \Phi M$]. The covariance matrix C; however is N2×N2 real Symmetric matrix, and determining the N2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors.

Consider the eigenvectors v_i of $A^T A$ such that

$$A^T A v_i = \mu_i v_i \qquad \textbf{(4.4)}$$

Premultiplying both sides by A, we have

$$A A^T A v_i = \mu_i A v_i \qquad \textbf{(4.5)}$$

Where we see that Av_i are the eigenvectors and µi are the eigenvalues of $C=AA^T$. Following these analysis, we construct the $M \times M$ matrix $L = A^T A$, where $L_{mn} = \Phi_m^T \Phi_n$ and find the M eigenvectors, v*i*, of L. These vectors determine linear combinations of the M training set face images to form the eigen faces U_I.

$$U_I = \sum_{k=1}^{M} V_{1k} \Phi_k, \quad I=1\ldots M \tag{4.6}$$

With this analysis, the calculations are greatly reduced; from the order of the number of pixels in the images (*N*2) to the order of the number of images in the training set (*M*). The associated eigenvalues allow us to rank the eigenvectors according to their usefulness in characterizing the Variation among the images.

A new face image (Γ) is transformed into its eigen face components (projected onto "face space") by a simple operation,

$$w_k = U_k^T (\Gamma - \Psi) \tag{4.7}$$

For $k = 1 \ldots M$, the weights form a projection vector,

$$\Omega^T = [w_1, w_2, \ldots w_T] \tag{4.8}$$

Describing the contribution of each eigen face in representing the input face image, treating the eigen faces as a basis set for face images. The projection vector is then used to find which of a number of predefined face classes that best describes the face.

5. EUCLIDEAN DISTANCE

The Euclidean distance between two vectors x and y in d-dimensional space is a typical distance measure that reflects their proximity in the space. Measuring the Euclidean distance is a fundamental operation in computer science, including the areas of database, computational geometry, computer vision and computer graphics. In machine learning, the Euclidean distance, denoted by dist(x; y), Euclidean distance widely used to measure data similarity for clustering, classification and so on.

$$d(\mathbf{p},\mathbf{q}) = \sqrt{(p_1-q_1)^2 + (p_2-q_2)^2 + \cdots + (p_n-q_n)^2} = \sqrt{\sum_{i=1}^{n} (p_i-q_i)^2}.$$

6. MANHATTAN DISTANCE

The Manhattan distance function computes the distance that would be travelled to get from one data point to the other if a grid-like path is followed. The Manhattan distance between two items is the sum of the differences of their corresponding components.

The formula for this distance between a point ***X***=(***X1***, ***X2***, etc.) and a point ***Y***=(***Y1***, ***Y2***, etc.) is:

$$d = \sum_{i=1}^{n} |X_i - Y_i|$$

Where n is the number of variables, and ***Xi*** and ***Yi*** are the values of the *i*th variable, at points ***X*** and ***Y*** respectively.

7. PERFORMANCE EVALUTION

The performance of CBIR system is calculated with the help of training set and test set. Here we can measure the accuracy and error rate by given formulas.

For example 100 images are there 80 used for training and remaining 20 used for testing.

$$\text{Accuracy} = \frac{\text{No. of training data}}{\text{Total No. of Image}}$$

$$\text{Error} = \frac{\text{No. of test data}}{\text{Total No. of image}}$$

8. SIMULATION RESULTS

We performed our simulations on the ORL database with the platform of MAT Lab 7.8. This database consists of 400 face images attained from 50 people. Each people have 10 images of different expression, poses and different lighting conditions. The resolution rate of each image is 112X92 and the gray scale is 256. Out of the 500 images in the ORL face database, first 499 were selected for training and each images were used for testing. Fig.8 shows sample images from the database.

Our experiment gives the result of Face image retrieval using LWT-PCA both in level1 and level2 decompositions. Here feature extraction is done by using LWT and further dimension reduction is done by using PCA.

The Similarity matching is achieved by using Euclidian distance method. Fig.8.a, b shows the Query face image and the retrieved face images of 5 most similar images illustrated respectively. The Average Retrieval accuracy and Average Standard deviations class wise retrieval accuracy and standard deviation using LWT-PCA for both level1 and level2 decomposition Table is shown in Table 1.

Fig 8.1 ORL Database

Fig 8.a. Query Image

Fig 8.b. Retrived Images

Methods	Average retrieval Accuracy in %	Average Standard Deviation
LWT-PCA (Level-1)	91.85	8.68
LWT-PCA (Level-2)	93.45	8.875

Table1: Average total Retrieval Accuracy and Total average Standard

9. CONCLUSION

The Face image retrieval using LWT with PCA are proposed. This method compared with Euclidean distance and Manhattan distance also. The DWT with PCA using 'db1' wavelet with Level2 method outperforms well for Retrieval Accuracy. LWT with PCA method gives less elapsed time. In future, enhanced the face image retrieval using other transform methods and will improve the retrieval accuracy. This proposed method used such as photo management, visual surveillance, criminal face identification and searching specific faces from the internet etc.

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