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Face Description Using Anisotropic Gradient: Thermal Infrared to Visible Face Recognition

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ABSTRACT

Face recognition technologies have been in high demand in the past few decades due to the increase in human-computer interactions. It is also one of the essential components in interpreting human emotions, intentions, facial expressions for smart environments. This non-intrusive biometric authentication system relies on identifying unique facial features and pairing alike structures for identification and recognition. Application areas of facial recognition systems include homeland and border security, identification for law enforcement, access control to secure networks, authentication for online banking and video surveillance. While it is easy for humans to recognize faces under varying illumination conditions, it is still a challenging task in computer vision. Non-uniform illumination and uncontrolled operating environments can impair the performance of visual-spectrum based recognition systems. To address these difficulties, a novel Anisotropic Gradient Facial Recognition (AGFR) system that is capable of autonomous thermal infrared to visible face recognition is proposed. The main contribution of this paper includes a framework for thermal/fused-thermal-visible to visible face recognition system and a novel human-visual-system inspired thermal-visible image fusion technique. Extensive computer simulations using CARL, IRIS, AT&T, Yale and Yale-B databases demonstrate the efficiency, accuracy, and robustness of the AGFR system.

Keywords: Infrared thermal to visible facial recognition, anisotropic gradient, visible-to-visible face recognition, non-uniform illumination face recognition, thermal and visible face fusion method

1. INTRODUCTION

Autonomous facial recognition systems have a broad range of real-life applications in fields such as law enforcement, biometric identification, cognitive psychology, entertainment and homeland security [1] [2]. Generally, an automatic real-time facial recognition system comprises of two steps [3] [4]: face detection and face recognition, and despite extensive work done in the field, the automatic facial recognition systems still lack in accuracy when compared to human performance [5]. Automated systems are prone to interference due to uncontrolled conditions caused by low-quality capture devices [6], difficulty of detecting the faces in videos, aging effects, unlawful face disguise, facial expressions, illumination variations and the difference in body positions (PIE) [7].

To address illumination challenge of visible facial recognition, thermal infrared camera has been populated and thermal infrared facial recognition system has appeared as a new modality in the literature, especially for biometric identification applications and military applications. Table 1 shows comparison between thermal infrared cameras and visible cameras in order to demonstrate the advantages and disadvantages of thermal-to-visible face recognition over regular visible face recognition system.

The main contributions of this paper are: 1) this paper proposes a promising autonomous thermal infrared to visible face recognition system (AGFR). AGFR, for the first time, utilizes novel face descriptors combined with anisotropic gradient concept. AGFR contains anisotropic gradient based on local polynomial approximation intersection of confidence intervals (LPA-ICI) inspired preprocessing, histogram of oriented gradients feature descriptor, support vector machine classifier. Detailed proposed algorithm will be introduced in section 4. 2) A new image-aware HVS based visible and thermal image fusion technique that makes use of the Parameterized Logarithmic Image Processing (PLIP) model is proposed in this

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paper. It provides a method to fuse both thermal and visible sensors, which can be a valuable fundamental work for future imaging fusion from multiple sensors. The discussion and detailed proposed fusion algorithm will be introduced in section 5.4. 3) Moreover, AGFR has been tested using vary face datasets to show its efficiency, accuracy, and robustness for infrared thermal to visible facial recognition as well as regular visible-to-visible face recognition, fused thermal-to-visible face recognition and non-uniform illumination face recognition. Comparison, demonstration and experiment testing protocol will be shown in Section 5.

Table 1 comparison between thermal infrared camera and visible cameras

	Infrared thermal cameras	**Visible cameras**
Objects can be observed in no light condition (dark environments)	yes	no
The detectors can pick up on features invisible to the human eye	yes	no
Record image through obstacles (such as thin walls or smoke)	yes	no
Color information	no	yes
Distinguish between objects in proximity or of similar temperatures	no	yes
Expensive	yes	no
Consumer use	no	yes
Detecting humans in nocturnal environments	yes	no
Low visibility areas	yes	no
Shaded areas	yes	no
Low spatial resolution	yes	no
Lower sensitivity	yes	no
Low image noise	yes	no
Low image quality in general	yes	no
Displays surface temperatures of solid objects	yes	no
Existing tools for facial recognition	fewer	more

