Direct Recognition of Motion Blurred Faces

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Abstract

The need to recognize motion blurred faces is vital for a wide variety of security applications ranging from maritime surveillance to road traffic policing. While much of the rich theory in the analysis of motion blurred images focuses on restoration of the same, we argue that this is an unnecessary (and expensive) step for face recognition. Instead we adopt a direct approach based on the set-theoretic characterization of the space of all motion blurred images that arise from a single sharp image. This set lacks the nice property of convexity that was exploited in a recent paper to achieve competitive results in real-world datasets of motion blurred faces. Keeping this non-convexity in mind, we propose a Bank-of-Classifiers approach for directly recognizing motion blurred face images. To that end, we divide the parameter space of motion blur into many different bins in such a way that the set of blurred images within each bin is a convex set. In each such bin, we learn SVM classifiers that ‘maximally’ separate the convex sets associated with each person in the reference database. Our experiments on synthetic and real datasets provide compelling evidence that this approach is a viable solution for motion blurred face recognition.

I. INTRODUCTION

The need to recognize motion blurred faces is vital for a wide variety of security applications ranging from maritime surveillance to road traffic policing. Figure 1 shows possible maritime surveillance scenarios: a) ship-to-shore (the camera is on the ship and subjects moving on-shore) and b) shore-to-ship (the camera mounted on-shore and subjects are in the ship). In either case, the face images have significant motion blur due to relative motion between the camera and subjects. In this chapter, we address the problem of recognizing faces from motion blurred images. An obvious approach of recognizing blurred faces would be to deblur the image first and then recognize it using traditional face recognition techniques [1]. However, this approach involves solving the challenging problem of blind image deconvolution [2], [3]. We avoid this unnecessary step and propose a direct approach for face recognition. Recently, in [4], we have shown that the set of all images obtained by blurring a given image forms a convex set. Further, this convex set is given by the convex hull of shifted versions of the original image. Based on this set-theoretic characterization, we have proposed a direct approach for recognizing blurred face
Fig. 1: Images captured by a distant camera for maritime surveillance: Maritime surveillance could entail either of the two scenarios: a) ship-to-shore (the camera is on the ship and subjects moving on-shore) and b) shore-to-ship (the camera mounted on-shore and subjects are in the ship). In either case, the face images have significant motion blur due to relative motion between the camera and subjects. In this chapter, we propose a motion blur robust face recognition algorithm which performs recognition directly on the blurred images, without trying to recover the corresponding sharp images using blind deconvolution techniques.

images. However, if we restrict our attention to only motion-blurred images, then this set is no longer a convex set; and hence we can not use the face recognition algorithm proposed in [4]. In this chapter, we propose a discriminative-model based face recognition algorithm that takes into account the non-convex nature of the motion blurred image-sets.

Motion blur is characterized by the direction and size of the blur [5]. We show that the set of all motion blurred images obtained from a sharp image is not a convex set. This non-convexity arises mainly because of the directional nature of the motion blur. However, if we fix the direction of blur, then all the blurred images along that direction forms a convex set. Keeping this conditional convexity in mind, we propose a Bank-of-Classifiers approach for directly recognizing motion blurred face images. We divide the parameter space of motion blur into many different bins in such a way that the set of blurred images within each bin is a convex set. In each such bin, we learn SVM classifiers that ’maximally’ separate the convex sets associated with each person in the reference database. Given a probe image, we use the SVM classifiers at each bin to find its likely identity at each bin. Finally, we use the majority rule to arrive at the final identity.

To summarize, the main technical contribution of this chapter are:
• We show that the set of motion blurred images obtained from a single sharp image is a non-convex set. The directional nature of motion blur is responsible for this non-convexity. Given a particular direction, the set of motion blurred images along that direction is a convex set.

• Based on this set-theoretic characterization, we propose a motion blur robust face recognition algorithm, which avoids solving the challenging and unnecessary problem of blind image deconvolution.

• We use the conditional convexity property of motion blur to propose a bank of classifiers based face recognition algorithm. This is a discriminative approach and hence it scales well with the number of face classes and training images per class.

A. 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. This is the approach taken in [6] and [1]. 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 [7], [2], [8], [9], [3], [10], [11], [12], [13], [14], it is an avoidable step for the face recognition problem. Also, in [1] statistical models are learned for each blur kernel type and amount; this step might become infeasible when we try to capture the complete space of blur kernels.

