Effect of different partitioning strategies of face imprint on thermal face recognition

Conference Paper · May 2014

DOI: 10.1109/IranianCEE.2014.6999701

Vahid Alizadeh
DePaul University

Soheil Rayatdoost
University of Geneva

Effect of Different Partitioning Strategies of Face Imprint on Thermal Face Recognition

Vahid Alizadeh, Soheil RayatDoost and Ehsan Arbabi
School of Electrical and Computer Engineering
College of Engineering, University of Tehran
Tehran, Iran
earbabi@ut.ac.ir

Abstract— **Face recognition using thermal images has received high attention by researchers in recent years. Since skin temperature can be visualized using thermographic cameras, a unique imprint can be achieved for thermal image of a person's face. In this study, we have investigated the effect of using different partitioning strategies of face imprint on thermal face recognition. First, we have proposed a simple and reliable approach for face extraction using ellipse mask. Then, the face imprint has been attained using anisotropic diffusion filter and morphological processing. The face imprint is related to distribution of blood vessels under the face skin. In the next step, the face imprint has been partitioned using different strategies including rectangular, circular and polar approaches. The number of minutiae point in each partition has been computed. Finally, a SVM classifier based on one-against-one approach has been used for face recognition. This paper presents a framework to find the best partitioning approach resulting in highest performance. Based on the results, the rectangular partitioning was found as the best partitioning approach for face imprint, due to its highest performance (92.27%).**

Keywords- face recognition; face imprint; thermal image processing; minutiae points; partitioning

I. INTRODUCTION

Biometric research has attracted a lot of interest over the last 20 years because of the great request of precise and reliable security systems. Face recognition has the highest acceptance by users comparing with the other biometric traits. The most important advantage of face recognition is its nonintrusive and natural characteristics. An increasing need for robust face recognition in security systems has motivated researchers to develop and improve exciting methods in this area. Some of the well-known approaches in this area are Eigenfaces where the Principal Component Analysis (PCA) is proposed to apply to face images [1], Fisherfaces that is based on linear discriminant analysis (LDA) [2], Elastic Bunch Graph Matching (EBGM) [3] and Hidden Markov Models (HMM) [4].

A lot of researches in face recognition deals with visible images of face. In the visible spectrum, changes in illumination and facial expressions cause many errors and lead to a weak performance in recognition systems. The use of infrared images in face recognition can overcome these limitations. Fig.1 shows visible and thermal images under two different illumination conditions.

The thermal IR band is related to thermal radiation emitted by the objects. The amount of emitted radiation depends on the temperature and the emissivity (a material's ability to emit thermal radiation) of the material. The thermal IR spectrum is divided into two main bands: the mid-wave infrared (MWIR) of the spectral range 3.0–5.0 μm and the long-wave infrared (LWIR) from 8.0–14.0 μm.

The human body emits thermal radiation in both bands of the thermal IR spectrum. Thermographic cameras detect radiation in the infrared range of the electromagnetic spectrum and produce 2D images, called thermograms. Skin temperature can be measured and visualized using this type of camera with a high sensitivity. Because of higher emissions in LWIR, most of the thermal-based face recognition systems use this band. The range of temperature in objects is usually different from human skin. Therefore, using disguises can be detected in thermal face recognition systems.

Recently, Thermal imagery has been used in many biometrics applications. Human identification has been done using vein structure in hands [5],[6], finger vein patterns [7],[8], and also vein structure in human face [9]. Moreover, visual and thermal images of face have been fused to improve the performance of recognition systems [10]. There is an overview of the state of the art approaches and databases in face recognition using infrared images in [11]. Also, a comparative analysis of face recognition performance in visual and infrared spectrums has been introduced in [12],[13].

Facial skin temperature is associated to the underlying blood vessels; thus by obtaining a thermal map of the human face, we can also extract the pattern of the blood vessels just below the skin. Some progressive techniques can be used to extract the thermal contours in each face to represent the underlying complex vascular network. These contours have been used for face recognition using distance transforms [14]. Some works have extracted thermal minutiae points from thermal contours and used them as a feature for face recognition [9], [15].

