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Infrared Faces Image Recognition Using Local Binary Pattern

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ABSTRACT

Face recognition has a broad range of uses for business and law enforcement, such as access control, security monitoring, and video surveillance. This paper proposes an effective algorithm for Infrared face recognition using a Local Binary Pattern (LBP) for extraction of features and a Canonical Correlation Analysis (CCA) for fusion and classification of features. The facial characteristics are extracted using LBP. The extracted characteristics are then converted into different domains for transformation. For dimensionality reduction, the two-Dimensional Principal Component Analysis (2DPCA) approach is used in the proposed algorithm to generate more lightweight, robust and discriminatory features, which are then combined using the CCA classifier. The spatial relationship between adjacent pixels is also maintained by 2DPCA, increasing the overall accuracy of recognition. In addition, the paper introduces a comparative study between infrared facial recognition systems using the proposed technique and previous work. Based on the recognition rate and time usage, the output is evaluated. The analysis of the findings shows that the technique proposed is the most efficient and the least time compared to previous techniques. The experimental results are tested on a dataset acquired by Equinox Corporation. The proposed technique achieves a recognition rate of 99.26% at 0.45 seconds.

INTRODUCTION

Face Recognition (FR) in recent decades has been one of the most efficient applications for computer vision and understanding due to its demanding nature and its wide variety of applications [1]. Face recognition, without interrupting user behavior, is a passive, intrusive device for user-friendly verification of personal identity. Recognition of the infrared face can work in the dark and dim light. Infrared imaging sensors become an ever more concerned area because thermal infrared images can increase face performance under uncontrolled lighting conditions [2]. The benefit of thermal IR imaging over visible spectrum sensors is that light is emitted within the thermal IR range instead of reflected. Thermal skin emissions, regardless of the light, are intrinsically important properties. Thus, face images taken with thermal IR sensors are almost invariant of environmental lighting changes. In any light condition, the IR energy may be observed and is less dispersed and/or absorbed by smoke or powder than visible light. The variability within the class is also significantly lower. The visible facial detection spectrum has been shown to profit from the infrared spectrum [3].

Many strategies have been suggested in the last two decades for overcoming these problems and creating an efficient FR system. Variation of illumination is among many issues in visible FR systems the most challenging issue in cooperative and non-cooperative user scenarios for subject identification [3-6]. Many invariant FR lighting methods have been proposed, including methods based on three-dimensional (3D) face shapes and thermal image-based methods that measure body temperature [7-12]. 3D methods, however, are costly and require high computational complexity. In order to offset lighting problems, other techniques such as the method presented in [13] were also introduced. However, the illumination problem in FR is not perfectly resolved. Infrared (IR) imaging has been used to treat lighting variations recently [14, 15].

When poor features are used, a description of face characteristics plays an even more important role and even the best classifier does not achieve a good recognition rate. Face extraction approaches can be described with holistic features or local features. The holistic approach uses the entire region of the face to create a subspace representing an image of the face.

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However, the local approach includes local characteristics that are first extracted from a sub-area of a face and then classified by merging and comparing them with appropriate local statistics [16]. Holistic features are more sensitive to differences in lighting, expression and occlusion, and cannot capture local differences in appearance. Local feature-based approaches are beneficial because the distribution of face images within the local feature region is less affected by changes in facial appearance. Consequently, in recent years, local feature-based approaches to face recognition have been extensively studied.

Since Ahonen et al's original work, local binary patterns (LBPs) have emerged as one of the most prominent facial analysis methods [17]. Due to its advantages, LBP has gained growing interest :(a) ease of implementation; (b) invariance with changes in monotone illumination; and (c) low computational complexity. However, there are still several limitations to the original LBP method: (1) long histogram production; (2) capture only of highly local texture structures rather than long-range information; (3) limited discriminatory capabilities on the basis only of binary local differences; and (4) limited noise robustness. Based on these problems, a number of LBP variants were suggested to improve face recognition performance.

