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DRBF and IRBF Based Face Recognition and Extraction of Facial Expressions from the Blur Image

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ABSTRACT

Background: Facial expression is the natural for human beings to show their emotions and motivations. When blurring comes to picture, face recognition becomes difficult. The main factors that make this problem challenging are image degradation due to blur and the appearance variations due to illumination and pose. Many of the approaches concentrate mainly on the blurring part alone. A blur-robust face recognition algorithm DRBF (Direct Recognition of Blurred Faces) and IRBF (Illumination-Robust Recognition of Blurred Faces) is proposed. It can be seen that both blur and illumination are taken together. **Objective:** To address the problem of unconstrained face recognition from remotely acquired images and also to extract the facial expressions from the blur image. **Results:** We evaluate the proposed algorithms: the "blur-only" formulation DRBF and the "blur and illumination" formulation IRBF on synthetically blurred PIE datasets. We compare our algorithm with the FADEIN approach and the LPQ approach. We then perform recognition using the DRBF algorithm in recognizing faces blurred by different types and amounts of blur and IRBF algorithm in recognizing blurred and poorly illuminated faces. Finally, the good performance by DRBF and IRBF further confirms the importance of jointly modeling blur and illumination variations. **Conclusion:** Motivated by the problem of remote face recognition, the problem of recognizing poorly blurred and illuminated faces has been addressed and also the facial expressions are identified. By eliminating the blur and illumination effects the figure can be restored and can easily be recognized. The challenging problem of face recognition in uncontrolled settings can alleviated to a greater extent using the blur and illumination robust face recognition method. Then the features of facial components, such as eyes, nose, and mouth in gray images of frontal view faces are extracted and the facial expressions are identified.

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INTRODUCTION

Face Recognition has been of great importance in different fields of technology. When blurring come to picture face recognition becomes difficult. There are many approaches proposed in the context like blind image deconvolution, image statistics etc. All these approaches concentrate mainly on the blurring part alone. In the proposed method the illumination defects are together considered with the blur problems. The problems of unconstrained face recognition from remotely acquired images are identified. The main factors that make this a challenging problem are image degradations due to blur and noise, and the variations in appearance are due to illumination and pose. In this paper, the problem of recognizing faces across blur and illumination is addressed. An obvious approach to recognizing blurred faces would be to deblur the image first and then recognize it using traditional face recognition techniques. In this approach, it solves the challenging problem of blind image deconvolution. We avoid the unnecessary steps and propose a direct approach for face recognition. 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. In the basic version of the algorithm, the distance of a given probe image from each of the convex sets is computed and assign it the identity of the closest gallery image.

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A blur-robust face recognition algorithm DRBF is proposed in this paper. In this algorithm we can easily incorporate prior knowledge on the type of blur as constraints. Using the low-dimensional linear subspace model for illumination, we then showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set. Again, based on this set-theoretic characterization, we proposed a blur and illumination robust algorithm IRBF. We also demonstrated the efficacy of our algorithms in tackling the challenging problem of face recognition in uncontrolled settings. Our algorithm is based on a generative model followed by nearest-neighbor classification between the query image and the gallery space, which makes it difficult to scale it to real life datasets with millions of images.

Fig. 1: Face images captured by a distant camera in unconstrained settings.

In the proposed approach it can be seen that both blur and illumination are taken together. At first the blur portion alone is considered which is resolved with the help of direct recognition of blurred face algorithm. Later on it is checked with the illumination correction algorithm. A blurred image consists of sharp image and a blur kernel. We do not assume any parametric or symmetric form for the blur kernels. We make our algorithm 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. Representation of a face recognition system is shown in Fig. 2.

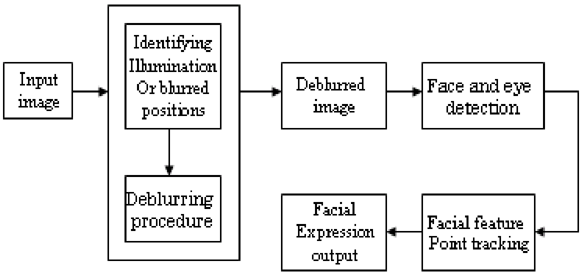

Fig. 2: Representation of a face recognition system.

