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RESEARCH ARTICLE

Spectral Graph Wavelet Theory with Statistical Features for Face Recognition

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ABSTRACT

Spectral Graph Wavelet Theory(SGWT) is one of the modern techniques in imaging science and is used for face recognition in this project.Spectral Graph Wavelet Theoryimplements an efficient approach for automatic face recognition.Like wavelet transform SGWT is defined atthe arbitrary finite weighted graph vertices and the transform functions are defined on the weighted graph vertices.At first the SGWT decay the given face image.The obtained sub-band energies are combined together and the corresponding image is considered as feature vector.Using nearest neighbor classifier,face images in the ORL database is analyzed in the proposed system.The input face image hasposevariations, and also variation in expression and face details,which is used in this study.Thus the proposed system based on Spectral Graph Wavelet Theory produced better result and achieved 96% of recognition accuracy.

Keywords: Robust face recognition, Multipartition, Representation of spectral graph, Wavelet transform, Linear regression classification.

1. INTRODUCTION

Face Recognition has become a hot research area owing to its convenience in daily life. Also automatic recognition of face has been famous for previous research outcomes.Face recognition is not perfect and struggles to perform under certain conditions. In this face recognition method, the comparison between the test image with the database image is proved in several ways to identify a person. [1] explained a hierarchical segmentation algorithm that starts with a very fine over segmentation and gradually merges regions using a cascade of boundary classifiers. This approach allows the weights of region and boundary features to adapt to the segmentation scale at which they are applied. The stages of the cascade are trained sequentially, with asymmetric loss to maximize boundary recall. On six segmentation data sets, our algorithm achieves best performance under most region-quality measures, and does it with fewer segments than the prior work. Our algorithm is also highly competitive in a dense over segmentation (super pixel) regime under boundary-based measures. [2] addressed the problem by proposing a discriminative deep face shape model that is constructed based on an augmented factorized three-way Restricted Boltzmann Machines model. Specifically, the discriminative deep model combines the top-down information from the embedded face shape patterns and the bottom up measurements from local point detectors in a unified framework. In addition, along with the model, effective algorithms are proposed to perform model learning and to infer the true facial point locations from their measurements. Based on the discriminative deep face shape model, 68 facial points are detected on facial images in both controlled and “in-the-wild” conditions. Experiments on benchmark data sets show the effectiveness of the proposed facial point detection algorithm against state-of-the-art methods.

[3] explained a unified framework which is capable to extract multiple

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information from the human faces and at the same time are robust against rigid and non-rigid facial deformations. A single feature vector corresponding to a given image is representative of person's identity, facial expressions, gender and age estimation. This feature set is called spatio-temporal multi feature (STMF) extracted from image sequences. An STMF is configured with three different feature components which is tested thoroughly to evidence its validity. The experimental results from four different databases show that this feature set provides high accuracy and at the same time exhibits robustness. The results have been discussed comparatively with different approaches. Another approach explained a novel framework [4] 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.[5] 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 being necessary from the subjects. Four source PS methods produce facial samples that achieve constantly better recognition and verification performance than 3 source PS regardless of the reconstruction methods applied. Gradient information containing pixel wise interaction properties within small scale neighbourhoods is first considered in [6] for face recognition systems. This information is then incorporated over regions of larger scale and finally encoded into more extended image patches by considering their relationships. The obtained features have several desirable properties and lead to accurate yet fast face recognition systems. [7] 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 is 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 [8]. 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. [9] A linear discriminate regression classification algorithm is implemented in [10] 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 [11]. Based on these two methods, Structured Sparse Error coding model for face recognition with occlusion is implemented. This method is more stable and has higher breakdown point in dealing with the occlusion problems in face recognition. It described a cost sensitive subspace analysis approach for face recognition. [12] 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 [13].

Kernel representation is represented by methods, which are called multipartition max pooling technology and 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 [9], it 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 [14].

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 that the probe image would have been taken in the same conditions as the gallery images.

[15] 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 [16]. 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 learning, a new method for Facial recognition using Spectral Graph Wavelet Theory is presented.

