Multisensor Fusion of Visual and Thermal Images for Human Face Identification using Different SVM Kernels

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***Abstract*—In this paper we present a novel method of face identification using different levels of pixel fusion (e.g. ratios for pixel information taken from the visual and thermal images are, 2:3, 1:1, 3:2 and 7:3) and classification of fused images using different kernels of Support Vector Machine (SVM). Visual imagery has been broadly used in face identification systems, but these are very sensitive to illumination changes. This limitation has been overcome by the Infrared (IR) spectrum that provides simpler and more robust solution to boost the identification performance in uncontrolled environments and deliberate attempts to obscure identity. But IR imagery is sensitive to temperature changes in the surrounding environment and variations in the heat patterns of the face and it is opaque to glass. All these facts degrade the face identification efficiency. This drove us to fuse information from both visual and thermal spectra, which have the potential to improve face identification performance as fusion of thermal and visual images provide improved images with more compact information. Once we get fused images those are reduced in dimension using Eigenvalue Decomposition based Candid Co-variance free Incremental Principal Component Analysis (EVD-CCIPCA) and these reduced fused images are classified using the three different kernels of SVM. The three kernels used here are: linear, polynomial and gaussian RBF. SVM is primarily a classifier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. In this paper, we have used multiclass SVM to carry out identification on face images and Quadratic Programming (QP) optimization method to train the SVM. For experiments, IRIS Thermal/Visual Face Database is used. Experimental results show that 97.28% is the highest average success rate achieved on the fused images of 70% visual and 30% thermal images using the linear kernel. However, the highest success rate of 100% is achieved for classes 4 and 10 in several cases.**

Keywords-face identification; thermal image; pixel fusion; Incremental Principal Component Analysis (IPCA); Support Vector Mechine (SVM)

I. INTRODUCTION

Human face identification has always been a difficult task to deal with. It has a vast application domain that covers some of the critical areas like security systems, defense applications, intelligent machines etc. It involves different image processing issues like face detection, feature extraction and identification [1], [2], [3]. Visual imagery was broadly used in face identification systems, but these are very sensitive to illumination changes. This limitation has been overcome by the Infrared (IR) spectrum that provides simpler and more robust solution to boost the identification performance in uncontrolled environments and deliberate attempts to obscure identity. But IR imagery is sensitive to temperature changes in the surrounding environment and variations in the heat patterns of the face and it is opaque to glass. All these facts degrade the face identification efficiency. This drove us to fuse information from both visual and thermal spectra, which have the potential to improve face identification performance. Image fusion is the concept of combining multiple images into composite products, through which more information than that of individual input images can be revealed [4]. The goal of image fusion is to integrate complementary multisensor, multi temporal and/or multi view data into a new image containing more information with some sort of panoptic view of the face image free from all the disturbances. With the availability of multiple image sources, image fusion has emerged as a new and promising research area.

It is not possible to obtain an image with all the information, but the emergence of various image-capturing devices has helped image fusion to be used in several applications like remote sensing, machine vision, biometrics etc. Sometimes, a complete picture may not be always feasible since optical lenses of imaging sensor especially with long focal lengths, only have a limited depth of field. Image fusion helps to obtain an image with all the information. Various approaches applied for various applications in recent years have helped in developing many algorithms and image fusion software. Recently, researchers have investigated the use of fusion of thermal infrared and visual face images for person

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identification to tackle the drawbacks of individual thermal and visual images [5], [6], [7], [8], and [9]. So far, research work on fusion has been carried out for years. The obtained fusion methods can be classified into two categories as stated in [4]. One is about weakly coupled fusion methods, and the other is about strongly coupled fusion methods. In the first category of fusion methods, fusion of data produced by sensory modules does not affect the operation of the modules. On the contrary, for strongly coupled fusion methods, the modules producing the data to be fused are being affected in some way by other information from other modules. There are three levels in multi resolution fusion scheme namely pixel based fusion, feature based fusion and decision fusion [4]. In pixel level fusion the fused pixel is derived from a set of pixels in the various inputs [10]. The original measured quantities are directly involved in the fusion process. Moreover, algorithms are computationally efficient and easy to implement, but the input images needs to be co-registered. Some efficient algorithms for pixel level fusion such as, weighted average, transform based approach, etc. have been proposed in [11], [12], [13], [14]. In feature level fusion, the feature sets are extracted from multiple data sources and a new feature set is created using those features to represent a particular individual [16]. In decision level fusion, each classifier applies a threshold on the match score and conveys the subsequent decision to the fusion engine [17].

