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Fusion of Wavelet Coefficients for Classification of Human Face Images Using Kernel Independent Component Analysis and Different SVM Kernels

Priya Saha[1], Mrinal Kanti Bhowmik[1], Debotosh Bhattacharjee[2], Barin Kumar De[3], Mita Nasipuri[2]

[1]*Department of Computer Science and Engineering*
Tripura University (A Central University)
Suryamaninagar, Tripura
[2]*Department of Computer Science and Engineering*
Jadavpur University, Kolkata
[3]*Department of Physics*
Tripura University (A Central University)
Suryamaninagar, Tripura

ABSTRACT

This paper integrates a non-linear feature extraction method namely Kernel Independent Component Analysis (KICA) and a Support Vector Machine (SVM) as a classifier for human face classification. In this proposed approach, wavelet based image fusion is used to fuse the face images in optical and infrared spectrum. Forward wavelet transform up to level five has been done before fusion of the coefficients. Inverse Daubechies wavelet transform of those coefficients generates fused face images. Since wavelet transform keeps high and low frequency sub-band components separately, reconstructed fused images, therefore, have the information in both low and high frequencies. Features of the fused images are extracted using KICA. Finally, we have used SVM to classify extracted features of face using three different kernels: linear, polynomial and RBF. Detailed experimentation is carried out using IRIS Thermal/Visual Face Database containing different subjects under different pose, illumination and expression. Experimental results show that the performance of the approach presented here gives success rate of 96.25%, 64.14%, and 96.06% on average for the three kernels respectively.

Keywords: Fusion; Wavelet transform; Kernel Independent Component Analysis (KICA); Support Vector Machine (SVM).

1. INTRODUCTION

Face recognition has been extensively spread within the research and development communities in the last decade. This technology has several commercial and law enforcement application. These applications range static matching of photographs such as passports, credit cards, photo ID, driver's licenses (Chellappa et al., 1995). Most of the face recognition techniques have been evolved in order to prevail over two main challenges: illumination and pose variation. These two problems can cause severe performance degradation in face recognition system (webpage). Visual image based face recognition are used the most at present, but in different lighting condition visual images loses their quality. To tackle these problems, thermal images are gaining much interest in these days because of their illumination invariant properties. Thermal images also have some limitations like facial hair, glasses, or cosmetics. Therefore, to extract the advantages from both types of images, fusion is the most constructive notion as it combines multiple information sources together and produces a more informative representation of the data (Maruthi and Sankarasubramanian, 2005).

Hanif et al. (Hanif and Ali, 2006) have discussed data fusion of thermal and visual images to overcome the drawbacks present in individual thermal and visual images. Bebis et al. (Bebis et al., 2006) discussed infrared (IR) imagery offers a promising alternative to visible imagery, due to its relative insensitivity to variations in face appearance caused by illumination changes. Thermal IR images have several shortcomings including that it is opaque to glass. Nikolov et al. (Nikolov et al., 2001) have presented some recent results on the use of wavelet algorithms for image fusion. A detailed overview on wavelet transform for image fusion using image decomposition and reconstruction has been proposed by M. K. Bhowmik et al. in (Bhowmik et al., 2010a). An image fusion technique based on the weighted average of Daubechies wavelet transform (db2) has been presented. The reason behind the use of wavelet decomposition and reconstruction is to separate the high frequency and low frequency information of an image and generate fused image of high and low frequency sub-bands separately in wavelet transform. M. K. Bhowmik et al. (Bhowmik et al., 2010b) have used the process of fusion of visual and thermal images using different wavelet transformations. Coefficients of discrete wavelet transforms from both optical and thermal images were computed separately and combined. They also used inverse discrete wavelet transformation in order to obtain fused face image. M. K. Bhowmik et al. (Bhowmik et al., 2010c) have investigated Quotient based Fusion of thermal and visual images, which were passed separately through level-1 and level-2 multi-resolution analyses. This approach is based on a definition of illumination invariant signature image that enables an analytic generation of the image space with varying illumination. Principal Component Analysis (PCA) was used for dimension reduction of quotient fused images and then, those images are classified using a multilayer perceptron (MLP). In another paper of M. K. Bhowmik et al. (Bhowmik et al., 2011), an image fusion technique based on the weighted average of Daubechies wavelet transform have presented, and a comparative study has conducted for dimensionality reduction based on Principal Component Analysis (PCA) and Independent Component Analysis (ICA). Different researchers have examined the performance of KICA on face images which has shown better recognition result than the other linear methods. J. H. Cao et al. (Cao et al., 2010) investigated face recognition method using KICA and Kernel-based improved PSVM that results better performance over native ICA method. Y. Huang et al. (Huang et al., 2010) proposed a new gabor based Kernel Independent Component analysis (GKICA) which got higher recognition rate than ICA and KICA.

