Thermal Face Recognition system in identical twins

R. Prema

Assistant Professor and Research scholar
Dept. of CSE
SCSVMV University Kanchipuram,
Tamil Nadu, India

***Abstract*: In this paper, 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.

INDEX TERMS: Face recognition, temporal variation, and Thermal face recognition.

I.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 identi es 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 opera-tional scenario, lighting conditions can vary due to different factors such as a different time of capture or weather. Unfor-tunately, the vast majority of the face recognition methods used in the visible domain are affected by these variations in illumination intensity [7], [9].

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 re ected 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 descrip-tor 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 fea-tures (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 illu-minators for face recognition (active recognition) [10], [11].

II.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 thermography.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 extrin-sic 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 pro-cesses of the subjects (e.g. disease). Both extrinsic and intrin-sic 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 physiolog-ical factors which cannot be controlled,

observing temporal metabolic variations of the subjects such as changes in their appearance during the capture period (beard, haircut, mous-tache, etc.).

The UCH Thermal TemporalFace (UCH-TTF) and the PUCV Thermal Temporal Face (PUCV-TTF) databases are used to carry out face recognition experiments in the thermal domain. The UCH-TTF and PUCV-TTF databases were cre-ated

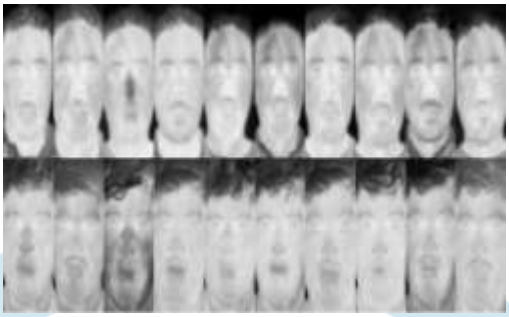

FIGURE 1. Thermal images of a subject with temporal variation obtained from: UCH-TTF database (upper) and PUCV-TTF database (lower).

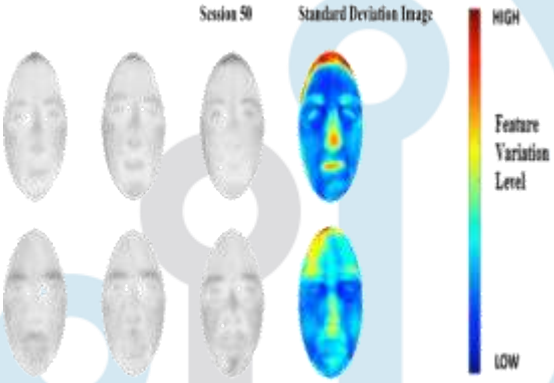

FIGURE 2. Regions with temporal variation in thermal imagery obtained with the ``Standard Deviation Image" approach. The subjects are from the UCH-TTF database. The colour scale indicates the presence of temporal variation.

A. UCHThermalTemporalFace DATABASE

The database consists of 350 thermal images of frontal faces cropped and aligned to 150 X81 pixels and 125 x225 pixels. The images were obtained in 2011 from 7 different subjects over a period of 69 different days, corresponding to 50 differ-ent images per subject (one image per acquisition session). The images were acquired using a FLIR TAU 320 cam-era, located approximately at 1.1m from the test subjects. Fig. 2 shows an example of a subject from ten different capture sessions.

B. PUCVThermalTemporalFace[1] DATABASE

This database was developed in 2015 for this research to validate the results obtained with the UCH-TTF database. The database contains thermal images acquired in multiple sessions over time and it allows us to study mainly temporal variations in thermal imagery. The database consists of 130 frontal face images without expression or objects (glasses, scarf, and artefacts) of 13 different subjects captured at 10 acquisition sessions, cropped and aligned to 150 81 pix-els and 125X 225 pixels. The images were acquired over a period of 2 months, and only one image per subject was acquired at each session. The capture setup consisted of a tripod with the FLIR Tau 2 camera, located at a height of 115 centimeters and at a distance of 91.5 centimeters from the subject. The background was a white wall (concrete) to avoid thermal and visible changes that might affect image acquisition.

The images of both databases were pre-processed by man-ually obtaining the coordinates of each eye and then each image was cropped and aligned in relation to the eyes coordi-nates, obtaining an image of 150X 81 and 125x 225 pixels.

