

Infrared Face Recognition in Forensics via Texture Analysis

Nihan Kahraman, Göktañ Sözen Özcan, Rohat İbişhükü

Abstract—Bad lighting was one of the difficulties that facial-recognition systems had to overcome as the large intra-class variations due to pose, lighting, and expressions. Recently, there are many works using thermal cameras in face recognition systems. This paper recommends a thermal face recognition method based on texture analyses in a complex database including different poses and expressions. Three different texture analyses methods are compared in this problem. Due to the pose variations in the database Scale Invariant Feature Transform algorithm is more successful to other methods explained in the paper.

Index Terms—Infrared Face Recognition, Biometrics, Texture Analyses, Local Binary Pattern

I. INTRODUCTION

A general declaration of the face recognition problem can be determined as identification or verification of images of one or more persons in a scene using a stored database of faces. Face recognition systems play a great part in many real world applications including both verification and identification. Some of these applications are personal identification such as driver's licenses and credit cards, admissions to restricted access areas, security using crowd behavior, forensics, border control, digital entertainment, etc. However, classical face recognition systems in visible spectrum have many challenges in outdoor facial images or in non-frontal facial images because of the image variation due to pose variations, illumination and due to changing facial expression.

The database acquired with infrared cameras has significant advantages over visible spectrum cameras. Infrared images of the faces can be acquired under any illumination condition, even in entirely dark environments. Face recognition from infrared images stands on temperature variations in blood vessels of face. Therefore, infrared appearance could be used to obtain robust biometric features which reveal a top level of uniqueness and repeatability. The variations in blood vessels can be observed as texture features of images.

Manuscript received January, 2015. This work is supported by Yildiz Technical University Cyber Security and Biometric Research Counseling and Testing Center.

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Texture analysis is one of the most important techniques used in image processing. In texture analysis, the most important task is feature extraction, which states the features that define the visual texture of an image [1]. These features can then be used for the description or classification of different texture images [2]. Two-dimensional surface textures can be described by two dealings: local spatial patterns and gray scale contrast [3].

Many researchers have issued various algorithms for texture analysis, such as the gray level co-occurrence matrixes, Markov random field (MRF) model, Gabor filtering and wavelet decomposition, Linear Discriminant Analysis, (LDA), Principle Component Analysis (PCA) and so on [4]. Initially, texture analysis was based on the first order or second order statistics of textures. The categories of textures were examined by statistical properties of the intensity values of pixels.

Compared with traditional face recognition systems, local feature extraction methods are more suitable for infrared face recognition due to low resolution of images. In 2006, the method based on local binary pattern was applied to infrared face recognition by Li et al [5] having better performance than statistical methods such as PCA and LDA. Considering the intensity or grayscale values of the image the co-occurrence matrix can measure the texture of the image. Because co-occurrence matrices are characteristically symmetrical around the diagonal, different of the matrix are often taken to get a more useful set of features. Features generated using this technique are usually called Haralick features, after R. M. Haralick [6]. Another method examined for infrared face recognition in this paper is Scale Invariant Feature Transform (SIFT). According to Lowe [7], SIFT can robustly identify objects even among clutter and under partial occlusion, because the SIFT feature descriptor is invariant to uniform scaling, orientation, and partially invariant to affine distortion and illumination changes.

The process in the thermal face recognition system is to match the thermal face data in the enrolled database to determine the identity of the possible candidate without negative influence of illumination or pose even in dark place. Here the novelty is in the database. The database has obtained in various situations of people such as cold or hot and also different poses.

In this paper, Section II describes some local feature extraction methods that used in the work and Section III explains the used database and obtained simulation results. Three different methods' recognition rates are compared and the paper is concluded with some remarks.

II. FEATURE EXTRACTION

A. Local Binary Patterns (LBP)

The Original Local Binary Patterns (LBP) operator was first introduced by Ojala et al and improved within years [8-10]. It has been used for texture description for years in face recognition. It uses the value of the center pixel as a threshold and calculates LBP code via the eight-neighbors with weights given to the corresponding pixels, and summing up the result. The operator produces a binary code '1' if the neighbor is greater or equal than the threshold otherwise produces a binary code '0'. Ojala and friends also determined uniform LBP descriptor which only if it has at most two bitwise transitions when the binary string is considered circular. For example, 00000110 (2 transitions), 11111111 (0 transitions) are uniform, while 01101001 (6 transitions) is non-uniform. All non-uniform LBP patterns are stored in a single bin in the histogram. Here, only 58 of the 255 possible values are uniform. These LBPs are used as local image descriptors and they are concatenated in order to produce global image representations by histograms in feature extraction. Figure 1 shows basic steps with LBP operator.

