State of the art in Infrared face recognition

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ABSTRACT: *Face recognition is an area that has attracted a lot of interest. Much of the research in this field was conducted using visible images. With visible cameras the recognition is prone to errors due to illumination changes. To avoid the problems encountered in the visible spectrum many authors have proposed the use of infrared. In this paper we give an overview of the state of the art in face recognition using infrared images. Emphasis is given to more recent works. A growing field in this area is multimodal fusion; work conducted in this field is also presented in this paper and publicly available Infrared face image databases are introduced.*

KEY WORDS: *Infrared, face recognition, features extraction, image fusion.*

1. Introduction

Face recognition is an area of computer vision that has attracted a lot of interest from the research community. A growing demand for robust face recognition software in security applications has driven the development of interesting approaches in this field. One of the well known approaches in this area is Eigenfaces (Turk *et al.,* 1991). A large number of techniques exist in face recognition, these techniques can be divided into holistic and feature based approaches. Holistic approaches use a subspace representation for dimensionality reduction and face recognition. Feature based approaches extract features from face images and use metrics obtained from these features or match similar features for face recognition. A survey of different techniques for face recognition can be found in (Zhao *et al.*, 2003) and (Kong *et al.*, 2005).

A large quantity of research in face recognition deals with visible face images. In the visible spectrum the illumination changes represent a significant challenge for the recognition system. Illumination change introduces a lot of errors during the recognition phase. Another challenge for face recognition in the visible spectrum involves the changes in facial expressions. Facial expression can lead to a poor performance of the face recognition system in visible images. To avoid these problems, researchers propose the use of 3D face recognition (Bronstein *et al.*, 2005) and infrared face recognition (Kong *et al.*, 2005). 3D face recognition can deal with illumination changes, while infrared can deal with changes in both illumination and facial expression. However, infrared face recognition suffers from the following limitations: opacity to eyeglasses in thermal infrared images (Figure 1) and thermal change in face regions due to cold, physical activities, etc. (Kong *et al.*, 2005, Siddiqui *et al.*, 2004). To overcome these limitations, fusion schemes were proposed in order to combine different face recognition modalities and achieve high recognition results in complex situations.

Figure 1. *Thermal face image showing infrared opacity to eyeglasses*

In this paper we present an overview of the state of the art in the field of face recognition using infrared images. Emphasis is given to more recent works. In recent years, the fusion of multiple modalities has attracted a lot of interest. The work in this field is also presented in this paper and available databases of infrared face images are introduced. Past reviews in the field of infrared face recognition are an interesting complement to our paper (Kong *et al.,* 2005, Prokoski 2000).

(Prokoski 2000) presented one of the first reviews in infrared face recognition. The author presents the work conducted in infrared face recognition prior to 2000. Many techniques are introduced: template matching, thermal contours, feature extraction for metrics matching, wavelet analysis for face matching, symmetry waveforms with bar code encoding of face waveforms and the use of facial minutiae. The author also introduces different areas where face recognition can be used.

A more recent review is given in (Kong *et al.,* 2005). The authors present a review of different face recognition techniques. Infrared face recognition is also presented. Some of the articles addressing infrared face recognition published before 2004 are presented in this paper.

2. Databases for infrared face recognition

The growing interest for the use of infrared images in face recognition created the need for face image databases that can be used for benchmarking the developed algorithms. Four databases of infrared face images are available publicly and are presented below.

2.1. *Equinox database*

The Equinox database (Equinox 2007) is a large collection of face images. These images were acquired using a special setup formed by visible and infrared cameras and a controlled lighting system (frontal, left and right lights), as shown in Figure 2 (Equinox 2007).

The following modalities are available: Visible (0.4-0.7 microns), long-wave infrared (LWIR, 8-12 microns), mid-wave infrared (MWIR, 3-5 microns) and short-wave (SWIR, 0.9-1.7 microns). The images are coregistered thus permitting easy testing of multimodal fusion approaches of face images. Figure 3 (Equinox 2007) shows an example of an image in different modalities.

The image acquisition was conducted under controlled conditions. Multiple facial expressions, illumination changes and facial images with and without glasses are available.

