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RESEARCH ARTICLE

A New Approach for Retrieving Unconstrained Blurred Images

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Abstract— Face Recognition has been of great importance in different fields of technology. But when blurring come to picture face recognition becomes difficult. There has many approaches proposed in this context like blind image deconvolution, image statistics etc. But all these approaches concentrate mainly on the blurring part alone. Here in this approach the illumination defects are together considered with the blur problems. With the calculation of minimum distance from the given blurred image to artificially blurred image the corresponding image can be mapped. Incorporation of the image features under different illumination conditions makes the face recognition much easier. To improve the performance, characteristics of the blur can be added along with. Weights are assigned to different pixels based on the priority. L1 norm is followed as it is robust misalignments in the pixels. Finally it can be seen that the method is not that complex even though it incorporates both blur and illumination but gives more clarity and perfection.

Key Terms: - Face recognition; blur kernel; Point Spread Function (PSF); Local Phase Quantization; Linear Ternary Patterns; L1 norm

I. INTRODUCTION

Face Recognition is one of the most explored areas over the past few years. Though significant strides have been made in tackling the problem in controlled domains (as in recognition of passport photographs), significant challenges remain in solving it in the unconstrained domain. The main factors that make this a challenging problem are image degradations due to blur and noise, and variations in appearance due to illumination and pose. In this paper, the problem of recognizing faces across blur and illumination is addressed. It can be shown that the set of all images obtained by blurring a given image forms a convex set, and more specifically this set is the convex hull of shifted versions of the original image. Thus each gallery image can be associated with a corresponding convex set. Based on this set-theoretic characterization, a blur-robust face recognition algorithm is proposed. In the basic version of the algorithm, the distance of a given probe image (which we want to recognize) from each of the convex sets is computed, and assign it the identity of the closest gallery image. The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. Any parametric or symmetric form for the blur kernels is not considered; however, if this information is available, it can be easily incorporated into the algorithm, resulting in improved recognition performance.

II. EXISTING METHODS

An obvious approach to recognizing blurred faces would be to deblur the image first and then recognize it using traditional face recognition techniques. However, this approach involves solving the challenging problem of blind image deconvolution. A direct approach for face recognition has been proposed. It can be shown that the set of all images obtained by blurring a given image forms a convex set, and more specifically, this set is the convex hull of shifted versions of the original image. Thus with each gallery image we can associate a corresponding convex set. Based on this set-theoretic characterization, we propose a blur-robust face recognition algorithm. In the basic version of the algorithm, the distance of a given probe image (which we want to recognize) from each of the convex sets is computed, and assign it the identity of the closest gallery image. The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. Further, the algorithm can be made robust to outliers and small pixel misalignments by replacing the Euclidean distance by weighted $L1$-norm distance and comparing the images in the LBP (local binary pattern) space. It has been shown that all the images of a Lambertian convex object, under all possible illumination conditions, lie on a low-dimensional (approximately nine dimensional) linear subspace. Though faces are not exactly convex or Lambertian, they can be closely approximated by one. Thus each face can be characterized by a low-dimensional subspace, and this characterization has been used for designing illumination robust face recognition algorithms. Based on this illumination model, the set of all images of a face under all blur and illumination variations is a biconvex set. If the blur kernel is fixed then the set of images obtained by varying the illumination conditions forms a convex set; and if the is fixed illumination condition then the set of all blurred images is also convex.

III. PROPOSED SYSTEM

In the proposed approach it can be seen that both blur and illumination are taken together. At first the blur portion alone is considered. It can be resolved with the help of direct recognition of blurred faces algorithm. Later on it is checked with the illumination correction algorithm. Basically a blurred image consists of sharp image and a blur kernel. The main issue here is to resolve the blur kernel or PSF i.e. point spread function. Many methods have been proposed like blind image deconvolution etc. but none proved that futile. Each and every method has got some drawback or the other. Blind image deconvolution finds the unknown blur kernel in a probabilistic manner and retrieves the image. Though this method returns correct results it is much time consuming. Also it does not consider any characteristics for the particular blur. In the latest cases like in the direct recognition approach it considers the characteristics of the blur. The blurs has got a number of characteristics like out of focus blur has circular symmetry etc. All these features can be incorporated for getting the bur kernel sooner. In the direct recognition of the blur it has got a database set preferably a ferret database. In the database each and every possible image is stored. It can be done in the following way.

A. *Implementing Direct Recognition of Blurred Images*

In this step we first review the convolution model for blur. Next, we show that the set of all images obtained by blurring a given image is convex and finally we present our algorithm for recognizing blurred faces. Blurred image can be called as a combination of the sharp image and a blur kernel. So once the blur kernel is estimated it becomes easy for recognition. As a first stage the blur kernel is estimated giving the sufficient constraints to make it perform better.