This paper is organized as follows. Section 2 shows the background information of infrared thermal imaging in real-life scenario. Section 3 presents the related work of infrared thermal to visible face recognition systems found in literature. In Section 4, the proposed thermal infrared to visible face recognition system (AGFR) is presented. Experimental results on thermal face databases will be shown in section 5. Moreover, in order to demonstrate the features of using LPA-ICI algorithms, non-uniformed illumination frontal face dataset and other commonly used face datasets were tested on and results are shown in Section 5. Finally, Section 6 summarizes the contributions of this work and discusses the future directions

2. BACKGROUND

Infrared thermal imaging is a promising and useful modality due to its insensitivity to visible lighting conditions. High illumination variability caused by the face surface reflectivity is one of the most difficult challenges for facial recognition. Thermal face recognition technology achieved high immunity to illumination changes, and as such the research and business communities have been exploring its applications [8]. Figure 1 below shows an example of a visible face image and corresponding infrared face images. Infrared thermal face image was first introduced as a robust facial identity signature in [9] [10] because infrared "appearance" consists of face temperature pattern and the blood vein branches; hence it is considered a reliable and distinguishable physiological biometric feature. In addition, thermal images are less affected by changes in pose or facial expression [11]. Thus, thermal face recognition is a powerful technology for biometric identification applications [12].

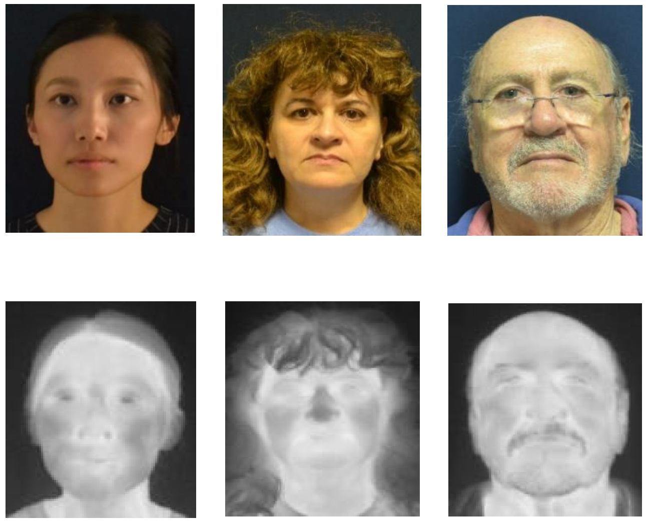

Figure 1: Visible face image and according infrared face images

Although thermal face image technology has all the mentioned advantages, it has several main drawbacks in the context of autonomous facial recognition system. The infrared face images provide the body heat pattern which can be easily affected by ambient temperature, air flow conditions, exercise, illness and drugs [13]. For example, figure 2 shows an example set of thermal face images in different lighting conditions, room temperature and skin temperature (variable due to outside weather conditions).

