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Research Article

Face Recognition System Based on Spectral Graph Wavelet Theory

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Abstract: This study presents an efficient approach for automatic face recognition based on Spectral Graph Wavelet Theory (SGWT). SGWT is analogous to wavelet transform and the transform functions are defined on the vertices of a weighted graph. The given face image is decomposed by SGWT at first. The energies of obtained sub-bands are fused together and considered as feature vector for the corresponding image. The performance of proposed system is analyzed on ORL face database using nearest neighbor classifier. The face images used in this study has variations in pose, expression and facial details. The results indicate that the proposed system based on SGWT is better than wavelet transform and 94% recognition accuracy is achieved.

Keywords: Chebyshev polynomial, face recognition, nearest neighbor classifier, spectral graph wavelet theory

INTRODUCTION

In computer vision and machine learning, automatic recognition of face has been a popular research field for the past two decades. In face recognition system, the comparison of test image with the database images is done in many ways to identifies one person. De Marsico *et al*. (2013) explained a novel framework for real world face recognition in uncontrolled settings. Its robustness comes from normalization strategies to address pose and illumination variations. It improves accuracy performance compared to state-of-art methods, for uncontrolled settings when the image acquisition conditions are not optimal.

Zafeiriou *et al*. (2013) described a new database collected in both 2D and 3D for real time face recognition based on Photometric Stereo (PS). The database is collected using a custom-made four-source PS device designed to enable data capture with minimal interaction necessary from the subjects. Four source PS methods produce facial samples that achieve constantly better recognition and verification performance than 3 sources PS regardless of the reconstruction methods applied. Gradient information containing pixel wise interaction properties within small scale neighbourhoods is first considered in Vu (2013) for face recognition systems. This information is then incorporated over regions of larger scale and finally encoded in more extended image patches by considering their relationships. The obtained features have several desirable properties and lead to accurate yet fast face recognition systems.

Vageeswaran *et al*. (2013) explained a blur robust face recognition algorithm. It is used to solve the problems of blur and recognizing blurred and poorly illuminated faces from remotely acquired images. Based on set theoretic characterization, illumination robust algorithm also implemented. These algorithms are based on a generative model followed by nearest neighbour classification between the query image and the gallery space. A nonnegative sparse representation approach, called two stages Sparse Representations (TSR), for robust face recognition on a large-scale database is described in He *et al*. (2013). Based on the divide and conquer strategy, TSR decomposes the procedure of robust face recognition into outlier detection stage and recognition stage. In the first stage, a general multi subspace framework is proposed to learn a robust metric in which noise and outliers are detected. In the second stage, based on the learned metric and collaborative representation, an efficient nonnegative sparse code algorithm is proposed to find an approximation solution of sparse representation.

A linear discriminate regression classification algorithm is implemented in Huang and Yang (2013a) to boost the effectiveness of the Linear Regression Classification (LRC) for face recognition. It embeds discriminate analysis into the linear regression classification algorithm for seeking an optimal projection matrix such that the LRC on that subspace has high discriminatory ability for classification. The intrinsic structure of the error incurred by occlusion from morphological feature and the probabilistic distribution is reviewed in Li *et al*. (2013). Based on these two methods, Structured Sparse Error coding model for face recognition with occlusion is

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implemented. This method is more stable and has higher breakdown point in dealing with the occlusion problems in face recognition.

Lu and Tan (2013) described a cost sensitive subspace analysis approach for face recognition. It uses a cost matrix specifying different costs corresponding to different types of misclassifications, into two popular and widely used discriminative subspace analysis methods and devises the cost sensitive linear discriminant analysis and cost sensitive marginal fisher analysis methods, to achieve a minimum overall recognition loss by performing recognition in these learned low dimensional subspaces. A novel robust kernel representation model with statistical local features for robust face recognition is employed in Yang *et al*. (2013). Kernel representation is represented by methods, which are multipartition max pooling technology is implemented to enhance the invariance of local features to image registration error and robust kernel representation model. It also adopts with robust regression function as the measure to effectively handle the occlusion in facial images.

A unitary regression classification algorithm implemented in Huang and Yang (2013b) is used to improve the robustness of face recognition, which could achieve total minimum projection error. It minimizes the total intra class reconstruction error from all classes to find an optimal projection for linear regression classification. In the recognition phase, the recognition is determined by calculating the minimum projection error on the unitary rotation subspace. Automatic approach for matching surveillance quality facial images to high-resolution images in frontal pose is described in Biswas *et al*. (2013). The basic intuition is to simultaneously transform the features from the probe and the gallery images such that the distances between them approximate the distances had the probe image been taken in the same conditions as the gallery images.

An *et al*. (2013) employed a multi camera face recognition system using dynamic bayesian network. It is suitable for applications such as surveillance monitoring in camera networks. This method uses videos from multiple cameras to provide complementary information for robust recognition result. An approach that explicitly models the cross modal data association is implemented in Tawari and Trivedi (2013). Two different rule based data association approaches are investigated. The use of audio data could improve the recognition performance in terms of computation as well as recognition accuracy.

