PCA based Feature Selection of Online Signature Verification system using DFrCT

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DECLARATION

I hereby declare that the work which is being presented in this dissertation, entitled **"PCA based Feature Selection of Online Signature Verification system using DFrCT"** for the award of degree of Master of Engineering in Electronics and Communication Engineering, is an authentic record of my own work carried out under the supervision of **Dr. Kulbir Singh (Professor)**, ECED, Thapar University, Patiala and refers other work which are listed in the reference section.

The results presented in this dissertation have not been submitted in part or in full to any other University/Institute for the award of degree or diploma.

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It is certified that the above statement made by the candidate is correct to the best of my knowledge and the contents of the dissertation have reached the requisite standard.

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ABSTRACT

Biometrics is defined as recognizing an individual on the basis of his/her distinctive characteristics. Several biometric verification techniques have been implemented to enhance the security. Amongst all the possible biometric modalities, the handwritten signature has been used for the longest period of time as a means of identification. Its application is mostly present in banking transactions, cheque authentication, online shopping, legal documents etc. These applications increase the demand for the use of signature for the identification purpose. This leads to the development of documents like electronic passports. Accurate verification can be done by using online signatures to achieve better results. Several verification techniques used are Dynamic Time Warping (DTW), Bayesian Learning, Hidden Markov Model (HMM), Neural Networks, Support Vector Machine (SVM), etc.

Many techniques have been applied on online signatures till now. One such technique employed Discrete Cosine Transform (DCT) which considered six features for verification process. However, only 7.04% of Equal Error Rate (EER) was achieved when DCT was applied. When the number of features got increased from six to ten, the EER further reduced to 5%. In order to attain much better results, a new methodology has been proposed in this dissertation which makes use of DCT with Principal Component Analysis (PCA) as a feature selector. PCA reduces the large dimensionality of data space to the small intrinsic dimensionality of the feature space, so as to capture the maximum variability in the data. The advantages of PCA include smaller representation of data along with the reduction in the noise. As a result, 3.5% of EER is obtained when eight features are considered, which clearly proves the superiority of DCT with PCA over DCT only.

Another effort has been put up to improve the signature verification which uses Discrete Fractional Cosine Transform (DFrCT). The DFrCT is a general form of DCT which has an additional free parameter, its fraction that gives an extra degree of freedom. But calculations done in the case of DFrCT are more than DCT, which increases the computational complexity of the signature verification system. When ten features of the test signature are extracted and verified using this technique, an EER of 3.25% is attained. Further, another method is proposed in this dissertation that

combines DFrCT with PCA for achieving more appropriate results. 3% of EER is obtained using eight features which is by far the least EER achieved.

The experiments described above are performed over a number of features ranging from five to ten. SVC2004 database is used for carrying out the work. In case of DCT and DFrCT alone, it is verified that the EER is minimum when ten features are used independently. When these techniques are combined with PCA, minimum EER is obtained at eight features only, thus reducing the computations.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ATMs	Automated Teller Machines
DCT	Discrete Cosine Transform
DFrCT	Discrete Fractional Cosine Transform
DFrFT	Discrete Fractional Fourier Transform
DFrST	Discrete Fractional Sine Transform
DFT	Discrete Fractional Transform
DST	Discrete Sine Transform
DWT	Discrete Wavelet Transform
EER	Equal Error Rate
EPW	Extreme Point Warping
FAR	False Acceptance Rate
FIR	Finite Impulse Response
FRR	False Rejection Rate
FrCT	Fractional Cosine Transform
FrFT	Fractional Fourier Transform
FrST	Fractional Sine Transforms
HMM	Hidden Markov Model
ID	Identity Document
LDA	Linear Discriminant Analysis
MLP	Multilayer Perceptron
NCA	Null Component Analysis
NCs	Null Components
PCA	Principal Component Analysis
PC	Personal Computer
PCs	Principal Components
PDAs	Personal Digital Assistants
ROC	Receiver Operating Characteristic
SVD	Singular Value Decomposition
SVM	Support Vector Machine

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Chapter-1
Introduction

1.1 Preamble

The advancement in the technology is increasing at a very fast rate from past few decades. With the growth of computer technology many transactions now have gone online. This requires the development of a secure technique or method to keep a proper check on these transactions. Forgeries by hackers and fast transactions results in loss of person concerned as well as society. Some alternative is required to verify whether person doing the transaction is genuine or forged. One of the methods for this check is a Biometric system. Biometric systems are classified into two types as [1]:

- **Physical:** In physical person's thumb, iris, palm etc. are used for verification.
- **Behavioural:** In behavioural voice, signature etc. are used for verification.

1.1.1 Signature as a Biometric

Various biometric techniques are widely used for the verification of identity of an individual. Out of all possible techniques handwritten signatures are most often used behavioral biometric for verification purpose, for example, in the case of bank transactions, commercial transactions, credit card payments etc. Errors encountered during authentication through signatures are not ample. Information that can be obtained during signing consists of pressure applied by pen, and other visible features like height, width, area etc. There are variations among different signatures of same person [2]. These variations are important to be considered for the verification purpose. This variability occurs due to the effect of physical and emotional conditions.

Main objective of handwritten signature verification system is to find forgeries in the signature. Forgeries are dependent on the intra and inter personal variability. These forgeries occurring in signature can be classified into three types [2] as shown in Figure 1.1.

- **Random forgery:** Random forgery is signature where forger has no idea about signature style and name of the signer.
- **Simple forgery:** Simple forgery is signature where forger has idea about the name of the signer.

- **Skilled forgery:** Skilled forgery is signature where forger knows the signer's name and style of signature.

For removing the possibility of forgery, dynamic features of the signature must be taken into account. Dynamic features are the one that are recorded during signing process which includes acceleration, pressure, time taken by the signer to sign, pen-tip angle etc. and these features vary with respect to time. By use of these additional features error rates can be improved and signature becomes an important option for verification during online processes.

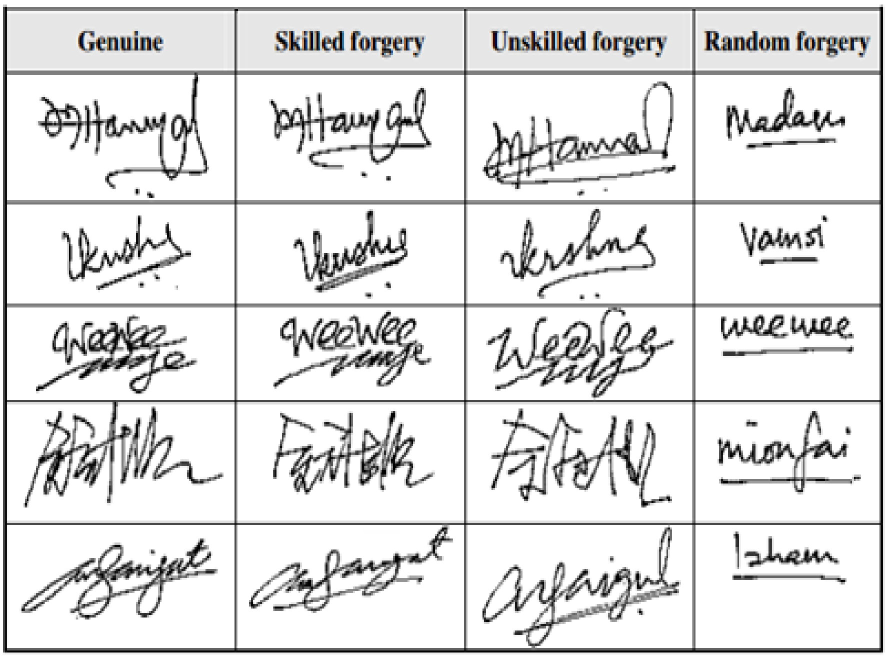


Figure 1.1: Types of Forgeries in Signature [3].

1.1.2 Terms and Concepts

As there is still development going on in the field of automatic signature verification, some terms used may have wrong interpretations. To avoid this misinterpretation, various terms used in this dissertation are briefly explained here.

Signature: Name of the person written in a particular format for the purpose of identification in some document.

Signer: A person who creates the handwritten signature.

Genuine signature: A signature originated from a genuine signer.

Forged signature: A signature which is the imitation of the genuine signature but is not originate from the corresponding signer.

Test signature: Signature under test, which is to be classified as either genuine or forged.

Reference signature: Signature stored in the database for comparison with test signature.

1.2 Types of Signature Verification Systems

On the basis of data acquisition signature verification can be classified in two groups i.e., Online (dynamic) and Offline (static) [4].

1.2.1 Online Signature Verification

Online signature verification consists of capturing the dynamic features of signature that varies with respect to the time while using electronic devices. It deals with structure as well as behavior of the signature. This can be done by tablet or pen with sensor. An example of data acquisition through tablet is shown in Figure 1.2.

Figure 1.2: Digital Tablet [5].

On the basis of features extracted, online signature verification can be categorized as [6]:

- **Global approach:** In this approach, global features like signature total duration, number of pen-ups etc. are acquired from the signatures, and classification is done based upon that.

- **Local approach:** In this approach, instead of classification based upon features, direct matching of time functions is done using distance measures, like Dynamic Time Warping (DTW).
- **Regional approach:** In this approach, classification is done based upon the estimation of some regional properties i.e. area, major axis length, minor axis length, eccentricity etc. Best technique implied in this approach is Hidden Markov Model (HMM). Further Wavelet and Cosine Transforms can also be applied to the coefficients.

1.2.2 Offline Signature Verification

In offline verification system, image of the signature is scanned and further used for processing. It deals only with the structure of signature. Verification can be done by comparing the scanned image with the already stored image or through statical features like height to width ratio, curvature etc. An example of offline signature is given in Figure 1.3. Offline signature accounts for lesser accuracy in verification.

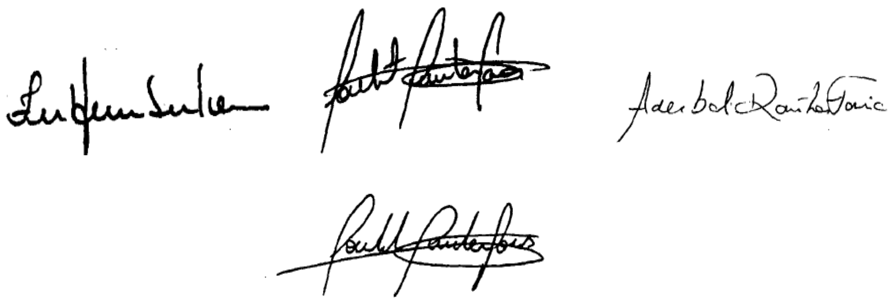


Figure 1.3: Offline Signatures [7].

