

Face Recognition using TSF Model and DWT based Multilevel Illumination Normalization

Midhun Madhusoodanan¹, Jini Cheriyan²

¹M.Tech Scholar (Signal Processing), Department of Electronics and Communication, TKM Institute of Technology, MusaliarHills, Karuvelil P.O, Ezhukone, Kollam-691505, Kerala, India

²Assistant Professor, Department of Electronics and Communication, TKM Institute of Technology, Musaliar Hills, Karuvelil P.O, Ezhukone, Kollam-691505, Kerala, India

Abstract: 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. Here Non-uniform blur and variations in illumination are considered. 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: TSF Model, DWT-MIN, Point Spread Functions, Blur kernel

1. Introduction

Facial recognition is a type of bio-metric software application that can identify a specific individual in a digital image by analyzing and comparing patterns. Facial recognition systems are commonly used for security purposes but are increasingly being used in a variety of other applications. Usually Facial recognition system compares the facial features extracted from the test image with that of a reference image. Now a days image capturing is done by different hand held capturing devices such as portable digital cameras, mobile cameras, spy cameras etc. While capturing an image by using such devices hand shake may occur and the resulting image gets blurred. This effect of blurring decreases the accuracy of the system.

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

2. Literature Survey

Local binary patterns (LBP) [10] are the feature used here for classification of face images in the system. It is a specific form of the Texture Spectrum model and the face feature

vector can be extracted in a straightforward manner. In previous methods Bayesian decision theory based classifiers are used which divide the difference vectors between pairs of face images into two classes: one representing intrapersonal differences and extra personal differences. But LBP is used here due to its simplicity. To find the feature vector, the image is divided into blocks of pixels and the LBP algorithm is applied on it.

As we have already said that the captured image from a hand held camera will have degradations due to different factors. The main factor that degrades the image is the non-uniform blur. So we need to more discuss about the existing blind deconvolution methods to remove blurring effects. The frequency-domain constraints on images or overly simplified parametric forms for the motion path during camera shake are typically used in Conventional blind deconvolution methods. But real camera motions can follow convoluted paths. So a spatial domain prior can better maintain visually salient image characteristics. Rob Fergus [11] had proposed a method which removes the effects of blurring arise from serious handshakes. The system 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. Sunghyun Cho [9] had proposed an algorithm for removing non uniform motion blurs from images. By using motion fitting method, the system first finds an initial idea about multiple different motions that appear in the images. Then the motion estimates are refined to make the system robust, image segmentation is done to get regions of homogeneous motions, and the motion Point Spread Functions are estimated for each region. The estimated spread functions are refined using an optimization technique that minimizes the energy function. The refined PSFs are used for deconvolution.

Michal Sorel Fergus [7] had proposed another non uniform model which removes the space-variant blur by considering that the PSFs at different regions are different. Here the blurred image is considered as a result of convolution of sharp image with a non-uniform blur kernel. The inputs are two images of the same scene, one of them sharp but underexposed or noisy and the other one is blurred. First the images are divided into blocks of pixels and are used in an algorithm to estimate the local blur kernels corresponding to each block, followed by detection and adjustment of the incorrect estimations. But the segmentation artifacts may occur in the above methods [7], [9]. In order to overcome this Paramanand Chandramouli [6] had proposed a method which says that, the blur kernel is different for different image regions and these blur kernels can be determined from linear combinations of the transformations of the original focused (unblurred) image.

Later Oliver Whyte [4] had proposed a geometrically consistent model of non-uniform image blur due to camera shake, arising from rotations of the camera based on the above method [6]. 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.

Early works [4], [6] address the non-uniform blur problem by a geometric model to describe the camera motion using the weighted sum of homographically transformed copies of sharp image. Although these algorithms show promising results, they have heavy computational loads. Zhe Hu [3] had proposed a novel single image deblurring algorithm to remove non-uniform blur with lesser computational load with tolerable redundancy which constrains the camera poses into certain range of rotations.

Priyanka Vageeswaran [2] had proposed another model which says that, the set of all images of a face under all blur and illumination variations forms a bi-convex set and by using this set-theoretic characterization a robust algorithm is generated. Here the parametric forms for the blur kernels are not assumed instead the algorithm uses simple steps for solving simple convex optimization problems. This system considers both blur and illumination simultaneously.

Later Abhijith Punnappurath [1] had proposed a Transformation spread Function (TSF) model based method for accurate recognition in such conditions. TSF model approximates the blurred image as a linear combination of the projectively transformed images. The optimum coefficients that minimize the error function are termed as TSF coefficients. In the framework, 6-dimensional geometrical transformations are applied to the original images from the database to get set of possible transformed images.