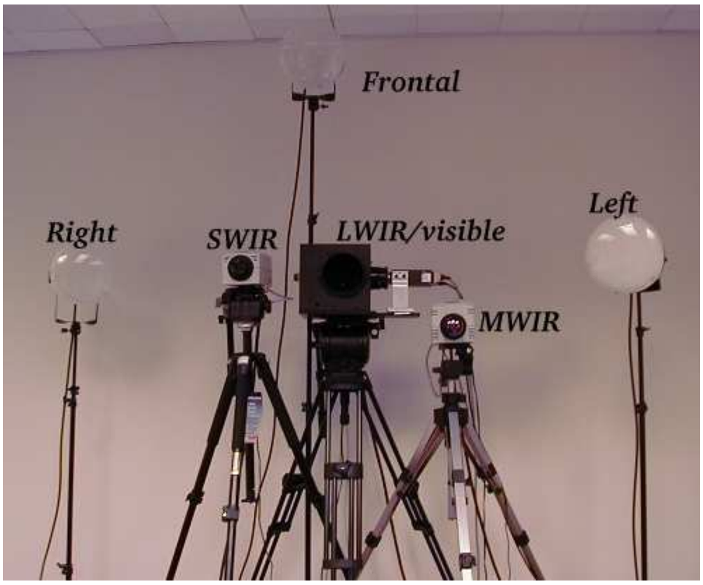

Figure 2. *Setup used for face image acquisition of the equinox database*

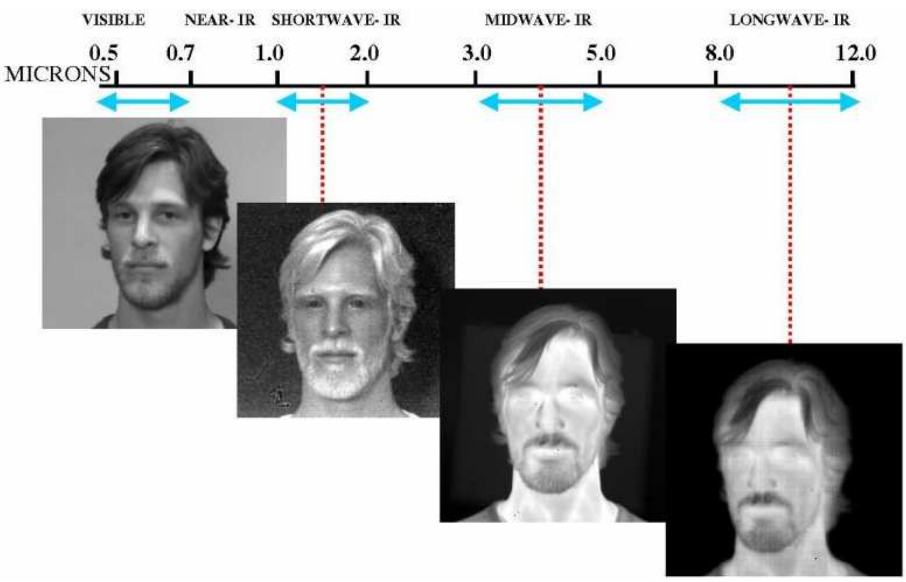

Figure 3. *Face image in different modalities*

2.2. *IRIS Thermal/Visible database*

The IRIS Thermal/Visible database (UTK 2007) contains 4228 pairs of thermal and visible images. A long-wave infrared camera (Raytheon Palm-IR-Pro) was used to capture thermal images. These images are unregistered. They were acquired under variable illuminations, facial expressions and poses. The image size is 320 x 240 pixels (visible and thermal). The setup used for face image capture is shown in Figure 4 (UTK 2007). This database was collected by the Imaging, Robotics, and Intelligent Systems Laboratory at the University of Tennessee.

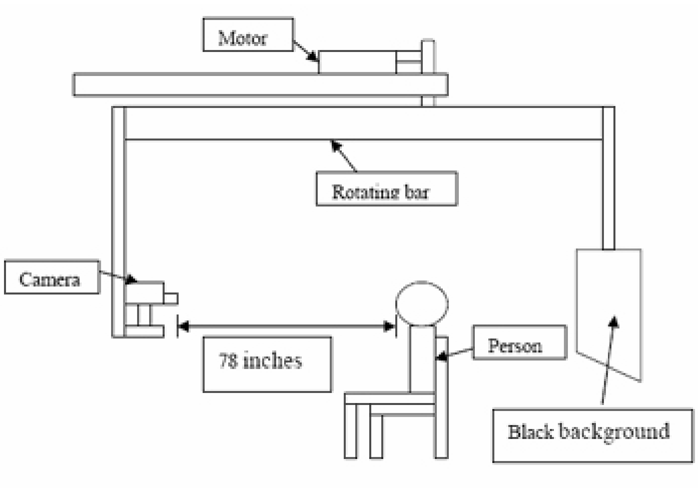

Figure 4. *Setup for the acquisition of IRIS thermal/visible database*

2.3. *More databases*

Two other databases of infrared face images are available. The first one is the University of Notre Dame Biometrics Database (UND 2007) collected by the Computer Vision Research Laboratory of Notre Dame University; this database contains visible and thermal images. The second database is from the Laboratory for Computational Vision of Florida State University, and contains a dataset of infrared face images (FSU 2007).

3. Infrared face recognition

Infrared face recognition is a growing area of research. Many of the techniques used in infrared face recognition are inspired from their visible counterparts. Known techniques used in visible face image recognition are also used with infrared images: Eigenfaces or Principal Component Analysis (PCA) (Turk *et al.*, 1991), Fisherfaces or Linear Discriminant Analysis (LDA) (Etemad *et al.,* 1997), Independent Component Analysis (ICA) (Liu *et al.,* 1999), Support Vector Machine (SVM) (Jonsson *et al.,* 2000), ARENA (Sim *et al.,* 2000), Bayesian framework (Liu *et al.*, 1998), Boosting algorithms (Lu *et al.,* 2006), FaceIt commercial software (Heo *et al.*, 2003, L1id 2007), etc. These techniques can be divided into holistic and feature based techniques.

3.1. *Holistic based techniques*

The most popular techniques in infrared face recognition are holistic based techniques. The most used is by far the Eigenfaces (PCA) technique (Turk *et al.*, 1991). This technique serves in many cases as a reference for performance comparison with other techniques. Other two popular holistic techniques include: Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA).