1.2.3 Need of Online Verification

As offline signatures are generally scanned, there may be noise due to hardware or paper misplacement. No information about time varying characteristics of signature is present in offline signature. There is also some variability among various genuine signatures of the same person. So, offline signature verification is a tedious task. On the other hand, online verification of signature is better than offline due to presence of dynamic features. As a result, any forgery present in the signature can be easily detected in case of online signatures [8].

1.2.4 Advantages of Signature Verification

In comparison with the other biometric techniques, signature verification has several advantages as follows [8]:

- Verification of a person based on signature is widely used in banks for transactions.
- Signatures are widely used for verification purposes in laptops, tablets, and Personal Digital Assistants (PDAs).
- Signature verification is not dependent upon the language used during signing. It only concentrates on the shape, size and other features.
- Signature can be changed if required, but it is not possible to change finger print or iris pattern. In case of any injury, finger print or iris pattern may get altered that accounts for mismatch during the verification.

Because of these advantages, automatic signature verification is widely used for electronic transactions, as well as in industries.

1.2.5 Applications of Signature Verification

Signature verification can be found in different applications as illustrated below [8]:

Computer System Authentication: To increase the security of a Personal Computer (PC), login can be done by combining signature verification system with fingerprint identification system. Other combinations like password with signature can also be used. This leads to a highly secure system which may contain confidential data.

Cheque Authentication: Signatures are used in banks for cheque verification from many years. Identification of signature by a human may result in error. So, here offline signature verification can be made.

Forensic Applications: Frauds occurring in cheques and forensics can be altered by using signature verification techniques.

Security in Commercial Transactions: Commercial sector is also using signature verification at a large scale. It is used for authentication of Automated Teller Machines (ATMs), for courier delivery companies.

1.3 Model of Signature Verification System

Figure 1.4 shows general model of handwritten signature verification. Data acquisition is done through devices like digital tablet or others. Signature is represented in the form of time-varying signals. Pre-processing removes fluctuations in the signature. Various features are extracted and then transformations are applied based on the technique used for verification. The verification system consists of test and reference signature. Comparison is made between the both, and then the result is declared as genuine or forgery based on that comparison. Identification of a signature can also be done by comparing it with the original template of signature present in enrolment phase. Various blocks present in the model of signature verification system are explained below:

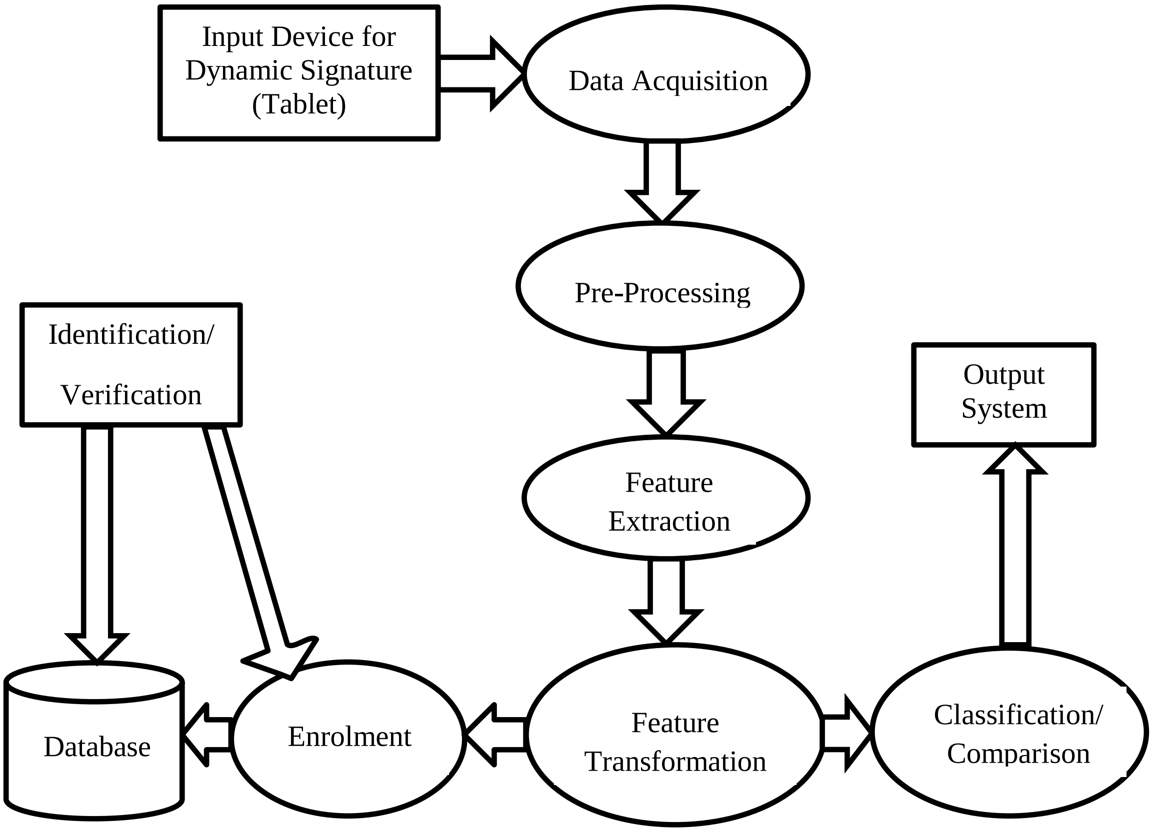


Figure 1.4: Online Signature Verification Model [9].

1.3.1 Input Signature

Dynamic input captured through a digital tablet is termed as input to the online signature verification system. This input is used further during pre-processing stag. After pre-processing, feature extraction is performed over the online data on the basis of which signature is verified.

1.3.2 Noise Removal and Pre-processing

For improvement of the verification system, some common pre-processing steps are applied. These may include filtering, size or location normalization, smoothing of the signature path and resampling [9]. Filtering is done for noise removal. Unevenness in the signature occurs due to lower resolution of tablet. So, to remove this irregularity smoothing techniques are applied. When there are a number of signatures taken for same person, size normalization is employed to make all signature of same size. Sometimes, resampling of data is done during pre-processing to remove any redundant data present.

1.3.3 Feature Extraction

Major part of signature verification is the extraction of features. Since aim of method is to verify signature based upon features extracted or some modification of these features, accuracy of system mainly depends upon these features. Global features refer to the properties of a full signature, whereas local features refer to the properties at a particular point. Global features include area of signature, height to width ratio, maximum vertical and horizontal histogram, signature's edge point numbers, signature's local maxima numbers, etc. [10]. On other side local features include signature initial direction, pen elevation of signature, horizontal position of signature, vertical position of signature, normal pressure of signature, log radius of curvature of signal, path tangent angle of signature, pen azimuth of signature, etc. [10].

Some external factors also contribute for selection of features. For example for a bank application, a fast and accurate extraction and verification of features is required. To obtain required features, certain criteria must be followed as given below [7]:

- High interpersonal variance must be there among the selected features so that the signatures can be separated into different classes.
- Low intrapersonal variance must be there among the selected features so that same type of signatures can be grouped together increasing the performance for the system.
- Feature extracted must be simple and easy to compute so as to develop a method having low computational power.
- Small number of features has to be extracted in order to store in a pen drive or smart card. Lower number of features also accounts for quick and fast computations. Moreover, to avoid risk the number of features must be large so as to identify the difference between signatures of different users. So, a proper trade off must be maintained.

- Reverse engineering of the features cannot be done to obtain the original signature back.

1.3.4 Feature Transformation

Different transformations are applied to the extracted features like Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), HMM, etc. Some parameters like mean, standard deviation, etc. can also be derived for each feature. Values of these parameters or transformations are stored for each signature as a reference. Each test signature is also treated same and comparison is made between the parameters.

1.3.5 Verification or Identification

In the verification stage, a signature and an Identity Document (ID) corresponding to that user are entered in the system. On basis of features extracted or the transformations in the features, a comparison is made between the test and reference signature already present in database [8]. Test signature is then treated as genuine or forgery based upon a defined threshold value. Block diagram of verification model is shown in Figure 1.5.

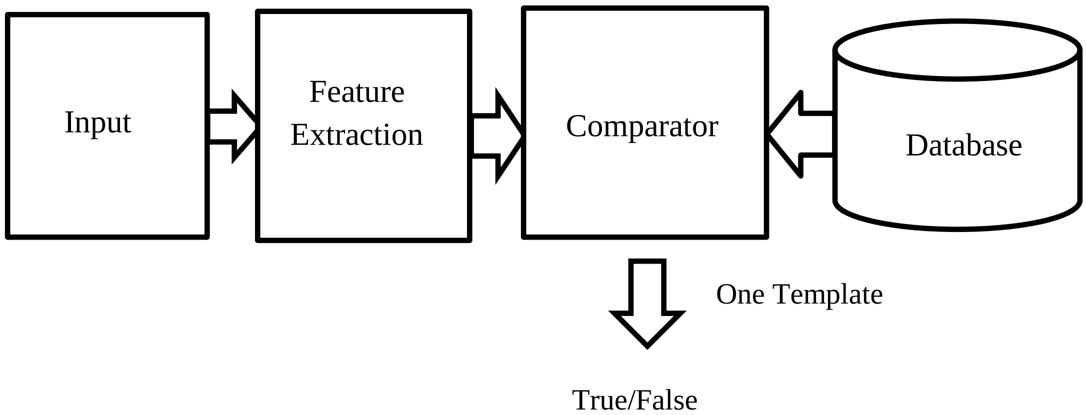


Figure 1.5: Model of Verification System [8].

In the identification stage, no user ID is submitted. Only the test signature is entered in the system. Comparison is made between test signature and every template signature present in database [8]. If test signature matches with one of the signature in the template, signature is said to be identified. Block diagram of identification model is shown in Figure 1.6.

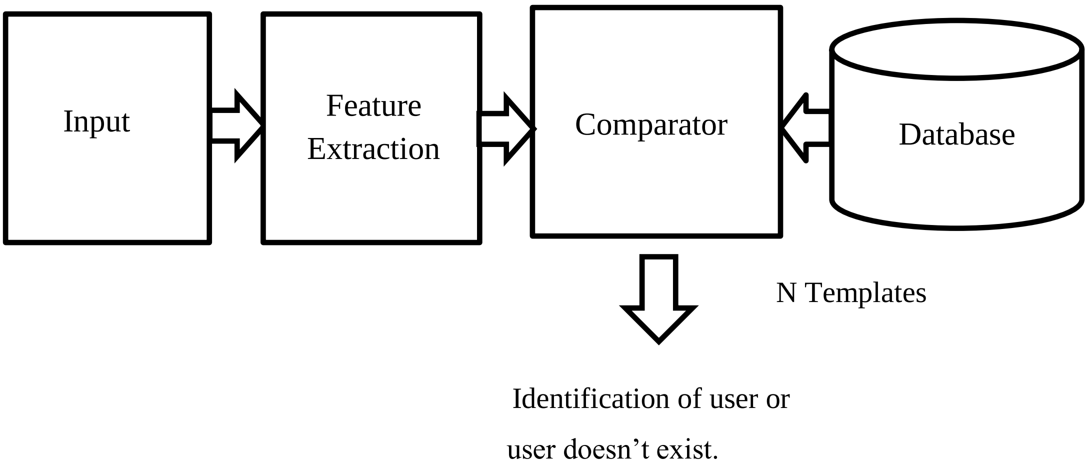


Figure 1.6: Model of Identification System [8].

