Non-Uniform Motion Blur For Face Recognition

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Abstract: As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention, especially during the past several years. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. In other words, current systems are still far away from the capability of the human perception system. 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. We propose a methodology for face recognition under non uniform motion blur and recognition of facial emotion.

I. INTRODUCTION

The accuracy of the face recognition systems is same as unconstrained settings. These degradations arise from Blur, illumination, pose, expressions and occlusions etc. The motion blur is special attention in mobile phones and hand held cameras. To capturing an image the camera shake is a very relevant problem because it reduces the quality of the image. The inbuilt sensors are gyros and accelerometers they have their own limitations in sensing the camera motion.

The illumination and pose could vary in uncontrolled environment the quality of the image is changes. It proves that system can recognize the face across non uniform motion blur illumination ad pose. Some typical applications of the face recognition are biometrics, information security, and law of enforcement, surveillance, smart cards, and access control during the past five years face recognition received increased attention and advanced technologies. [1] Now many commercial systems using face recognition are available.

The camera shake problem is modeled as convolution model and a single blurred kernel. The blurred data is assumed to be uniform across the image. If it is space variant blur it frequently encountered in hand held cameras. It is very difficult to find the blurred data in focused gallery images. The approaches of the face recognition can be broadly classified as
1. Deblurring based probe image
2. Joint deblurring and recognition
3. Blur invariant features for face recognition
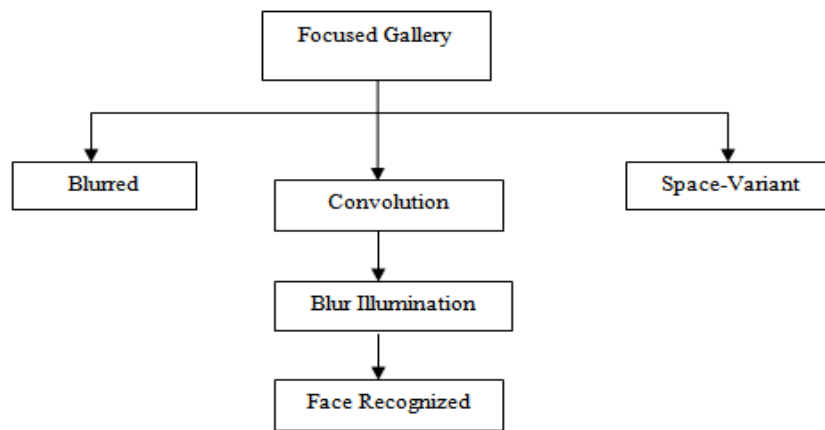4. Direct recognition probe image.

Figure 1: General Block diagram for Face recognition

The above all approaches are simplistic space invariant blur model. For handling illumination they are mainly two directions 1. 9D subspace model for face 2 Illumination matching and extracting the facial features. To combine the above two methods it includes the initial illumination for face recognition under difficult lightning conditions. The face recognition across pose can be broadly classified as 2D and 3D techniques.

In face recognition first 2D technique is used to eliminate the errors in 2D technique we go to 3D technique. The 3D technique is useful for face recognition. In face recognition the image formation process is important the input is blurred image and the output is the sharp image do the convolution operation we get the blur kernel image [2]. The natural image statistics are de noising, super resolution, and intrinsic images, in painting, reflections and video matting.

In recent work addresses the problem identification from the distant cameras for both blur and illumination are observed, so the illumination is nearly approximated to the convolution model. The face recognition algorithm that is non uniform motion blur arising the relative motion between the camera to subject. Assume that only one gallery image is available the camera transformations range from in-plane rotations to out of plane translations it is done in 6D motion.

In face recognition across non uniform motion blur, illumination and pose having the algorithm is TSF (Transformation Spread Function) algorithm. The weights corresponding to the wraps are referred to as the Transformation Spread Function. And each warp is considered as its weight. While the significant progress is used removing blur from given images finally convolution of a sharp image with spatially uniform filter is formed [3]. It consider the limitation of blind deblurring, where only one single blur is available to add some noise to that image again same scene is available but some noise is added to the image the task of recovering an image it is called as blind-de blurring.

The working of the TSF model is shows the set of gallery images obtained by the particular gallery image. And the optimal TSF is compared with the LBP (Local Binary Pattern). It proposes the extension to the basic frame work for handle the variations illumination and pose. It is done in 9D subspace model. And the next algorithm is MOBIL (motion Blur Illumination and Pose) the motion blurs and illumination uses the alternating minimization (AM) scheme. The AM scheme is used for solve the TSF weights it is in the first step and the second step is to solve the nine coefficients totally. And finally transform the gallery image and it compare with the probe in LBP space.