The contribution of the paper is to provide systematic KICA based method to classify the fused images of visual and infrared images for efficient face recognition. To cope up with the complex non-linear variations due to illumination changes, and facial expressions, that influence the recognition performance nonlinear feature extraction method, KICA has introduced in this paper. The paper is organized as follows: system overview is given in section II; experimental results with discussions on them as well as with a comparative study are given in section III; and the conclusions are drawn in section IV.

2. SYSTEM OVERVIEW

In this work, thermal and visual images are used to decompose with level five and from these images; the fused image is generated using db4. In the first step, decomposition of both the infrared and visual images up to level five has been done using wavelet decomposition. Then fused image is generated from both the decomposed images. In this process, Kernel Independent Component Analysis (KICA) is performed for feature extraction, and then Support Vector Machine (SVM) classifier is used to classify input images.

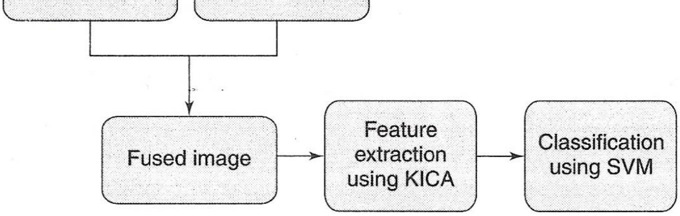

Fig 1 System Overview

Generating Registered Images

Image Registration allows geometrical transformation which aligns points in one view of an object with corresponding points in another view of that object or another object. In this paper, we have used registered visible and registered thermal IR images before they are fused. First, we have taken the frontal image as the base image and another unregistered image for registration in case of both thermal and visual images (separately). In the second step, pair of control points was selected from both the base and unregistered images. Next task is to choose the transformation type, infer its parameters, and transform the unregistered image to generate the registered image. Affine transformation is used in this work as it has six degrees of freedom and is equivalent to the combined effect of translation, rotation, isotropic scaling, and shear (non-uniform scaling in some direction). This image registration process was applied for the visual and thermal images separately as well as for each expression and illumination type of each person i.e. out of the 11 images of different rotations; we have considered the frontal image as the base image and registered the other 10 images with respect to the frontal image.

Image Decomposition and Reconstruction

The Daubechies (db4) is used for decomposition and reconstruction of the images in case of generation of fused imaging technique. Daubechies wavelets, a wavelet used to convolve image data, can be orthogonal, having scaling functions with same number of coefficients as the wavelet functions, or biorthogonal with different number of coefficients. The main idea behind the fusion algorithm: (a) the two images are to be processed and re-sampled to the one with the same size; and (b) they are respectively decomposed into the sub-images using forward wavelet transform, which have the same resolution at the same levels and different resolution among different levels; and (c) information fusion is performed based on the high-frequency sub-images of decomposed images; and finally the resultant image is obtained using inverse wavelet transform (Shu-long, 2004).

Let $A(x, y)$ and $B(x, y)$ be the images to be fused, the decomposed low-frequency sub-images of $A(x, y)$ and $B(x, y)$ be respectively $lA_j\,(x, y)$ and $lB_j\,(x, y)$ (j is the parameter of resolution). The decomposed high-frequency sub-images of $A(x, y)$ and $B(x, y)$ be respectively $hA^k{}_j\,(x, y)$ and $hB^k{}_j\,(x, y)$ (j is the parameter of resolution and $j = 1, 2, \ldots, J$. For every j, $k = 1, 2, 3$). Then the fused high-frequency sub-images $F^k{}_j\,(x, y)$ are: if $hA^k{}_j\,(x, y) > hB^k{}_j\,(x, y)$ then $F^k{}_j\,(x, y) = hA^k{}_j\,(x, y)$ and if $hA^k{}_j\,(x, y) < hB^k{}_j\,(x, y)$ then $F^k{}_j\,(x, y) = hB^k{}_j\,(x, y)$; and the fused low-frequency sub images $F_j\,(x, y)$ are as follows:

$$F_j\,(x, y) = k_1 \cdot lA_j\,(x, y) + k_2 \cdot lB_j\,(x, y) \tag{1}$$

In Eqn. 1, k_1 and k_2 are given parameters, if the image B is fused into A, then $k_1 > k_2$ and vice-versa (Shu-long, 2004).

