Face Recognition across Non-Uniform Motion Blur, Illumination, and Pose

M.Ramesh kumari

lecturer(Senior Grade), Department of Computer Science Ayyanadar janaki ammal polyechnic college, Sivakasi

Abstract- **Face recognition algorithms perform very unreliably when the pose of the probe face is different from the stored face typical feature vectors vary more with pose than with identity. In the existing Approaches for performing face recognition in the presence of blur are based on the convolution model and cannot handle non-uniform blurring situations that frequently arise from tilts and rotations in hand-held cameras. In this project, we propose a face recognition algorithm that is robust to non-uniform motion blur arising from relative motion between the camera and the subject. Our project addresses the problem of recognizing faces across blur and illumination. Taken a set of images obtained by Dataset which is called as probe image and gallery images. Each synthesize gallery image, obtained the nine bases each synthesize gallery image find the optimal TSF and illumination coefficients. Transform the synthesize gallery images. Compare the LBP features of the probe images with those of the transformed gallery images and also to classify the SVM classifier both gallery and probe images which performs almost as fast as the recognition method to find the closest match.**

Index Terms- **Face recognition, SVM, Matlab.**

I. INTRODUCTION

1.1 GENERAL

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

1.1.1 THE IMAGE PROCESSING SYSTEM

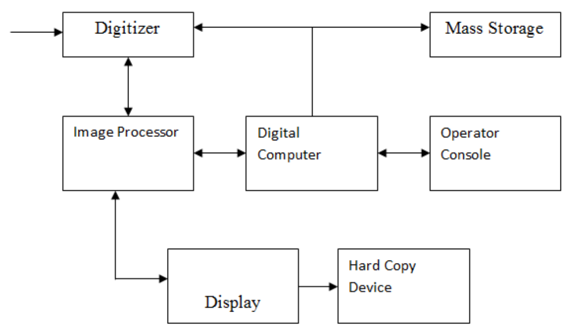


Figure 1: Block Diagram for Image Processing System

DIGITIZER

A digitizer converts an image into a numerical representation suitable for input into a digital computer. Some common digitizers are

1. Microdensitometer
2. Flying spot scanner
3. Image dissector
4. Videocon camera
5. Photosensitive solid- state arrays.

IMAGE PROCESSOR

An image processor does the functions of image acquisition, storage, preprocessing, segmentation, representation, recognition and interpretation and finally displays or records the resulting image. The following block diagram gives the fundamental sequence involved in an image processing system.

As detailed in the diagram, the first step in the process is image acquisition by an imaging sensor in conjunction with a digitizer to digitize the image. The next step is the preprocessing step where the image is improved being fed as an input to the other processes.

Preprocessing typically deals with enhancing, removing noise, isolating regions, etc. Segmentation partitions an image into its constituent parts or objects. The output of segmentation is usually raw pixel data, which consists of either the boundary of the region or the pixels in the region themselves. Representation is the process of transforming the raw pixel data into a form useful for subsequent processing by the computer. Description deals with extracting features that are basic in differentiating one class of objects from another. Recognition assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects. The knowledge about a problem domain is incorporated into the knowledge base. The knowledge base guides the operation of each processing module and also controls the interaction between the modules. Not all modules need be necessarily present for a specific function. The composition of the image processing system depends on its application. The frame rate of the image processor is normally around 25 frames per second.

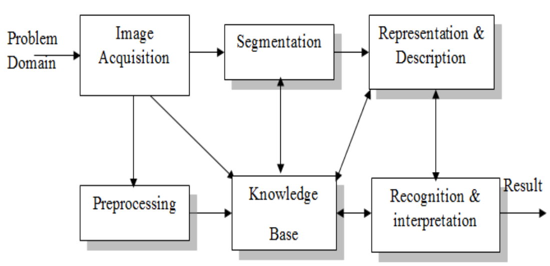


Figure 2: Block Diagram of Fundamental Sequence Involved In an Image Processing System

BIOMETRICS

Biometrics refers to metrics related to human characteristics. Biometrics authentication (or realistic authentication) is used in computer science as a form of identification and access control. It is also used to identify individuals in groups that are under surveillance.

