On the Use of Finger Knuckle Patterns For Person Identification

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ABSTRACT

An accurate hand biometric modality for person authentication is studied within the scope of this research. Patterns are being extracted from minor and major finger knuckle patterns in this work utilizing texture-based feature extraction methods. These patterns are being used for biometric systems. The use of images of the finger knuckles in biometric systems is still relatively new, but it has lately garnered a significant amount of interest in the research literature. Finger knuckle biometrics has gained an increasing amount of interest in the biometrics literature, and a variety of matching algorithms have been researched in order to increase the accuracy of the matching. Finger knuckle patterns have received a lot of attention in the biometrics world during the past decade's worth of research. The finger dorsal skin patterns created between the metacarpal and the proximal phalanx bones of fingers have been researched in the scientific literature for their potential use as a biometric feature. These patterns are formed as the metacarpal bone moves closer to the proximal phalanx bone. On a few finger knuckle databases, research is done to determine whether or not these patterns are unique. This thesis focuses on finger knuckle patterns, namely minor and major variations in finger knuckle patterns, as well as texture-based feature extraction approaches. In order to come up with a reliable way for identifying individuals, many different texture-based approaches for finger knuckle biometrics are investigated. Experiments are carried out on finger knuckle databases that are accessible to the public, such as the PolyU Finger Knuckle Print Database and the IIT Delhi Finger Knuckle Database. A number of texture-based methods, namely Local Binary Patterns (LBP), Binarized Statistical Image Features (BSIF), Local Phase Quantization (LPQ) and Weber Local Descriptor (WLD), are utilized in the process of finger knuckle identification in this thesis. Experiments are conducted to show the influence of various texture-based approaches on the identification of finger knuckles.

Keywords: finger knuckle identification, biometrics, texture-based features

ÖZ

Bu araştırma kapsamında kişi kimlik doğrulaması için özgün ve doğru bir el biyometrik yöntemi üzerinde çalışılmıştır. Bu çalışmada doku tabanlı öznitelik çıkarma yöntemleri kullanılarak küçük ve büyük parmak eklemi modellerinden desenler çıkarılmaktadır. Bu modeller biyometrik sistemler için kullanılmaktadır. Parmak eklemlerinin görüntülerinin biyometrik sistemlerde kullanılması hala nispeten yenidir, ancak son zamanlarda araştırma literatüründe önemli miktarda ilgi toplamıştır. Parmak eklemi biyometrisi artan bir ilgi görmüştür. Biyometri literatüründe ve eşleştirmenin doğruluğunu artırmak için çeşitli eşleştirme algoritmaları araştırılmıştır. Parmak eklemi desenleri, son on yılda biyometri dünyasında büyük ilgi görmüştür. Parmakların metakarpal ve proksimal falanks kemikleri arasında oluşturulan parmak sırtı cilt desenleri, biyometrik bir özellik olarak potansiyel kullanımları için bilimsel literatürde araştırılmıştır. Bu desenler, metakarpal kemik proksimal falanks kemiğe yaklaştıkça oluşur. Birkaç parmak eklemi veritabanında, bu desenlerin benzersiz olup olmadığını belirlemek için araştırma yapılmıştır. Bireyleri tanımlamanın güvenilir bir yolunu bulmak için, parmak eklemi biyometrisini incelemek için birçok farklı doku tabanlı yaklaşım araştırılmıştır. PolyU ve IIT Delhi veritabanları gibi halka açık parmak eklemi veritabanlarında deneyler gerçekleştirilmiştir. Deneylerde parmak eklemi tanıma için Yerel İkili Örüntü (LBP), İkili İstatistiksel Görüntü Öznitelikleri (BSIF), Yerel Faz Niceleme (LPQ) ve Weber Yerel Tanımlayıcı (WLD) gibi bir dizi doku tabanlı yöntem kullanılmıştır. Çeşitli doku temelli yaklaşımların parmak eklemlerinin tanınması üzerindeki etkisi deneylerde gösterilmiştir.

Anahtar Kelimeler: parmak eklemi tanıma, biyometri, doku tabanlı öznitelikler

DEDICATION

I would like to thank all of my close friends and family for their support throughout this process. Thank you my lovely parents for their support. They have never left my side.

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LIST OF ABBREVIATIONS

BSIF	Binarized Statistical Image Features
CNN	Convolutional Neural Network
DIP	Distal Interphalangeal
FPK	Finger Print Knuckle
IITD	Indian Institute of Technology Delhi
KNN	K-Nearest-Neighbour
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
LPQ	Local Phase Quantization
PCA	Principal Component Analysis
PIP	Proximal Interphalangeal
RAM	Random Access Memory
RGB	Red Green Blue
SIFT	Scale Invariant Feature Transform
SURF	Speeded-Up Robust Features
SVM	Support Vector Machine
WLD	Webel Local Descriptor

Chapter 1

INTRODUCTION

There has been a lot of promising results in using images of finger knuckles as a biometric identifier in online commerce and forensics. Biometric availability, user preference, and the type of the application all play significant roles in selecting a biometric feature. An emerging biometric, finger knuckle recognition is ideal for many use cases, including law enforcement, privacy-conscious users (such as the elderly), and users with limited mobility. Study results were obtained using joint images captured in a non-contact imaging environment, and they show excellent matching accuracy, at least on par with fingerprints. The structure of the bones in the proximal phalanx, metacarpal phalanx, metacarpophalangeal joint, and the tissues around these joints all contribute to the uniqueness of the finger knuckle's physiological biometric pattern. This dissertation evaluates the accuracy of the suggested method alongside that of previously published finger knuckle detection studies employing a variety of texture-based methods on the Finger Knuckle Print (FKP) datasets [1]. The FKP and IITD databases are hosted on a publicly accessible platforms at The Hong Kong Polytechnic University and Indian Institute of Technology Delhi, making them available to researchers and students. These databases were compiled between 2006 and 2015, with the help of a mobile phone and a hand-held camera, at the Indian Institute of Technology in Delhi, at The Hong Kong Polytechnic University, and in a few Indian villages. Both the PolyU database and the IIT finger knuckle database were used in extensive experiments.

1.1 Significance of Finger Knuckle Usage

Hand geometry-based methods, which include fingerprints, palmprints, and other similar identifiers, are the most common of all of these biometric characteristics since they have a higher user acceptance rate. Recently, after conducting an exhaustive examination, it was discovered that the creases and folds of the skin in the joints of the outer finger knuckle prints are distinct. Therefore, they can be utilized as a unique biometric identifier [2]. This discovery was made relatively recently. When finger knuckles are compared to fingerprints, it offers additional benefits, such as the fact that it is less likely to become damaged. While the outside half is only used very seldom because only the inner area of the palm is often utilized when we fold our hands. In addition, it does not participate in any illegal activities of any type, which enables it to be perfectly acceptable for usage [3]. Another good thing about this is that it can't be faked because no one's knuckle print shows up on the surfaces of things they touch or handle. This is because no one touches or handles the thing.

