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FACE RECOGNITION ACROSS NON UNIFORM MOTION BLUR, ILLUMINATION AND POSE

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Abstract: Current Face recognition systems consider the motion blur as a space invariant feature and uses simple convolution model for approximating motion blur. But in natural imaging, motion blur is non-uniform. So for face recognition in the presence of space varying motion blur, a methodology comprising of arbitrarily-shaped kernels is used. The blurred face is modeled as a convex combination of geometrically transformed instances of the focused gallery face using TSF Model. The probe image is compared with the convex combinations to find the best match. To handle illumination variations illumination normalization using DWT is used for the test image.

Keywords: Non uniform motion blur**,** TSF Model, DWT-MIN, Transformation Spread Functions, Illumination.

I. INTRODUCTION

The goal of a Face recognition system is to automatically identify a person's identity from a digital image Normally the system compares any of the features of the face image and finding a best match for recognition. But in case of a degraded image the system fails to recognize. This method presents a Face recognition system which aims to identify a person's face, even if, the captured image is degraded by non uniform blur, change in illumination and pose variations. A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame. One of the ways to do this is by comparing selected facial features from the image with a facial database. Non-uniform blurring situations may arise due to tilts and rotations in hand-held cameras. Also degradations occur due to changes in illumination, pose, expression, partial occlusions etc. Image captured at certain illumination condition and pose is taken as reference image. The lighting conditions and pose for the test images will not be same as that of reference image. So the resulting images will have illumination and pose variations and this may also affects the accuracy of the system. Hence a facial recognition system that overcomes these difficulties is required. At present individual systems that can recognize across non uniform blur, change in illumination and pose variations are available. Also the system, that available for blur, considers the blur as a space invariant feature. In practical case blurring effect is space variant or non-uniform in nature. But the requirement is a system that can

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accommodate these degradations simultaneously at a time and that considers blur as a space variant feature.

Single image deblurring algorithm [6] to remove non-uniform blur with lesser computational load with tolerable redundancy which constrains the camera poses into certain range of rotations. Hierarchical knowledge-based method is composed of the multi-resolution hierarchy of images and specific rules defined at each image level .The algorithm to remove the effects of blurring arise from serious handshakes [1] considers the assumptions that camera blur is space-invariant or uniform all over the image and the camera in-plane rotation is negligible. But the uniformity of blur over the entire image is rarely true for practical cases. So for real conditions a space-variant model of blurring is required. The geometrically consistent model of non-uniform image blur due to camera shake, arising from rotations of the camera based on the above method [18]. The model develops a global representation of parametrically non-uniform blur, using a single "blur kernel" analogous to a convolution kernel. The system is based on principle that, under the pinhole model of a camera, all views seen by the camera are projectively equivalent, excluding boundary effects. That is the image at one camera orientation is related to the image at any other camera orientation by a 2D projective transformation, or homography. And it extracts possible face candidates based on the general look of faces. This method suffers from many factors especially the RST variation and doesn't achieve high detection rate Face Detection Using Color Information work has [7] proposed to combine several features for face detection. They used color information for skin-color detection to extract candidate face regions Face detection based on random labeled graph matching. The probabilistic method to locate a face in a cluttered scene based on local feature detectors and random graph matching [5]. The facial feature detectors averagely find 10-20 candidate locations for each facial feature, and the brute-force matching for each possible facial feature arrangement is computationally very demanding. Adaptive appearance model is the traditional deformable template matching techniques, the deformation constraints are determined based on user-defined rules such as first- or second-order derivative properties [14]. The traditional techniques are mainly used for shape or boundary matching, not for texture matching.

II. PROPOSED SYSTEM

The proposed system is mainly composed of three parts. The first one is for the recognition across non uniform blur which can be implemented by Transformation Spread Function model. The remaining is for recognition across change in illumination and pose variations. Illumination problems can be solved by using DWT-MIN method and pose variations can be modeled by 3D morphable model of face. The detailed block diagram for the face recognition across non-uniform motion blur and change in illumination and is shown in the Figure 1. Gallery or Database of the system contains perfect, focused face images of the persons to be identified. Weight matrix algorithm computes the weight matrix for each of the gallery images. Weight matrix is a matrix which weighs different regions in the face differently. The gallery image and the test image are multiplied with this weight matrix before processing.

