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Illumination Invariant NIR Face Recognition using Directional Visibility

Srijith Rajeev, Shreyas Kamath K.M, Qianwen Wan, Karen Panetta;
Department of Electrical and Computer Engineering, Tufts University, Medford, MA, USA
Sos S. Agaian, Department of Computer Science, CUNY, New York, NY, USA

Abstract

Biometric face recognition technology has received substantial attention in the past several years due to its potential for a wide variety of applications in both law enforcement and non-law enforcement fields. However, most current face recognition systems are designed for indoor and cooperative-user applications. Moreover, ambient lighting fluctuates greatly between days and among indoor and outdoor environments. Furthermore, illumination is the most significant factor affecting the appearance of faces. Most existing systems, academic and commercial, are compromised in accuracy by changes in environmental illumination. Furthermore, state-of-the-art techniques designed to combat this issue have very low accuracy. This paper attempts to combat the issue by proposing an illumination invariant near infrared face recognition architecture that consists of (1) generating a sequence of directional visibility images using quadrant and circular filters, (2) extracting Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) features, and (3) performing SVM based classification. This technique a) improves the accuracy of the face recognition system, b) works under illumination variations, and c) does not need registration of face information. Furthermore, extensive computer simulations performed on the TUFTS (NIR) database and IIT Delhi NIR Face Database demonstrate that the proposed technique produces 94.52% and 80.41% respectively

Introduction

Algorithms performing face recognition have many profound implications in the fields of homeland security, commercial, law enforcement, and even social networking [1, 2]. Face recognition system is a noninvasive process and has distinct advantages over other biometric systems such as fingerprint, palmprint, and iris [3-5]. Facial images of an individual can be captured from a distance, and the identification/verification does not require direct interaction. Besides, face recognition serves the crime deterrent purpose because face images that have been recorded and archived can later help identify a person of interest. Face recognition is widely used to comb through the data collected in CCTV footages [6].

Astounding developments have been made in the implementation of facial recognition algorithms over the past few decades. Authentication systems rely on identifying unique facial features and pairing alike structures for recognition. However, in a practical application environment, illumination variation coupled with other problems such as pose variation and expression variation increase the complexity of automatic face recognition [7]. Moreover, face recognition encounters severe challenges in detection, tracking, and recognizing individuals due to varying weather conditions (for instance rain, fog, snow), uncontrolled environmental conditions caused by low-quality sensors, low tolerance to the variance in facial expressions, cluttered background, and difference in body positions [8]. Some of the variations were captured in the Tufts face database (NIR), and a few sample images are shown in Figure 1. It is shown from the tests of FERET, FRVT, and FRGC that variations in illumination are still one of the bottlenecks in face recognition system [9].

Various approaches addressing the challenges faced during illumination invariant face recognition have been proposed in the past years. A study on illumination variation in face recognition concluded that most state-of-the-art methods are based on illumination normalization. A well-known approach to solving illumination variation problem is to use active imaging techniques such as near-infrared imagery to obtain face images captured inconsistent illumination condition [10].

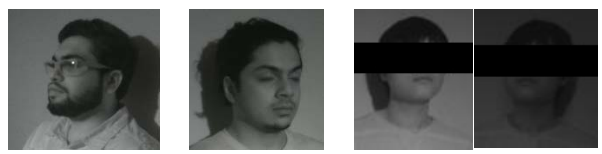
Variable pose Eyes closed Varying illumination

Figure 1: *shows the variable changes in near-infrared imagery* [11]

Note: some of the images are partially hidden for privacy purposes

Tan and Triggs [12] proposed a heterogeneous feature fusion-based recognition framework. This framework employed a preprocessing chain that combines Gamma correction, Difference of Gaussian filtering, masking and contrast equalization to eliminate most of the illumination effects while still preserving needed essential appearance details. Further, a combination of Gabor wavelets and local binary patterns (LBP) with robust illumination normalization and a kernelized discriminative feature extraction method was used for higher performance.