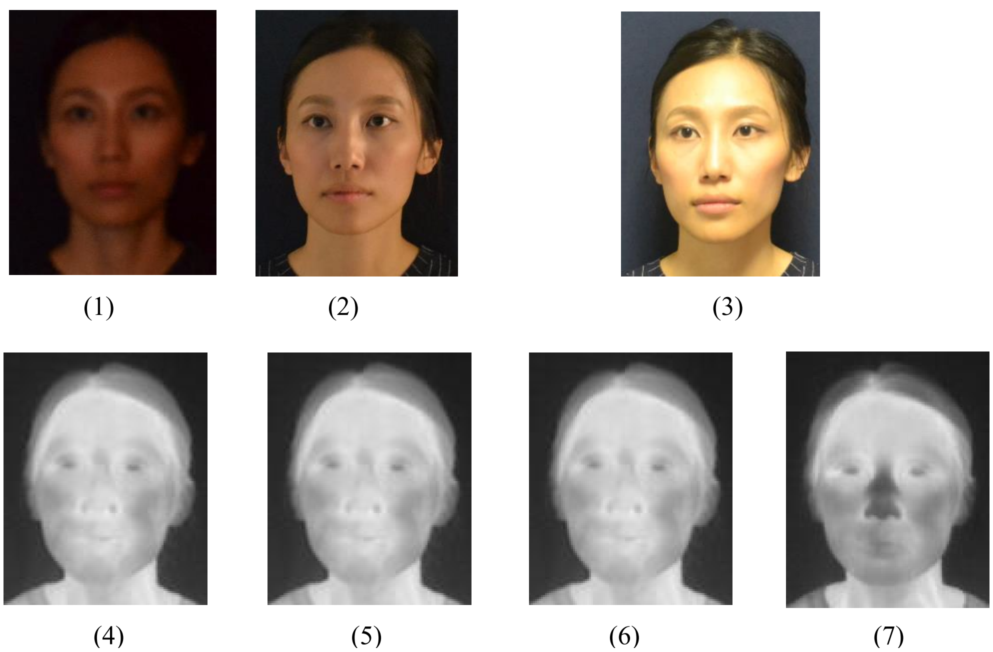

Figure 2: An example set of visible and accordingly thermal face images in different lighting conditions, room temperature and outside cold weather. (1) and (4) are visible face and accordingly thermal face image in no light condition; (2) and (5) are visible face and accordingly thermal face image in low light condition; (3) and (6) are visible face and accordingly thermal face image in normal light condition; (7) is thermal face image in cold room condition.

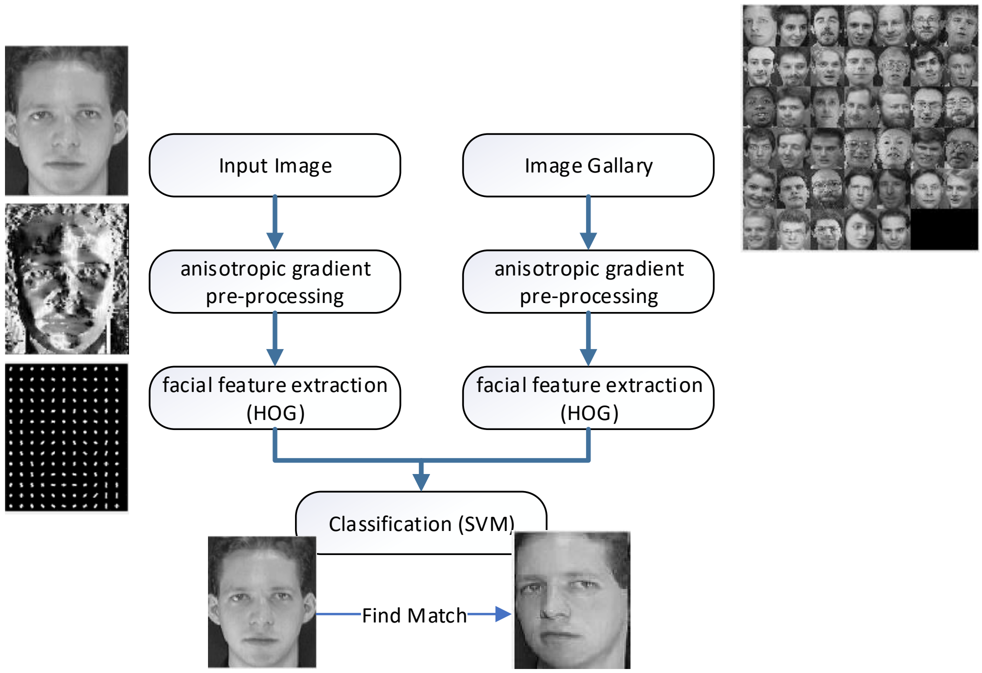

Figure 3: Refined system diagram for AGFR

3. RELATED WORK

Due to the popularity of the thermal face recognition methodology, increasing number of facial feature extraction methods, machine learning techniques and classifiers are applied to constructing thermal face recognition systems [14] [15]. Image feature based methods are commonly used not only in visible to visible face recognition, but also widely applied in thermal to thermal face recognition. One of the earliest works on thermal face recognition was a thermal image feature based method proposed in 1997 [16], which measures gray level histogram and locally averages gray level values, followed by neural network training and supervised classification.