Fusion of low frequency sub-images are computed as weighted sum of corresponding coefficients, found from both the images (thermal and its corresponding visual) and for high-frequency sub-images, larger coefficient is considered as final output. After generating the decomposed fused image, the inverse Daubechies Wavelet is applied to generate synthesized fused image. When the decomposition scheme is being repeated more, the approximation image more concentrates in the low frequency energy. Finally, the reconstructed image is used as an input to feature extracted algorithm.

Kernel Independent Component Analysis

Kernel Independent Component Analysis (KICA) is a method based on kernel function, which allows data space to be mapped into high dimensional feature space, and also an improved feature extraction method from existing ICA. The KICA algorithm developed by F.R. Bach and M.I. Jordan was primarily used for separating randomly mixed auditory signals (Martiriggiano et al., 2005). However, this method has been begun to use in bidimensional images. The concept of kernel in ICA has been introduced in face images due to the failure of linear methods of feature extraction. Linear methods like Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA), which are three powerful tools largely used for data reduction, and feature extraction in the appearance-based approaches (Turk and Pentland, 1991; Belhumeur et al., 1997) are inadequate to describe complex non-linear variations due to illumination changes, facial expressions and aging. Non-linear extension of linear methods has been initiated to eliminate these problems. The steps of KICA are presented here as follows:

1. Centering of Fused Image, 2. Whitening and Initializing of De-mixing matrix, 3. Memory Initialization for storing de-mixing matrix and Hilbert Space Independent Component (HSIC) at each iteration where maximum iteration is 20, 4. Define the width of Gaussian kernel, sigma as 1, 5. Memory utilization by Incomplete cholesky, and default Convergence threshold value is 1 for cholesky precision, 6. Independence measures based on RKHS covarience operator, 7. Computation of Euclidean Gradient, 8. Compute Approximate Hessian, 9. Check for convergence and find the final De-mixing matrix.

Support Vector Machine (SVM)

Support Vector Machine is originally a model for binary classification that performs classification tasks by constructing optimal separating hyperplanes in multidimensional space (webpage1). Although, the roots of the SVM approach were about to classify linearly separable data, but recently it is widely used in nonlinear data classification (Sivanandam et al., 2006). In this paper, we have used multiclass SVM to carry out recognition on face images, and Quadratic Programming (QP) optimization method to train the SVM.

Linear Classification

Consider a given training set $\{x_k, y_k\}_{k=1}^{N}$ with input data $x_k \in \Re^n$ and output data $y_k \in \Re$ with class labels $y_k \in \{+1, -1\}$, where x_k is the input and y_k is the output vector and finally the linear classifier can be shown as, $y(x) = \text{sign}\,[w^T x + b]$, where w is weight of the classifier and b is the threshold of classifier.

Nonlinear Classification

In the extension from linear SVM classifier to nonlinear SVM classifier, we can formally replace x by $\varphi(x)$ and apply the kernel trick (continuous function $k(x, z) = \varphi(x)^T\, \varphi(z)$). The primal problem in non-linear SVM cannot be solved in the same way as in linear SVM because the unknown w can be infinite dimensional (Suykans at al., 2002).

Examples of kernels that have been widely used for different classification tasks are polynomial and Gaussian.

Polynomial Kernel: The function for the polynomial kernel is given by the expression, $k(x_i, x_j) = (1 + x_i^T\, x_j)^p$, where p is the polynomial degree.

Gaussian Kernel: The expression for gaussian kernel is,

$$k(x_i, x_j) = \exp\,(-\, \|x_i - x_j\|^2/2\sigma^2),\ \text{where } \sigma \text{ is the radius.}$$

Linear Kernel: The expression for linear kernel is, $k(x_i, x_j) = (1 + x_i^T\, x_j)$.

