International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 05 Issue: 02 | Feb-2018 www.irjet.net p-ISSN: 2395-0072

INFRARED THERMAL FACE RECOGNITION UNDER TEMPORAL VARIATION

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Abstract - Albeit unmistakable face acknowledgment has been a dynamic zone of research for quite a few years, cross-modular face acknowledgment has just been investigated by the biometrics group moderately as of late. Thermal-to-visible face recognition is one of the most difficult cross-modal face recognition challenges, because of the difference in phenomenology between the thermal and visible imaging modalities. We address the cross-modular acknowledgment issue utilizing a halfway slightest square (PLS) relapse based approach comprising of preprocessing, include extraction, and PLS display building. The preprocessing and feature extraction stages are designed to reduce the modality gap between the thermal and visible facial signatures, and facilitate the subsequent one-vs.-all PLS-based model building. We incorporate multi-modal information into the PLS model building stage to enhance cross-modal recognition. The performance of the proposed recognition algorithm is evaluated on three challenging datasets containing visible and thermal imagery acquired under different experimental scenarios: time-lapse, physical tasks, mental tasks, and subject-to-camera range. These scenarios represent difficult challenges relevant to real-world applications. We demonstrate that the proposed method performs robustly for the examined scenarios.

Key Words: Face recognition, temporal variation, thermal face recognition.

1. INTRODUCTION

In computer technology image based on identical twin face recognition technology is challenging task. Traditional facial recognition system exhibit poor performance in differentiating identical twins and similar person under practical conditions. The following methods for differentiate identical twins. Face recognition is one of the most used applications in the area of computer vision, where a computer automatically identities a person by means of digital images of his/her face. Face recognition systems are used to access to applications on mobile devices [1], [2], search for suspects in airports or controlling access to restricted areas. Therefore, since face recognition systems are mainly used in security related tasks, they must be robust, which is analyzed in several surveys of techniques [4], [5]. Face recognition is often performed using images in the visible spectrum due to the low cost of conventional CCD/CMOS cameras, and there is a variety of literature about visible face recognition [6] [8]. However, in a real operational scenario, lighting conditions can vary due to different factors such as a different time of capture or weather. Unfortunately, the vast majority of the face recognition methods used in the visible domain are affected by these variations in illumination intensity [7]. A possible solution to overcome the lighting problem in visible imagery is the use of infrared (IR) images, specifically thermal images captured in the range between 8-12 m. IR images remain invariant to changes in light-ing conditions. The invariance of IR images is due to the spectral range of thermal radiation, since the diffuse energy is directly emitted by a human face and captured by the IR camera not reacted by the face, as with the visible spectrum. Thus, the spatial distribution of diffuse energy is unique for each subject and can be used as a descriptor governed by Planck's law. In addition, using Wien's displacement law, it is possible to state that human IR emissivity (0.97) is contained precisely within the thermal range: 8-12 m. Another option to perform infrared face recognition is the use of NIR images, which are located above the visible spectrum (0.7- 1.1 m). These types of images have facial features (metabolism, emotional and health conditions) that are less variable than the visible and thermal spectrum, which can be used for face recognition. However, facial heat emission in NIR sub-bands is very small and requires appropriate illuminators for face recognition (active recognition).

1.1 Creating Thermal Face Databases

Infrared IR images are acquired using thermal cameras that estimate the temperature of a body and generate an image through a process called thermograph. The energy collected by thermal sensors is a sum of several energy components related to the different elements present in the scene captured by the camera. A scene can be divided into three elements: the object to be measured, the background and the atmosphere. Variations in one of these components may affect the temperature estimation performed by the IR camera and consequently affect facial recognition system. Thereby, the main challenges of the use of thermal face images for face recognition include: undesirable variations produced by the changes of environment temperature and weather known as extrinsic factors and intrinsic factors such as variable sensor response when the IR camera is working for long periods of time, and physiological changes in the metabolic processes of the subjects (e.g. disease). Both extrinsic and intrinsic factors generate temporal variations in the face images affecting the thermal face recognition performance which is also known as the time-lapse problem. For both databases, all the images were acquired in a controlled environment, between 23 C and 24 C, allowing the minimization of the effects of the background or any atmospheric factors that may lead to thermal variations in the thermal face images. Thus, the images were only tentatively affected by physiological factors which cannot be controlled, observing temporal metabolic variations of the subjects such as changes in their appearance during the capture period (beard, haircut, moustache, etc.).

