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Blur and Illumination Robust Face Recognition Using Set Theory and SVM

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Abstract: **This paper work addresses the problem of unconstrained face recognition from remotely acquired images. The main factors that make this problem challenging are image degradation due to blur and appearance variations due to illumination and pose. In this paper we address the problems of blur and illumination. We show that the set of all images obtained by blurring a given image forms a convex set. Based on this set theoretic characterization, we propose a blur-robust algorithm whose main step involves solving simple convex optimization problems. We do not assume any parametric form for the blur kernels; however, if this information is available it can be easily incorporated into our algorithm. Further, using the SVM classification for illumination variations, we show that the set of all images obtained from a face image by blurring it and by changing the illumination conditions forms a bi-convex set. Based on this characterization we propose a blur and illumination robust algorithm. Our experiments on a challenging real dataset obtained in uncontrolled settings illustrate the importance of jointly modeling blur and illumination.**

Keywords: **SVM classification, Blur And Illumination Robust Face Recognition Using Set Theory.**

1. INTRODUCTION

Face Recognition becomes one of the most biometrics authentication techniques from the past few years. Face recognition is an interesting and successful application of Pattern recognition and Image analysis. Face recognition system has two main tasks: verification and identification. Various biometric features can be used for the purpose of human recognition like fingerprint, palm print, hand geometry, iris, face, speech, gaits, signature etc. The problem with finger print, iris palm print, speech, gaits are they need active co-operation of person while face recognition is a process does not require active co-operation of a person so without instructing the person we can recognize the person. So face recognition is much more advantageous compared to the other biometrics. Face recognition has a high identification or recognition rate of greater than 90% for huge face databases with well-controlled pose and illumination conditions. The first step in face recognition system is to detect the face in an image. The main objective of face detection is to find whether there are any faces in the image or not. If the face is present, then it returns the location of the image and extent of the each face. Pre-processing is done to remove the noise and reliance on the precise registration. There are various factors that make the face detection a challenging task. Pose presence or absence of structural components, Facial expression, Occlusion, Image orientation.

2. LITERATURE SURVEY

Kaushik Mitra and Rama Chellappa address the problem of unconstrained face recognition from remotely acquired images. The main factors that make this problem challenging are image degradation due to blur and appearance variations due to illumination and pose. Teja G.P and Ravi.S proposed a face recognition using subspace techniques for face recognition using kernel methods. Ming Hsuan Yang has demonstrated their success in face detection, recognition and tracking using PCA. The representations in these subspace methods are based on second order statistics of the image set, and do not address higher order statistical dependencies such as the relationships among three or more pixels. Wright.et all proposed a classic and contemporary face recognition algorithms work well on public data sets, but degrade sharply when they are used in a real recognition system. This is mostly due to the difficulty of simultaneously handling variations in illumination, image misalignment, and occlusion in the test image.

3. METHODOLOGY

3.1 Existing System:

The existing system use DRBF (Direct Recognition of Blurred Faces) and IRBF(Illumination-robust Recognition of Blurred Faces) for Face Recognition of Blurred Faces.

3.1.1DRBF:

In this algorithm the probe image (blurred image) is compared with 591 sets of gallery images from that the closest match is found out. The various steps involved to find the closest match are explained below:

a) Kernel estimation:

A **kernel**, **convolution matrix**, or **mask** is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of convolution between a kernel and an image.

b) Convolution:

The values of a given pixel in the output image are calculated by multiplying each kernel value by the corresponding input image pixel values.

kernel=fspecial('gaussian', size(img), 1.0);

c) Blurring:

This process involves blurring of gallery image. The image is blurred based on the kernel values estimated from the above expression.

d) LBP Features extraction:

In the extraction of LBP features, minimum Euclidean distance and Eigen vectors are calculated.

e) Matching:

The LBP Features of gallery image and probe image are compared, the closest match is found.