Few other approaches have been proposed that utilize near-infrared (NIR) imagery for face recognition. Farokhi [13] presented a technique that employed a combination of global features extracted by the calculation of Zernike moments (ZMs) and local features extracted from partitioned image patches Hermite kernels (HKs) to cope with variations in facial expression, changes in head pose and scale, occlusions due to wearing eyeglasses and the effects of time lapse. Principal component analysis and linear discriminant analysis was applied to both global and local features, and multiple feature vectors were obtained.

Zhou [14] introduced a face recognition system that employed an active near-infrared imaging system (ANIRIS) as face images acquisition equipment. The kernel discriminative common vector (KDCV) and the radial basis function (RBF) neural network were used for feature extraction and classification purposes, respectively. The results concluded that changes in illumination had very little influence on the NIR images.

Zhang [15] used a convolutional neural network (CNN) for NIR face recognition. CNN's were used to automatically learn features from images. Although it performed slightly better than

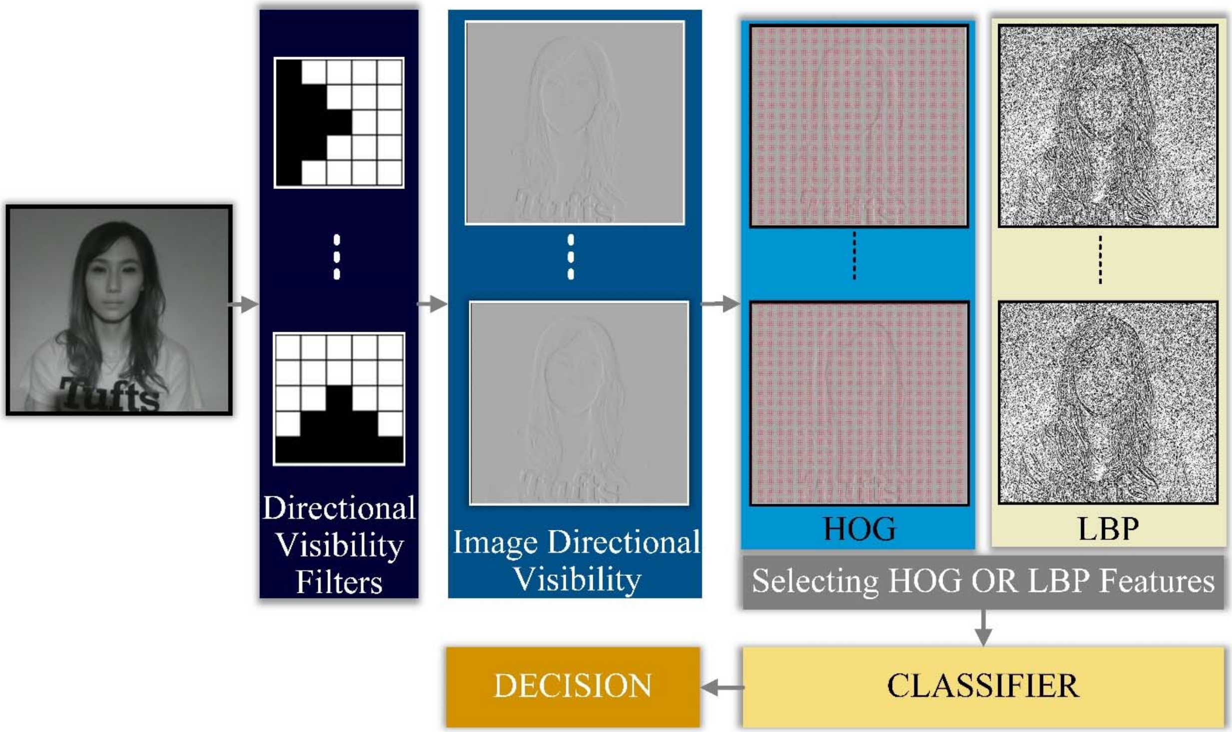

Figure 2: *Block diagram of the proposed system. This provides a visual flow of the algorithm to perform NIR face recognition system using directional visibility.*

Gabor-DBC and ZMHK, the model does have higher training and testing computations.