Biometric identifiers are the distinctive, measurable characteristics used to label and describe individuals. Biometric identifiers are often categorized as physiological versus behavioral characteristics. Physiological characteristics are related to the shape of the body. Examples include, but are not limited to fingerprint, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent. Behavioral characteristics are related to the pattern of behavior of a person, including but not limited to typing rhythm, gait, and voice. Some researchers have coined the term behaviometrics to describe the latter class of biometrics.

More traditional means of access control include token-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number. Since biometric identifiers are unique to individuals, they are more reliable in verifying identity than token and knowledge-based methods; however, the collection of biometric identifiers raises privacy concerns about the ultimate use of this information.

Many different aspects of human physiology, chemistry or behavior can be used for biometric authentication. The selection of a particular biometric for use in a specific application involves a weighting of several factors. (1999) identified seven such factors to be used when assessing the suitability of any trait for use in biometric authentication. Universality means that every person using a system should possess the trait. Uniqueness means the trait should be sufficiently different for individuals in the relevant population such that they can be distinguished from one another. Permanence relates to the manner in which a trait varies over time.

More specifically, a trait with 'good' permanence will be reasonably invariant over time with respect to the specific matching algorithm. Measurability (collectability) relates to the ease of acquisition or measurement of the trait. In addition, acquired data should be in a form that permits subsequent processing and extraction of the relevant feature sets. Performance relates to the accuracy, speed, and robustness of technology used (see performance section for more details). Acceptability relates to how well individuals in the relevant population accept the technology such that they are willing to have their biometric trait captured and assessed. Circumvention relates to the ease with which a trait might be imitated using an artifact or substitute.

II.TYPES OF BIOMETRICS

DNA MATCHING

Chemical Biometric The identification of an individual using the analysis of segments from DNA.

EAR
Visual Biometric The identification of an individual using the shape of the ear.

EYES - IRIS RECOGNITION
Visual Biometric The use of the features found in the iris to identify an individual.

EYES - RETINA RECOGNITION
Visual Biometric The use of patterns of veins in the back of the eye to accomplish recognition.

FACE RECOGNITION
Visual Biometric The analysis of facial features or patterns for the authentication or recognition of an individual's identity. Most face recognition systems either use Eigen faces or local feature analysis.

FINGERPRINT RECOGNITION
Visual Biometric The use of the ridges and valleys (minutiae) found on the surface tips of a human finger to identify an individual.

FINGER GEOMETRY RECOGNITION
Visual/Spatial Biometric The use of 3D geometry of the finger to determine identity.

GAIT
Behavioral Biometric The use of an individual's walking style or gait to determine identity.

HAND GEOMETRY RECOGNITION
Visual/Spatial Biometric The use of the geometric features of the hand such as the lengths of fingers and the width of the hand to identify an individual.

ODOUR
Olfactory Biometric The use of an individual's odor to determine identity.

PROJECT DESCRIPTIONS:
Face recognition has been a sought after problem of biometrics and it has a variety of applications in modern life. The problems of face recognition attracts researchers working in biometrics, pattern recognition field and computer vision . Several face recognition algorithms are also used in many different applications apart from biometrics, such as video compressions, indexing's etc. The conventional authentication system only requests the user to provide the authorized account and password to log into the system once they start to use a computer or a terminal. However, under this authentication framework, the machine can only recognize the user's identity from the login information. It lacks the information to know who is using it.
It is well-known that the accuracy of face recognition systems deteriorates quite rapidly in unconstrained settings. This can be attributed to degradations arising from blur, changes in illumination, pose, and expression, partial occlusions etc. Motion blur, in particular, deserves special attention owing to the ubiquity of mobile phones and hand-held imaging devices. Dealing with camera shake is a very relevant problem because, while tripods hinder mobility, reducing the exposure time affects image quality. Moreover, in-built sensors such as gyros and accelerometers have their own limitations in sensing the camera motion. In an uncontrolled environment, illumination and pose could also vary, further compounding the problem. The focus of this project is on developing a system that can recognize faces across non-uniform (i.e., space-variant) blur, and varying illumination.
Traditionally, blurring due to camera shake has been modeled as a convolution with a single blur kernel, and the blur is assumed to be uniform across the image. However, it is space-variant blur that is encountered frequently in hand-held cameras. While techniques have been proposed that address the restoration of non-uniform blur by local space-invariance approximation , recent methods for image restoration have modeled the motion-blurred image as an average of protectively transformed images.

