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Research Article

FACE RECOGNITION UNDER NON-UNIFORM MOTION BLUR, ILLUMINATION AND POSE VARIATIONS

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A B S T R A C T

The current face recognition algorithms are unreliable when the pose, illuminating conditions of the test face is not the same as the stored face. In order to overcome the drawbacks of the current techniques in identifying the individual face in different atmospheric conditions such as blur, illumination and the pose, our paper proposes an approach which can identify the face irrespective of the variations. A pose contingent linear transformation of the identity vector in the presence of noise is implemented and the measured vector is generated. The blur face is modeled as a convex combination of geometrically transformed instances of the focused gallery face, and the set of all images obtained by non-uniform blur produces a convex set. The proposed method uses a feature extraction approach using CCA to extract the from the test face. The extracted features are compared with the features available in database to identify the person face.

INTRODUCTION

It is well known that the precision of the face recognition systems break down quickly and so the database is added with images emerging from blur, changes in illumination, pose and expression, incomplete occlusions. This was produced by the geometric framework and the face spotting. The focus of this paper is on developing a system that can recognize faces across non-uniform (space-variant) blur, and varying illumination and pose.

Face recognition algorithms have, over the days, developed from simple geometric models to complex mathematical representations and sophisticated transmitter matching procedures. The technical advancements in computation and range of a image acquisition technique have propelled face recognition technology into the spotlight and researchers are interested more than ever to develop novel techniques to efficiently and robustly recognize facial expressions to give finally help in providing computer with cognitive capableness. Facial expression sensing and recognition has, thus, developed into a very active research surface area specializing on how to extract and recognize faces within images or videos. 'Face detection' is the fundamental process of finding and extracting facial features within images or videos. 'Face recognition' is the process of matching the detected facial features to one of many of the faces known to the system.

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With face recognition and detection system finding used in surveillance, automatic photography and tracking, novel and robust algorithmic program improving spotting rate and recognition are coming up.

Existing methods for performing face recognition in the presence of blur depend on the convolution model and can't deal with non-uniform blurring situations that emerge as often as possible from tilts and rotation of cameras. Recognition algorithms compute vectors from the image layout and look the database for the nearest vector.

It is well-known that the accuracy of face recognition systems is seriously affected by unconstrained settings [1]. The significant factors include changes in illumination, pose, and expression, partial occlusions etc. Special attention is required for motion blur due to the ubiquity of mobile phones and hand-held imaging devices. Camera handshake is to be dealt as it affects image quality. Moreover, in-built sensors such as gyros and accelerometers have their own restriction in sensing the camera motion. In an uncontrolled environment, illumination and pose could also vary, further compounding the problem. In this paper, a single blur kernel is used to model the non-uniform (i.e., space-variant) blur, and varying illumination and pose., blurring due to camera shake by assuming the blur to be uniform across the image [2] [3]. Space-variant blur is encountered frequently in hand-held cameras [4]. Techniques have been proposed that restore non-uniform blur by local distance-invariability approximation [5] -[7], recent methods for image restoration have modeled the motion-blurred image as an average of projectively transformed images [8] -[12].

Convolution

The convolution of two signals to produce a third output signal is given symbolically by,

Convolution of two functions *a* and *b*

c = ab $\otimes$ * b

In two dimensional continuous outer space, it is represented as,

c(x,y)=a(x,y)*b(x,y)=$\iint a(X,\xi)b(x-X,y-\xi)dXd\xi$

In discrete space,it is represented as,

c[m,n]=a [m,n] $\otimes$ b[m,n]=ΣΣa [j,k] b [m-j,n-k

Proposed Method

The proposed technique performs expression realization within the space-varying motion blur involving randomly shaped portions. An outline of the blurred face is formed combining the geometrically transformed representative of the focused gallery face, and the set of all range of images obtained by non-uniformly blurring a given image forms a convex set. This enhances the recognition of the face.

TSF: The proposed geometric scheme is utilized to model the blurred face as the weighted normal of geometrically warped instance of the focused gallery images by assuming planar constructon of te face. The twisted instances can be viewed as the intermediate images observed during the exposure time. A weight that denotes the fraction of the exposure duration for that translation is assigned for each twist. The weight corresponding to the twists are referred to as the transformation spread function (TSF).