2. PROCEDURE

2.1. Spectral Graph Wavelet Theory (SGWT)

The spectral graph wavelet transform [17] is created by wavelet operators that are operator-valued functions of Laplacian. A quantifiable function of flourished self-ad joint rectilinear operator on Hilbert space is well-defined by means of the endless functional calculus [18]. This is attained by using spectral representation of an operator. The analysis is carried out by means of equations (2.1),(2.2),(2.3),(2.4),(2.5) and (2.6). Specifically, for our method, spectral graph wavelet kernel g, the wavelet operator $Tg = g(L)$ will be represented as given function f by modifying each Fourier mode as:

$$Tgf\Delta$$

$$Tgf\nabla(l) = g(\boldsymbol{\lambda l})\boldsymbol{f}\Delta(\boldsymbol{l})(2.1)$$

Using the inverse Fourier transforms yields:

$$(Tgf)(m) = \varepsilon N - 1g(\lambda l)f\Lambda(l)Xl(m)(2.2)$$

The wavelet operators at scale t is defined by $Tgt = g(tL)$ .It would be stressed that even though the "spatial domain" graph is discrete, domain of the kernel g is continuous and so scaling may be explained for any positive real number t. The SGWT is then standardized through focusing these operators and by applying them to the compulsion on an only one vertex, i.e.:

$$\psi tn = Tgt\delta n \qquad (2.3)$$

Expanding this openly in graph area shows:

$$\psi t,n(m) = N\xi - 1g(t\lambda l)Xl*(n)X*(n)Xl(m) \qquad (2.4)$$

Formally, the given function f of the wavelet coefficients are manufactured by taking the inside product with these wavelets, given as:

$$Wf(t,n) = \psi t,n,f \quad (2.5)$$

Employing the orthonormality of {X1}, this {X1} can be seen as the wavelet coefficients and also can be reached directly from the wavelet operators, as:

$$Wf(t,g) = (Tgtf)(n)$$

$$= \sum_{n=N}^{N-1} g(t\lambda l)f\ (l)Xl(n) \quad (2.6)$$

By formation, the spectral graph wavelets $\psi t,n$ are completely orthogonal to zero eigenvector X0 and nearly orthogonal to X1for $\lambda 1$ near to zero. In order to steadily characterize, the small frequency content of f is denoted as the vertices of the graph such that it is convenient to acquaint with next class waveforms, equivalent to the low pass remaining classical wavelet analysis in a scaling function. These spectral graph scaling functions have an equivalent construction to the SGW. They will be explained by only one real valued function h:R $\longrightarrow^{+} R$. Spectral graph wavelet acts as a low pass filter and fulfills h(0)>0 and h(x) $\longrightarrow$ 0 as x $\longrightarrow$ 0. The scaling function are given by h_n=()n and the coefficients by S_f(n)= $\varphi n, f$.

3. PROPOSED METHODOLOGY

In the proposed methodology, feature extraction is the main step for face recognition. The spatial domain has input face image which transforms in to SGWT. By this module, a frequency domain analysis and wavelet transform are regarded to be similar. The main motivation of using the SGWT is that they give synchronized localization in time domain and frequency domain. Figure A1shows the completely automated process for facial recognition based on Spectral Graph Wavelet Theory. Spectral Graph Wavelet Theory is a filtering technique, in which the response energies are used structurally. The response energies are calculated by squaring SGWT coefficients of decomposed sample at each sub-band. The Squaring Spectral Graph Wavelet Theory calculates the response energies and this module decomposes coefficient at sub-band. All the sub-bands are joined to form a feature vector. For recognition, those feature vector consists of energies of sub-bands. All the selected training samples are computed by proposed feature vector and it is used for training the classifier. The SGWT decomposed the face image which has to be recognized and computed. The corresponding unknown face image is proposed in the future. Then for each person feature vectors in the database as shown in figure 1 are to be compared with the feature vector and using the Euclidean distance which has a minimum distance it is to be recognized.

Figure 1.All views of a sample subject in the ORL face database

4. EXPERIMENTAL RESULT

In result and discussion the appraisal of proposed facial recognition using Spectral Graph Wavelet Theory is disputed. The fact is that the face images database have high degree of variability in expression, pose and facial details so that ORL face database is chosen [16].There are 400 images of 40 individuals in this database. Figure 1.shows sample subject which has in all 10 views. The ORL face database has all the images to be considered for the recognition test. The proposed system performance is analyzed by increasing the tested training samples and remaining samples. Thus the accuracy of face recognition is used as a performance measure. As the features are taken out by decomposing the input face image by SGWT specifically by changing the decomposition level of SGWT the performance of the system is analyzed.

