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Sparse Representation for Thermal to Visible Face Recognition under Temporal Variation

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Abstract: Thermal face recognition has been well researched but still its performance is narrowed by varying illumination conditions. Illumination conditions are major source of the uncertainty in face recognition systems performance when it is used in outdoor setting. In order to augment the performance of visible light face recognition system's performance, infrared facial images as a new modality has been used in the literature. The other intriguing factor in using the infrared, especially thermal infrared imaging for facial recognition is the night time surveillance with little or no light to illuminate the faces. The problems produced by temporal variations of infrared face images when used in face recognition. Heterogeneous face recognition (HFR) has a prominent importance in sophisticated face recognition systems. Thermal to visible scenario, where the gallery and the probe images are respectively captured in visible and long wavelength infrared(LWIR) band, is one of the most challenging and interesting HFR scenarios. The temporal variations present in thermal face images are mainly due to different environment conditions. It is mostly immune to temporal variations, which is noticeable when the face images have been acquired with a time lapse, while the rest of the methods are clearly affected and are not suitable for practical infrared face recognition.
Keywords: Temporal variation, Classifier, LWIR, HFR, Face recognition.

I. INTRODUCTION

In the last two decades automatic face recognition has reliably been one of the most active research areas of computer vision and applied pattern recognition. Systems based on images acquired in the visible spectrum have reached a important level of development with some practical achievement. However, a range of trouble factors continue to create serious problems when visible spectrum based face recognition methods are applied in a real-world setting. Dealing with illumination, pose and facial expression changes, and facial disguises is still a major challenge. To overcome these limitations several solutions have been examined. Several methods have been proposed for thermal infrared face recognition. Some of the methods used in visible light face recognition are used on thermal IR face recognition. A possible solution to overcome the lighting problem in visible imagery is the use of infrared (IR) images, specially thermal images captured in the range between 8-12 µm. IR images remain invariant to changes in lighting 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 reflected 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 µm.

Another option to perform infrared face recognition is the use of NIR images, which are located above the visible spectrum (0.7-1.1µm).we analyze the temporal variation problem in infrared face recognition also considering face recognition methods that have been designed to be robust to occlusion, pose and artifacts and that may overcome the performance issues of appearance-based methods.

In particular, we propose the use of the following face recognition methods: Local Binary Pattern (LBP), Weber Local Descriptor (WLD), Gabor Jet Descriptor (GJD), Scale Invariant Feature Transform Method (SIFT), and Speeded Up Robust Features (SURF) to study their performance against images acquired in multiple sessions and then to perform a comparative study. In addition, since there are few databases available with thermal images acquired over multiples sessions over time, we build two open access databases and propose two new criteria that allows to quantify the temporal variations between datasets in order to analyze the robustness of the face recognition methods.

A. *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.).

II. RELATED WORK

Recently, Li *et al.* [1] have developed a method and system for illumination invariant face recognition using near infrared images. They build an active near infrared imaging system that is able to produce face images of good condition regardless of visible lights in the environment. They further show that the resulting face images encode intrinsic information of the face, subject only to amonotonic transform in the gray tone, thus combining with Local Binary Pattern (LBP) features to compensate for themonotonic transform, they derive an illumination invariant face representation. Using this system, high accurate face recognition can be achieved, with the only difficulty of pose variations and facial expressions. Heisele*et al.* [2] introduce one component-based method. Facial components are extracted and combined into a single feature vector. Then the feature vector is classified by a Support Vector Machine. The component-based method is compared with two comparable global systems. The two global systems recognize faces by classifying a single feature vector consisting of the gray values of the whole face image.

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.

III. PROPOSED CONCEPT

Although visible face recognition has been an active area of research for several decades, cross-modal face recognition has only been explored by the biometrics community relatively recently. 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.

	Head Rotation	*Expression*	*illumination*
LBP	79.33	96.27	98.35
Moment Invariant	59.37	91.76	94.51
HOG	90.27	98.78	99.18
Our Method	98.00	99.40	100.00

Table 1: Face position detection

IR images are established using thermal cameras that evaluate the temperature of a body and create an image through a technique called thermography.

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A scene can be separated into three elements:
1) The object to be measured,
2) The background and
3) The atmosphere. Differences in one of these components may upset the temperature evaluation achieved by the IR camera and subsequently affect facial recognition.

Thereby, the main issues of the use of thermal face images for face recognition include: unwanted variations created by the changes of environment temperature and weather. The UCH Thermal Temporal Face (UCH-TTF) and the PUCV Thermal Temporal Face (PUCV-TTF) databases are used to carry out face recognition experiments in the thermal domain.

