International Journal of Research and Review
Vol. 9; Issue: 11; November 2022
Website: www.ijrrjournal.com
Research Paper *E-ISSN: 2349-9788; P-ISSN: 2454-2237*

Review of Application of Thermal Imaging for Face Recognition

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DOI: https://doi.org/10.52403/ijrr.20221117

ABSTRACT

Recent advances in facial recognition utilizing infrared as a source are described. Recent research has concentrated on face identification using visible light, with the main issue being that the lighting on the face varies in outside circumstances. Recent studies employ infrared light as a source to produce infrared face pictures to overcome this and increase performance. This is known as a thermal face image, and it is extremely valuable in a variety of application systems. Night surveillance systems and military applications are two applications where night vision comes into picture. The choice of infrared, intensity fluctuation, and angle of incidence all play crucial roles in these applications.

Keywords: Face recognition, multi spectral images, LBP, SIFT

INTRODUCTION

Visible images are more prone to illumination effects. The environmental conditions affect the image quality and are hard to classify them in outdoor environments as well as in night vision applications. This decreases the system efficiency because of increase in number of samples to be stored for classification. In order to overcome above mentioned limitations visible images are replaced with IR images. Thermal imaging technique reduces the space required to store the samples during processing as it is independent of illumination conditions.

Here, we propose few algorithms which can recognize faces from the IR images and give the best results.

Computer vision has played a major role in pattern recognition in recent past and application of this for face recognition is immensely used. Though visual imaging gives out the best result for recognizing faces it poses a limitation when it comes to night vision.

Division of Infrared spectrum of consists of majorly 2 regions: reflected IR ranging from 0.7 to 2.4 µm and thermal IR ranging from 2.4 µm to 14mm.

The reflected IR is used for short range and provides a constant illumination while the thermal IR (LWIR) is for long range which operates in darkness.

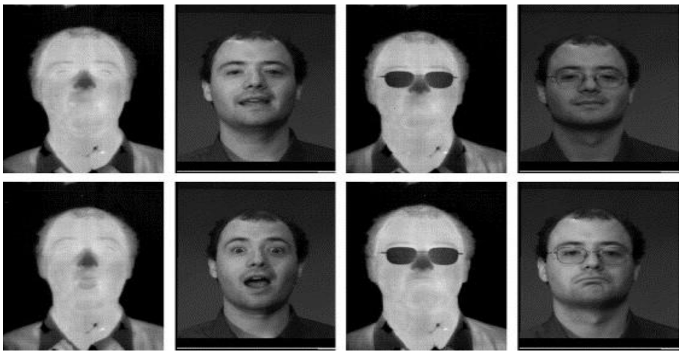

Fig1. Comparison of visible and thermal-IR images for different emotions of a person [11].

Face recognition using thermal IR imaging plays a major role in robotics field where robots are involved in human interaction. This specifically helps in robots by providing the best efficiency and diversity in unconstrained environments by using one image per person and giving result in real time.

Fig.1 shows comparison of images captured from a visible sensor and thermal IR sensor of a person at different conditions. To complement for the visible images, LWIR images are the best suite. The facial images obtained in this spectrum have less variation which reduces false recognition using various recognition algorithms.

There are several methods to detect faces using LWIR technique. These images can also be fused with visible images to obtain the best results which is called as integrated image fusion. This paper emphasizes on thermal imaging-based face recognition using local binary patterns, SIFT descriptors and fusion methods which are popular technique for face representation.

METHODOLOGY

A. Local binary patterns

The approach for LBP has 3 different levels of locality – pixel, regional and holistic. The pixel and regional levels divide the actual face image into smaller parts from which the extraction of LBP features is done and the texture information is represented using histograms.

The introduction to the LBP operator is given in and there are also extensions for the original operator. The kernel is a 3x3 matrix in which local -spatial- structure of an image is summarized.

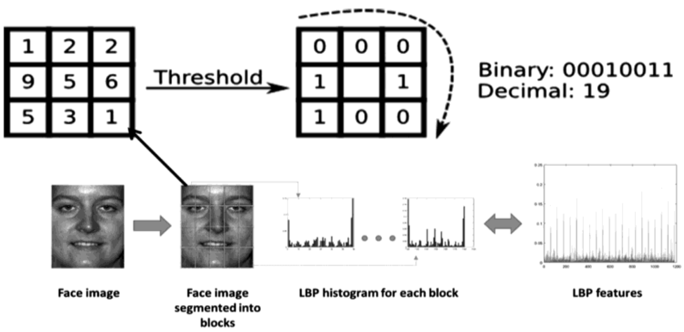

Fig 2. Local binary patterns [16].