Thermal local binary pattern (LBP), SIFT, and speeded up robust features [17] were investigated [18]; however with a limited success. A patch-wise self-similarity features [19] were studied against pose variance for images captured by infrared imaging technology. A disguise detection method in visible/thermal face images classified the local facial regions into biometric and non-biometric (regions with disguise) classes [18, 20]; then the biometric part was used for feature extraction and matching.

Moreover, the wavelet transform has been studied for extracting robust face appearance features in infrared spectrum due to its ability to gain information in both frequency and spatial domain [21]. In [22], a four-stage system was applied: the faces are separated from the background using adaptive fuzzy connectedness segmentation; wavelet transform using Gabor filtering; the derivative filtered images were modeled using Bessel forms and the simple L2-norm, followed by a Bayesian classifier to find the exact match. In addition, machine learning techniques and modern classifiers were researched for thermal face recognition in recent years. For instance, optimized super-pixel and AdaBoost classifier were combined for human thermal face recognition [23]; Generative Adversarial Network (GAN) based method [24] was developed for challenges like occlusions, high pose, different skin tone and limited training data in thermal face recognition.

Limited work has been done on thermal to visible face recognition. In [25], in order to match the thermal face image to the visible face image, algorithms that reduce the modality gap were proposed. Specifically, partial least squares-discriminant analysis (PLS-DA) was applied to correlate the difference between thermal face signatures to the visible face signatures. Thermal-to-visible face recognition system using a partial least squares (PLS) regression cross-modal recognition approach was proposed in [26], which consisted of preprocessing, feature extraction, and PLS model building.

The modality gap between thermal and visible face recognition is one of the most difficult face recognition challenges, which has been approached with limited success [25]. Hence, we believe our proposed thermal to visible face recognition system, AGFR, is valuable in both academic and commercial field.

4. PROPOSED THERMAL TO VISIBLE FACE RECOGNITION SYSTEM

4.1 Proposed thermal to visible face recognition system

Our proposed architecture for thermal to visible face recognition system, AGFR, consists of three different procedures: the anisotropic gradient based image pre-processing, facial feature extraction (HOG), and SVM classification. Figure 3 is a refined representation of the entire system schematic diagram.

4.2 Anisotropic gradient based image pre-processing

Since thermal and visible face images have very different signatures, preprocessing is important in solving the thermal-to-visible face recognition problem. LPA-ICI (local polynomial approximation - intersection of confidence intervals). Anisotropic gradient [27] is used as a pre-processing step for the AGFR facial recognition system. Often medical image contains a fuzzy at the surfaces of objects; hence an adaptive filtering based on the local polynomial estimations with ICI rule (LPA-ICI) is used in order to eliminate the noise in thermal face images [28]. The LPA-ICI technique combines two independent ideas [29]: Local polynomial approximation (LPA; performs a pixel-wise polynomial fit on a certain neighborhood using a bank of linear filters of various bandwidth), and intersection of confidence interval rule (ICI; an adaptation algorithm, which defines the most suitable neighborhood on a polynomial surface).

The anisotropic gradient concept allows the existence of a few neighborhoods V_i at the pixel p with the corresponding a few possible different vectors $(\nabla f(p))_l$ such that

$$f(p+v) - f(p) - v^T\big(\nabla f(p)\big)_l = o(|v|), v \in V_l \tag{1}$$

The LPA-ICI is aim to estimate the 'ideal' neighborhood by simultaneously looking into the gradient $(\nabla f(p))_l$ and the neighborhoods V_i. Figure below shows example outputs of thermal images after anisotropic gradient image pre-processing.