2. EXISTING SYSTEM

In existing system studies face recognition by using hyper-spectral imagery in the visible light bands. The spectral measurements over the visible spectrum have different discriminatory information for the task of face identification, and it is found that the absorption bands related to hemoglobin are more discriminative than the other bands. Hence, highlight band determination in view of the physical ingestion qualities of face skin is performed, and two component band subsets are chosen. Then, three methods are proposed for hyper-spectral face recognition, including whole band $(2D)^2$PCA, single band $(2D)^2$PCA with decision level fusion, and band subset fusion-based $(2D)^2$PCA. A simple yet efficient decision level fusion strategy is also proposed for the latter two methods. To testify the proposed techniques, a hyper-spectral face database was established which contains 25 subjects and has 33 bands over the visible light spectrum (0.4-0.72 μm). The trial comes about exhibited that hyper-ghastly face acknowledgment with the chose include groups beats that by utilizing a solitary band, utilizing the entire groups, or, strikingly, utilizing the traditional RGB color bands.

3. PROPOSED SYSTEM

In proposed system , we analyze the problems produced by temporal variations of infrared face images when used in face recognition. The temporal variations present in thermal face images are mainly due to different environment conditions. To perform this work, we created two thermal face databases that include sessions with real and variable conditions. The thermal face recognition systems have been developed using the following two techniques. local binary pattern(LBP) and Scale invariant feature transform(SIFT).The results indicate LBP method suitable for thermal face recognition under temporal condition and SIFT not suitable for practical infrared face recognition. Calculate Standard deviation produced between the face images during the different environmental conditions. Here, we are going to compute the accumulated distances which produces the changes in intensity of the face pixels and the overall sessions are compared. The range of human face and body temperature varying from 35.5°C to 37.5°C providing a consistent thermal signature.

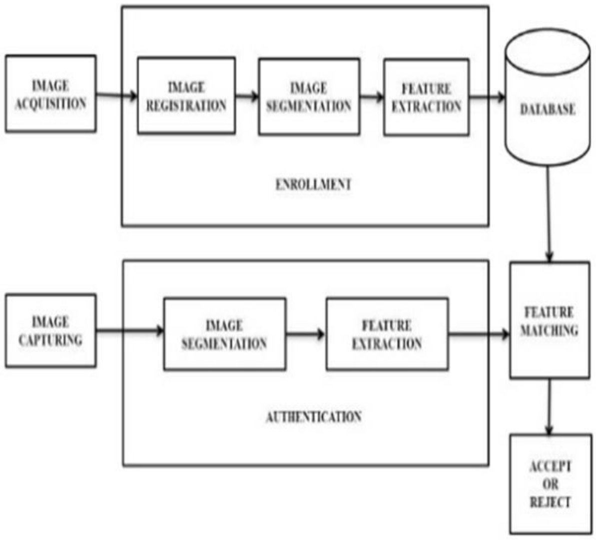

Fig -1: Block diagram for proposed system

3.1 Description of face recognition methods

A. Local Binary Pattern histograms (LBP)

Local Binary Pattern was proposed for the rst time in [18]. Brie y, the method compares the intensity differences between the central pixel and its neighborhood in a 3 3 region to generate a binary code which represents the local information of the face. The method uses three levels of locality: pixel level, regional level and the holistic level, where a global description of the face is obtained by combining the regional LBP extracted features using histograms by region. In the implementation of LBP histograms, the number of regions of the image used to give a holistic feature was 80 divisions (20 4 regions).Allows first talk about how to compute the LBP Descriptor. Initially, we change over the information shading picture to grayscale, since LBP deals with grayscale pictures. For each pixel in the grayscale image, a neighbourhood is selected around the current pixel and then we calculate the LBP value for the pixel using the neighbourhood. In the wake of ascertaining the LBP estimation of the present pixel, we refresh the comparing pixel area in the LBP veil (It is of same stature and width as the information.) with the LBP value calculated as shown below. In the image, we have 8 neighbouring pixels