Table 1.Recognition accuracy obtained by SGWT with polynomial order of 10

Decay level	#Training samples				
	1	2	3	4	5
1	72.66	82.45	91.00	91.80	95.00
2	72.68	82.41	87.67	98.67	92.00
3	77.90	78.90	90.89	93.90	92.00
4	72.90	83.45	88.67	87.90	92.00
5	72.89	84.14	89.76	90.84	94.00

Table1 shows recognition accuracy obtained by SGWT. While calculating the decay image of SGWT, the polynomial of lapalacian applied to the input vectors is 11 and images of maximum 50% size are used by nearest neighbour classifier for training.

This shows when number of training images increases the recognition accuracy of the approach increases. It is also noted that accuracy of recognition is not affected by the increase in the decomposition of level. Therefore the proposed approach attains98% accuracy while using training images of 62%. Out of the 300 test images only 10 face images were wrongly recognized. As the decay of Spectral Graph Wavelet Theory which depends on the chebyshev polynomial is also affected on changing the polynomial order, it is examined. Figure 2 denotes the different polynomial order used by performing the proposed method. Figure 2 shows that while changing the polynomial order there is change in the narrow band and also in the recognition system which is very low. The SGWT used by the proposed face recognition system is being compared with the state-of-art wavelet transform technique. Figure 3 shows the comparison between the computed recognition accuracy of the proposed system and the wavelet transform on the ORL database.

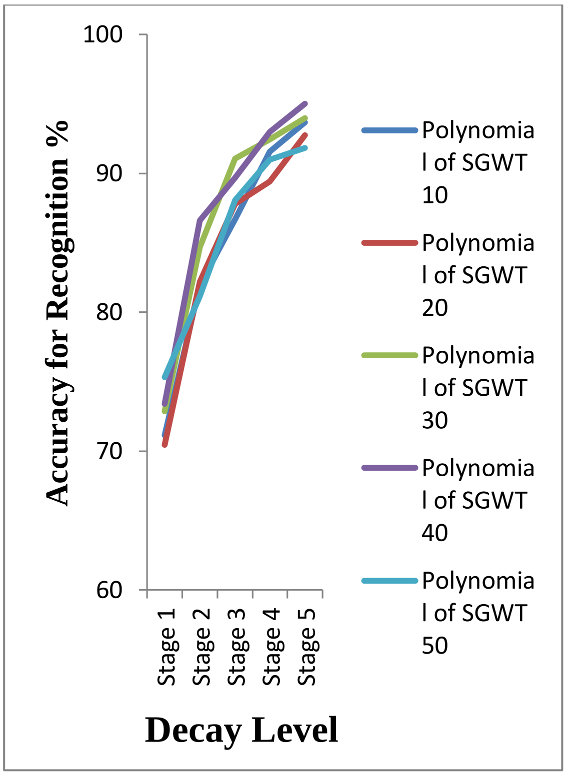

Figure 2.Accuracy for recognition Vs polynomial order of SGWT on the ORL database of face

Thus the result shows that the proposed method using the Spectral Graph Wavelet Theory produced better result and good performance than the wavelet transform technique. The face recognition accuracy of proposed method is approximately over 5% when compared to the wavelet transform.

Thus the practical results define that the Face recognition Spectral Graph Wavelet Theory is excellent than the wavelet based techniques.