The 3 dimensions are for translations and 3 dimensions are for rotations. By using these transformed images the TSF

model for the test image is produced and finding the optimum TSF coefficients by matching the TSF model with the test image. A 9D subspace face model is considered for taking the illumination changes into account. The optimum TSF parameters from the above process are used to find the 9 illumination coefficients and are used to find the different illumination conditions. To take the non-frontal situations a 3D morphable model is used. The test image is recognized by matching the test image with the image set produced by possible transformations illumination variations and pose changes.

Earlier 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 or space invariant in nature. So for face recognition in the presence of space varying motion blur, a methodology comprising of arbitrarily shaped kernels is to be used. Hence the blurred face is modeled as a convex combination of geometrically transformed instances of the focused gallery face using TSF Model and the probe image is compared with the convex combinations to find the best match. To handle illumination variations DWT based Multilevel Illumination Normalization (DWT-MIN) is used.

3. Methods / Approach

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. 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.

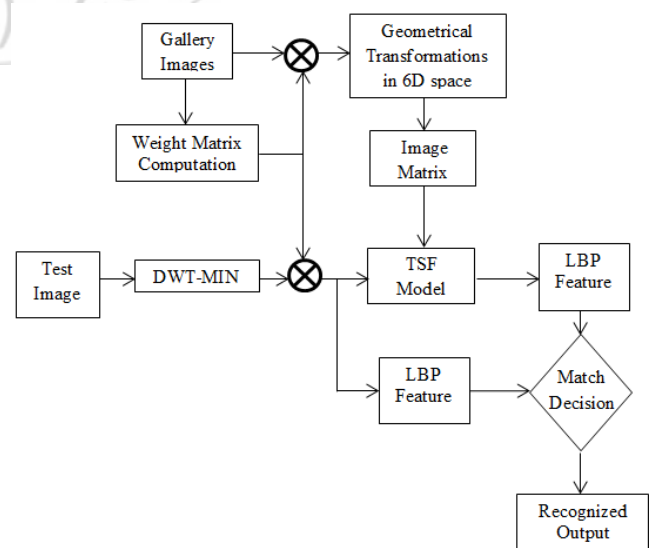


Figure 1: Block Diagram

The detailed block diagram for the face recognition across non-uniform motion blur and change in illumination and is shown in the Figure 4.2. 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.

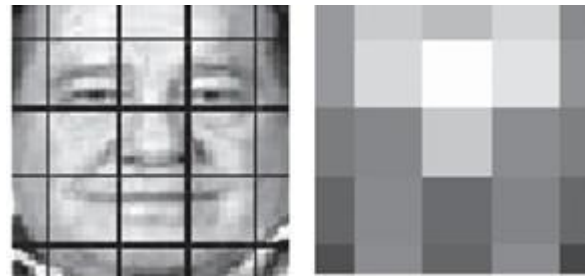


Figure 3.1: Image and its Weight matrix

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.

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.

3.1 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.

- Step 1 :** Start.
- Step 2 :** Input a gallery image.
- 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.

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 I_j and a probe image I_b .
- Step 3 :** For each gallery image, I_j find the optimum blur kernel h_j by solving the following equation.

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

Where A_j is a matrix contains projectively transformed versions of the gallery image.

- Step 4 :** Blur each gallery image with its corresponding I_j 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.

3.2 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 \mathbb{R}^2 or both \mathbb{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 $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ be the perfect focused face image captured by a still camera. Assume that the origin is at the camera center

and let $X = [X\ Y\ Z]^T$ be the spatial coordinates of a point on the face.

Let the corresponding image coordinates for the spatial coordinates X be $m = \frac{vX}{Z}$ and $n = \frac{vY}{Z}$, where v is the focal length of the camera. The projection of X on the image plane $m = K_v X$, where K_v is the camera calibration matrix and is given by,

$$K_v = \text{diag}(v, v, 1)$$

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 subject. Here, $T_\tau = [T_{x_\tau} T_{y_\tau} T_{z_\tau}]^T$ is the translation vector, and R_τ represents the rotation matrix parameterized in terms of the angles of rotation θ_x, θ_y and θ_z about the three axes using the matrix exponential $R_\tau = \exp(\theta)$ where,

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

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 point x_τ , at which X_τ gets projected in the camera, can be obtained through a homography H_τ as $x_\tau = H_\tau x$ where,

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

If g_τ be the geometrically transformed image captured at time instant τ , then we can write $g_\tau(x) = f(H_\tau^{-1}x)$, where H_τ^{-1} denotes the inverse of H_τ . 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 by,

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

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.