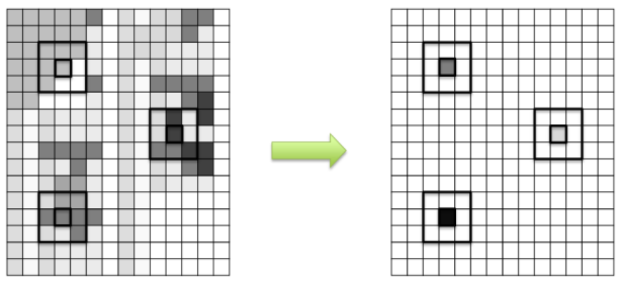

Fig -2: Grayscale Image to LBP Mask

` The whole process is shown in the image below (Figure 2). The current (central) pixel has value 7. We start comparing from the neighbouring pixel where the label 0. The value of the neighbouring pixel with label 0 is 2. Since it is less than the current pixel value which is 7, we reset the 0th bit location in the 8 bit binary array to 0. We then iterate in the counter-clockwise direction. The next label location 1 have value 7 which is equal to the current pixel value, so we set the 1st bit location in the 8 bit binary to 1. We then continue to move to the next neighbouring pixel until we reach the 8th neighbouring pixel. Then the 8-bit binary pattern is converted to a decimal number and the decimal number is then stored in the corresponding pixel location in the LBP mask.

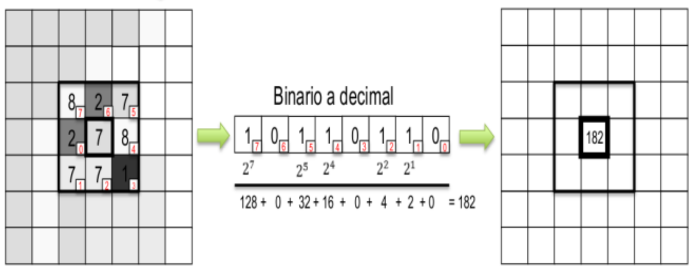

Fig -3: Calculation of LBP values

One preferred standpoint of LBP is that it is brightening and interpretation invariant. We have chosen a 8 point neighborhood, however most executions utilize a round neighborhood as demonstrated as follows. In the code, we will use a circular neighbourhood.

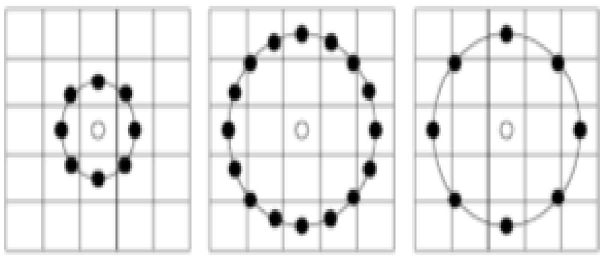

Fig -4: Circular Neighbourhood

B. Scale Invariant Feature Transform (SIFT)

Commonly, nearby intrigue focuses are extricated autonomously from both a test and a reference picture, and after that described by invariant descriptors, and finally the descriptors are coordinated until guaranteed transformation between the two images is obtained. Lowe's system, using SIFT descriptors and a probabilistic hypothesis rejection stage, is a popular choice for implementing object recognition systems, given its accuracy and reasonable speed. In the present study, we used Lowe's system to build a face recognition system.

A SIFT feature is a selected image region (also called keypoint) with an associated descriptor. Keypoints are extracted by the SIFT detector and their descriptors are computed by the SIFT descriptor. It is also common to use independently the SIFT detector (i.e. figuring the keypoints without descriptors) or the SIFT descriptor A SIFT keypoint is a roundabout picture district with an introduction. It is described by a geometric frame of four parameters: the keypoint center coordinates x and y, its scale (the radius of the region), and its orientation (an angle expressed in radians). The SIFT finder utilizes as keypoints picture structures which look like "blobs". By searching for blobs at multiple scales and positions, the SIFT detector is invariant (or, more accurately, covariant) to translation, rotations, and re scaling of the image.

The keypoint introduction is additionally decided from the neighborhood picture appearance and is covariant to picture pivots. Contingent upon the symmetry of the keypoint appearance, deciding the introduction can be vague. In this case, the SIFT detectors returns a list of up to four possible orientations, constructing up to four frames (differing only by their orientation) for each detected image blob.

