ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 7, July 2015

Set-Theoretic Characterization for Blur Face Recognition

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ABSTRACT: This paper proposes a novel method for recognizing faces degraded by blur and illumination variation using set-theoretic characterization method. In the unconstrained environment, face recognition becomes difficult because of Blur, noise and illumination. In this paper, we address problem of face recognition in unconstrained domain. The convex set is set of all images which are obtained by blurring a given image. In this algorithm, various blur characteristics are taken under consideration. By blurring image by various blur function convex set is formed and that corresponding convex set is associated with each gallery image. Face recognition algorithm is implemented based on this set-theoretic characterization.

The (LBP) Local Binary Pattern feature of Blurred probe image (which we need to recognize) is extracted. Each convex set is associated with every gallery image in the database. The Local Binary Pattern (LBP) features of all gallery images are extracted. These Local Binary Pattern (LBP) features of probe input image is compared with the LBP features of every image in convex set from the gallery and closest match is identity of probe image. The face recognition is depends on the factor called Similarity between probe image and gallery image. The robust version of this algorithm the input image is divided into different regions and we divide each input image into blocks. These images weight differently when computing the distance of probe image (*Ib*) and gallery sets (*Bj*). As a result of this algorithm is able to recognize human faces with good accuracy and for different blur types.

KEYWORDS: unconstrained, Blur, Local Binary Pattern (LBP), convex set.

I. INTRODUCTION

During past few decades, face recognition has received great attention because of various applications such as security system, ATM cards and CCTV control. Because of rapid advancement in technology like mobile, digital cameras and internet the face recognition is becoming growing area [1]. The requirements of a good face recognition algorithm are high verification rate and tolerance towards various environmental factors such as variations in light, different facial poses, facial expression of different types, and background of image also have good computational and less amount of complexity. Images have two types first is constrained domain (images captured under controlled conditions like light, focal length, example Passport photo) and other is unconstrained domain images (images under uncontrolled conditions like blur and noise) depends upon condition in which image is captured. There are many challenging issues are available for face recognition under uncontrolled conditions like blur, noise and variation in light. The face recognition becomes challenging problem because of degradations of image due to different blur types, noise and changes in appearance due to light variations called illumination and pose. The faces acquired by distant cameras and imperfections in the capturing process are some problems that occur during face recognition. However, the recorded image invariably represents a degraded version of the original scene. Due to cameras improper focused lens, the relative motion between the camera and the scenes or atmospheric turbulence blur can be introduces within any image. There are different types of blur in images that are classified according to these types (i) Atmospheric blur, the cause of this blur is due to long-time atmospheric exposure (ii) Out-of–Focus blur is caused by defocused optimal system and (iii) Motion blur which is caused due to relative motion between the scenes and recording devices. For face recognition, significant steps have been made in solving problems in controlled domains (Recognition of passport photograph) but still challenges remain for recognition of faces in uncontrolled domain. Because of variations in appearance due to illumination, pose, noise and degradations of image due to different types of blur the face recognition is becoming challenging problem.

A few existing methods are attempts to handle this problem of blur. An obvious way is to recognizing blurred faces are to deblur the image first and then recognize it by using traditional face recognition techniques. But, it is necessary to solve the blind image deconvolution problem [3] in this approach. The Blind deconvolution is the processes of recovery of a sharp version of a blurred image when the blur kernel is unknown [2] or blind deconvolution is to restore image without prior knowledge about function that blurred the image.

H.Hu and G. D. Haan [4] proposes facial deblur estimation, to obtain blur map of image a robust local blur estimation is applied and deblurred the image which is blurred and then used for recognition. In multi-focusing technique, the blur in image is estimated first and all-in-focus images are restored, but the drawback of this is during restoration process sensor noise may get amplified.

M. Nishiyama, A. Hadid, and O. Yamaguchi, [5] uses Facial deblur inference (FADEIN) approach which first deblur face image but drawback of the approach is to solve Blind image deconvolution.