The PCA or Eigenfaces technique permit a dimensionality reduction by subspace representation of faces. Average face image is constructed from the training set and used to derive the eigenvectors representing the face space approximation. Under the assumption that the training set is a good representation of possible face images, the selected vectors are a good approximation of all possible faces (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002). By selecting the eigenvectors corresponding to high eigenvalues we construct a low dimensional projection space of face images. One of the first works in infrared face recognition used the PCA technique (Cutler 1996). Tests were conducted using MWIR images of frontal, 45^o and profile views and high accuracy was achieved. Since then, many other authors used the PCA technique. (Wilder *et al.,* 1996) used PCA in LWIR images. (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002) conducted a comparison between visible and LWIR images using different techniques including PCA (Figure 5). The tests were conducted in various situations including faces with and without glasses and with various facial expressions and variable illumination conditions. The authors reported good performances of PCA in LWIR images. (Wu *et al.,* 2005) propose a transformation technique to convert LWIR infrared images to blood perfusion data. The images obtained are meant to represent the internal skin temperature and are independent of ambient temperature variations. Face recognition is performed using PCA and RBF neural network. The authors report an increase in recognition rates using the transformed images over the direct use of thermal images. (Kang *et al.*, 2006) used PCA for face recognition using short-wave infrared (SWIR) images. A lighting system in 940nm spectrum was used in this system. (Li *et al.*, 2006, 2006a) used near infrared (NIR) images for face recognition with an 850nm lighting system. SWIR and NIR images are less sensitive to illumination changes than visible images (Figure 6). This characteristic increases the performance of face recognition in this type of images.

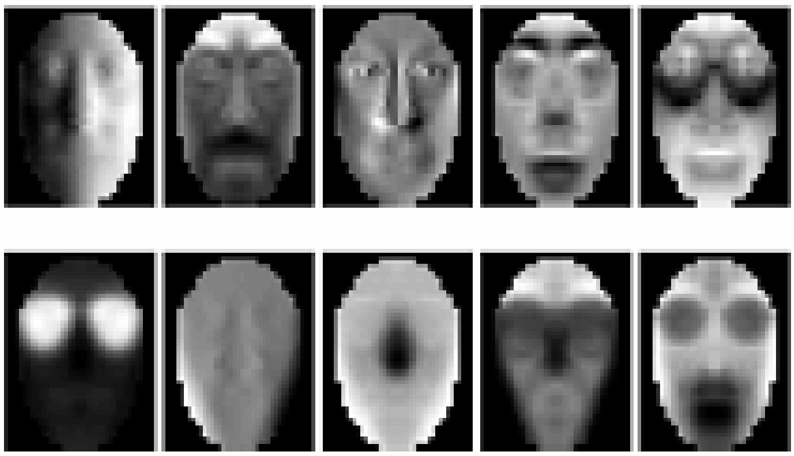

Figure 5. *First five Eigenfaces(PCA) in visible (top) and LWIR (bottom) images*

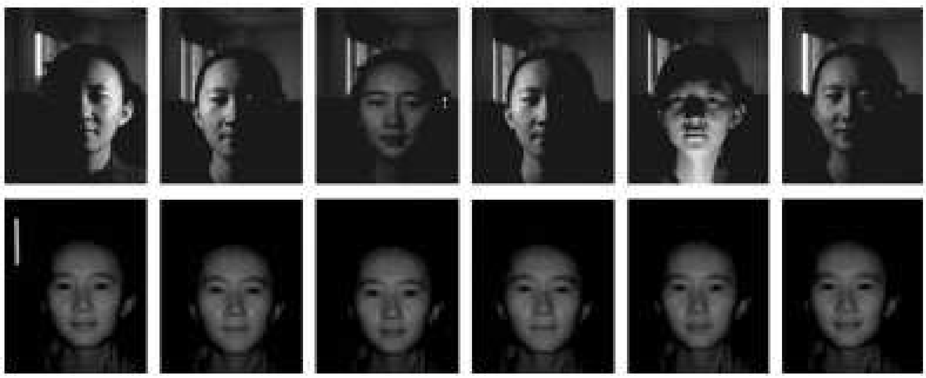

Figure 6. *Visible images (top) and NIR images (bottom), we can see that NIR is less sensitive to illumination changes*

The second most popular technique in infrared face recognition is LDA, also known as Fisherfaces technique. Like PCA, this technique permits a dimensionality reduction by subspace representation of faces. Instead of principal components decomposition, in LDA the data are separated linearly in the Eigenspace using Singular Value Decomposition (SVD) (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002). In (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002), the authors conducted comparisons between different face recognition techniques, including LDA, in visible and LWIR images (Figure 7). In their tests, LDA was the best performing technique in visible and LWIR face recognition. (Zou *et al.*, 2005, 2006) used LDA for NIR face recognition. Four techniques, available in a machine learning toolbox named WEKA (WEKA 2007), were used for classification: Radial Basis Function (RBF) neural network, Adaboost classifier, Support Vector Machine (SVM), and Nearest Neighbour (NN). Tests show that the results obtained in LDA space for NIR images outperform the results obtained with ambient light images, specially using SVM and NN classifiers. (Kang *et al.*, 2006) used LDA for face recognition of SWIR images with interesting results. Another work using NIR images and LDA was done by (Li *et al.*, 2006, 2006a). In this work the combination of LDA with Linear Binary Patterns (LBP) features gave the best performance.