Facial Expression Classification is an interesting research problem in recent years. Facial expression is the natural means for human beings to show their emotions and motivations. The ability to recognize and understand facial expression has become a new challenge of a human-computer interaction research. Neutral, angry, disgust, fear, happy, sad and surprise are the seven basic emotion schemes of facial expressions. Many of researches have been done on machine recognition of human facial expressions. However, the estimation of their precise properties in real images was difficult and facial features extraction techniques developed to date have not been reliable enough for the facial expression recognition. In this, the features of facial components, such as eyes, nose, and mouth, in gray images of frontal view faces are extracted.

Related Work:

Face recognition from blurred images can be classified into four major approaches. In the first approach, the blurred image is first deblurred and then used for recognition. The drawback of this approach is that we first need to solve the challenging problem of blind image deconvolution. Though there have been many attempts at solving the blind deconvolution problem (Levin, A., 2011; Fergus, R., 2006; Levin, A., 2006), it is an avoidable step for the face recognition problem. In the second approach, blur invariant features are extracted from the blurred image and then used for recognition (Ahonen, T., 2008; Gopalan, R., 2012). In (Ahonen, T., 2008), the local phase quantization (LPQ) (Ojansivu, V. and J. Heikkilä, 2008) method is used to extract blur invariant features. Though this approach works very well for small blurs, it is not very effective for large blurs

(Nishiyama, M., 2011). In (Gopalan, R., 2012), a blur subspace is associated with each image and face recognition is performed in this feature space. It has been shown that the (blur) subspace of an image contains all the blurred version of the image. The (blur) subspace will include many other images apart from the blurred images. The third approach is the direct recognition approach. In this approach, the artificially blurred versions of the gallery images are created and the blurred probe image is matched to them (Stainvas, I. and N. Intrator, 2000). By using this method it is not possible to capture the whole space of blur kernels. We avoid this problem by optimizing over the space of blur kernels. Finally the fourth approach is to jointly deblur and recognition the face image (Zhang, H., 2011). This involves solving for the original sharp image, blur kernels and identity of the face image, and hence it is a computationally intensive approach.

The most problematic trouble affecting the performance of face recognition systems are strong variations in pose and illumination. Variation between images of different faces in general is smaller than taken from the same face in a variety of environments i.e. the differences between images of one face under different illumination conditions are greater than the differences between images of different faces under the same illumination conditions. There are mainly two approaches for recognizing faces across illumination variation. One approach is based on the low-dimensional linear subspace model. In this approach, each face is characterized by its corresponding low dimensional subspace. Given a probe image, its distance is computed from each of the subspaces, and it is then assigned to the face image with the smallest distance. The other approach is based on extracting illumination insensitive features from the face image and using them for matching. Many features have been proposed for this purpose such as self quotient images (Wang, H., 2004), correlation filters (Kumar, B., 2006), Eigenphases method (Savvides, M., 2004), and image preprocessing algorithms (Gross, R. and V. Brajovic, 2003), gradient direction (Chen, H., 2000; Osadchy, M., 2007) and albedo estimates (Biswas, S., 2009).

Direct Recognition of Blurred Faces (DRBF):

First review the convolution model for blur. Next, it is shown that the set of all images obtained by blurring a given image is convex and finally present our algorithm for recognizing blurred faces. We proposed a blur-robust face recognition algorithm DRBF. In this algorithm we can easily incorporate prior knowledge on the type of blur as constraints. Using the low-dimensional linear subspace model for illumination, we then showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set.

Fig. 3: Original image.

Convolution model for blur:

A pixel in a blurred image is a weighted average of the pixel's neighborhood in the original sharp image. Thus, blur is modeled as a convolution operation between the original image and a blur filter kernel which represents the weights. Let I be the original image and H be the blur kernel of size $(2k + 1) \times (2k + 1)$, then the blurred image I_b is given by,

$$I_b(r,c) = I * H(r,c) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} H(i,j) I(r-i, c-j) \tag{1}$$

Where $*$ represents the convolution operator and r, c are the row and column indices of the image. Blur kernels also satisfy the following properties- their coefficients are non negative, $H \geq 0$, and sum up to 1. The blur kernel may possess additional structure depending on the type of blur (such as circular-symmetry for out-of focus blurs), and these structures could be exploited during recognition.

Face Recognition Algorithm:

The basic version of our blur-robust face recognition algorithm is first presented. Let I_j , j=1,2,…, M be the set of M sharp gallery images. Every gallery image I_j has an associated convex set of blurred images. If there are multiple gallery images per class (person), we can use the k-nearest neighbor rule. In this algorithm we can also incorporate additional information about the type of blur. The most commonly occurring blur types are the out-of-focus, motion and the atmospheric blurs. By making some minor modifications to the basic algorithm, we can make it robust to outliers and small pixel misalignments between the gallery and probe images. In face recognition, it is well known that different regions in the face have different amounts of information. To incorporate this fact we divide the face image into different regions and weigh them differently when computing the distance between the probe image and gallery sets.