1.3.6 Performance Evaluation

Signature verification system’s performance is described by its ability to exactly differentiate between genuine and forged signature. Performance evaluation of system is done on the basis of parameters like False Rejection Rate (FRR), False Acceptance Rate (FAR) and Equal Error Rate (EER) [11]. FRR is the ratio of number of genuine signatures rejected to the total genuine signatures submitted. FAR is the ratio of number of forged signatures accepted to the total forgery signatures submitted. FAR and FRR are inversely dependent on each other. Changes done in the threshold value to decrease FRR will result in increase of FAR and vice versa. The point at which an equality among FRR and FAR occurs is said to be EER. For an accurate verification system EER must be as low as possible.

Some matching score is generated base on similarity or dissimilarity among the test and reference signature. This score is compared to a threshold to decide whether to reject or accept the signature. Various FAR and FRR combinations can be obtained by changing the threshold value.

1.3.7 Output

Output of the signature verification system is the deciding factor for authenticity of the person providing the signature. Output of the verification system will be either the match of a particular signature with its template stored in the database or the mismatch. In the identification system input signature of a person is compared with all the templates present in the database and matching template refers to identity of that person.

1.4 Motivation of the Dissertation

The main motivation of this dissertation is to develop a method that provides signature verification with minimum computations and minimum errors. It employs PCA for feature selection of the signature using DFrCT. DFrCT provides the fractional order, which can be varied to get the appropriate results of verification. The PCA reduces the dimensions of the feature vector that leads to reduction in the number of operations performed on the signature.

1.5 Organization of the Dissertation

This dissertation is organized in the form of chapters as discussed below:

Chapter 2: Literature Review, A study is done about various existing online and offline signature verification techniques. Work done in fractional transforms and Principal Component Analysis (PCA) is discussed separately.

Chapter 3: PCA based feature selection of Signature Verification using DFrCT, Steps related to work done in automatic signature verification are discussed. The details of the approach applied in each step are also provided.

Chapter 4: Results and Discussions, Results of verification of signature using Discrete Fractional Cosine Transform (DFrCT) with PCA as a feature selector are given in this chapter and comparison is also done with other methods.

Chapter 5: Conclusion and Future scope, The work done is concluded in this chapter and based upon the observations future scope is given.

Chapter-2
Literature Review

2.1 Introduction

This chapter overviews the methods and work presented by various researchers in the domain of online/offline signature verification. It also includes the signature verification methods using Discrete Fractional Transform (DFT) and PCA. The gaps are identified and objectives of dissertation are drawn, along with a brief overview of the proposed methodology.

2.2 Online Signature Verification

Online signatures are used in transactions where a pen based tablet is provided for signing. When the user signs his signature on that tablet, the signature is recorded in the computer. Tablet captures different features like pressure, pen ups, pen downs, etc. and stores them in the computer [12]. Then, verification process is carried upon for checking the originality of the signature.

Signatures used in online signature verification system are captured through a high quality data acquisition device like digitized tablet, digitized pen, etc. Pre-processing steps are performed to remove different fluctuations occurred during data acquisition and thus, improves the performance of system. It is mainly executed in three stages [12]:

- **Smoothing**: Due to low resolution of tablet, errors occur in the captured signature. In this case direct feature extraction without smoothing leads to poor performance.
- **Normalization**: Size and location of signature are mostly normalized. This is done to remove the difference in size of signatures of the same person.
- **Segmentation**: It is a tedious task which affects the verification system. Different signatures of a single person can also vary from one another. So, care must be taken while applying segmentation.

In online verification, dynamic features are extracted from the signature which can be further classified as global or local features. Global features describe the signature as a whole for e.g., height and width of signature, ratio of height to width. Local features are taken out of a limited signature portion, for e.g., grid. Various techniques applied for the verification of online signature are as follows:

- String matching
- Fractional transforms
- Neural networks classifiers
- Hidden Markov Model (HMM)
- Dynamic Time Warping (DTW)
- Discrete Cosine Transform (DCT)
- Artificial Neural Networks (ANN)
- Singular Value Decomposition (SVD)

Many methodologies have already been explored for feature extraction and verification stage, but still there is a scope of improvement. Different verification techniques are employed by many authors from time to time. Brief description of some of the previous work done in online signature verification field is discussed below.

Q. Z. Wu *et al.* [13] has given verification technique based on measurement of similarity in log spectrum. Principal components are extracted out of each signature's log spectrum. Then comparison is done between log spectrum of test and reference template to find out any correlation among them.

A. Zimmer *et al.* [14] developed a hybrid system combined for online and offline verification. Segmentation of offline signature is done based upon online data acquired. Through learning some points of focus are determined in the image. Local and global features are taken and based upon the similarity, authentication of work is defined.

H. Feng *et al.* [15] applied a warping technique called Extreme Point Warping (EPW) in place of DTW. This technique proved to be more effective and accurate than DTW for signature verification. DTW warps the whole signal whereas EPW warps only selected important points. EER improved by a factor 1.3 over DTW. Moreover, computational time also gets reduced by a factor of 11.

B. L. Van *et al.* [16] described a system using two complementary informations using HMM. 25 features are extracted and normalized for the improvement of system's performance. Training set consists of 5 signatures from each user. A signature is said to be identified when arithmetic mean of two similarity scores exceeds some threshold value. Similarity scores are related to likelihood and segmentation. Various databases used for the experiment are BIOMET, PHILIPS, MCYT, and SVC2004. Fusion of segmentation with likelihood given by HMM improves the quality of the system.

D. Muramatsu *et al.* [17] proposed verification system based upon camera. Sequential Monte Carlo method is used. Distance calculation is done from signature, and final score is computed based upon combination of distances. A private database has been used for performing out the experiment.

R. Rahmat *et al.* [18] performed verification using SVD technique. SVD finds a number of singular vectors having most of the variations and maximum energy of signature. For the purpose of authentication, average distance is calculated between template and test sample. Performance of system has been checked using reduced sensors data glove. Selection of data glove is done on the basis of F value of sensor.

P. Thumwarin *et al.* [19] discussed a method which is based upon Finite Impulse Response (FIR) system using velocity and change in direction of barycenter trajectory. DCT is applied over six features extracted from the signature. Three FIR systems are provided with these DCT features as input and output and hence impulse response is obtained for each system. Difference between the impulse response for test and reference signature is used for comparison with the threshold and hence verification is performed. MCYT signature database has been used for caring out the work.

S. Emerich *et al.* [20] applied a TESPAR DZ based method to find out features from signature. Parameters extracted out of signature are applied with wavelet transform technique and thus decomposed to multi signals. A feature vector is obtained corresponding to each parameter extracted. SVC2004 database has been used and training of model is done through Support Vector Machine (SVM). Fusion strategy is used at each feature.

C. T. Yuen *et al.* [21] used dynamic features like pressure, position and velocity for verification algorithm. Verification is performed over SUSIG database. Pre-processing of data includes normalization, sampling and smoothing of test as well as reference signature. During verification, difference comparison of test and reference signature is done using threshold standard deviation method. This enhanced the performance resulting in FAR and FRR of 14.8% and 2.64% respectively.

S. Rashidi *et al.* [22] proposed verification of signature based on DCT extracting 19 features from position, pressure and angle of pen. Mean and variance of error signal are used for verification purpose. Test is performed using different classifiers and EER of 5.07% is obtained on SVC2004 database and 4.33% on SUSIG database.

R. C. Sonawane *et al.* [23] described a method characterizing signature as pen strokes producing x, y coordinates. Spatial and time domain both characteristics are considered for calculation of features. Individually strokes are determined by points having decrease in pen pressure, velocity and change in the angle of pen tip.

T. Yoshida *et al.* [24] developed a technique to remove point of lesser turning points in Chinese or Japanese signature using DCT. It is found that DCT spectrum is not small enough for acceptance; therefore DCT spectrum distance after DP matching is used. Also, DCT spectra have individuality in low frequency domain. Experiment is carried out over 20 Japanese signatures. EER of 4.6% is obtained which is similar to system using full XY position of data.

M. Arora *et al.* [25] introduced a new verification method employing DFrCT. 6 features are extracted from the signature based upon the characteristics of handwritten signature. Verification is done by applying three FIR filters. Group of two features is used as input and output of the FIR filter and impulse responses of the filter are combined to form a feature vector. Difference in Euclidean norm of test and reference signature is compared with a threshold for verification of originality of signature. 5% of EER is achieved resulting in improvement than DCT technique applied over SVC2004 database.

C. P. Wibowo *et al.* [26] proposed method characterizing stable signature features by forward and backward signature variance. K L coefficients of these forward and backward variances are used as a comparison parameter between reference and signature under test. Verification is done using MCYT database having 5000 signatures of 100 users resulting in an EER of 4.49%.

M. Aroro *et al.* [27] presented various verification techniques based on distance measurement. Feature extraction is done using histogram feature extraction technique. Comparison is done between three methods of distance calculation, i.e. Manhattan, Chebyshav and Euclidean. Results after verification concluded that Euclidean distance base verification is more accurate. EER for Manhattan and Chebyshev technique is 8.5% and for Euclidean distance is 6.5%.

N. Li *et al.* [28] collected data on touch screen phone and the features extracted are area, pressure, coordinates, etc. Four different classifiers SVM, Loggistic Regression, AdaBoost and Random Forest are used for the model. Comparison of accuracies for these classifiers is done. AdaBoost provided the best results out of all.

2.3 Offline Signature Verification

In offline verification dynamic features extraction is not possible as 2D image of signature is applied as an input. Due to this information gap, accurate offline systems are less possible. This system has the advantage of not having the requirement for the presence of signer during verification as the template already present is compared with the image of input signature.

The first step applied is pre-processing for improving the signature's quality thus increasing the accuracy of system. Quality of pixels in a digital image is also improved. Pre-processing of offline signatures consists of binarization, noise removal, skeletonization, skew removal, etc. [29].

