



## FACE IDENTIFICATION SYSTEM

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**Abstract--** Face Identification System utilize the Recognition of faces among non-uniform of blur, illumination and pose. The proposed methodology for face recognition in the presence of space varying motion blur comprising of arbitrarily-shaped kernels. We model the 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. We 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  $l_1$ -norm constraint on the camera motion. The framework is then extended to handle illumination variations by exploiting the fact that the set of all images obtained from a face image by non-uniform blurring and changing the illumination forms a bi-convex set. Finally, we propose an elegant extension to also account for variations in pose.

**INDEX TERMS—** Face recognition, Face database, Non- Uniform of Blur, illumination, pose, Sharpness, Sparsity.

## INTRODUCTION

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 projectively transformed images. It is well-known that the accuracy of face recognition systems deteriorates quite rapidly in unconstrained setting. This can be attributed to degradations arising from blur, changes in illumination, pose, and expression, 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, and varying illumination and pose. 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. Deblurring-based in which the probe image is first deblurred and then used for recognition. However, deblurring artifacts are a major source of error especially for moderate to heavy blurs.

- (i) Joint deblurring and recognition, the flip-side of which is computational complexity.
- (ii) Deriving blur-invariant features for recognition. But these are effective only for mild blurs.
- (iii) The direct recognition approach 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. For handling illumination, there have mainly been two directions of pursuit based on (i) the 9D subspace model for face and (ii) extracting and matching illumination insensitive facial features. Tan et al. combine the strengths of the above two methods and propose an integrated framework that includes an initial illumination normalization step for face recognition under difficult lighting conditions.

A subspace learning approach using image gradient orientations for illumination and occlusion-robust face recognition has been proposed. Practical face recognition algorithms must also possess the ability to recognize faces across reasonable variations in pose. Methods for face recognition across pose can broadly be classified into 2D and 3D techniques.

## II. MOTION BLUR MODEL FOR FACES

### A. Multiscale Implementation

Since we are fundamentally limited by the resolution of the images, having a very fine discretization of the transformation space  $\mathbf{T}$  leads to redundant computations. Hence, in practice, the discretization is performed in a manner that the difference in the displacements of a point light source due to two different transformations from the discrete set  $\mathbf{T}$  is at least one pixel. It should be noted that since the TSF is defined over 6 dimensions, doubling their sampling resolution increases the total number of poses,  $N_T$ , by a factor of  $2^6$ . As the number of transformations in the space  $\mathbf{T}$  increases, the optimization process becomes inefficient and time consuming, especially since only a few of these elements have non-zero values. Moreover, the resulting matrix  $\mathbf{A}$  will have too many columns to handle. We resort to a multiscale framework to solve this problem. We perform multiscaling in 6D. We select the search intervals along each dimension according to the extent of the blur we need to model, which is typically a few pixels for translation and a few degrees for rotation.

### B. Face Recognition Across Blur

Suppose we have  $M$  face classes with one focused gallery face  $\mathbf{f}_m$  for each class  $m$ , where  $m = 1, 2, \dots, M$ . Let us denote the blurred probe image which belongs to one of the  $M$  classes by  $\mathbf{g}$ . Given  $\mathbf{f}_m$ s and  $\mathbf{g}$ , the task is to find the identity  $m^* \in \{1, 2, \dots, M\}$  of  $\mathbf{g}$ . Based on the discussions

$$\mathbf{h}^* \mathbf{T} \mathbf{m} = \operatorname{argmin} \|\mathbf{W}(\mathbf{g} - \mathbf{A} \mathbf{m} \mathbf{h}^* \mathbf{T})\|_2^2 + \beta \|\mathbf{h}^* \mathbf{T}\|_1 \mathbf{h}^* \mathbf{T}$$

subject to  $\mathbf{h}^* \mathbf{T} \geq 0$ .

Next, we blur each of the gallery images with the corresponding optimal TSFs  $\mathbf{h}^* \mathbf{T} \mathbf{m}$ . For each blurred gallery image and probe, we divide the face into non-overlapping rectangular, extract LBP histograms independently from each patch and



Fig. 1. Sample images from *ba* and *bj* folders in the FERET database. (a) Gallery, (b) probe, (c)-(g) probe blurred synthetically using random transformations

from the TSF intervals listed in Setting 1 - Setting 5 of Section III-C.

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**Algorithm 1** NU-MOB: Non-Uniform Motion Blur-Robust Face Recognition

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**Input:** Blurred probe image  $g$  and a set of gallery images  $f_m, m = 1, 2, \dots, M$ .