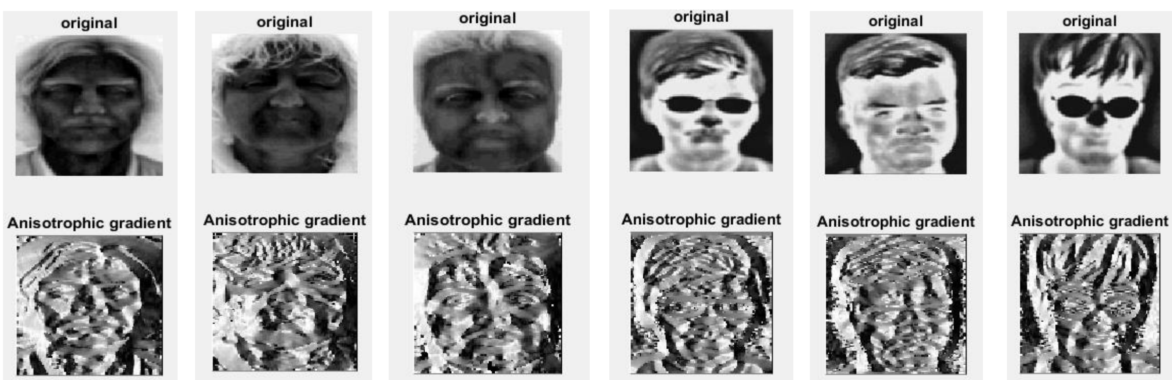

Figure 4: example outputs of thermal images after anisotropic gradient image pre-processing

4.3 Facial feature extraction (HOG)

After preprocessing, feature extraction using Histograms of Oriented Gradients (HOG) is used in AGFR thermal-to-visible face recognition algorithm. Dalal and Triggs [30] first introduced HOG features for human detection; then HOG features have been proven to be highly effective for face recognition [31]. In the proposed AGFR, HOG serves to encode the edge orientation features after preprocessing step. Other than HOG feature extraction, Local Binary Patterns (LBP) [32] were tested as well. LBP efficiently summarizes the local structures of a face image, which has recently received increasing interest for facial representation [33], [34] because of its high tolerance against illumination changes. In this work, we choose HOG due to its better performance than LBP.

4.4 Classification

Support Vector Machine (SVM) [35]was designed for binary classification, however it has been widely used in face recognition [36], which is a multi-class classification problem. The extracted facial features are mapped onto a high-dimension space via certain non-linear transformation, in which the optimal hyperplane can be constructed. Data are then classified by finding the matching hyperplane. For high-dimensional features, SVM has advantages of memory saving, computational efficiency and functional stability for multiple classes classification.

5. EXPERIMENT RESULTS

5.1 Thermal face dataset

Two popular thermal face datasets have been used for experimental protocol design and testing. IRIS thermal/visible face database [37] contains simultaneously captured thermal and visible face image pairs under variable illuminations, expressions, and poses. This database has a total of 4228 pairs of thermal and visible images (320×240 pixels) from 30 individuals. Each subject was captured under 11 pose rotations, 3 facial expressions, and 5 illumination conditions. Carl Database contains 41 pairs of visible and thermal images, which have been acquired using a thermographic camera TESTO 880-3. Details about the thermographic camera configuration were described in [38] and [39]. Carl database provides a resolution of 160×120 pixels for thermal images and 640×480 for visible images. Figure X below shows example images from IRIS thermal/visible.

Figure 5: Example images from IRIS thermal/visible database

5.2 Used non-uniformed illumination frontal face dataset and other commonly used face datasets

Yale-B database [40] [41], Yale face database [42], and AT&T [43] database have been used to test the accuracy for potential use of the proposed AGFR. Yale B database has face images from 28 human subjects under 9 poses and 64 illumination conditions. It has been widely used in face recognition research specifically on variant illumination conditions. Yale face database contains face images of 15 individuals. 11 images were collected for each individuals following facial expressions or configurations: center-light, with or without glasses, happy, left-light, normal, right-light, sad, sleepy, surprised, and wink. AT&T database, also as known as ORL face database, contains ten different images each of 40 distinct subjects. Images were taken under varying lighting, facial expressions (open and close eyes, smiling, neutral) and different facial accessories. Figure 6 below shows example images from non-uniformed illumination frontal face dataset and other commonly used face datasets.

Yale-B database AT&T face database Yale face database

Figure 6: Example images from Yale-B, AT&T and Yale database

5.3 Experimental Protocols and Results Comparison

5.3.1 Experimental Protocol thermal to visible face recognition

For IRIS thermal/visible face database, we choose one thermal image and one visible image for each participant. Both thermal image and visible face image were noted as a same pose angle. However, for IRIS database, the thermal camera and 2D camera were not set up in a same distance. Hence for testing this specific dataset, we included a face normalization step. For Carl Database face database, we choose one thermal image and one visible image for each participant.

