ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 10, March 2016

FACE RECOGNITION ACROSS NON-UNIFORM MOTION BLUR

*T.Besley **Mr.R.Sivasubramanian
Inst. Of Road and Transport Technology, Erode

ABSTRACT-Existing methods for performing face recognition in the presence of blur are based on the convolution model and cannot handle non-uniform blurring situations that frequently arise from tilts and rotations in hand-held cameras. In this project, that propose a methodology for face recognition in the presence of space-varying motion blur comprising of arbitrarily-shaped kernels. Blurred face as a convex combination of geometrically transformed instances of the focused gallery face, and show that the set of all images obtained by non-uniformly blurring a given image forms a convex set. First propose a non-uniform blur-robust algorithm by making use of the assumption of a sparse camera trajectory in the camera motion space to build an energy function with constraint on the camera motion.

General Terms: Face recognition, non-uniform blur, sparsity.

1.INTRODUCTION

It is well-known that the accuracy of face recognition systems deteriorates quite rapidly in unconstrained settings [1]. This can be attributed to degradations arising from blur and, partial occlusions etc. Motion blur, in particular, deserves special attention owing to the ubiquity of mobile phones and hand-held imaging devices. Dealing with camera shake is a very relevant problem because, while tripods hinder mobility, reducing the exposure time affects image quality. Moreover, in-built sensors such as gyros and accelerometers have their own limitations in sensing the camera motion. In an uncontrolled environment, illumination and pose could also vary, further compounding the problem. The focus of this paper is on developing a system that can recognize faces across non-uniform (i.e., space-variant) blur. Traditionally, blurring due to camera shake has been modeled as a convolution with a single blur kernel, and the blur is assumed to be uniform across the image [2], [3]. However, it is space-variant blur that is encountered frequently in hand-held cameras [4]. While techniques have been proposed that address the restoration of non-uniform blur by local space- invariance approximation [5], recent methods for image restoration have modeled the motion-blurred image as an average of projectively transformed images [8][12]. Face recognition systems that work with focused images have difficulty when presented with blurred data. Approaches to face recognition from blurred images can be broadly classified into four categories. (i) Deblurring-based [13], [14] (ii) Joint deblurring and recognition [15], (iii) Deriving blur- invariant features for recognition [16][17]. But these are effective only for mild blurs. (iv) The*direct* recognition approach of [18] and [19] in which reblurred versions from the gallery are compared with the blurred probe image.It is important to note that all of the above approaches assume a simplistic space-invariant blur model. Although the problem of blur is individually quite challenging and merit research in their own right, a few attempts have been made in the literature to jointly tackle some of these issues under one framework. A very recent work [19] formally addresses the problem of recognizing faces from distant cameras across blur and wherein the observed blur can be well-approximated by the convolution model. To the best of our knowledge, the only attempt in the literature at recognizing faces across non-uniform blur has been made [17] in which the uniform blur model is applied on overlapping patches to perform recognition on the basis of a majority vote. The warped instances can be viewed as the intermediate images observed during the exposure time. Each warp is assigned a weight that denotes the fraction of the exposure duration for that transformation. The weights corresponding to the warps are referred to as the point spread function (PSF) in the literature.

1.1 OBJECTIVE

Face recognition has been a sought after problem of biometrics and it has a variety of applications in modern life. The problems of face recognition attracts researchers working in biometrics, pattern recognition field and computer vision. Several face recognition algorithms are also used in many different applications apart from biometrics, such as video compressions, indexing's etc. The conventional authentication system only requests the user to providethe authorized account and password to log into the system once they start to use a computer or a terminal. However, under this authentication framework, the machine can only recognize the user's identity from the login information. It lacks the information to know who is using it.

