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Non Uniform Blur and Illumination Variance Face Recognition Using Local Binary Pattern

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Abstract- Face recognition has made significant advances in the last decade, but robust commercial applications are still lacking. Current authentication/identification applications are limited to controlled settings, e.g., limited pose and illumination changes, with the user usually aware of being screened and collaborating in the process. Among others, pose and illumination changes are limited. To address challenges from looser restrictions, this paper proposes a novel framework for real-world face recognition in un-controlled settings named Face Analysis for Commercial Entities (FACE). Its robustness comes from normalization correction strategies to address pose and illumination variations. 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 paper, we propose a 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.

1. INTRODUCTION

Real word face recognition in unconstrained scenarios is still a major challenge for biometrics. The reasons are manifold. Among them is the fact that gallery (stored) enrolled face images are usually captured in controlled settings, using a predefined arrangement of subjects and capture devices, whereas the probes (test images) are captured in quite different settings. The latter usually present looser restrictions, which significantly increase intra class variability, so that pose and illumination, as well as expression and occlusions, may become disturbing factors. The goal for Face Analysis for Commercial Entities (FACE), the novel framework for automatic authentication of biometric face images that we present in this paper, is to address the existing challenges and to advance biometric identity management for real-world commercial applications. Illumination and pose variations are among the crucial factors that may and actually do hinder correct recognition within such operational scenarios. Becker and Ortiz evaluated some of the most popular and well-established algorithms for face recognition (principal component analysis (PCA), LDA, ICA, and SVMs) to assess the feasibility of real-world face recognition in uncontrolled setting using data drawn from Facebook. The cited work reports that none of the algorithms evaluated is robust enough to cope with the variations occurring during the data capture stage and that face recognition performance for real application is significantly lacking.

A major issue in uncontrolled settings is the quest of performance invariance relative to the above mentioned factors. There is thus much need for a stepwise and robust quantitative assessment during biometric system operation regarding the following: 1) the quality of biometric samples; 2) the reliability of the recognition responses; and 3) their combined effect on the identification decisions made. Such an assessment helps with decision making, including the choice for further guided biometric processing. FACE currently performs identification (1: N matching) using both closed- and open-set recognition assumptions. Among the possible variations affecting face recognition, it specifically addresses pose and illumination changes. Toward that end, FACE implements correction procedures to normalize the face biometrics captured to a frontal pose using uniform illumination. In addition, it implements a related strategy for the derivation of indices for image quality and their combined use data fusion during authentication. The experimental results reported show that this significantly reduces the impact of image variability on the accuracy of the face recognition system. The proposed procedures employ a cloud of interest points on the input face image, which are used to correct the pose through affine transformations of their corresponding regions two quality indices, are defined for this purpose, which are inversely related to the "effort" that would be needed to correct the original biometric image. The Sample Pose (SP) index accounts for pose quality (which is inversely proportional to measured distortion), and the Sample Illumination (SI) index accounts for illumination quality (which is inversely proportional to measured variations). In both cases, a high index value indicates high quality; owing to these quantitative indices, some biometric samples can be discarded.

2. LITERATURE

Traditionally, blurring due to camera shake has been modelled 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]–[7], recent methods for image restoration have modelled the motion-blurred image as an average of protectively 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) De-blurring-based [13], [14] in which the probe image is first de-blurred and then used for recognition. However, de-blurring art-facts are a major source of error especially for moderate to heavy blurs. (ii) Joint de-blurring and recognition [15], the flip-side of which is computational complexity. (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 re-blurred 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 [20] and (ii) extracting and matching illumination insensitive facial features [21], [22]. Tan et al. [23] 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 in [24]. 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. A good survey article on this issue can be found in [25].

3. POSE AND ILLUMINATION DISTORTIONS

A way to measure the quality of a FACE probe is to consider the amount of effort that would be needed to correct for pose and illumination distortions in the image, with larger corrections yielding lower quality distortion indices. The normalization procedure aims at recovering a frontal pose of the face presented in the input image, starting from the points located using the STASM approach in, as sketched previously. The distribution of such points on the face is a good starting point to evaluate the degree of distortion that needs to be corrected by the pose normalization process.

3.1 The illumination problem

Images of the same face appear differently due to the change in lighting. If the change induced by illumination is larger than the difference between individuals, systems would not be able to recognize the input image. To handle the illumination problem, researchers have proposed various methods. It has been suggested that one can reduce variation by discarding the most important Eigen face. And it is verified in [18] that discarding the first few Eigen faces seems to work reasonably well. However, it causes the system performance degradation for input images taken under frontal illumination.

In [19], different image representations and distance measures are evaluated. One important conclusion that this paper draws is that none of these method is sufficient by itself to overcome the illumination variations. More recently, a new image comparison method was proposed by Jacobs et al. [20]. However this measure is not strictly illumination-invariant because the measure changes for a pair of images of the same object when the illumination changes.