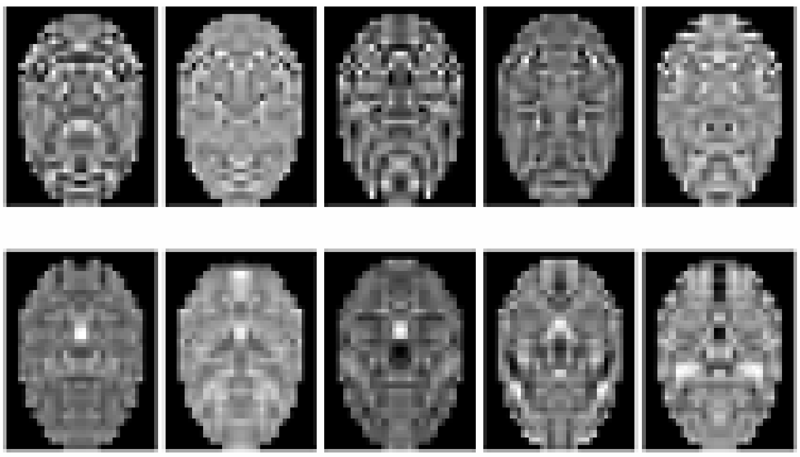

Figure 7. *First five Fisherfaces (LDA) in visible (top) and LWIR (bottom) images*

Another popular holistic technique is the Independent Component Analysis (ICA) (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002). ICA is a statistical technique capable of finding hidden factors representing random data. The ICA model assumes that the data variables are a linear combination of unknown non Gaussian and mutually independent variables. (Socolinsky *et al.*, 2001, 2002, 2003, Selinger *et al.*, 2002) used ICA for LWIR and visible face recognition (Figure 8). They compared its performance to PCA and LDA. ICA performed well in visible images (closely following the best performing technique: LDA).

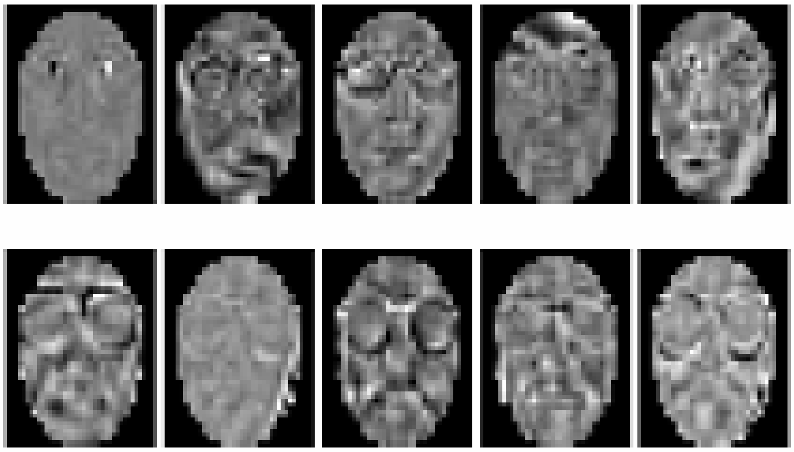

Figure 8. *First five Independent Component Analysis (ICA) in visible (top) and LWIR (bottom) images*

Another holistic technique that can be used for dimensionality reduction is a Discrete Cosine Transform (DCT). (Zhao *et al.*, 2005) present an active NIR system for face recognition using DCT. They propose the use of DCT lowest frequencies and an SVM classifier for face recognition. Interesting results are reported by the authors.

3.2. *Feature based techniques*

Feature based approaches extract features from face images and use metrics obtained from these features or match similar features for face recognition.