In the second approach, blur invariant features are extracted from the blurred image and then used for recognition; [15] and [16] follow this approach. In [?], the local phase quantization (LPQ) [17] 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 [1]. In [16], 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. However, this analysis does not take into account the convexity constraint that the blur kernels satisfy, and hence the (blur) subspace will include many other images apart from the blurred images. The third approach is the direct recognition approach. This is the approach taken in [18], [4] and by us. In [18], artificially blurred versions of the gallery images are created and the blurred probe image is matched to them. Again, it is not possible to capture the whole space of blur kernels using this method. Finally, the fourth approach is to jointly deblur and recognition the face image [19]. However, this involves solving for the original sharp image, blur kernel and identity of the face image, and hence it is a computationally intensive approach.

Set theoretic approaches for signal and image restoration have been considered in [20], [21], [22]. In these approaches the desired signal space is defined as an intersection of closed convex sets in a Hilbert
space, with each set representing a signal constraint. Image deblurring has also been considered in this context [21], where the non-negativity constraint of the images has been used to restrict the solution space. We differ from these approaches as our primary interest lies in recognizing blurred and poorly illuminated faces rather than restoring them.

The organization of the rest of the chapter is as follows: In section II we provide a set-theoretic characterization of the space of motion-blurred images. In section III we present our bank of filters approach for recognizing motion blurred face images and in section IV we perform experiments to evaluate the our algorithms against other standard algorithms.

II. THE SET OF ALL MOTION BLURRED IMAGES

We review the convolution model for blur, and based on it we compare and contrast the set of all blurred images with the set of only motion blurred images. In [4], it is shown that the set of all blurred images is a convex set. However, we show here that the set of only motion blurred images is non-convex.

A. 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 [5]. 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

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

(1)

where $\ast$ 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 (i.e. $\sum_{i=-k}^{k} \sum_{j=-k}^{k} H(i, j) = 1$). The blur kernel for motion-blur has additional structure such as it is linear along a certain direction.

B. The set of all blurred images Vs. the set of motion blurred Images

The set of all blurred images $B$ obtained from $I$ is given by:

$$B \triangleq \{I \ast H|H \geq 0, ||H||_1 = 1\}$$

(2)

This set is clearly convex since given any two blur kernels $H_i$ and $H_j$, both satisfying $H \geq 0$ and $||H||_1 = 1$, there convex combination $(\lambda H_i + (1 - \lambda)H_j, 0 \leq \lambda \leq 1)$ will also satisfy the above
Fig. 2: The set of all blurred images Vs. the set of only motion-blurred images: As established in [4], the set of all blurred images (obtained from a single sharp image) is a convex-set, which is the convex hull of various shifted versions of the sharp image. However, the set of only motion blurred images is not a convex set. This is because of the directional nature of motion blur. To see this, consider two motion blur kernels: a horizontal blur kernel and the vertical blur kernel. Their convex combination is no longer a motion blur kernel, which proves that the set of only motion blurred images is not a convex set. However, if we consider a particular direction of motion blur, then the set of images blurred along that direction is a convex set. Further, this convex set is given by the convex hull of shifted images along that direction.

mentioned constraints. Moreover, this set is the convex hull of shifted versions of the image $I$. This is because the set $(H|H \geq 0, ||H||_1 = 1)$ is the convex hull of $H$ matrices which have a single non-zero entry. These $H$ matrices in turn gives rise to shifted-versions of the original image $I$ and thus the set of blurred images is the convex hull of these shifted images, see [4].

Now, we consider the set of motion blurred images. Motion blur arises due to the movement of the camera or the scene objects at the time of exposure. If the exposure-time is small, the blur can be
considered as linear, that is, the image is blurred along a line. If the motion blur is along a particular
direction, say \( \theta \), then the blur kernel \( H \) satisfies the following conditions [5]:

\[
H(i, j) > 1/L \text{ if } \arctan(i/j) = \theta, \text{ else } H(i, j) = 0,
\]