3.1.2 IRBF:

In this algorithm the probe image (blurred and illuminated image) is compared with 591 sets of gallery images. The various steps involved to find the closest match are explained below:

a) Kernel estimation:

A **kernel**, **convolution matrix**, or **mask** is a small matrix useful for blurring, sharpening, embossing, edge-detection, and more. This is accomplished by means of convolution between a kernel and an image.

b) Convolution:

The values of a given pixel in the output image are calculated by multiplying each kernel value by the corresponding input image pixel values.

kerneln = fspecial('gaussian', size(imgn), 1.0);where n=1,2,...9.

c) Blurring:

This process involves blurring of gallery image. The image is blurred based on the kernel values estimated from the above expression.

d) LBP Features extraction:

In the extraction of LBP features, minimum Euclidean distance and eigen vectors are calculated.

e) Matching:

The LBP Features of gallery image and probe image are compared, the closest match is found.

3.2 Proposed System:

The proposed system use SVM (Support Vector Machine) classifier for face recognition in blurred images. It is a theoretically superior machine learning methodology with great results in pattern recognition. Especially for supervised classification of high-dimensional datasets and has been found competitive with the best machine learning algorithms. First, LBP features will be extracted in the training stage. Second, the features will integrate to the SVM classifier. Third, classify it with the testing image and identify the face.

3.2.1 SVM:

A support vector machine constructs a hyperplane or a set of hyperplanes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

Whereas the original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not_linearly seperable in that space. SVMs belong to a family of generalized linear classifiers. A special property is that they simultaneously minimize the empirical classification error and maximize the geometric margin; hence they are also known as maximum margin classifiers.

The various modules of SVM are explained below:

- Training
- Testing
- Classification

i) Training:

The first step is taking a set of blurred training images and computes the optimal blur kernel. The second step is finding the Local Binary Patterns (LBP).

- SVMStruct = svmtrain (Training, Group) returns a structure, SVM Struct, containing information about the trained support vector machine (SVM) classifier.
- SVMStruct =svmtrain(Training,Group,Name,Value) returns a structure with additional options specified by one or more Name, Value pair arguments.

ii) Testing:

After training, the SVM provides us training data. After that, taking a testing image (Probe image) and Compute the optimal blur kernel. Find the Local Binary Patterns (LBP).

iii) Classification:

Finally, SVM classification classifies the training data and testing data and produces the closest match output. Experimental results show that SVMs achieve significantly higher search accuracy than existing system. SVMs are also useful in medical science to classify proteins with up to 90% of the compounds classified correctly. Hand-written characters can be recognized using SVM.

4. RESULT AND COMPARISON

The probe image is given as input and it is compared with the set of 591 gallery images and the image with less Euclidean distance is displayed as the closest match. Finally the performance of existing system and the proposed system are compared.

4.1 Result of DRBF:

The below figure represent the closest match of face recognition for Direct Recognition of Blurred Faces.

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Fig.4.1 Output figure for DRBF

Table 4.1: Performance results for DRBF

KER SIZE	**1.2**	**1.1**	**1.0**	**0.9**	**0.8**
EUC DIST	2.3E+11	2.2E+11	2.1E+11	2.0E+11	1.9E +11
EIG FACE	2.5E+3	2.7E+3	2.9E+3	3.1E+3	2.8E+3

The above table shows the performance result of Direct Recognition of Blurred Faces such as Euclidean distance and Eigen faces for various Kernel sizes.

4.2 Result of IRBF:

The below figure represent the closest match of face recognition for Illumination Robust Face Recognition of Blurred Faces.

Fig.4.2 Output figure for IRBF

Table 4.2: Performance results for IRBF

KER SIZE	**1.2**	**1.1**	**1.0**	**0.9**	**0.8**
EUC DIST	1.0E+1	1.3E+1	1.5E+1	1.6E+1	1.9E+1
EIG FACE	4.6E+3	5.1E+3	5.4E+3	5.8E+3	5.9E+3

The above table shows the performance result of Illumination Robust Face Recognition of Blurred Faces such as Euclidean distance and Eigen faces for various Kernel sizes.

4.3 Result of SVM:

The below figure represent the closest match of face recognition for Support Vector Machine.