1.2 Literature Review on Finger Knuckle Detection

The feasibility of using images of minor finger knuckles for identification has been explored in 2014 [1]. That paper's coarse-to-fine segmentation technique is quite self-made, as it improves matching accuracy without any outside help. Based on data from 503 people, the experimental results presented in this work show that using only contactless finger knuckle image can achieve promising outcomes. The results of the experiments in that paper show that finger knuckle images can be used together to improve performance in an important way but is not possible when using only images of the minor or major knuckles. The Proximal Interphalangeal (PIP) and Distal Interphalangeal (DIP) joints of the finger have critical retrograde motion and, as a result, require a tecnique to prohibit dislocation and luxation. This mechanism is a product of the interplay between the bony constraints, ligaments, extension muscle connective tissue biomechanical and attachments action of muscles, all of which are inherent to the fingers. Because of the stress or folding pattern of (additional) dorsal skin at PIP and DIP joints, the knuckle patterns closely mimic the anatomical features of his or her fingers. Additionally, that study has elaborated a tentative but first promising decision to determine the stability of finger knuckle patterns.

Kumar et al. [2] developed a novel strategy for boosting the efficiency of a finger vein identification system. The system takes images of both the finger vein and the low-resolution fingerprint at the same time. Then, it uses a new score level combination strategy to put the two pieces of evidence together. Authors analyze the proposed finger vein identification methods from the past and create a new method that clearly outperforms the published ones. The matching performance of low-resolution fingerprint images are not inherited from a digital camera. Authors construct and study two novel score level combinations, namely holistic and nonlinear fusion, and compare and contrast them to other popular score level fusion methods to determine their efficacy in their intended system. The results of authentication and recognition trials using data on 6,264 images from 156 people show significant progress. The authors have presented a comprehensive and fully machine-controlled finger image matching system by combining data from finger surface and finger submerged options from finger texture and finger vein images. The author's new formula for identifying finger veins makes it easier to pick out the finger vein from the options and is much more accurate than what was expected from other finger vein identification methods. In practice, the author's finger vein matching theme achieves the highest levels of accuracy in the most realistic settings.

The authors plan and investigate two new score level combination approaches: a nonlinear one and a holistic one to effectively combine scores for matching finger veins and finger textures that are generated at the same time. The nonlinear method outperformed other potential methods that were considered throughout this work, including the average, product, weighted additions, Dempster-Shafer as well as probability quantitative relationship approaches. Phase Only Correlation (POC) is a technique for matching images that uses the component elements in second distinct Fourier transforms of provided images.

Aoyama et al. [3] explored the potential of a Band-Limited Phase Only Correlation (BLPOC), native-block matching algorithm for FKP detection. Phase Only Correlation (POC) is an image matching technique that takes advantage of the fragment elements in the second dimensional Fourier Transforms of the given images. Many biometric recognition algorithms make use of a variant of POC called BLPOC, which is specifically designed to measure image similarity. Since most POC-based biometric recognition algorithms rely on component information obtained from the full image, they are incapable of dealing with the nonlinear deformation of images. The diagrammatic representation of the nonlinear deformation of FKP images is made up of the minute translational displacement that occurs between native image blocks. Hence the suggested algorithmic program uses native block matching exploitation BLPOC to deal with it. The authors use phase-based texture matching to fix the global change between FKP images that can be computed. Then, the authors use BLPOC-based native block matching to fix the tiny translational error between each native image block. After accumulating the average BLPOC functions from the various local image block tests, the authors get a standard score for all FKP images by using the correlation peak price of the average BLPOC function. Using BLPOC, authors can determine the amount by which the two ROI images have been translated relative to one another and authors have aligned the images so that the translation is visible in both. Once the shared area between the two images has been identified, it can be removed. The BLPOC operation is determined between ROI images if the global magnitude relation of the shared region is less than the boundary. In the end, the optimal peak cost for the BLPOC operation is acquired due to the similarity score between the two FKP images. The BLPOC operation improves matching performance over the original BLPOC operation when applied to regions shared by both images.

Particularly in the context of the Internet of Things, FKP recognition has been the topic of a significant amount of study [12-17] in the disciplines of identity and authentication security. When compared to other systems, those that use straightforward classifiers such as SVM have provided innovative biometric authentication with a new research that is based on the master finger joint pattern. The deep learning approach is ideal for this verification because of its high accuracy percentage. The use of Convolutional Neural Networks, often known as CNNs, is what makes feature extraction and image comparison so efficient. When training is done, backpropagation, random gradient descent, and minibatch learning are all used in conjunction with a neural network to create a Convolutional Neural Network (CNN) [18].

Hammouche et al. suggested a new approach of FKP authentication based on phase matching with a Gabor Filter bank [19]. Along with this, authors suggested a new computational framework that could implement a new method for FKP recognition that was more effective in the extraction of features. The authors performed an in-depth analysis of three local properties that are frequently employed: phase fit, phase orientation, and local orientation. In addition to this, researchers devised a technique for accurately calculating all of the attributes by making use of phase coherence [20].

A technique for identifying FKPs was developed by Muthukumar and Kavipriya [21] using the Gabor feature with a Support Vector Machine to perform the analysis. In the innovative FKP biometric system that Heidari and Chalechale developed [22], the entropy-based pattern histogram (EPH) was used for feature extraction. In order to determine which of the collected characteristics was the most appropriate, a genetic algorithm (G.A.) was used to the data.This assertion has been validated by the utilization of the PolyU dataset [22].

On the other hand, Singh and Kant [23] improved a multimodal biometric system for the verification of persons that makes use of both FKP and iris features. In this particular system, Principal Component Analysis (PCA) method was applied for the purpose of feature extraction, and the neuro-fuzzy neural network classifier was applied for the purpose of the identification stage of the process. Chlaoua et al. [24] suggests using Principal Component Analysis to understand the two phases of filter banks. Then, feature vectors are classified using straightforward methods like binary hashing and block histograms. The researchers also looked into a multimodal biometric system that uses a score-matching fusion algorithm to mix different sorts of data [24].

In Zohrevand et al. [25], a simple CNN end-to-end model for FKP recognition is shown. The suggested model is tested on the Poly-U FKP dataset, and it achieves the best accuracy of 99.83% (0.76 and 99.18%, respectively) in terms of recognition. This model is built with two sets of connected layers and three convolutional layers, and it is based on a simple method for data augmentation with a limited number of trainable parameters. There are a variety of deep learning models that have been implemented for use in a variety of computer vision applications. The problem of learning deterioration in deep CNNs is addressed head-on by ResNet [26], which puts into practice the novel concept of including an identity block as part of the CNN design.

MobileNet [27] is yet another fascinating CNN that makes use of inverted residual in order to construct connections between bottleneck layers. That model's compact size makes it well-suited for usage on portable electronics. Further, ShuffleNet [28] is another CNN model that fares well on mobile devices. Since its architecture takes so minimal computational resources, it can be put to a wide variety of purposes. The efficient computation of this CNN can be attributed mainly to two operations: channel shuffling and pointwise group convolution. To improve CNN performance, EfficientNet [29] offered several unique ideas. Increasing a CNN's depth, number of layers, width, number of filters, and input image resolution are all ways to improve its performance, as outlined by EfficientNet. The depth, width, and resolution of each version of this architecture (b0 through b7) are different. FKP is frequently fused with additional biometrics, such as those provided in [30-34], to improve the efficacy of a biometric security system. Many FKP recognition algorithms have been published [35,36], but they all suffer from the same difficulties that have been carried over from machine learning and computer vision. As a consequence of this, there is still potential for advancement, particularly with regard to the application of deep learning strategies on FKP images.