It is possible that both the feature level and decision level image fusion resulting inaccurate and incomplete transfer of information. To overcome this, Hanif et al. [6] have proposed data fusion methods by taking some percentage of the pixel information from the visual and corresponding thermal image to fuse an image. Gyaourova et al. [18] tried to implement pixel based fusion scheme in the wavelet domain, and feature based fusion in the eigenspace domain. But, this method was unable to diminish the illumination effects present in the visible images entirely; however, considerable improvements were noticed in overall recognition performance. Pavlidis and Symosek [19] demonstrated 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. An optimized image fusion approach consisting structural similarity, Principle Component Analysis and Discrete Wavelet is discussed in [20]. In [21] many multisensor data fusion architectures are presented to create a more informative fused image.

The conventional PCA, in the sense of least mean squared error minimisation, is susceptible to outlying measurements. To address this important issue, Y. Li [44] presented an algorithm of incremental PCA (IPCA), and then extended it to robust PCA. Various IPCA training and relearning strategies are proposed in [15] and applied to the candid covariance-free incremental principal component (CCIPCA) algorithm. In [22] Yan and Tang proposed an iterative algorithm, referred as LET-IPCA, to incrementally update the eigenvectors corresponding to the leading eigenvalues.

In this work, the classification performance of Support Vector Machine employed with three different kernels, namely Linear, Polynomial, and Gaussian Radial Basis Function have been studied with an emphasis on the investigation that how these kernels may affect and improve the face identification process using the four different levels of pixel fusion. This paper is organized as follows: in Section II, the overview of the system is discussed. Section III contains experimental results and discussions. Finally, in Section IV the conclusions and future work is provided.

II. THE SYSTEM OVERVIEW

In this work we have used thermal and visual face images from the Imaging, Robotics, and Intelligent Systems (IRIS) database. All the thermal and visual face images are first registered and then combined to generate fused image. The block diagram of the system is given in Fig. 1.

Different levels of fusion have been considered by varying the pixel data percentage from visual and thermal images, to find out the best possible features from thermal and visual images. After fusion, candid co-variance free incremental principal component analysis is applied to all fused images for feature extraction/dimension reduction and a Support Vector Machine classifier is used to classify them. For training Support Vector Machines, quadratic programming has been used. Extensive experiments with real datasets show that these algorithms can be compared with standard implementations of SVM in terms of generalization accuracy and computational cost, while being much simpler to implement [23].

A. Image Registration

Image registration is the process of transform ing two images into the same coordinate system. It's a fundamental task in image processing used to align two different images [24]. Many of the Image Registration techniques have been proposed and reviewed in [24], [25], [26]. Image registration techniques can be generally classified in two categories [27]. The first category utilizes image intensity to estimate the parameters of a transformation between two images using an approach involving all pixels of the image. In second category a set of feature points extracted from an image and utilizes only these feature points instead of all whole image pixels to obtain the transformation parameters. In this paper we have used the second category.

We have done registration of Visual and Thermal IR images before they are fused. In our experiment we have taken images from different expressions and illumination types of each person from IRIS database and registered the thermal and visual images separately with respect to the frontal image of each expression and illumination types. The steps followed for our registration procedure are:

Step 1: First, we have taken both frontal and corresponding images and loaded them separately in case of Visual and Thermal images;

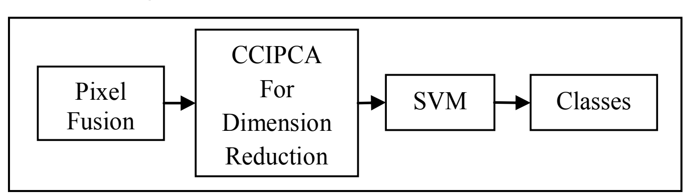

Figure 1. Block diagram of the system.

Step 2: Pair of control points chosen in both the images. Control points are landmarks that we can find in both images and save them;

Step 3: Specifying the affine transformation based on those control points and infer parameters for the transformation;

Step 4: Transform the unregistered image and so on for all the visual and thermal IR images.

Affine transformation has six degrees of freedom and is equivalent to combined effect of translation, rotation, isotropic scaling and shear (non-uniform scaling in some direction). Properties like parallelism, ratio of lengths of collinear or parallel segments, ratio of areas, and linear combination of vectors are invariant under affine transformation.