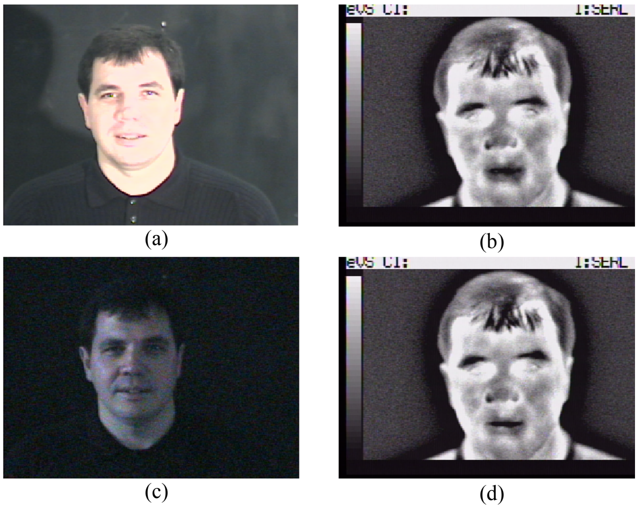


Figure 1. (a) Visible image under normal illumination, (b) Thermal image under normal illumination, (c) Visible image under lower illumination, (d) Thermal image under lower illumination. (IRIS thermal/visible face database [20])

In this study we have extended the research in [9] and used the idea of partitioning in [15]. However, instead of using fixed block size on registered thermal images [15], we have applied different partitioning approaches in order to find the best partitioning strategy matching human face imprints. The proposed partitioning approaches do not need to apply on registered thermal images. In addition, we proposed a reliable and simple method for face extraction using ellipse mask.

The paper is arranged as follows: Section II describes the face extraction and face imprint algorithms in details. In Section III, the results regarding the performance comparison have been reported. Finally, Section IV concludes this article.

II. Method

Thermal facial images contain information about blood vessels network. In this work, we extract face imprint and thermal minutiae points using this information. Then, we apply different partitioning methods to create a feature vector for classification phase. The proposed method can be divided into six steps, as illustrated in Fig.2. These steps will be further detailed in the following sections.

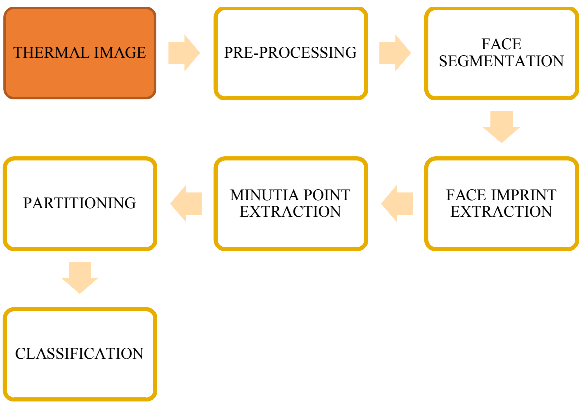


Figure 2. Main steps of thermal face recognition system.

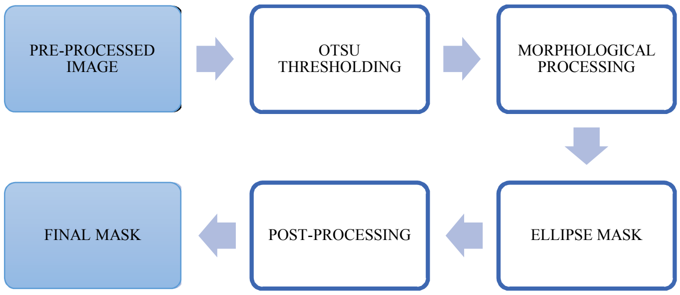


Figure 3. Main steps of face segmentation process.

A. *Pre-Processing*

Image noises such as sensor-dependent variations can decrease the recognition performance. The impact of this type of noises can be reduced by some pre-processing steps. For this purpose, histogram equalization and pixel normalization has been applied to thermal image to compensate and diminish the variation of brightness and differences between sensors.

B. *Face Segmentation*

In this step, thermal image is divided into regions which share certain features, aiming to separate face from the rest of the image. We have proposed and used a segmentation process composed of four main steps. Fig.3 illustrates the schematic block diagram of the face segmentation phase.

Image Thresholding: An important characteristic of thermal face images is high contrast between foreground and background. We have performed the Otsu threshold [16] to obtain a binary image. Fig.4 (a) and Fig.4 (b) show the original and thresholded images, respectively.

Morphological Filtering: In order to solve problems such as holes inside the face region, we have used morphological filling, closing and opening with a disk element. Then, we have found the biggest connected component in the resulted binary image (see Fig.4 (c))

Ellipse Mask: The shape of human face is almost similar to ellipse. Thus, we have tried to find the best ellipse fitting the shape of face in the binary images. The center of mass of the binary image can be considered as the ellipse center. In order to find major axes, the distances from the center to the highest and the most right handed points on the white image boundary should be calculated. Finally, by using this information, an ellipse can be created in order to enclose the interested region of the binary image. The result of this step is shown in Fig.4 (d).