1.3 The Work Done in This Study

In this dissertation, techniques for the extraction of features based on texture were applied in order to detect and identify finger knuckles. This system will then be used to identify and categorize a set of images of finger knuckles using the characteristics that it was trained to recognize. This research makes use of over 500 unique fingers sourced from two distinct datasets. The experiments are divided into four unique stages: the stage for data gathering, the stage for data preprocessing, the stage for data feature extraction, and the stage for matching. In order to extract features with using subspace method from images of finger knuckles, the techniques of Principal Component Analysis [8], Local Binary Patterns (LBP) [4], Binarized Statistical Image Features (BSIF) [5], Local Phase Quantization (LPQ) [6], and Weber Local Descriptor (WLD) [7] are used in this thesis. A different set of finger knuckles than those used for training are used to test how well the system works. This helps to establish an accurate system.

The remaining parts of the thesis are structured as described below. Chapter 2 explains both the preprocessing that was used and the design of the finger knuckle identification system. In Chapter 3, the feature extractors that were employed are described in depth. Experimentation and its subsequent analysis are covered in Chapter 4 and conclusions are presented in Chapter 5.

Chapter 2

FINGER KNUCKLE DETECTION SYSTEM

2.1 Introduction

The method used in this thesis to find finger knuckles is made up of four steps: pre-processing, acquisition, feature extraction, and 9atching. For the research, the Polyu FKP and ITTD datasets are used. Automatic finger knuckle recognition is done in the same order as most automatic face recognition methods from images: data acquisition, data pre-processing, data feature extraction, and matching. In general, there are two parts to classify finger knuckles: the training and the testing stage. In the training part, the images follow the steps mentioned above to find features that will be utilized to create classes for each finger. In testing part, an image is preprocessed and compared to the trained images, which will correctly classify the finger knuckle. Figure 2.1 shows how a finger knuckle recognition system works.

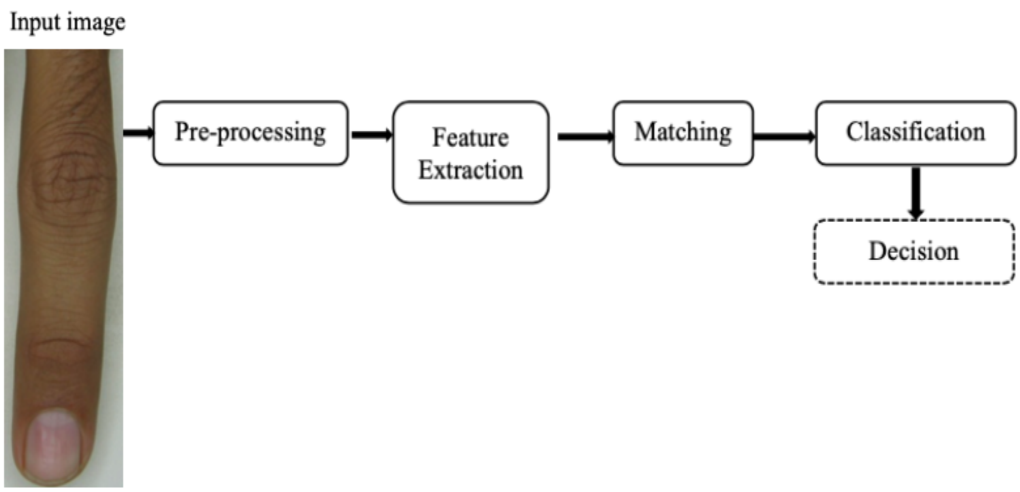

Figure 2.1: Finger Knuckle Recognition System

2.2 Acquisition

In the system's design, this is a critical step because this is where the features that will be used for trainning the system are taken from the images that have been collected. These images have been largely acquired in The Hong Kong Polytechnic University campus and IIT Delhi Campus during 2006-2015 using a contactless setup that simply uses a hand held camera.

2.3 Pre-processing

There are different ways to do pre-processing depending on the system of identification that will be used [9]. In this work, the pre-processing method that is cutting off the knuckles of the fingers to show more of the important parts of the images, get rid of the parts of the image that are not needed, and make it easier to find the important parts of the image. Finger knuckles on different fingers come in distinct shapes and sizes so a standard is necessary to pull out the important parts of the images. This is done by resizing the images to a common scale.

2.4 Feature Extraction

An image's features are its inherent, distinguishable characteristics that are extracted in order to represent the image's distinctiveness in comparison to other images and to show the content of images in a form that is more condensed and has fewer dimensions. Features are also known as image characteristics. In order to construct features of an image, global and local aspects of an image are retrieved. These qualities include an image's spatial information, shape, contrast, edges and color. Another method is known as feature fusion, and it refers to the process of combining various relevant aspects of an image in order to obtain more robust features [24]. Image processing makes use of a variety of feature extraction strategies and algorithms, the most notable of which are the BSIF [5], LBP [4], SURF, SIFT, DSIFT and PHOW DSIFT is a variation of SIFT that finds important points in each pixel of an image. PHOW is based on DSIFT and finds features in an image with grid sizes that get bigger and bigger. The preceding methods are what are known as texture-based algorithms, and they are utilized in this thesis. They do this by taking a grayscale image and extracting characteristics based on the image's texture. These algorithms extract features that are different in the manner in which they represent the characteristics of the image from which they are extracted. It is possible to enhance the retrieved features by using mathematical formulas and manipulating vectors. This will allow the features to be more suited for tackling a variety of issues pertaining to computer vision and machine learning. The retrieved characteristics are utilized for training a machine learning model, which, after it has been deployed, will be used for recognition, and classification.

2.5 Mathching and Classification

Matching Distance is done though distance metrics which are a key part of several machine learning algorithms. These distance metrics such as Euclidean, Manhattan, Minkowski and Hamming Distance are used in both supervised and unsupervised learning, generally to calculate the similarity between data points. An effective distance metric improves the performance of our machine learning model, whether that is for classification tasks such as Nearest Neighbors, Support Vector Machines (SVM), Artificial Neural Networks (ANN), k-Nearest Neighbors (k-NN), Random Forests (RF), Logistic Regression (LR) and Naive Bayesian Classification.

Chapter 3

FEATURE EXTRACTION

3.1 Introduction

In this section, the methods employed in this thesis are described in great detail. Finger Knuckle images are used for feature extraction with five different techniques to be employed in training and testing. Different methods were employed to extract unique features from the images, including PCA[8], LBP [4], BSIF[5], LPQ [6] and WLD [7]. The workings of each algorithm used are described below.

3.2 Principal Component Analysis

The statistical method of PCA has been successfully implemented in various areas including image reduction and facial recognition. It is a frequently used method for exploring high-dimensional data for patterns. Principal Components Analysis (PCA) technique may decode a complex image into a usable format by isolating the most important features. Eigenvectors and Eigenvalues are the mathematical representations of the covariance matrix of images where each image is merely a point in a very large space [n n], with referring to image dimensions. Even though a covariance matrix may have a large number of Eigenvectors, only a small subset of those will be truly important. Still, each Eigenvector can be utilized to indicate a unique range of differences in the knuckle images. However, only principal Eigenvectors are of interest to us because they explain large differences between a set of images. When applied to data, they can reveal the strongest associations between different dimensions. The highest Eigenvalues are corresponding to

Eigenvectors that make up the bulk of the image data collection. Eigen knuckles can be built with this collection of Eigenvectors. Here is an explanation of the algorithm for finding Eigen knuckles in finger knuckle images with similar sizes :

Step 1: Create the bunch of images $\{\Gamma_i | i = 1, \dots \dots . M|\}$ where M is the number of images

Step 2: Find the average image of bunch of images.

$$\psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \qquad (3.1)$$

Step 3: Find the constructed images [img1-avg,img2-avg,…...imgn-avg]

$$\Phi_i = \Gamma_i - \Psi \ ; \ \text{I=1............M} \qquad (3.2)$$

Step 4: Calculate the covariance matrix

$C = AA^T$ where $A = [\Phi_1 \dots \dots \dots , \Phi_M]$ is the test's representation in the Eigen Knuckle space.