Feature extraction is the next step. Transition in the image of signature from white to black and vice versa shows the transitional features. Extraction of static features is done in an offline system. Feature extracted consist of cell size, area, aspect ratio, histogram, edge points, etc. Various techniques applied over the offline signature consist of:

- Triangle matching
- Hungarian method
- Critical points approach

- Graph matching technique
- Robust signature verification
- Support Vector Machine (SVM)

K. Huang *et al.* [30] presented verification method using model based approach. Directional features of signature are used as a structure descriptor of signature. Statistical method of verification based upon geometry of the signature is applied for comparison of reference sample to test samples. For complex signatures structural verification is applied which finds out structural correlation in genuine and forged signatures.

E. J. R. Justido *et al.* [31] contributed to signature verification taking into account forgeries found in HMM framework. It is found that simple and random forgery signatures are closely related to each other with respect to EER. Representation of principal fraud cases in terms of simple forgery as areal application is shown in the result.

E. Ozgundus *et al.* [32] used global, grid and directional features of the signature for the recognition system. Technique used for verification and classification is SVM and resulted in 0.95 classification ratio. As signature verification is a multiclass problem so SVM technique is compared with that of ANN back propagation technique.

S. I. Abuhabia *et al.* [33] represented a verification method dependent upon intensities of raw binary pixel and use of complex feature sets is avoided. Verification of signature is treated as a graph matching problem. Genuine and forgery signatures of five persons are carried upon resulting in an EER of 26.7% and 5.6% for skilled and random forgery respectively.

I. Guler *et al.* [11] proposed an automatic verification system that depends upon the global features consisting of dynamics of producing a signature. Thickness and size of signature are not considered for carrying out the process. First step included pre-processing and noise removal through the signature. Based upon the analysis done specifications are taken out and placed in a string for carrying out the comparison. Signature is classified as genuine or forgery using DTW technique in its adaptive version.

A. Hamadane *et al.* [34] proposed a new technique based upon combination of two approaches, writer dependent and writer independent signature verification. Contourlet transform captures the directions of the signature and co-occurrence matrix counts the number of directions. CEDAR dataset is used in order to perform the experiment. SVM is applied for the classification leading to an effective use of contourlet transform as compared to other existing techniques.

S. Pal *et al.* [35] developed a new feature encoding technique on the basis of combination of SURF features (G-SURF) with features based upon Gabor filter. Features extracted out of a signature are given to SVM. GPDS dataset is used consisting of 1500 forged and 1200 genuine signatures resulting in 96.2% accuracy.

O. Khalifa *et al.* [36] discussed a highly secured technique for recognition of identity of a person through signature. Offline verification is done using ANN approach. While explaining the characteristics of offline signature comparison is done between different verification approaches and recognition methods.

R. K. Barathi *et al.* [37] combined an approach based on transforms with dimensionality reduction technique. DCT is applied over signature image so as to get upper left corner block as a feature representative. Linear Discriminant Analysis (LDA) is applied over the features for reduction and thus representation of signature with minimal number of features. Classification is done using SVM. Performance measurement is done using FAR and FRR. Verification process is carried upon CEDAR, GPDS-160, and MUKOS dataset of regional language.

2.4 Fractional Transform

The Fourier transform is an important tool that is used in signal and image processing. Different types of Fourier transform are explained in the next sections to help understand the methodology covered in this dissertation.

2.4.1 Fractional Fourier Transform

The representation of time and frequency domains is done with the help of Fractional Fourier Transform (FrFT) in signal processing domain. It is a dominantly used tool in signal processing field. Fractional Fourier transform is a generalized case of Fourier transform. It computes the mixed time and frequency components of signature which means the signal rotation in time frequency plane [38]. Its discrete form i.e. Discrete

Fractional Fourier Transform (DFrFT) is considered as weighted sum of signal and spectrum.

L. B. Almaida *et al.* [38] introduced FrFT and number of its properties. Some new results like interpretation of FrFT as rotation in time frequency plane and FrFTs relationship with time-frequency representation like ambiguity function, Wigner distribution, etc. are provided. Some examples of FrFT of simple signals are given along with the example of its applications which showed how the usage of FrFT allowed analysis of swept frequency filters that is same to classical analysis of shift invariant filter with the Fourier transform. The extension of classic Fourier transform is also presented which is designated as fractional Fourier transform. The transform depends upon the parameter alpha.

M. H. Yeh *et al.* [39] have given an approach for the DFrFT calculation. By the use of this method, the DFrFT of any angle can be computed by a weighted summation of the DFrFTs with the special angles.

S. C. Pie *et al.* [40] explored the continuous FrFT. Here a discrete version of FrFT is also calculated. The obtained results are no same as in case of continuous case. It provided similar transform as continuous FrFT. It has become powerful tool for signal processing.

2.4.2 Fractional Cosine Transform

Generalization of Cosine transform can be done to Fractional Cosine Transform (FrCT). Dealing with even functions becomes easy in case of one sided FrCT. In many applications it can be used in place of FrFT. It is a very useful tool in signal processing domain.

T. Alieva *et al.* [41] discussed that fractional Cosine and Sine transforms are additive on the index. Both reserve the same relationships with the FrFT as the FT has with ordinary Sine and Cosine Transform (ST, CT). The key features of the FrCT and Fractional Sine Transform (FrST) are computed. There are distinct methods for the fractionalization of transforms like the CT, the ST, and the FT. Fractional CT and ST are also measured in relative to the fractional transform.

S. C. Pei *et al.* [42] discussed DFrCT and Discrete Fractional Sine Transform (DFrST). Eigen decomposition of DCT and DST (Discrete Sine Transform) kernels are used to define DFrCT and DFrST. The same procedure is followed by the DFrFT. Eigen vector and Eigen value relationships between DFrFT, DFrST and DFrCT are established.

2.5 Principal Component Analysis

PCA is a very important method mostly applied in the areas of image compression, classification and recognition. It reduces the dimensions of the input data by projecting it to an uncorrelated low dimension space from a correlated high dimension space [43]. It mathematically changes correlated components to uncorrelated components which are said as Principal Components (PCs). Maximum variations in the data are found in first principal component and further components accounts for lower variability and so on. It changes the internal structure of data in a way so as to best explain variance in the data.

B. Li *et al.* [43] described a method for stroke based verification using Null Component Analysis (NCA) and PCA. To make same length of all the segment sequences segmentation and flexible matching technique is applied. Feature vectors are converted to PCs and Null Components (NCs) by K L transform. Stable and unstable components are analyzed using NCA and PCA.

S. Sayeed *et al.* [44] has done analysis of data based upon glove based signature identification. Signals are captured by 14 electrode data gloves. Electrodes reduction leads to volume reduction but also reduces the system efficiency. For condensing the volume and reducing noise PCA is applied. 7.5% EER is achieved in this process.

K. Ahmed *et al.* [45] presented a method for dimensionality reduction using PCA. After PCA vectors are sent to Multilayer Perceptron (MLP) neural network. Features exracted from the system includes altitude, angle, pen down time, pressure, etc. One way ANOVA is applied to find out X coordinates in 6 groups. This process is repeated for Y coordinates. Vector formed is compared with the threshold to declare genuine and forgery.

V. Iranmanesh *et al.* [46] used MLP over a subset of PCA features. This technique reduced the error rates by focusing on the discarded features from PCA evaluation. Experiment is done on SIGMA database giving an FAR of 7.4% and an FRR of 6.4%.

2.6 SVC 2004 Database

For the first signature verification contest (SVC2004) database [47] was constructed in 2003 for the usage of participants. *Wacom Intuos 2 A6 tablet* was used to capture the signature, consisting of x and y position, pressure and 2 angles (inclination and azimuth) from each user's signature. 20 genuine signatures were contributed by every user. Actual signatures were not taken for sake of privacy; instead every user signed a new signature. 20 forgery signatures were taken from four other users. Forgers were provided with genuine signature in order to forge the same using a software application. Writing sequence of signature was replayed using this software application, which helped forgers to forge the signature. Skilled forgery was performed by the forgers. Signatures of Chinese users were there in the database, in Latin or Chinese characters as chosen by user.

2.7 Gaps in Study

Several approaches have been proposed in the literature, which take advantage of the dynamic and static features of the signature. The following problems have been encountered.

- Various signature verification systems utilize different sets of features to authenticate a signature. This leads to variations in the results when a signature is tested with different approaches.
- The feature analysis of the signature involves various computations. With more number of features considered to increase the efficiency of the technique, the number of computations also increases.
- The variations in the signatures of single user may also lead to some suspicions about the authenticity of signature.
- There is a need to evaluate the various features of the signature on the basis of their errors, so as to develop a verification technique which utilizes the features with minimum error, thus, reducing the computations.

2.8 Objectives of the Dissertation

On the basis of literature review of existing signature verification systems and identified gaps following are the objectives of this work:

- To develop an algorithm for PCA based feature selection of online signature verification system using DFrCT.
- To compare the proposed algorithm with existing ones.

2.9 Methodology

Several techniques are available in literature for the verification of a person through signatures. Proposed work aims at online signatures because of the use of dynamic features like speed, acceleration, pressure, etc. PCA technique is applied for the feature selection by redundancy removal and data reduction in online signature verification system employing DFrCT. Euclidean norm is calculated by using impulse responses of FIR systems. Signatures are verified by calculating the difference between the average of Euclidean norms of reference signatures and the Euclidean norm of signature to be verified.

2.10 Chapter Summary

In this chapter, different techniques for signature verification have been studied. Online signature verification techniques like DTW, DCT, HMM, SVD, SVM, fractional transforms, neural networks, etc. and offline techniques like G-SURF, graph matching technique, robust signature verification, triangle matching, etc. are studied. Literature review for fractional transforms and PCA is also done. At the end, objectives are drawn based upon the gaps identified and a methodology is explained for the fulfilment of these objectives.

Chapter-3

PCA Based Feature Selection of Signature Verification Using DFrCT

3.1 System Overview

The method provided by M. Arora *et al*. in [25] for the verification of online signatures using DFrCT. The authors extract six features and three FIR filters are employed with two features as input to one filter. The difference of Euclidean norm between test and reference signature is then compared with threshold for verification of authenticity of the signature. The proposed approach is extended from this method. In the proposed approach, PCA is introduced for feature selection to reduce the redundant information. As a result, the system becomes more time efficient and less complex. Figure 3.1 shows the block diagram of the proposed online signature verification system. The proposed system consists of following steps:

- **Input Signature**: Signatures used for carrying out the experiment are taken from a standard database SVC2004 [47]. Database consists of 40 signatures for one person out of which 20 are genuine and 20 are forgery.
- **Pre-processing**: Every signature exhibits fluctuations even when signed by genuine person every time. To remove those fluctuations, pre-processing of signature is done which consists of normalization of the size, location and trajectory of barycenter of the given signature.
- **Feature Extraction**: After the pre-processing step, twelve features of signature are extracted consisting of horizontal pen point movement, vertical pen point movement, areal velocity, displacement, velocity, change of angle trajectory of barycenter, area pressure, motion pressure, tangential acceleration, centripetal acceleration, tangential jerk and centripetal jerk. PCA is applied over different combinations of these features. After that, DFrCT is applied on PCs extracted through PCA. On the basis of number of features taken, FIR systems are defined by PCs to characterize a given signature.
- **Signature Verification**: Impulse responses of FIR systems are used for verification of a given signature. A feature vector is formed by combination of all the impulse responses. A threshold level is set for the signature based on

the Euclidean norm of this vector. If the difference of Euclidean norm of reference and given signature is less than the threshold, the given signature is genuine else it is a forgery.