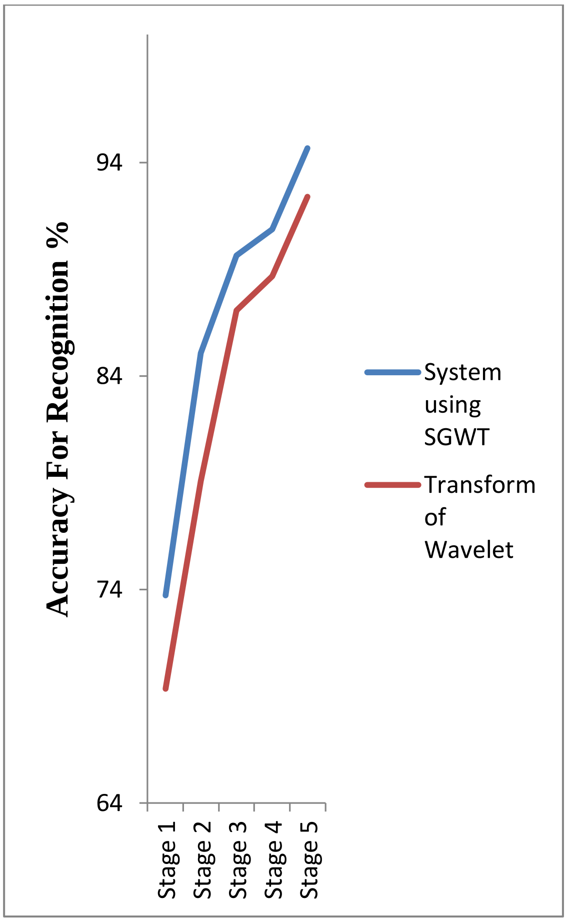

Figure 3.Comparison between the computed recognition accuracy of proposed system based SGWT and the wavelet transform on the ORL database

5. CONCLUSION

In this proposed method excellent and efficient Spectral Graph Wavelet Theory is used by the face recognition method. Spectral Graph Wavelet Theory is equivalent to the wavelet transform. At each level the proposed method performance is assessed and also the computed accuracy of recognition is tabulated. For face recognition a Euclidean distance measure and the nearest neighbor classifier is used. Thus the experimental result shows that the efficiency of face recognition accuracy of proposed method with wavelet transform on the ORL database is great.

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APPENDIX A

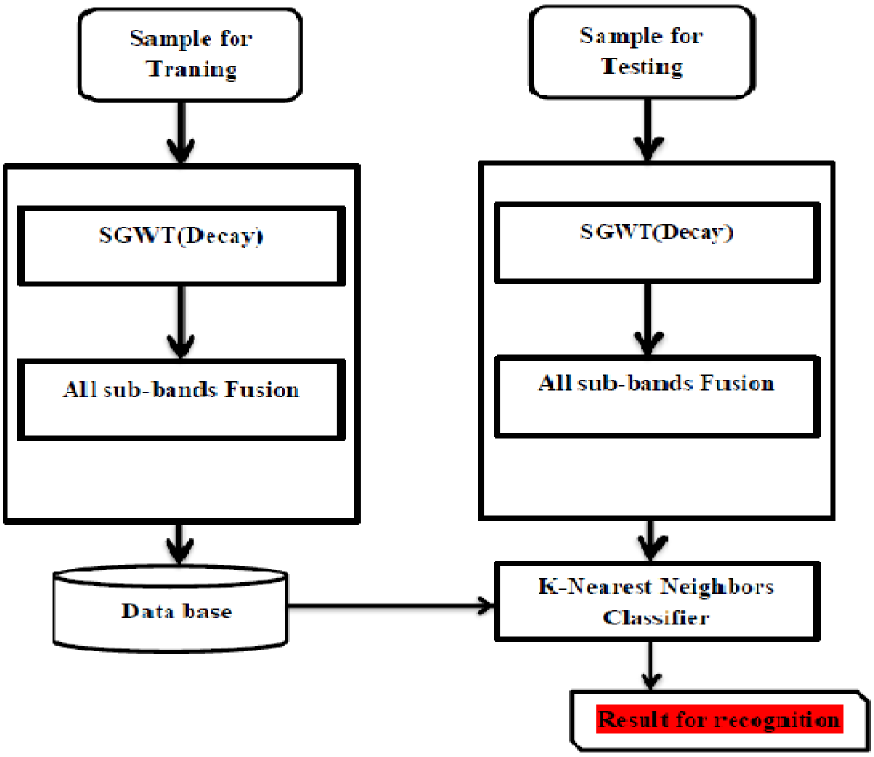

Figure A1. Automated process for facial recognition using Spectral Graph Wavelet Theory