Each gallery image, blurred using the corresponding optimal TSF, is compared with the probe in the LBP (local binary pattern) space. This direct method of recognition allowed us to circumvent the challenging and ill-posed problem of single image blind-deblurring. The idea of reblurring followed by LBP and the basic non-uniform motion blurs (NU-MOB)-robust face recognition algorithm is based on the TSF model. On each focused gallery image, all the possible transformation that exist in the 6D space (3 dimensions for translations and 3 for rotations) were applied the resulting transformed images are stacked as columns of a matrix. The convexity result proved for the simple convolution model was extended to the TSF model and appearance at the set of all images obtained by blurring a particular gallery image is a convex set given by the convex hull of the columns of the corresponding matrix. To recognize a blurred probe image, we minimize the distance between the probe and the convex combination of the columns of the transformation matrix was minimized corresponding to each gallery image. The gallery image whose distance to the probe is minimum is identified as a match. No constraints were imposed on the nature of the blur. We assume that the camera motion trajectory is sparse in the camera motion space. This allows us to construct an optimization function with $l1$-average constraint on the TSF weights. Minimizing this cost function has given us an estimate of the transformations that when applied on the gallery image results in the blurred test image.

PCA: PCA normally referred to as the use of 'eigenfaces' reduces the dimension of information by data concretion and exposes the effective depression dimensional structure of facial patterns. The images must be of same size and must also be normalized to line up the eyes and mouth of subjects within the images. The resolution of the images into what are called 'eigenfaces' (which are analogous to 'eigenvectors' in a matrix), which are orthogonal unrelated components, removes all useless extra carrier data. Each face image may be represented as a weighted sum ('feature vectors') of eigenfaces, which are stored in a one-dimensional array. Then the distance between the feature vectors of the test image and the image in database is calculated, and match is found based on a minimum distance standard.

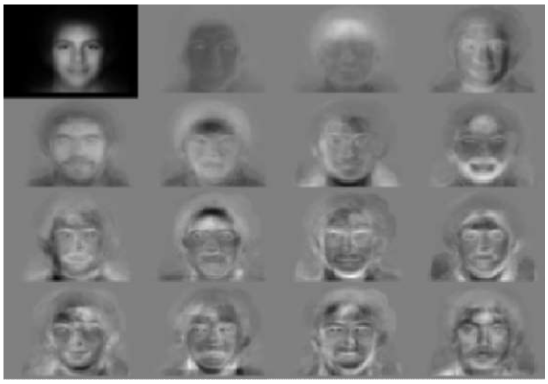

Fig Feature Vectors Derived using 'eigenfaces'

Convolution Model For Space -Invariant Blur: Convolution model is sufficient for describing blur due to in-plane camera translations, a major restriction is that it cannot describe several other blurring effects (including out-of-plane motion and in-plane rotation) arising from general camera movement. In order to demonstrate the failing of the convolution model in handling images blurred due to camera shake, we synthetically blur the focused gallery image to generate a probe, and provide both the gallery image and the blurred probe image as input to two algorithmic program- the convolution model which assumes place invariant blur, and the non-uniform motion blur model which represents the place-variant blurred image as a weighted average of geometrically twisted instances of the gallery.

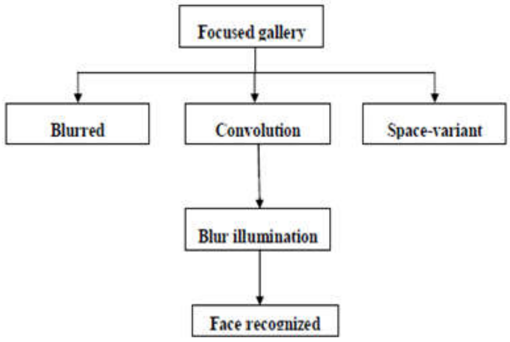

Fig Face recognition model

Algorithm

Step(1): To Create a data base of images.
Step(2): To Compute the key comparative features like TSF and principle components of all data base images using PCA.
Step(3): To Store all these features in the database.
Step(4): The test image which is under different noisy, blurry, pose and illuminating conditions is to be considered.
Step(5): To convert the image from color to gray if it is in color format.
Step(6): To denoise the image i.e., remove the noise from it.
Step(7): Computation of TSF.
Step(8): The TSF of test image is to be compared with the TSF of data base image. If any match is found then display the match and step(14) is to be performed, otherwise step(9).
Step(9): To blur the data base images with the test TSF and then compare them one by one with the test image. If any

match is found then the match is displayed and step(14) is to be performed, otherwise step(10).