Template matching and distance metrics computation are used in various works. In (Friedrich *et al.,* 2002), the authors use of Euclidian distances between LWIR images. The results obtained show that face recognition in the infrared spectrum gives better results even in the presence of changes in face/head orientation and facial expressions. In (Heo *et al.,* 2003a), the authors conducted performance comparisons of face recognition in LWIR images. They used coregistered visible and LWIR images from the Equinox database. Performance tests used visible and infrared images under different operating conditions. The face recognition system used is FaceIt (A commercial software). This software use metrics computed from extracted features in the face image (eyes, nose, mouth, etc.). The results obtained show that thermal images outperformed visible light images when no eyeglasses were present. (Heo *et al.*, 2005, 2005a) propose the use of correlation filters to improve face recognition performance in LWIR thermal images. The correlation filters are known to be distortion invariants, thus the combination with thermal images that are less sensitive to illumination variations can lead to higher accuracy. The authors present two correlation filters used in their comparative study: minimum average correlation energy (MACE) filters and optimum trade-off synthetic discriminant function (OTSDF) filters. Experimental results show that the proposed correlation filters applied to thermal images outperformed their use in visible images. In this work, OTSDF performed better than MACE. Also, OTSDF produced the best results compared to PCA, FaceIt and normalized correlation. In (Pan *et al.*, 2003), the authors used mahalanobis distance between sampled face regions from two NIR images. The objective of this work is to conduct spectral measurement of subsurface tissue over the NIR spectrum. The hypothesis behind the use of subsurface tissue is its difference from person to person, its stability over time and its quasi-invariance to face orientations and expressions. Experiments were conducted in 31 spectral bands in the range of 0.7-1.0 micron. The authors report interesting results, but performance degradation appears in changing conditions (pose, expressions and time). In (Pavlidis *et al.*, 2006, Buddharaju *et al.*, 2005, 2006, 2007, 2007a), the authors propose a face recognition technique based on the extraction of physiological information from face images. The extracted physiological information represents the network of blood vessels under the skin (Figure 9). This network is unique for each individual. Mid-wave Thermal infrared images (MWIR) are used to extract this information. The authors use mathematical morphology techniques to extract the vascular network from thermal information. The branching points of the skeletonized vascular network are referred to as Thermal Minutia Points (TMP). The TMP constitute the feature database used in the matching process. The authors report successful results in tests conducted with various thermal images. (Srivastava *et al.*, 2001, Buddharaju *et al.*, 2004) propose the decomposition of infrared images in their spectral components using band-pass filter banks. Gabor filters are used in this decomposition. The resulting filtered images are then used to derive the Bessel form estimated using the second and fourth moments of the filtered image (variance and kurtosis). The comparison was performed using a L^2-metric between Bessel parameters in different images. Experiments were performed in LWIR thermal images. The authors show that the proposed technique outperforms PCA and ICA face recognition techniques.

A neural network approach is used in (Socolinsky *et al.*, 2001). The authors used an algorithm called ARENA. The ARENA algorithm first reduces the dimensionality of training observations. This is done by reducing the image resolution to 15x20 pixels (by averaging square neighbourhoods in the image). Then a nearest-neighbour classification is performed. Experimental results show that the best performance was obtained for LWIR images in the presence of illumination variation, compared to visible images.

(Wilder *et al.*, 1996) conducted an evaluation of face recognition performance in visible and LWIR infrared images. In their work, transform coding of greyscale projections, Eigenfaces and matching pursuit filters were used. The authors reported that the best performance in infrared face recognition was achieved using greyscale projections.

Figure 9. *Thermal face image segmented and processed (left), extracted vascular network (center)and result of TMPs extraction (right)*

3.3. *Factors affecting infrared face recognition*

Face recognition is performed in normalized and aligned images. This normalisation is based on the localisation of eyes positions. (Selinger *et al.*, 2004) studied the effect of eye location in PCA face recognition. The eyes are located in LWIR images and visible images. For LWIR images the authors used Haar-like features available in OpenCV library (Intel 2007). For visible images a dark circle surrounded by a lighter background is located using a Hough transform algorithm. The performance of eye location was compared with manually located regions, and face recognition performance was evaluated in normalized images using the located eyes. Eye location experiments were conducted on subjects not wearing glasses. The results show that the error in eye location is higher for infrared images than in visible images. For face recognition evaluation, the results show that errors in eye location degrade the performance of face recognition. This degradation is more noticeable when eye location is performed in LWIR images. The performance of face recognition using the located eyes for face normalization is even worse in the case of the PCA algorithm. The Equinox proprietary algorithm (Equinox 2007) is reported to give better results. Similar results were obtained by (Kang *et al.*, 2006) for SWIR face recognition using PCA and LDA. The positions of the eyes have important implications on the face recognition performance.

(Siddiqui *et al.*, 2004) studied the effect of cold and the presence of eyeglasses in thermal images. The core of the face recognition system is the PCA technique. The proposed approach detects and replaces cold regions and eyeglasses by average values from other face areas. The authors reported an increase in the success rate with the proposed approach. In (Heo *et al.*, 2005, 2005a), degradation in the recognition performance was noticed in the presence of eyeglasses in thermal images. Detecting glasses and replacing them with an eye template obtained by averaging eye regions from multiple images (Figure 10), led to an increase in recognition performance in the presence of eyeglasses. The same approach is used in (Kong *et al.*, 2007) and combined with a multiscale fusion strategy.

Figure 10. *Example of eyeglass detection and replacement with an eye template*

4. Multimodal fusion

Face recognition using infrared images gives interesting advantages over visible face recognition, especially when lighting and face expression changes are present. However, visible face recognition performs better in controlled lighting situations and when the subject wears eyeglasses. In recent years more emphasis has been placed on fusing visible and infrared images in order to achieve high recognition rates. Fusion can be divided in two categories: Decision based fusion and data based fusion. In decision based fusion, the obtained results are fused by a combination of the obtained scores. In data based fusion, the images are fused using a combination of pixel values.