It is well-known that the accuracy of face recognition systems deteriorates quite rapidly in unconstrained settings. Christo Ananth et al. [7] proposed a system in which the cross-diamond search algorithm employs two diamond search patterns (a large and small) and a halfway-stop technique. It finds small motion vectors with fewer search points than the DS algorithm while maintaining similar or even better search quality. The efficient Three Step Search (E3SS) algorithm requires less computation and performs better in terms of PSNR. Modified objected block-base vector search algorithm (MOBS) fully utilizes the correlations existing in motion vectors to reduce the computations. Fast Objected - Base Efficient (FOBE) Three Step Search algorithm combines E3SS and MOBS. By combining these two existing algorithms CDS and MOBS, a new algorithm is proposed with reduced computational complexity without degradation in quality.

Traditionally, blurring due to camera shake has been modeled as a convolution with a single blur kernel, and the blur is assumed to be uniform across the image. However, it is space-variant blur that is encountered frequently in hand-held cameras. While techniques have been proposed that address the restoration of non-uniform blur by local space-invariance approximation, recent methods for image restoration have modeled the motion-blurred image as an average of protectively transformed images.Face Recognition has received significant attention, especially during the last few years. Recently it gain special importance because of its strong need in few application areas. There are at least two reasons for this trend.

- The first is the wide range of commercial and law enforcement application.
- Second is the availability of feasible technologies after 30 years of research. Face recognition have substantial potential in two areas:
- It can help the users to caught criminals and suspected terrorists.
- In minimizing cyber-crimes where it can be used in controlling access to areas where security risks are especially high.

Today's environment there is a great deal of interest in using face recognition for verification of identities. Recently face recognition software did not identified the bombers. The technology come up empty even though images exist in official database. The bombers also have driver's license which is provided after complete verification and adding their face as identity in face database. The bombers also had legally immigrated that means they gone through the face verification carried out in airport for security. The responsible officers told that the face recognition system might be failed in this particular case because the bomber had used sunglasses. This means face recognition technique still need to prove its metal. Face recognition has become one of the most challenging tasks in the pattern recognition.

FACE RECOGNITION APPLICATIONS:

Face recognition is also useful in human computer interaction, virtual reality, database recovery, multimedia, computer entertainment, information security e.g. operating system, medical records, online banking, Biometric. Personal Identification - Passports, driver licenses.

Automated identity verification - border controls, Law enforcement e.g. video surveillances, investigation, Personal Security - driver monitoring system, home video surveillance system.

Access Control:

In many of the access control applications, such as office access or computer logon, the size of the group of people that need to be recognized is relatively small. The face recognition system of this application can achieve high accuracy without much co-operation from user

Security:

Today more than ever, security is a primary concern at airports and for airline staff office and passengers. Airport protection systems that use face recognition technology have been implemented at many airports around the world.

Image database investigations:

Searching image databases of licensed drivers, benefit recipients, missing children, immigrants and police bookings.

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 3, Special Issue 10, March 2016

2. SYSTEM ANALYSIS

We develop our basic non-uniform motion blur (NU-MOB)-robust face recognition algorithm based on the PSF model. On each focused gallery image, we apply all the possible transformations that exist in the 6D space (3 dimensions for translations and 3 for rotations) and stack the resulting transformed images as columns of a matrix. We extend the convexity result proved for the simple convolution model to the PSF model and show that 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. Face recognition systems that work with focused images have difficulty when presented with blurred data.

2.1 PROPOSED SYSTEM

Extensions to the basic framework to handle variations in blur. Approximate the face to a convex Lambertian surface, and the bi-convexity property of a face under blur variations in the context of the PSF model. The scheme wherein to solve PSF weights for the probe image in the first step and use the estimated PSF to solve for the blurred gallery image coefficients in the second, and go on iterating till convergence. Finally transform (re blur and relight) each gallery image and compare it with the probe in the LBP space. In this project, we propose a face recognition algorithm that is robust to non-uniform motion blur arising from relative motion between the camera and the subject.