Step 5: Figure out what each class's average weight is (Average class projection into "knuckle space"). Image database has more than one image of a person's knuckles for the same finger. This is so that the database can handle small changes in lighting and view angles better. For each person, a group of images can be used as follows

$$\Omega_\psi = 1/ \sum_{i=1}^{q_i} \Omega_i \qquad (3.3)$$

This mean class projection can be used as one of the vectors for comparison with the test image vector (representing a class of images rather than an image vector). By finding the Euclidean distance between the test image vector and the mean of each class's training image vector, it is assumed that the test image belongs to the closest class and Nearest Neighbor classifier is used to classify images.

3.3 Local Binary Patterns

The steps of the LBP method are as follows :

Step 1: An image of pixels are used to create a feature vector.

Step 2: Select a 3x3 block of image pixels, compare the average of those pixels to the surrounding 8 pixels, and establish a threshold for the middle value. If the calculated value is more than the median threshold value, a 1 is given, and if it is less, a 0 is assigned.

Step 3: Assuming the vicinity to be a circle with a radius R and a size of P pixels helps with the second step. A distinct number of neighbors P is selected for the LBP feature calculation based on the extent of the radius's reach. The procedure is depicted in Figure 3.2.

Step 4: Constructing standard type is the next stage. When a binary pattern is extracted, it is uniform if the pattern changes from 0 to 1 or 1 to 0 only once. A circle is the name given to this type of arrangement. If the value is less than the center pixel value, the surrounding circle will be white, and if it is greater than the middle pixel value, the surrounding circle will be dark. Patterns are featureless, and the image as a whole lacks significance, when all of the adjoining pixel values are either larger than or smaller than the center thresholded value. The pixel values and the LBP binary representation of an image are displayed in Figure 3.3. In LBP, an edge is represented by a sharp deviation from the initial, uniform, set of pixel values. Example of how LBP displays the discovered edge can be seen in Figure 3.4. An algorithm for machine learning is given the extracted features so that it can learn how to classify things. Simple machine learning models, such as k-nearest neighbor, are effective. Then the use of straightforward machine learning models, such as the k-nearest neighbor algorithm, produces satisfactory results with the help of LBP. LBP can be formally computed as follows:

$$LBP_t(x,y) = \sum_{n=1}^{N} LBP_t^n(x,y) \times f^n, \forall t \varepsilon [1,c] \quad (3.4)$$

f^n is a weighting function defined as

$$LBP_t^n(x,y) = \{ \quad \} \quad (3.5)$$

$$f^n = (2)^{n-1}, \forall n \epsilon [1,N] \quad (3.6)$$

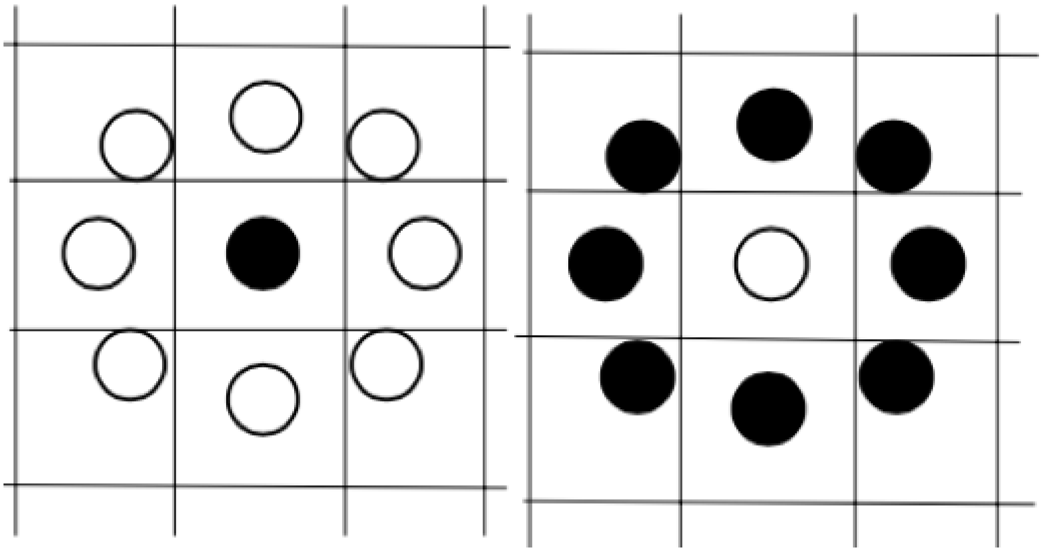

Figure 3.2: Two distinct patterns of output produced by a uniform LBP (1,8) [6].

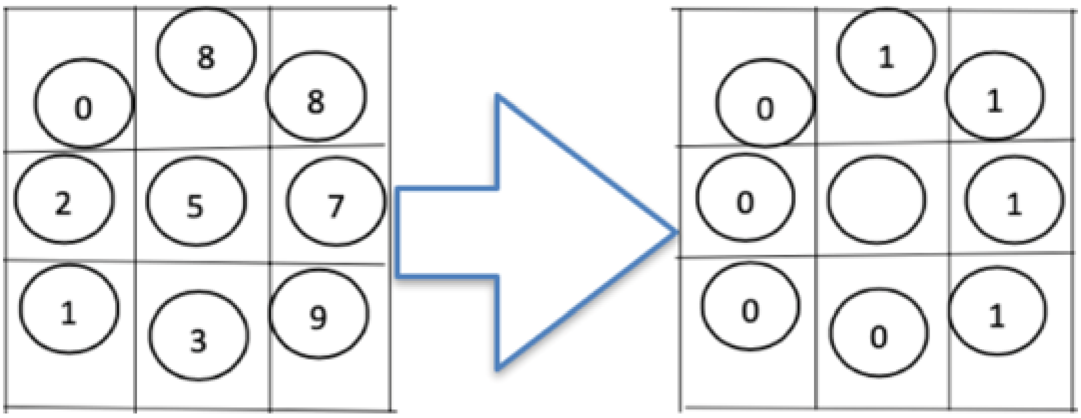

Figure 3.3: Binarized LBP output [6]

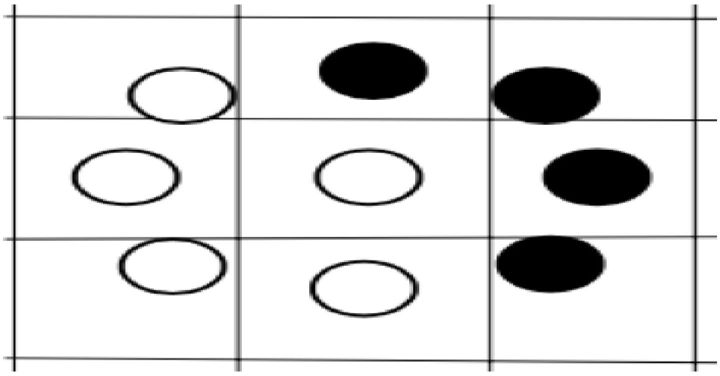

Figure 3.4: LBP detection of an edge [6]

3.4 Binarized Statistical Image Features

An image's texture characteristics are used to construct a descriptor called BSIF. Using a set of filters that have been learned from natural images through Independent Component Analysis is at the core of this method. The output of binary strings is provided by the individual pixels that make up each neighborhood of an image. The output of various filters is a distinct set of code. The generated code is then binarized so that it can be utilized as image descriptors.