Image deblurring is one of the best topics in the face recognition. The image deblurring received a lot of best attention in the computer field [4]. De blurring is defined as it is the combination of main two sub problems they are one is the PSF estimation and another one is de blind convolution. The above two problems are long standing problems in image processing, computer vision and computer graphics.

To extend this formulation and propose another algorithm to handle blur, illumination and pose that is MOBILAP (Motion blur Illumination And pose). And it is used for non-frontal faces. In this type of algorithm also the gallery image is compared with the LBP probe image. In hand-held cameras tilts and rotations are occur frequently. Only using the plane transformation model it reduces the both PSF and TSF. In the proposed work the state of the art is discussed in many ways:

1. It is the first attempt to prove synthetically addresses the face under i. Combined effects of blur illumination and pose ii. Non uniform motion blurs.
2. It proves that the set of all images obtained by non- uniformly blurring a given image and forms a bi-convex set.

3. And it proposes the multi scale implementation in this type the memory usage is high.

II. LBP (LOCAL BINARY PATTERN)

LBP is very powerful method to explain the texture and model of a digital image. In LBP the face is first split into different small regions and the LBP histograms are extracted finally it concentrated on a single image. The vector the efficient representation of the face and it can be used to measure the similarities between the images. The area of the LBP (local Binary Pattern) is originally designed for texture description. In the LBP histograms mainly used for facial representation this features mainly depends on the facial expression recognition. Main properties of the LBP are their tolerance against the illumination changes for computational simplicity.

III. CONVOLUTION MODEL FOR SPACE – IN VARIANT BLUR

Convolution model is very sufficient for describing blur in plane camera translations. While the focused gallery image is generate a probe. The TSF algorithm follows the multi channel blind de convolution technique [5]. It is accurately determine the blur kernels from two images. The blur kernels are the either of the depth layers. They are mainly two layers one is TSF and PSF they form a linear equation and it solve the least mean square error. The convolution model presents the non uniform motion blur, space invariant blur and the input is focused gallery. It presents the space invariant blur and its weighted coefficients are considered as geometrically warped instances of the gallery. And finally compare the errors between the probe and gallery re blurred image.

IV. MOTION BLUR FOR FACES

In plane translations the camera motion is not restricted. Using the space-variant blur the image cannot explain perfectly so, the TSF have non zero weights in plane translations. The effects of blur are normally arising due to out of focus lens, atmospheric turbulence, and relative motion in between the sensor and objects in scene [6]. The goal of the de blurring is to estimate the clean image observed in the blur image.

Non Uniform Motion Blur-Robust Face Recognition (NU-MOB):
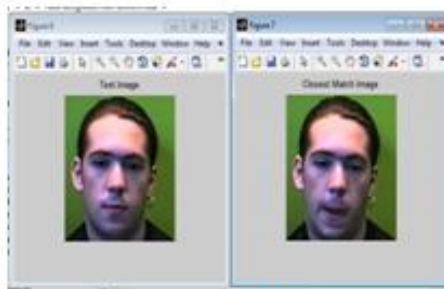*Input:* Blurred probe Image g, and set of gallery Images f_m, m=1,2,….M
Output: Identity of the Probe Image.
1. For each gallery image f_m, the Optimal TSF ht_m.
2. Blur each gallery f_m, with its corresponding ht_m and extract LBP features.
3. Compare the LBP features of the probe image g, with those of the transformed gallery images and find the closest match.
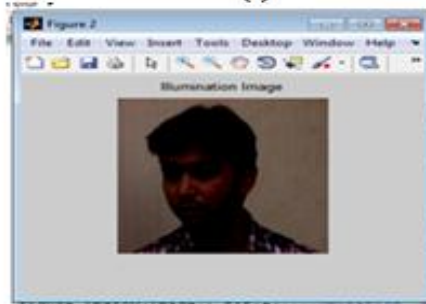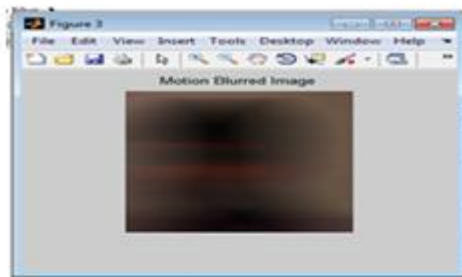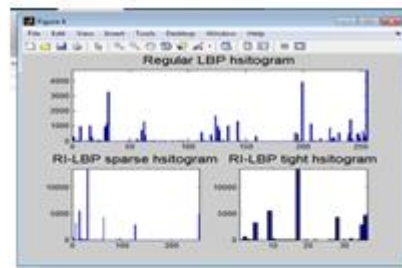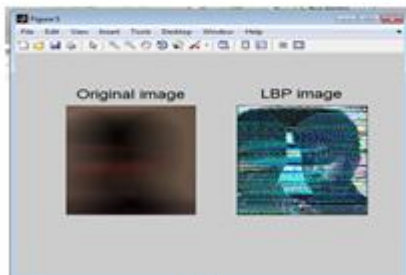