II. LOCAL BINARY PATTERN

III.

To perform face recognition feature extraction is important process where useful features are extracted from the face image. For the extraction of features the Local Binary Pattern is used. The Local Binary Pattern is used to describe shape of digital image and image texture. The face image is divided into small regions and then every pixel of an image is assigned with the label by the operator and by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering that result as a binary number [7]. For texture description 256–bin histogram of the labels can be used.

The center pixel as threshold is considered by LBP operator and then works with eight neighbours of a pixel using center value. To each neighbour pixel value '1' is assigned if that neighbour pixel is having higher gray value than the central pixel (or the same gray value) and value '0' is assigned to that pixel if neighbour is having lower gray value than central pixel

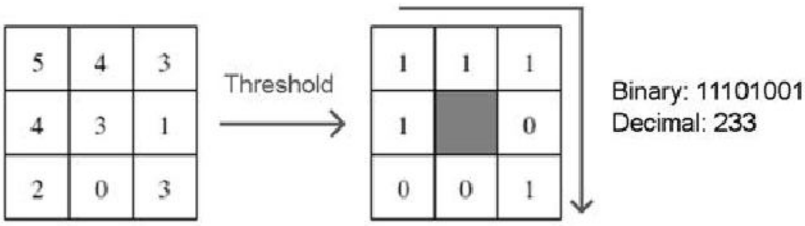

Figure 1: The LBP Operator

IV. FACE RECOGNITION ALGORITHM

A. DIRECT RECOGNITION OF BLURRED FACES (DRBF)

In Direct recognition of blurred faces (DRBF), there is comparison between blurred images (probe image) with sets of gallery images where closest match is found out. We first review convolution model for blur and in second step we review convex sets that is sets of all blurred images and last face recognition algorithm and its robust version is implemented. The various blur types are considered such as Motion blur, Gaussian blur and General blur.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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a. *Convolution Model for Blur*

In any blurred image, blurring is form of bandwidth reduction of the ideal image which results to imperfect reduction of ideal image. In any blurred image, a pixel is weighted average of pixels neighbourhood in original sharp image. To model blur, convolution operation is performed between original images and blur kernel. The blur image (Ib) is given by

$$Ib=I*H(r,c)$$

Where r is row and c is column indices of image and convolution operator is represented by ***** operator. This convolution model is expressed by function kblur= fspecial ('motion', 25, 90) in this algorithm. The blur kernel may possess additional structure depending on the type of blur. The types of blur which are implemented in the algorithm are Motion blur, Gaussian blur and General blur.

b. *Set of Blurred images*

We are going to characterize the set of all images obtained by blurring image *I*. Two types of Gaussian blur three types of motion blur, one disc blur and a general blur are total seven types of blur implementation in our algorithm. β is convex set which is obtained by blurring an image.

$$\beta \triangleq \{\boldsymbol{Ah} | \boldsymbol{h} \geq 0, \quad ||h||1=1\}$$

c. *Geometric Face Recognition algorithm*

Let $I\, j$, $j = 1, 2, \ldots, M$ be the set of M sharp gallery images. To the every image in gallery (Ij) associated convex set of blurred images (represented by *B*j) is formed. For every gallery image LBP features are extracted. The extracted LBP feature of probe image is compared with every LBP feature of gallery image. The gallery image with similarity and that image having closest match is the identity of blurred image.

Algorithm 1 DRBF/rDRBF Algorithm: Algorithm for Recognizing Blurred Faces

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Input: (Blurred) probe image *Ib* and *Ij* is set of gallery images.

Output: Identity of probe image

1. For each gallery image Ij, the convex set associated with each gallery image is formed.
2. Blur each gallery image Ij with every blur type and extract LBP features.
3. Compare the probe image LBP features with gallery images LBP features and find the closest match.

V. IMPLEMENTATION

In this paper, by using set-theoretic characterization methods, an algorithm performs face recognition across varying blur condition. In this, convex set is formed which is set of all images is obtained by blurring a given image so corresponding convex set is associated with each gallery image.