BSIF is a more effective quantization method than both LBP and Local Phase Quantization. A histogram of the binary values of an image's pixels is the format used to store the data in this method. Component analysis and thresholding are used, as in linear binary projection, to create the code. In this method, filters are constructed from a limited amount of images and then it is utilized to binarize the pixel's surrounding neighbors. For various uses of the approach, various filters are employed and they output bit string features of varying lengths. The intensity pattern of neighboring images is used to generate a candidate image's texture features, which are then represented as binarized output codes. When an image is tiled into 8x8 segments, the resulting feature vector representation is a representation of the image's features. Each region's descriptors are calculated, and then all of those descriptors are added together to form the full image's description.The BSIF algorithm is described in detail below. The following are the steps of the method used by Binarized Statistical Image Features:

Step1: The filter response s_i is found by taking an image patch X of size lxl pixels and a linear filter w_i of the same size, with b_i as the binarized feature, and plugging those values into an equation.

$$s_i = \sum_{u,v} w_i(u,v) \times (u,v) = w^t x \tag{3.7}$$

Concatenating the output of N linear filters yields a matrix of size which can then be used to calculate all of the binarizing a number of different descriptors the results of solving equation (3.4.1) using the disctinct filters. where w_i and x_i are vectors, the features bi in binary form are obtained if s_i > 0 equates 1 and 0 otherwise. Given number of linear filters N, they can be used all at the same time by concatenating them to form a matrix of size N×I to compute all the different descriptors by binarizing output of equation (3.4.1) from the different filters. With image restoration, we can keep the results of equation (3.4.1) statistically independent, allowing us to create a collection of filters with good performance.

Step 2: To reduce the dimension of the filters, whitening of the training filters are done using Principal Component Analysis to determine the principal components of the natural image patches, where the principal components are taken and divided by their standard deviation to obtain whitened data samples.

Step 3: The final filter for extracting BSIF descriptors is obtained by using a typical ICA technique to the whitened data samples, yielding a matrix that is orthogonal. **Step4:** The filters that were constructed in steps 1, 2, and 3 for the purpose of extracting the image's texture are used to extract feature descriptors from an image.

3.5 Local Phase Quantization

The LPQ descriptor was first designated for use in the classification of blurry textures [6]. LPQ is built to keep an image in the local invariant information to artifacts created by various kinds of blur. This is achieved through its construction. This descriptor makes use of local phase information that has been recovered from a Short Time Fourier Transform (STFT) over a rectangular M x M neighborhoods ateach pixel position x of the image f(x). The LPQ is an effective strategy that is suggested as a solution to the problem of expression variations. This idea served as inspiration for the LPQ. It is used as LPQ operator in each of the 25 sub-regions that make up the hand region, and in the end, a histogram of the values obtained from each of the sub-regions was concatenated into a single feature vector that had 6400 dimensions as shown in Figure 3.5.

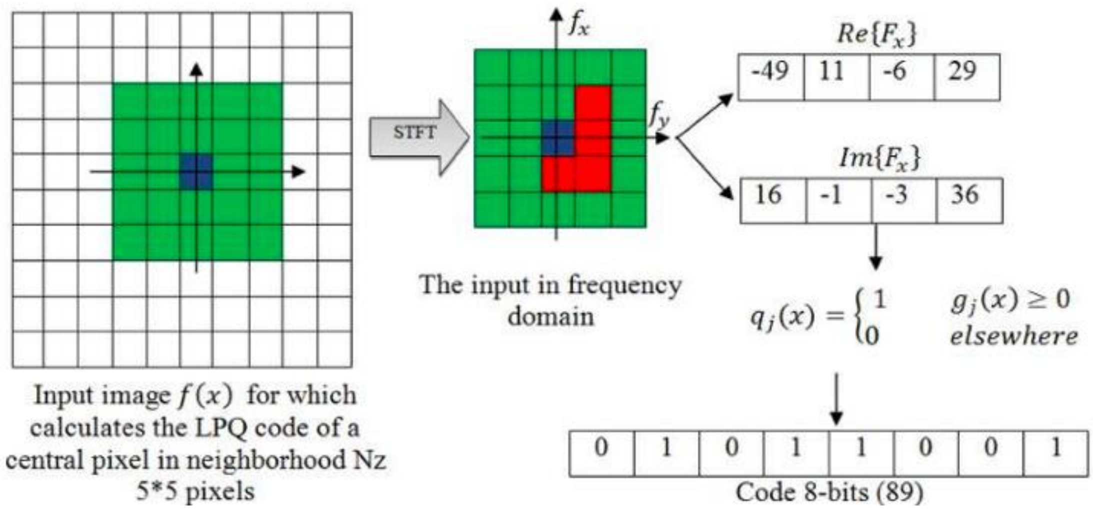

Figure 3.5 Features of Local Phase Quantization [6]

LPQ makes use of a binary encoding strategy that is comparable to that of LBP, but it examines the patch that surrounds in order to construct a descriptor, the target pixel must be located in the Fourier domain that is immune to centrally symmetric blur [19]. To be more specific, it utilizes the information of local phase that was computed applying the STFT. To construct an 8-bit feature, after retrieving four coefficients' predetermined frequencies, it then quantizes those coefficients using binary operations. The only thing that is recorded for each coefficient is the sign of the real and imaginary parts of the coefficient. Therefore, the patch retains only very basic phase information. Estimating a characteristic orientation and obtaining a directed descriptor are two key operations that are required in order to generate the version of LPQ that is rotation-invariant. The typical orientation of each pixel position is defined as (x) = b(x), where the sign of the maginary part of this vector denoted is preservedAs shown below :

$$b(x) = \sum_{i=0}^{M-1} c_i \, e^{j\phi_i} \tag{3.8}$$

Here, it can get the binary descriptor vector by applying a method that is similar to the LPQ method. The only difference is that the area around pixel X is turned in the way that matches the orientation that is characteristic (x). After calculating the four local Fourier coefficients, each component's phase is recorded. In this case, a histogram is made and used as a 256-dimensional feature vector in the next step of the classification process as shown below :

$$LPQ^{ri} = \sum_{i=1}^{8} q_i \, 2^{i-1} \tag{3.9}$$

3.6 Weber Local Descriptor (WLD)

Differential orientation and excitation are the two building blocks that make up WLD.Differential excitation can be explained by the following equation :

$$\varepsilon(x) = arctan\left[\sum_{i=0}^{7} \frac{x_i - x}{x}\right] \tag{3.10}$$

where x represents the target pixel and its neighbors in a 3 by 3 grid that are denoted by x_i's.As a result, the characteristic has a value of zero in smooth regions of the image, but its magnitude grows wherever there are interruptions in the process. In a high-intensity area, it might be hard to tell the difference, but in a low-to-medium intensity area, it might be a big deal. This situation is summed up by Weber's law, which says that the difference between two stimuli that it is noticeably proportional to stimulus size. Based on this principle, this difference determines the pixel's intensity.