Imaging in the infrared and near- infrared spectrum has been at the forefront of face recognition in the last few years [10, 16, 17]. Near-infrared (NIR) face recognition systems were introduced to overcome the challenges of no illumination in the environment [18]. This paper proposes a novel architecture for illumination invariant face recognition. First, a sequence of directional visibility images is generated. Second, Local Binary Patterns (LBP) or Histogram of Oriented Gradients (HOG) features are extracted from these images. The resulting face images encode intrinsic information of the face, subject only to a monotonic transform in the gray tone; based on this, LBP features or HOG features are used to compensate for the monotonic transform, thus deriving an illumination invariant face representation. Finally, SVM based Classification is performed.

The proposed algorithm has several advantages over other previous algorithms: (1) it presents a novel directional visibility based local feature extractor to generate complementary data types; (2) it does not require images captured under different lighting conditions to create a normalizing coefficient, and (3) it does not need to align the images for recognition.

The novelty of this new method is the use of an embossing technique to process face images before forwarding it to a typical face recognition system. The performance of the proposed method is evaluated by testing the proposed method on the widely used databases. Furtermore, the experimental results will demonstrate the successfulness of the proposed method.

The rest of the paper is organized as follows. In Section 2, a detailed description of the proposed matching system is provided. Section 3 provides a glance at the computer simulations and the results obtained. Section 4 concludes the paper and suggests the future work.

2. Proposed Method: Illumination invariant face recognition system using Directional Visibility

The proposed architecture consists of three different stages: directional visibility image generation, facial feature extraction, and SVM classification. Figure 2 shows a refined representation of the entire system's schematic diagram.

Directional Visibility Image Generation

Directional visibility filters are linear filters that have been developed to extract directional contrast information. Two directional visibility shapes quadrant and circular were proposed and can be visualized in Figure 3.

Quadrant directional visibility filter: This is a local directed filter which takes advantage of four different directions in a *k x k* window. This can be visualized in Figure 3 (a). The black area represents the values under consideration whereas the white are zeros. For example, when a *5 x 5* kernel is considered, nine pixels are considered for each direction. The center pixel is then replaced with a pixel value obtained after applying either equation 1, 2 or 3.

$$I_{max}/I_{min} \quad (1)$$

$$(I_{max} - I_{min})/(I_{max} + I_{min}) \quad (2)$$

$$(I_{lc} - \alpha \times I_{mean})/(I_{lc} + \alpha \times I_{mean}) \quad (3)$$

where I_{max} is the maximum pixel intensity, I_{min} is the minimum pixel intensity, I_{lc} is the local center pixel, I_{mean} is the mean of the pixels in consideration and α can vary between 0 to 1.

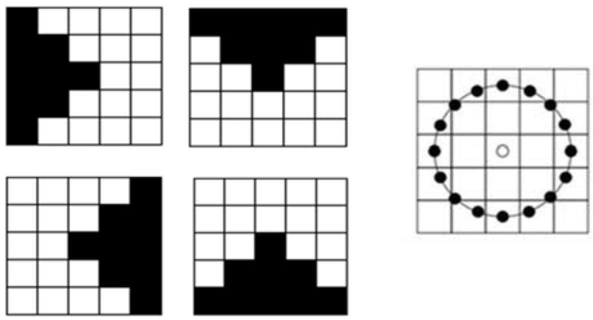
(a) Quadrant (b) Circular

Figure 3: *The proposed directional visibility image filters. (a) shows the quadrant filters and (b) shows the circular filter*

An example of the visibility image obtained when the quadrant directional filters are applied with equation 3 is shown in Figure 4. It can be seen that only facial features along each direction are extracted for each directional visibility image.

