Face Recognition across Non-Uniform Motion Blur Using Efficient Feature Extraction Algorithm

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Abstract:
Efficient face recognition has been a challenging problem for researches in the field of image analysis for years. The main factors that make this problem a challenging are image degradation due to blur, illumination and pose. Face recognition system should be able to detect the faces automatically in all unconstrained environments. As security of information is important, security cameras are common nowadays. Current Face recognition systems are based on convolution model is insufficient for describing non-uniform motion blur arising from relative motion between camera and subject. But the existing system, proposed a method for face recognition in the presence of space varying motion blur which is not explained by the convolution model with a single blur kernel in which blur is uniform across the image. We propose an efficient algorithm for face recognition in non-uniform (i.e., space-varying) motion blurs using Scale Invariant Feature Transform (SIFT) for facial feature extraction. Face recognition rate, in the existing system using Local Binary Pattern (LBP) is comparatively lower than the proposed system, especially for images with low PSNR. In the proposed system, face recognition rate, can be increased by using Scale Invariant Feature Transform (SIFT). This fast and efficient algorithm is able to recognize human faces with good accuracy in unconstrained environments like blur. First section describes the existing system and the second section describes the proposed system.

I. INTRODUCTION

Face recognition is becoming growing because of rapid advancement in technology like mobile, digital cameras and internet. It has been conducted now for almost 50 years. It has always been a very challenging task for the researches. It is used for the verification and recognition of individuals. We can find many other identifications such as password, PIN, fingerprints, iris etc. and verification techniques, but face recognition is the main attraction because facial recognition system works automatically without the cooperation of persons and the passers are not aware of the system. As face recognition system can identify individuals among the crowd, they can be used in airports and other public places. Other biometrics cannot perform this mass identification. An unauthorized person can come up with guessed PIN and passwords on getting a lost ATM card or credit card. Facial recognition systems are used to confirm employee attendance at work places. There are many other applications of face recognition system including security system [1]. Surveillance system in air ports helps to identify criminals, terrorists and wanted individuals passing through the airport. Facial recognition software can be used to prevent voter fraud, people from obtaining fake identification cards and driver’s licenses. This technology could be used as a security measure at ATMs, instead of using a bank card or personal identification number. The customer’s face is captured by the ATM and confirms its identity, by comparing it in the bank data base. Facial recognition systems are also used to unlock software on laptops and mobile devices. Facial recognition is used to ensure, only this person can use certain applications which they choose to secure.

Current face recognition systems perform well under controlled conditions like focal length. But the performance of the face recognition system affected under uncontrolled conditions like blur, changes in illumination, pose etc. which may cause significant image degradations. Figure below shows the focused image and synthetically blurred image obtained by applying random in-plane translations and rotations on the focused image.

Fig 1.1 (a)Focused image and (b) synthetically blurred image.

In real-world, face images blur is unfortunately often present. It is usually originated from uncontrolled conditions like camera motion, focusing. Motion blur is caused due to relative motion between the scenes and recording devices. For face recognition, significant steps have been made in solving problems in controlled conditions but the face recognition is becoming challenging problem in uncontrolled conditions. The camera motion is a pertinent problem because the in-built sensors of the camera have the limitations in sensing the camera motion.

A basic face recognition system is shown in figure below. Recognition algorithms extract feature vectors from a probe image and search the database for the closest vector to decide a match or non-match.
The transformation matrix corresponding to each gallery texture operator has been using minimizing the optimization.

The space varying blur across the image cannot be explained by the convolution model with a single blur kernel. The presence of space varying blur across the image which is explained by the LBP operator. Due to this reason, LBP operator is also useful in analyzing simplicity in computation, LBP
teach pixel and the result produced as a binary number. Due to its property of the LBP operator. Due to this reason, LBP operator is also useful in analyzing

The proposed system presents an efficient Face recognition model using Scale Invariant Feature Transform (SIFT) along with the Local Binary Pattern (LBP). The face recognition system in the existing system using LBP and the proposed system using SIFT with LBP to extract facial features for recognizing faces. SIFT provides higher face recognition rate than LBP because SIFT detects important, stable feature points in an image which are invariant to rotation and scale. The face recognition proceeds by matching facial features of probe image to a database of features from a set of gallery images using a fast nearest-neighbor algorithm.

Local Binary Pattern (LBP) is a simple texture operator which labels the pixels of an image by comparing the neighborhood of each pixel and the result produced as a binary number. Due to its simplicity in computation, LBP texture operator has been using in various applications. Robustness is the most important property of the LBP operator. Due to this reason, LBP operator is used in real-world applications like illumination variations. LBP operator is also useful in analyzing images in real-time settings by its important property called computational simplicity.