III. SYSTEM ANALYSIS

Face recognition systems that work with focused images have difficulty when presented with blurred data. Approaches to face recognition from blurred images can be broadly classified into four categories. (i) Deblurring-based, in which the probe image is first deblurred and then used for recognition. However, deblurring artifacts are a major source of error especially for moderate to heavy blurs. (ii) Joint deblurring and recognition, the flip-side of which is computational complexity. (iii) Deriving blur-invariant features for recognition. But these are effective only for mild blurs. (iv) The direct recognition approach which reblurred versions from the gallery are compared with the blurred probe image. It is important to note that all of the above approaches assume a simplistic space-invariant blur model.

For handling illumination, there have mainly been two directions of pursuit based on (i) the 9D subspace model for face and (ii) extracting and matching illumination insensitive facial features. It combine the strengths of the above two methods and propose an integrated framework that includes an initial illumination normalization step for face recognition under difficult lighting conditions. A subspace learning approach using image gradient orientations for illumination and occlusion-robust face recognition has been proposed. Practical face recognition algorithms must also possess the ability to recognize faces across reasonable variations in pose. Methods for face recognition across pose can broadly be classified into 2D and 3D techniques.

the basic framework to handle variations in illumination as well as pose. We approximate the face to a convex Lambertian surface, and use the 9D subspace model and the bi-convexity property of a face under blur and illumination variations in the context of the TSF model. Our motion blur and illumination (MOBIL)-robust face recognition algorithm uses an alternating minimization (AM) scheme wherein we solve for the TSF weights in the first step and use the estimated TSF to solve for the nine illumination coefficients in the second, and go on iterating till convergence.

Over the past decade, face recognition has emerged as an active research area in computer vision with numerous potential applications including biometrics, surveillance, human–computer interaction, video-mediated communication, and content-based access of images and video databases The number of real world applications and the availability of cheap and powerful hardware also lead to the development of commercial face recognition systems. Taken a set of images obtained by Dataset which is called as probe image and gallery images. Each synthesize gallery image, obtained the nine bases each synthesize gallery image find the optimal TSF and illumination coefficients. Transform the synthesize gallery images. Compare the LBP features of the probe images with those of the transformed gallery images and also to classify the SVM classifier both gallery and probe images which performs almost as fast as the recognition method to find the closest match. We already developed LBP feature extraction based face recognition. In our proposed system we developed a algorithm for face detection by combining the LBP feature and SVM methods which performs almost as fast as the recognition method but with a significant improved speed.

IV. SYSTEM IMPLEMENTATION MODULES

- Algorithm
- Dataset training
- Apply blur
- LBP feature extraction
- Comparison by using SVMclassifier

ALGORITHM

Suppose we have M face classes with one focused gallery face fm for each class m, where m = 1, 2, . . . , M. Let us denote the blurred probe image which belongs to one of the M classes by g. Given fms and g, the task is to find the identity $m{*} \in \{1, 2, . . . , M\}$ of g. Based on the discussions, the first step is to generate the matrix Am for each dataset face. Then, since g belongs to one of the M classes, it can be expressed as the convex combination of the columns of one of these matrices. Therefore, the identity of the test image can be found by minimizing the projection error of go onto {Am}s.

- The case of space-invariant blurs, the set of all images under varying illumination and blur forms a bi-convex set, i.e., if we fix the blur or the illumination, the resulting subset is convex. As discussed, according to the motion blur model for faces, the set of all motion-blurred images obtained by blurring a focused dataset image using the TSF model also forms a convex set. Therefore, the result extends equally well to our situation i.e., the set of all images under varying illumination and non-uniform motion blur also forms a bi-convex set.
- We develop our non-uniform motion blur and illumination (MOBIL)-robust face recognition algorithm. To determine the identity of the

probe, we transform (reblur and re-illuminate) each of the train images fm using the estimated TSF hTm and the illumination coefficients αm,i , compute the LBP features from these transformed train images and compare them with those from the test image to find the closest match.

DATASET TRAINING

Face data set image is stored in the system. This gray-level frontal view face database comprises 200 images from 40 persons. There are females and males, each of whom has 5 images with different facial expressions. To extract the LBP feature in the image. Each and every face image extracts the LBP feature. Feature is stored into .mat file.