B. *Multisensor Images*

Visual and thermal images are the two multisensor images used here. Visual image may be defined as a pictorial representation of the perception that arises from the eyes. Though, these are the most commonly used images for face identification, but are very sensitive to illumination changes and do not work well in uncontrolled environment. Visual face recognition also has difficulty in detecting disguised faces, which is critical for high-end security applications. This fact inspired the researchers to think of thermal face images for a viable solution of these obstacles while face identification. Thermal infrared face images are formed as a map of the major blood vessels present in the face. Therefore, a face identification system designed based on thermal infrared face images cannot be avoided or deceived by forgery, or disguise, as can occur using the visible spectrum for facial identification. Compared to visual face identification systems, this system will be less vulnerable to varying conditions, such as head angle, expression, or lighting etc.

C. *Fusion of Visual and Thermal Face Images*

Image fusion is a technique which combines information from different sources together, using pixel, feature, or decision 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 unique identity determination 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. 3.

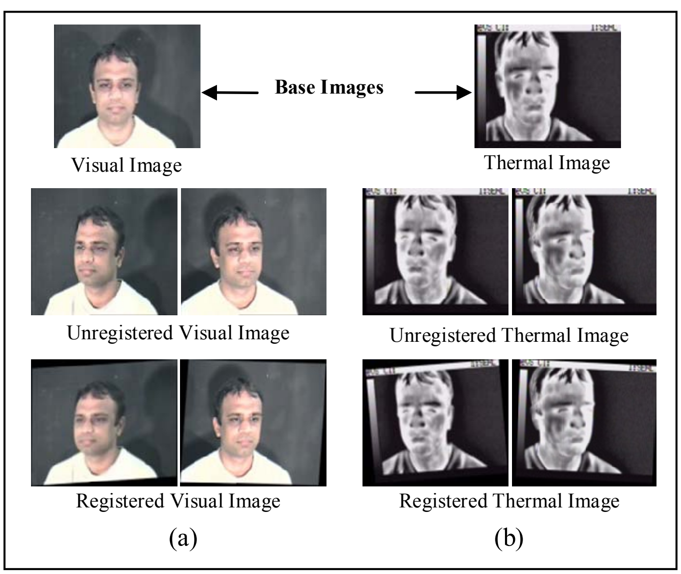

Figure 2. Image registration of visual and thermal images.

Ideally, the fusion of common pixels can be done by pixel-wise weighted summation of visual and thermal images [35], as given below:

$$F(x,y)=a(x,y)V(x,y)+b(x,y)T(x,y). \quad (1)$$

where, $F(x,y)$ is a fused output of a visual image, $V(x,y)$, and a thermal image, $T(x,y)$, while $a(x,y)$ and $b(x,y)$ represent the weighting factors for visual and thermal images respectively.

In this work, we have considered $a(x,y)$ = 0.40, $b(x,y)$ = 0.60; $a(x,y)$ = 0.50, $b(x,y)$ = 0.50; $a(x,y)$ = 0.60, $b(x,y)$ = 0.40; and $a(x,y)$ = 0.70, $b(x,y)$ = 0.30 respectively for the four different levels of pixel fusion.

D. *Candid Co-variance Free Incremental PCA*

We have used Eigenvalue Decomposition based Candid Co-variance Free Incremental Principal Component Analysis (EVD-CCIPCA) for dimensionally reduction of the fused images to increase the identification rates. EVD-CCIPCA algorithm generates observations in a complementary space for

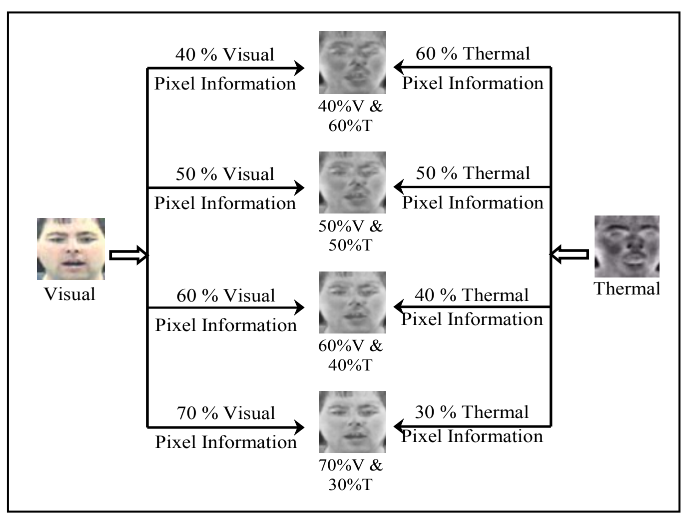

Figure 3. Sample images of fused images generated using different ratios of visual and thermal images.