Liu et al. [18] presented a simple approach to robust facial recognition using LBP-like descriptors based on local accumulated pixel differences, angular differences and radial differences. These local differences have been decomposed into complementary components of signs and magnitudes, but the high sensitivity of lighting variations has affected its method. Face recognition techniques are categorized into two basic types; techniques based on geometry and techniques based on templates. Geometric techniques offer a vector that shows the geometric distances between face characteristics. Usually, the distance classifier is used for measuring the distance between the vector tests and all vectors. Instead, template-based methods use a feature vector that represents the entire face template. For classifying the test template in one of the training templates, different classifiers or minimum distance techniques can be used.

This paper presents a precise template-based technique to recognize the IR face. A two-dimensional main component analysis (2DPCA) processes multiple features, extracted from different transform domains, to reduce the dimensionality of the features obtained by maintaining only dominant features. The Canonical Correlation Analysis (CCA) for fusion and classification characteristics is also used. The paper is organized as follows: the proposed face recognition algorithm is described in section 2. The experimental results are discussed in section 3 and the conclusion of section 4.

The Proposed Face Recognition Algorithm

The proposed face recognition algorithm consists of four steps. Frist, the ellipse fitting method is applied to detect the face region in every image. Second, the LBP is used to extract the features then by applying transform such as FFT, DCT and DWT to obtain more features that enhance the classification. Thirdly, a dimensionality reduction technique is necessary to enhance the efficiency of the proposed algorithm. Two Dimensional Principal Component Analysis (2DPCA) which maintains an adjacent pixel spatial relationship is used separately for each matrix transforming output function. Finally, the CCA is used to fuse and classify features.

Face Detection

Facial detection is a challenging operation, particularly in outdoor or semi-outdoor environments where lighting varies widely. In this work, Infrared imaging is chosen due to its inherent nature of being resistant towards drastic ambient light changes. The face detection utilizes the segmentation of the face region from the scene. The proposed technique extracts regions of interest using the local threshold segmentation technique and the least ellipse fitting algorithm. Histogram Equalization, Binary thresholding and Morphological operation are the preprocessing steps that are applied on the image before detecting the face region. Since the faces are virtually elliptical objects, the use of the ellipse can represent certain features of the faces in thermal images. The overall conic equation is as follows:

$$E(A,T) = ax^2 + bxy + cy^2 + dx + ey + f = 0 \qquad \textbf{(1)}$$

Where $A = [a,b,c,d,e,f]$, and $T = [x^2, xy, y^2, x, y, 1]^T$. The researchers suggested different methods for fitting conics with restrictions such as $a + c = 1$, $f = 1$, and $a^2 + \frac{1}{2}b^2 + c^2 = 1.$ if the parameters are limited quadratically, the minimization can be resolved by a generalized system of its Eigen value, which is defined

$$D^T DA = SA = \lambda CA \qquad \textbf{(2)}$$

Where $D = [x_1, x_{2,\dots,x_n}]^T$ is called the design matrix, *and* $S = D^T D$ is called the scatter matrix and C is a constant matrix. The direct least conic fitting algorithm, while applying the restriction $A^T C A = 1$, it is a non-iterative algorithm for ellipse fitting that provides the best, least square fitting of the ellipse. This technique has a low eccentricity bias, is affine-invariant, and is extremely resistant to noise. The less direct ellipse fitting algorithm used in this paper for facial detection. The results of the pre-processing and facial detection steps are shown in figure (1).