APPLY BLUR

To give test face image into input of the system. To apply blur in the face image for Gaussian noise. Matlab has a command fspecial function for generating different types of blur kernels. The command imfilter function can then be used to blur the image with this kernel, it is equivalent to a 2D convolution.

LBP FEATURE EXTRACTION

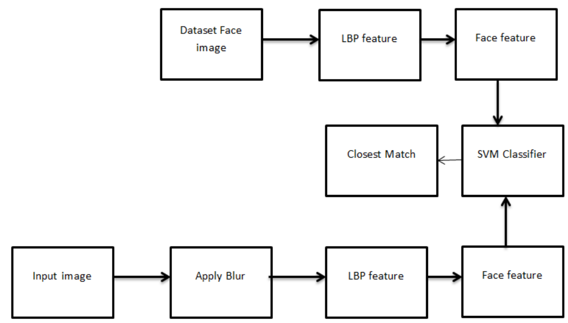
In the LBP approach for feature extraction, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature based methods are more robust against variations in blur than holistic methods.

COMPARISON BY USING SVM CLASSIFIER

To compare the test face image with training data set image. This algorithm is applied to feature space. The high dimensional feature space increases the difficulty for computing the scalar products in the feature space exists. Kernel functions used to compute these scalar products. By using kernel functions there is no need to compute the feature space explicitly. The SVM method was originally developed as a linear classifier. By utilizing kernel methods it also applied for non-linear mapping of data. The way of data separation by SVM is demonstrated on a simplified.

V. SYSTEM DESIGN

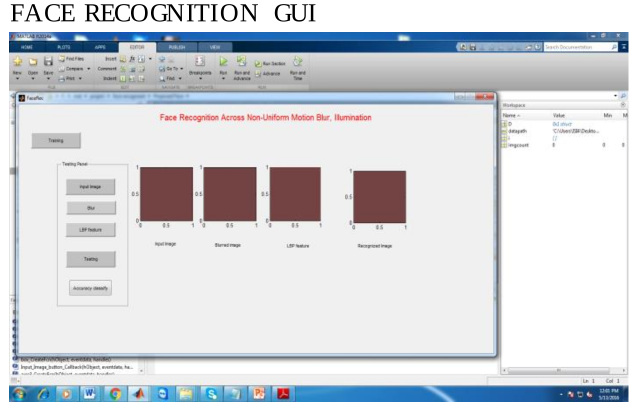
BLOCK DIAGRAM



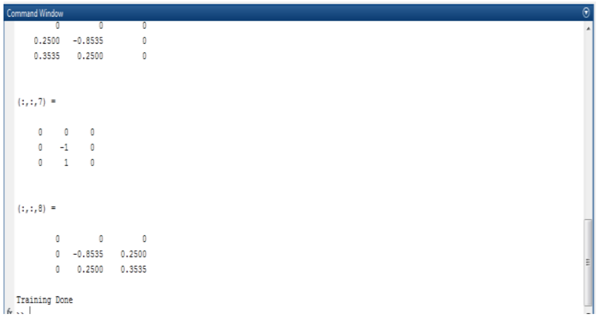
The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