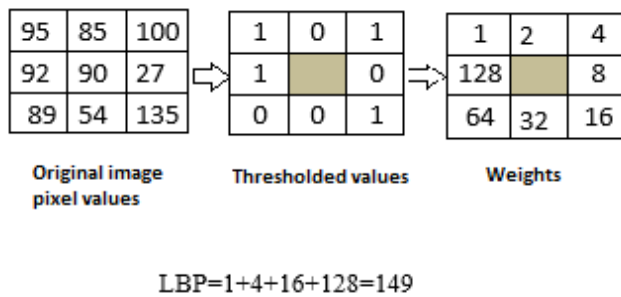


Fig 1. Local binary pattern operator

B. Gray Level Co-occurrence Matrix (GLCM):

Gray-level Co-occurrence Matrix is a statistical method of examining textures. It firstly proposed to calculate co-occurrence of pixel values. It calculates the number of times that the pixel with specified value occurred in the spatial relationship. By default, the spatial relationship is defined as the pixel to its immediate horizontally adjacent. An LBP histogram calculated over the entire image characterizes only the occurrences of the patterns. However, GLCM displays the distributions of the intensities and the information about relative positions of neighboring pixels of an image. Infrared face recognition using LBP and GLCM can limit the drawbacks of face recognition in visible light such as illumination or expressions [11].

C. SIFT (Scale Invariant Feature Transform)

SIFT detector and descriptor is first developed by Lowe in 1999. This approach describes the image with a group of local feature vectors. These vectors are invariant to many modifications such as image translation, scaling, and rotation and illumination. The SIFT algorithm has four steps, scale-space extrema detection (DoG), keypoint localization by looking for locations that are maxima or minima of a

difference-of-Gaussian function, orientation assignment, keypoint descriptor (image gradients). For indexing, the SIFT keys should be stored for sample images and then used for identifying matching keys from new images [12, 13].

III. SIMULATION RESULTS

A. The Database

The database used in this paper has obtained in Yildiz Technical University Cyber Security and Biometric Research Counseling and Test Center. FLIR E8 with MSX® Enhancement Infrared Camera is used to collect the data with ten different poses, temperature conditions, with/ without eyeglasses. There are 230 images in the database from 20 people with 10 poses for each. The images of 3 people were captured both with/without eyeglasses. Figure 2 shows some examples from database.

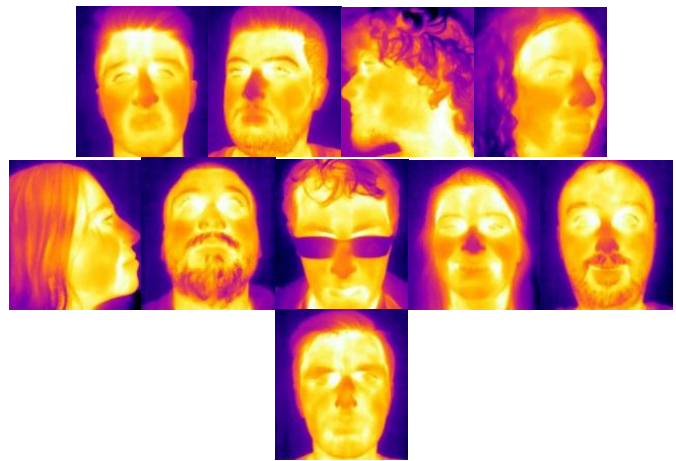


Fig 2. Infrared face database samples with 320x240 resolution

This paper proposes a thermal face recognition method based on texture analyses in this complex database including different poses and expressions. The method applied to the database is shown in Figure 3 which is consisting of three sub-ways for comparing recognition results.

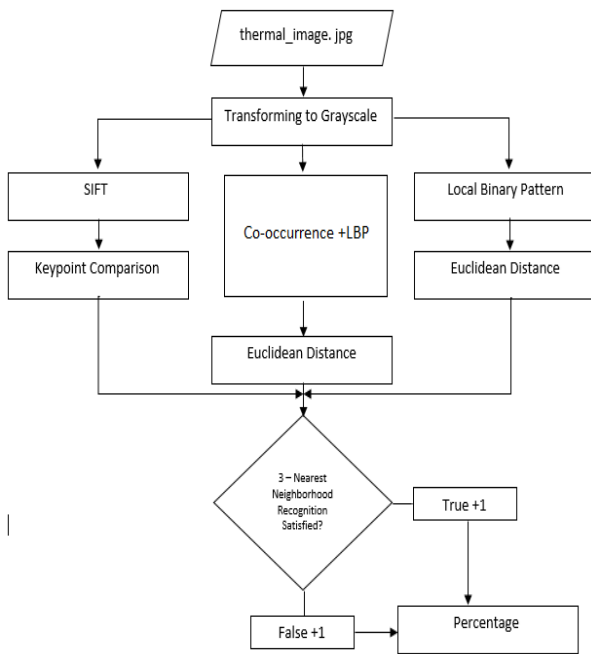


Fig 3. Flow chart of the study

For all different kind of texture analyses, first stage includes infrared face detection and normalization. Thermal image is converted to 8-bit gray level image by using $[0.2989 * R + 0.5870 * G + 0.1140 * B]$ coefficient/parameter. After normalization, the value of infrared face data ranges from 1 to 255 (gray level) and the size of infrared face image is the same (Figure 4).