(a) (b)

Fig. (1): The steps of direct least ellipse fitting algorithm face detection. (a) original Infrared Image, (b) face detected region with the ellipse fitting algorithm

Local Binary Pattern

Local binary pattern is one of the most widely used methods for face recognition. LBP is an efficient description of texture operator. It can extract information on the local neighbor's texture from a gray image. The main features of LBP are their computational simplicity and tolerance to light variations. First, LBP calculates the binary relationship between each image pixel and their local neighbor grayscale points. Binary relationships weighed in line with certain rules into an LBP code. Finally, the LBP histogram sequence, which is extracted from the facial expression image sub-region, is described as an image feature. The pixels g_p *(P = 0, . . ., 7)* of an imagery are labeled by the operator by a threshold a 3 × 3 neighborhood of each pixel, with the center pixel f_c value and a binary number $f(g_p$-$g_c)$.

$$f\left(g_p - g_c\right) = \begin{cases} 1 & if\ g_p \geq g_c \\ 0 & otherwise \end{cases} \qquad \textbf{(3)}$$

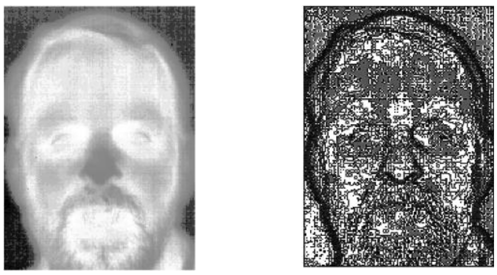
Then, by assigning a binomial factor 2^P for each $f\,(g_p$-$g_c)$, the LBP is calculated as follows:

$$LBP = \sum_{P=0}^{7} f\left(g_p - g_c\right) 2^P \qquad \textbf{(4)}$$

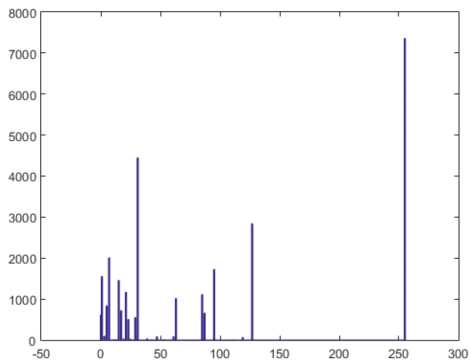
For a statistical representation of LBP codes, the LBP histogram usually is employed. In this case, all pixel LBP codes for an input image are gathered as a texture descriptor into a histogram, i.e

$$LBPH\left(i\right) = \sum_{x,y} \delta\left\{i, LBP\left(x,y\right)\ \right\} \quad i = 0, \ldots\ldots\ldots 2^7 \qquad \textbf{(5)}$$

Where $\delta(.)$ is the Kroneck product function. In order to capture local texture information, the LBP operator extracts many different texture primitives, such as spot, line end, edge and corner, typically collected into a histogram over a region. The face image is divided into several regions after face detection, from which the distributions of the LBP feature are extracted and concatenated into an improved feature vector to be used as a face descriptor. The LBP is used as a robust local descriptor against scaling, rotation, changes in illumination, and background clutter. The transform domain features are achieved by applying more than one transform, such as FFT, DCT and DWT. The use of multiple transformations enhances the overall accuracy of recognition and increases redundant data. The 2DPCA is carried out by calculating the covariance matrix for each transformed features set, where dominant eigenvectors are used as the projection matrix.



(a) (b)



(c)

Fig. (2): show the step of LBP (a) Infrared image, (b) LBP image and (c) LBP Histogram of image

Two Dimensional Principal Component Analysis (2DPCA)

In order to illustrate their similarities and differences, Principal Components Analysis (PCA) is a method of classifying data patterns and representing the data in such a way in order to highlight their similarities and differences. Since data patterns can be difficult to find in high-dimensionality data, where the addition of graphical representation is not an option, PCA is a powerful data analysis tool. Compressing the data, by reducing the number of dimensions, without much information loss, is the main advantage of PCA. The Two Dimensional PCA (2DPCA) method has many advantages over the PCA method for facial recognition (23). 2DPCA has a higher recognition rate, more efficient in image feature extraction. 2DPCA is used in this work since it processes the data in its 2D form maintaining the spatial temporal relation between adjacent feature components. The computation of 2DPCA for a dataset is listed in the following steps:

- Read all K training size images (X, Y), where X represents the number of rows, Y the number of columns, K the number of all training images for each face image. The covariance matrix S, of size ($Y \times Y$), for the K training images is calculated from:

$$S = \frac{1}{K}\sum_{J=1}^{J=K}\left(M_{X\times Y\times J} - \bar{A}\right)^{T}\left(M_{X\times Y\times J} - \bar{A}\right) \quad (6)$$

- It is not necessary to use all of the feature vectors obtained, but only those corresponding to the dominant Eigen vectors. *A* set of y Eigen vectors, V_q of size ($X \times 1$) corresponding to the dominant Eigen values q, where q = 1, 2, 3……y, for the S matrix is obtained.