3.3 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, we 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 $h_T: T \rightarrow \mathbb{R}_+$, 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.,

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

The Transformation Spread Function is defined on the discrete transformation space T . It can be considered as a vector in \mathbb{R}_{N_T} 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, $N = N_{T_x} * N_{T_y} * N_{T_z} * N_{\theta_x} * N_{\theta_y} * N_{\theta_z}$. In discrete domain it can be written as

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

where $g(m, n)$ and $f(m, n)$ represents the intensity at pixel location (m, n) 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,

$$g = A h_T; h_T \geq 0, \|h_T\|_1 = 1$$

Where $A \in \mathbb{R}^{N * N_T}$ is the matrix, whose N_T 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_τ^{-1} corresponding to each transformation. Since only a fraction of the total poses N_T 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.

$$E(h_T) = \|g - A h_T\|_2^2 + \beta \|h_T\|_1; h_T > 0$$

Let f_m be a focused gallery face for each m , where $m = 1, 2, 3, \dots, M$. The blurred probe image g belongs to one of the M images. The problem is to find the identity of g to get $m^* \in \{1, 2, 3 \dots, M\}$. The first step is to compute the convex hull A_m for each gallery image f_m . 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 $\{A_m\}$ s. The optimum coefficients can be computed by solving,

$$h_{T_m} = \text{argmin}_{h_T} \|W(g - A h_T)\|_2^2 + \beta \|h_T\|_1; h_T \geq 0$$

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 above equation the optimal TSF coefficients h_{T_m} can be computed. Gallery images can be synthetically blurred with corresponding optimal TSFs h_{T_m} .

3.4 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 [5]. 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 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.

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, we multiply each element in the detail coefficient matrices with a scale factor $Sf (> 1)$.

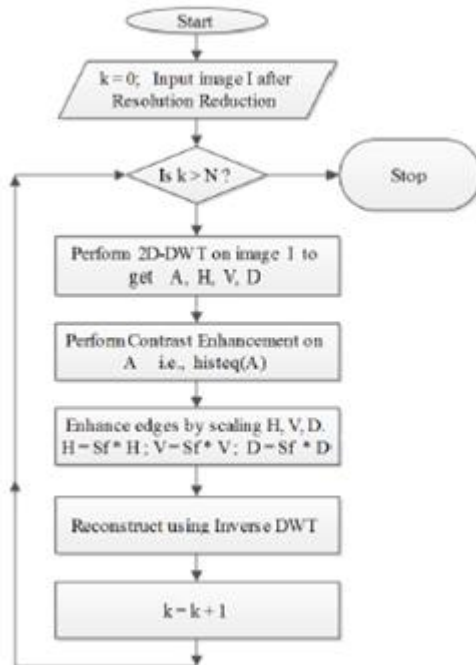


Figure 3.2: Flowchart of the DWT-MIN method with scale factor „Sf“

3.5 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 in 1994. Local Binary Pattern (LBP) is a simple and robust texture operator which labels the pixels of an image by comparing the neighborhoods to each pixel and gives the result as a binary number. LBP texture operator is suitable for various applications due to its computational simplicity and discriminative power.

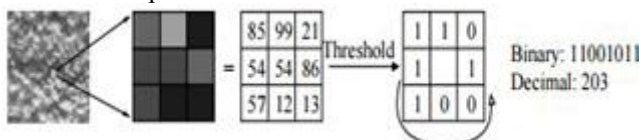


Figure 3.3: LBP Computation

LBP computation is shown in the figure. 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 neighbours. 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.

Step 7 : Stop

4. Results / Discussion

As the database images obtained from the camera contains regions other than the face of a person and the image is of various sizes in RGB format, the obtained image should be cropped, converted to gray scale and re-sized before processing. Simulation is performed using the MATLAB R2010a. The preprocessed images are used for the work and the simulation results are as follows:

4.1 Input Images

Focused and degraded face images is collected from various photographic collections and from the site:

<http://crcns.org/data-sets/vc/vim-1>

From those images, the focused images are taken as gallery image and the blurred or degraded images are taken as test image.

4.2 Weight Matrix Computation

The weight matrix is computed using the algorithm and the image is multiplied with the weight vector obtained. The result is shown in the Figure 4.1. Figure 4.1(a) shows the input image and Figure 4.1(b) shows the corresponding weight matrix computed and Figure 4.1(c) shows the weighted image.