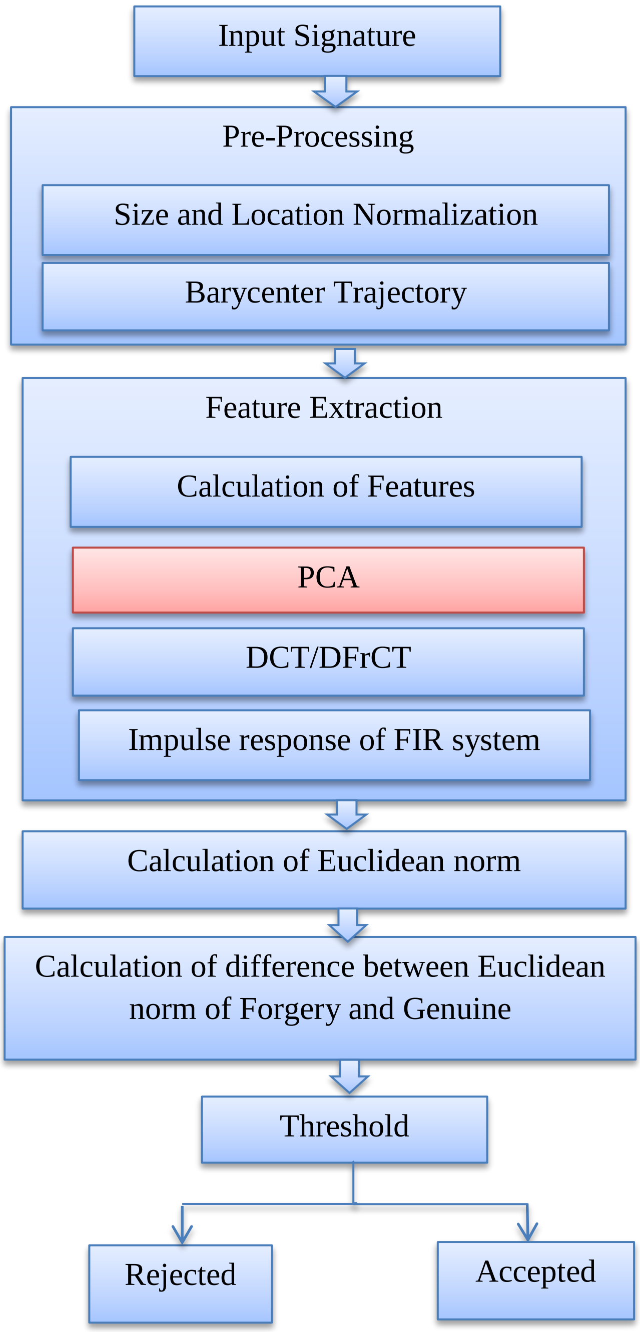


Figure 3.1: Block diagram of Presented Online Signature Verification System.

3.2 Pre-processing

When signature is captured using graphical tablet, some of the features are stored at that time from the signing process. These consist of horizontal and vertical directions of the movement of pen. During signing different signatures from the same person also suffers fluctuations. These fluctuations are removed by steps given as:

3.2.1 Normalization of Size

Fluctuations present in the signature size are minimized by standardizing the size of signature [19].

$$\hat{s}(t_{\Psi}) = \frac{s(t_{\Psi}) - s_{\min}}{s_{\max} - s_{\min}} \tag{3.1}$$

where, t_{Ψ} is the sampling time, $s = x, y, p; s_{\min} = \min(t_{\Psi});\ s_{\max} = \max(t_{\Psi})$.

3.2.2 Normalization of Location

Due to different locations of signing the same signature at different times some fluctuations occur. These are minimized by shift of signature's center point to origin [19].

$$l_s = \frac{1}{N} \sum_{\Psi=0}^{N-1} \hat{s}(t_{\Psi}) \tag{3.2}$$

$$\tilde{s} = \hat{s}(t_{\Psi}) - l_s \qquad (\Psi = 0,1,2,3,......., N-1)$$

where, equation 3.2 calculates the center point l_s and N represents the number of samples of movement of pen.

3.2.3 Barycenter Trajectory

Fluctuations produced due to movement of pen point are minimized by barycenter trajectory. Two adjoining positions of pen point and center position are used to calculate barycenter trajectory. Barycenter trajectory of a signature is calculated as given by [19]:

$$b_s(t_{\Psi}) = \frac{\tilde{s}(t_{\Psi}) + \tilde{s}(t_{\Psi+1})}{3} \tag{3.3}$$

3.3 Feature Extraction

Following features are examined for the verification process out of many existing features for an online signature as given in [19, 22]:

- Horizontal direction of movement of pen.
- Vertical direction of movement of pen.
- Areal velocity along the trajectory of signature [19].

$$A(t_{\Psi}) = \frac{1}{2}\begin{vmatrix} s_x(t_{\Psi-1}) & s_y(t_{\Psi-1}) \\ s_x(t_{\Psi}) & s_y(t_{\Psi}) \end{vmatrix} \tag{3.4}$$

- Displacement from the signature's center to barycenter trajectory [19].

$$d(t_{\Psi}) = \sqrt{s_x(t_{\Psi})^2 + s_y(t_{\Psi})^2} \tag{3.5}$$

- Magnitude of velocity of barycenter trajectory [19].

$$v(t_{\Psi}) = \sqrt{(l_x(t_{\Psi}))^2 + (l_y(t_{\Psi}))^2} \tag{3.6}$$

where,

$$l_x(t_{\Psi}) = s_x(t_{\Psi+1}) - s_x(t_{\Psi})$$
$$l_y(t_{\Psi}) = s_y(t_{\Psi+1}) - s_y(t_{\Psi}).$$

- The direction change of barycenter trajectory [19].

$$\theta(t_{\Psi}) = \tan^{-1}\left(\frac{s_y(t_{\Psi+1}) - s_y(t_{\Psi})}{s_x(t_{\Psi+1}) - s_x(t_{\Psi})}\right) \tag{3.7}$$

- Area pressure which is defined as area of the triangle firmed by joining pen pressure, pen point position, and signature's centre [22].

$$a_p(t_{\Psi}) = \frac{1}{2} \times \hat{p}(t_{\Psi}) \times \sqrt{\tilde{x}(t_{\Psi})^2 + \tilde{y}(t_{\Psi})^2} \tag{3.8}$$

- Motion pressure which is defined as diagonal distance between pen pressure and two adjacent pen point positions [22].

$$m_p(t_{\Psi}) = \sqrt{\hat{p}(t_{\Psi})^2 + r(t_{\Psi})^2} \tag{3.9}$$

where,

$$dx(t_\Psi) = \hat{x}(t_{\Psi+1}) - \hat{x}(t_\Psi)$$
$$dy(t_\Psi) = \hat{y}(t_{\Psi+1}) - \hat{y}(t_\Psi)$$
$$dp(t_\Psi) = \hat{p}(t_{\Psi+1}) - \hat{p}(t_\Psi)$$
$$r(t_\Psi) = \sqrt{(dx(t_\Psi))^2 + (dy(t_\Psi))^2 + (dp(t_\Psi))^2}$$

- Tangential acceleration [22].

$$a_t(t_\Psi) = \frac{v_x(t_\Psi)a_x(t_\Psi) + v_y(t_\Psi)a_y(t_\Psi)}{v(t)} \tag{3.10}$$

where,

$$v_x(t_\Psi) = v\cos\theta$$
$$v_y(t_\Psi) = v\sin\theta$$
$$dv_x(t_\Psi) = v_x(t_{\Psi+1}) - v_x(t_\Psi)$$
$$dv_y(t_\Psi) = v_y(t_{\Psi+1}) - v_y(t_\Psi)$$
$$a(t_\Psi) = \sqrt{(dv_x(t_\Psi))^2 + (dv_y(t_\Psi))^2}$$
$$a_x(t_\Psi) = a\cos\theta$$
$$a_y(t_\Psi) = a\sin\theta$$

- Centripetal acceleration [22].

$$a_c(t_\Psi) = \frac{v_x(t_\Psi)a_x(t_\Psi) - v_y(t_\Psi)a_y(t_\Psi)}{v(t)} \tag{3.11}$$

- Tangential jerk [22].

$$j_t(t_\Psi) = \frac{a_x(t_\Psi)\, j_x(t_\Psi) + a_y(t_\Psi)\, j_y(t_\Psi)}{a(t)} \tag{3.12}$$

where,

$$da_x(t_\Psi) = a_x(t_{\Psi+1}) - a_x(t_\Psi)$$
$$da_y(t_\Psi) = a_y(t_{\Psi+1}) - a_y(t_\Psi)$$
$$j(t_\Psi) = \sqrt{(da_x(t_\Psi))^2 + (da_y(t_\Psi))^2}$$
$$j_x(t_\Psi) = j\cos\theta$$
$$j_y(t_\Psi) = j\sin\theta$$

- Centripetal jerk [22].

$$j_c(t_\Psi) = \frac{a_x(t_\Psi)\, j_x(t_\Psi) - a_y(t_\Psi)\, j_y(t_\Psi)}{a(t)} \tag{3.13}$$

3.4 Principal Component Analysis

After feature extraction, PCA is applied over different combinations of features ranging from five to ten. PCA is a technique applied for finding maximum contributing features in the data available. It is also a common technique for extracting features from the data in a high dimensional space. It decreases the vector's dimension with assurance that the data loss would be lowest. New orthogonal and uncorrelated vectors are made by PCA. Each basis vector is chosen so that the variance of the projection along it is maximized. Maximum variations in the data are found in the first principal component and further components account for lower variability and so on.

Assuming, there are M observations of N variables. The data is available as a matrix $Z\ (M \times N)$, where M is the number of samples and N is the number of variables. Principal components are the projections of original variables along directions determined by K Eigen vectors ($K < N$) corresponding to the K largest Eigen values of the covariance matrix S. These K principal components will determine the subspace with largest variations among all possible K dimensional subspace projected from Z. By discarding the noisy principal components that do not contribute significantly to overall variation, dimensionality can be significantly reduced. The procedural steps are as follows [49].