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Then 6D projectively transformed versions of the weighted Gallery image is computed where the 6D corresponds to 3D in rotations and 3D in translations. These projectively transformed versions of each of the gallery images are arranged as a column to form the image matrix. TSF model takes each column in the image matrix and weighted test image with blur as input and the model approximates the blurred test image as a weighted average of projectively transformed versions of the focused gallery image.

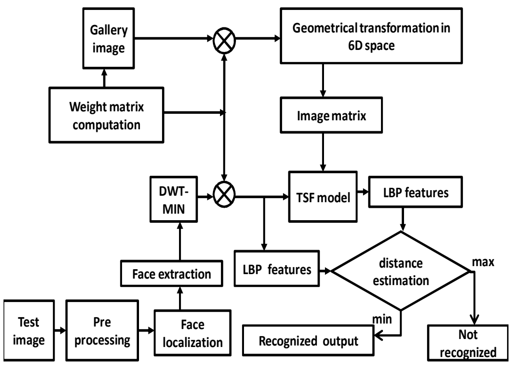

Figure.1: block diagram of face recognition system

The optimum TSF co-efficients are computed by comparing the linear combinations of each row in the image matrix with the blurred test image. These TSF parameters are used to find the synthetically blurred versions which are the approximations of naturally blurred images. The DWT MIN method is used for re-illuminate the test image. Local Binary patterns are taken for weighted test images and synthetically blurred and illuminated images before matching. The LBP histogram of the pose adjusted test image is compared with that of the synthetically blurred and illuminated image for recognition.

A. Weight Matrix Computation

The weight-matrix is used here to make the system robust to errors due to variabilities in facial expressions and misalignment. In case of face recognition, the most distinguishable parts in a face image are high frequency regions such as eyes, eye brows, nose, lips etc. and the unimportant parts are low frequency regions such as cheeks and forehead. Weight matrix helps to increase the importance of pixels in the high-frequency regions of the face in the kernel-estimation step by giving less weightage to low frequency regions.

The weight assignments for different parts of the face can be verified from Figure, where the weights obtained for the low frequency regions such as hair, cheeks and neck are very small; as these regions are less prone to show non-rigid variability. Finally, the eye regions are weighed the most since they are the more distinguishable features of the human face. This validates our hypothesis that more textured (high-frequency) regions of the face should contribute more towards the estimation problem. The algorithm for weight matrix computation is as follows.

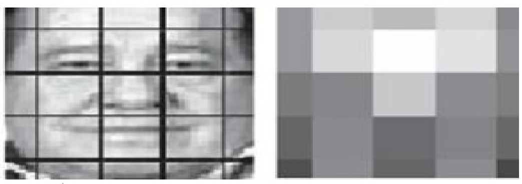

Figure.2: image and weight matrix

Step 1: Start.

Step 2: Input a gallery image.

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Step 3: Blur the input image with a Gaussian kernel.

Step 4: Partition the input and blurred images into patches.

Step 5: Find the recognition rate for each patch using Direct Recognition of Blurred faces algorithm.

Step 6: Assign weights for each patch proportional to the recognition rate observed.

Step 7: Stop.

1. DRBF Algorithm

DRBF (Direct recognition of Blurred Faces) is an algorithm for recognizing blurred faces from a set of gallery images by using the convolution model for blur. DRBF assumes that the set of all images obtained by blurring a given image is a convex set and the blurred face is a weighted average of the convex set. The algorithm is as follows.

Step 1: Start.

Step 2: Input a gallery image Ij and a probe image Ib

Step 3: For each gallery image, Ij find the hj by solving the following equation 4.1.

$$h_j = \operatorname{argmin}_h \|I_b - A_j h\|_2^2 \,;\, h > 0, \|h\|_1 = 1 \text{ ------ (1)}$$

In equation 1, A_j is a matrix contains projectively transformed versions of the gallery image.

Step 4: Blur each gallery image with its corresponding Ij and extract LBP features.

Step 5: Compare the LBP features of the probe and blurred gallery image to find the closest match.

Step 6: Stop.

B. Geometrical transformation in 6D space

Functions whose domain and range are sets of points are called Geometric transformations and these are required to be one to one functions and hence they have inverses. Usually the domain and range of a transformation are both R^2or both R^3. Often Non-uniform blurring situations arise due to tilts and rotations in hand-held cameras and geometrical transformations are used to explain the effect of motion blur on the resulting image. The convolution model can be used for describing uniform blurring effects which are due to in-plane camera translations. But to describe other blurring effects which are due to out-of-plane translations and in-plane rotations of the camera, the convolution model cannot be used. In order to overcome this difficulty 6D subspace geometrical warping is done where, 3D corresponds to rotations and remaining corresponds to translations, about the X, Y and Z axes.