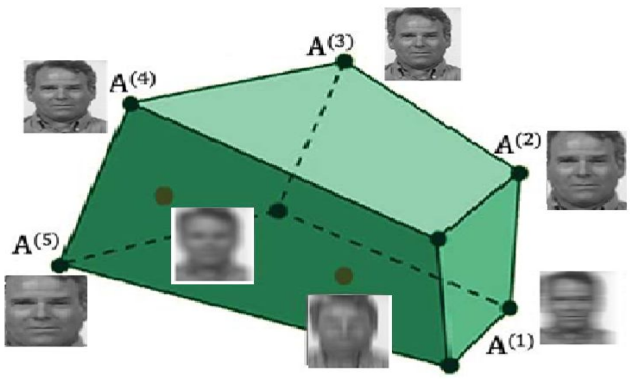


Figure 2: Convex set

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 7, July 2015

The distance of probe image (which is to be recognize) from each convex set is to be computed and assign it to closest gallery image. The algorithm computed with closest image by LBP (Local Binary Pattern) space. Figure shows the implementation block diagram of DRBF algorithm. This set-theoretic characterization method is used for implementing a blur-robust face recognition algorithm.

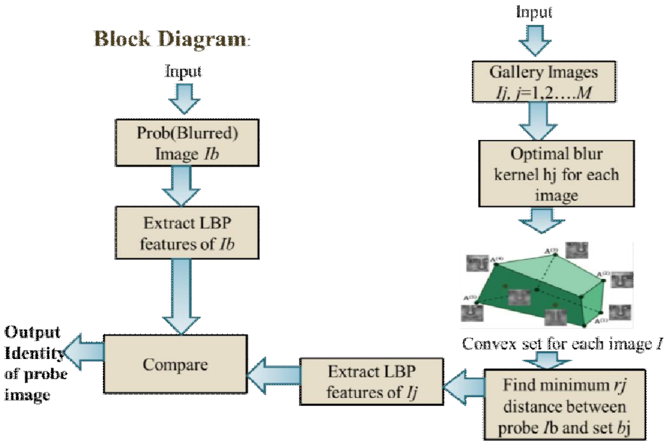


Figure 3: Implementation Block Diagram of DRBF algorithm

To evaluate the proposed algorithm DRBF on different types and amount of blur, we synthetically blur face image from FERET dataset with seven different types of blur: General blur, Disk blur, Motion blur and Gaussian blur. The following table shows various types of blur and blurs functions implemented in our algorithm.

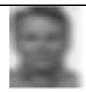
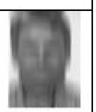
Input Image	Blur Type	Name of Blur& Blur kernel Function	Blurred images
	Type a	General Blur kblur1=[0 0 0;0 1 0;0 0 0]	
	Type b	Disk Blur kblur2=fspecial ('disk', 8)	
	Type c	Motion Blur kblur3=fspecial ('motion', 25, 90)	
	Type d	Motion Blur kblur4= fspecial ('motion', 21, 0)	
	Type e	Motion Blur kblur5= fspecial ('motion', 9, 45)	
	Type f	Gaussian Blur kblur6=fspecial ('gaussian', 9, 0.5)	
	Type g	Gaussian Blur kblur7=fspecial ('gaussian', 15, 0.2)	

Table 1: Types of Blur and Blur Function

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 3, Issue 7, July 2015

In Robust version of algorithm rDRBF, the input image is divided into different regions and weight them differently when computing the distance of probe image (*Ib*) and gallery sets (*Bj*). The different face regions have different amount of information. Here input image is divided into blocks 30×30 pixels. LBP features of divided regions are extracted and that are matched with LBP features of gallery images to find the closest matched.