- Stack one projection matrix with the y-dominant Eigen vectors $V = [V_1 V_2 V_3 \ldots V_Y]$ of size $X \times y$.

The obtained projection matrix (*V*) is used to project all training and testing images maintaining projected feature vectors of size $Y \times y$ containing only dominant data instead of original size $X \times Y$. In the proposed approach, the obtained compact feature descriptors are to be reshaped into vector form, and all vectors (for all performers) that belong to the same class are to be grouped together into one matrix representing that class. All training sets are stored in order to be used during testing phase, where Canonical Correlation Analysis (CCA) is used to match the testing set to the closest training set.

Canonical Correlation Analysis (CCA)

Canonical analysis is a method for the measurement of the linear relationship of two multidimensional variables [24, 25]. Given two random sets $f \in R^{m_1 \times n_1}$ and $g \in R^{m_2 \times n_2}$, a pair of transformations u and v called canonical transformations are found so that the correlation between $f' = u^t f$ and $g' = v^t g$ is maximized. The function to be maximized is defined in equation

$$r = \frac{E\left[f', g'\right]}{\sqrt{E[f'^2]E[g'^2]}} = \frac{E[u^t f, v^t g]}{\sqrt{E[u^t ff^t u]E[v^t gg^t v]}} = \frac{u^t C_{fg} v}{\sqrt{u^t C_{ff} u v^t C_{gg} v}} \quad \textbf{(7)}$$

The maximum of the canonical correlation (r_{max}) with respect to *u* and *v* is given by

$$r = \max_{u,v} \frac{u^t C_{fg} v}{\sqrt{u^t C_{ff} u v^t C_{gg} v}} \quad \textbf{(8)}$$

Where E[h] represents the expectation of h and C_{ff}, C_{fg} and C_{gg} are covariance matrices. The basic function of CCA in the proposed approach is to transform each training/testing pair to a new space where similar pairs become highly correlated. Multiple canonical correlations are obtained, r_1, r_2, .. r_n, where $n \le \min\left(m_1, m_2\right)$. CCA between the testing feature set and all the training feature sets are calculated in order to match the testing set to the closest training set. The highest Canonical Correlation is found between the testing set and the training set of the same class.

RESULTS AND DISCUSSION

A large dataset of images, acquired by Equinox Corporation, is used for training the recognition systems in order to compare the proposed method with other recent methods. This database contains 3,244 (1,622 per modality) co-registered visual and Long Wave IR (LWIR) face images from 90 individuals. With different lighting conditions, different facial expressions and also pictures with and without glasses, these images were captured. Images are divided into two categories: image for training and image for testing.

Different deformations were applied on the standard database in order to evaluate the performance against deformation types and levels. Each image was subjected to different types of noise (salt and pepper, Gaussian, poison and speckle), changes of illumination, geometric deformations (scaling, rotation and cropping) and blurring. The results of the proposed technique with respect to number of Eigen faces are given in figure (3) and figure (4) for original and deformed datasets, respectively. As seen from the figures, the maximum recognition rate using the original data images reaches 99.26% at 20 Eigen faces. While using deformed data images, the proposed algorithm achieves 97.43% at 25 Eigen faces, which indicates that the proposed technique achieves a high performance on original data images and deformed data images. The proposed technique is tested in the presence of Gaussian noise. At a noise variance of 0.05, it achieves the same recognition rate of 99.26 per cent. As shown in figure (5), increasing the noise variance above 0.05 degrades the performance. In the presence of salt and pepper noise, the proposed method is being tested. At a noise variance of 0.1, it offers a recognition rate of 98.43 per cent. As shown in figure (6), increasing the noise variance above 0.1 degrades the performance. Similarly, the increasing of the speckle noise variance decreases the recognition rate as shown in figure (7).

