Optimum Fusion of Visual and Thermal Face Images for Recognition

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Abstract—**In this paper one investigation has been done to find the optimum level of fusion to find a fused image from visual as well as thermal images. Because of the use of face recognition system in critical areas like, authenticating an authorized person in highly secured areas, investigation of criminals, online monitoring etc, face recognition system should be very robust and accurate one. This work is an attempt to fuse visual and thermal face images at optimum level to extract the advantages of visual as well as thermal images. In our work, Object Tracking and Classification Beyond Visible Spectrum (OTCBVS) database has been used for the visual and thermal images. Among all the experiments a maximum recognition result obtained is 93%.**

Keywords- face recognition; optimum fusion; fused image; eigenspace projection; multilayer perceptron (MLP)

I. INTRODUCTION

Face recognition in the Infrared (IR) spectrum provides the simplest and more robust solution to enhance better recognition performance in uncontrolled environments and deliberate attempts to obscure identity [1]. But IR imagery has few disadvantages like it is sensitive to temperature changes in the surrounding environment and variations in the heat patterns of the face and it is opaque to glass. In contrast to thermal imagery visual imagery is more robust to the above factors but very sensitive to illumination changes. This suggests that effective algorithms to fuse information from both visual and thermal spectra have the potential to improve face recognition performance. Four different fusion levels have been considered in our work: 70% visual and 30% thermal, 60% visual and 40% thermal, 50% visual and 50% thermal, and 40% visual and 60% thermal.

This paper is organized as follows: in section II, review of some previous related works in this field is presented. In section III, the overview of the system is discussed. Section IV contains experimental results and discussions. Finally, section V concludes this work.

II. PREVIOUS WORK

Face recognition in the IR spectrum using IR imagery could not grow much interest among the earlier researchers due to higher cost of thermal sensors versus visible video equipment, lower image resolution, higher image noise, and lack of widely available data sets. These disadvantages appear to be less relevant as infrared imaging technology advances, making it attractive to consider thermal sensors in the domain of face recognition [2]. IR images represent the heat patterns emitted from an object. Objects emit different amounts of IR energy according to their temperature and characteristics. The amount of emitted radiation depends on both the temperature and the emissivity of the material [3]. The range of human face and body temperature is quite uniform, varying from 35.5 to 37.5°C providing a consistent thermal signature. Skin temperature in a 21°C ambient room temperature also has a small variable range between 26 and 28°C. The thermal patterns of faces are derived primarily from the pattern of superficial blood vessels under the skin. The vessels transport warm blood throughout the body, and heat the skin. Skin directly above a blood vessel is on the average 0.1°C warmer than adjacent skin. The vein and tissue structure of the face is unique for each person, and therefore the IR images are also unique. It is known that even identical twins have different thermal patterns. The range and sensitivity are well within the specification of current IR imaging technology. The passive nature of the thermal IR systems lowers their complexity and increases their reliability. Some applications of IR imagery include face detection, localization and segmentation and these become easier even within smaller class variance, as IR images inherits the advantages like: they are nearly invariant to changes to illumination and in facial expressions, and the thermal images also capable of working even in total darkness, and detecting disguises. It has several drawbacks also like: glasses block most of thermal energy; due to speed and window glasses it is not possible to recognize vehicle occupants; ambient temperature or activity level may change thermal characteristics, low image resolution [4].

Multiple technologies are currently available, with decreasing cost and increasing performance, which are capable of image measurement in different regions and appearances of a human face in the visible, shortwave infrared (SWIR range 1.4 – 3μm,) midwave infrared(MWIR range 3.0 – 8.0 μm),and long wave infrared (LWIR range 8.0