Step(10): To deblur the test image and match it with the database images. If match is found, display it and step (14) is to be performed, otherwise step (9).

Step(11): To perform PCA and extraction of the principal components of the test image.

Step(12): To match the PCA features of test image with those of data base images.

Step(13): If match is found then display the match and step(14) is to be performed, otherwise display error message is to be displayed.

Step(14): End.

RESULTS

The simulated results obtained for the face recognition under various conditions (Blur, Illumination, Pose) are as follows:

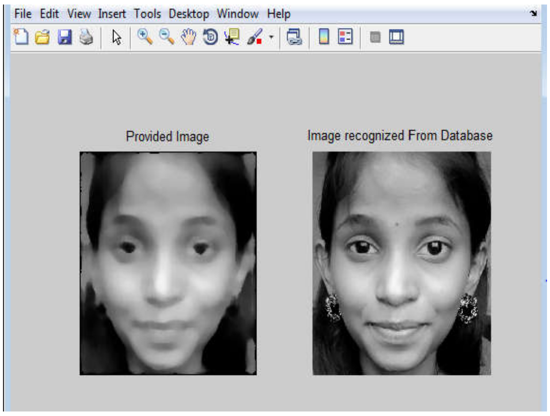

Fig Test and retrieved images with non-uniform motion blur variation

In this figure the image with blur variation is given as the test image (provided image) and it was recognized and the matched image from the database is displayed.

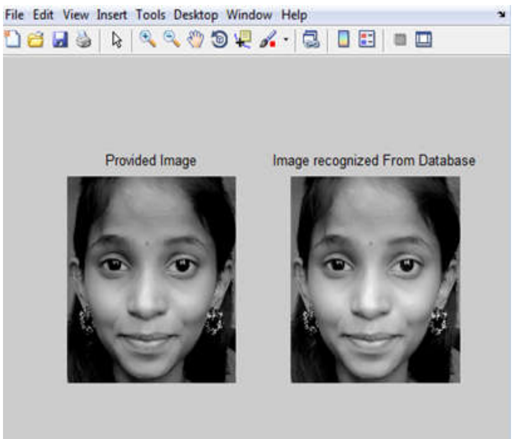

Fig Test and retrieved images with illumination variation

In this figure the image with illumination variation is given as the test image (provided image) and it was recognized and the matched image from the database is displayed.

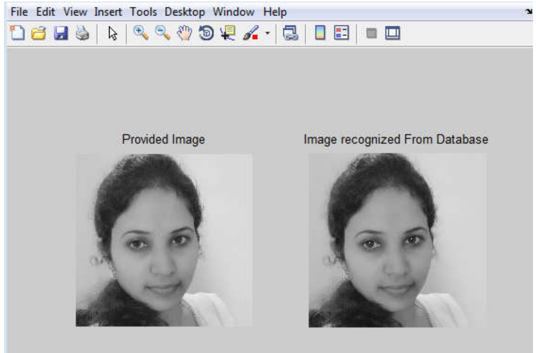

Fig Test and retrieved images with pose variation

In this figure the image with pose variation is given as the test image (provided image) and it was recognized and the matched image from the database is displayed.

CONCLUSION

A methodology to perform face recognition under the combined effects of non-uniform blur, illumination, and pose was implemented. The convex set comprised of the convex hull of warped instances of the image is formed by non-uniformly blurring the given image using the TSF model. This convex set obtained is used to implement non-uniform motion blur robust face recognition algorithm NU-MOB. We then showed that the set of all images obtained from a given image by non-uniform blurrinssssg and changes in illumination forms a bi-convex set, and used this result to develop our non-uniform motion blur and illumination-robust algorithm MOBIL. We then extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose. We established the superiority of this method called MOBILAP over contemporary techniques. Extensive experiments were given on synthetic as well as real face data. The limitation of our approach is that significant occlusions and large changes in facial expressions cannot be handled. The future enhancement of this approach is to perform face recognition with large changes in facial expressions across non-uniform (i.e., space-variant) blur including varying illumination and pose conditions.

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