In previous work, blurring due to camera shake is a convolution model with a single blur kernel, and the blur is assumed to be uniform across the image. However, it is space-variant blur that is present frequently in hand-held cameras which is not explained by the convolution model. The existing system explains a method for face recognition in the presence of space varying blur across the image which is produced by the relative motion between the camera and object. The space varying blur across the image cannot be explained by the convolution model with a single blur kernel.

I. Face Recognition Across Non-Uniform Motion Blur

The energy function of transformation spread function is given,

\[ E(h_T) = \frac{1}{2} \beta \| h_T \|^2_1 + \gamma \| g - A h_T \|_2^2 \]

This energy function provides an estimate of the transformation when it is minimized. This estimate is applied to the gallery image to produce the blurred image. In the above equation, all the pixels receive equal weight. But all the regions in the face contains different information. So the above equation is modified by including a weighted matrix W. This weighted matrix gives different weights to different regions in the face.

The reconstruction error between gallery image and probe image is obtained by minimizing the energy function [15] that is,

\[ dm = \min_{h_T} \| W(g - A h_T) \|_2^2 + \beta \| h_T \|_1 \]

The value of \( dm \) can be computed for each \( m=1,2,\ldots,M \) and assign \( g \) the identity of the gallery image with minimum \( dm \). For face recognition, \( dm \) is not preferable as a metric, so local binary patterns (LBP) [14] can be used which is robust to errors. For this first find optimal TSF \( h_{Tm} \) for each gallery image.

\[ h_{Tm} = \arg \min_{h_T} \| W(g - A h_T) \|_2^2 + \beta \| h_T \|_1 \] \hspace{1cm} (3)

where \( w \) is a weighing matrix which weighs differently at different regions in the face.

Now each gallery image is blurred by the corresponding \( h_{Tm} \). Divide each blurred gallery image and probe image into rectangular blocks and extract LBP histograms from each block and concatenate the histograms. Then compare the obtained histograms (global descriptor) as feature vectors for the best match between probe image and gallery image.

The system used gray scale images resized to 64x64 pixels and one image per subject in the gallery from FERET database. This database contains only focused images. The algorithm evaluated on five different blur settings. The steps are given in the algorithm 1 below.

1.3 Block diagram of Existing system

**Algorithm 1:** Algorithm for Recognizing Blurred Faces in the existing system

**Input:** Blurred probe image and a set of gallery images.

**Output:** Identity of the probe image

1. Find the optimal TSF using the equation (3)
2. Form the convex set of blurred images associated with each gallery image by the corresponding optimal TSF.
3. Extract LBP features of both probe image and blurred gallery images.
4. Compare the LBP features of probe image with the LBP features of blurred gallery images and find the closest match.

This face recognition algorithm is based on TSF model. All possible transformations that exist in 6D space are applied on each gallery image and stack the resulting transformed images as
columns of a matrix. The set of all blurred images form a convex set. A probe image is recognized by minimizing the distance between the probe and the convex combination of the columns of the transformation matrix corresponding to each gallery image. The gallery image whose distance to the probe is minimum is identified as a match.

III. PROPOSED SYSTEM

In this project we adopt an efficient feature extraction method to improve the accuracy of the existing system for face recognition across non-uniform motion blur. Our proposed approach to deal with the recognition of blurred faces in presence of space varying motion blur is described in Algorithm 2 below. It includes two feature extraction methods - LBP and SIFT.

Algorithm 2: Algorithm for Recognizing Blurred Faces in the proposed system

Input: Blurred probe image and a set of gallery images.

Output: Identity of the probe image
1. Find the optimal TSF and form the convex set of blurred images associated with each gallery image by the corresponding optimal TSF.
2. Extract LBP features of probe image and each blurred gallery image. Then compare these features and decide a match or non-match.
3. Extract SIFT features of probe image and each blurred gallery image. Then compare these SIFT features and decide a match or non-match.

The main advantage of the existing method is the face recognition in the presence of space varying motion blur which is not explained by the convolution model with a single blur kernel in which blur is uniform across the image. However, our experiments have showed that the additional feature extraction method using Scale Invariant Feature Transform (SIFT) provides robust matching and provides higher face recognition rate than LBP especially in images with low PSNR. SIFT algorithm is fast, reliable and efficient than LBP and lots of codes are available for its algorithm.