– 15.0 μm) spectra. In the infrared, the near-infrared (NIR range 0.75 – 1.4μm) and SWIR spectra are still reflective and differences in appearance between the visible, NIR and SWIR are due to reflective material properties [3]. Many methods have been proposed for face recognition. For instance, A. Gyaourova et al. [5] tried to implement pixel-based fusion scheme in the wavelet domain, and feature based fusion in the eigenspace domain. Although their fusion approach was not able to fully discount illumination effects present in the visible images, they showed substantial improvements in overall recognition performance. They also indicated that IR-based recognition performance degrades seriously when eyeglasses are present in the probe image but not in the gallery image and vice versa. On the other hand for the improvement of the performance of face recognition when face images are occluded by wearing eye-glasses, Jeong-Seon Park et al. [6] first detect the regions occluded by the glasses and generate a natural looking facial image without glasses by recursive error compensation using PCA reconstruction. George Bebis et al. [7] investigated that two different fusion schemes. The first one is pixel based and operates in the wavelet domain using Haar-like transforms, while the second one is feature-based and operates in the eigenspace domain. In both cases, they employ a simple and general framework based on Genetic Algorithms (GAs) to find an optimum fusion strategy. A. Aran et al. [8] demonstrated the spectral band invariant Wave MACH filters which are designed using images of CCD/IR camera fused by Daubechies wavelet transform and implemented in hybrid digital–optical correlator architecture to identify multiple targets in a scene. They have fusion of infrared and CCD camera because the performance of CCD camera is better under good illumination conditions where-as IR camera gives a better output under poor illumination as well as in the night conditions. The authors in [23] proposed data fusion of visual and thermal images using Gabor filtering technique which extracts facial features, meant for a face recognition technique. It has been found that by using the proposed fusion technique Gaborfilter can recognize a face even with variable expressions and light intensities, but not in extreme condition. D. A. Socolinsky and A. Selinger [10] studied and compared results for thermal face recognition under indoor and outdoor conditions with a success compared to visual face recognition. It is clear from their experiments that face recognition at outdoor with visible imagery is far less accurate than that when performed under fairly controlled indoor conditions. For outdoor use, thermal imaging provides us with a considerable performance boost. Thermal recognition performance suffers a moderate decay when performed outside against an indoor enrollment set, probably as a result of environmental changes. Jingu Heo et al. [11] describes Comparison results on three fusion-based face recognition techniques like Data fusion of visual and thermal images (Df), Decision fusion with highest matching score (Fh), and Decision fusion with average matching score (Fa) and showed that fusion-based face recognition techniques outperformed individual visual and thermal face recognizers under illumination variations and facial expressions. Decision fusion with average matching score consistently demonstrated superior recognition accuracies as per their results. I. Pavlidis and P. Symosek [12] demonstrate a theoretical and experimental argument that a dual-band (upper and lower band) fusion system in the near infrared can segment human faces much more accurately than traditional visible band disguise face detection systems. D. A. Socolinsky and A. Selinger [13] performed a clear analysis that LWIR imagery of human faces is not only a valid biometric, but almost surely a superior one to comparable visible imagery. X. Chen, P. J. Flynn and K. W. Bowyer [14] showed that the combination of IR plus visual imagery can outperform either IR or visual alone. They find a combination method that considers the distance values and performs better than one that only considers ranks. C. K. Eveland et al. [15] introduced a methodology for tracking human faces in calibrated thermal infrared imagery of LWIR and MWIR indoor image sequences. In this work, our basic objective is to find an optimum level of fusion, that is, amount of contributions in per centum from visual and thermal images to be taken into account.

III. THE SYSTEM OVERVIEW

In this work we have used thermal and visual face images from Object Tracking and Classification Beyond Visible Spectrum (OTCBVS) benchmark database. Every corresponding thermal and visual face images, which are aligned, are first combined and converted into fused image. To find the optimum contributions from thermal and visual images different levels of fusion were considered by varying, pixel data percentage from visual and thermal images. These transformed images are separated into two groups namely training set and testing set. An eigenspace is computed using training images. Once these conversions are done the next task is to use a classifier to classify them. A Multilayer Perceptron is used for this purpose. The block diagram of the system is given in Fig. 1.

A. Visual face images

There are few problems regarding visual face recognition in case of uncontrolled operating environments such as outdoor situations and low illumination conditions. Visual face recognition also has difficulty in detecting disguised faces, which is critical for high-end security applications and this is why thermal face recognition has achieved attention from researchers.