The image [] is a threshold using the original LBP operator. The binary comparison of the pixel intensities is done between the center pixel and the neighboring pixels resulting in an LBP code. The whole image gets divides into smaller rectangular regions and LBP codes' histograms are calculated for each of the regions.

The equivalent LBP decimal code is shown in eqn1.

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \quad (1)$$

Where, i_c is the grey value of the centre pixel (xc, yc) ,i_n is the grey values of the eight surrounding pixels, and function s(x) is defined as:

$$s(x) = \begin{cases} 1 & \text{if} \quad x \geq 0 \\ 0 & \text{if} \quad x < 0 \, . \end{cases} \quad (2)$$

Local micro pattern such as edges, flat areas and spots are obtained in the histogram. The spatial information is also retained for face representation in an efficient way.

$$H_{i,j} = \sum_{x,y} I\{f_l(x,y) = i\} \, I\{(x,y) \in R_j\} \quad (3)$$

where i = 0 to [n -1] and j = 0 to [m -1]. Rj represents the regions into which the image is divided and the eqn3. Shows the spatially enhance histogram. Here, the information regarding 3 regions that were mentioned earlier is summarized.

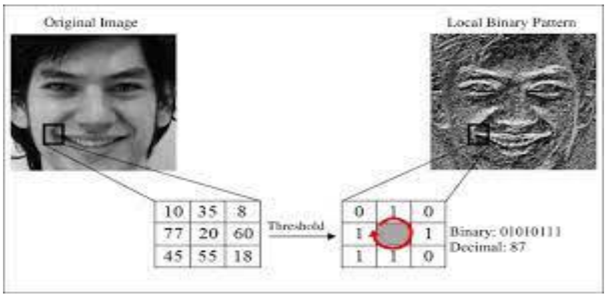

Fig 3. LBP operator [15]

The LBP operator reserves the intensity of pixel in the immediate neighborhood for grey scale transformation. This technique is becoming very popular in pattern recognition because of its very low computational cost and texture discriminative property.

B. Extended LBP

Only the first deviation information of the images can be reflected using LBP but not velocity of local variation. For this purpose, extended LBP was introduced. In this technique the gradient magnitude image is encoded along with the original image. These are the kernels used for extended LBP and this is applied to both gradient and original image.

C. Scale invariant feature transform

To transform image into co-ordinates which are invariant to scale relative to local features, this technique is used. Complete range of scales and locations are covered by the featured generated using SIFT.

The reference image and test image give rise to interests points and invariant descriptors are used to characterize these images. Until a given transformation is obtained between these two images the descriptors are matched.

D. Image Fusion

Thermal infrared sensors are less sensitive to alterations in facial expressions induced by changes in light since they assess heat energy radiation but not object reflectance. The performance of fused multispectral imaging outperforms that of either visible or thermal infrared images.