III. DETECTING TEMPORAL VARIATION FEATURES

In this section, two different approaches to evaluate dynamic changes produced by the difference in the acquisition of the thermal images are proposed and further described. The rst approach consists of obtaining an image of the standard devi-ation produced between the face images during the different capture sessions. The second approach is to compute the accumulated distances

produced by the changes in intensity in the face's pixels over all sessions compared to the rst session. Finally, for each approach we de ne a criterion to quantify the temporal variation of a database. The result is a global indicator of the temporal variation present in the entire database. So, it will be possible to compare databases and say that a database presents more temporal variation than other.

A. STANDARD DEVIATION IMAGE

The rst approach consists of obtaining an image of the stan-dard deviation of the thermal patterns of the face for all the sessions. The main idea is to show the areas with highest vari-ability regarding changes in the thermal patterns of the face, using all the standard deviations of each pixel. To perform this approach, all the images were properly aligned relative to the position of the eyes. Equation 2 (Standard Deviation Image) is then applied to obtain an image that shows the standard deviation of each pixel produced by the temporal variation of the faces over time:

$$I\sigma_{ij} = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(x_{ij_k} - \overline{x}_{ij}\right)^2} \quad \text{---1}$$

$$\overline{I\sigma_R} = \frac{1}{N}\sum_{S=1}^{N} I\sigma_{SR} \quad \text{---2}$$

B. ACCUMULATED DISTANCES IMAGE

The second approach consists of analyzing the accumulated distances between the rst session of acquisition and the remaining acquisition sessions in the database. The process is performed using (4):

$$ID_{ij} = \sum_{k=2}^{n}\left|x_{ij_1} - x_{ij_k}\right| \quad \text{---3}$$

$$\overline{ID_R} = \frac{1}{n}\left(\frac{1}{N}\sum_{S=1}^{N} ID_{SR}\right) \quad \text{---4}$$

IV. DESCRIPTION OF FACE RECOGNITION METHODS

A. LOCAL BINARY PATTERN HISTOGRAMS (LBP)

Local Binary Pattern was proposed for the rst time in [28]. Brie y, the method compares the intensity differ-ences 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 combin-ing 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).

B.SCALE INVARIANT FEATURE TRANSFORM (SIFT)

Typically, local interest points are extracted independently from both a test and a reference image, and then charac-terized by invariant descriptors, and nally the descriptors are matched until a given transformation between the two images is obtained. Lowe's system, using SIFT descrip-tors 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.

V. EXPERIMENTS

A.EXPERIMENT 1: FACE RECOGNITION METHODS VERSUS TEMPORAL VARIATION

In the case of PUCV-TTF, the results indicate that some current face recognition methods are robust against the tem-poral problem, obtaining average recognition rates over 90%. Broadly, the same behavior can be seen with UCH-TTF for the face recognition methods as with the PUCV-TTF database. The main difference is that the WLD approach obtained a recognition rate of 98.43%, ranking rst, followed by the LBP method, which obtained 93.3%. The GJD method is in third place with a recognition rate of 89.2%. The GJD method shows an overall decline in recognition rates com-pared to the rates obtained with images from the UCH-TTF database. The SIFT and SURF methods again show poor performance.

Method	UCH-TTF		PUCV-TTF	
	$\bar{X}$[%]	σ	$\bar{X}$[%]	σ
LBP-HI 81x150	92.0	8.2	92.3	7.2
GJD-BC 125x225	**96.6**	**6.8**	89.2	10.4
WLD-HI 81x150	94.9	6.9	**98.5**	**3.2**
SIFT-Lowe 125x225	73.7	17.4	76.2	15.2
SURF 125x225	76.6	15.7	79.2	12.1
PCA 81x150	67.8	14.3	69.2	9.2

VI. CONCLUSIONS

A comparative study was performed on ve 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, speci cally the problem due to environmental variations and metabolic changes in the individuals at the moment of the image acqui-sition. However, before conducting the experiment, the tem-poral 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 rst one uses the original databases with temporal variation, and the second one uses the modi ed 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 vari-ation and the other analysis related to study the performance of the methods under real acquisition conditions.

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