Table 1 shows the recognition rates of the proposed and previous techniques on the original data. From Table 1, it is clear that the proposed algorithm gives the best recognition rate among the compared recent techniques. The proposed algorithm has the best recognition rate since it is maintaining the spatial temporal relation between adjacent feature components.

Table 2 provides the recognition rates of the proposed and previous techniques applied on deformed data. The proposed algorithm achieves the best recognition rate for deformed data because the LBP is robust against scaling, rotation, illumination changes and background clutter.

Table 3 calculates the recognition time for the proposed technique and previous techniques. The proposed technique requires a recognition time of 0.45 second. According to the results the proposed algorithm has the best recognition rate and minimum computation time with respect to the compared techniques. The proposed technique was implemented by MATLAB R2019b in a laptop Intel core i5 and 6G RAM in Windows 10 professional 64 bit.

Table (1): The Recognition rate between the proposed and previous techniques on original data

Algorithm	Recognition rate
PCA [19]	96.66%
ZM [19]	96.66%
KLDCCA [20]	97.23%
SPDCCA [21]	96.11%
LSRC [22]	94.21%
CCA [23]	95.32%
HOG [26]	93.2%
MKL fusion [27]	97.32%
DCT+LBP [28]	97.50%
Proposed	**99.26%**

Table (2): The Recognition rate between the proposed and previous techniques on deformed data

Algorithm	Recognition rate
PCA [19]	91.14%
ZM [19]	92.25%
KLDCCA [20]	95.21%
SPDCCA [21]	93.25%
LSRC [22]	92.57%
CCA [23]	94.14%
HOG [26]	90.12%
MKL fusion [27]	95.58%
DCT+LBP [28]	95.82%
Proposed	**97.43%**

Table (3): The computational time between the proposed and previous techniques

Algorithm	Time consumption
PCA [19]	٠,٦٧
ZM [19]	1.3
KLDCCA [20]	0.72
SPDCCA [21]	0.95
LSRC [22]	0.87
CCA [23]	0.58
HOG [26]	0.61
MKL fusion [27]	0.73
DCT+LBP [28]	0.63
Proposed	**0.45**

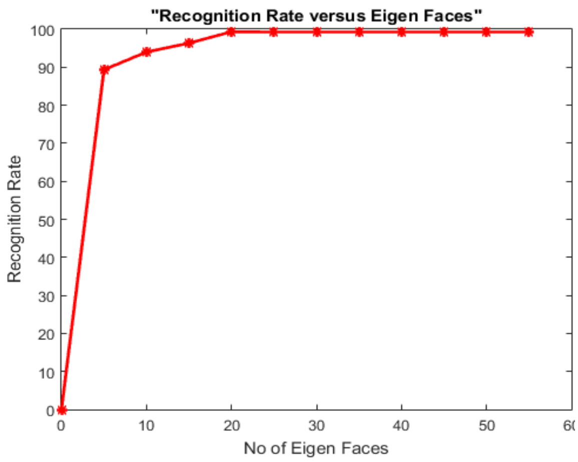


Fig. (3): the recognition rate against the number of Eigen faces on original dataset

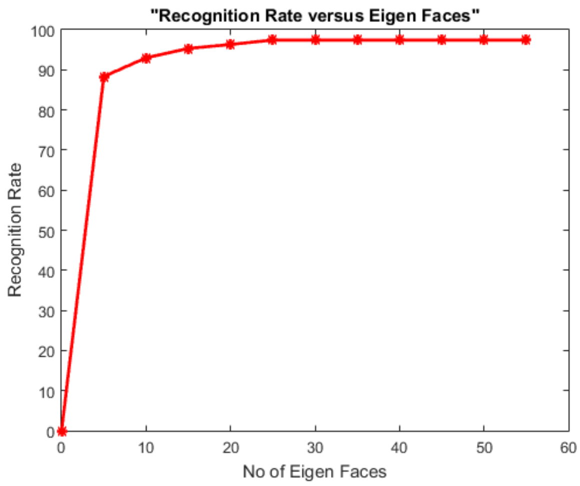


Fig. (4): the recognition rate against the number of Eigen faces on deformed dataset