(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

(i)

(j)

(k)

(l)

(m)

(n)

(o)

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(q)
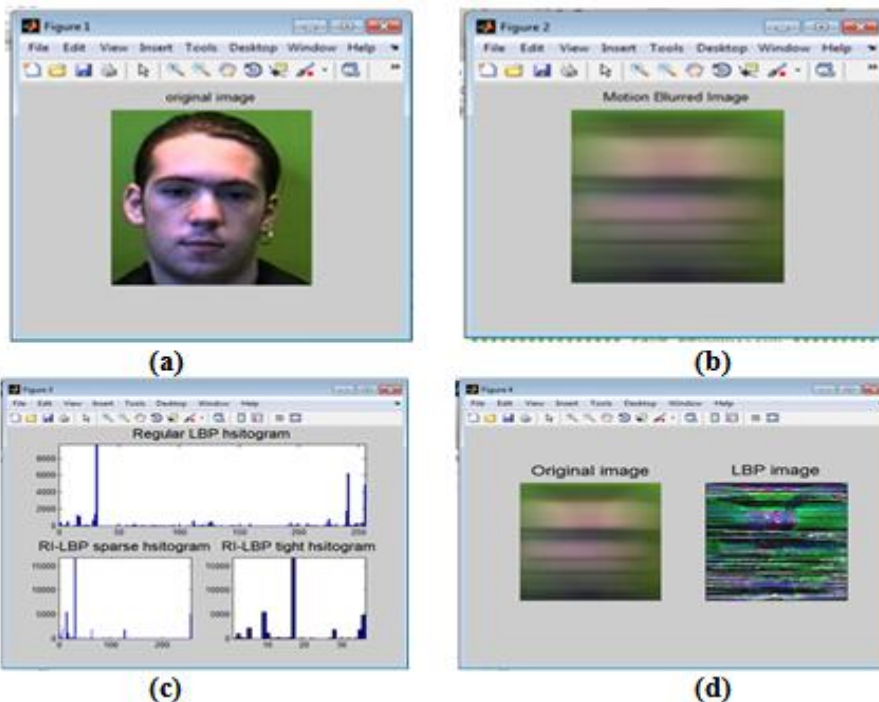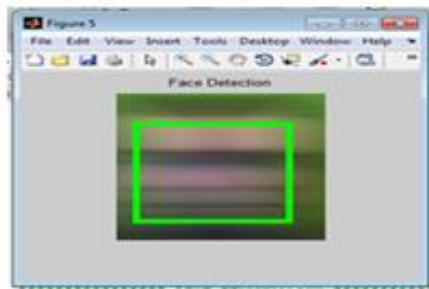
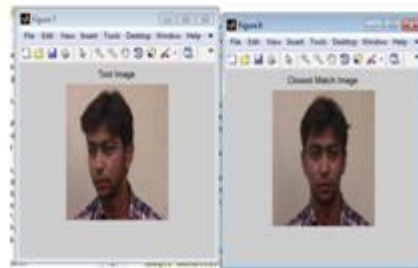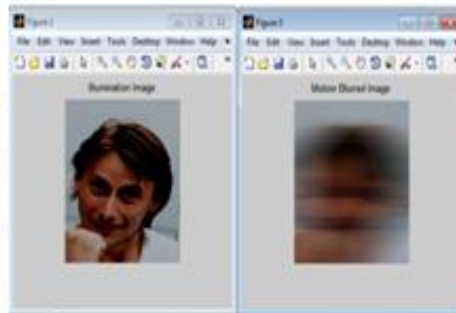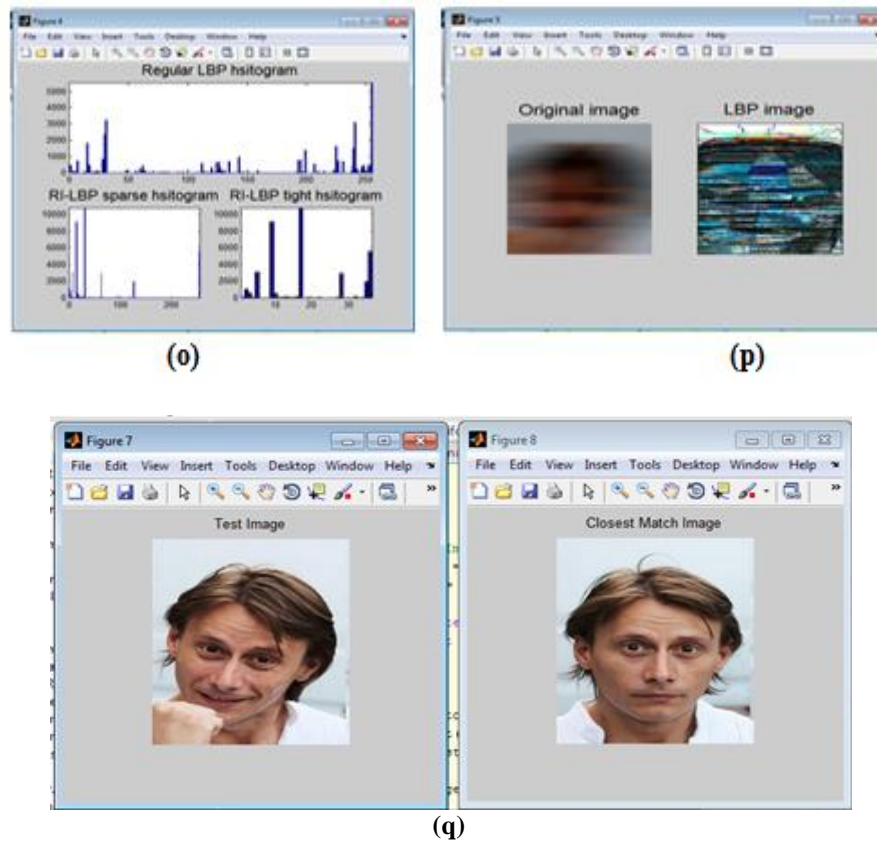**Figure 2: (a) Original Image (b) Non Uniform Motion Blurred Image (c) Regular LBP histogram for Blurred Image (d) original Image and its corresponding image (e) Detected face image (f) Detected face image and its corresponding closest match (g) Original image (h) Illumination Image (i) Blurred and Illuminated Image (j) Regular histogram for input image (k) Original image and its corresponding LBP image (l) Detected face image and its corresponding Closest match (m) Original Image for Illumination and motion blur (n) Illumination and motion blur (o) Regular LBP histogram for input image (p) Original image and its corresponding LBP image (q) Detected face image and its corresponding closest match.**