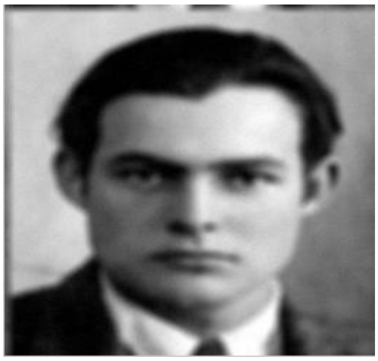

Fig. 4: Blurred image with noise.

Recognition of blurred faces:

By making some minor modifications to the basic algorithm, we can make it robust to outliers and small pixel misalignments between the gallery and probe images. In face recognition literature, it is well known that different regions in the face have different amounts of information. To incorporate this fact we divide the face image into different regions and weigh them differently when computing the distance between the probe image I_b and gallery sets. 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. 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, which could arise due to variations in expression, we propose to replace the L2 norm by the L1 norm.

Fig. 5: Direct recognition of blurred image.

Incorporating The Illumination Model:

The facial images of a person under different illumination conditions can look very different, and hence for any recognition algorithm to work in practice, it must account for the illumination 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. Then we propose a recognition algorithm based on minimizing the distance of the probe image from such sets.

Low-dimensional Linear Model for Illumination Variations:

When an object is convex and Lambertian, the set of all images of the object under different illumination conditions can be approximately represented using a nine dimensional subspace. Though the human face is not exactly convex or Lambertian, it is often approximated as one; and hence the nine-dimensional subspace model captures its variations due to illumination quite well. The nine dimensional linear subspaces corresponding to a face image *I* can be characterized by 9 basis images. In terms of these nine basis images I_m, m = 1, 2... 9, an image *I* of a person under any illumination condition can be written as

$$I = \sum_{m=1}^{9} \alpha_m I_m \tag{2}$$

Where α_m, m = 1, 2... 9 are the corresponding linear coefficients. To obtain these basis images, we use the "universal configuration" of lighting positions. These are a set of 9 lighting positions s_m, m = 1, 2... 9 such that images taken under these lighting positions can serve as basis images for the subspace. These basis images are generated using the Lambertian reflectance model:

$$I_m(r,c) = \rho(r,c)\max(\{ s_m, n(r,c)\},0) \tag{3}$$

where ρ*(r, c)* and *n(r, c)* are the albedo and surface-normal at pixel location *(r, c)*. We use the average 3-D face normals for *n* and we approximate the albedo *ρ* with a well-illuminated gallery image under diffuse lighting. In the absence of a well-illuminated gallery image, we could proceed by estimating the albedo from a poorly light image.

Illumination-Robust Recognition of Blurred Faces (IRBF):

Using the low-dimensional linear subspace model for illumination, we showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set. Again, we propose a blur and illumination robust algorithm IRBF. We also demonstrated the efficacy of our algorithms in tackling the challenging problem of face recognition in uncontrolled settings. Our algorithm is based on a generative model followed by nearest-neighbor classification between the query image and the gallery space, which makes it difficult to scale it to real life datasets with millions of images.

Corresponding to each sharp well-lit gallery image, we obtain the nine basis images. The optimization problem is the major computational step of the algorithm. The complexity of the overall alternation algorithm is O(T (*N* + *K*3)) where *T* is the number of iterations in the alternation step, and O(N) is the complexity in the estimation of the illumination coefficients.

Face Recognition across Blur and Illumination:

Illumination changes between indoor and outdoor environments are an unsolved problem for face recognition. Moreover, it is a multi-class problem. Additional preprocessing may be required for the face images that are captured under non-ideal conditions. The SVM techniques of quality assessment algorithm associate the quantitative quality score of the image that has a specific type of irregularity such as blur, noise and illumination. This enables the application of the most appropriate quality enhancement algorithm on the non-ideal image. Further the SVM quality enhancement algorithm which simultaneously applies selected enhancement algorithm, selects the best quality regions from the global enhanced image. The selected regions are used to generate single high quality image.

Fig. 7: Illumination-Robust Recognition of Blurred Faces.

Facial Feature Point Tracking:

The ability to recognize and understand facial expression has become a new challenge of a human-computer interaction research. Neutral, angry, disgust, fear, happy, sad and surprise are the seven basic emotion schemes of facial expressions. Many of researches have been done on machine recognition of human facial expressions. In this, the features of facial components, such as eyes, nose, and mouth, in gray images of frontal view faces are extracted.