where \( L \) is the number of non-zero locations in \( H \). With this definition of motion blur, we show that
the set of all motion blurred images is non-convex, see figure 2. We prove this by producing two motion
blur kernels, whose convex combination does not satisfy the motion blur-kernel constraints, and hence is
not a motion blur kernel. Consider the horizontal motion blur kernel \( H_1 = \begin{pmatrix} 0 & 0 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 0 & 0 \end{pmatrix} \) and the
vertical motion blur kernel \( H_2 = \begin{pmatrix} 0 & 1/3 & 0 \\ 0 & 1/3 & 0 \\ 0 & 1/3 & 0 \end{pmatrix} \). Their convex combination, corresponding to \( \lambda = 0.5 \),
is \( H_3 = \begin{pmatrix} 0 & 1/6 & 0 \\ 1/6 & 1/3 & 1/6 \\ 0 & 1/6 & 0 \end{pmatrix} \), which is clearly not a motion-blur kernel. Thus the set of all motion blur
images is not a convex set. However, if we consider a particular direction of motion blur \( \theta \), then the set
of images blurred along that direction is a convex set. Further, this convex set is given by the convex
hull of shifted images along that direction. Again, this is because the blur kernel \( H \) is the convex hull
of \( H \) matrices that are shifted impulse functions, which gives rise to shifted images along the direction
of \( \theta \). We use the above set-theoretic analysis to propose a face recognition algorithm that can robustly
handle motion blurred images.

III. BANK OF CLASSIFIERS (BOC) APPROACH FOR RECOGNIZING MOTION BLURRED FACES

In the previous section we have shown that the set of all motion blurred images is a non-convex
set. The main reason for this non-convexity is the directional nature of the motion blur. However for a
particular direction, the set of blurred images is a convex set and is given by the convex hull of shifted
images along that direction. We design our face recognition algorithm based on the above set-theoretic
characterization. We first divide the parameter space of motion blur- the direction and size of blur, into
a certain number of bins. Within each bin, the set of blurred images is a convex set and is given by
the convex hull of appropriately shifted versions of the sharp image. We use these shifted images as
training data to learn a system of SVM classifiers for each bin, that distinguishes between the \( C \) face
classes. Combining these systems of SVM classifiers for each bin, we get a bank-of-classifiers. Given
Fig. 3: The Bank-of-Classifiers (BOC) approach for recognizing motion-blurred face images: The set of all motion blurred images, obtained from a sharp image, is a non-convex set. However, for a particular motion blur direction, the set of blurred images is a convex set. We design our face recognition algorithm based on this set-theoretic characterization. We first divide the parameter space of motion blur—the direction and size of blur, into a certain number of bins. Within each bin the set of blurred images is a convex set and is given by the convex hull of appropriately shifted versions of the sharp image. We use these shifted images as training data to learn a system of SVM classifiers for each bin, that distinguishes between the C face classes. In this figure, we show three such systems corresponding to the appropriately shaded bin. Combining the systems of SVM classifiers for each bin, we get a bank-of-classifiers. Given a test motion blurred image, we use this entire bank-of-classifiers to identify the correct class.

A test image that is motion-blurred, we use this entire bank-of-classifiers to identify the correct class. Figure 3 gives an overview of our BOC approach. In the following paragraphs, we describe our algorithm in more detail.

Motion blur is characterized by the direction(θ) and size of blur(S) [5]. We divide the size of blur into a certain number of bins, say $N_s$. For each blur size, we divide the angle space (between 0 – 180
degrees) into a certain number of equally spaced bins, say $N_{\theta_s}$. We choose the number of angular bins as a function of the blur-size. This is because we are working with discrete kernels. For instance, angular bin centers for kernels of size 3 would be 0, 45, 90, 135, 180 degrees; for size 5 we would get bin-centers at 0, 22.5, 45, · · · , 180 degrees. The total number of bins in the parameter space is $N = \sum N_{\theta_s}$, for $s = 1, \cdots , N_S$.

From our analysis in section II-B, the set of motion blurred images obtained from a sharp image within each bin is a convex set. This set is a convex hull of shifted images which depends on the direction and size of motion blur determined by the particular bin. To find these shifted images we find the non-zero entries of the blur kernel $H$. If the blur angle of the bin is between $\theta_1 \leq \theta < \theta_2$ and the blur size is $K \times K$, then the non-zero entries of the blur kernel are given by:

$$H(i, j) > 0 \text{ if } \theta_1 \leq \arctan\left(j/i\right) < \theta_2. \quad (4)$$

There are as many shifted images as the number of non-zero entries in $H$ and each shifted image is obtained by convolving the sharp image with a kernel that is a shifted delta-function. These shifted images then define the convex hull for the bin. We use these shifted images as the training data for learning SVM classifiers, as describe below.