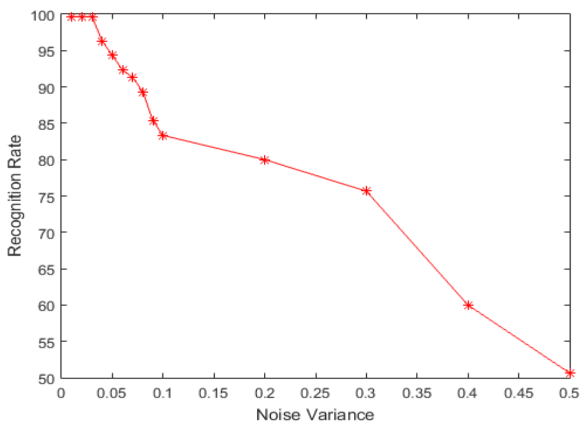


Fig. (5): Recognition rate with Gaussian noise

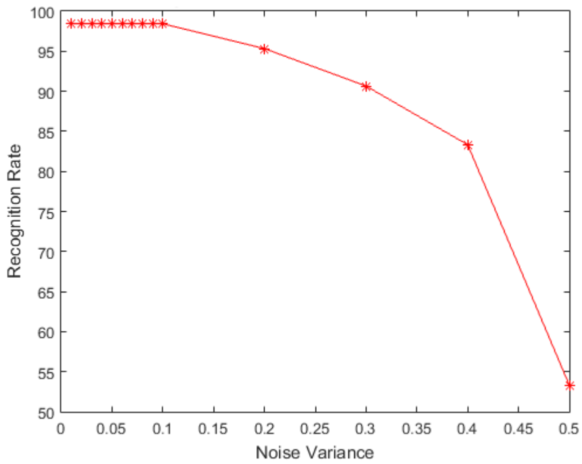


Fig. (6): Recognition rate with Salt and pepper noise

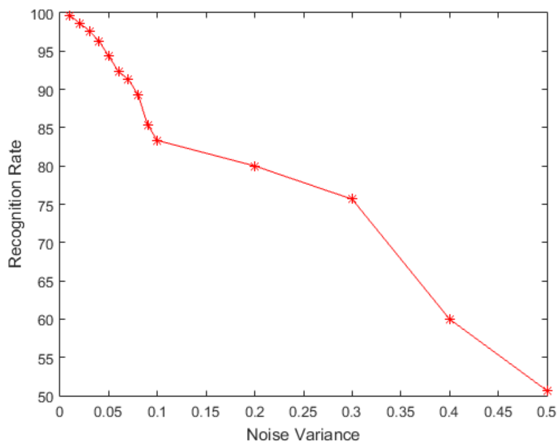


Fig. (7): Recognition rate with Speckle noise

CONCLUSION

An efficient algorithm for Infrared face recognition algorithm is presented. Different features have been extracted and transform domain properties have been exploited to enhance recognition accuracy. 2DPCA was used to reduce the number of redundant data. The CCA was used as a classifying metric by the proposed method that outperformed a number of well-known classifiers. In various transformation domains, multiple characteristics have been extracted and merged using CCA. The proposed algorithm achieved high recognition accuracy with low computational requirements. This paper also presented a performance comparison with previous work between the proposed LBP infrared face recognition algorithms. Many aspects, such as the recognition rate and time consumption, were considered in the analysis. Results show that all other descriptor-based techniques are outperformed by our proposed approach, and are comparable with other much more complex descriptors based on learning. The algorithm proposed has the best rate of recognition and minimum computation time.

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