Recognition of Blurred Faces via Facial Deblurring Combined with Blur-Tolerant Descriptors

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Abstract

Blur is often present in real-world images and significantly affects the performance of face recognition systems. To improve the recognition of blurred faces, we propose a new approach which inherits the advantages of two recent methods. The idea consists of first reducing the amount of blur in the images via deblurring and then extracting blur-tolerant descriptors for recognition. We assess our analysis on real blurred face images (FRGC 1.0 database) and also on face images artificially degraded by focus blur (FERET database), demonstrating significant performance enhancement compared to the state-of-the-art.

1. Introduction

Current face recognition systems perform well under relatively controlled environments. However, the design of algorithms that are effective over a wide range of viewpoints, occlusions, aging of subjects and complex outdoor lighting is still a major area of research, despite the great deal of progress during the recent years [4]. Other factors which also affect the performance of face recognition systems include blur which may cause significant image degradations (see examples of blurred faces in Fig. 1). Blur is unfortunately often present in real-world face images and is usually originated from camera motion or misfocused optics. It affects the appearance of faces in images, causing two main problems for face recognition: (i) the facial appearance of an individual changes drastically due to blur; (ii) and different individuals tend to appear more similar when blurred [5].

Surprisingly, while there has been an enormous amount of research on face recognition under pose and illumination changes, problems caused by blur are mostly overlooked. The focus of this paper is thus on blur, and particularly on how to improve the recognition of blurred faces.

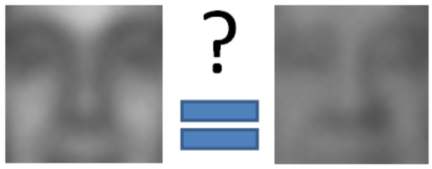

Figure 1. Examples of blurred face images

Basically, there are two main approaches in existing techniques for face recognition under blur. The first direction consists of deblurring the face images via deconvolution with an aim of recovering sharp images ready for processing using any conventional face recognition algorithm. Another way of handling the recognition of blurred faces consists of deriving blur-invariant features directly from the blurred images without having to recover the sharp images which, anyway, are not necessarily needed for recognition [2]. We noticed that the two approaches depict different and **complementary** characteristics. This observation is behind our proposed approach which is presented in this paper.

The rest of this paper is organized as follows. Section 2 briefly describes a recent approach using facial deblurring [5] while Section 3 discusses another promising technique based on blur-invariant descriptors [2]. These two methods can be considered as state-of-the-art in recognition of blurred faces. Section 4 reveals the pros and cons of each method, explains the motivations and introduces an adequate fusion scheme for combining the advantages of both methods. We perform extensive experimental analysis in Section 5, demonstrating significant performance enhancement. We also compare the results against those of various fusion schemes and other state-of-the-art methods like local binary patterns (LBP) [1]. A conclusion is drawn in Section 6.

2. Facial Deblurring

As mentioned above, one way to deal with the recognition of blurred faces is to restore the sharp images via image deconvolution and then use conventional face recognition algorithms for matching. Many methods have indeed been proposed for deblurring from a single image [3]. However, it appears that most the existing methods attempt to infer the point spread function (PSF) representing the process of blur without prior knowledge of the image contents. This generally yields in deblurring results that are often insufficient for accurate face recognition.

Very recently, Nishiyama et al. [5] introduced an approach exploiting face prior information for facial deblurring, yielding in very promising results. The idea is to exploit prior knowledge of how facial appearances are changed by blur. The method first chooses a representative set of PSFs. Then, sharp training images are artificially blurred using each PSF to build a statistical model of facial appearance under that PSF. Given a query image (with unknown identity and amount of blur), the method infers a PSF by comparing the image to each model during testing. The inferred PSF is then used to deblur the query image and perform face recognition. Experiments on real and artificially blurred face images showed high PSF inference and good recognition performance. We therefore adopt Nishiyama et al.'s approach as a baseline method for face recognition using deblurring.

3. Blur-Invariant Descriptors

An alternative to deal with the recognition of blurred faces is to extract features which are invariant or tolerant to the presence of blur. This is an emerging direction and not much work has been done before. To the best of our knowledge, the only notable work on explicit construction of blur-invariant descriptors for face recognition is that of Ahonen et al. [2] who derived blur invariant features from the blurred face images using the phase information in the frequency domain [6]. The method, called local phase quantization (LPQ), showed very promising results.

In the LPQ approach, the spatial blurring is represented by a convolution between the image intensity and a PSF. In the frequency domain, this results in a multiplication G = F · H, where G, F, and H are the Fourier transforms of the blurred image, the sharp image, and the PSF respectively. Considering only the phase of the spectrum, the relation turns into a sum ∠G = ∠F + ∠H. If the PSF is centrally symmetric, the transform H becomes real valued and the phase angle ∠H must equal 0 or π. Furthermore, the shape of H for a regular PSF is close to a Gaussian or a sinc-function, which makes at least the low frequency values of H to be positive. At these frequencies, ∠H = 0 causes ∠G = ∠F to be a blur invariant property. This phenomenon is the basis of the local phase quantization (LPQ) method.