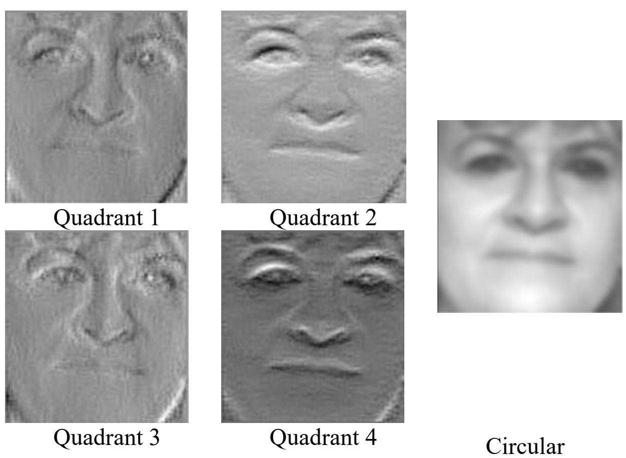

Figure 4: *Shows directional visibility images generated using the quadrant and circular directional visibility filters*

Circular directional visibility filter: This is a local filter which takes advantage of neighborhood pixels around the center in a k x k window. It can be visualized for a 5x5 window as shown in Figure 3 b. The black dots are the pixels taken into consideration. The value of the point in between two or more pixels was interpolated. The local center is then replaced with the mean value of the pixels into consideration. An example of the output of the filter can be visualized in Figure 4.

Facial feature extraction (LBP/HOG) [19-21]

Feature extraction and description are predominantly performed for object classification, image-recognition, and retrieval in the field of Computer Vision [22-24]. Features can be extracted either locally or globally, but it makes more sense to extract local features for face recognition. Local features aim at collecting points that are generally invariant to many factors depending on the type of detector. In this work, local features such as Histograms of Oriented Gradients (HOG) and Local Binary Patterns (LBP) are employed.

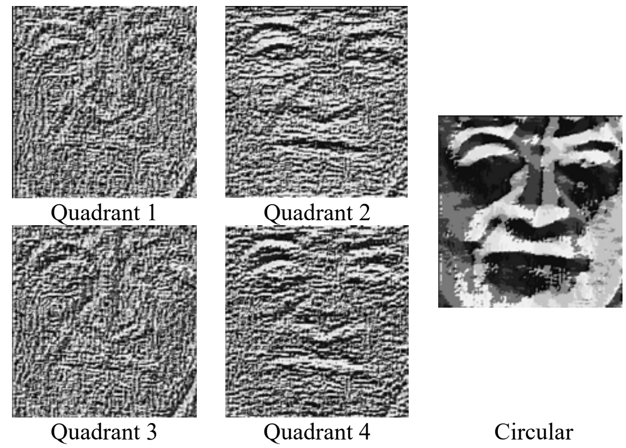

Figure 5: *shows the extracted LBP features after passing it through the directional visibility filters*

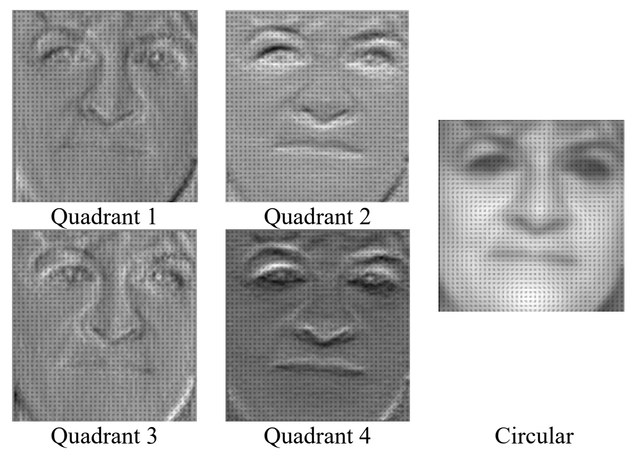

Figure 6: *shows the extracted HOG features after passing it through the directional visibility filters*