4.1. *Decision based fusion*

In decision based fusion many score combination schemes have been proposed. In (Chen *et al.*, 2003, 2003a, 2005) the authors propose a decision level fusion by a rank-based strategy (sum of the ranks for each class) and a score-based strategy (sum of the scores for each class). They report that the fusion of visible and infrared images outperforms the individual spectrum recognition. They also show that the score-based strategy gives the best results and improves the performance significantly. (Socolinsky *et al.*, 2004, 2004a) used a sum of the resulting recognition scores of visible and LWIR images. The results show a significant improvement in recognition rates using the proposed fusion strategy. (Chen *et al.*, 2005a) used a decision based fuzzy integral fusion of the visible and LWIR face recognition results. In their approach, the Eigenfaces algorithm is applied in each modality and a set of Eigenface components are mapped to a features vector and normalized. A fuzzification technique is applied to the extracted visible and infrared vectors using a modified histogram based technique. The fuzzy integral fusion permitted an increase in recognition rates.

(Buddharaju *et al.*, 2007a) propose the combination of the method described in (Pavlidis *et al.*, 2006, Buddharaju *et al.*, 2005, 2006, 2007), with a classical PCA face recognition method applied to visual images (Figure 11). The proposed multispectral approach bases its final score on a decision level fusion by combining the individual scores from the visual and thermal infrared recognition algorithms. The proposed fusion strategy gives better results than the two individual approaches alone.

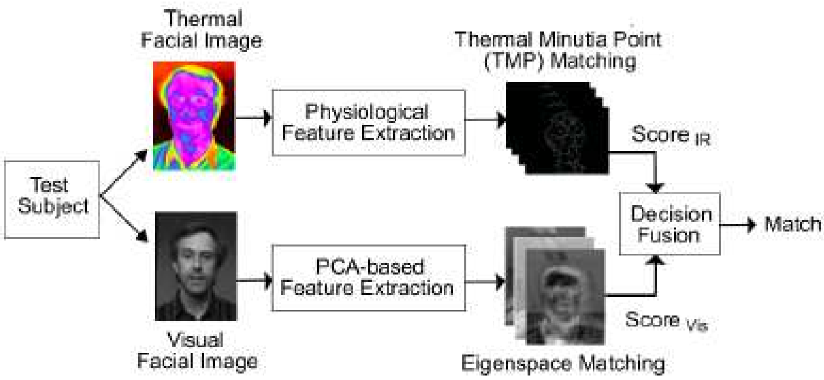

Figure 11. *Multispectral fusion presented by Buddharaju et al.*

(Bowyer *et al.*, 2006) studies the use of visible, 3-D and infrared images (LWIR) for face recognition. The authors analyse the performance of a multimodal approach combining visible images with 3-D and infrared images, and a multisample approach using multiple intensity images. The authors report significantly higher performance for the combination of different types of imagery (multimodal approach) compared to the use of individual modalities. The best performance was obtained by combining all the three modalities (Visible, infrared and 3D). They report also a significantly higher recognition rate when combining multiple intensity images (multisample approach). They used a weighted score fusion approach with PCA and obtained interesting results.

(Kakadiaris *et al.*, 2005, 2005a) present a multimodal face recognition approach using visible and thermal images (Figure 12). The proposed framework uses the following characteristics: 3D geometry, 2D visible texture and 2D infrared texture, over time. A range scanner is used to capture the 3D face geometry. Texture mapping is then used to map a face image in the 3D model. The 3d mapped models are then projected in a parametric 2D space (UV space) to produce a deformation model of the face used in the recognition phase. Haar wavelets are then used for data compression. Infrared images are used to extract skin regions used for recognition. The vascular network is also extracted from thermal images and projected to the parametric UV space. Recognition is performed by comparing the signatures obtained from:

– The parametric deformation image,

– The parametric thermal image, and

– The visible spectrum texture map.

The authors report good performance obtained with the proposed method even in the presence of facial expressions.