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Table 4.3: Performance results for SVM

KER SIZE	1.2	1.1	1.0	0.9	0.8
EUC DIST	1.0E+11	1.1E+11	1.3E+11	1.5E+11	1.7E+11
EIG FACES	5.58E+3	6.45E+3	6.67E+3	6.82E+3	7.20E+3

The above table shows the performance result of Support Vector Machine such as Euclidean distance and Eigen faces for various Kernel sizes.

4.4 COMPARISON TABLE:

Table 4.4.1: Comparison of Kernel Size and Euclidean Distance

KER SIZE		*1.2*	*1.1*	*1.0*	*0.9*	*08*
EUC DIST	*DRBF*	2.4E+11	2.2E+11	2.1E+11	2.0E+11	1.9E+11
	IRBF	1.0E+11	1.3E+11	1.5E+11	1.6E+11	1.9E+11
	SVM	1.0E+11	1.1E+11	1.3E+11	1.5E+11	1.7E+11

The above table represents the comparison of existing system and proposed system against Kernel Size and Euclidean distance.

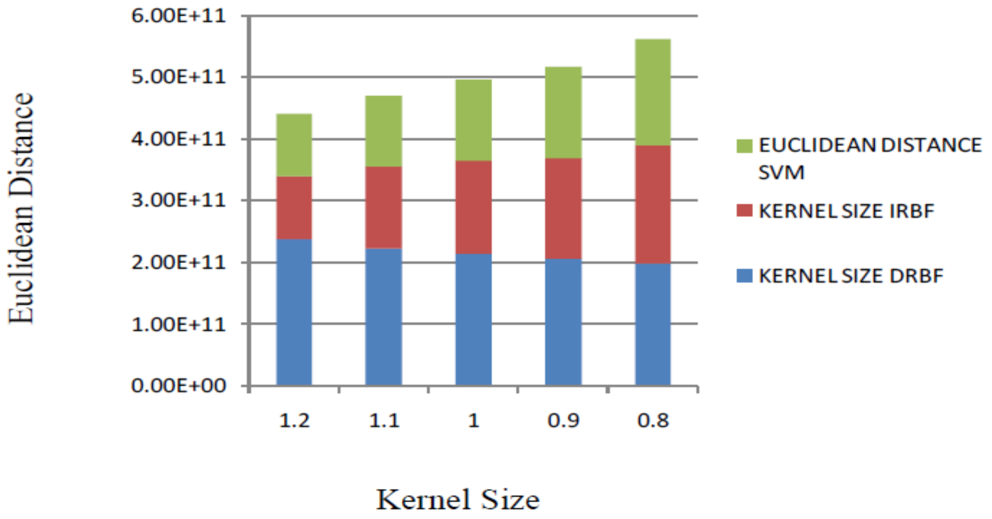

Fig. 4.4.1 Comparison graph for Kernel Size against Euclidean distance

From the above graph it is clear that as kernel size increases Euclidean distance decreases. Comparing the existing system and proposed system, the Euclidean distance for proposed system is less so the accuracy is high.

Table 4.4.2: Comparison of Kernel Size and Eigen Faces

KER SIZE		**1.2**	**1.1**	**1.0**	**0.9**	**0.8**
EIG FACE	**DRBF**	2.5E+3	2.8E+3	2.9E+3	3.1E+3	2.8E+3
	IRBF	4.6E+3	5.1E+3	5.4E+3	5.8E+3	5.9E+3
	SVM	5.5E+3	6.4E+3	6.6E+3	6.8E+3	7.2E+3

The above table represents the comparison of existing system and proposed system against Kernel Size and Euclidean distance.