3. SYSTEM DESIGN

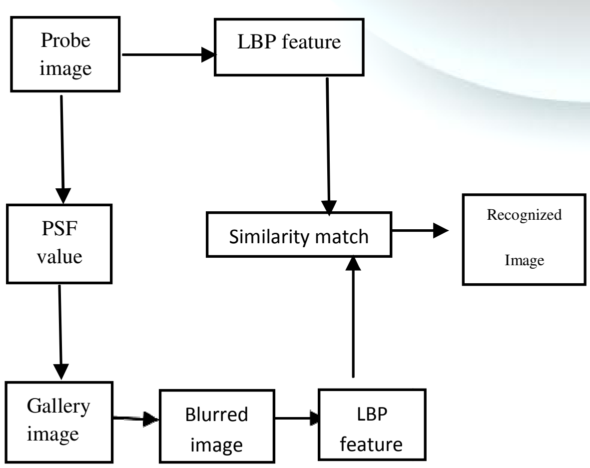


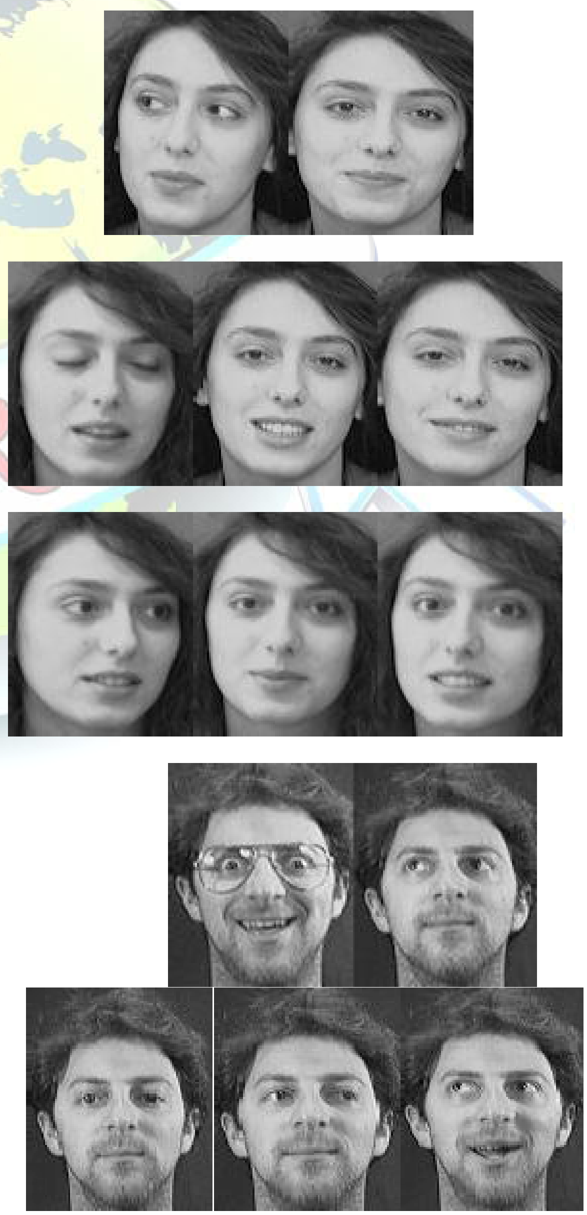
Figure 1. Block Diagram

3.1MODULES

- Dataset
- Probe image
- PSF value generation
- Blurred gallery image
- LBP feature calculation
- Comparison

3.1.1Dataset

Face data set image is stored in the system. This gray-level frontal view face database comprises 400 images from 40 persons. There are females and males, each of whom has 10 images with different facial expressions.



Probe image

The probe image in the module represents an image from the testing dataset, which contains the blurred facial dataset where blurring is done with the help of the imfilter function.

imfilter
Multidimensional image filtering

Syntax

B = imfilter (A, H)

B = imfilter (A, H, option1,option2,...)