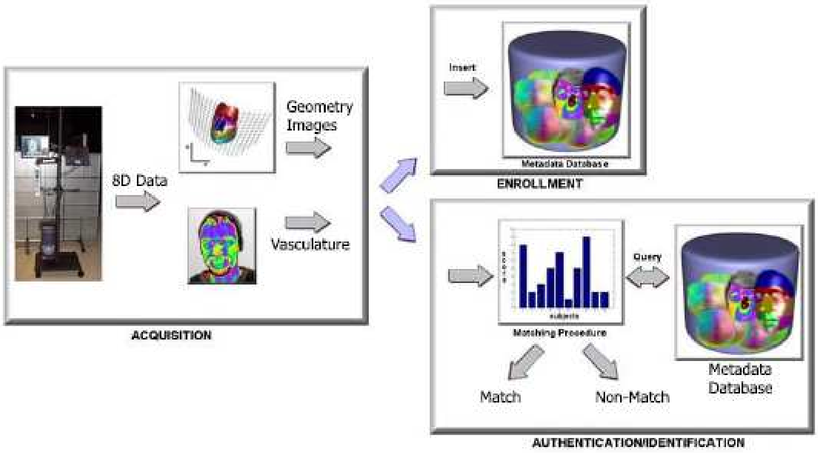

Figure 12. *Multimodal face recognition system*

4.2. *Data based fusion*

Data based fusion in infrared face recognition has attracted a lot of interest in recent years. Most of the work use wavelets decomposition for data fusion. (Gyaourova *et al.*, 2004, Singh *et al.*, 2004) propose a data fusion scheme of infrared and visible images for face recognition. The proposed approach aims to overcome the limitations caused by the opacity of infrared imagery to eyeglasses. Since visible imagery is less sensitive to eyeglasses and infrared imagery is less sensitive to illumination variation, the fusion of the two modalities lead to better results. The fusion strategy operates in the wavelet domain by combining the coefficients of Haar wavelets. A Genetic Algorithms (GAs) approach is employed in order to fuse the wavelet coefficients from the LWIR and visible images. The GAs find the appropriate way to fuse these coefficients by choosing which coefficients to use and how to combine them. Considerable improvement is achieved with fused images when eyeglasses are present. Haar wavelets are also used in (Chang *et al.*, 2006, 2006a) and (Kong *et al.*, 2007). (Chang *et al.*, 2006, 2006a) propose a data fusion scheme for illumination adjustment to improve face recognition rates. Tests were conducted in fused multispectral images. Two techniques were used: A weighted fusion and a Haar wavelet based pixel level data fusion. The face recognition performance was tested using FaceIt commercial software and a better performance was obtained with the fused images. (Kong *et al.*, 2007) present a multiscale fusion strategy of visible and thermal images. The registration method uses directional derivative maps (Boughorbel *et al.*, 2004) and multiscale data fusion is performed using discrete Haar discrete wavelet decomposition (DWT). Data fusion consists of a weighted combination of DWT coefficients of visible and thermal images. The fusion of visible and infrared images is reported to give better results than single modality face recognition. The work of (Singh *et al.*, 2007) proposes a hierarchical fusion of infrared and visible images (Figure 13). The algorithm uses Gabor wavelets to perform image fusion. 2D log polar Gabor wavelet extracts amplitude and phase features. A learning strategy based on Adaptive Support Vector Machine (SVM) is used to select the features in amplitude and phase images. These features are then used to generate the fused image. Multiple tests were conducted by fusing different wavelengths. The fusion of SWIR and visible face images was reported to give the best results.

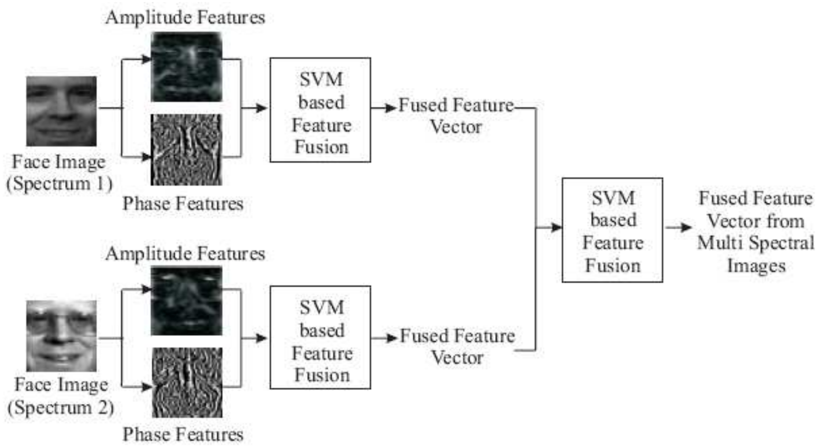

Figure 13. *Fusion system proposed by Singh et al.*

In (Bebis *et al.*, 2006), the authors, proposed an eigenfeatures fusion strategy. Eigenfeatures were extracted directly form visible and infrared images and a genetic algorithm was used for selecting the appropriate eigenfeatures for fusing visible and infrared images. The authors report an increase in recognition performance with the proposed fusion approach.

(Hariharan *et al.*, 2006) present a fusion of LWIR and visible images using an Empirical Mode Decomposition (EMD). EMD decomposes non-linear non-stationary signals into Intrinsic Mode Functions (IMFs). The visible and infrared images are vectorized and EMD is performed on these vectors to obtain the visible and infrared IMFs. A number of IMFs are selected for fusion. These IMFs are multiplied by weights that were empirically obtained in order to enhance non-mutual information between visible and infrared images. The enhanced IMFs are combined and face recognition is performed on the resulting fused image. Experiments were conducted on coregistered images from the Equinox database. The commercial face recognition software FaceIt was used, and the recognition performance was evaluated on fused images obtained by: Averaging, PCA fusion, wavelet based fusion, and EMD fusion (Figure 14). The authors report that the best performance was obtained with EMD fused images even in changing illumination conditions and different facial expressions.

Figure 14. *From left to right: Visible image, Infrared image; Averaging fused image; PCA fused image; Wavelet based fused image; and EMD fused image*

4.3. *Hybrid decision and data based fusion*

Fusion techniques using a both decision and data fusion approaches have been introduced. (Heo *et al.*, 2003b, 2004, Abidi *et al.*, 2004) describe a fusion of visible and infrared images for face recognition. Image fusion is performed at data and decision levels (Figure 15). Data level fusion permits the integration of visible and infrared images. Decision level fusion permits the combination of the obtained visible and infrared recognition scores. The authors propose three fusion techniques: Data fusion of infrared and visible images, decision fusion with a highest matching score, and decision fusion with an average matching score. The proposed data fusion is achieved using a weighted average of visible and thermal images in order to obtain an illumination invariant image. Weights are determined using the brightness distribution in the face images. In low illumination the weight of visible images is lower than that of thermal images and in high face temperature the thermal image weight is lower than that of the visible image. Decision level fusion is performed by combining the individual scores of visible and thermal face recognition obtained using FaceIt. Tests were performed using coregistered visual and LWIR images from the Equinox database. Experimental results show that thermal images and fusion techniques outperformed the visible face image recognition when no eyeglasses were present. When eyeglasses are present, the fusion techniques with an eyeglass removal algorithm produced the best results.