Post-processing: To avoid possible mistakes, we have extended the major and minor axes of the ellipse mask by 5 percent. The overlapping area of the binary image and the ellipse mask forms the final mask. This final mask can be used to extract the required face region from the rest of thermal image. Fig.4 (e) and Fig.4 (f) illustrate the resulting final mask and the extracted face after the post-processing step, respectively.

C. *Face Imprint Extraction*

A standard Perona-Malik anisotropic diffusion filter [17] is applied to the entire thermal image to reduce spurious and speckle noise effects and enhance the image for additional processing. This process smoothens regions while preserving and improving the contrast at sharp intensity gradients and enhance regions of high thermal activity for extracting the thermal contours.

In the diffusion filter, a 2D network structure of 8 neighboring nodes is considered for diffusion conduction. The conduction coefficient function used for the filter is given by

$$C(x, y, t) = \frac{1}{1 + \left(\frac{\|\nabla I\|}{K}\right)^2} \qquad (1)$$

Where ∇I is calculated for 8 directions, and K is the gradient modulus threshold that controls the conduction.

After applying the filter, we have used morphological operators, opening and top-hat segmentation, in order to find the structure of the blood vessels. It is assumed that the blood vessels are tubule like structures. The result from opening is subtracted from the original image to achieve the top-hat segmentation. The result of this process is the maxima of the image [9].

After obtaining the maxima of the image, the image is skeletonized in order to have a structure with one pixel thickness. Skeletonization is a process for reducing foreground regions in an image to a skeletal remnant that largely preserves the extent and connectivity of the original region while throwing away most of the original foreground pixels. The final result is referred to as a face imprint. The vessel structure and final imprint is shown in Fig.4 (g) and Fig.4 (h).

D. Minutiae point extraction

We have used the concept of minutiae point extraction from finger print recognition from [18],[19]. Fingerprint's ridges are similar to vessel networks of face imprint. We have found thermal minutiae points by considering 3×3 windows, centered at each pixel of the so-called vessel in face imprint. If the central cell has only one neighbor or more than three neighbors with value one, then it is an end point or branch point, respectively. Fig.5 shows the explained concept. The location and type of each minutiae point are kept for next steps.

Due to noises in the face imprint images, the minutiae extraction procedure produces a large number of false minutiae points. Therefore, distinguishing spurious minutiae from real minutiae is important for accurate face recognition. Fig.6 shows final minutiae points. Blue and red points represent the endpoints and the branch points, respectively.

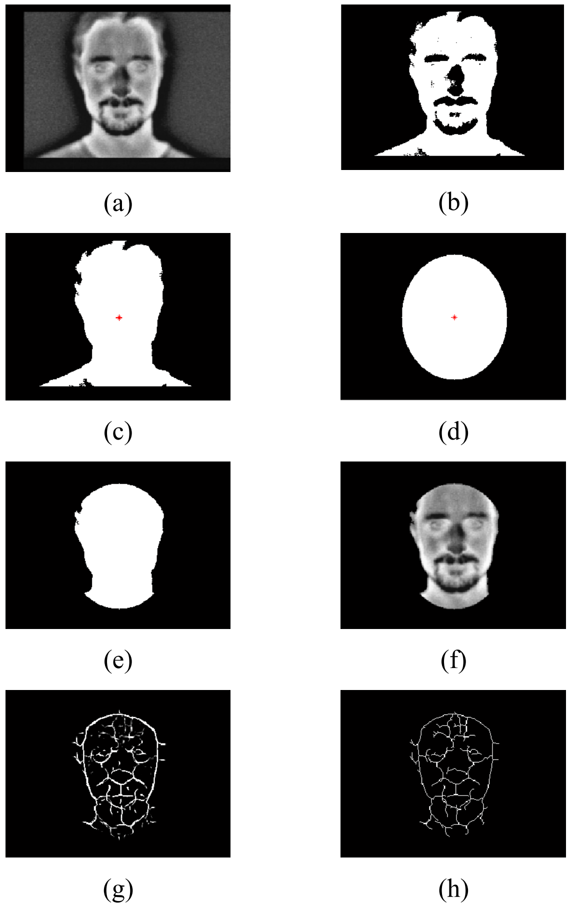


Figure 4. Results of face imprint extraction steps. (a) Original thermal face image, (b) Otsu threshold, (c) Morphological processing, (d) Ellipse mask, (e) Final mask, (f) Extracted face, (g) Vessel structure, (h) Face imprint