**Output:** Identity of the probe image.

- 1: For each gallery image  $f_m$ , find the optimal TSF  $h_{T_m}$  solving equation (13).
  - 2: Blur each gallery image  $f_m$  with its corresponding  $h_{T_m}$  and extract LBP features.
  - 3: Compare the LBP features of the probe image  $g$  with those of the transformed gallery images and find the close match.
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### C. Experiments

We evaluate the proposed algorithm NU-MOB on the standard and publicly available FERET database. Since this database contains only focused images, we blur the images synthetically to generate the probes. The camera motion itself is synthesized so as to yield a connected path in the motion space. The resulting blur induced mimics the real blur encountered in practical situations. In all the experiments presented in this paper, we use grayscale images resized to  $64 \times 64$  pixels and we assume only one image per subject in the gallery. To evaluate our NU-MOB algorithm, we use the *ba* and *bj* folders in FERET, both of which contain 200 images with one image per subject. We use the *ba* folder as the gallery. Five different probe sets, each containing 200 images, are obtained by blurring the *bj* folder using the settings mentioned above. The lighting and the pose are the same for both gallery and probe since the objective here is to study our algorithm's capability to model blur. Notice, however, that *small* facial expression changes exist between the gallery and the probe, but the weighting matrix makes our algorithm reasonably robust to these variations. We set the

number of scales in the multiscale implementation to 3 as it offered the best compromise between running time and accuracy.

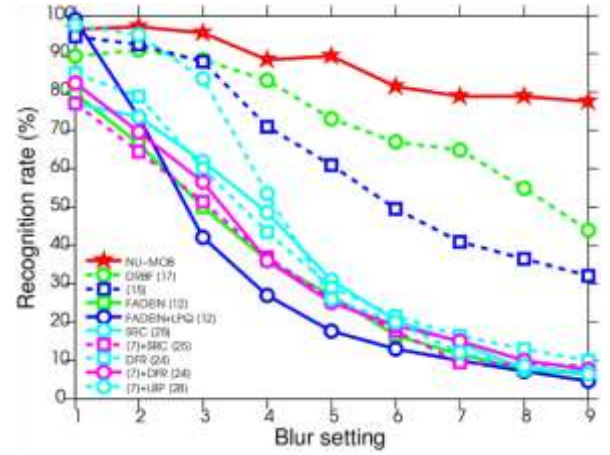


Fig. 2. Effect of increasing the blur. (Refer to the text for blur settings along the X-axis.)

**1) Effect of Increasing the Blur:** We now examine our algorithm's performance as the extent of the blur is increased. The gallery, as before, is the *ba* folder. We select random transformations from the following nine sets of intervals to blur the images in the *bj* folder and generate the probes.

**2) Effect of Underestimating or Overestimating the TSF Search Intervals:** In all the above experiments, we have assumed that the TSF limits are known, and we used the same transformation intervals as the ones used for synthesizing the blur, while attempting recognition. Although in some applications we may know the extent of the blur, in many practical settings, we may not. Hence, we perform the following experiments to test the sensitivity of our algorithm to the TSF search intervals.

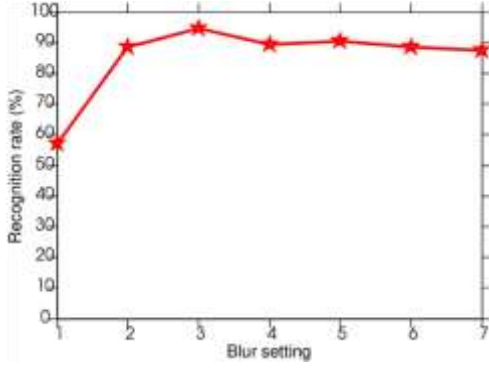


Fig. 3. Effect of underestimating or overestimating the TSF search intervals (Refer to the text for blur settings along the X-axis.)

### III. FACE RECOGNITION ACROSS BLUR, ILLUMINATION, AND POSE

Poor illumination is often an accompanying feature in blurred images because larger exposure times are needed to compensate for the lack of light which increases the chances of camera shake. Pose variation is another challenge for realizing the true potential of face recognition systems in practice. This section is devoted to handling the combined effects of blur, illumination and pose.