3. EXPERIMENT RESULTS AND DISCUSSIONS

The benchmark database OTCBVS (Object Tracking and Classification Beyond Visible Spectrum) contains both thermal and visual face images under the same situation like pose, illumination etc. The whole experiment consists of expression, illumination, and full datasets with 660 images in 20 classes, 748 images with 17 classes and 1626 images with 28 classes respectively. For the sake of experiment, the registered visual and thermal images are then cropped into 50×50 dimensions. The cropped visual and thermal images are fused using wavelet transformation, which is described previously. After that, all the fused images are taken for feature extraction using KICA. These images are taken for training and testing purposes from different classes of different datasets. From 660 face images, support vector machine multiclass classifier considers 20 persons as 20 classes taking 33 images from each class. The experiment has done using 'k-fold' cross validation where expression, illumination and full dataset are tested using '3-fold', and '4-fold' respectively. Number of folds is taken as per the total number of images in each class in each dataset. In K-fold cross-validation, K-1 folds are used for training and the last fold is used for evaluation. This process is repeated K times, leaving one different fold for evaluation each time. Linear kernel, Polynomial kernel with degree 3, Gaussian kernel with scaling factor 1 and penalty factor c with value 1 are used in our SVM kernel functions. The accuracy of a classification process defined as the portion of true positives, and true negatives in the population of all instances, classification accuracy A = (TP+TN)/(TP+TN+ FP+FN). TP=True Positives, TN=True Negatives, FP=False positives and FN=False Negatives. All these values have been taken from the confusion matrix acquired from the classifier performance. "True positives" are active compounds which have correctly been classified as active, and "false positives" are inactive compounds which have wrongly been classified as Active (Janecek et al., 2008). The maximum classification accuracies of three SVM kernels are listed below. It has been observed from the conducted experiment that linear kernel in both datasets, expression and illumination, have performed better. Linear kernel is performed 0.15% and 0.40% better than other two kernels in expression and illumination dataset respectively. Linear kernel and polynomial kernel both generate 99.08% correct rate in Full datasets. In Table 2, a comparative study has been shown based on different techniques used by different researchers.

Table 1 Experiment Results

Dataset	*Recognition Rates of three SVM Kernels*		
Expression	Linear	Polynomial	Gaussian RBF
	95.15%	95.00%	95.00%
Illumination	Linear	Polynomial	Gaussian RBF
	94.52%	94.12%	94.2%
Full Datasets	Linear	Polynomial	Gaussian RBF
	99.08%	4.80%	99.08%

Table 2 Comparison between different methods of Face Recognition

Methods		*Classification accuracy*
Present Methods	Linear	96.25%
	Polynomial	64.14%
	RBF	96.06%
Simple Spatial Fusion (Hanif and ali, 2006)		91.00%
Fusion of Thermal and Visual (Singh et al., 2004)		90.00%
Gabor based KICA using Polynomial kernel (Huang et al., 2010)		ORL-95% YALE-87.78%
Fusion of Visual and LWIR + PCA (Socolinsky and Selinger, 2004)		87.87%

4. CONCLUSION

This paper formulates Daubechies wavelet (db4) for fusion of optical and infrared image, KICA for feature extraction method and SVM for classification purpose in human face classification. We have used IRIS thermal/visible face database. The visual and thermal face images have their own advantages and disadvantages. Therefore, we have tried to combine the advantages from visual and thermal image. The experimental results show that linear kernel gives better classification accuracy than polynomial and RBF kernels. We can conclude that our approach has achieved efficient classification performance for face recognition purpose. We will further investigate different wavelet fusion methods and other classifiers for face recognition.