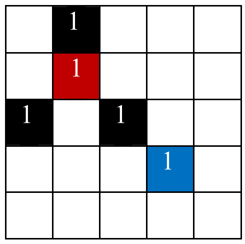


Figure 5. Example of branch point (red) and end point (blue)

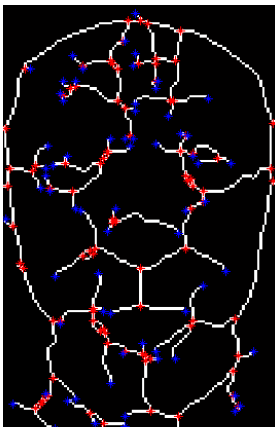


Figure 6. Branch Points (red) and EndPoints (blue)

E. Face Imprint Partitioning

In this step, each face imprint is cropped to its bounding box and divided into number of partitions. Then, the number of minutiae points in each partition is calculated and kept in a vector. Thus, we have one feature vector for each person's face in database and the total number of feature vectors is equal to the total number of thermal faces. In order to find the best partitioning method fitting human vessel structure and/or human face imprint for face recognition, we have examined three different partitioning approaches.

Rectangular Partitioning: The cropped face imprint is segmented to N parts horizontally and M parts vertically. Thus, there would be N×M partitions and the size of each feature vector is N×M (see Fig.7 (a)).

Circular Partitioning: The cropped face imprint is segmented to circular/ring shaped regions with different radii. The center of all circles/rings is chosen as same as the center of mass of the masked binary image (see Fig.7 (b)).

Polar Partitioning: The cropped face imprint is segmented using different angels and radii. For this purpose, the Cartesian coordinates has been converted to polar coordinates (see Figure 7. (c)).

F. Face Classification

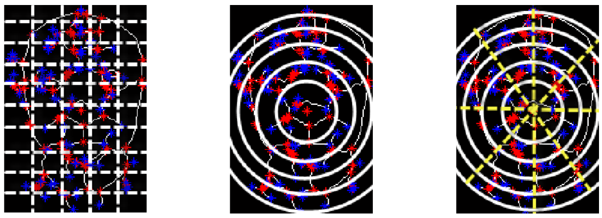
We have used non-linear Support Vector Machines with RBF kernel for classifying the feature vectors and face recognition. Since we have more than two classes, one-against-one approach can be applied. The approach builds binary classifiers between every pair of classes and the classification is done by majority of voting strategy.

III. Results

To evaluate the explained algorithm and compare different face imprint partitioning methods, we used IRIS thermal/visible face database [20]. This database contains images from 30 individuals with different expressions and poses under five illumination conditions. We have only considered images of 22 persons in our evaluation. In fact, images of 8 persons have been removed in this study due to using glasses or lack of enough number of images in frontal pose. For each person, ten different frontal pose images have been selected. Then we have used leave-one-out cross-validation (LOOCV) method for separating training and testing data. This type of cross-validation involves using one image per each person for testing, and considering the remaining nine images for training the SVM classifier. This process has been repeated ten times with different testing data (in order to use each image exactly once for testing). Therefore, ten different results have been obtained. Finally, the results have been averaged in order to have a single value as a correct classification rate (CCR). The advantage of this method over repeated random sub-sampling method is that all the images are used for both training and validation. This procedure has been done for each partitioning approach with different partitioning sizes, separately (see TABLE I). As it can be seen in TABLE I, the best result has been achieved by using the rectangular partitioning strategy.

TABLE I. Evaluation of different partitioning methods of face imprint for face recognition.

Partitioning	Number of Partitions	CCR%
Rectangular	36	75.45
	64	92.27
	100	86.82
Circular	20	68.18
	30	77.73
	50	59.09
Polar	30	63.64
	40	79.55
	50	88.18



(a) (b) (c)

Figure 7. Different partitioning approaches. (a) Rectangular, (b) Circular, (c) Polar.

IV. Conclusion

In this paper, we have tried to find the best face partitioning strategy fitting facial vessel structure and face imprint, for face recognition by using thermal images. For this reason, first, we have applied our simple proposed face extraction approach to select suitable image region for feature extraction. Then we have used morphological processing to create a unique face imprint from thermal image of faces. Three different partitioning approaches have been suggested to compute number of minutiae points and create a feature vector for each person's face. Finally, a non-linear SVM classifier has been used to evaluate the methods. We have achieved the success rate of 92.27% for the method using rectangular partitioning, which was higher than the methods using the other partitioning approaches. The results can imply that face imprints and facial vessel structure may differ significantly among different people, when we compare them in rectangular segments. Therefore, we suggest considering this kind of face partitioning, rather than other face partitioning, in further research on face recognition, using thermal images.

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