LBP efficiently summarizes the local structures of a face image, which has recently received increasing interest for facial representation [2, 25] because of its high tolerance against illumination changes. Figure 5 shows the LBP features extracted from the directional visibility filtered images. HOG feature descriptor uses the histogram of the direction of oriented gradients as features. This is useful as the magnitude of gradients is large along edges and corners. Figure 6 shows the extracted HOG features with the directional visibility images. LBP and HOG feature extraction methods serve to encode the edge orientation features in each directional visibility images. Finally, all the extracted feature vectors from each directional visibility images are concentered altogether and output as the final feature.

SVM Classification

Cortes and Vapnik [26] introduced support Vector Machine widely known as SVM for classification and regression purposes. The main idea of SVM is to maximize the shortest distance from the separating hyperplane to the nearest example. It was primarily designed for binary classification. However, it has been widely used in face recognition [27], which is a multi-class classification problem. The extracted facial features are mapped onto a high-dimension space via certain non-linear transformation, in which the optimal hyperplane can be constructed. Data are then classified by finding the matching hyperplane. The feature vectors generated from previous steps will be fed into the SVM classification.

3. Computer Simulations

The evaluation and testing of the proposed recognition system was conducted on two publicly available databases.

The NIR Tufts Face Database (TD) [11]: This database contains NIR images of 100 participants and were divided into 4 different subsets. Among them, Set1 was selected to compute the performance of the proposed system. This subset contained 675 images (25 participants x 27 images). NIR images were captured using a quad camera (crafted by the authors [11]) which captured images with a wavelength of 850nm. These images were obtained from nine locations surrounding the participant with a resolution of 3280x2464 pixels. As it contained irrelevant information, it was cropped to a size of 1000x1000 pixels with only face information. As usage of images with 1000x1000 resolution was computationally expensive, it was further resized to 101x101. An example of this dataset can be visualized in Figure 7.

Figure 7: *Example of NIR face images captured from 9 different positions available in the NIR Tufts Face Database.*

Figure 8: *Example of 6 different IR face images obtained from IIT Delhi NIR Face Database*

IIT Delhi NIR Face Database [28]: This database contains IR images of 115 participants and were divided into 4 different subsets. Among them, Set1 (or experiment 1) was employed which contained 288 images (48 participants x 6 images). The resolution of these images were 768 x 576 pixels. The resolution was further reduced to 154x116 for faster computation. An example of this dataset can be visualized in **Error! Reference source not found.**.

Both these databases were randomly split into 70:30, 80:20, and 90:10 ratios of training and testing sets for a fair evaluation. The performance of the proposed method was computed using several combinations of directional visibility filters with feature detectors as described below:

1. Local Binary Pattern (LBP)
2. Directional Visibility filter (Quadrant) with LBP
3. Directional Visibility filter (Circular) with LBP
4. Histogram of Oriented Gradients (HOG)
5. Directional Visibility filter (Quadrant) with HOG
6. Directional Visibility filter (Circular) with HOG

Table 1: Recognition rate of the proposed illumination invariant near-infrared image based recognition (in %)

Database →		The NIR Tufts Face Database			IIT Delhi NIR Face Database		
Training/ Testing Ratios →		70:30	80:20	90:10	70:30	80:20	90:10
1	LBP	30.84	29.36	36.84	38.14	30.61	22.44
2	Quadrant with LBP	35.32	37.3	28.94	25.77	16.32	28.57
3	Circular with LBP	3.98	3.96	3.94	2.06	2.04	2.04
4	HOG	92.53	96.82	**94.73**	73.19	81.63	**75.51**
5	Quadrant with HOG	93.53	93.65	93.42	74.22	75.51	**75.51**
6	Circular with HOG	**94.52**	**96.82**	90.78	**80.41**	**87.75**	73.46

Note: The bold text indicates the best performance for the particular ratio (column-wise).