SIFT is a method to detect and describe important stable feature points in an image. For every such point, it provides a set of features that describe a small region around that point. These features not vary with scale, rotation, blur, illumination etc. SIFT is used in many applications and these applications need to detect these feature points in two or more images and compare the match between them.

One could try matching patches around the salient feature points. But these patches will themselves change if there is change in object pose or illumination. So these patches will lead to several false matches. SIFT provides features characterizing a salient point that remain invariant to changes in scale or rotation.

2.1 Local Binary Patterns (LBP)

The LBP method has been used in face recognition system due to its computational simplicity and distinguishing feature. The LBP texture analysis operator was first proposed in [16]. For image processing divide the face into small rectangular regions (e.g. 16x16 pixels for each cell). This helps to get the minute details of face and each pixel of an image is assigned with a pixel value. Then compare the pixel value of a central pixel with eight neighbors (3x3 neighborhood) and considering that result as a binary number. Follow the pixels along a circle, i.e. clockwise or counter-clockwise.

To each neighbor pixel value, ‘1’ is assigned if that neighbor pixel is having higher gray value than the central pixel (or the same gray value) and value ‘0’ is assigned to that pixel if neighbor is having lower gray value than central pixel. This gives an 8-digit binary number. Compute the histogram in one rectangular region and concatenate histograms of all rectangular regions. This gives a feature vector for the face.

1. The LBP histogram which contains the information about the patterns on a pixel-level.
2. Regional histogram which contains the information on a regional level is obtained by summing the pixel level histogram.
3. Global description of the face which contains the appearance and spatial relations of the face is obtained by concatenating the regional level histograms.

**Fig: 2.2 LBP Operator**

To increase the applicability of the local binary patterns (LBP) many methods have been proposed. For example, dominant local binary patterns were proposed in [16] to improve the accuracy of the face recognition system. The interest region descriptors (SIFT) is used in this project along with LBP.

**Figure 2.3: Face description with local binary patterns.**
2.2 Scale Invariant Feature Transform (SIFT) 

Scale invariant feature transform (SIFT) is an approach to detect and describe local facial features in images. It detects important stable feature points in an image called key points. It is called scale-invariant feature transform because the image is transformed into scale-invariant coordinates relative to local facial features. For every key point, it provides a small image region around the point. These features are invariant to rotation and scale. For the face recognition, the scale-invariant key points are first extracted from a set of reference images and stored in a database. The test image is recognized by individually comparing the scale-invariant features of test image to the features in the data base and finding the best match based on the Euclidean distance of their feature vectors.

The patches around the salient feature points are sufficient for matching in the face recognition across non-uniform motion blur. But these patches will themselves change if there is change in object pose or illumination and leads to false matches in these conditions.

Steps of SIFT algorithm

1. Determine approximate location and scale of salient feature points (also called key points).
2. Refine their location and scale.
3. Determine orientation(s) for each key point.
4. Determine descriptors for each key point.

Scale invariant feature transform (SIFT) algorithm generates a large number of key points. The number of key points is important for image recognition.

2.2.1 Approximate Key Point Location:
The points of interest in the image are termed key points in the SIFT framework. To detect key points with different scale, scale-space filtering can be used. Gaussian function in [18] and [19], is taken as the scale-space kernel. The scale space of an image is defined as a function, \( I(x,y) \). The scale space of an image is obtained by the convolution of a variable-scale Gaussian \( G(x,y,\sigma) \) and input image, \( I(x,y) \):

\[
L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) = \frac{1}{(2\pi\sigma)^{2}} e^{-\frac{(x^2+y^2)}{2\sigma^2}} I(x,y)
\]

where \( G(x,y,\sigma) = (1/(2\pi\sigma^2)) e^{-\frac{(x^2+y^2)}{2\sigma^2}} \) and \( * \) is the convolution operation in x and y. Convolution operator refers to the application of a filter. Scale refers to the \( \sigma \) of the Gaussian. The image is convolved with Gaussian filters at different scales, and then the difference of successive Gaussian-blurred images is taken. Difference of Gaussians subtracts one blurred version of an original grayscale image from another, less blurred version of the original. The Difference of Gaussians can be used to get all details including the edges present in a digital image. For getting difference of Gaussian (DoG), the image is Gaussian blurred with two different scale parameters \( \sigma \) and \( k\sigma \). This process is repeated for each octave in the Gaussian Pyramid. Scale space is separated into octaves. Stable key point locations in scale space have proposed. The convolution of difference-of-Gaussian function (DoG) and the input image \( I(x,y) \) can be computed from the difference of two adjacent scales in an octave.

\[
D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y) = L(x,y,k\sigma) - L(x,y,\sigma)
\]

DoG is used to identify key points that are invariant to scale and orientation. By using this function \( D \) can be computed by simple image subtraction.