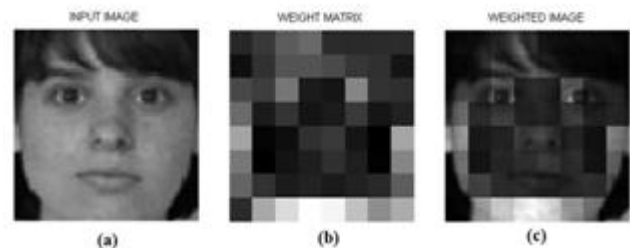


Figure 4.1: Weight Matrix Computation

In the weighted image, more importance or weightage is given to the distinguishable parts (high frequency regions) of the face such as eyes, nose, lips etc. This makes different faces distinguishable and recognition becomes more accurate.

4.3 6D Geometrical Transformations

We select the transformation intervals on the image plane, both for generating synthetically blurred images and recognizing them, as follows: The in-plane translations are in the range = $(-2 : 2 : 2)$ pixels, out-of-plane translations are in the range = $(-0:8 : 0:8 : 0:8)$ pixels, in-plane and out-of-plane rotations in the range = $(-2^\circ : 2^\circ : 2^\circ)$. The focal length is set to 200 pixels.

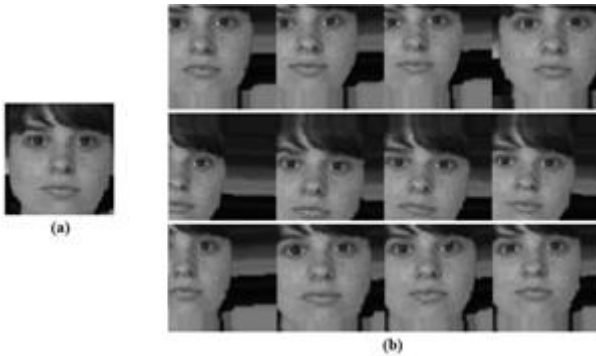


Figure 4.2: (a) Input Image, (b) Result of Geometrical transformations.

Figure 4.2(a) shows the input image and Figure 4.2(b) shows the corresponding results of 6D geometrical transformations. Only some of the transformation results are shown.

4.4 TSF Model

A Synthetically blurred image equivalent to the naturally blurred test image is produced using TSF Model. The result is shown in the Figure 4.3. Figure 4.3(a) is the naturally blurred test Image and Figure 4.3(b) is the synthetically blurred image using TSF Model.

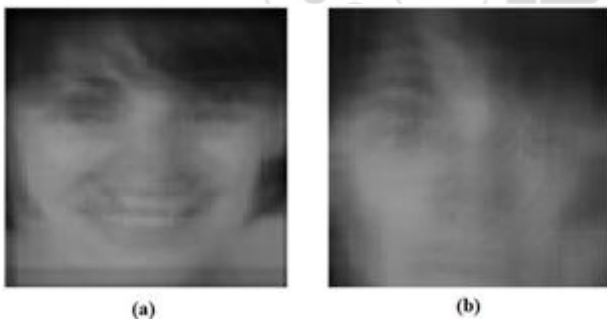


Figure 4.3: (a) Test Image, (b) Synthetically Blurred image

4.5 DWT-MIN Method

The results of the DWT-MIN [5] method for illumination variations are shown in Figure 4.4. Figure 4.4(a) is the input image and Figure 4.4(b) is the illumination normalized image output. In an existing model [1] the system uses 9D subspace model for illumination variations instead of the DWT-MIN. For the same set of images, system that uses 9D subspace model, the recognition rate is 89% and for the DWT-MIN system the accuracy is increased to 94%.



Figure 4.4 : (a) Input image (b) Illumination normalized image output.

4.6 LBP Feature Extraction

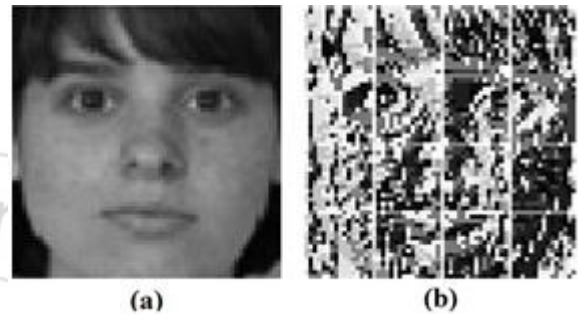


Figure 4.5: (a) Input Image, (b) LBP

Here to find LBP image is divided into cells of „16*16“ pixels and the processing is done. The results of LBP feature extraction is shown in Figure 4.5. Figure 4.5(a) is the input image and figure 4.5(b) is the corresponding LBP.

