DT-CWT Based Face Recognition Using PNN and SVM

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Abstract

Face recognition is a biometric tool for authentication and verification. In this paper we investigate the performances of some face recognition systems. We use DT-CWT for feature extraction and PNN and SVM for classification. The DT-CWT has approximate shift invariance, good directional selectivity and can provide effective feature representation for face images. ORL face database is used for experiment. We compare the performance results of PNN and SVM methods. We also show that the system developed with DT-CWT has better results than the system developed with DWT.

Key words: Face recognition, DT-CWT, PNN, SVM

1. Introduction

Face recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame [1]. Biometric identification is becoming more popular now a day's, due to the existing security requirements of society in the field of information, business, military, e-commerce and etc. [2].

Many techniques have been proposed in the literature for feature extraction part of face recognition. Some of these include principal components analysis [3], discrete wavelet transform [4, 5], and discrete cosine transform [6]. Gabor wavelets have been extensively implemented in many face recognition approaches [7, 8].

Even though Gabor wavelet-based face image representation is optimal in many respects, it has got two important drawbacks that shadow its success. First, it is computationally very complex. A full representation encompassing many directions (e.g., 8 directions), and many scales (e.g., 5 scales) requires the convolution of the face image with 40 Gabor wavelet kernels. Second, memory requirements for storing Gabor features are very high. The size of the Gabor feature vector for an input image of size 128x128 pixels is 128x128x40 = 655360 pixels when the representation uses 8 directions and 5 scales [9].

There are lots of studies about face recognition in the literature. Karmakar and Murthy are proposed a facial feature extraction method where color face images are autocropped and control points are extracted, both using the same segmentation mechanism [10]. Mohamed et al. present a new approach to face recognition based on the combination of feature extraction methods, such as two-dimensional DWT-2DPCA and DWT-2DLDA, with probabilistic neural networks [11]. Sastry and Yi Ma provide a comprehensive review of five

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representative l_1 minimization methods, i.e., gradient projection, homotopy, iterative shrinkage-thresholding, proximal gradient, and augmented Lagrange multiplier [12]. Huang et al. propose a method for face recognition by using the two dimensional discrete wavelet transform (2D-DWT) and a new patch strategy [13]. Wagner et al. propose a conceptually simple face recognition system that achieves a high degree of robustness and stability to illumination variation, image misalignment, and partial occlusion [14]. Patil et al. propose A methodology for automatic facial expression recognition in image sequences is proposed, which makes use of the Candide wire frame model and an active appearance algorithm for tracking, and support vector machine (SVM) for classification [15].

In this paper, a face recognition algorithm based on DT-CWT using PNN and SVM classifiers is presented. The success performance of the methods used are evaluated and compared. The rest of the article is organized as follows: In the second section details of the proposed methods have been described. Face recognition process and its evaluation will be described in the third section. Finally, in the fourth section the results obtained from the study will be described.

2. Materials and Methods

2.1. 2D DT-CWT

For one dimensional (1-D) signals, a naive implementation of the CWT is to use a single analysis filter bank with complex coefficients satisfying perfect reconstruction (PR) properties. However designing such complex filters is a difficult task. Furthermore, complex filters that have PR properties amplify noise during the reconstruction stage. For 1-D, signals dual tree implementation of the CWT uses two analysis filter banks each with real coefficients. The two filter banks are designed such that the wavelet associated with one filter bank is an approximate Hilbert transform of the wavelet associated with the other filter bank. For 2-D signals, the two filter banks are applied to the rows followed by the columns of the data [16]. Hence, as shown in Figure 1, at each resolution there are six subbands as opposed to 2D DWT case, which has three subbands.

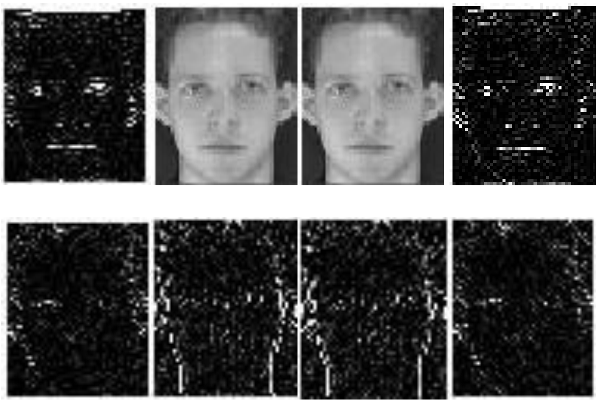

Figure 1. Dual tree complex wavelet coefficients images

DT-CWT has the following properties to overcome the drawbacks of DWT: 1. Approximate shift invariance; 2. Good directional selectivity in 2-dimensions (2-D) with Gabor like filters also true for higher dimensionality: m-D); 3. Perfect reconstruction; 4. Limited redundancy: 2× redundancy in 1-D (2d for d-dimensional signals), this is less than the log2N× redundancy of a perfectly shift-invariant DWT; 5. Efficient order N computation [2].