VI. RESULTS

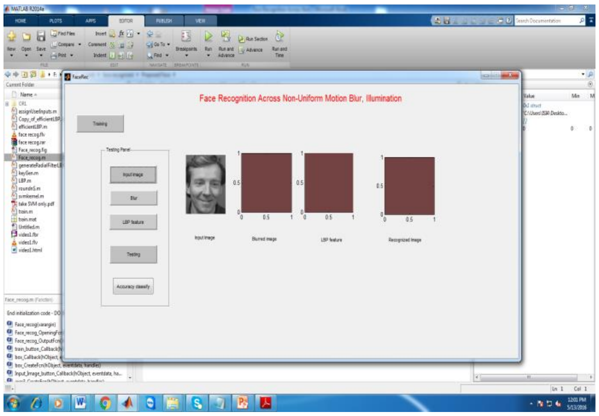
FACE RECOGNITION GUI



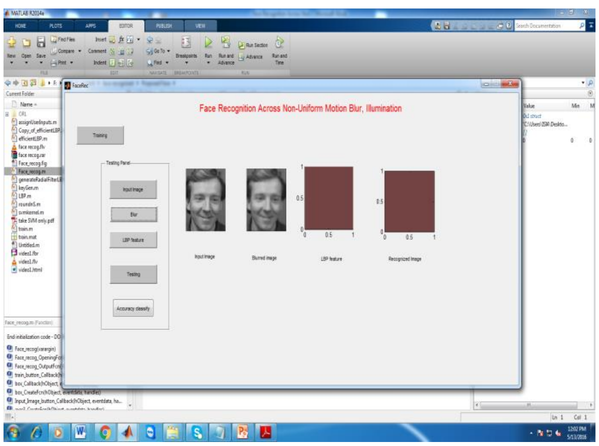
FACE RECOGNITION ORL DATASET TRAINING



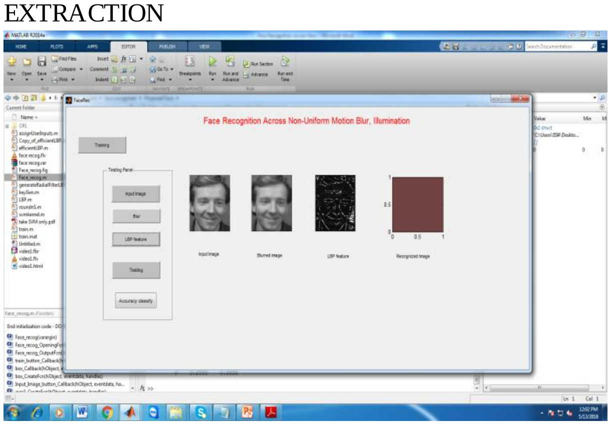
FACE RECOGNITION INPUT IMAGE



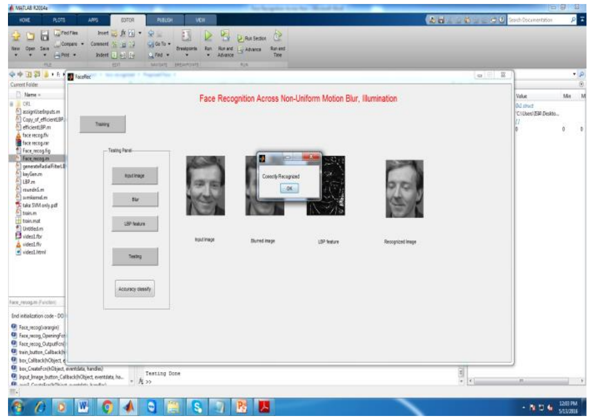
FACE RECOGNITION BLUR IMAGE



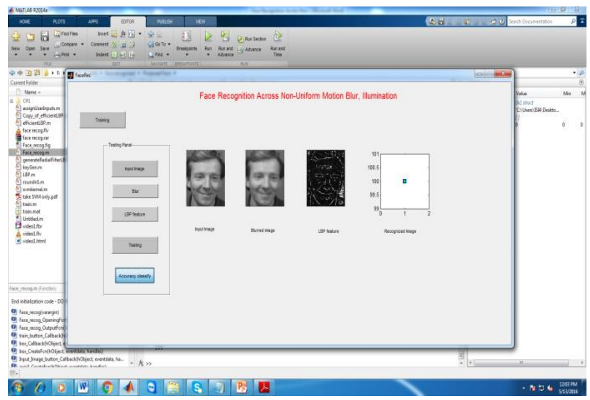
FACE RECOGNITION LBP FEATURE EXTRACTION



CLASSIFY BY USING SVM CLASSIFIER



ACCURACY CLASSIFICATIONS



VII.CONCLUSION

Finally concluded the proposed methodology to perform face recognition under the combined effects of non-uniform blur, illumination. We showed that the set of all images obtained by non-uniformly blurring a given image. Face Recognition becomes one of the most biometrics authentication techniques from the past few years. In this work, implement the SVM classification classifies the training data and testing data and produces the closest match output. Face recognition features will integrate to the SVM classifier. SVMs achieve significantly higher search accuracy than existing system. SVMs are also useful in medical science to classify proteins with up to 90% of the compounds classified correctly. The recognition rate can be easily influenced by some variations such as lighting, expression and pose in the face images. Our experiment results conclude that this method can get better recognition rate.

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