VI. EXPERIMENT AND DISCUSSION

In this section, the algorithm is applied and is used to test performance of set-theoretic characterization method on different kind of blur input faces. An experimental result is performed on some publically available dataset for face recognition such as FERET dataset. We consider only 102 gray scale gallery images from FERET dataset for our experiment. The set-theoretic characterization method is used. The frontal images are selected and images are blurred by various type of blur. We investigate motion blur which is caused due to relative motion between camera and the scene, Gaussian blur which is caused by long-time atmospheric exposure. In this, we have set of 102 gallery images and for every gallery image its associative convex set is formed. The input to our algorithm is blurred image. Every gallery image is blurred by different type of blur like General blur, disk blur, three types Motion blur and two types of blur. Following figure shows Convolution Model for blur. The convolution operation of blur is applied for every gallery image.

a) No blur (b) σ = 8 (c) M (25, 90) (d) M (21, 0) (e) M (9, 45) (f) General-I (g) General-II

Figure 4: Different types of Blur images (Convolution Model for Blur).

Based on algorithm, the input blur face image of an unknown is compared with face images of known individuals from a large database. By set theoretic characterization method, every gallery image is blurred by various blur function and convex set is formed for each image, then LBP features are extracted from every gallery images.

Following are experimental steps for direct recognition of blurred faces.We provide input image from FERET dataset.The input probe image is blurred by type of Motion blur (type c) as shown below.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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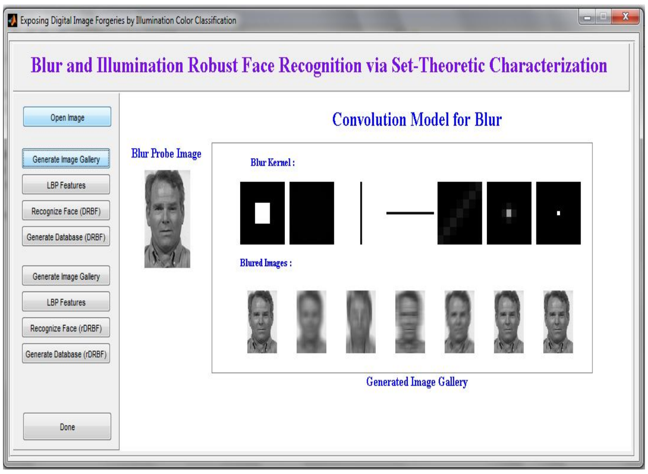
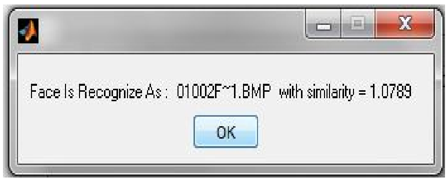
Vol. 3, Issue 7, July 2015

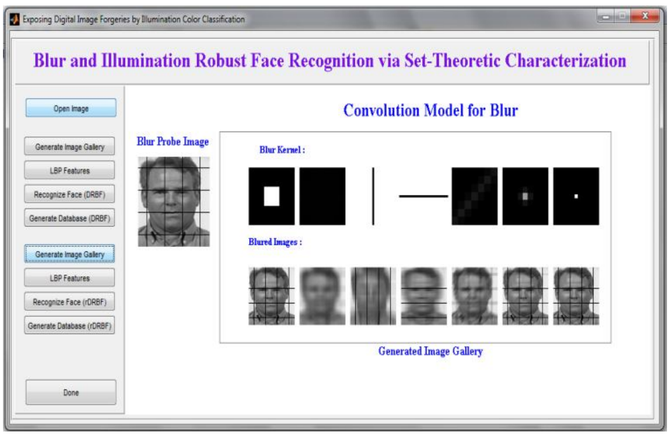
For the every image in gallery, convex set is formed that is set of all images which are obtained by blurring the image. The convolution model for blur as shown below



Then Local Binary Pattern (LBP) of Probe input image are extracted and in the gallery for every image convex set is formed and their LBP features are extracted for comparison with probe image. The LBP feature of probe image is compared with LBP features of all the gallery images. If LBP features of input image are found with similarity of LBP features of face images from the database then we said that face image is successfully recognized. Two images are completely similar, that is identical, objects give the maximum similarity (usually 1 but0 in our experiment since we consider zero as maximum similarity of images), whereas the least similar pairs reach the minimum value 1.