Table 1 shows quantitative comparisons of the aforementioned combinations. The key difference between HOG and LBP is how each method utilizes the gradient information. The proposed circular directional visibility filters in conjunction with HOG detector performs favorably when compared to other combinations. This is because the circular directional filter tends to combine most of the relevant face information in each kernel for recognition purposes while reducing high frequency components. Furthermore, the design of HOG detector which uses only one direction for each filter favors lower frequency components. On the contrary, the directional filters with local binary patterns fail as LBP feature detector depends on drastic variation in the pixel intensity. Due to the averaging caused by the circular directional visibility filters (seen in Figure 4), there is no significant difference between the pixels as the high frequency information is suppressed. Moreover, LBP stems from the fact that it uses all 8 directions for each pixel and the binning employed by LBP makes it lose more information.

4. Conclusion

In this paper, an illumination invariant near infrared image-based recognition system using directional visibility technique is presented. To generate directional visibility images, two kernels namely quadrant based, and circular based kernels were presented. This technique has an advantage of identification/verification of face images under different lighting conditions by creating a normalization coefficient. Furthermore, face registration or alignment of faces is not required at any stage; thus, making it suitable to be employed for partial face recognition systems. Computer simulations indicate that circular visibility filter applied prior to HOG feature detector perform better than the classical LBP, HOG, and other combinations. This performance is tested by employing NIR Tufts Face database and IIT Delhi NIR Face database. As a part of future work, the authors intend to apply the presented technique on all the sets of the aforementioned databases and conduct further research regarding the authentication system on that database. Secondly, the proposed method will be tested on face images from different sensors for example thermal, and visible.

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Author Biography

Srijith Rajeev received his B.E. degree in electronics and communication engineering from the Visvesvaraya Technological University, India, in 2014, and M.S degree in electrical and computer engineering from the University of Texas at San Antonio, USA, in 2016. He is currently pursuing his Ph.D. in electrical and computer engineering at Tufts University, USA. His current research interests include signal/image processing, video processing, machine-learning, 3D sensors and modeling, digital forensic, and biomedical applications.

Shreyas Kamath K.M received his bachelor's degree (B.E.) in Electronics and Communication engineering from the Visvesvaraya Technological University, Belgaum, India, in 2014. He completed his M.S degree in Electronic and Computer Engineering at the University of Texas at San Antonio, USA. He is currently pursuing his Ph.D. in electrical and computer engineering at Tufts University, USA. He is working as a graduate research assistant in the Visual and Sensing Lab, Tufts.

Qianwen Wan received her B.S. in information engineering from Wuhan University of Technology (Wuhan, China), B.S. in law from Wuhan University (Wuhan, China), and M.S. in electrical and computer engineering from Tufts University (Medford, MA, USA). She is currently pursuing her Ph.D. in electrical and computer engineering at Tufts University. Her current research interests include designing automated tools for cognitive science, analyzing mobile eye tracking data, facial recognition, image and video processing, and machine-learning applications.

Karen Panetta received the B.S. degree in computer engineering from Boston University, Boston, MA, and the M.S. and Ph.D. degrees in electrical engineering from Northeastern University, Boston. Dr. Panetta is currently a Dean of Graduate Engineering Education and a Professor in the Department of Electrical and Computer Engineering and Adjunct Professor of Computer Science at Tufts University, Medford, MA, and Director of the Dr. Panetta's Vision and Sensing System Laboratory.

Sos Agaian is currently a Distinguished Professor at The City University of New York/CSI. His research interests include computational vision and machine learning, large scale data analytic analytics, multi-modal data fusion, signal/image processing modeling, multimodal biometric and digital forensics, 3D imaging sensors, information processing, and security, and biomedical and health informatics. He is a Fellow of the SPIE, a Fellow of IEEE, Fellow of the IS&T, and a Fellow of the AAAS.