Description

B = imfilter (A, H) filters the multidimensional array A with the multidimensional filter H. The array, A, can be a nonsparse numeric array of any class and dimension. The result, B, has the same size and class as A. Each element of the output, B, is computed using double-precision floating point. If A is an integer array, then output elements that exceed the range of the integer type are truncated, and fractional values are rounded. B = imfilter (A, H, option1, option2,...) performs multidimensional filtering according to the specified options. Option arguments can have the following values.

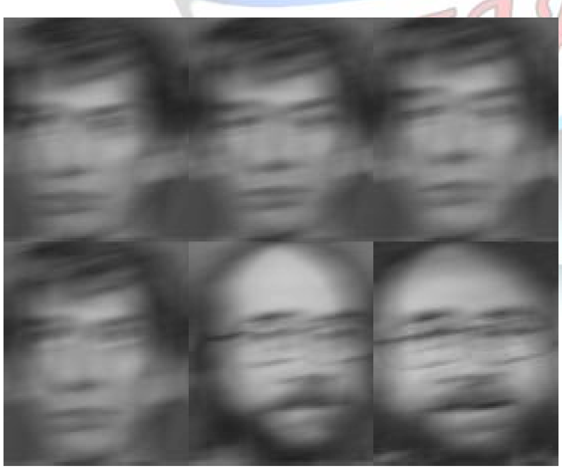


Figure 3. Some of the Blurred input set

PSF value generation

The ideal **point spread function** (**PSF**) is the three-dimensional diffraction pattern of light emitted from an infinitely small **point** source in the specimen and transmitted to the image plane through a high numerical aperture (NA) objective.

The generated PSF value of the probe image is now used to blur the gallery image.

```
PSF = fspecial ('motion', LEN, THETA);

blurred = imfilter (I, PSF, 'conv', 'circular');

imwrite (blurred, [R, num2str(k),'.jpg']);

psf =[psf PSF];
```

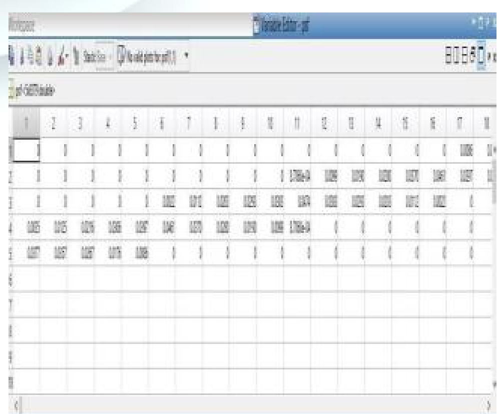


Table 1.PSF value

Matlab has a command fspecial function for generating different types of blur kernels. The command imfilter function can then be used to blur the image with this kernel, it is equivalent to a 2D convolution.

Blurred gallery image

- The gallery image represents an image of the training dataset. Here, the ORL dataset containing the facial images is taken as the training dataset.
- The entire dataset is now blurred with the help of the PSF value generated using the probe image considered.

LBP feature extraction

- The Local Binary Pattern (LBP) feature has to be extracted for both the probe image and every blurred image in the training dataset, which is blurred in the previous module.
- One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations.
- These local feature based methods are more robust against variations in blur than holistic methods. Feature is stored into dbspsf.m file

Comparison

- The computed LBP features can be used to find the similarity between any two images.
- The LBP value of the probe image is compared individually with all the image's LBP value present in the blurred-training dataset.
- The similarity matching is now done by considering the nearest value and the similar
  10 images are displayed in the descending order.

4. CONCLUSION

The proposed methodology to perform face recognition under the combined effects of non-uniform blur, Showed that the set of all images obtained by non-uniformly blurring a given image using the PSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, then showed that the set of all images obtained from a given image by non-uniform blurring and changes in blurring forms a bi-convex set, and used this result to develop our non-uniform motion blur. We then extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose. Extensive experiments were given on synthetic as well as real face data.

REFERENCES

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," *ACM Comput. Surv.*, vol. 35, no. 4, pp. 399–458, Dec. 2003.