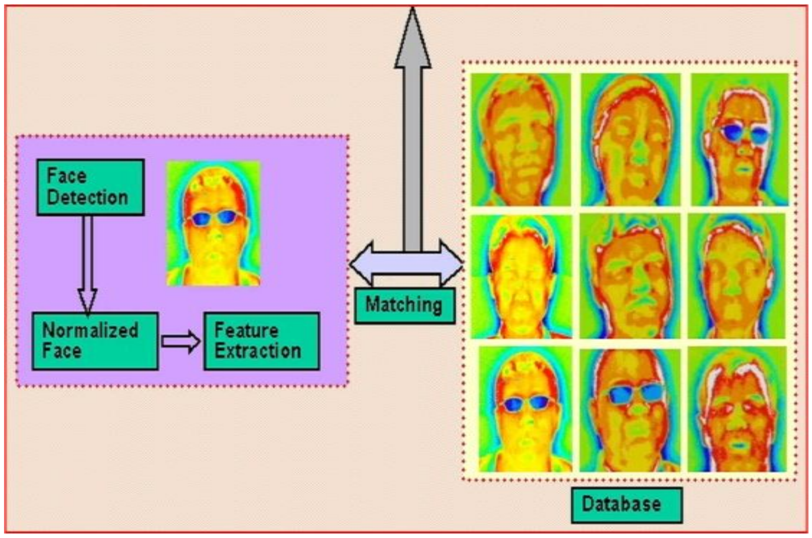

Fig 1:Blockdiagram of sparse process

A. Sparse Representation For Heterogeneous Face Recognition

In this section, for the first time we introduce applying the sparse representation in the heterogeneous face recognition problems. In the sparse representation approach, the probe image of a person is reconstructed by means of the gallery images of the same person. However, in the heterogeneous face recognition problems, the probe and gallery images are not in the same modality and there is a significant difference between these two types of images.

Although this difference is not caused by variable lighting or illumination conditions, the probe image of a person can be considered as the destroyed gallery image of the same person in the heterogeneous face recognition scenarios the sparse representation theory [9] for thermal to visible face recognition problem and reconstruct the thermal probe image of a person by means of the all visible images of the same person in the gallery set.

Since thermal to visible face recognition is one of the challenging heterogeneous face recognition scenarios, first by applying different preprocessing steps, we try to reduce the inherent differences between the thermal and visible images of a person as much as possible. Then ,applying the sparse representation theory in the heterogeneous face recognition problems and reconstruction of the thermal image of a person by means of the visible gallery images of the same person seem reasonable.

IV. PERFORMANCE EVALUATION

The main idea is to show the areas with highest variability 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:

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

where *i*, *j* are the rows and columns of the image, respectively c,*n* is the number of temporal images per subject, *x k* is the face image acquired in the k-th session, and *x* is the temporal face average (from sessions 1 to k).

Where K is known as the camera parameter matrix, which can be expressed making use of the calibration output variables as Thermal face image analysis has many applications such as sensation evaluation and face recognition. Facial feature extraction in the IR image is an essential step in these applications. Certain facial areas such as particular, nasal, cheeks and neck region produce different thermal patterns for different activities or emotions [10].

Skin temperature of facial features, such as the nose and forehead, could be an effective indicator in objectively evaluating human sensations such as stress and fatigue [9, 8]. Most existing approaches manually locate the facial feature in IR image or the subject are required to wear marker [5], as it is hard to automatically locate facial features, even for the obvious features such as the corners of the eyes and mouth.

This problem is caused by poorer contrast between the features and the face in IR images. In our experiment, we have found out that by using the proposed face detection using Cascade structure with Haar-like in both Thermal and Visual can detect faces automatically.

After the detection of supra orbital area in thermal IR image morphology is applied on the diffused image to extract the blood vessels that are relatively low contrast compared with the surrounding tissue.

Here, We employ top-hat segmentation method which is the combination of the erosion and dilation operations. We are interested in the bright (hot) like structure which correspond to Blood Vessel.

Algorithm: HDTP. Find histograms that capture normalized dynamic thermal patterns in thermal videos for a participant

Inputs:

- p, a participant video data set that represents a set of all videos watched by the participant
- F, a function that calculates a statistic for a two dimensional matrix

Output:

- H, a set of histograms for p based on values obtained by F

Method:

```
for each video v(p)
   for each block location loc(p)
        for each facial block region b(v,loc)
                for each frame f(b)
                s_vbf ← F(f(b))
                end for
        end for
   end for
end for
for each block location loc(p)
   for each facial block region b(loc)
   bin_width(b) ← calculate_bin_width(b)
   bin_locs(b) ← calculate_bin_locations(bin_width(b))
   end for
end for
for each video v(p)
   for each block location loc(p)
        for each facial block region b(v,loc)
        h ← partition_data(b, bin_locs(b))
        end for
   end for
end for
```

Algorithm 1:Histogram Algorithm

V. CONCLUSION

Sparse representation classification algorithmis regularized for heterogeneous cases, and is utilized by the different base learners in our proposed ensemble classifier for handling the challenging heterogeneous face recognition scenario, thermal to visible face recognition. 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.

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