### IV. FACE RECOGNITION ACROSS BLUR, ILLUMINATION

#### A. Handling Illumination Variations

To handle illumination variations, we modify our basic blur-robust algorithm (NU-MOB) by judiciously utilizing the following two results:

- In the seminal work, it has been shown that if the human face is modeled as a convex Lambertian surface, then there exists a configuration of nine light source directions such that the subspace formed by the images taken under these nine sources is effective for recognizing faces under a wide range of lighting conditions. Using this “universal configuration” of lighting positions, an image  $f$  of a person under any illumination condition can be written as

$$\mathbf{f} = \sum_{i=1}^9 \alpha_i \mathbf{f}_i$$

where  $\alpha_i, i = 1, 2, \dots, 9$  are the corresponding linear coefficients. The  $\mathbf{f}_i$ s, which form a basis for this 9D subspace, can be generated using the Lambertian reflectance model as

$$\mathbf{f}_i(\mathbf{r}, \mathbf{c}) = \rho(\mathbf{r}, \mathbf{c}) \max(\mathbf{n}(\mathbf{r}, \mathbf{c})^T \mathbf{s}_i, 0)$$

where  $\rho$  and  $\mathbf{n}$  are the albedo and the surface normal, respectively, at the pixel location  $(\mathbf{r}, \mathbf{c})$ , and  $\mathbf{s}$  is the illumination direction. We approximate

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#### Algorithm 2 MOBIL: Motion Blur and Illumination-Robust Face Recognition

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**Input:** Blurred and differently illuminated probe image  $\mathbf{g}$ , and a set of gallery images  $\mathbf{f}_m, m = 1, 2, \dots, M$ .

**Output:** Identity of the probe image.

- 1: For each gallery image  $\mathbf{f}_m$ , obtain the nine basis images  $\mathbf{f}_{m,i}, i = 1, 2, \dots, 9$ .
  - 2: For each gallery image  $\mathbf{f}_m$ , find the optimal TSF  $\mathbf{h}_{T_m}$  and illumination coefficients  $\alpha_{m,i}$  by solving equation (16).
  - 3: Transform (blur and re-illuminate) the gallery images  $\mathbf{f}_m$  using the computed  $\mathbf{h}_{T_m}$  and  $\alpha_{m,i}$  and extract LBP features.
  - 4: Compare the LBP features of the probe image  $\mathbf{g}$  with those of the transformed gallery images and find the closest match.
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the albedo  $\rho$  with a frontal, sharp, and well-illuminated gallery image captured under diffuse lighting, and use the average (generic) 3D face normals for  $\mathbf{n}$ .

- It has been shown that for the case of space-invariant blur, the set of all images under varying illumination and blur forms a bi-convex set, i.e., if we fix either the blur or the illumination, the resulting subset is convex.

#### B. Handling Pose Variations

Most face recognition algorithms are robust to small variations in pose ( $\sim 15^\circ$ ), but the drop in performance is severe for greater yaw and pitch angles. In our experiments, we found this to be true of our MOBIL algorithm also. The reason behind this drop in accuracy is that intra-subject variations caused by rotations are often larger than inter-subject differences. Clearly, there is no overstating the



Fig. 3. Example images of a subject from the PIE database under new poses. The images in (a) and (b) are synthesized from the frontal gallery image using the average face depthmap shown in (c). For midable nature of the problem at hand - recognizing faces across blur,



illumination and pose. To this end, we next propose our MOBILAP algorithm which, using an estimate of the pose, matches the incoming probe with a synthesized non-frontal gallery image. To the best of the authors' knowledge, this is the first ever effort to even attempt this compounded scenario.

## V. EXPERIMENT

Using the PIE dataset, we further go on to show, how our MOBILAP algorithm can handle even pose variations. Note that, as before, we blur the images synthetically to generate the probes as these two databases do not contain motion blur

**Algorithm 3** MOBILAP: Motion Blur, Illumination and Pose-Robust Face Recognition

**Input:** Blurred and differently illuminated probe image  $g$  under a different pose, and a set of gallery images  $f_m, m = 1, 2, \dots, M$ .

**Output:** Identity of the probe image.

- 1: Obtain an estimate of the pose of the blurred probe image using the method in [34].
- 2: For each gallery image  $f_m$ , synthesize the new pose  $f_{syn_m}$  based on the above estimate.
- 3: For each synthesized gallery image  $f_{syn_m}$ , obtain the nine basis images  $f_{syn_{m,i}}, i = 1, 2, \dots, 9$  using normals recomputed from the rotated depthmap.
- 4: For each synthesized gallery image  $f_{syn_m}$ , find the optimal TSF  $h_{T_m}$  and illumination coefficients  $\alpha_{m,i}$  by solving equation (16).
- 5: Transform (blur and re-illuminate) the synthesized gallery images  $f_{syn_m}$  using the computed  $h_{T_m}$  and  $\alpha_{m,i}$  and extract LBP features.
- 6: Compare the LBP features of the probe image  $g$  with those of the transformed gallery images and find the closest match.