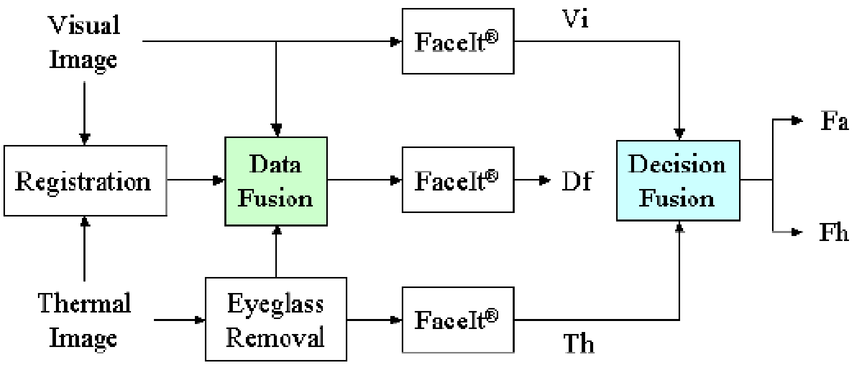

Figure 15. *Heo et al. Fusion system*

(Arandjelovic *et al.*, 2006, 2006a, 2007) propose a multistep fusion scheme for face recognition. The fusion is carried out at the decision and modality level using visual and LWIR thermal images (Figure 16). The proposed approach consists in three main steps: data pre-processing, eyeglasses detection and fusion of holistic and local face features using visual and thermal modalities. For feature based fusion, the local patches around the eyes and mouth and the face image are matched using a PCA face recognition technique. The similarity score is obtained using a weighted sum. Different constant weights are used for visible and thermal images. Modality fusion is conducted by a weighted combination of visible and thermal images. Weights are high in the visible spectrum if the recognition rate is high in this spectrum. The proposed fusion method with eyeglasses detection outperformed other techniques explored in their experiments.

(Ali *et al.*, 2006) use a set of Gabor filters to process the face images. The obtained filtered images are used to extract feature points. The feature points are selected if they represent a maximum response of Gabor kernel in a predefined window. A fusion strategy using a weighted average of visible and thermal images similar to (Heo *et al.*, 2003, 2004) is used. The scores of thermal, visible and data fused images are combined using a weighted average sum. The experimental results show that the proposed fusion strategy proposed in the paper outperforms the other techniques compared by the authors.

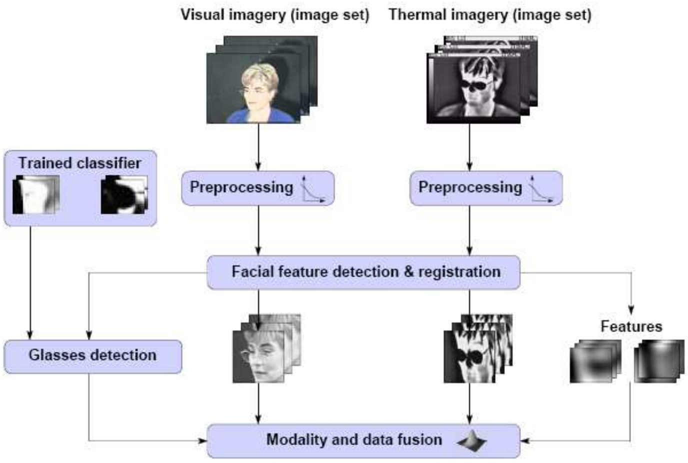

Figure 16. *Overview of the fusion strategy proposed by Arandjelovic et al.*

5. Conclusion

This paper proposes an overview of the state of the art in infrared face recognition. Most recent works in this growing field are presented. Many of them explore the use of different infrared wavelengths in face recognition (NIR, SWIR, MWIR and LWIR).

The use of infrared in face recognition allows the limitations of visible face recognition, like changes in illumination and facial expression, to be overcome. However, infrared suffers from other limitations like the opacity to glasses. This limitation degrades the face recognition when subjects wearing eyeglasses are present. More recently, a great interest in the research community has focussed on the fusion of different modalities (visible, infrared, 3D). Multimodal fusion comes with the promise of combining the best of each modality and overcoming their limitations. This is an area where much work is currently being conducted with promising results. Good performance rates are reported by the authors when multimodal fusion is used for face recognition.

A large number of techniques have been proposed in the area of infrared face recognition. Many of them are inspired from their visible face recognition counterpart. Eyeglasses are still a challenging issue in infrared face recognition and more work is expected in this area. Multimodal fusion can help solve this problem. Active and passive infrared are still used independently in face recognition. This is an interesting subject to investigate and multimodal recognition systems can be developed in order to take advantage of these two infrared modes. Also, more research can be done in order to better understand the effects of cold, face temperature change, and time in infrared face recognition performance.

With the decrease in infrared camera costs, we can expect a growing interest in this field in the near future.

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