B. *Recognition of blurred faces*

Face recognition is also sensitive to small pixel misalignments and, hence, the general consensus in face recognition literature is to extract alignment insensitive features, such as Linear Binary Patterns (LBP), and then perform recognition based on these features. We then blur each of the gallery images with the corresponding optimal blur kernels **hj** and extract LBP features from the blurred gallery images. And finally, we compare the LBP features of the probe image with those of the gallery images to find the closest match. To make our algorithm robust to outliers, who could arise due to variations in expression, we propose to replace the L_2 norm by the L_1 norm.

C. *Incorporating the Illumination Model*

As a next step, the facial images of a person under different illumination conditions [3] can look very different, and hence for any recognition algorithm to work in practice, it must account for these variations. First, we discuss the low-dimensional subspace model for handling appearance variations due to illumination. Next, we use this model along with the convolution model to define the set of images of a face under all possible lighting conditions and blur. We then propose a recognition algorithm based on minimizing the distance of the probe image from such sets.

D. *Illumination-Robust Recognition of Blurred Faces (IRBF)*

Corresponding to each sharp well-lit gallery image, we obtain the nine basis images. . The major computational step of the algorithm is the optimization problem. The complexity of the overall alternation algorithm is $O(T\ (N + K3))$ where T is the number of iterations in the alternation step, and $O(N)$ is the complexity in the estimation of the illumination coefficients.

E. *Face Recognition across Blur and illumination using SVM*

Illumination changes between indoor and outdoor environments are an unsolved problem for face recognition. Moreover, it is a multi-class problem. We assume *N* is the number of classes (e.g. N different individuals). The proposal is ″one against the rest approach″. This technique includes *N* binary classifiers, and each of them separates a single class from all the remaining classes. The final output is the class that corresponds to the binary classifier with the highest output value. The main idea of SVM comes from a nonlinear mapping of the input space to a high dimensional feature space, and given two linearly separable classes, designs the classifier that leaves the maximum margin from two classes in the feature space. SVM displays good performance, has been applied extensively for pattern classification and handwriting recognition.

F. *Concentration on face*

When the image as such is taken from the database there can be problem from with the image retrieval. That is the exact image may not be retrieved. Hence as an addition the basic features of the image are taken. Hence when retrieval come to picture only essential features are compared and get the image more accurately.

IV. EXPERIMENTAL RESULTS

In the existing method it can be seen that different blur removal techniques were used. But the time consumed was much more and does not return accurate results. But in the proposed approach it can be seen that it much faster and returns more accurate results when compared with the previous approaches. It can be pictorially sown as follows.

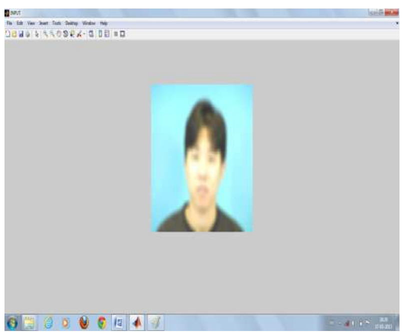


Fig 1. Blurred Image

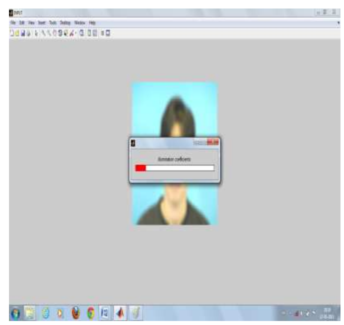
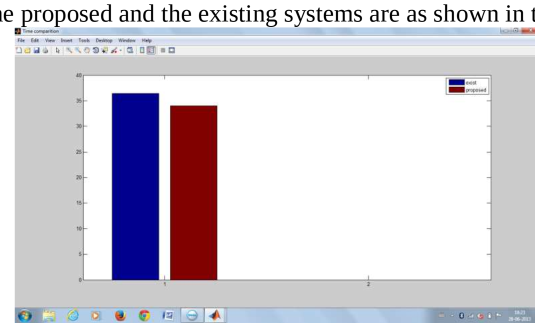


Fig 2. Calculating coefficient

Fig 3. Output Image

The comparison between the proposed and the existing systems are as shown in the graph.



V. Conclusion

Motivated by the problem of remote face recognition, the problem of recognizing blurred and poorly illuminated faces has been addressed. By eliminating the blur and illumination effects the figure can be restored and can easily be recognised. The challenging problem of face recognition in uncontrolled settings can alleviated to a greater extent using the blur and illumination robust face recognition method. By incorporating the features of different types of blur and by giving weights to different pixels, much better results are obtained compared to the other contemporary methods.

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