For a given image, each pixel is labeled with a blur invariant LPQ code. The occurrences of these LPQ codes are collected into a histogram. The classification is then performed using the χ^2 (Chi-square) dissimilarity metric for comparing a target histogram S to a model histogram $M : \chi^2(S, M) = \sum_{i=0}^{l} \frac{(S_i - M_i)^2}{S_i + M_i}$, where l is the length of feature vector used to represent each face.

For an efficient representation, facial images are first divided into several local regions from which LPQ histograms are extracted and concatenated into an enhanced feature histogram which is used as the blur-invariant face descriptor. The experiments showed that such LPQ descriptors are highly discriminative and produce good face recognition results for both sharp and blurred face images. We therefore adopt this approach as a baseline method for face recognition using blur-invariant features.

4. Proposed Approach

Our proposed approach to deal with the recognition of blurred faces is described in Algorithm 1.

GIVEN A QUERY IMAGE (WITH UNKNOWN IDENTITY AND AMOUNT OF BLUR) TO RECOGNIZE:

1. ESTIMATE THE PSF BY COMPARING THE QUERY IMAGE TO THE MODELS (BUILT DURING THE TRAINING AS IN [5])
2. USE THE INFERRED PSF TO DEBLUR THE QUERY IMAGE
3. DIVIDE THE DEBLURRED IMAGE INTO LOCAL BLOCKS
4. EXTRACT BLUR TOLERANT HISTOGRAMS FROM EACH LOCAL BLOCK USING LPQ [2]
5. CONCATENATE THE LOCAL HISTOGRAMS INTO AN ENHANCED FEATURE HISTOGRAM
6. PERFORM HISTOGRAM MATCHING

THE NEAREST-NEIGHBOR (NN) DETERMINES THE IDENTITY OF THE QUERY IMAGE.

Algorithm 1: Steps of the proposed approach

The main advantage of deblurring approaches is that once sharp images are restored, any conventional face recognition technique can be chosen and applied. However, our experiments have showed that the deblurring process is rarely perfect as it can only reduce (though significantly) the amount of blur while avoiding notable artifacts. So, in practice, some amount of blur still remains after deblurring. On the other hand, our experiments also revealed that blur-invariant descriptors generally work very well with small amount of blur but suffer when the amount of blur increases. These observations are behind our idea of proposing a hybrid approach to deal with the recognition of blurred faces. The proposed approach, sketched in Algorithm 1, consists of first reducing the amount of blur via image deblurring and then extracting blur-tolerant descriptors for robust face recognition.

5. Experimental Analysis

To assess the performance of the proposed approach in recognizing blurred (and also sharp) faces, we performed extensive experiments on two publically available face databases namely FERET [8] and FRGC 1.0 [7], considering both artificial and real blurred images.

We first analyzed synthesized images by blurring sharp query faces from FERET database as in [5]. Sharp faces are blurred by Gaussian PSFs ($\sigma = 2{,}4{,}6{,}8$). White Gaussian noise of 30dB is also added to the synthesized images. Examples are shown in Figure 2. The database includes three subsets: 'bk', 'fa', and 'fb' having 200, 1196, and 1195 images, respectively. Each subset contains a single image per person. Subset 'bk' is used as a training set. We evaluated the recognition accuracy on the 1001 images that remain in subsets 'fa' and 'fb' after removing the individuals present in subset 'bk'. The identification target set is 'fa' and the query set is 'fb'.

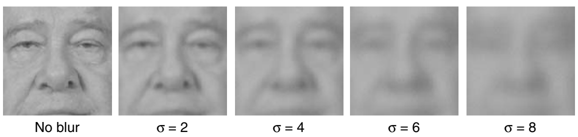

Figure 2. Examples of synthesized images of focus blur from FERET

Fig. 3 compares the results of four different approaches including LBP [1] as one of the state-of-the-art in recognition of sharp face images, LPQ [2] as a baseline for blur-invariant descriptors for face recognition, deblur [5] as a representative of facial deblurring and DeblurLPQ which is the proposed method in this work (Section 4). From the results, we can notice that LBP is very sensitive to blur although it is one of the state-of-the-art methods in face recognition. We also notice that the blur-invariant descriptor approach (LPQ) works very well with small amount of blur but its performance deteriorates when the amount of blur increases. The facial deblurring approach seems to handle large amount of blur much better than LBP and LPQ. As expected, our proposed approach (DeblurLPQ) significantly enhances the recognition performance compared to the use of LPQ and deblur separately, yielding in the best results.