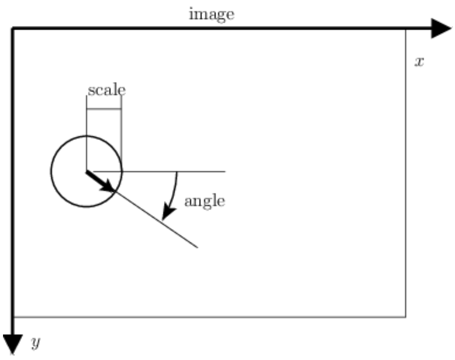

Fig -5: SIFT keypoints are circular image regions with an orientation

There are a few parameters that impact the location of SIFT keypoints. To start with, looking keypoints at various scales is gotten by building a supposed "Gaussian scale space". The scale space is just a collection of images obtained by progressively smoothing the input image, which is analogous to gradually reducing the image resolution. Traditionally, the smoothing level is called size of the picture. The development of the scale space is impacted by the accompanying parameters, set while making the SIFT channel question

- Number of octaves
- First octave index
- Number of levels per octave
- Peak threshold
- Edge threshold

A SIFT descriptor is a 3-D spatial histogram of the image gradients in characterizing the appearance of a keypoint. The slope at every pixel is viewed as an example of a three-dimensional rudimentary element vector, framed by the pixel area and the inclination introduction. Samples are weighed by the gradient norm and accumulated in a 3-D histogram h, which (up to normalization and clamping) forms the SIFT descriptor of the region. An extra Gaussian weighting capacity is connected to give less significance to slopes more remote far from the keypoint focus. Orientations are quantized into eight bins and the spatial coordinates into four each, as follows:

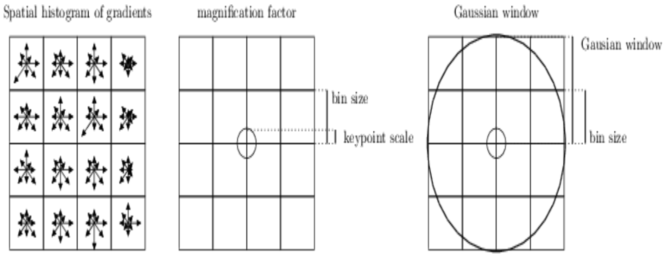

Fig -6: The SIFT descriptor is a spatial histogram of the image gradient

Channel descriptors are enlisted by either calling vl_ sift_ calc_ keypoint_ descriptor or vl _ sift_ calc_ raw_ descriptor. They acknowledge as info a keypoint outline, which determines the descriptor focus, its size, and its introduction on the picture plane. The following parameters influence the descriptor calculation:

- Magnification factor
- Gaussian window size

VLFeat SIFT descriptor uses the following convention. The y pivot focuses downwards and points are estimated clockwise (to be steady with the standard picture tradition). The 3-D histogram (comprising of 8×4×4=1288×4×4=128 canisters) is stacked as a solitary 128-dimensional vector, where the speediest shifting measurement is the introduction and the slowest the y spatial organize. This is illustrated by the following figure.

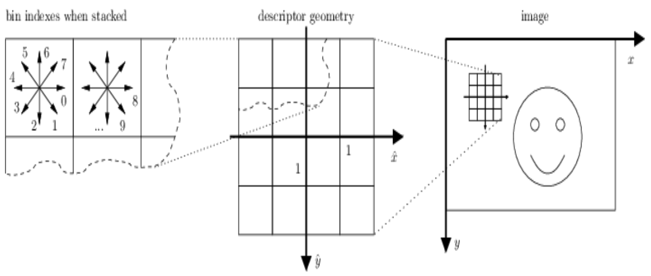

Fig -7: VLFeat conventions

Note

Keypoints (frames) D. Lowe's SIFT usage tradition is marginally extraordinary: The y hub focuses upwards and the points are estimated counter-clockwise.

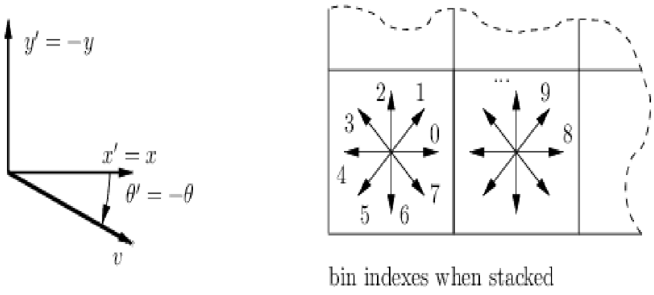

Figure 8: D. Lowes' SIFT implementation conventions

3.2 SIMULATION RESULTS

STEP 1: First run the procedure to change the way organizer.

STEP 2:Browse the input images from the trained image folder.