Figure 2.4: Construction of DoG

Figure above shows an efficient approach to obtain \( D(x,y,\sigma) \). Here octave is equivalent to doubling of \( \sigma \). Two nearby Gaussian blurred images within an octave, differ by a constant factor \( k \). If an octave contains \( s+1 \) images, then \( k = 2^{(1/s)} \). The scale of the first, second, third images have the scales \( \sigma_0, k\sigma_0, k^2\sigma_0 \) respectively and the last image has scale \( k^s\sigma_0 \). Scale space. Scale space images in an octave are obtained by the repeated convolution of the initial image with Gaussian. Such sequences of images convolved with Gaussians of increasing \( \sigma \) constitute a so-called scale space. The difference of Gaussian is obtained by subtracting adjacent Gaussian images on the right. For the next octave, the Gaussian image is down-sampled by a factor of 2. Thus the next level will start with \( \frac{1}{4} \) the size of the previous octave and the process repeated.

2.2.2 Detection of Local maxima and minima

After finding the differences of Gaussian (DoG), find the local maxima and minima in the image over scale and space. Figure shows the method of finding local maxima and minima. The pixel marked at X is compared with its 8 neighbors as well as 9 pixels in the next and previous scales. If this point is a local maxima or minima, it is considered as a potential key point.

IV. EXPERIMENT AND DISCUSSIONS

In this section we have addressed the problem of face recognition in non-uniform motion blur. The algorithm applied is used to test the performance of the system. To conduct experiment probe image is synthetically generated by blurring the focused images in the database. For the computational simplicity we use gray scale images resized to 64x64 pixels. Every focused gallery image of size 64x64 is synthetically blurred with the TSF which is created by four blur settings. For each image, thus a convex set is formed. To compare the performance of the proposed approach in face recognition of blurred faces, we evaluated the existing system and the proposed system. To evaluate the proposed system, first extract LBP features from the probe image and every gallery images. Then extract the SIFT features of probe and every gallery images. SIFT features transform image data into scale-invariant coordinates relative to local features. After this, compare the LBP features first and then the SIFT features. SIFT algorithm uses stable, robust and distinctive local feature matching.

The system is said to be successfully recognized when the features of the probe and gallery images are found similar. When two images are completely similar, produces maximum value (equal to one). Whereas, the least similar pair produces the minimum value (equal to zero). When run on the algorithm, the
proposed system shows a high recognition rate than the existing system. Table below compares the results of two approaches LBP and SIFT. We can notice that SIFT works very well at low PSNR (peak signal to noise ratio).

![Fig 3.1 a- Probe image, b- focused gallery image, 1 to 4 synthetically blurred gallery images.](image)

RESULT:

![Fig3.2](image)

TABLE 1: Recognition Results (%) of existing and the proposed system with comparisons

<table>
<thead>
<tr>
<th>PSNR of probe image</th>
<th>LBP</th>
<th>SIFT</th>
</tr>
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<tbody>
<tr>
<td>5</td>
<td>55</td>
<td>68</td>
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<tr>
<td>35</td>
<td>90</td>
<td>96</td>
</tr>
</tbody>
</table>

![Fig3.3](image)

**Comparison Graph**

![Fig 3.4](image)

Fig 3.4 Recognition Results (%) of existing and the proposed system with comparisons (series1-Existing System and Series2-Proposed System)

![Fig 3.5](image)

Fig 3.5 Recognition Rate of existing system using LBP

![Fig 3.6](image)

Fig 3.6 Recognition Rate of Proposed system using SIFT

**V. CONCLUSION**

Face recognition has got great attention by its wide applications in the field of image processing. We proposed an efficient, robust and reliable face recognition algorithm across non-uniform motion blur. We performed experiments on existing system and proposed system to compare the performance of these systems. The combined effect of the LBP and SIFT algorithms are used in the proposed system. SIFT detects important, stable feature points in an image and these features are invariant to rotation and scale. The results show that the proposed system is very sensitive to space varying motion blur. We also notice that this SIFT works very well at low peak signal to noise ratio (PSNR). The limitation of our approach is that space variants like illumination and pose cannot be handled.

**VI. REFERENCES:**