The orientation is just the gradient orientation. The angle made by the vector whose parts are the vertical and horizontal differences between the image's center at point x and the reference axis can be represented in the following equation:

$$\theta(x) = angle(x_7 - x_3, x_5 - x_1) \tag{3.11}$$

Since $\theta(x)$ can take on any value between 0 and 2, linear quantization in T dominates orientations. The quantization function can be shown as follows:

$$\theta_q(x) = \frac{2t}{T}\pi \tag{3.12}$$

Where $t = \left(mod\left[\frac{\theta'}{2\pi/T + \frac{1}{2}}\right], T\right)$ (3.13)

For simplicity, θ is further quantized into T dominant orientations. Before the quantization, we perform the mapping f :θ $\rightarrow$θ′ and $\theta' = arctan\,2\,(vs_s^{11}, vs_s^{10}) + \pi$ where θ∈ [-π/2, π/2] and θ′ ∈ [0, 2π].

This chapter describes the experimental setup, datasets and the experiments utilized in this thesis. It begins with the preparation of databases for training the system, explains how each method extract the features and concludes with an evaluation of the performance of the system. All experiments are conducted using a MAC OS with 8 GB 1600 MHz DDR3 and 1.8 GHz Dual-Core Intel Core i5.

4. 2 Database Descriptions

In this thesis, 4 different databases are used and these are The Hong Kong Polytechnic University Contactless Finger Knuckle Images Database (Version 1.0) (PolyU-1), The Hong Kong Polytechnic University Contactless Hand Dorsal Images Database (PolyU-D), The Hong Kong Polytechnic University Contactless Finger Knuckle Images Database (Version 3.0), IIT Delhi Finger Knuckle Database (Version 1.0) (IITD). Table 4.1 summarizes the details related to each database.

Table 4.1: Number of Individuals and Samples of Images For FKP Databases

Abbreviation	Databases	Acquisiton Device	Images	Subjects	Numbers of Samples	Partially Included FT Parts
PolyU-1	The Hong Kong Polytechnic University contactless finger knuckle images database (Version1.0)	Hand Held Camera	2515	503	6	Distal phalanx and middle phalanx bones
PolyU-3	The Hong Kong Polytechnic University contactless finger knuckle images database (Version3.0)	Hand Held Camera	1950	221	6	Distal phalanx and middle phalanx bones
PolyU-D	The Hong Kong Polytechnic University Contactless Hand Dorsal Images Database	mobile and hand held camera	2505	501+214=712	6	Proximal and the metacarpal phalanx bones
IITD	The IIT Delhi finger knuckle image database	digital camera	790	158	4	Proximal and the metacarpal phalanx bones

The Hong Kong Polytechnic University contactless finger knuckle images database (Version 1.0) (PolyU-1) is contributed from the male and female volunteers. This database has been largely acquired in The Hong Kong Polytechnic University campus and IIT Delhi Campus during 2006-2013 using a contactless setup that simply uses a hand held camera. This database has 2515 finger dorsal images from the middle finger of 503 subjects, all the images are in bitmap (*.bmp) format. In this dataset about 88% of the subjects are younger than 30 years. This database also provides two session finger knuckle images acquired after very long interval (4 to 7 years) to ascertain stability of knuckle crease and curved lines. Sample images from PolyU-1 dataset are shown in Figure 4.1.

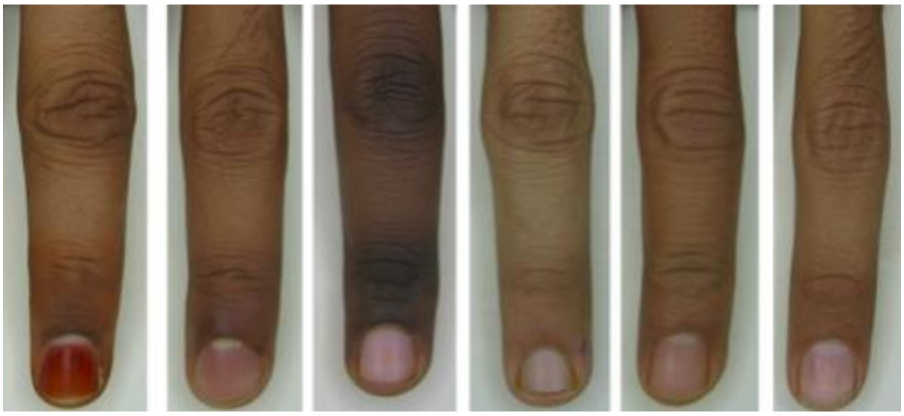

Figure 4.1: Sample from The Hong Kong Polytechnic University contactless finger knuckle images database (Version1.0) (PolyU-1)

The Hong Kong Polytechnic University contactless finger knuckle images database (Version 3.0) (PolyU-3) is contributed from the male and female volunteers. This database has been largely acquired in The Hong Kong Polytechnic University campus and IIT Delhi Campus during 2006-2013 using a contactless setup that simply uses a hand held camera. This database has 1950 finger knuckle images from the index finger of 221 subjects. All the images are in .JPG format. This database also provides two session finger knuckle images acquired after very long interval (4 to 7 years) to ascertain stability of knuckle crease and curved lines. Besides, this database also includes segmented finger knuckle images, contrast-enhanced images and center point information of every finger knuckle images used for segmentation to extract a normalized region. Samples of images from HongKong Polytechnic University (version 3.0are shown in Figure 4.2.

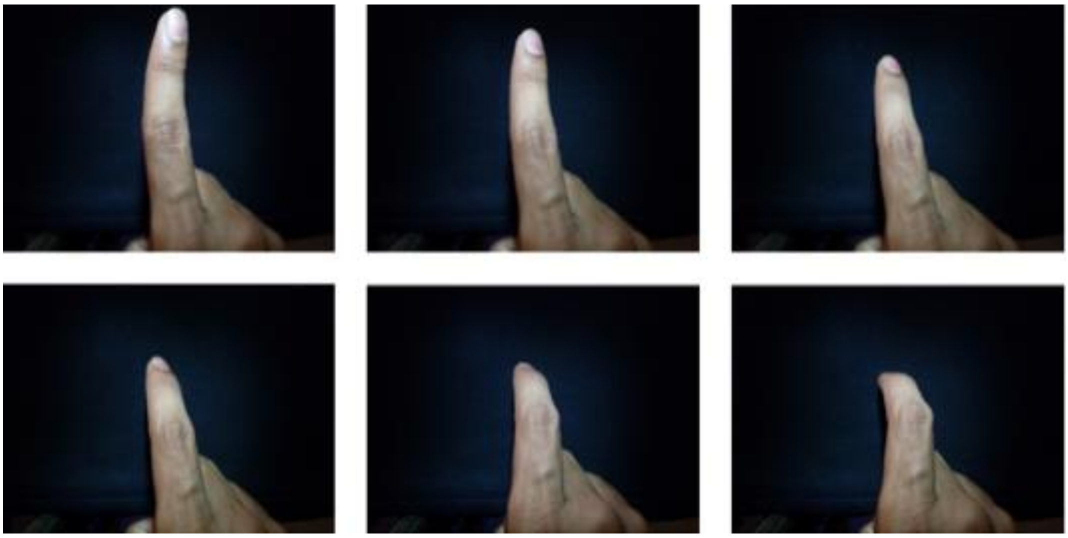

Figure 4.2 :The Hong Kong Polytechnic University Contactless Finger Knuckle Images Database (Version3.0) (PolyU-3)

The Hong Kong Polytechnic University Contactless Hand Dorsal Images Database (PolyU-D) is contributed from the male and female volunteers. This database has been largely acquired in IIT Delhi Campus in The Hong Kong Polytechnic University campus and in some villages in India during 2006-2015, mostly by using a mobile and hand held camera. This database has 2515 hand dorsal images from the right hand of 503 different subjects that illustrate three knuckle patterns in each of the four fingers from the individual subject. All the images are in bitmap (*.bmp) format. This database also has additional hand dorsal images from 211 different subjects but these images lack clarity or does not have second minor knuckle patterns. The combined database from 712 different subjects hand dorsal images is made publicly available. This database also provides two session hand dorsal images, with many samples in different age groups that have been acquired after very long interval (4 to 8 years) to support studies relating to the stability of knuckle patterns. This database also provides segmented/normalized major, first minor and second minor knuckle images using completely automated segmentation.Such images are made available for all the subjects and different/respective fingers and can be easily identified using the names of respective images/folders in the database. Samples images from PolyU-D dataset are shown in Figure 4.3.