[2] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," *ACM Trans. Graph.*, vol. 25, no. 3, pp. 787–794, Jul. 2006.

[3] Q. Shan, J. Jia, and A. Agarwala, "High-quality motion deblurring from a single image," *ACM Trans. Graph.*, vol. 27, no. 3, pp. 73:1–73:10, Aug. 2008.

[4] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, "Understanding blind deconvolution algorithms," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2354–2367, Dec. 2011.

[5] M. Šorel and F. Šroubek, "Space-variant deblurring using one blurred and one underexposed image," in *Proc. 16th IEEE Int. Conf. Image Process.*, Nov. 2009, pp. 157–160.

[6] H. Ji and K. Wang, "A two-stage approach to blind spatially-varying motion deblurring," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2012, pp. 73–80.

[7] Christo Ananth, A.Sujitha Nandhini, A.Subha Shree, S.V.Ramyaa, J.Princess, "Fobe Algorithm for Video Processing", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE), Vol. 3, Issue 3,March 2014 , pp 7569-7574

[8] Y.-W. Tai, P. Tan, and M. S. Brown,

"Richardson- Lucy deblurring for scenes under a projective motion path," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 8, pp. 1603–1618, Aug. 2011.

[9] O.Whyte, J. Sivic, A. Zisserman, and J. Ponce, "Non-uniform deblurring for shaken images," *Int. J. Comput. Vis.*, vol. 98, no. 2, pp. 168–186, 2012.

[10] A. Gupta, N. Joshi, L. Zitnick, M. Cohen, and B. Curless, "Single image deblurring using motion density functions," in *Proc. Eur. Conf. Comput. Vis.*, 2010, pp. 171–184.

[11] Z. Hu and M.-H. Yang, "Fast non-uniform deblurring using constrained camera pose subspace," in *Proc. Brit. Mach. Vis. Conf.*, 2012, pp. 1–11.

[12] C. Paramanand and A. N. Rajagopalan, "Non- uniform motion deblurring for bilayer scenes," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2013, pp. 1115–1122.

[13] H. Hu and G. de Haan, "Adaptive image restoration based on local robust blur estimation," in *Proc. 9th Int. Conf. Adv. Concepts Intell. Vis. Syst.*, 2007, pp. 461–472.

[14] M. Nishiyama, A. Hadid, H. Takeshima, J. Shotton, T. Kozakaya, and O. Yamaguchi, "Facial deblur inference using subspace analysis for recognition of blurred faces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 4, pp. 838–845, Apr. 2011.

[15] H. Zhang, J. Yang, Y. Zhang, N. M. Nasrabadi, and T. S. Huang, "Close the loop: Joint blind image restoration and recognition with sparse representation prior," in *Proc. Int. Conf. Comput. Vis.*, Nov. 2011,
pp. 770–777.

[16] T. Ahonen, E. Rahtu, V. Ojansivu, and J. Heikkila, "Recognition of blurred faces using local phase quantization," in *Proc. 19th Int. Conf. Pattern Recognit.*, Dec. 2008, pp. 1–4.

[17] R. Gopalan, S. Taheri, P. Turaga, and R. Chellappa, "A blur-robust descriptor with applications to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 6, pp. 1220–1226, Jun. 2012.

[18] I. Stainvas and N. Intrator, "Blurred face recognition via a hybrid network architecture," in *Proc. 15th Int. Conf. Pattern Recognit.*, vol. 2. Sep. 2000, pp. 805–808.

[19] P. Vageeswaran, K. Mitra, and R. Chellappa, "Blur and illumination robust face recognition via set- theoretic characterization," *IEEE Trans. Image Process.*, vol. 22, no. 4, pp. 1362–1372, Apr. 2013.

[20] K.-C. Lee, J. Ho, and D. Kriegman, "Acquiring linear subspaces for face recognition under variable lighting," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 5, pp. 684–698, May 2005.