In this study, a new approach for face recognition system based on Spectral Graph Wavelet Theory (SGWT) is presented.

METHODOLOGY

Spectral graph wavelet theory: The spectral graph wavelet transform (Hammond *et al*., 2011) is generated by wavelet operators that are operator-valued functions of the Laplacian. A measurable function of abounded self-ad joint linear operator on a Hilbert space is defined using the continuous functional calculus (Reed and Simon, 1980). This is achieved using the spectral representation of the operator. In particular, for our spectral graph wavelet kernel g, the wavelet operator $T_g = g(L)$ acts on a given function f by modulating each Fourier mode as:

$$\widehat{T_g f}(l) = g(\lambda_l)\hat{f}(l) \tag{1}$$

Employing the inverse Fourier transforms yields:

$$(T_g f)(m) = \sum_{l=0}^{N-1} g(\lambda_l)\hat{f}(l)X_l(m) \tag{2}$$

The wavelet operators at scale t are then defined by $T_g^t = g(tL)$. It should be emphasized that even though the "spatial domain" for the graph is discrete, the domain of the kernel g is continuous and thus the scaling may be defined for any positive real number t. The spectral graph wavelets are then realized through localizing these operators by applying them to the impulse on a single vertex, i.e.:

$$\psi_{t,n} = T_g^t \delta_n \tag{3}$$

Expanding this explicitly in the graph domain shows:

$$\psi_{t,n}(m) = \sum_{l=0}^{N-1} g(t\lambda_l)\chi_l^*(n)\chi_l(m) \tag{4}$$

Formally, the wavelet coefficients of a given function f are produced by taking the inner product with these wavelets, as:

$$W_f(t,n) = \langle \psi_{t,n}, f \rangle \tag{5}$$

Using the orthonormality of the $\{\chi_l\}$, it can be seen that the wavelet coefficients can also be achieved directly from the wavelet operators, as:

$$W_{f(t,n)} = (T_g^t f)(n) = \sum_{l=0}^{N-1} g(t\lambda_l)\hat{f}(l)\chi_l(n) \tag{6}$$

By construction, the spectral graph wavelets $\psi_{t,n}$, are all orthogonal to the null eigenvector χ_0 and nearly orthogonal to χ_l for λ_l near zero. In order to stably represent the low frequency content of f defined on the vertices of the graph, it is convenient to introduce a second class of waveforms, analogous to the low pass residual scaling functions from classical wavelet analysis. These spectral graph scaling functions have an analogous construction to the spectral graph wavelets. They will be determined by a single real valued function h: $R^+ \rightarrow R$, which acts as a low pass filter and satisfies $h(0)>0$ and $h(x)\rightarrow 0$ as $x\rightarrow 0$. The scaling functions are then given by $\phi_n = T_h\delta_n = h(L)\delta_n$ and the coefficients by $S_f(n) = \langle \phi_n, f \rangle$.

PROPOSED METHOD

The main step in the proposed face recognition system is feature extraction. This module transforms the input face image which is in the spatial domain into SGWT, a frequency domain analysis similar to wavelet transform. The primary motivation to use SGWT is that they provide synchronized localization in both time and frequency domain. Figure 1 shows the overall automated process for face recognition based on SGWT.

As SGWT is a filtering technique, the response energies are used as features. The response energies are calculated by squaring SGWT decomposed coefficients at each sub-band. Then the sub-band energies are fused to form the feature vector. Thus the feature vector consists of energies of all sub-bands for recognition. The proposed feature vector is computed for all selected training samples and used for training the classifier. The face image to be recognized is decomposed by SGWT and the proposed feature vector for the corresponding unknown face image is computed as in the training step. Then the feature vector is compared with that of each person feature vectors in the database and recognized with a minimum distance method using Euclidean distance.

RESULTS AND DISCUSSION

In this section, the assessment of the proposed face recognition system based on SGWT is discussed. The ORL face database (Samaria and Harter, 1994) is chosen for evaluation due to the fact that the face images in the database have high degree of variability in expression, pose and facial details. This database consists of 400 images of 40 individuals. Figure 2 shows all 10 views of a sample subject. All the images in the ORL face database are considered for the recognition test. The performance of the proposed system is analyzed by increasing the training samples and remaining samples are tested. The recognition accuracy is used as performance measure.

As the features are extracted by decomposing the input face image by SGWT, the performance of the system is analyzed by changing the decomposition level