B. Thermal Face Images

Thermal infrared face images are formed as a map of the major blood vessels present in the face. Therefore, a face recognition system that is designed based on thermal infrared face images cannot be evaded or fooled by forgery, or disguise, as can occur using the visible spectrum for facial recognition. Compared to visual face-recognition systems this recognition system will be less vulnerable to varying conditions, such as head angle, facial expression, or lighting.

C. Fusion of Visual and Thermal Face Images

Image fusion is a technique which combines information different sources together, using pixel, feature, or decision

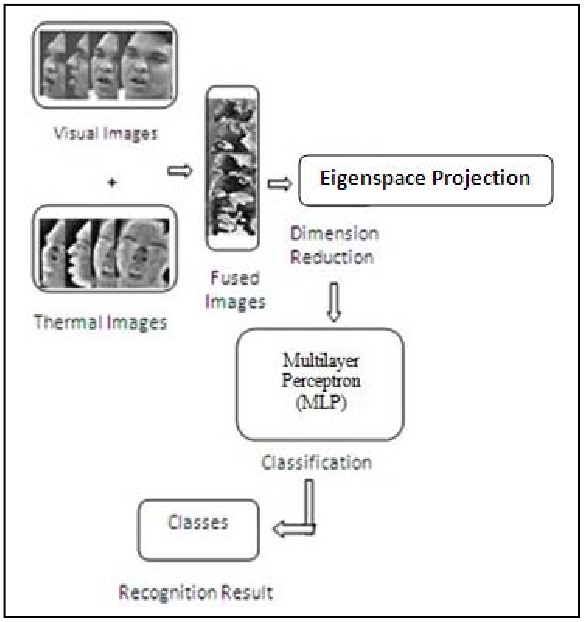

Figure 1. Block diagram of the system presented here.

level techniques to produce a single image. The reason behind the fusion using different images is that, the task of interpreting either visual images or thermal images is an unconstraint problem. The thermal image can at best yield estimates of surface temperature that in general, is not specific in distinguishing between object classes. The features extracted from visual intensity images also lack the specificity required for uniquely determination of the identity of the imaged object. The mechanisms that produce thermal images are different from those that produce visual images. Thermal image produced by an object's surface can be interpreted to identify these mechanisms. There are so many techniques used to produce fused images. In our work we have used weighted sum of corresponding pixels from visual and thermal images. Experiments were conducted to find the optimum weights to be associated with individual domains, which are shown in Fig. 2.

D. Eigenfaces for Recognition

In mathematical terms, we wish to find principal components [16], [17], [18] of the gray level distribution of faces, or the eigenvectors of the covariance matrix of the gray levels of the set of face image. These eigenvectors can be thought of as set of features which together characterize the variations between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as sort of imaginary ghostly face which we call an eigenface. Each face image in the training set can be presented exactly in terms of a linear combination of the eigenfaces. The number of a possible eigenfaces is equal to the number of face images in the training set. However the faces can also be approximated using only the "best" eigenfaces i.e. those that have the largest eigenvalues, and which therefore account for the most variance within the set face images. The best U eigenfaces constitute a U-dimensional subspace, which may be called as "face space"