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References

1. Bebis, G., Gyaourova, A., Singh, S. and Pavlidis, I., 2006: *Face Recognition by Fusing Thermal Infrared and Visible Imagery*, Image and Vision Computing, **24**, 727-742.
2. Belhumeur, P.N., Hespanha, J.P. and Kriegman, D.J., 1997: *Eigenfaces vs. Fisherfaces: recognition using class specific linear projection* IEEE Trans. Pattern Analysis and Machine Intelligence, **19**, 711–720.
3. Bhowmik, M. K., Bhattacharjee, D., Basu, D. K., Nasipuri, M., 2011: *Independent Component Analysis (ICA) of fused Wavelet Coefficients of thermal and visual images for human face recognition*, Proc. SPIE Defense, Security, and Sensing.
4. Bhowmik, M.K., Bhattacharjee, D., Nasipuri, M., Basu, D.K. and Kundu, M., 2010a: *Fusion of Daubechies Wavelet Coefficients for Human Face Recognition*, Int. J. Recent Trends in Engineering, **3**, 137-143.
5. Bhowmik, M.K., Bhattacharjee, D., Nasipuri, M., Basu, D.K. and Kundu, M., 2010b: *Fusion of Wavelet Coefficients from Visual and Thermal Face Images for Human Face Recognition – A Comparative Study*, Int. J. Image Processing, **4**, 12-23.
6. Bhowmik, M.K., Bhattacharjee, D., Nasipuri, M., Basu, D.K. and Kundu, M., 2010c: *Quotient Based Multiresolution Image Fusion of Thermal and Visual Images Using Daubechies Wavelet Transform for Human Face Recognition*, Int. J. Computer Science Issue, **7**, 18-27.
7. Cao, J.H., Ran, Y.Z. and Xu, Z.J. 2010: *A New Kernel Function Based Face Recognition Algorithm* Proc. Int. Conf. Computer, Mechatronics, Control and Electronic Engineering, 226 – 230.

8. Chellappa, R., Wilson, C.L. and Sirohey, S., 1995: *Human and Machine Recognition of Faces: A Survey*, Proc. IEEE, **83**, 705-740.
9. Hanif, M. and Ali, U., 2006: *Optimized visual and thermal image fusion for efficient face recognition,* Proc. IEEE Conf. on Information Fusion, 1-6.
10. Huang, Y., Li, M., Lin, C. and Tian, L., 2010: *Gabor-based Kernel Independent Component Analysis for Face Recognition* Proc. Int. Conf. Intelligent Information Hiding and Multimedia Signal Processing, 376-379.
11. Janecek, A.G.K., Gansterer, W.N., Demel, M.A. and Ecker, G.F., 2008: *On the Relationship Between Feature Selection and Classification Accuracy* Proc. JMLR Workshop and Conference Proceedings, **4**, 90-105.
12. Martiriggiano, T., Leo, M., D"Orazio, T. and Distante, A., 2005: Face *Recognition by Kernel Independent Component Analysis* In Innovations in Applied Artificial Intelligence, Ali, M. and Esposito (eds), Vol. 3533, pp. 55-58, Springer Berlin Heidelberg.
13. Maruthi, R. and Sankarasubramanian, K., 2007: *Multi focus image fusion based on the information level in the region of the images*, J. theoretical and applied information technology, **3**, 80-85.
14. Nikolov, S., Hill, P., Bull, D. and Canagarajah, N., 2001: *Wavelet for image fusion* In Wavelets in Signal and Image Analysis: from Theory to Practice, Petrosian, A.A. and Meyer, F.G. (eds), Vol. 19, Springer.
15. Shu-long, Z., 2004: *Image Fusion using Wavelet Transform*, Symp. Geospatial Theory, Processing and Applications, 5-9.
16. Singh, S., Gyaourva, A., Bebis, G. and Pavlidis, I., 2004: *Infrared and Visible Image Fusion for Face Recognition* Proc. *SPIE*, **5404**, 585-596.
17. Sivanandam, S.N., Sumathi, S. and Deepa, S.N., 2006: *Introduction to Neural Networks using Matlab 6.0* Tata McGraw-Hill Pub. Co.: New Delhi.
18. Socolinsky, D.A. and Selinger, A., 2004: *Thermal Face Recognition in an Operational Scenario* Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition, **2**, 1012-1019.
19. Suykans, J.A.K., Gestel, T.V., Brabanter, J.D., Moor, B.D. and Vandewalle, J., 2002 *Least Squares Support Vector Machines* World Scientific Pub. Co.: Singapore.
20. Turk, M.A. and Pentland, A., 1991: *Eigenfaces for recognition* J. Cognitive Neuroscience, **3**, 71–86.
21. Webpage: http://www.fingertec.com/download/tips/whitepaper-02.pdf
22. Webpage1: http://www.statsoft.com/textbook/support-vector-machines.