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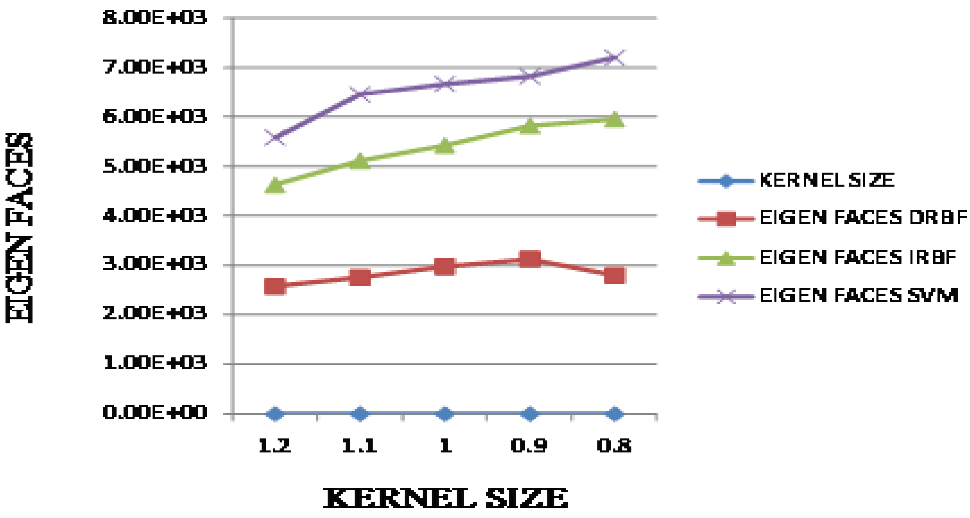

Fig. 4.4.2 Comparison graph for Kernel Size against Eigen Faces

From the above graph it is clear that as kernel size increases Eigen faces decreases. Comparing the existing system and proposed system, the performance of proposed system increases.

Table 4.4.3: Comparison of Kernel Size and Eigen Vector

KER SIZE		**1.2**	**0.7**	**0.6**	**0.5**
EIG VEC	**DRBF**	1.9E-14	7.3E-15	2.8E-15	6.6E-15
	IRBF	3.9E-15	8.7E-16	8.5E-15	9.4E-15
	SVM	5.4E-14	9.5E-15	9.8E-15	9.7E-15

The above table represents the comparison of existing system and proposed system against Kernel Size and Euclidean distance.

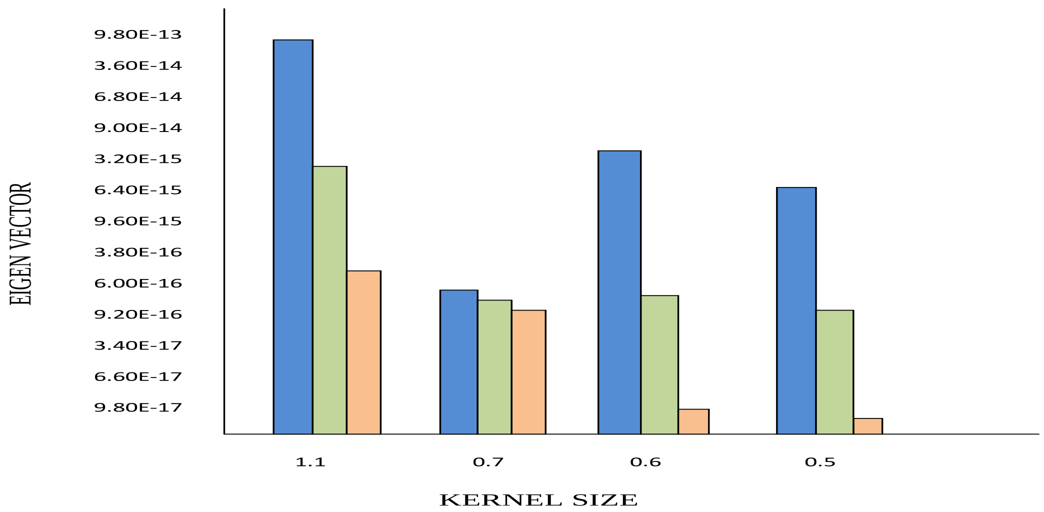

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Fig. 4.4.3 Comparison graph for Kernel Size against Eigen Vector

From the above graph it is clear that as kernel size increases Eigen vector decreases .Comparing the existing system and proposed system, the proposed system has less value hence the performance increases.

5. CONCLUSION

We observed that blur and illumination variations in image cause difficulty in object recognition. Our proposed method consist of Support Vector Machine (SVM) in order to recognize blurred images and hence used for classifying images. The System performance is also increased by the use of SVM. From this it is concluded that the method used is robust to blur and illumination changes in images .The accuracy is also high.

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