The image is divided into different blocks so, the face can be seen as a micro patterns. Then it is encoded by LBP histogram while the whole shape of the face is recovered by the global histogram. The global histogram encodes the both face appearance and facial region while the TSF ht_m performs the non blind de blurring of a probe. The de blurring introduces to reduce the accuracy of face recognition nearly 15% to 20% it is preferable for perfect face.

To recognizing the blurred faces it would be de blur first and then it recognized [7]. In the set-theoretic characterization it proposes the blur-robust algorithm. It finds the distance of the probe image and the set of the gallery images. It does not assume parametric form for the kernel images if the information is available otherwise there is no information in the gallery probe image. Fix the blur kernel then changes occur in the pose and illumination and form a convex set. The working of the NU-MOB algorithm is blur the images and generates the probes. In this type assume the gallery image pixels is 64x64 it is only for one image per subject in our gallery. Using the multi scale implementation to obtain the speedup of algorithm. The algorithm's performance is high as well as the blur in the image is increased.

V. FACE RECOGNITION ACROSS BLUR, ILLUMINATION AND POSE

Poor illumination is not preferred for blurred images because of it contains lack of light and increases the chances to camera shake. And the pose is another challenging task in face recognition it handles the combined effects of blur and illumination. To modify the NU-MOB algorithm to avoid the changes in illumination variations in an image.