Figure 4.3: Samples from The Hong Kong Polytechnic University Contactless Hand Dorsal Images Database (PolyU-D)

The IIT Delhi finger knuckle image database (IITD) consists of the images acquired from the students and staff at IIT Delhi, New Delhi, India. This database has been acquired in IIT Delhi campus during August 2006 – Jun 2007 using a digital camera. The currently available database is from 158 users, all the images are in bitmap (*.bmp) format. All the subjects in the database are in the age group 16-55 years. This database of 790 images have been sequentially numbered for every user with an integer identification/number. The resolution of these images is 80 × 100 pixels and all these images are available in bitmap format. Samples images from IITD dataset are shown in Figure 4.4.

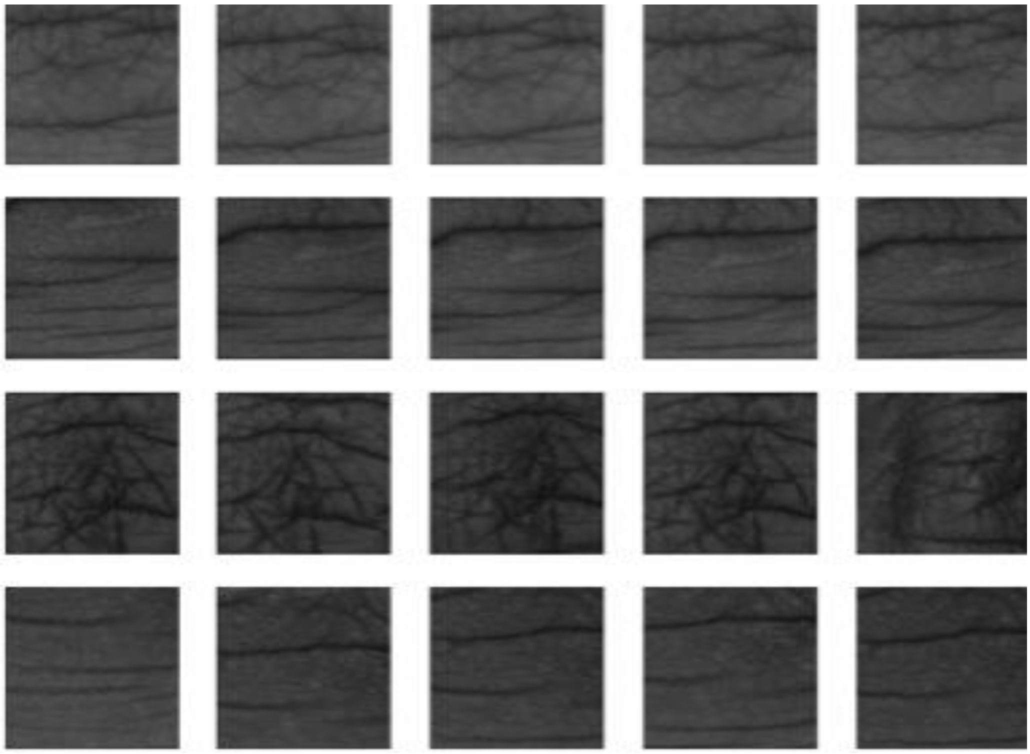
Figure 4.4: Samples from The IIT Delhi finger knuckle image database (IITD)

4.3 Experimental Methods

In this thesis, five feature extraction techniques, namely PCA, LBP, BSIF, LPQ and WLD, are applied on all databases. In addition, Euclidean distance is used for all feature extraction techniques in the matching stage. In Principal Component Analysis (PCA), the images are converted into grayscale. Before applying the PCA technique to train and test images, train and test images are resized to 80 x 60 pixels and then Histogram Equalization was applied to improve quality of images.

In LBP, images are transformed to grayscale and then the Gabor filter is applied. Both the training images and the test images are subdivided into 80 by 60-pixels. The LBP algorithm is applied on each block, and it uses the (P, R) neighborhood to figure out the descriptors for each pixel by making a circular symmetric pattern across each pixel. In this thesis, the neighboring pixels are P = 8 and the radius is R = 2. Because of this, with LBPu,2 is used to figure out the LBP descriptors. The LBP method is used to figure out the algorithm with (8,2) neighborhood and the length of the features depends on the size of each cell. The features of the complete cells in an image are compiled into a single feature vector by concatenating the characteristics of each block. In this study, various image cell sizes were evaluated, with the 32-by-32-pixel cell size yielding the greatest performance. The images are first converted into grayscale in BSIF. Both the training images and the test images are resized into 80-by-60-pixel cells and using the algorithm's description of the filters that have already been learned, the experimental images are first converted into grayscale, and then the code descriptors are made from the image using a 9x9 filter with 12 bits. When you slide an image over a 9x9 filter, descriptors are made from each cell, giving each image a 1 by 4096 feature vector.

The images are first converted into grayscale in LPQ. Both the training image and the test image are resized into 80-by-60-pixel cells and used with the default settings for Short Time Fourier Transform (STFT), which are M = 36 and r = 0.2, and a 9X9 window is used.

In WLD, both the training and test images are divided into 80 by 60 pixels. In this work, we used radius=3, neighborhood=8 as experimental parameters, which is typically capable of extracting effective features as in [11]. Then, the gradient orientation is calculated. Experiments are conducted using Euckidean distance metrics and Nearest Neighbor classifier.

4.3 Experimental Results

This section describes the methodology based on experimentation used to design the suggested system. Five different algorithms are put into action in order to evaluate how accurately they recognize finger knuckles. PCA [8], LBP [4], BSIF [5], LPQ [6], and Weber Local Descriptor (WLD) [7] are studied using each available dataset in recognizing the finger knuckle images. The accuracy of five algorithms on each dataset is calculated using 2 Train and 2 Test, 3 Train and 2 Test, 4 Train and 1 Test. To conclude, the accuracy of the system is evaluated by the following equation (4.1) to determine how well it performed with each dataset. Tables 4.2 through 4.7 present the findings on finger knuckle recognition

Accucary = (Number of test images correctly classified / Total number of test image $\times$ 100 (4.1)

Table 4.2: Accuracy results (%) using PCA method

Database	2 Train 2 Test	3 Train 2 Test	4 Train 1 Test
IITD	60.127	70.886	56.329
PolyU-1	45.390	48.965	48.079
PolyU-3	24.434	20.814	21.719
PolyU-D	92.307	75.000	82.051

Table 4.3: Accuracy results (%) using LBP method

Database	2 Train 2 Test	3 Train 2 Test	4 Train 1 Test
IITD	95.569	65.189	72.784
PolyU-1	82.107	58.747	66.600
PolyU-3	60.504	59.243	73.109
PolyU-D	98.717	80.769	91.026