the calculation of the higher order principal components [28]. We have not used PCA for dimensionality reduction as all PCA-based face identification systems are hard to scale up because of memory requirement burden and high computational cost [28]. To minimize this limitation we have used Incremental approach, which is also widely used for few decades. EVD-CCIPCA is an incremental version of popular PCA technique. The main difference between PCA and CCIPCA is that the traditional PCA algorithm computes eigenvectors and eigenvalues for a sample covariance matrix derived from a well known given image data matrix, by solving an eigenvalue system problem [29], whereas EVD based Candid Co-variance Free Incremental PCA methods allow new images and updating the PCA representation each time a new image is introduced [30].

Algorithm for Candid Co-variance free Incremental Principal Component Analysis (CCIPCA):

Step 1: Input a square image of M×M;

Step 2: Calculate the mean of the input image;

Step 3: Update the mean for reconstruction of face (Updated Mean is the changed mean of matrix X);

Step 4: Generate the centered image by subtracting input image to mean image;

Step 5: Calculate the eigenvectors and eigenvalues of the input image;

Step 6: Compute the projection matrix by multiplying eigenvalue and centered image;

Step 7: Generate the reconstructed image of input face.

E. Classification using SVM

Support Vector Machine, proposed by Vapnik [41], is originally a model for binary classification that performs classification tasks by constructing optimal separating hyperplanes in multidimensional space [42]. Although, the roots of the SVM approach was about to classify linearly separable data, but recently it is widely used in nonlinear data classification [43]. 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. The main idea behind support vector machines is that for constructing the optimal hyperplane one does not need to consider the feature space in explicit form. One only has to compute the inner products between support vectors and the vectors of the feature space.

1) Linear Classification: Consider a given training set $\{x_k, y_k\}_{k=1}^{N}$ with input data $x_k \in \mathbb{R}^n$ and output data $y_k \in \mathbb{R}$ 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, $y(x) = sign[w^T x + b]$ where, w is weight of the classifier and b is threshold of classifier; when the data of two classes are separable depending on y_k one can say,

$$w^T x + b \geq +1, \text{ if } y_k = +1 . \quad (2)$$

$$w^T x + b \leq -1, \text{ if } y_k = -1 . \quad (3)$$

The two sets of inequalities (2) and (3) can be combined into one single set as follows:

$$y_k \left[w^T x + b \right] \geq 1, \quad k = 1, \ldots\ldots, N . \quad (4)$$

SVM formulations are done within the context of convex optimization theory due to the fact that all training data points needed to be correctly classified. This gives the following primal (p) problem in w as, $Min\ J_p(w) = 1/2\, w^T w$, such that, $y_k \left[w^T x + b \right] \geq 1$, where, $k = 1, \ldots, N$.

2) 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 linear SVM because, the unknown w can be infinite dimensional [31]. The optimization problem becomes,

$$\min_{w,b,\xi} J_p(w, \xi) = \frac{1}{2} w^T w + c \sum_{k=1}^{N} \xi_k . \quad (5)$$

Such that, $y_k \left[w^T \varphi(x_k) + b \right] \geq 1 - \xi_k$, $k = 1, \ldots, N$ and $\xi_k \geq 0$, $k = 1, \ldots, N$.

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

a) Polynomial Kernel: The function for the polynimial kernel is given by the expression, $k(x_i, x_j) = (1 + x_i^T x_j)^p$, where p is the polynomial degree. The motivation of using polynomial kernel is that, for vectors x_i that are linearly dependent on p dimensions, the kernel function of order p can be used to transform them into linearly independent vectors on those p dimensions.

b) Gaussian Kernel: The expression for gaussian kernel is, $k(x_i, x_j) = \exp\left(-\|x_i - x_j\|^2 / 2\sigma^2 \right)$, where σ is the radius. This kernel is basically suited best to deal with data that have a class-conditional probability distribution function approaching the Gaussian distribution. It maps such data into a different space where the data becomes linearly separable [32].