Motion Blur, Illumination and Pose-Robust Face Recognition (MOBILAP)
    Input: Blurred And Differently Illuminated Probe Image g Under a Different Pose, and a set of gallery Images f_m, m=1,2…...M.

Output: Identity of the Probe Image.
1. Obtain an Estimate of Pose of the blurred probe image.
2. For each gallery image f_m, synthesize the new pose f_{synm}.
3. For each synthesized gallery image f_{synm} obtain the nine basis images $f_{synm,i}$ i=1,2,…9 using normal recomputed from the rotated depthmap.
4. For each synthesized gallery image f_{synm} find the optimal TSF ht_m and illumination coefficients $\alpha_{m,I}$.
5. Transform the Synthesized Gallery Images f_{synm} using the computed ht_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.

The algorithm performance is measured in terms of sparsity and fidelity of the original signals [8]. The individual base elements are selected by using dictionary and it has particular schematic meaning and it is generated from random matrices. The sparsest representation is normally discriminative. The sparsest rejects the invalid samples and not arising any training samples from database.

$$[h_{Tm,}\propto_{m,i}] = argmin||W\left(g - \sum_{i=1}^{9}\propto_i A_{m,i} h_T\right)|| + \beta||h_T||$$

Subject to $h_T \geq 0$

$\alpha_m = \{\alpha\ m,1, \alpha\ m,2, \alpha\ m,3\ldots\ldots,\alpha\ m,9\}$ $\alpha_{m,I =}$ Illumination coefficients

Using local photometric features the object recognition is more general it becomes very widely context [9]. The bag of key points is not matched to the face recognition because it does not retain the any settings in the facial description detected from local regions. The texture analysis has developed a variety of different descriptors for the appearance of different image patches.
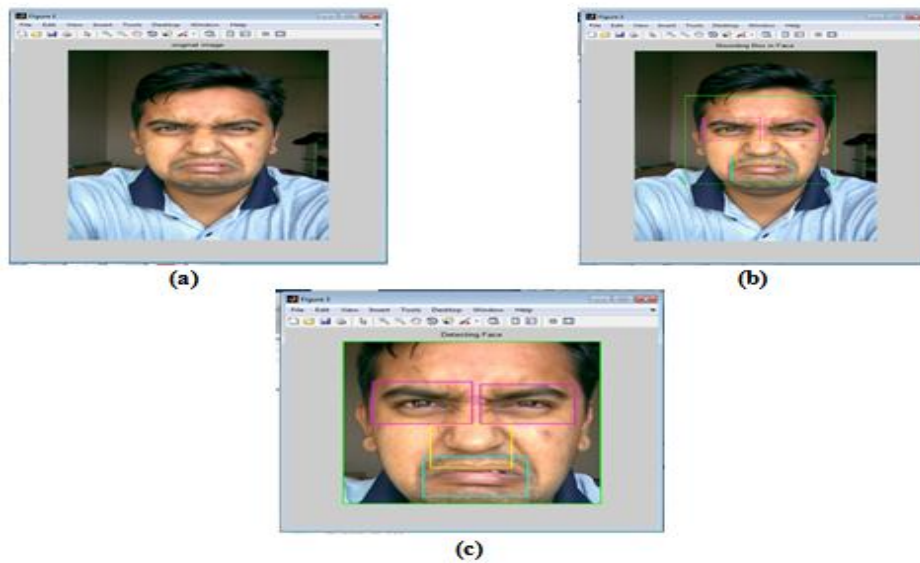

Figure 3: (a) original Image (b) Bounding Box of Eyes, nose and lips (c) Cropped face (d) Binary face detection (e) Detecting the facial emotion

In true pose being returned only 45-55% of the time. The probes when registered using gallery to the eye detected centers. In disease diagnosis the humans have a large number of genes only some small number of persons contributes the certain disease [10]. In neuroscience the neural representation of sounds in the auditory cortex of animals in the sparse. Finding sparse representation is fundamentally important in many fields.

Table1: Comparison of Proposed and Existing Methods

Parameters	NU-MOB	MOBILAP
Time	More Execution Time Above 60%	Less Execution Time 45-55%
Complexity	More Complex	Less Complex

VI. CONCLUSION

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 non-uniform motion blur-robust face recognition algorithm NU-MOB and 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. Finally extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose. The superiority of this method called MOBILAP over contemporary techniques.

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