An illumination subspace for a person has been constructed in [21, 22] for a fixed view point. Thus under fixed view point, recognition result could be illumination–invariant. One drawback to use this method is that we need many images per person to construct the basis images of illumination subspace.In [23], the authors suggest using Principal Component Analysis (PCA) to solve parametric shape-from-shading (SFS) problem. Their idea is quite simple. They reconstruct 3D face surface from single image using computer vision techniques. Then compute the frontal view image under frontal illumination. Very good results are demonstrated.

I will explain their approach in detail later. Actually, there are a lot of issues in how to reconstruct 3D surface from single image.

3.2 The pose problem

The system performance drops significantly when pose variations are present in input images. Basically, the existing solution can be divided into three types: 1) multiple images per person are required in both training stage and recognition stage, 2) multiple images per person are used in training stage but only one database image per person is available in recognition stage, 3) single image based methods. The second type is the most popular one.

3.3 Motion Blur Model for Faces

Motion blur is the apparent streaking of rapidly moving objects in a still image or a sequence of images such as a movie or animation. It results when the image being recorded changes during the recording of a single exposure, either due to rapid movement or long exposure.The apparent motion of scene points in the image will vary at different locations when the camera motion is not restricted to in-plane translations. In such a scenario, the space-varying blur across the image cannot be explained using the convolution model and with a single blur kernel. In this section, we present the space-variant motion blur model [8]–[10], [29] and illustrate how this model can explain geometric degradations of faces resulting from general camera motion.

To implement the motion filter, once convolved with an image, the linear motion of a camera by len pixels, with an angle of theta degrees in a counterclockwise direction. The filter becomes a vector for horizontal and vertical motions. The default len is 9 and the default theta is 0, which corresponds to a horizontal motion of nine pixels.

To compute the filter coefficients, h, for 'motion':

- Construct an ideal line segment with the desired length and angle, centered at the center coefficient of h.
- For each coefficient location (i,j), compute the nearest distance between that location and the ideal line segment.
- h = max(1 - nearest_distance, 0);
- Normalize h:h = h/(sum(h(:)))

3.4 Local Binary pattern

Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994. It has since been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets.

The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g. 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e. clockwise or counter-clockwise.
- Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

The feature vector can now be processed using the Support vector machine or some other machine-learning algorithm to classify images. Such classifiers can be used for face recognition or texture analysis.

4. EXPERIMENTAL RESULTS

The following are some of the input images used as database.

Fig -1: input face images

Each image is varied with different illumination changes, pose variations and motion blur both uniform and non uniform.

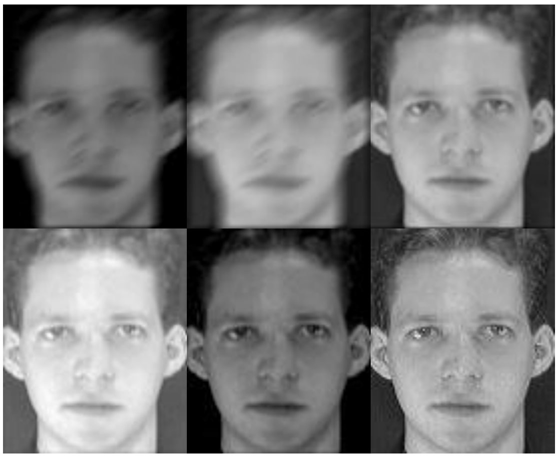

Fig -2: a combination of input images with illumination variations

Fig -3: Combination of input images with motion blurs variations uniform and non uniform

Fig -4: Input images with pose variations

Once LBP features are extracted from the images, they are saved in the database. When the test image, is given the feature of the test image is matched with the database features and the recognized feature is matched.

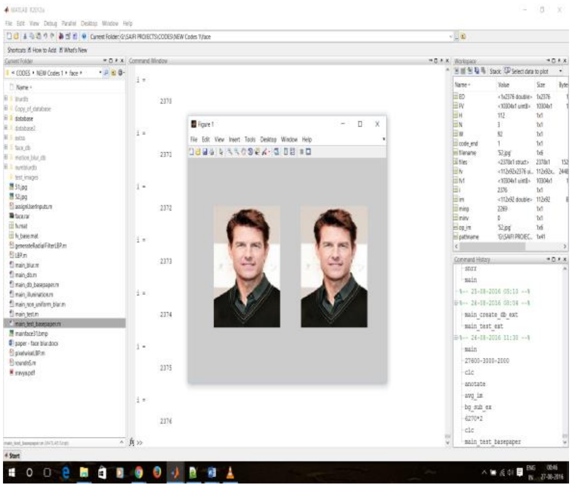

Fig -5: face recognition result

5. CONCLUSION

We 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. Capitalizing on this result, we initially proposed a 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 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

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