III. Experiment Results and Discussions

This work has been simulated using MATLAB 2008a in a machine of the configuration Pentium(R) Dual-Core CPU T4200 @ 2.00GHz Processor and 2048MB of Physical Memory in 32 bit operating system. Experiments were conducted using Object Tracking and Classification Beyond Visible spectrum (OTCBVS) database set, which is a standard benchmark database for thermal and visual face images. The OTCBVS 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 110 visual images and 110 thermal images and with the combination of these images registered and fused images were produced with the variation of pixel data percentage of visual and thermal images. Out of 110 total fused images used in this work, 110 images were considered for training and 110 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 SVM has been used for classification. For the sake of experiment, images are resized into 50×50 face images. From 220 face images, support vector machine multiclass classifier considers 10 persons as 10 classes taking 22 images from each class. We have used 'one against all' multiclass strategy and the '5-fold Cross Validation' in our experiment. The classification accuracy is listed in the below four tables. The accuracy of a classification process defined as the portion of true positives and true negatives in the population of all instances, i.e.; classification accuracy A = (TP +TN)/ (TP +TN +FP +FN); where, 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 [33]. Linear kernel, Polynomial kernel (degree = 3) and Gaussian Radial Basis Function kernel (gamma = 2) are used in our SVM kernel. In 'one against all' strategy, when testing an unknown example, the classifier producing the maximum output is considered the winner, and this class label is assigned to that example [34].

Table I shows the classification accuracy of the classes when fused images are of 40% visual and 60% thermal. It can be seen that the highest accuracy is achieved for class 8 using the linear kernel and the accuracy is 98.64%. However, the highest accuracies for polynomial and RBF kernels are 97.73% and 93.64% achieved for class 6 and 4 respectively.

In Table II (using fused images of 50% visual and 50% thermal images), class 4 achieves 100% classification accuracy for both linear and polynomial kernels; and class 5 achieves the highest accuracy for RBF kernel, which is 95%. Moreover, class 9 achieves more than 98% accuracy in case of linear and polynomial kernels.

Table III, which uses the fused images of 60% visual and 40% thermal images, shows that the highest accuracy has been achieved using class 4 for polynomial kernel which is 100%. Using linear kernel the best accuracy is 99.55% and it is obtained using the images of class 4, 9 and 10. Using RBF kernel, class 5 provides the best accuracy of 95%. Again, above 98% accuracy is obtained by class 1 for linear and polynomial kernels, which is considerably better than the other classes.

Results shown in Table IV, are of the experiments done over the fused images of 70% visual and 30% thermal images. 100% classification accuracy is obtained by class 4 and 10 for linear kernel. Using polynomial kernel, class 1 and 4 obtain best accuracy of 99.55% which is better than the classes. For RBF kernel, class 3 obtains best accuracy of 95.91%. Other than these, more than 98% accuracy is achieved by class 1, 5, 7 and 9 for linear kernel; and by class 5, 9 and 10 for polynomial kernel.

In Table V, a comparative study between the present methods, some of our previous methods and some methods proposed by other researchers are shown. It shows the average results obtained for each of the above discussed experiments using the three different SVM kernels. It can be seen that, the linear kernel obtains higher accuracy than polynomial and RBF kernels for each type of image data. It can also be noticed that, use of the fused image data of 70% visual and 30% thermal images provides better accuracy for each of the three SVM kernels, in comparison to the other fused images. So, the best accuracy obtained among the present methods is the one that uses the above mentioned fused images using linear SVM kernel and it is 97.28% on an average. This is also the best accuracy among all the other methods shown in the Table.

TABLE I. CLASSIFICATION ACCURACY OF THE CLASSES WHEN FUSED IMAGES ARE OF 40% VISUAL AND 60% THERMAL

Class	**Classification Accuracy**		
	Linear kernel	***Polynomial kernel***	***RBF kernel***
1	0.9455	0.9227	0.9045
2	0.8773	0.8273	0.9227
3	0.9045	0.8864	0.9182
4	0.9273	0.9318	0.9364
5	0.8727	0.8682	0.9000
6	0.9591	0.9773	0.9227
7	0.9273	0.9409	0.9318
8	0.9864	0.9682	0.9000
9	0.9318	0.9045	0.9000
10	0.9318	0.9045	0.9000