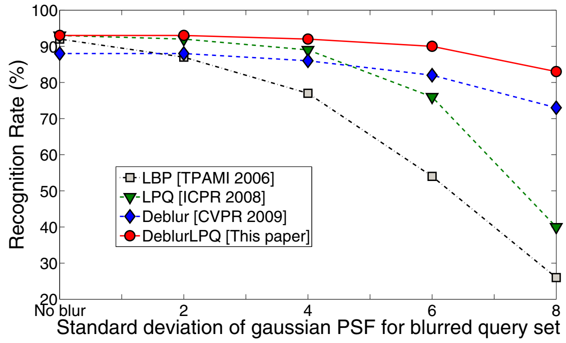

Figure 3. Recognition performance on FERET for artificial camera focus blur

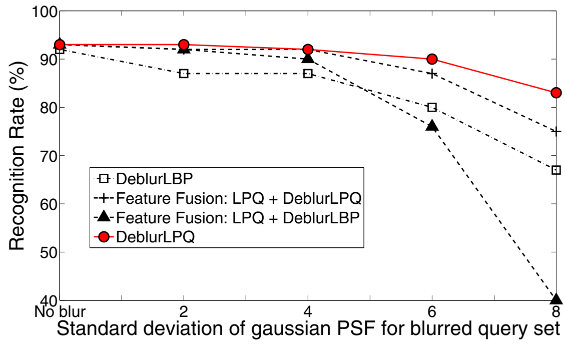

Figure 4. Results of different fusion schemes for artificial camera focus blur

Our proposed approach consists of associating LPQ and deblurring in a complementary manner: it extracts blur-tolerant descriptors from the deblurred face images. Thus, it inherits the advantages of both methods. To gain insight into the proposed approach, we also studied other combination schemes such as (i) extracting LBP histograms from the deblurred face images (DeblurLBP); (ii) fusing LPQ descriptors with DeblurLBP representation at feature level (LPQ+DeblurLPQ); (iii) and fusing LPQ descriptors with DeblurLBP at feature level (LPQ+DeblurLPQ). The results of these combination schemes are shown in Fig. 4, demonstrating that the proposed association (DeblurLPQ) yields in the best performance.

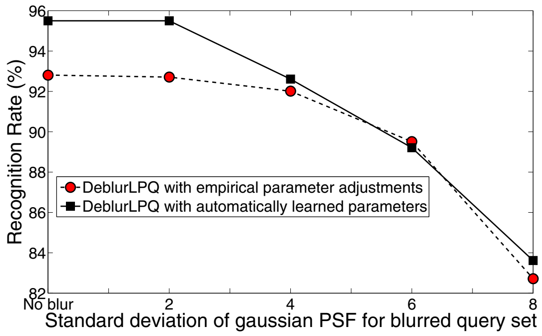

Figure 5. Empirical vs. automatic parameter tuning

An important parameter in the proposed approach is the size of the local neighborhood (K-by-K) that is used to compute the LPQ label [2] at each image pixel. So far, the value of K is empirically determined during training and then kept constant in testing. However, we noticed that the optimal value of K is function of the amount of blur (σ) in every blurred query which is variable. We therefore trained a linear regression model to learn the relationship between K and σ. Fig. 5 shows the results when K is automatically determined by the regression model given σ which is estimated during the deblurring stage. The result shows further performance enhancement, indicating the importance of the choice of the local neighborhood size when using LPQ.

Table 1. Recognition rates on FRGC 1.0 for real blurred images

Method	LBP	DeblurLBP	LPQ	DeblurLPQ
Rate(%)	33.4	33.7	74.8	**79.6**

In addition to artificial blur, we also considered real blurred images from FRGC 1.0. face database. We evaluated identification performance under the setup 'Exp4' that is evaluated on uncontrolled still query images including blurred faces. Each query set consists of 608 images of 152 individuals. We count that 366 query images are degraded by camera focus blur. Target images are collected under a controlled still condition. A single image is captured per person for target. The number of target images is 152. The amount of blur in both the target and query images is not constant and is unknown. We applied the illumination normalization preprocessing [9] before facial deblurring. We report in Table 1 the recognition performance. The results show again that the proposed approach (DeblurLPQ) yields in the best performance, confirming our earlier findings.

6. Conclusion

The salient contributions of this paper are: (**i**) a novel fusion scheme for improving the recognition of blurred faces is proposed; (**ii**) state-of-the-art in face recognition under blur is reviewed and pros/cons of each method are revealed; (**iii**) various fusion schemes are studied and evaluated; and (**iv**) extensive experimental analysis on artificial and real blurred face images is conducted, demonstrating significant performance enhancement using the proposed approach compared to the state-of-the-art.
As a future work, it is of interest to expand the evaluation of the proposed approach by explicitly considering severe motion blur caused, for instance, by camera shake.

ACKNOWLEDGMENT
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