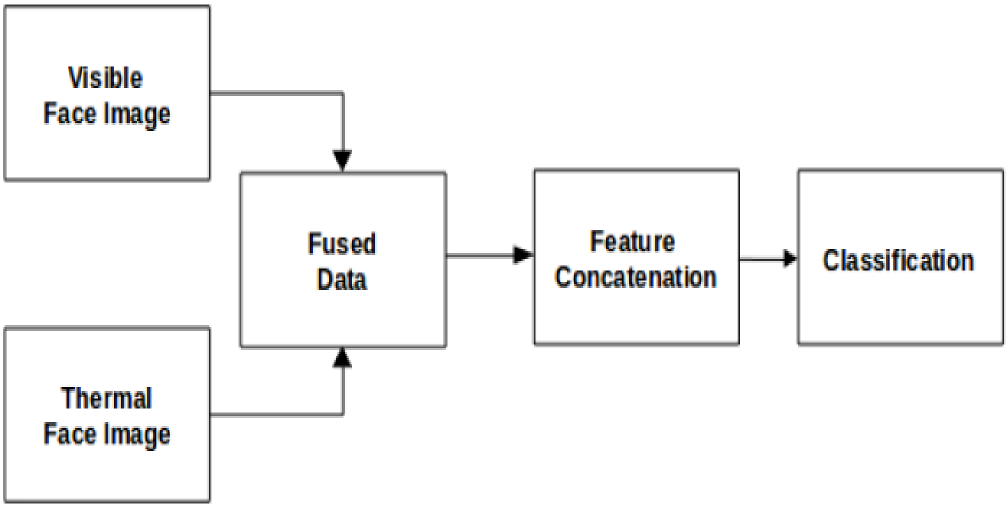

Fig 4. Block diagram of fused data

A combined face recognition system is depicted in Figure 4 where the visible and thermal-IR images are combined prior to feature extraction. During testing, the merged image can recognise faces that were either visible or thermally captured because it represents both modalities. The cross-modal face recognition system in the figure uses both visible and thermal infrared images.

Fig 5. visible image (a), thermal IR image (b), fused image (c) [14].

The algorithms to merge LWIR and visible face data at the image level, and their respective matched scores are covered in the following sections. First , both the images are fused using 2v- GSVM. The image fusion algorithm analyses the characteristics of the multispectral -face images at various resolution and granularity degree which determines the quintessential information , combining which gives rise to fused image.

Image fusion using the 2-GSVM for multispectral face data

In multispectral face image recognition , visible images provide reflectance properties and thermal IR images provide thermal property . To improve the recognition performance, in 2v-GVSM image fusion both the properties are combined.

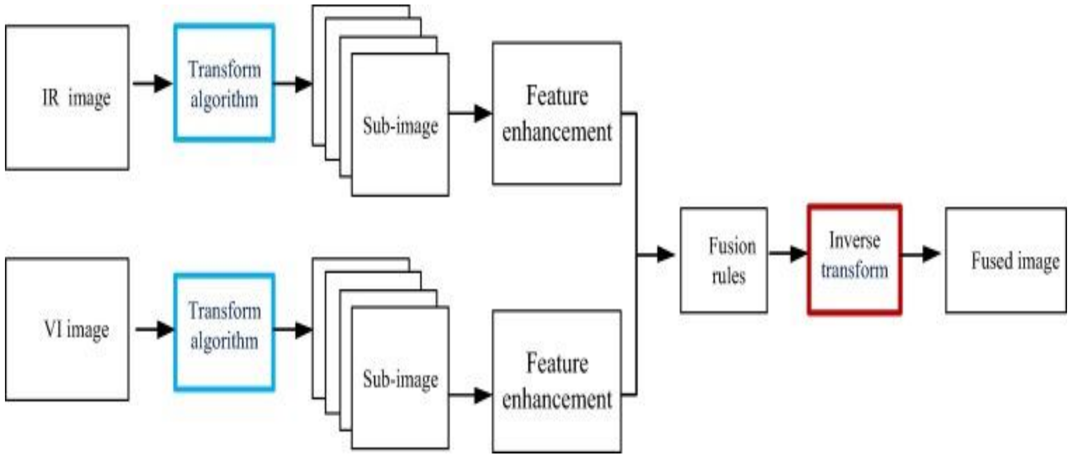

Fig 6. Steps of fusion algorithm [9].

Fig 6. lustrates the block diagram of fusion algorithm. Image registration and image fusion are the 2 steps of this fusion algorithm.

1.1 Image registration

The variation can be caused by angle of the camera, geometric deformations, and expression when the images are captured at different time. The best way to fuse two multi-spectral images is to reduce the linear and nonlinear discrepancies between the two images. The common information between the visible and IR images can be represented as below when V and I are input parameters for visible and IR images for face recognition

$$a = \sqrt{\frac{1}{XY}\left[\sum_{i=0}^{X-1}\sum_{j=1}^{Y-1}\{(V(i,j)-V(i,j-1)\}^2 + \sum_{j=0}^{Y-1}\sum_{i=1}^{X-1}\{(V(i,j)-V(i-1,j)\}^2\right]}, \quad (4)$$

$$M(V, I) = H(V) + H(I) - H(V, I) \quad (5)$$

The entropy of the image is H (.), and the joint entropy is H(V, I). Algorithms for common points information-based registration is sensitive to distribution changes brought on by variations in overlap regions . To address the above issue a normalized common point information is proposed which is represented as

$$NM(V, I) = \frac{H(V) + H(I)}{H(V, I)}. \quad (6)$$

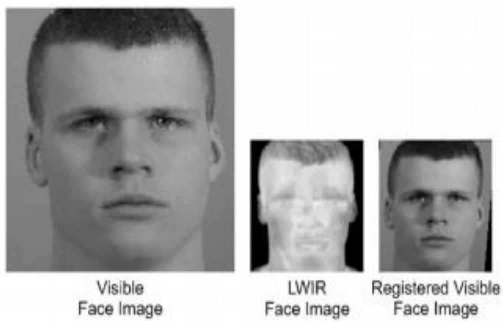

Fig 7. Visible image registered with respect to IR image [13].