Step 1: Calculate the mean $\bar{Z}$ of data Z as:

$$\bar{Z} = \frac{\sum_{i=1}^{M} Z_i}{M} \tag{3.14}$$

Step 2: Form a matrix by subtracting mean calculated in above equation from value of each sample. This adjusts the data to a new format.

$$\phi_i = Z_i - Z \tag{3.15}$$

Step 3: Calculate covariance S of the above calculated matrix by combining two variables each out of x, y, p one by one given as:

$$Cov(S) = \frac{\sum_{i=1}^{M}(X_i - \bar{X})(Y_i - \bar{Y})}{M-1} \tag{3.16}$$

Step 4: Find out the Eigen values using the above covariance matrix formed. This can be done as:

$$\left| S - \lambda I \right| = 0 \tag{3.17}$$

Step 5: Also, compute the Eigen vectors for the Eigen values calculated.

$$(M - \lambda_j I)e_j = 0 \tag{3.18}$$

Step 6: The first K largest Eigen vectors are taken as principal components.

3.5 Discrete Fractional Cosine Transform

Fourier transform is given in generalized form as fractional Fourier transform. It performs operation of revolving by some angle in time frequency plane. The DFrCT is the generalized form of DCT and it computes the mixed time and frequency components of signals [42]. DFrCT $R^{\alpha}(m)$ of the principal components is calculated [48] as:

$$R^{\alpha}(m) = B_{\alpha} \sum_{\Psi=0}^{N-1} K_p(m, \Psi) r(\Psi) \tag{3.19}$$

$$(\Psi = 0, 1, 2, \dots\dots\dots, N-1)$$

where, $r(\Psi)$ is the principal component, α is the rotation angle. Parameter B_{α} and kernel $K_p(m, \Psi)$ are given as follows:

$$K_p(m, \Psi) = \exp\left(\frac{i(m^2 + \Psi^2)\pi \cos\alpha}{N}\right)\cos\left(\frac{2\pi m \Psi}{N}\right) \tag{3.20}$$

$$(m, \Psi = 0, 1, 2, \dots\dots\dots\dots, N-1)$$

$$B_{\alpha} = \sqrt{\frac{2 - i2\cot\alpha}{\pi}}\sqrt{\frac{2\pi\sin\alpha}{N}} \tag{3.21}$$

Value of α is varied in the range of 0 to 1 to get an optimal value. This process is repeated to attain a minimum value for EER.

3.6 Signature Verification

FIR filters are introduced [19] to establish a relation among two principal components. The principal components $R_r(m)$ and $R_s(m)$ are treated as input and the output to the FIR system.

$$R_s(k) = \sum_{k=0}^{M} h_l(k) R_r(m-k) \quad (3.22)$$

where, l is the number of filters.

This is repeated for different combinations of two features considering number of filters ranging from three to five for different number of features respectively. Here $h_1(k), h_2(k), ..., h_l(k)$ are impulse responses of FIR filters, M is the order of the system.

With r and s as input and output of filter, the optimal impulse response h of filter is calculated as [50]:

$$\Lambda h = b \quad (3.23)$$

$$\Lambda = \lambda_{c,m} \quad (3.24)$$

$$\lambda_{c,m} = \sum_{n=0}^{N} R_s(n-m) R_r(n-c) \quad (3.25)$$

$$(c, m = 0, 1, ..., M)$$

where, R_s and R_r are autocorrelation functions of s and r.

$$b = [b_1, b_2, ..., b_M]^T \quad (3.26)$$

$$b_c = \sum_{n=0}^{N} R_s R_r(n-c) \quad (3.27)$$

If Λ is non-singular, the optimal impulse response is given as:

$$h = \Lambda^{-1} b \quad (3.28)$$

Signature is verified by forming a feature vector of impulse responses calculated. This is done using the steps given as [19]:

Step 1: Impulse responses of FIR filters are combined to form a feature vectors defined as:

$$
\begin{aligned}
h_1' &= [h_1(0), h_1(0), \ldots\ldots\ldots\ldots\ldots, h_1(n)] \\
h_2' &= [h_2(0), h_2(0), \ldots\ldots\ldots\ldots\ldots, h_2(n)] \\
&. \\
&. \\
h_l' &= [h_l(0), h_l(0), \ldots\ldots\ldots\ldots\ldots, h_l(n)]
\end{aligned}
\tag{3.29}
$$

Step 2: Combine the feature vectors to form a single feature vector corresponding to a signature as:

$$
h' = [h_1' h_2' h_3' \ldots\ldots\ldots h_l'] \tag{3.30}
$$

Step 3: The Euclidean norm of feature vector of signature to be verified is compared with the Euclidean norm of the reference signature. If this difference is less then threshold of a particular signature then the signature is consider to be genuine otherwise it is a forge signature i.e.

$$
\begin{cases} \textbf{true} & \text{if } \|h_{ref} - h\| < \beta, \\ \textbf{false} & \text{otherwise} \end{cases} \tag{3.31}
$$

where, $\|.\|$ represents the Euclidean norm and β represents a threshold value.

3.7 Chapter Summary

This chapter explains the methodology applied in this work for the verification of online signatures. It comprises of pre-processing, feature extraction, DFrCT, PCA and verification. Pre-processing includes normalization of size and location and extraction of barycentre trajectory. Twelve features horizontal direction, vertical direction, areal Velocity, displacement, velocity, direction, area pressure, motion pressure, tangential acceleration, centripetal acceleration, tangential jerk, and centripetal jerk are extracted from the signature. After that DFrCT is applied to have extra degree of freedom. PCA is applied for feature selection. FIR filters are introduced to establish a relation among two principal components and at the end verification of signature is done on the basis of Euclidean norm calculated by combination of filter impulse responses. Each step is explained one by one in separate sections and with relevant mathematical equations wherever required.

Chapter-4

Results and Discussions

4.1 Introduction

Considering the lack of embedding dynamic signature features speed, pressure etc., the proposed work aims at PCA based feature selection of online signature verification using DFrCT. PCA technique is applied to remove redundancy and reduce dimensionality of features extracted from the signature. Euclidean norm is calculated by using impulse responses of FIR systems. Signature is verified by calculating the difference between the average of Euclidean norms of reference signatures and the Euclidean norm of signature to be verified. Simulation results obtained with SVC2004 signature database are compared with existing methods using parameters FAR, FRR and EER.

4.2 Pre-processing

Original signature of a user is shown in Figure 4.1. It is clear from the figure that there is variability among different signatures of the same user.

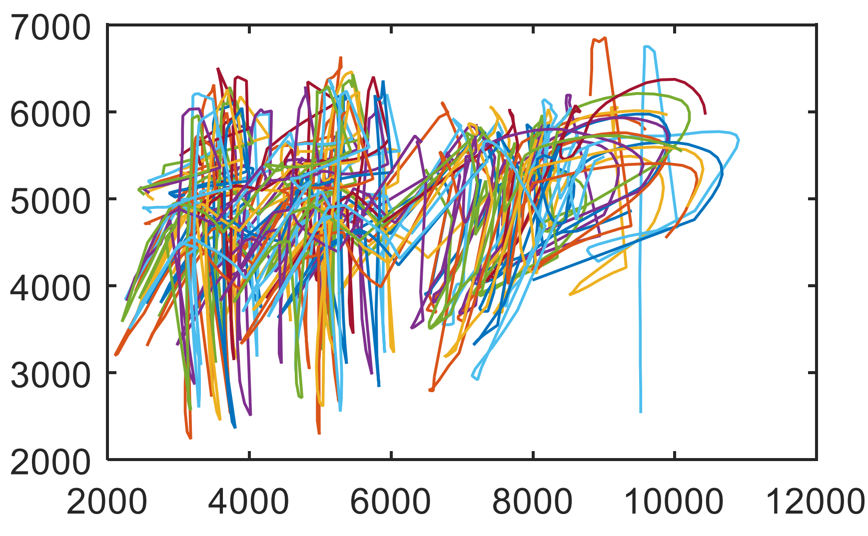


Figure 4.1: Original Signature [47].

4.2.1 Normalized Signature

Fluctuations due to size and location are removed through normalization to make all signatures of a standard size. Figure 4.2 shows the signature after size normalization and Figure 4.3 shows signature after size and location normalization both. Standard size signatures are obtained which implies that size and location fluctuations are removed.

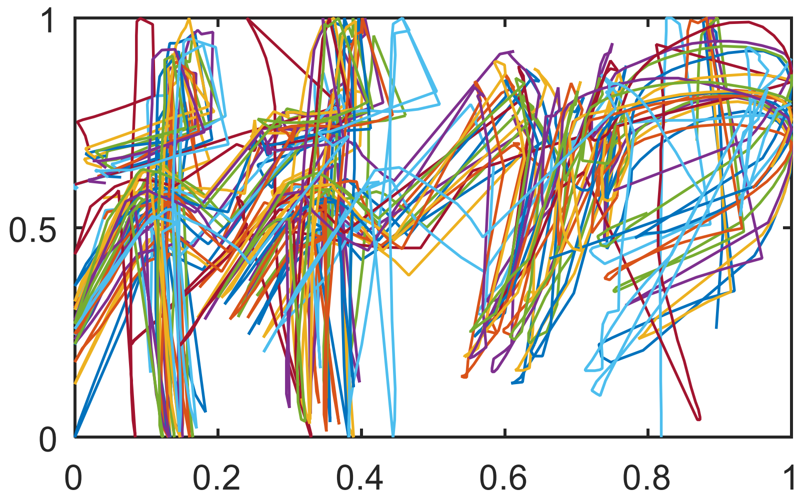


Figure 4.2: Signature after Size Normalization.

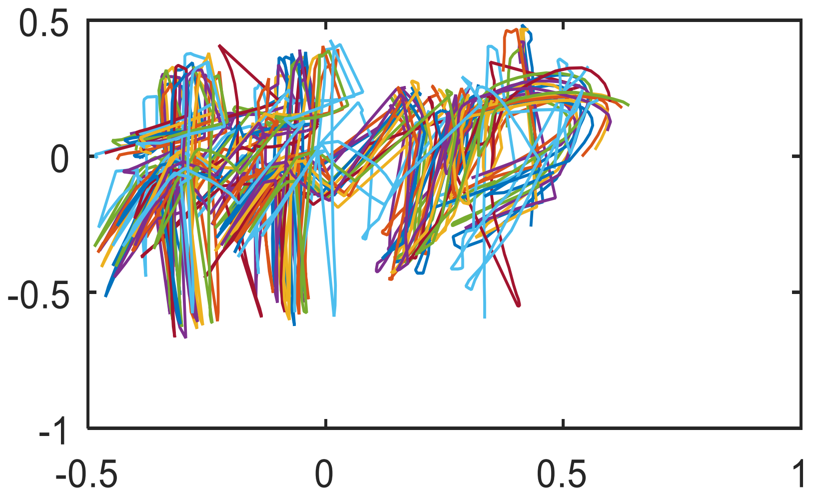


Figure 4.3: Signature after Size and Location Normalization.