Table 4.4: Accuracy results (%) using BSIF method

Database	2 Train 2 Test	3 Train 2 Test	4 Train 1 Test
IITD	60.759	65.189	50.000
PolyU-1	79.722	53.677	70.886
PolyU-3	65.289	62.217	66.063
PolyU-D	58.403	55.882	65.546

Table 4.5: Accuracy results (%) using LBP method

Database	2 Train 2 Test	3 Train 2 Test	4 Train 1 Test
IITD	27.215	25.000	32.278
PolyU-1	57.256	42.544	53.082
PolyU-3	35.714	39.916	48.739
PolyU-D	84.615	58.333	61.538

Table 4.6: Accuracy results (%) using LBP method

Database	2 Train 2 Test	3 Train 2 Test	4 Train 1 Test
IITD	44.304	32.595	34.177
PolyU-1	51.594	37.872	46.123
PolyU-3	39.076	40.336	15.126
PolyU-D	89.103	82.692	64.103

It is evident that BSIF and LBP have obtained the highest accuracy according to the other methods in all datasets. Only PolyU-1 Session2 dataset managed to stay in the first rank in terms of performance in all algorithms. Generally, it can be seen that when we used 2 Train and 2 Test , it obtained the best results. Only when it increases the number of trains in the LPQ method, it can be seen that the performance also increases except PolyU-1 Session2 and PolyU-3 Session2.

However, the situation is not the same in other methods. Table 4.2 demonstrates that for the PCA approach, PolyU-1 Session2 achieved the maximum accuracy with 92.37%. On PolyU-1 Session2 dataset, the LBP approach recognizes images of finger knuckles with 100 percent accuracy. PolyU-1 Session2 and ITTD datasets produced the highest accuracies for the BSIF approach as 98.717 and 95.569%, respectively. Tables 4.5 and 4.6 display the classification results for LPQ and WLD, which had the lowest accuracy compared to the other methods. Table 4.7 shows different methods employed to extract unique features from the images that compares accuracies with different databases.

Table 4.7: Comparison the with the State-of-the-Art for Finger Knuckle Recognition

Ref	Publication Year	Features	Classification	Databases	Accuracy
[37]	2013	Principal Component analysis(PCA)	Nearest Neighbor Classifier	Polyu	55.7 %
		Liner Discriminant Analysis (LDA)	Nearest Neighbor Classifier		76.0 %
		Liner Discriminant Embedding(LDE)	Nearest Neighbor Classifier		76.2 %
		Weighted Linear Embedding	Nearest Neighbor Classifier		78.2 %
		Gabor Feature and OLDA	Nearest Neighbor Classifier		98.06 %
		Orthogonal Complex Locality Preserving Projections	Fused angle and Euclidean distance		87.87 %
		Modified Finite radon Transform	Distance measure		98.6 %
		Competitive Code	Angular distance		97.96 %

Ref	Publication Year	Features	Classification	Databases	Accuracy
[39]	2017	WLE Random Sample Consensus (RANSAC) PCA+LDA Locality preserving projection (LPP)	Euclidean distance	PolyU	78 % 96.91 % 90.63 % 98.8 % 99.6 %
[40]	2018	Support Vector Machine (SVM)	Radial Basis Function (RBF) kernel	The Vision and Signal Processing Research Lab in Queensland University of Technology	92.99 %
[41]	2019	Logistic Regression Weighted Exponential Hyperbolic Tangent	Euclidean Distance	KVKR-Hand Dorsal Images Database	98.31 % 98.88 % 100 %
[42]	2019	LBP	Bernoulli	The IIT Delhi finger knuckle image database	96.36 %

Ref	Publication Year	Features	Classification	Databases	Accuracy
[43]	2021	Binary Statistical Image Feature(BSIF) Binary Statistical Image Feature(BSIF) Binary Statistical Image Feature(BSIF) Binary Statistical Image Feature(BSIF)	Cosine Mahalanobis Distance	The Hong Kong Polytechnic University contactless finger knuckle images database (Version1.0) Minor finger knuckle Major finger knuckle Dorsal finger knuckle	99.60 % 94.04 % 95.43 % 98.31 %
This Study	2022	Principal Component analysis (PCA) Local Binary Pattern (LBP)) Binary Statistical Image Feature(BSIF) Local Phase Quantization (LPQ) Weber Local Descriptor (WLD)	Euclidean Distance	IITD PolyU-1 PolyU-3 PolyU-D IITD PolyU-1 PolyU-3 PolyU-D IITD PolyU-1 PolyU-3 PolyU-D IITD PolyU-1 PolyU-3 PolyU-D IITD PolyU-1 PolyU-3 PolyU-D	%60.127 %45.390 %24.434 %92.30 %60.759 %79.722 %65.289 %58.403 %95.56 %82.10 %60.504 %98.717 %27.215 %57.256 %35.714 %84.615 %44.30 %51.594 %39.076 %89.103

Table 4.7 is summary of the comparison with the state-of-the-art for Finger Knuckle Recognition and it is related to t thesis work. Table 4.7 compares the performances

of the methods used from 2013 to 2021. In Table 4.7, the highest performance was obtained using 100 % Hyperbolic Tangent algorithm with using KVKR-Hand Dorsal Images dataset. Hyperbolic Tangent for feature extraction process and the Euclidean distance for the matching process. In this thesis, we used 5 algorithms as PCA, LBP, BSIF, LPQ, and WLD. While applying the PCA method, we achieved the highest performance of 92% with the PolyU-D dataset. The performance obtained with the PolyU dataset in [41, 43] is very similar to the accuracy in this study. It did not mention which version of PolyU dataset they used in their studies. The work [46] inferred that finger knuckle print was recognizable utilizing LBP and Bernoulli classifier that gives %96.36 accuracy in IITD dataset. In addition, we applied LBP with Euclidean Distance in same dataset and our results are close to theirs. It uses BSIF for feature extraction process and the Nearest Neighbor Classifier that employed the cosine Mahalanobis distance for the matching process [48]. In this study, PolyU-1 and PolyU-D datasets were used and 98.5% and 98.3% accuracy were obtained. It can be said that we almost achieved the same accuracies with the same dataset. Moreover, LPQ and WLD feature extraction methods were applied and acquired the highest results on the PolyU-D dataset as 84.615% and 89.103% respectively. These methods have not been used for Knuckle Patterns for Person Recognition in the literature. However, satisfactory results have not been obtained in other datasets but can be developed in the future.

Chapter 5

CONCLUSION

Finger knuckle recognition can be used in a variety of security contexts, including airport checkpoints, visa processing, police department database checks for criminal records, voting registration, and ATM card verification. Researchers in the biometrics, pattern recognition sector, and computer vision fields have paid considerable attention to the challenge of recognizing finger knuckles.

In this thesis, texture-based feature extraction methods are mostly applied for finger knuckle pattern recognition. The HongKong Polytechnic University (PolyU) Contactless Finger Knuckle Pattern images and Indian Institute of Technology Delhi (IITD) fingers knuckle pattern databases are used to assess the accuracy of a finger knuckle recognition system based on PCA, LBP, BSIF, and WLD feature extractors. Results from the experiments show that BSIF and LBP performed better than PCA, LPQ and WLD when using Euclidian distance metrics and Nearest Neighbor Classifier.

More images of finger knuckles should be included in a more thorough system for future studies. Additionally, portable finger knuckle detection system for use with smartphones will be a useful future study. Moreover, major and minor finger knuckles can be fused in order to obtaion higher accuracy compared to the accuracy of individual systems.

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