5.3.2 Experimental Protocol for visible to visible face recognition

For AT&T and Yale, we tested against the complete dataset. For each subject, 70% images were selected as training images and 30% images were used as testing images.

5.3.3 Experimental Protocol face recognition under non-uniformed illumination

Yale-B dataset we tested against the complete dataset in order to show the performance of AGFR for non-uniformed illumination face recognition. For each subject, 70% images were selected as training images and 30% images were used as testing images.

The table below shows the recognition rate against different images datasets using different algorithms. The proposed AGFR provides a promising improvement in thermal to visible face recognition system while giving an outstanding performance in visible to visible face recognition system under regular and non-uniformed illumination conditions.

Table 2 Recognition rate against different image datasets using different algorithms

Database	**LBP**	**HOG**	**Proposed AGFR**
IRIS face database	6.7%	23.3%	50.0%
Carl Database	5%	17.1%	60.0%
AT&T	55.8%	88.3%	89.2%
Yale	62.2%	91.1%	93.4%
Yale-B	17%	80.4%	83.3%

5.4 Discussion on using both thermal and visible images for face recognition system

The most notable benefit of the joint use of thermal and visible sensors is the complementary nature of different modalities that provide the thermal and visible-light information of the scene. For instance, firefighters can use the combination of thermal infrared camera and visible RBG cameras in rescue and scenarios where traditional visibility is impossible due to smoke, obstructed space, and possible fire. Meanwhile, the complementarity of information captured by the different modalities (such as supplementing thermal images with color information) can increase the reliability and robustness of a face recognition or surveillance [44].

In this paper, we explore the advantages of using both thermal and visible sensors, which we believe can be a valuable fundamental work for any image fusion from multiple sensors. To accomplish this, a new image-aware HVS based visible and thermal image fusion technique that makes use of the Parameterized Logarithmic Image Processing (PLIP) model is proposed in this paper. The PLIP model [45], a generalized version of LIP model, views images in terms of their gray-tone functions and processes them using new arithmetic operators replacing the standard arithmetical operators. They also overcome the shortcomings of the LIP model, namely the potential of clipping and the loss of information inherent to the framework. The gray-tone function Ψ, for a given image, is generated using

$$\Psi = \alpha - I \tag{2}$$

Where α is a model parameter and its value, for this paper, is made image dependent and set to $\max(I)$, the maximum intensity value in the image I. In contrast to having a constant value for α (255 usually), setting its value to be dependent on image statistics provides for a more robust image-aware fusion. Based on the above formulated gray-tone function, the fused image can be obtained by using,

$$fusedImage = \widehat{\Psi_1} \,\widetilde{\oplus}\, \widehat{\Psi_2} \,\widetilde{\oplus}\, \widehat{\Psi_3} \tag{3}$$

Where, $\widetilde{\oplus}$ is the PLIP addition operator, and $\widehat{\Psi_i}$ is the result of PLIP scalar multiplication as defined below.

$$\Psi_1 \,\widetilde{\oplus}\, \Psi_2 = \Psi_1 + \Psi_2 - \left(\frac{\Psi_1 \Psi_2}{\max(\Psi_1, \Psi_2)}\right) \tag{4}$$

$$\widehat{\Psi_i} = (\Omega_i \,\widetilde{\otimes}\, \Psi_i) = \max(\Psi_i) - \max(\Psi_i)\left(1 - \frac{\Psi_i}{\max(\Psi_i)}\right)^{\Omega_i} \tag{5}$$

For this paper, Ψ_1 is the visible image, Ψ_2 is the thermal image, and Ψ_3 is the maximum-combined image obtained by selecting the maximum intensity value of thermal and visible image at each pixel location. The constants Ω_i should be selected in such a way that $\sum \Omega_i = 1$. In this paper, $\Omega_1 = 0.2989$, $\Omega_2 = 0.5870$, and $\Omega_3 = 0.1141$ are selected. The results of the thermal and visible image fusion using the prosed PLIP inspired fusion method are shown in figure 7.

(a) (b) (c) (d) (e)

Figure 7: Thermal-visible image fusion. First row shows the visible images, second row shows the thermal image and the third row shows the fusion result.