4.2.2 Barycenter Trajectory

Fluctuations in signature because of pen point movement are reduced by barycenter trajectory as shown in Figure 4.4.

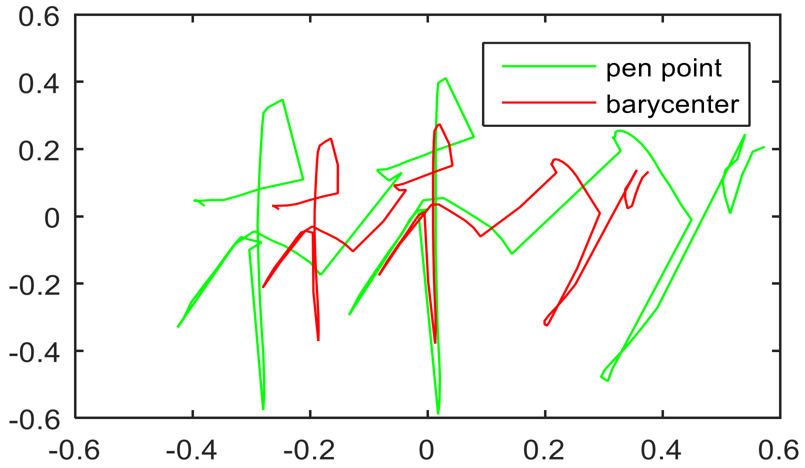


Figure 4.4: Trajectory of Barycenter of Signature.

4.3 Features Extracted

Different features extracted from the signature are shown in Figure 4.5.

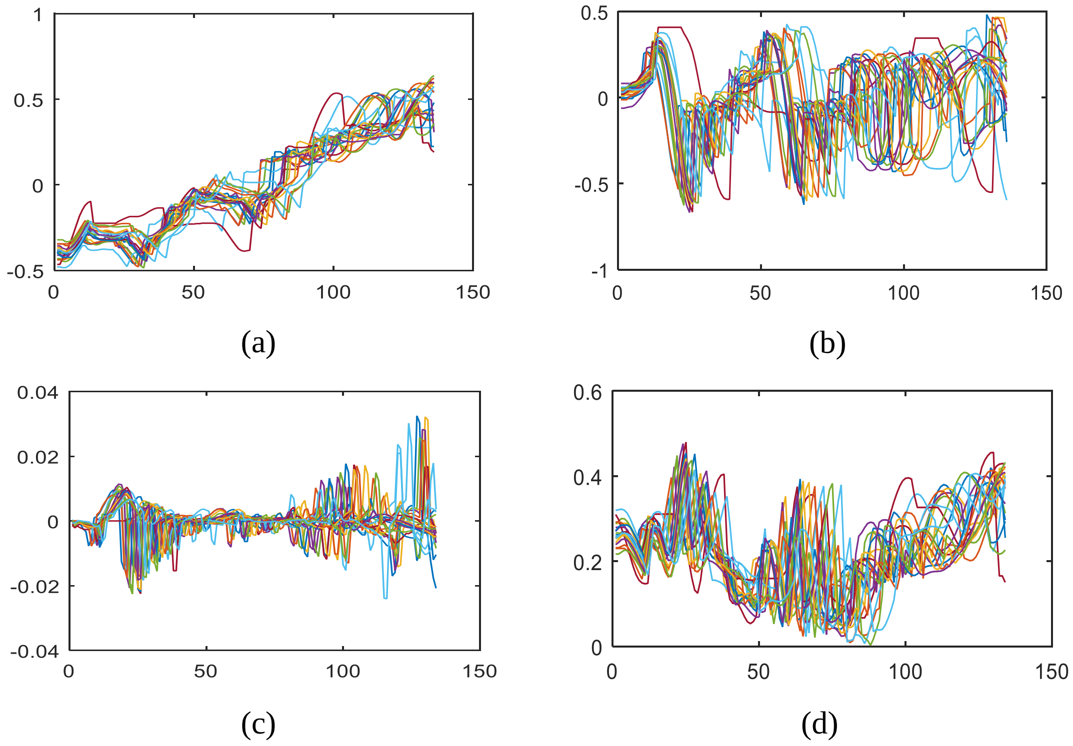
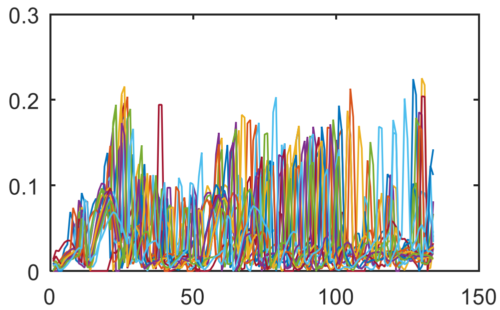
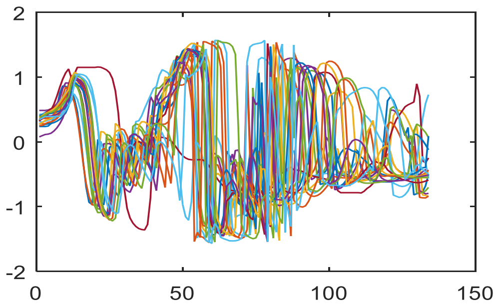


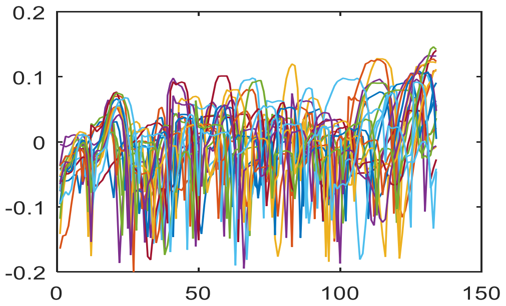
Figure 4.5: Features Extracted from the Signature, (a) Horizontal Direction, (b) Vertical Direction, (c) Areal Velocity, (d) Displacement (contd.).



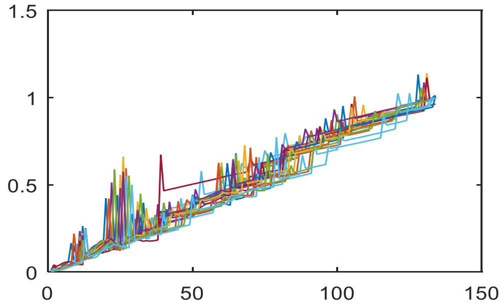
(e)



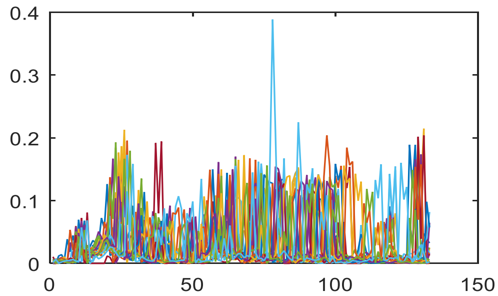
(f)



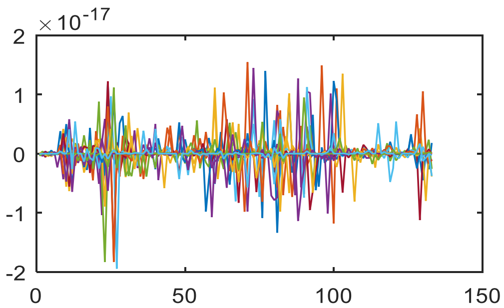
(g)



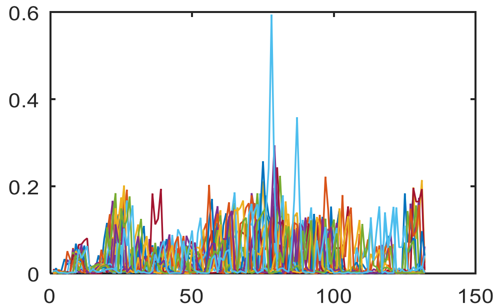
(h)



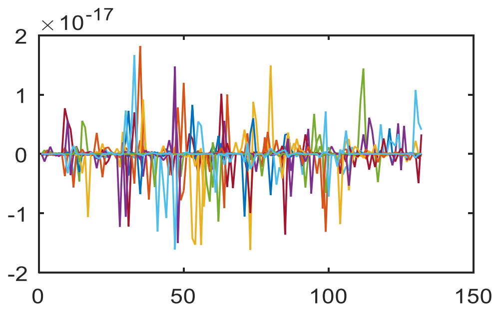
(i)



(j)



(k)



(l)

Figure 4.5: Features Extracted from the Signature, (e) Velocity, (f) Direction, (g) Area Pressure, (h) Motion Pressure, (i) Tangential Acceleration, (j) Centripetal Acceleration, (k) Tangential Jerk, and (l) Centripetal Jerk.

4.4 DFrCT's of Signature Features

Figure 4.6 and Figure 4.7 shows DFrCT's of different extracted features for genuine as well as forged signature. Forged signatures encounter more fluctuations.