TABLE II. CLASSIFICATION ACCURACY OF THE CLASSES WHEN FUSED IMAGES ARE OF 50% VISUAL AND 50% THERMAL

Class	**Classification Accuracy**		
	Linear kernel	***Polynomial kernel***	***RBF kernel***
1	0.9364	0.9500	0.9091
2	0.8955	0.8727	0.9273
3	0.9409	0.9045	0.9364
4	1.0000	1.0000	0.9000
5	0.9591	0.9682	0.9500
6	0.9182	0.8864	0.9182
7	0.9636	0.9545	0.9455
8	0.9182	0.9273	0.9364
9	0.9864	0.9818	0.9000
10	0.9591	0.9455	0.9000

TABLE III. CLASSIFICATION ACCURACY OF THE CLASSES WHEN FUSED IMAGES ARE OF 60% VISUAL AND 40% THERMAL

Class	Classification Accuracy		
	Linear kernel	***Polynomial kernel***	***RBF kernel***
1	0.9864	0.9818	0.9273
2	0.9045	0.9455	0.9273
3	0.9500	0.9455	0.9409
4	0.9955	1.0000	0.9000
5	0.9773	0.9727	0.9500
6	0.9136	0.8909	0.9091
7	0.9727	0.9682	0.9364
8	0.9364	0.9318	0.9091
9	0.9955	0.9682	0.9045
10	0.9955	0.9773	0.9000

TABLE IV. CLASSIFICATION ACCURACY OF THE CLASSES WHEN FUSED IMAGES ARE OF 70% VISUAL AND 30% THERMAL

Class	Classification Accuracy		
	Linear kernel	***Polynomial kernel***	***RBF kernel***
1	0.9864	0.9955	0.9318
2	0.9273	0.9364	0.9273
3	0.9591	0.9682	0.9591
4	1.0000	0.9955	0.9045
5	0.9909	0.9864	0.9455
6	0.9364	0.9227	0.9318
7	0.9864	0.9727	0.9455
8	0.9455	0.9455	0.9409
9	0.9955	0.9864	0.9045
10	1.0000	0.9864	0.9000

TABLE V. COMPARATIVE STUDY OF DIFFERENT FACE IDENTIFICATION METHODS

Methods		**Performance Accuracy**
Pixel fusion using 40% visual and 60% thermal images + IPCA + SVM *(Present method)*	Linear kernel	92.64%
	Polynomial kernel	91.32%
	RBF kernel	91.36%
Pixel fusion using 50% visual and 50% thermal images + IPCA + SVM *(Present method)*	Linear kernel	94.77%
	Polynomial kernel	93.91%
	RBF kernel	92.23%
Pixel fusion using 60% visual and 40% thermal images + IPCA + SVM *(Present method)*	Linear kernel	96.27%
	Polynomial kernel	95.82%
	RBF kernel	92.05%
Pixel fusion using 70% visual and 30% thermal images + IPCA + SVM *(Present method)*	Linear kernel	**97.28%**
	Polynomial kernel	96.96%
	RBF kernel	92.91%
Wavelet fusion of visual and thermal images using db2 + IPCA + SVM [38]	Linear kernel	95.77%
	Polynomial kernel	95.14%
	RBF kernel	92.68%
Wavelet fusion of visual and thermal images using db2 + PCA + MLP [39]		85.00%
Wavelet Decomposition + Quotient + Reconstruction + Wavelet Fusion of visual and thermal images + PCA + MLP [40]		94.00%
Simple spatial fusion [6]		91.00%
Fusion of Thermal and Visual [5]		90.00%
Segmented infrared images via Bessel forms [36]		90.00%
Abs max selection in DWT [6]		90.31%
Window base absolute maximum selection [6]		90.31%
Fusion of visual and LWIR + PCA [37]		87.87%

IV. CONCLUSION AND FUTURE WORK

In this paper, the efficiency of the different SVM kernels are tested against the four different levels of pixel fusion of visual and thermal face images for the purpose of human face identification. After the fusion of images as weighted sum, the fused images are projected into eigenspace. Those fused eigenfaces are classified using Support Vector Machine. Eigenspace is constituted by the images belonging to the training set of the SVM. The efficiency of this scheme has been demonstrated on Imaging, Robotics, and Intelligent Systems (IRIS) Thermal/Visual benchmark face database. The proposed technique has proven to be helpful even for variable expressions and light conditions. The future work includes addressing the problem of expression changes using pixel based fusion scheme along with environmental effects in thermal and visual both and different feature based as well as decision fusion techniques for human face identification. We will also find which dimension reduction/ feature extraction methods are more compatible and effective with SVM.

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