STEP 3:Load the datasets. We are going to load the datasets which are trained and stored already

STEP 4: Simulation output. The simulated output uses the MATLAB software. The simulated outputs are draw from the stored datasets which are stored in.

STEP 5: The final output of the process infrared thermal face recognition. which retrieves the output from the reconstructed and trained images which are known as template.

Output Screenshots:

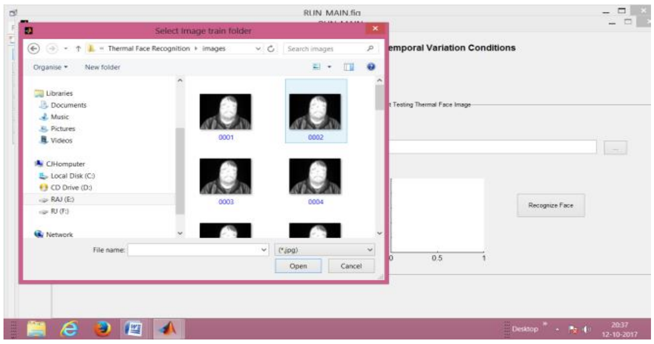

Fig -9: Trained images

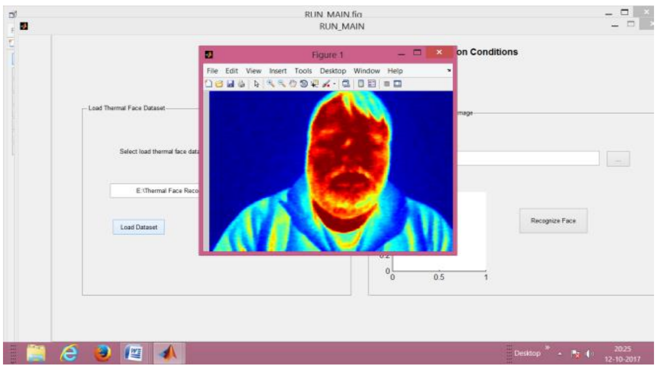

Fig -10: Input image

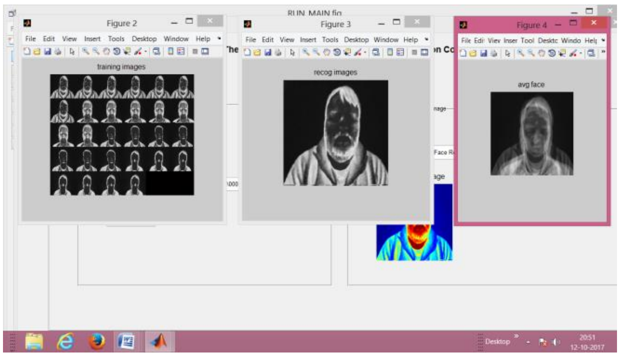

Fig -11: Dataset Simulation Output

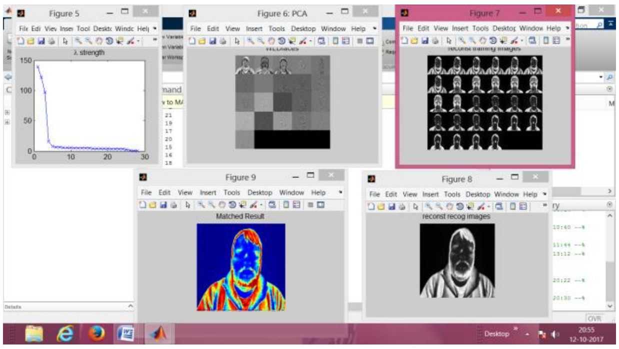

Fig -12: Simulation Final Result

4. CONCLUSION

A comparative study was performed on five current face recognition methods and a classic appearance based method to analyze the capability of each in overcoming the temporal variation problem in thermal face recognition, specifically the problem due to environmental variations and metabolic changes in the individuals at the moment of the image acquisition. However, before conducting the experiment, the temporal variation of the faces was analyzed. Two different approaches were used to check the existence of temporal variations, which appears principally in the nose and parts of the forehead. The proposed criteria allowed us to quantify the temporal variations between datasets. Two experiments were done to study the performance of the selected face recognition methods. The first one uses the original databases with temporal variation, and the second one uses the modified databases with real conditions such as occlusions and noise. Two analyses were then performed: one aimed to study the robustness of the methods to temporal variation and the other analysis related to study the performance of the methods under real acquisition conditions.

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