The basic facial expression analyses are: face detection of an image segment, extraction of the facial expression information, and classification of the expression according to emotion categories. By systematically representing and modeling inter relationships among different levels of facial activities and information, the proposed model achieved significant improvement for both facial feature tracking and compared to state of the art methods for six basic expressions recognition. For each emotions expressed, it can establish a characteristic motion pattern by taking the feature points between a neutral facial expression and the six particular emotive expressions (angry, disgust, fear, happy, sad, and surprise).

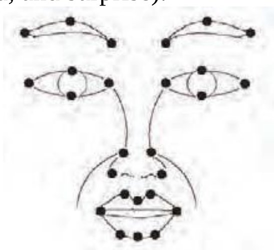

Fig. 6: Face Feature points used for the project.

Experimental Evaluations:

We evaluate the proposed algorithms: the "blur-only" formulation DRBF and the "blur and illumination" formulation IRBF on synthetically blurred PIE datasets and a real dataset of remotely acquired faces with significant blur and illumination variations, which we will refer to as the REMOTE dataset, see Fig.1. To evaluate our algorithm DRBF on different types and amounts of blur, we synthetically blur face images from the FERET dataset with four different types of blurs: out-of focus, atmospheric, motion and general non-parametric blur. We use Gaussian kernels of varying standard deviations to approximate the out-of focus and atmospheric blurs (Lagendijk, R.L. and J. Biemond, 2009), and rectangular kernels with varying lengths and angles for the motion blur. We compare our algorithm with the FADEIN approach (Nishiyama, M., 2011) and the LPQ approach (Ojansivu, V. and J. Heikkilä, 2008). The FADEIN approach first infers the deblurred image from the blurred probe image and then uses it for face recognition. On the other hand in the LPQ (local phase quantization) approach a blur insensitive image descriptor is extracted from the blurred image and recognition is done on this feature space. We also compare our algorithms with 'FADEIN+LPQ' (Nishiyama, M., 2011), where LPQ features extracted from the deblurred image produced by FADEIN is used for recognition. To handle small variations in illumination, we histogram equalize all the images in the gallery and probe datasets. We then perform recognition using the DRBF algorithm and its robust version rDRBF, with the additional constraint of circular symmetry imposed on the blur kernel.

To perform recognition using our 'blur and illumination' algorithm IRBF, we first obtain the nine illumination basis images for each gallery image as described in section IV-A. We impose the circular symmetry constraints while solving the recognition problem using DRBF and IRBF. Since FADEIN does not model variations due to illumination; we preprocess the intensity images with the self-quotient method (Wang, H., 2004). The main optimization step in the IRBF (Ahonen, T., 2008) and rIRBF (Gopalan, R., 2012) is a bi-convex problem, i.e. it is convex w.r.t. to blur and illumination variables individually, but it is not jointly convex. Finally, we evaluate our algorithms, DRBF and IRBF, on the real and challenging dataset of REMOTE and also the facial expressions are identified.

Concentration on Face:

The first step is to adjust the gray level of a flame image according to its statistical distribution. Segmentation process is to be handled. According to the image size the segmentation size may vary. That is the exact image may not be retrieved. Hence the basic features of the image are taken as an addition. Hence when retrieval come to picture only essential features are compared and get the image more accurately.

Facial Expression as an Output:

The basic human face expressions are identified using the facial feature points recognizing and activity model of the human faces. Facial expression database contains the human face activity models. The deblurred recognized face expressions are identified as an output.

Conclusion:

Motivated by the problem of remote face recognition, the problem of recognizing poorly blurred and illuminated faces has been addressed and also the facial expressions are identified. We have shown that the set of all images obtained by blurring a given image is a convex set given by the convex hull of shifted versions of the image. We proposed a blur-robust face recognition algorithm DRBF. In this algorithm we can easily incorporate prior knowledge on the type of blur as constraints. Using the low-dimensional linear subspace model for illumination, we then showed that the set of all images obtained from a given image by blurring and changing its illumination conditions is a bi-convex set. Again, based on this set-theoretic characterization, we proposed a blur and illumination robust algorithm IRBF. We also demonstrated the efficacy of our algorithms in tackling the challenging problem of face recognition in uncontrolled settings.

By eliminating the blur and illumination effects the figure can be restored and can easily be recognized. 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. Modeling the pose-variation under the same framework would be a very promising direction for future work.

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