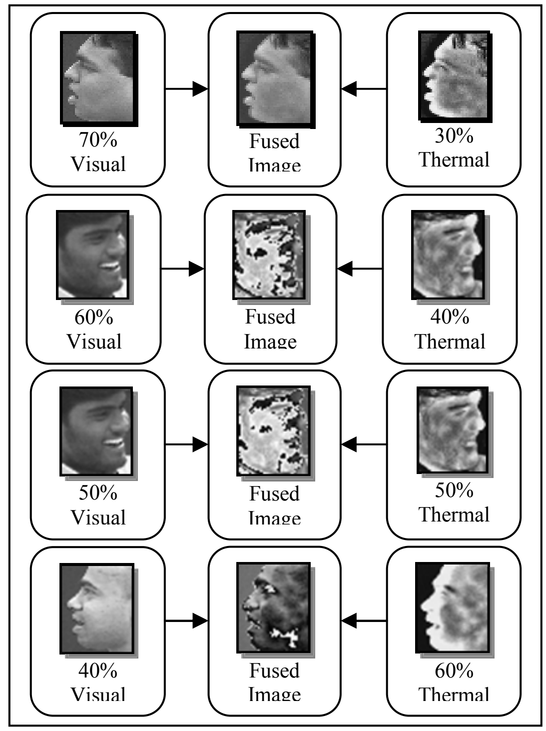

Figure 2. Sample images of fused images generated using different ratios of visual and thermal images.

of all possible images. Identifying images through eigenspace projection takes three basic steps. First the eigenspace must be created using training images. After that all those training images are projected into the eigenspace and call them eigenfaces. A classifier is trained using these eigenfaces. Finally, the test images are identified by projecting them into the eigenspace and classifying them by the trained classifier.

E. ANN using Backpropagation

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information which has been given to analyze. The backpropagation learning algorithm is one of the most historical developments in Neural Networks. It has reawakened the scientific and engineering community to the modeling and processing of many quantitative phenomena using neural networks. This learning algorithm is applied to multilayer feed forward networks consisting of processing elements with continuous differentiable activation functions. Such networks associated with the back propagation learning algorithm are also called back propagation network [19].

IV. EXPERIMENT RESULTS AND DISCUSSIONS

In this work, experiments were conducted using Object Tracking and Classification Beyond Visible spectrum (OTCBVS) database, which is a standard benchmark database for thermal and visual face images. This database contains several sets of data. The benchmark contains videos and images recorded in and beyond the visible spectrum; which contains different set of data like: OSU Thermal Pedestrian Database, IRIS Thermal/Visible Face Database, OSU Color-Thermal Database, Terravic Facial IR Database, Terravic Weapon IR Database, and CBSR NIR Face Dataset. Among all of these different datasets, IRIS Thermal/Visible Face Dataset has only been considered in this work. There are 2000 images of visual and 2000 thermal images of 16 different people. From this database we have taken 210 visual images and 210 thermal images and with the combination of these images fused images were produced with the variation of pixel data percentage of visual and thermal images. Out of 210 total fused images used in this work, 140 images were considered for training and 70 images for testing. For some subjects, the images were taken on different occasions, which contain quite a high degree of variability in lighting, facial expression, pose and facial details. In this work MLP has been used for classification. Multilayer perceptron are supervised networks for which they require a desired response to be trained.

In our experiment we have used 3-fold cross-validation method for testing the model. Cross-validation, sometimes called rotation estimation [20], [21], [22] is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. The original samples means the images used for the experiment is partitioned into 3 subsets. Of the 3 subsamples, a single subsample is retained as the validation data for testing the model , and the remaining (3 – 1) = 2 subsamples, are used as training data. The cross-validation process is then repeated 3 times (the folds), with each of the 3 subsamples used exactly once as the validation data. The maximum recognition rate of our experiment is 93.00%.

Table 1 shows the data of the experiments using four different levels of fused images for the entire database. Table 2 shows the data of the experiments using fused images of different levels of fusion of pixel data with variations in pose, illumination and expression. The number of training images, the number of testing images, the number of total images and the number of image classes used in the experiment for each fold are 30, 15, 45 and 5 respectively. Maximum recognition rate is found to be 93% for fused images of pixel data of 40% visual and 60% thermal. The experimental results of different level of fused images with eye-glasses are shown in Table 3. In Table 3, we can also see the number of training images, number of testing images, total number of images and number of image classes for each fold in the experiment using images with eye-glasses for several levels of fused images is 36, 18, 54 and 3 respectively. Here the maximum recognition rate is 78%.

Some sample images with variations in pose along with their respective fused images with different levels are shown in Fig. 3. Presence of eye-glass introduces complicacies in face recognition and for that reason another set of images with eye-glasses along with their respective fused images with different levels are shown in Fig. 4.