For each bin of the blur parameter space we learn a system of SVM classifiers to distinguish between the $C$ face classes. We learn one-vs-all SVM classifiers [23]. Thus for each face-class, we have a bank of $N$ classifiers. Given a test image, we query it against this bank of classifiers and find the likely class for each bin. We finally chose the class that occurs the most number of times.

IV. EXPERIMENTAL EVALUATIONS

In this section, we first analyze the performance sensitivity of our proposed algorithm bank-of-classifiers (BOC) with the motion blur angle and size. We then study the recognition performance of BOC on synthetically generated motion blurred images from the PIE dataset [24] and on a real dataset REMOTE [25]. We compare it with competing algorithms for blur-robust recognition such as DRBF [4] and LPQ [17].

A. Sensitivity analysis of our BoC approach

In our BoC approach, we divide the parameter space of motion blur- the direction and size of blur, into many bins and learn SVM classifier for each bin. Here we study the sensitivity of the recognition rate with respect to the blur angle and amount. For this we use the PIE dataset [24] which has 68 subjects. The
To study the sensitivity of recognition rate with respect to the blur angle, we blur the test images with a blur kernel of angle $90^\circ$ and a sequence of different blurs of sizes: 7, 9, 11, 13, 15. We then use the learned SVM classifiers at different angular bins (and the correct size) to compute the recognition rate, see subplot (a). The recognition rate is quite good and is almost 100% for the correct angle bin (of $90^\circ$). As we go further away from the correct angular bin, the performance falls off. The performance fall off also depends on the size of blur kernel. For small blur sizes, 7 and 9, the performance is quite insensitive to the bin angles, but for large blur sizes $\geq 11$ it is quite sensitive. In subplot (b), we study the sensitivity of recognition rate towards blur size. We blur the test images with a blur kernel of angle $0^\circ$ and a sequence of blur sizes: 13, 15, 17, 19, 21, 25. We then use the learned SVM classifiers at different blur size bins (of angle $0^\circ$) to compute the recognition rate. For small blur sizes 13, 15, 17, the recognition rate is almost 100% for the correct blur size bins. But for large blur sizes $\geq 19$ performance falls off even at the correct bin. This is because at large blur sizes, the face classes get confused between themselves and learning good SVM classifiers is difficult.

Training and testing sub-folders are chosen such that their pose and illumination conditions are roughly constant. We choose sub-folders $(c27 - f21, c27 - f20)$ for training and $(c27 - f9, c27 - f11)$ for testing. We bin the kernel-size into 7 bins corresponding to sizes $(3, 5, \cdots, 15)$. For each kernel size, we bin the angle-space appropriately to get a total of $N = 89$ bins. At each bin and for each face class, we generate training images, which are shifted versions of the original sharp image and learn SVM classifiers based on them. To study the sensitivity of recognition rate with respect to blur angle, we blur the test images with a blur kernel of angle $90^\circ$ and a sequence of different blur sizes: 7, 9, 11, 13, 15. We then use the learned SVM classifiers at different angular bins (with the correct kernel-size) to compute the recognition rate, see Figure 4(a). The recognition rate is quite good and is almost 100% for the correct angle bin.
of 90°. As we go further away from the correct angle bin, the performance falls off. The performance fall off also depends on the size of blur kernel. For small blur sizes- 7 and 9, the performance is largely insensitive to the bin angles, but for larger blur sizes (≥ 11) we start observing a bell-shaped curve. In Figure 4(b), we study the sensitivity of recognition rate with blur size. We blur the test images with a blur kernel of angle 0° and a sequence of blur sizes: 13, 15, 17, 19, 21, 25. We then use the learned SVM classifiers at different blur size bins (of angle 0°) to compute the recognition rate. For small blur sizes 13, 15, 17, the recognition rate is almost 100% for the correct blur size bins. But for large blur sizes ≥ 19 performance falls off even at the correct bin. This is because at large blur sizes, convex hulls corresponding to different face classes either intersect or are very close to one another. Hence, it becomes difficult for the SVM classifier to learn an appropriate decision surface.