In robust version the face images are divided into blocks 30×30 pixels. Their LBP features are extracted and that are matched with LBP features of gallery images to find the closest matched. Because of robust version of DRBF our algorithm is robust to outliers, which could arise due to variations in expressions are handled. Following figure shows experimental result of robust DRBF. The Robust direct recognition of blurred faces is shown below where input image is divided into blocks of 30×30 pixels.



ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 3, Issue 7, July 2015

In the next step, the LBP features of input image are calculated and that are matched with the LBP features of all gallery images and the closest match is the identity of probe image. In robust version of DRBF (rDRBF), the similarity factor is more accurate as compared with the DRBF algorithm.

Input Blur Image	Blur Types	LBP Values	Face Recognition with Similarity	
			DRBF	rDRBF
01000F~1	a	2167	0	0.11965
	b	828	0.93875	0.095412
	c	1196	0.71445	0.086792
	d	761	0.72965	0.096316
	e	920	0.6162	0.093076
	f	1371	0.4309	0.084364
	g	2167	0	0.11965
Input Blur Image	**Blur Types**	**LBP Values**	**Face Recognition with Similarity**	
			DRBF	**rDRBF**
01005F~1	a	2440	0	0.12592
	b	851	0.85295	0.089003
	c	933	0.92629	0.092723
	d	887	0.97445	0.10037
	e	850	0.70723	0.87529
	f	1319	0.49525	0.08046
	g	2440	0	0.12592

Table 2: DRBF and rDRBF face recognition with similarity values

The Table 2 shows the similarity values of recognized face for various blur type in DRBF and Robust DRBF (rDRBF) algorithm. We use FERET dataset as a gallery input set and we create probe image by synthetically blurring the image from FERET dataset using various blur types or blur kernel functions as shown in Table 1.

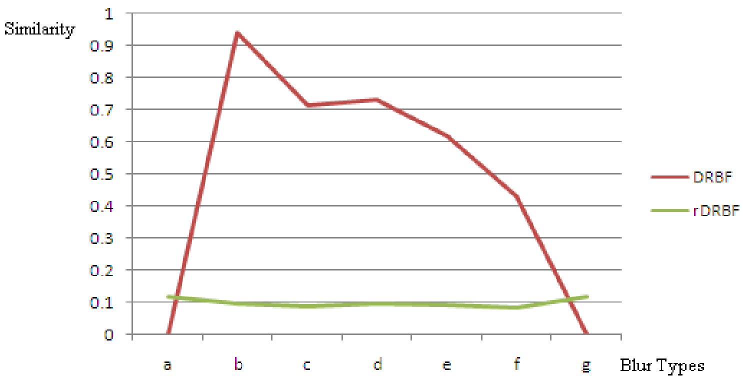

Figure 5: Similarity values in Face recognition (DRBF and rDRBF)

In gallery, the FERET dataset is used as database and convex set of all gallery images are formed in the database. Table 2 shows input images, that are tested for different blur types and recognized successfully for both DRBF and rDRBF algorithm. The similarity values of DRBF are much better than the rDRBF for various blur like motion blurs (type c, d, e) and Gaussian blur (type f and g). Figure 5 shows, the similarity values are close to zero value (Maximum similarity) that is, rDRBF values are better than DRBF.

VII. CONCLUSION

In remote face recognition, there are problems like recognizing blurred and poorly illuminated faces. In this paper, blur-robust face recognition algorithm (DRBF) based on set-theoretic characterization is presented. The Local Binary

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 7, July 2015

Features are based on this set-theoretic characterization. We propose DRBF for blurred face and rDRBF for the robust version of DRBF algorithm. The proposed algorithm tackles the challenging problem of face recognition under uncontrolled condition.

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