Figure 8 shows a refined architecture of visible-thermal fused image to visible recognition. The fused images from Carl detest has been used to test the validity of the proposed AGFR, a recognition rate of ***83.3%*** has been achieved. This effectively shows the importance of the fusion for face recognition systems. The increase in the accuracy of the recognition system can be related to the increase in the structural and textural information of the fused image. The fused image contains the characteristics of both visible and the thermal images combining the advantages of both the modalities. An important step for successful image fusion is image registration of thermal and visible images. The recognition rate can be further increased by improving the image registration. As seen in Figure 7 (b), the nose is not correctly aligned in the fused image and this can adversely affect the recognition.

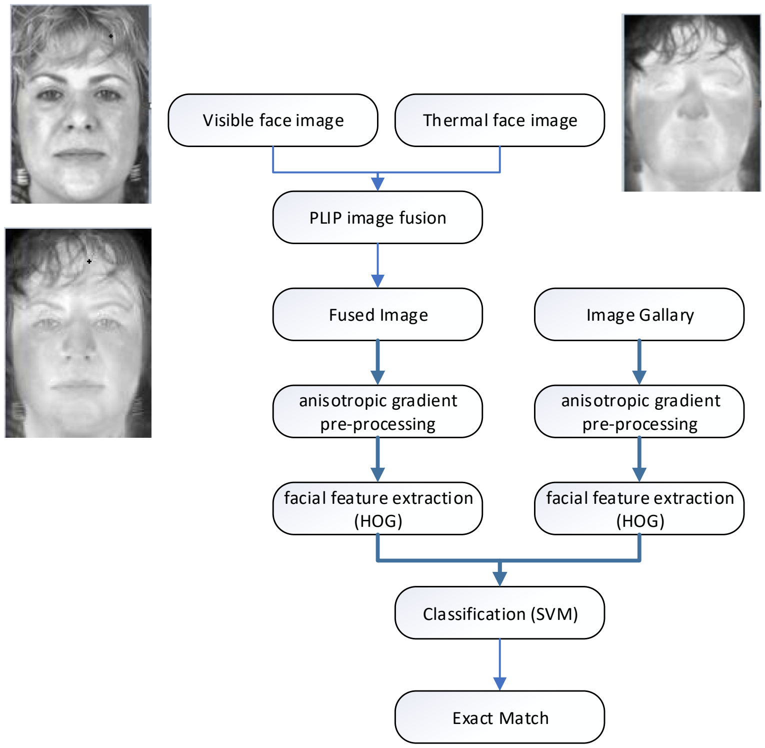

Figure 8: A refined architecture of fused image to visible image recognition; an example fused image was shown as well.

6. CONCLUSION AND FUTURE WORK

Automated face recognition is an active topic of research and has potential use in a wide range of commercial and law enforcement applications. Non-uniform illumination, scattering or absorption by smoke or dust are some of the major challenges faced by the visible-spectrum face recognition systems. Thermal infrared imaging, although lacking in color and textural information, is an excellent alternative as they are invariant to illumination and are very less prone to scattering and absorption. Motivated by these facts, the paper presents a novel system framework for performing infrared thermal and visible-thermal fused image to visible image face recognition system. In addition, a new image-aware fusion technique based on HVS is also proposed. The fusion method makes use of PLIP operators to perform non-linear operations on the images to form effective multi-modal fused images.

The proposed system framework consists of three phases: (1) face image pre-processing using anisotropic gradient LPA-ICI method, (2) features extraction using HOG, (3) classification using SVM classifier. Numerous experiments were conducted to evaluate the proposed system (i) using Carl thermal database, IRIS thermal database; (ii) using non-uniform illumination frontal face database: Yale-B; (iii) using standard RGB face database, Yale and AT&T. Computer simulation results successfully show that AGFR outperforms traditional LBP and HOG based face recognition systems for infrared thermal to visible face recognition. Moreover, AGFR also performs better in non-uniform illumination conditions. Furthermore, with the help of the novel image fusion algorithm, the recognition rate of the system can be further improved.

Future works include: 1) employing parallel algorithms to speed up the computation in order to realize real-time thermal to visible face recognition applications; 2) exploring the accuracy using the proposed system for detecting dangerous objects in different thermal datasets such as cargo, security check; 3) extending the study of the proposed AGFR for near-infrared thermal image recognition and other face modalities.

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