![Fig. 5: Recognition result for synthetically generated motion blurred images](image)

Fig. 5: Recognition result for synthetically generated motion blurred images: We compare the performance of our proposed approach BoC with DRBF [4], LPQ [17] and LBP [15]. We synthetically blur images in the PIE dataset with various motion blur kernels. We vary the blur size from 3 to 15 and at each blur size we randomly generate 10 different blur angles. The above plot shows the mean recognition rate vs. the blur size. BoC gives the best performance followed by DRBF, LPQ and LBP. At each blur size, we also show the standard deviation as error bars. Since we model the blur direction explicitly in BoC, the standard deviation for BoC is almost zero; whereas for the other algorithms, it is much larger.
Fig. 6: Sample probe images from REMOTE dataset [25]: The images in this dataset were captured in two settings: ship-to-shore and shore-to-ship. Since there are moving objects in the scene and also images were captured from a moving camera, the images have significant motion blur. This dataset has 17 subjects. The gallery folder of the dataset has 5 frontal, sharp and well-illuminated images for each subject. The probe folder is divided into 3 sub-folders: 1) Blur only, 2) Illumination only and 3) blur and illumination. We use the blur sub-folder for our experiment. This sub-folder has 75 probe images.

B. Performance evaluation on synthetically generated motion blurred images

We synthetically blur the PIE dataset with many motion blur kernels and compare our BoC approach with other algorithms such as DRBF [4], ‘FADEIN+LPQ’ [1] and LBP [15]. We use face images with a frontal pose ($c_{27}$) and good illumination ($f_{21}, f_{20}$) as our gallery and $c_{27}$-($f_{9}, f_{11}, f_{12}$) as probe. We vary the blur size from 3 to 15 and at each blur size we randomly generate 10 different blur angles. Figure 5 shows the mean recognition rate vs. blur size. BoC gives the best performance followed by DRBF, LPQ and LBP. At each blur size, we also show the standard deviation as error bars. Since, we model the blur direction explicitly in BoC, the standard deviation for BoC is almost zero, whereas, for the other algorithms it is much larger.
Fig. 7: Recognition results on the unconstrained dataset REMOTE: We compare our algorithm BoC with DRBF [4], PLS-based (Partial least squares) face recognition algorithm [26], a sparse representation-based face recognition algorithm [27] (SRC), LPQ and PCA+LDA+SVM [25]. We plot the recognition rate vs. the number of gallery images. Our algorithm BoC outperforms the other algorithms significantly when the number of gallery of images is 3 or less. It is noteworthy that the other algorithms use more informative features (for e.g. PLS uses Gabor-Jets, LBP and HOG), which likely makes them robust to illumination and registration effects. Hence, it could be interesting to see the effects of modeling illumination and pose in our BoC framework.

C. Performance evaluation on the real dataset REMOTE

We test our algorithm on the REMOTE dataset where the images have been captured in an unconstrained manner [25], [26]. The images were captured in two settings: ship-to-shore and shore-to-ship. The distance between the camera and the subjects ranges from 5 meters to 250 meters. Since there are moving objects in the scene and also images were captured from a moving camera, the images have significant motion blur. This dataset has 17 subjects. The gallery folder of the dataset has 5 frontal, sharp and well-illuminated image for each subject. The probe folder is divided into 3 sub-folders: 1) Blur only, 2) illumination only and 3) blur and illumination. We use the blur sub-folder for our experiment. This sub-folder has 75 probe images, see Figure 6. We register the images as a pre-processing step and normalize the size of the images to 120 × 120 pixels. We then evaluate the recognition performance of our algorithm and compare it with other state of the art algorithms such as DRBF [4], PLS-based (Partial least squares) face recognition algorithm [26], a sparse representation-based face recognition algorithm [27] (SRC), LPQ and PCA+LDA+SVM [25]. We plot the recognition rate vs. the number of gallery images. Our algorithm
BoC outperforms the other algorithms significantly when the number of gallery of images is 3 or less. It is noteworthy that the other algorithms use more informative features (for e.g. PLS uses Gabor-Jets, LBP and HOG), which likely makes them robust to illumination and registration effects. Hence, it could be interesting to see the effects of modeling illumination and pose in our BoC framework.

V. DISCUSSION

We address the problem of recognizing faces from motion blurred images. We show that the set of motion blurred images obtained from a single sharp image is a non-convex set. The main reason for this non-convexity is the directional nature of motion blur. However, if we fix the direction of blur, then all the blurred images along that direction forms a convex set. Keeping this conditional convexity in mind, we propose a Bank-of-Classifiers approach for directly recognizing motion blurred face images. This is a discriminative approach and hence it scales well with the number of face classes and training images per class. Our experiment on both synthetic and real datasets show that the our algorithm gives state of the art performance. In future, we would like to model the effect of illumination and pose in our framework.

REFERENCES