2.2. Probabilistic Neural Network

Probabilistic Neural Network (PNN) is well-known as the Bayesian-Parzen classifier technique. Consider a pattern vector x with m dimensions that belongs to one of two categories K_1 and K_2. Let $F_1(x)$ and $F_2(x)$ be the probability density functions (pdf) for the classification categories K_1 and K_2, respectively. From Bayes' decision rule, x belongs to K_1 if

$$F_1(x)/F_2(x) > L_1P_2/L_2P_1 \quad (1)$$

conversely, x belongs to K_2, where L_1 is the loss or cost function associated with misclassifying the vector as belonging to category K_1 while it belongs to category K_2, L_2 is the loss function associated with misclassifying the vector as belonging to category K_2 while it belongs to category K_1, P_1 is the prior probability of occurrence of category K_1, and P_2 is the prior probability of occurrence of category K_2. If $F_1(x)$, $F_2(x)$, L_1 and L_2 are known, then the vector x can be identified with maximum probability to which class it belongs [17]. In many situations, the loss functions and the prior probabilities are equal. Hence using the Parzen the estimation of the probability density functions for the classification categories is [18]:

$$F(x) = 1/(2\pi)^{m/2}\sigma^m n \sum_{i=1}^{n} exp[-(x-x_i)^T(x-x_i)/2\sigma^2] \quad (2)$$

where n is the number of training patterns, m is the input space dimension, i is the pattern number, and σ is an adjustable smoothing parameter.

2.3. Support Vector Machines

We first explain the basics of Support Vector Machines (SVMs) for binary classification. Then we discuss how this technique can be extended to deal with general multi-class classification problems [19].

2.3.1. Binary classification

SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes by finding a decision surface that has maximum distance to the closest points in the training set which are termed support vectors. We start with a training set of points $x_i \in n$, i=1,2,…,N where each point x_i belongs to one of two classes identified by the label y_i={-1, 1}. Assuming linearly separable data, the goal of maximum margin classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. This hyperplane is called the optimal separating hyperplane (OSH) (Figure 2). The OSH has the form:

$$f(x) = \sum_{i=1}^{l} \alpha_i y_i x_i \cdot x + b \quad (3)$$

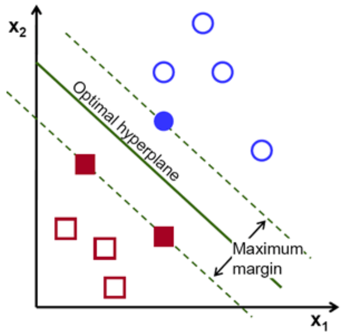

Figure 2. Optimal Separating Hyperplane in case of Maximum Margin

The coefficients α_i and the b in Eq. (3) are the solutions of a quadratic programming problem. Classification of a new data point x is performed by computing the sign of the right-hand side of Eq. (3). In the following the equation given below:

$$d(x) = \sum_{i=1}^{l} \alpha_i y_i x_i \cdot x + b \Big/ \left\| \sum_{i=1}^{l} \alpha_i y_i x_i \right\| \quad (4)$$

will be used to perform multi-class classification. The sign of d is the classification result for x, and $|d|$ is the distance from x to the hyperplane. Intuitively, the farther away a point is from the decision surface, i.e., the larger $|d|$, the more reliable the classification result.

2.3.2. Multi-class classification

There are a number of strategies for solving q-class problems with binary SVM classifiers. Popular are the one-vs-all and the pairwise approach: (i) In the one-vs-all approach q SVMs are trained. Each of the SVMs separates a single class from all remaining classes; (ii) In the pairwise approach $q(q-1)/2$ machines are trained. Each SVM separates a pair of classes. We opted for one-vs-all.

3. Proposed System

For our application ORL face database is used. We use 200 face images acquired of 40 individual (5 images per individual). 140 images are used for training and 60 images are used for testing. Flowchart of the face recognition system is shown in Figure 3.