The registration is carried out on a transformation space T , where T is specified as:

$$T = \begin{bmatrix} a & b & 0 \\ c & d & 0 \\ e & f & 1 \end{bmatrix}, \quad (7)$$

Here, the translational parameters are represented by e, f while the shear, scale, and rotational parameters are represented by a, b, c, d. Transform parameters are represented by the symbol T*, which is defined as:

$$T^* = \arg \max_{\{T\}} \{NM(I, T(V))\}. \quad (8)$$

Where T is the search space. Images with several wavelengths T* transformation parameters are used to register V and I. This registration procedure follows a linear pattern. Figure illustrates a visible picture registered with respect to an infrared image.

1.2 Image fusion algorithm

Using 2v- GSVM and the DWT , the visible and infrared thermal images are combined. This approach employs the activity level , a, of face images. Training, classification, and fusion are two different parts of fusion algorithm .

Training 2v- GSVM is described as follows process –

1. First, using DWT, the visible and IR training face pictures approximated into three levels: horizontal, vertical, and diagonal sub-band.
2. Each sub band of the visible and infrared facial pictures is divided into 8x8 windows and their activity levels.
3. The activity levels of all identified training face images are then sent into the 2v-GSVM . During training , 2 - GSVMs are learnt, one for infrared face images and the other for visible face images .
4. The above procedure is performed to determine the data to be + 1(Good) and 1(Bad) images, categorises the IR facial images into +1 and 1 classes.

Classifying the images and forming the fusion –

The classification of the two IR and visible facial images are made using trained 2v-GSVM. The visible and thermal IR face data are weighed and are dynamically computed using this classification in multispectral image fusion. The steps involved in classification and fusion are discussed below –

An individual's visible and infrared facial images are given as input. The supplied facial images are split into three levels of DWT, and the activity levels of 8x8 windows are calculated.

Let aV and aI represent the activity levels determined from the both images which are visible and IR, respectively.

Later, the above specified training steps are followed to obtain a binary decision matrix (dV) which is established with the values 1 for a high level of activity and 0 for a low level of activity.

Similar to the preceding approach, infrared facial image activity levels are categorized and similar matrix making decision is generated which is dI.

Decision matrices (*dV* and *dI*) are used to compute w_v and $w_{i,}$, which are the weight of matrices and the give rise to different cases:

1. If the visible and infrared image matches the activity levels, it is rated as good and case 1 is given equal weights.
2. When the rating is +1 for visible and 1 for IR case 2 comes into picture where, higher weight is assigned to visible image window.
3. The same rating procedure is conducted and visible face image window is rated as 1 and the infrared face image window is rated as +1, a greater weight is placed on the infrared facial image window as per case 3.
4. Now these two images are then fused using the equaltion 9.

$$F_{j_{8\times8}}(i) = \omega_V(i)V_{j_{8\times8}}(i) + \omega_I(i)I_{j_{8\times8}}(i), \quad (9)$$

Fj being fused sub band, j stands for the horizontal, vertical , and diagonal sub-bands, 8x8 indicates that the fusion was carried out at level of window with a size of 8x8, and I is the count of window.

At the end, fused sub-bands gives rise to fused multispectral image by applying inverse of DWT.

CONCLUSION

Long wave IR images have a complimentary property of Visible images, both the properties are needed for accurate image recognition, regardless of lighting condition, so fusion of these two images are better suited for accurate result for face recognition.

Two different thermal face recognition algorithms namely local binary patterns and Scale invariant feature transform along with image fusion algorithm is proposed. Common data is registered in multispectral - face images in the image -fusion algorithm , and then the fusion of the images are performed.

The attributes of both the images are contained in fused image and the result of face recognition is more efficient when compared to other existing algorithms.

Acknowledgement: None

Conflict of Interest: None

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How to cite this article: Apoorva Subash, Kiran V. Review of application of thermal imaging for face recognition. *International Journal of Research and Review*. 2022; 9(11): 100-107. DOI: *https://doi.org/10.52403/ijrr.20221117*

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