Let f: $R^2 \rightarrow R$ be the perfect focused face image captured by a still camera. Assume that the origin is at the camera center and let X =[X Y Z] ^{T} is the spatial coordinates of a point on the face.

Let the corresponding image coordinates for the spatial coordinates X bem = vX Z and n = vY Z, where v is the focal length of the camera. The projection of X on the image plane m = KvX, where Kv is the camera calibration matrix and is given by, $Kv = (v, v, 1)$

To get the image coordinates (m, n), the standard practice is to express m in homogeneous form i.e., scale m by its third element. At each instant of time τ during exposure, the coordinates of the 3D point X changes to $X\tau = R\tau X + T\tau$ due to relative motion between the camera and the

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subject. Here, $T\tau = Tx\tau\ Ty\tau\ Tz\tau\ T$ is the translation vector, and $R\tau$ represents the rotation matrix parameterized in terms of the angles of rotation x , θy and θz about the three axes using the matrix exponential $R\tau = \exp\theta$. θ is represented in equation 2.

$$\theta = \begin{bmatrix} 0 & -\theta_{z_\tau} & \theta_{y_\tau} \\ \theta_{z_\tau} & 0 & -\theta_{x_\tau} \\ -\theta_{y_\tau} & \theta_{x_\tau} & 0 \end{bmatrix} \text{------- (2)}$$

By modeling the face by a flat surface i.e., all the points are at a distance d_0 from the camera. Therefore, the depth is constant, and the points, at which $X\tau$ gets projected in the camera, can be obtained through a homographyH_τ as $x_\tau = H_\tau\ x$.It is represented in equation 3 where d_0 is the distance between flat surface points and the camera.

$$H_\tau = K_v(R_\tau + \frac{1}{d_0}[0\ 0\ 1])K_v^{-1} \text{--------- (3)}$$

If g_τ be the geometrically transformed image captured at time instant τ, then it is written $g_\tau\ x = (H\tau^{-1}x)$, where $H\tau^{-1}$denotes the inverse of $H\tau$. Now the blurred face g can be interpreted as the average of transformed versions of f during exposure. Therefore, the intensity at an image point x on the blurred face is given in equation 4.

$$g(x) = \frac{1}{T}\int_0^T f(H_\tau^{-1}x)d\tau \text{--------- (4)}$$

Where$T$ is the total exposure duration. By using this homography geometric warping can be done for different cases to get projectively transformed versions of the focused image.

C.TSF Model and Image Matrix

Transformation Spread Function model is used to handle non-uniform blurring effects that arises due to tilts and rotations of hand-held cameras. According to TSF model the set of all images obtained by applying all blurring conditions on a particular gallery image is a convex set and it is given by a convex hull of the columns of the Image matrix. The blurred face can be modeled in terms of the gallery face by appropriately taking the linear combinations of the set of possible transformations. To recognize a blurred test image, minimize the distance between the test and the convex combination of the columns of the transformation matrix corresponding to each gallery image. The gallery image having minimum distance to the probe is identified as a match.

Let T denote the set of all possible geometrical transformations. Let: $T \rightarrow \mathbb{R}+$, the transformation spread function (TSF) is a mapping from T to positive real numbers. The value of the TSF, $h_T(\tau)$, for each transformation $\tau \in T$, denotes the fraction of the total exposure time for which the capturing device stayed in the position that made the transformation H_τ^{-1} on the pixels. So the blurred image can be written as an average of projectively transformed versions of f weighted by the TSF co-efficients, H_T, i.e.,

$$g(x) = \int_0^{T_e} h_T(\tau) f(H_\tau^{-1}x)d\tau \text{--------- (5)}$$

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The Transformation Spread Function is defined on the discrete transformation space T. It can be considered as a vector in $\mathbb{R}NT$ where N is the total number of transformations present in the space T and N is controlled by the number of translation steps and the number of rotation steps about each axis. Hence, $N = NTx * NTy * NTz * N\theta x * N\theta y * N\theta z$ .In discrete domain it can be written as represented in following equation.

$$g(m,n) = \sum_{k=1}^{N} h_T(\tau_k)\, f(H_{\tau_k}^{-1}[mn\ 1]^T) \quad \text{---------} \ (6)$$