DWT, 1 level and 2 levels DT-CWT are used for feature extraction. Low frequency regions of DWT and DT-CWT results are used. The resizing operations are implemented to low frequency regions. The sizes of result images are 11x9 after resizing.

Face image matrixes obtained from resized image are converted to vectors (length of vector: 11x9=99). Then, the feature vectors are merged as a matrix. The dimension of matrix is 140x99 for training and 60x99 for testing. PNN and SVM classifiers are used for classification. The matrix is used as input of PNN and SVM. After some experiments it is acquired that PNN gives better performance than SVM. We acquire better performance when we use DT-CWT for feature extraction. The process times and recognition rates for two feature extraction and classification methods are shown in Table 1. Process times consist of training and testing times.

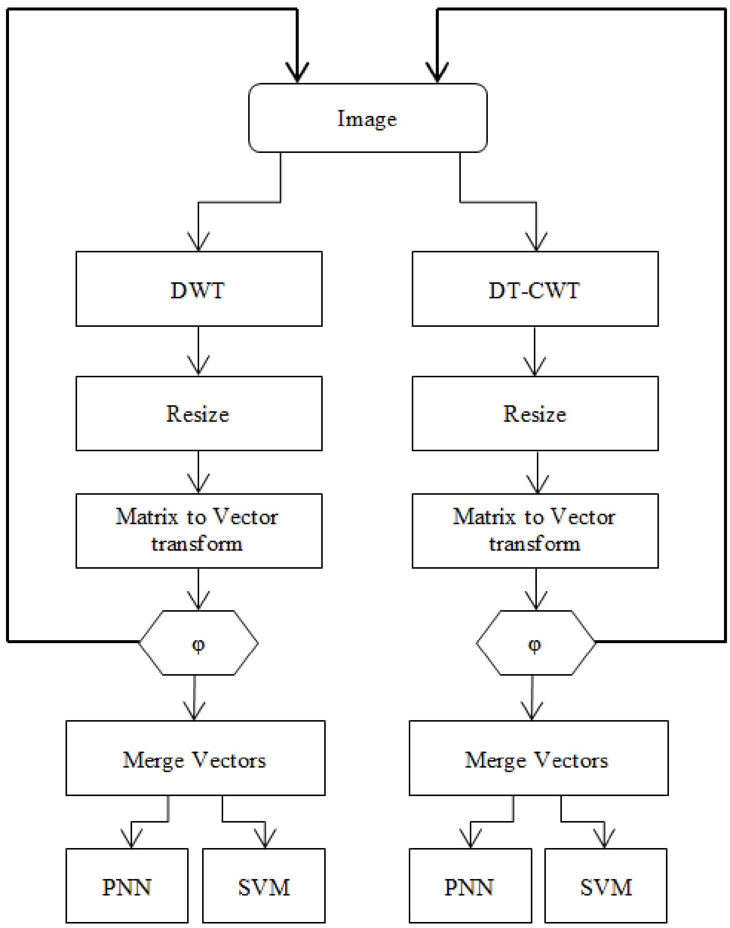

Figure 3. Flowchart of the face recognition system

Table 1. PNN and SVM performances after DWT and DT-CWT

	Time for feat. ext. (sec.)	PNN (%)	Time for PNN (sec.)	SVM (%)	Time for SVM (sec.)
DWT	0.988	93.3333	0.894	88.3333	1.094
DT-CWT	1.531	96.6668	0.903	88.3333	1.073
Two levels DT-CWT	2.082	96.6668	0.917	91.6667	1.086

Conclusions

In this paper, DT-CWT based face recognition system has been developed using PNN and SVM classifiers. Performances of both classifiers are compared and results are shown in table 1. Different tests are implemented using 1 level DT-CWT and 2 levels DT-CWT. In summary some conclusions are obtained. While the recognition rates after 2 levels DT-CWT are the same as the recognition rates after 1 level DT-CWT, more processing time is required for 2 levels DT-CWT for feature extraction. So it is determined that implementing 1 level DT-CWT is more advantageous according to implementing 2 levels DT-CWT. It is shown that the system developed with DT-CWT has better results than the system developed with DWT. SVM classifier performs better result when used 2 levels DT-CWT according to 1 level DT-CWT. In addition, PNN classifier is performed higher success according to SVM.