MOBILAP's results on the Labeled Faces in the Wild dataset (which is a publicly available real dataset) using the 'Unsupervised' protocol. We also evaluate the performance of MOBILAP on our own real dataset captured using a handheld camera that contains significant blur, illumination and pose variations, in addition to small occlusions and changes in facial expressions.

### A. Recognition Across Blur and Illumination

We first run our MOBIL algorithm on the illum subset of the PIE database which consists of images of 68 individuals under different illumination conditions. We use faces with a frontal pose ( $c_{27}$ ) and frontal illumination ( $f_{11}$ ) as our gallery. The probe dataset, which is also in the frontal pose ( $c_{27}$ ), is divided into two

categories- 1) Good Illumination (GI) consisting of subsets  $f_{06}, f_{07}, f_{08}, f_{09}, f_{12}$  and  $f_{20}$  (6 different illumination conditions) and 2) Bad Illumination (BI) consisting of subsets  $f_{05}, f_{10}, f_{13}, f_{14}, f_{19}$  and  $f_{21}$  (6 different illumination conditions)B. Recognition Across Blur, Illumination, and Pose

TABLE I Recognition results for mobilap on our real dataset along with comparisons

| Method            | Recognition rate (%) |
|-------------------|----------------------|
| MOBILAP           | 76.27                |
| IRBF [19]         | 58.32                |
| [17]              | 42.50                |
| FADEIN [14]       | 20.45                |
| FADEIN + LPQ [14] | 36.36                |
| SRC [27]          | 54.09                |
| [9] + SRC [27]    | 43.59                |
| DFR [26]          | 43.00                |
| [9] + DFR [26]    | 33.82                |
| [9] + LBP [30]    | 43.14                |

movement of the subjects during image capture, and, therefore, a subset of these images could possibly have both camera and object motion. We manually cropped the faces and resized them to  $64 \times 64$  pixels. Some representative images from the gallery and probe are given. Observe that, as compared to the gallery, the probes can be either overlit or underlit depending on the setting under which they were captured. We generate the nine illumination basis images for each image in the gallery and then run MOBILAP. It has been pointed out that in most practical scenarios, a 3D TSF is sufficient to explain the general motion of the camera. In view of this observation and in consideration of computation time, we select the search intervals for the TSF as  $[-4 : 1 : 4]$  pixels for in-plane translations, and  $[-2^\circ : 1^\circ : 2^\circ]$  for in-plane rotations. The recognition results are presented in Table I. Although the accuracy of all the methods drop due to the unconstrained and challenging nature of this dataset, the effectiveness of the proposed technique in advancing the state-of-the-art in handling non-uniform blur, illumination, and pose in practical scenarios is reaffirmed yet again.

### B. Recognition Across Blur, Illumination and Pose

Finally, we take up the very challenging case of allowing for pose variations in addition to blur and illumination. We once again use the PIE dataset. We begin by selecting four *near-frontal* poses (pitch and yaw angles within  $\sim 15^\circ$ ) and explore the robustness of MOBIL itself to small variations in pose. As before, the camera position  $c_{27}$  (frontal pose) and flash position  $f_{11}$  (frontal illumination) constitute the gallery. In this experiment, however, the probe set, divided into good and bad illumination subsets, contains the four nearfrontal poses  $c_{05}$  ( $-16^\circ$  yaw),  $c_{07}$  ( $0^\circ$  yaw and  $-13^\circ$  tilt),  $c_{09}$  ( $0^\circ$  yaw and  $13^\circ$  tilt) and  $c_{29}$  ( $17^\circ$  yaw).

$$[\mathbf{hTm}, am, i] = \operatorname{argmin} \|\mathbf{W}(\mathbf{g} - ai\mathbf{Am}, i\mathbf{hT})\|_2^2 + \beta \|\mathbf{hT}\|_1 \quad \mathbf{hT}, ai \quad i=1 \text{ subject to } \mathbf{hT} \geq 0$$

Next, we select differently illuminated probes in two non-frontal poses  $c_{37}$  ( $-31^\circ$  yaw) and  $c_{11}$  ( $32^\circ$  yaw). See Fig. 9 columns 5 and 6. Once again, the frontal camera position  $c_{27}$  and flash position  $f_{11}$  constitute the gallery. For such large changes in pose, we found that MOBIL returned recognition rates less than 15%.

## VI. CONCLUSIONS

The proposed a methodology to perform face recognition under the combined effects of non-uniform blur, illumination, and pose. We showed that the set of all images obtained by non-uniformly blurring a given image using the TSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, we initially proposed a novel non-uniform motion blur-robust face recognition algorithm. We then showed that the set of all images obtained from a given image by non-uniform blurring 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.

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