In equation.6, $(m,\ n)$ and $(m,\ n)$ represents the intensity at pixel location m, for the blurred image and focused image respectively. If g, f represent the blurred image and the focused image in vector form, respectively then above equation can be expressed in matrix-vector notation as,

$$g = Ah_T\,;\ h_T \geq 0\,, \|h_T\|_1 = 1 \quad \text{---------} \ (7)$$

In equation 7, $A \in \mathbb{R}N{*}NT$ is the matrix, whose NT columns contain transformed copies of focused image$f$, H_T is the weight vector and N is the total number of pixels in the image. The projectively transformed versions of f are obtained by applying the homography matrix $H\tau^{-1}$corresponding to each transformation. Since only a fraction of the total poses NT for motion blur will have non-zero weights, h_T is sparse. The optimization problem can be solved by computing the optimum TSFs that minimizes the following energy function, which provides an estimate of the transformations to be applied on the gallery image to produce the blurred image.

$$E\,(h_T) = \|g - Ah_T\|^2{}_2 + \beta\, \|h_T\|_1;\ h_T > 0 \quad \text{-------} \ (8)$$

Let fm be a focused gallery face for each m, where m = 1, 2, 3.., M. The blurred probe image$g$ belongs to one of the M images. The problem is to find the identity of g to get $m{*} \in \{1, 2, 3.., M\}$. The first step is to compute the convex hull Am for each gallery image. Since g belongs to one of the M gallery images, the identity of the probe image can be found by minimizing the projection error of g onto $\{s\}$. The optimum coefficients can be computed by solving equation 9.

$$h_{Tm} = argmin_{HT}\, \|W\,(g - Ah_T)\|^2{}_2 + \beta\ h_T\ 1;\ h_T \geq 0 \quad \text{-----}(9)$$

Where W is the weight matrix computed which is having highest weights for regions around the eyes and de-emphasizes the hair and cheeks. By solving equation.9 the optimal TSF coefficients h_{Tm} can be computed. Gallery images can be synthetically blurred with corresponding optimal TSFs h_{Tm}.

D.DWT-based Maximum Illumination Normalization (DWT-MIN)

Extrinsic factors like varying illumination conditions could pose a problem in FR. These illumination problems can be solved using illumination normalization [11]. Wavelet based illumination normalization of the face image is a photometric normalization technique done using the 2D - Multilevel Haar Wavelet Transform. The proposed DWT-MIN uses the 2D-Multilevel Haar Wavelet Transform to decompose an image into approximation coefficients and

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detail coefficient at different levels. The approximation coefficient matrix corresponds to the insensitive features, and the three detail coefficient matrix corresponds to the pose, expression and structure features. Contrast and edge enhancements are done at each level in this technique.

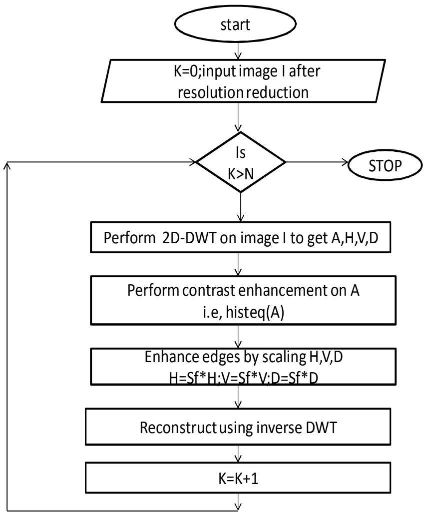

Figure 3: Flowchart of the DWT-MIN method with scale factor

Histogram equalization of the approximation coefficients is done for contrast enhancement. Histogram equalization modifies the dynamic range (contrast range) of the image and as a result, some important facial features become more apparent. Edge enhancement is done to highlight the fine details in the original image. This can be done by enlarging the amplitude of the high frequency components in the image. To enhance details, multiply each element in the detail coefficient matrices with a scale factor Sf (> 1).

E. Local Binary Pattern Histogram

Local binary patterns (LBP) are a type of feature used for classification of images. It is the specific case of the Texture Spectrum model and was first proposed. Local Binary Pattern (LBP) is a simple and robust texture operator which labels the pixels of an image by comparing theNeighborhoods to each pixel and gives the result as a binary number.