TABLE I. DIFFERENT LEVELS OF FUSION WITH ALL TRAINING AND TESTING DATA WITH THEIR RECOGNITION RATES AND FALSE REJECTION RATES USING 3-FOLD CROSS VALIDATION METHOD

Fusion Level	Number of Training Images (a)	Number of Testing Images (b)	Total Number of Images (a+b)	Number of Classes	Fold Number	Recognition Rate	False Rejection Rate	Maximum Recognition Rate
Fused Images (70%Visual and 30% Thermal)	140	70	210	14	First Fold	87%	13%	89%
					Second Fold	74%	26%	
					Third Fold	89%	11%	
Fused Images (60%Visual and 40% Thermal)	140	70	210	14	First Fold	93%	7%	93%
					Second Fold	77%	23%	
					Third Fold	84%	16%	
Fused Images (50%Visual and 50% Thermal)	140	70	210	14	First Fold	77%	23%	90%
					Second Fold	90%	10%	
					Third Fold	90%	10%	
Fused Images (40%Visual and 60% Thermal)	140	70	210	14	First Fold	93%	7%	93%
					Second Fold	77%	23%	
					Third Fold	79%	21%	

TABLE II. DIFFERENT LEVELS OF FUSION WITH TRAINING AND TESTING DATA OF IMAGES WITH DIFFERENT POSE, ILLUMINATION, EXPRESSION, VARIATION WITH THEIR RECOGNITION RATES AND FALSE REJECTION RATES USING 3-FOLD CROSS VALIDATION METHOD

Fusion Level	Number of Training Images (a)	Number of Testing Images (b)	Total Number of Images (a+b)	Number of Classes	Fold Number	Recognitio n Rate	False Rejection Rate	Maximum Recognition Rate
Fused Images (70%Visual and 30% Thermal)	30	15	45	5	First Fold	80%	20%	87%
					Second Fold	73%	27%	
					Third Fold	87%	13%	
Fused Images (60%Visual and 40% Thermal)	30	15	45	5	First Fold	60%	40%	73%
					Second Fold	73%	27%	
					Third Fold	73%	27%	
Fused Images (50%Visual and 50% Thermal)	30	15	45	5	First Fold	73%	27%	73%
					Second Fold	67%	33%	
					Third Fold	71%	29%	

Fused Images (40%Visual and 60% Thermal)	30	15	45	5	First Fold	87%	13%	93%
					Second Fold	67%	33%	
					Third Fold	93%	7%	

TABLE III. DIFFERENT LEVELS OF FUSION WITH TRAINING AND TESTING DATA OF IMAGES WITH EYE-GLASSES WITH THEIR RECOGNITION RATES AND FALSE REJECTION RATES USING 3-FOLD CROSS VALIDATION METHOD

Fusion Level	Number of Training Images (a)	Number of Testing Images (b)	Total Number of Images (a+b)	Number of Classes	Fold Number	Recognition Rate	False Rejection Rate	Maximum Recognition Rate
Fused Images (70%Visual+ 30% Thermal)	36	18	54	3	First Fold	47%	53%	61%
					Second Fold	61%	39%	
					Third Fold	53%	47%	
Fused Images (60%Visual+ 40% Thermal)	36	18	54	3	First Fold	67%	33%	78%
					Second Fold	67%	33%	
					Third Fold	78%	22%	
Fused Images (50%Visual+ 50% Thermal)	36	18	54	3	First Fold	78%	22%	78%
					Second Fold	78%	22%	
					Third Fold	74%	26%	
Fused Images (40%Visual+ 60% Thermal)	36	18	54	3	First Fold	72%	28%	72%
					Second Fold	44%	56%	
					Third Fold	56%	44%	