References

[1] Vidya V, Nazia Farheen, K Manikantan, S Ramachandran, Face recognition using threshold based DWT feature extraction and selective illumination enhancement technique, 2nd International Conference on Communication, Computing & Security [ICCCS-2012], 2012.

[2] Ramesha K, K B Raja, Dual Transform based Feature Extraction for Face Recognition, IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 5, No 2, September 2011.

[3] Bruce A. Draper, Kyungim Baek, Marian Stewart Bartlett, and J. Ross Beveridge, Recognizing faces with PCA and ICA, Computer Vision and Image Understanding 91, 2003 p. 115–137.

[4] Rinky B P, Payal Mondal, K Manikantan, S Ramachandran, DWT based feature extraction using edge tracked scale normalization for enhanced face recognition, 2nd International Conference on Communication, Computing & Security [ICCCS-2012], 2012.

[5] Pallavi D.Wadkar, Megha Wankhade, Face Recognition Using Discrete Wavelet Transforms, International Journal of Advanced Engineering Technology, IJAET/Vol.III/ Issue I/January-March, 2012, p. 239-242.

[6] Aman R. Chadha, Pallavi P. Vaidya, M. Mani Roja, Face Recognition Using Discrete Cosine Transform for Global and Local Features, Proceedings of the 2011 International Conference on Recent Advancements in Electrical, Electronics and Control Engineering (IConRAEeCE) IEEE Xplore: CFP1153R-ART; ISBN: 978-1-4577-2149-6

[7] Arindam Kar, Debotosh Bhattacharjee, Dipak Kumar Basu, Mita Nasipuri, Mahantapas Kundu, High Performance Human Face Recognition using Independent High Intensity Gabor Wavelet Responses: A Statistical Approach, International Journal of Computer Science & Emerging Technologies (E-ISSN: 2044-6004) 178 Volume 2, Issue 1, February 2011

[8] Jie Chen, Shiguang Shan, Peng Yang, Shengye Yan, Xilin Chen1 and, Wen Gao, Novel Face Detection Method Based on Gabor Features, S.Z. Li et al. (Eds.): Sinobiometrics 2004, LNCS 3338, p. 90–99, 2004.

[9] K. Jaya Priya, Dr. R.S. Rajesh, Dual Tree Complex Wavelet Transform based Face Recognition with SingleView, ITC 2010.

[10] Karmakar, D., & Murthy, C. A. (2015, February). Face Recognition using Face-Autocropping and Facial Feature Points Extraction. In Proceedings of the 2nd International Conference on Perception and Machine Intelligence (pp. 116-122). ACM.

[11] Mohamed, B., & Mohamed, S. (2013, April). Face recognition approach based on two-dimensional subspace analysis and PNN. In Programming and Systems (ISPS), 2013 11th International Symposium on (pp. 65-73). IEEE.

[12] Yang, A. Y., Zhou, Z., Balasubramanian, A. G., Sastry, S. S., & Ma, Y. (2013). Fast-minimization algorithms for robust face recognition. Image Processing, IEEE Transactions on, 22(8), 3234-3246.

[13] Huang, Z. H., Li, W. J., Shang, J., Wang, J., & Zhang, T. (2015). Non-Uniform Patch Based Face Recognition via 2D-DWT. Image and Vision Computing.

[14] Wagner, A., Wright, J., Ganesh, A., Zhou, Z., Mobahi, H., & Ma, Y. (2012). Toward a practical face recognition system: Robust alignment and illumination by sparse representation. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 34(2), 372-386.
[15] Patil, R. A., Sahula, V., & Mandal, A. S. (2012). Features classification using support vector machine for a facial expression recognition system. Journal of Electronic Imaging, 21(4), 043003-1.
[16] Selesnick, I. W., Baraniuk, R. G. ve Kingsbury, N. G., "The Dual-Tree Complex Wavelet Transform", IEEE Signal Processing Magazine, vol. 22 p. 123-151, 2005.
[17] Goh, T. C., Probabilistic Neural Network for Evaluating Seismic Liquefaction Potential, Proc. IEEE Int. Symp. on Intelligent Systems, p. 16-20 Varna, Bulgaria, 2002.
[18] Parzen, E., On Estimation of a Probability Density Function and Mode, Annals of mathematical statistics, Vol 33, p. 1065 - 1076, 1962.
[19] Heisele, B., Ho, P., Wu, J. and Poggio, T., Face recognition: component-based versus global approaches, Academic Press, Computer Vision and Image Understanding 91 (2003) 6–21, 2003.