4.7 Recognition across Blur and Illumination

Face recognition across different illumination and blurring conditions are achieved. The Graphical user interface (GUI) for the system designed is shown in figure 4.6.



Figure 4.6: Recognition System GUI.

The left hand side of the GUI is for handling the gallery images. The *Add new* button is to select a gallery image from a particular location. The selected image will be displayed in the preview box. *Add to gallery* button is pressed to add the previewed image to gallery. Added gallery images will be displayed in the *GALLERY*. To erase all the gallery images added press the *Clear Database* button.

The right hand side of the GUI consists of recognition controls. To load a test image from a particular location press the *Choose Test Image* button and the chosen test image will be displayed in the *TEST IMAGE* preview box. Then press

the *Recognize* button to start recognition. The result will be displayed in the *OUTPUT IMAGE* preview box. To recognize another test image press *clear* button and do the previous steps again.

The recognition results for two different faces at two different degradations are shown in the figures below.



Figure 4.7: Recognition result in GUI for degraded image 1

Figure 4.7 and Figure 4.8 shows the recognition results for two differently degraded versions of face 1.



Figure 4.8: Recognition result in GUI for degraded image 2



Figure 4.9: Recognition result in GUI for degraded image 3



Figure 4.10: Recognition result in GUI for degraded image 2

Figure 4.9 and Figure 4.10 shows the recognition results for two differently degraded versions of face 2.

5. 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 Transformation Spread Function (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.

6. Future Scope

The recognition across pose variations with reduced complexity and increased accuracy.

References

- [1] AbhijithPunnappurath, Ambasamudram Narayanan Rajagopalan, SimaTaheri, Rama Chellappa, and GunaSeetharaman, "Face Recognition Across Non-Uniform Motion Blur, Illumination, and Pose", IEEE Transactions On Image Processing, Vol. 24, No. 7, July 2015
- [2] P. Vageeswaran, K. Mitra, and R. Chellappa, "Blur and illumination robust face recognition via set-theoretic characterization," IEEE Trans.ImageProcess.vol. 22, Apr. 2013.
- [3] Z. Hu and M.-H. Yang, "Fast non-uniform deblurring using constrained camera pose subspace," in Proc. Brit. Mach. Vis. Conf., 2012.
- [4] O. Whyte, J. Sivic, A. Zisserman, and J. Ponce, "Non-uniform deblurring for shaken images," Int. J. Comput. Vis., vol. 98, no. 2, 2012.
- [5] K. Manikantan, Milan S Shet, Minal Patel and S Ramachandran, "DWT-based Illumination Normalization and Feature Extraction for Enhanced Face Recognition", International Journal of Engineering and Technology, 1 (4), 483-504, Mar. 2012
- [6] C. Paramanand and A. N. Rajagopalan, "Inferring image transformation and structure from motion-blurred images," in Proc. Brit. Mach. Vis. Conf., 2010.
- [7] M. orel and F. roubek, "Space-variant deblurring using one blurred and one underexposed image," in Proc. 16th IEEE Int. Conf. Image Process., Nov. 2009.
- [8] J. Liu, S. Ji, and J. Ye, "SLEP: Sparse Learning With Efficient Projections," in Tempe, AZ, USA: Arizona State Univ., 2009.
- [9] S. Cho, Y. Matsushita, and S. Lee, "Removing non-uniform motion blur from images," in Proc. Int. Conf. Comput. Vis., Oct. 2007
- [10] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to

face recognition,"IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, Dec. 2006.

- [11] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, "Removing camera shake from a single photograph," ACM Trans. Graph., vol. 25, no. 3, Jul. 2006.
- [12] K.C. Lee, J. Ho, and D. Kriegman, "Acquiring linear subspaces for face recognition under variable lighting," IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 5, May. 2005.

Author Profile



Midhun Madhusoodanan received his B. Tech degree in Electronics and Communication Engineering from University of Kerala in 2013. He is currently pursuing second year M. Tech in Signal Processing at TKM Institute of Technology.



Jini Cheriyan received her B. Tech degree in Electronics and Communication Engineering from University of Kerala in 2009 followed by M. Tech in Computer Vision and Image Processing from Amrita University in 2011. She is currently working as Assistant Professor in Electronics and Communication Engineering Department at TKM Institute of Technology