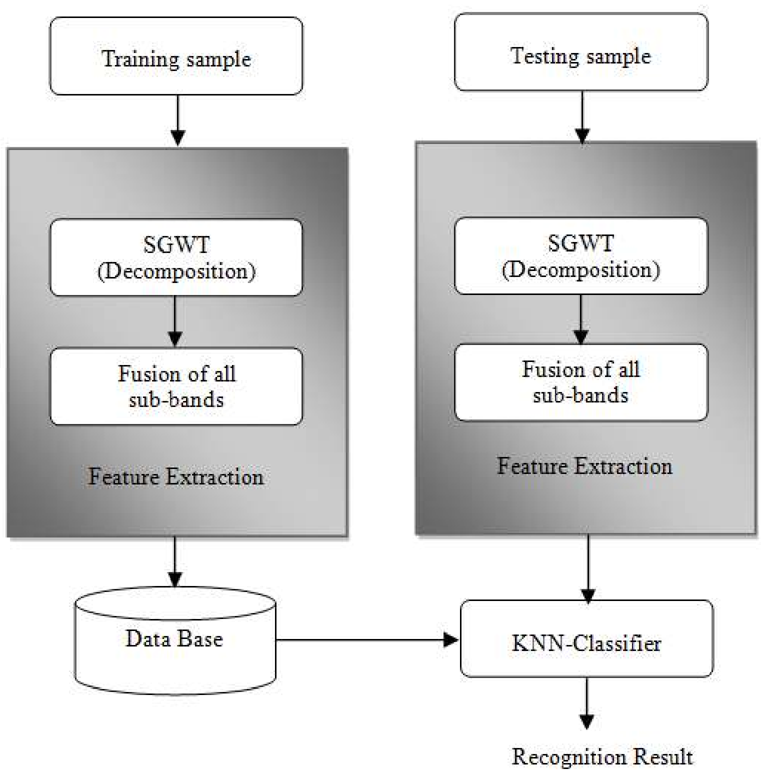

Fig. 1: Overall automated system for face recognition using spectral graph wavelet theory

Fig. 2: Sample face images of a subject from the ORL database

Table 1: Recognition accuracy using SGWT with polynomial order of 10

Decomposition level	# Training samples 1	2	3	4	5
1	71.67	83.44	90.00	90.83	94.00
2	71.67	83.13	88.57	90.42	93.00
3	72.78	83.44	88.57	90.00	93.00
4	72.78	83.13	88.21	89.58	93.00
5	72.78	83.13	89.64	90.83	93.00

of SGWT. Table 1 shows the recognition accuracy obtained by the proposed system. While calculating, SGWT decomposed image, the chebyshev polynomial of Laplacian applied to the input vector is 10 and maximum of 50% images are used for training the nearest neighbour classifier.

The results show that the recognition accuracy of the proposed approach increases as the number of training images increases. Also it is noted that the effect on increasing the level decomposition does not affect the recognition accuracy. The proposed system achieves 94% accuracy while using 50% of training images. Among the 200 test images only 12 face images are wrongly recognized. As the decomposition of SGWT depends on the chebyshev polynomial, the impact on changing the polynomial order is also analyzed. Figure 3 shows the performance of the proposed approach over different polynomial order used.

It is clearly observed from the Fig. 3 that the change in the recognition accuracy is very low and the changes are in a narrow band while changing the polynomial order. Hence, the polynomial order of 10 is chosen for the proposed approach. The proposed face recognition system using SGWT is compared with state-of-art wavelet transform technique. Figure 4 shows the computed recognition accuracy of proposed system in comparison with wavelet transform on the ORL database.

It is seen that the proposed approach based on SGWT performs better than wavelet transform. The recognition accuracy of the proposed system is over 3% approximately in comparison with wavelet transform. The experimental results also indicate that SGWT

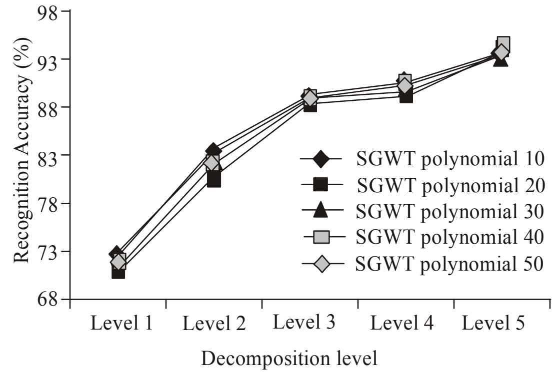

Fig. 3: Recognition accuracy vs. polynomial order used in SGWT on the ORL database

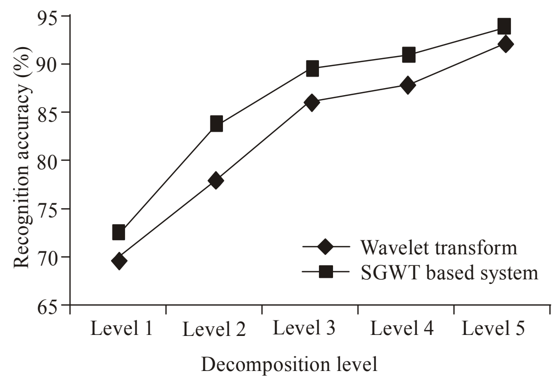

Fig. 4: Recognition accuracy of proposed system vs. wavelet transform on the ORL database

based face recognition is superior than wavelet based features.

CONCLUSION

In this study, an efficient face recognition system based on SGWT is proposed. SGWT is analogous to the wavelet transform. The face image is decomposed at various level of decomposition. The performance of the proposed approach is evaluated at each level and the computed recognition accuracy is also tabulated. The nearest neighbor classifier with Euclidean distance measure is used for recognition. The experiments on ORL database shows the effectiveness of the proposed system for face recognition in comparison with wavelet transform.

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