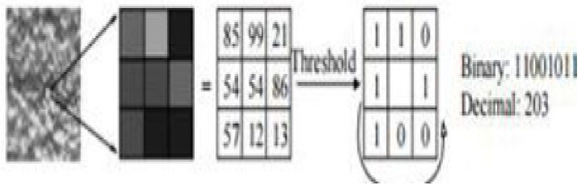

Figure.4: LBP computation.

The algorithm for finding the local binary pattern is as follows.

Step 1: Start.

Step 2: Divide the examined window into cells (e.g. 16x16 pixels).

Step 3: For each pixel in a cell, compare the pixel to each of its 8 neighbors. Follow the pixels along a circle, i.e. clockwise or counter-clockwise.

Step 4: If the center pixel's value is greater than the neighbor's value, write "1". Otherwise, write "0". This gives an 8-digit binary number (which is usually converted to decimal for convenience).

Step 5: The pixel value is replaced with the decimal value computed.

Step 6: Concatenate the cells which gives the feature vector for the image.

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Step 7: Stop

F. RESULTS

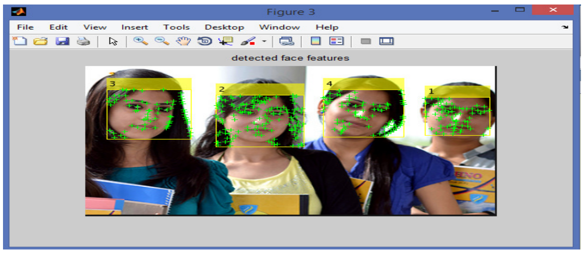


Figure 5: Detection of face from group image

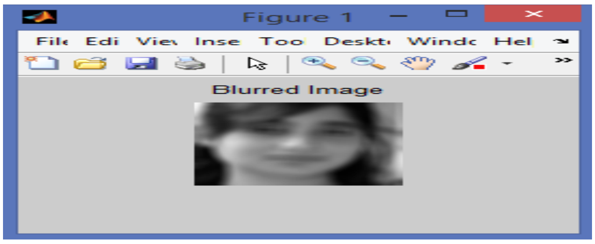


Figure 6: blurred face after applying motion blur

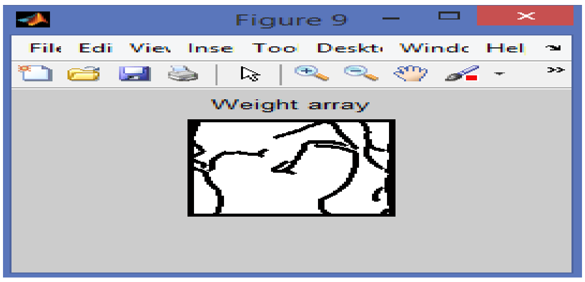


Figure7 :weighted matrix calculation for an image

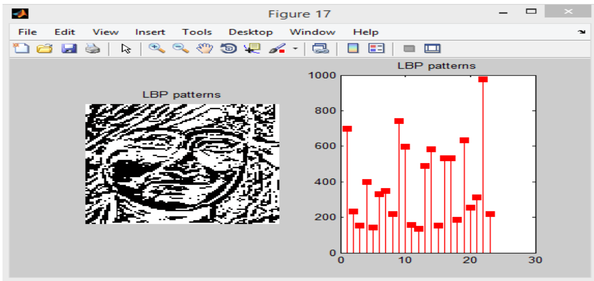
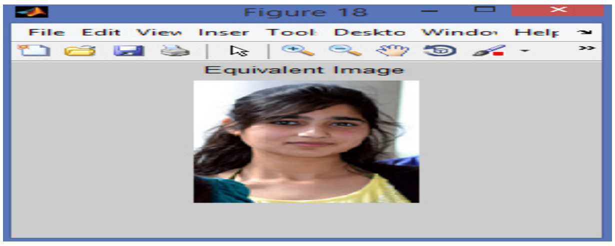


Figure 8: Extracted LBP features of test image



G. CONCLUSION

In natural imaging using hand-held cameras, handshake introduces blurring situations due to rotations and tilts of the camera. The blur formed is non-uniform or space variant in nature. In unconditioned situations illumination changes and pose variations also occurs. By using TSF model, the non-uniformly blurred images can be approximated as a linear combination of the projectively transformed versions of the focused image. The DWT-MIN method is used to accommodate the illumination variations. Using both these models the recognition cross non uniform motion blur and illumination variations is achieved with a better recognition rate of 94% as compared to the other models. The limitation of our approach is that significant occlusions and large changes in facial expressions cannot be handled. This may be developed in future applications.

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