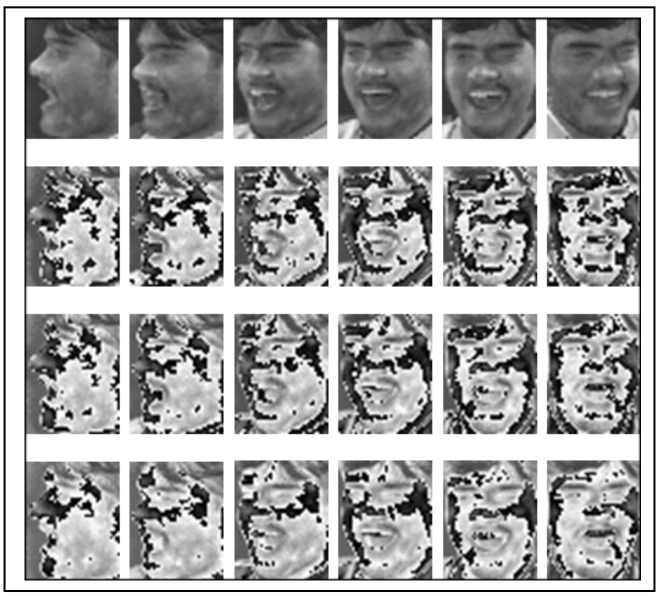

Figure 3. Example fused images of (a) 70% visual and 30% thermal images, (b) 60% visual and 40% thermal images, (c) 50% visual and 50% thermal images, (d) 40% visual and 60% thermal images with pose variation.

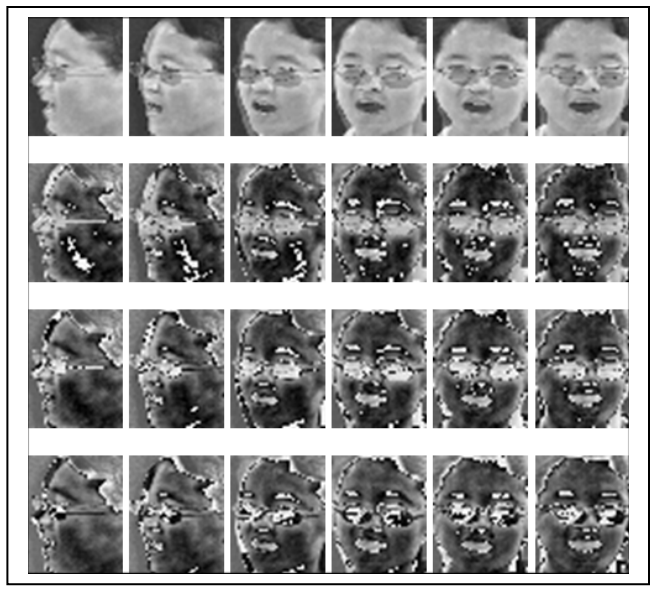

Figure 4. Fused images with of (a) 70% visual and 30% thermal images, (b) 60% visual and 40% thermal images, (c) 50% visual and 50% thermal images, (d) 40% visual and 60% thermal images with eye-glasses.

The comparison between the present method and other fusion methods is shown in Table 4.

TABLE IV. COMPARISON BETWEEN DIFFERENT IMAGE FUSION TECHNIQUES

Image Fusion Technique	Recognition Rate
Optimum fusion of Visual and Thermal face images	93.00% [maximum]
Simple Spatial Fusion [23]	91.00%
Fusion of Thermal and Visual [24]	90.00%
Segmented Infrared Images via Bessel forms [25]	90.00%
Abs max selection in DWT [23]	90.31%
Window base absolute maximum selection: [23]	90.31%
Fusion of Visual and LWIR + PCA [10]	87.87%
Only Thermal [19]	84.88%
Only Visual [9]	85.63%

V. CONCLUSION AND FUTURE WORK

In this paper, an optimum level of pixel fusion from visual and thermal images for human face recognition has been proposed. After the fusion of images as weighted sum, the fused images are projected into eigenspace. Those fused eigenfaces are classified using Multilayer Perceptron. Eigenspace is constituted by the images belong to the training set of the MLP. The efficiency of this scheme has been demonstrated on Object Tracking and Classification Beyond Visible spectrum (OTCBVS) benchmark database. The future work includes addressing the problem of expression changes using pixel based fusion scheme along with environmental effects in thermal and visual both.

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