Fig 4. a) Infrared face image b) Gray level of infrared image

Stage two: For the first subway, obtaining SIFT keypoints is the second stage. Gray level co-occurrence matrix (GLCM) and LBP are applied on normalized infrared face image to get LBP code for the second and third way, respectively. Gray level image was divided 10*10 region. LBP code is calculated for each region and at the end a histogram is obtained (Figure 5).

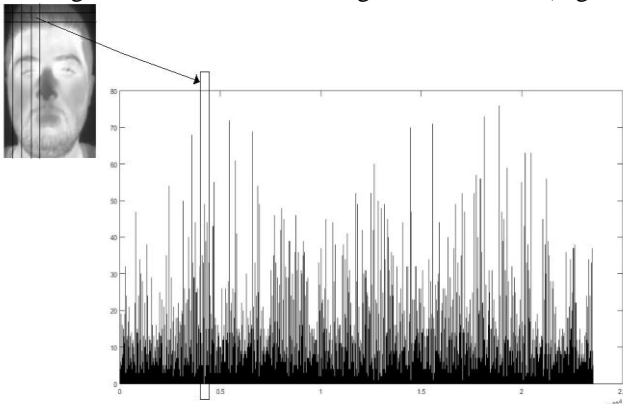


Fig 5. LBP code for Figure 4.b

Stage three: LBP co-occurrence matrix proposed in Section II is applied to build the discriminative representation in the second way.

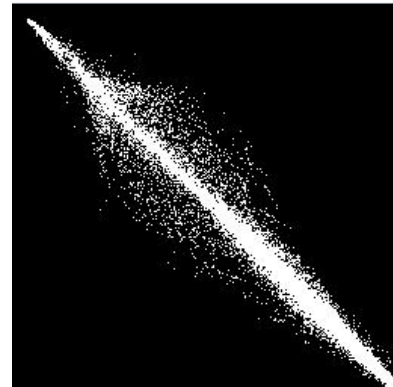


Fig 6. Co-occurrence of Figure 4b

Stage four: For the first subway in Figure 3, SIFT descriptors are used, for second and third ways the k nearest neighborhood classifier is employed to perform the classification mission.

The recognition in used database is calculated for two different test sets. First test set (T1) includes only frontal data, pose variations in thermal images do not affect the recognition rate where T2 test set includes both frontal data and pose variations. As seen from Table 1, three different texture analyses have applied to the database. In T1 test set, recognition rates are near to each other. However, when the test set includes pose variations (T2), recognition rates for the first and the second method decrease so much. Furthermore, in SIFT algorithm as mentioned in the Section II, pose variations do not change the result so much. Table I also proves this information.

TABLE I
RECOGNITION RATES FOR INFRARED FACE RECOGNITION

Methods	% Recognition Rate (T1)	% Recognition Rate (T2)
LBP+ KNN	78,26	50
GLCM+LBP+KNN	82,61	63,04
SIFT	87,5	81,25

IV. CONCLUSION

The main purpose of this article was to offer an approach for face recognition problem. Face recognition methods can be easily spoofed by photographs, videos or 3D masks. In order to avoid these attacks, thermal face recognition methods are recommended in the literature. However, the databases in the literature has little variations like illumination, temperature changes and pose variations. In this work, three main texture analyses are examined in order to achieve a high accuracy in thermal face recognition problem. The main problem of LBP features is that despite its capability to extract high discriminative face features, the number of features is limited to the number of pixels. This problem makes the LBP features unsatisfactory to achieve a high recognition rate face detector. To improve LBP performance GLCM is generated. GLCM+LBP is not influenced by variations in illumination,

because it depends on magnitude relation between a center pixel and adjacent pixels. However GLCM+LBP still suffers from pose variation problem. In order to reach a sufficient accuracy in infrared face detection, we can say that SIFT is a good solution.

ACKNOWLEDGMENT

This paper is invited for publication in IJCCIE from “Proceedings of 2016 Annual International Conference on Innovative Technologies and Advanced Computing, ICIAC16”. This work is supported by Yildiz Technical University Cyber Security and Biometric Research Counseling and Testing Center.

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