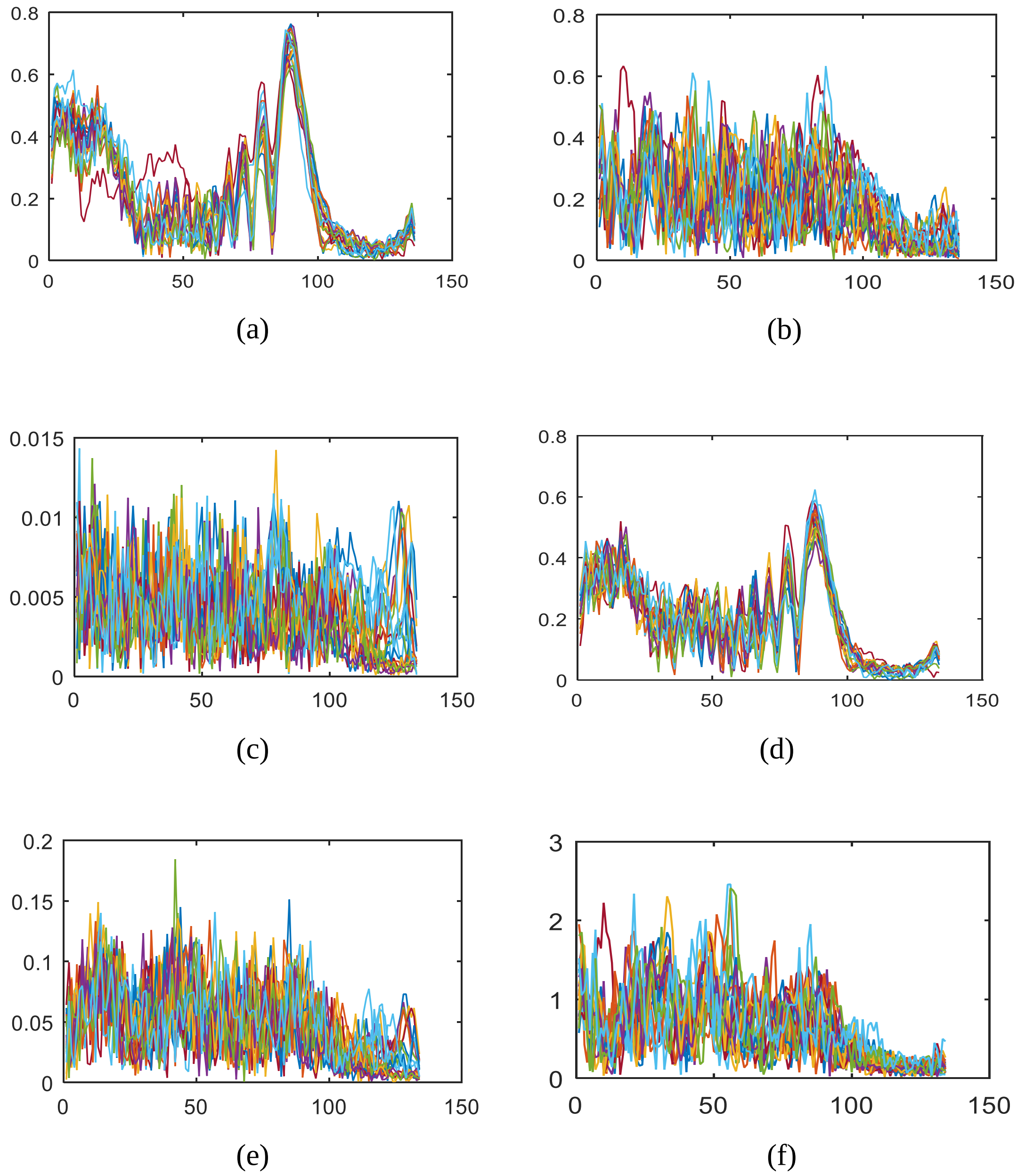


Figure 4.6: DFrCT's of Extracted Features of Genuine Signature, (a) Horizontal Direction, (b) Vertical Direction, (c) Areal Velocity, (d) Displacement, (e) Velocity, (f) Direction (contd.).

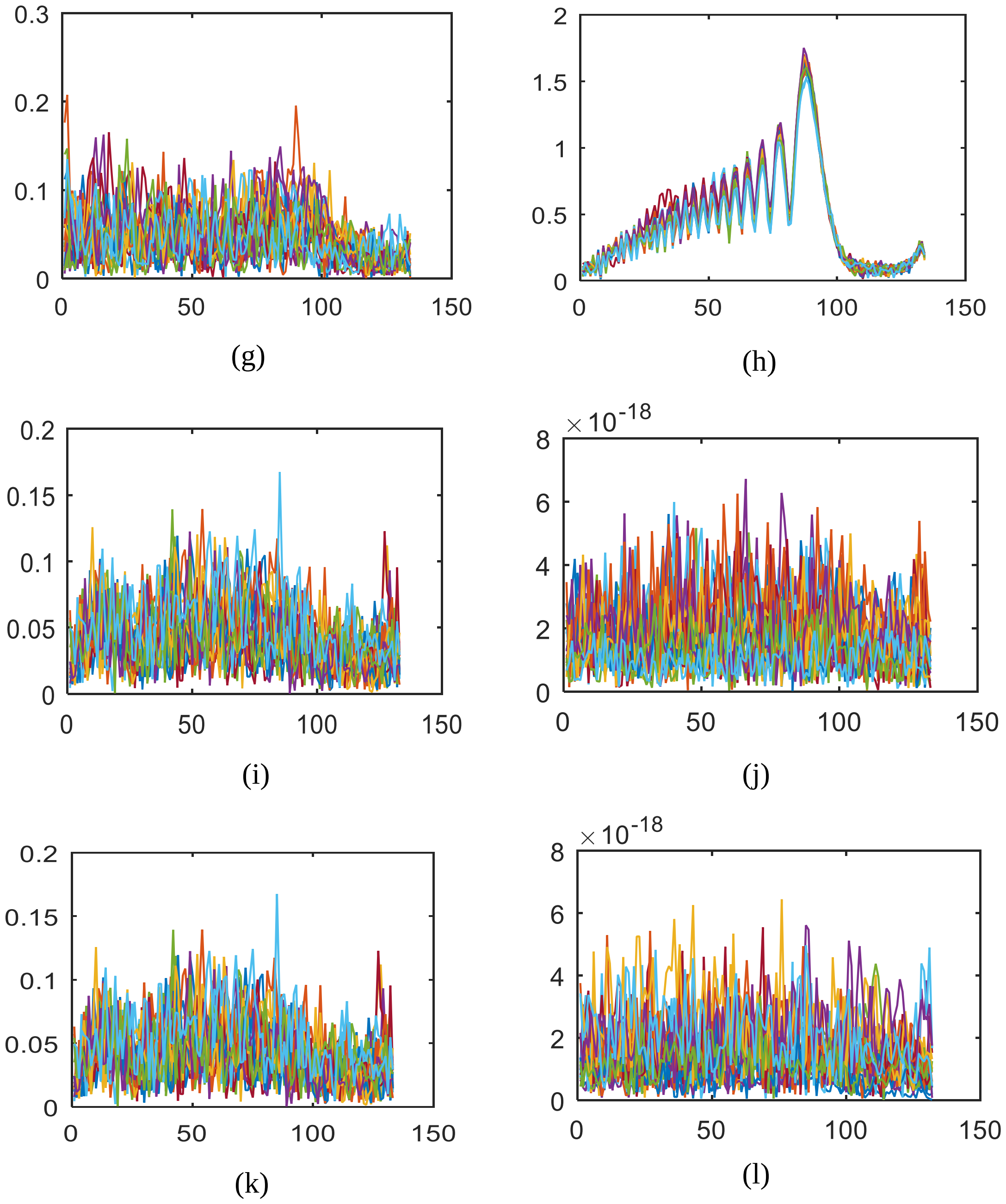


Figure 4.6: DFrCT’s of Extracted Features of Genuine Signature, (g) Area Pressure, (h) Motion Pressure, (i) Tangential Acceleration, (j) Centripetal Acceleration, (k) Tangential Jerk, and (l) Centripetal Jerk.

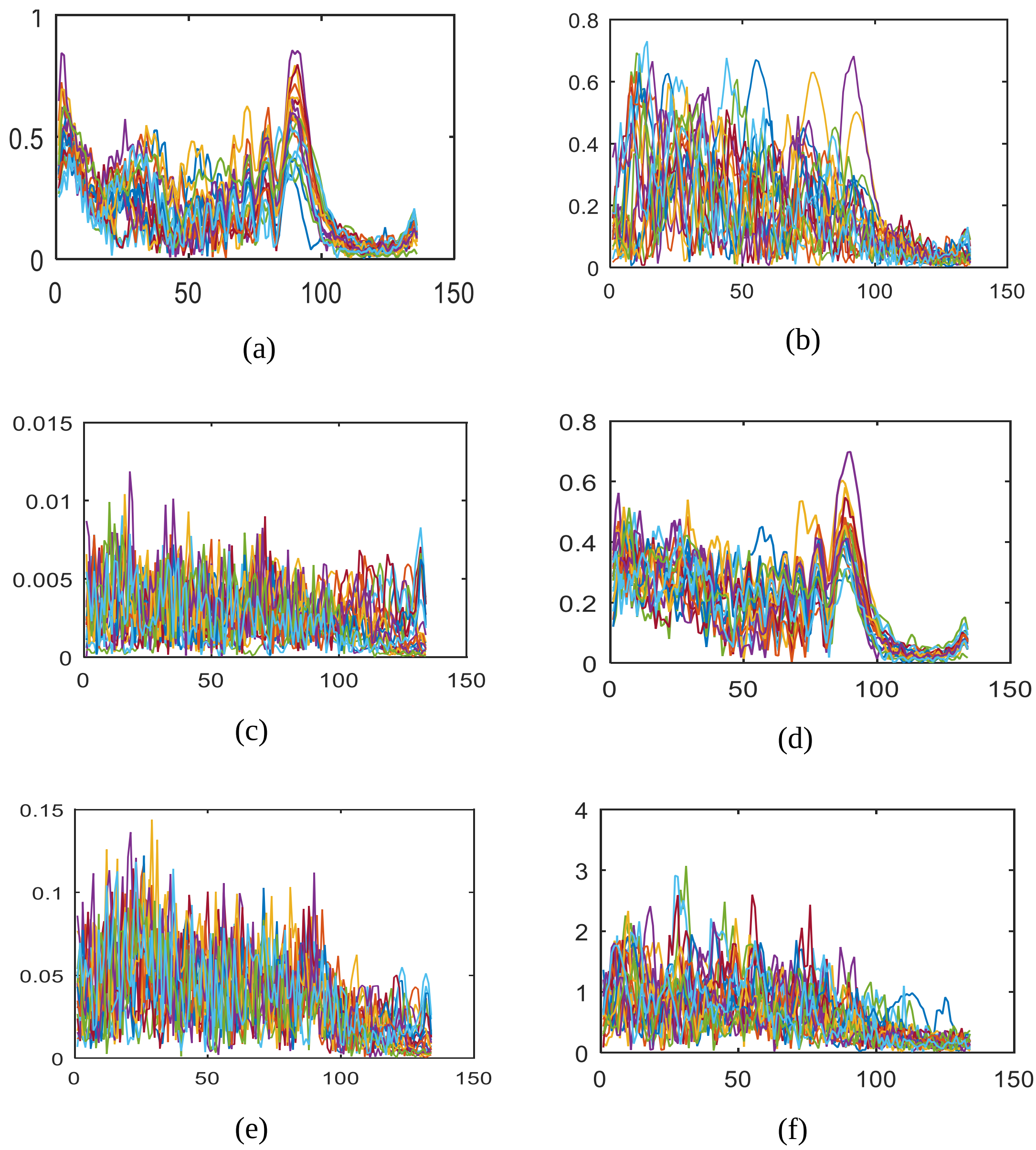


Figure 4.7: DFrCT's of Extracted Features of Forged Signature, (a) Horizontal Direction, (b) Vertical Direction, (c) Areal Velocity, (d) Displacement, (e) Velocity, (f) Direction (contd.).

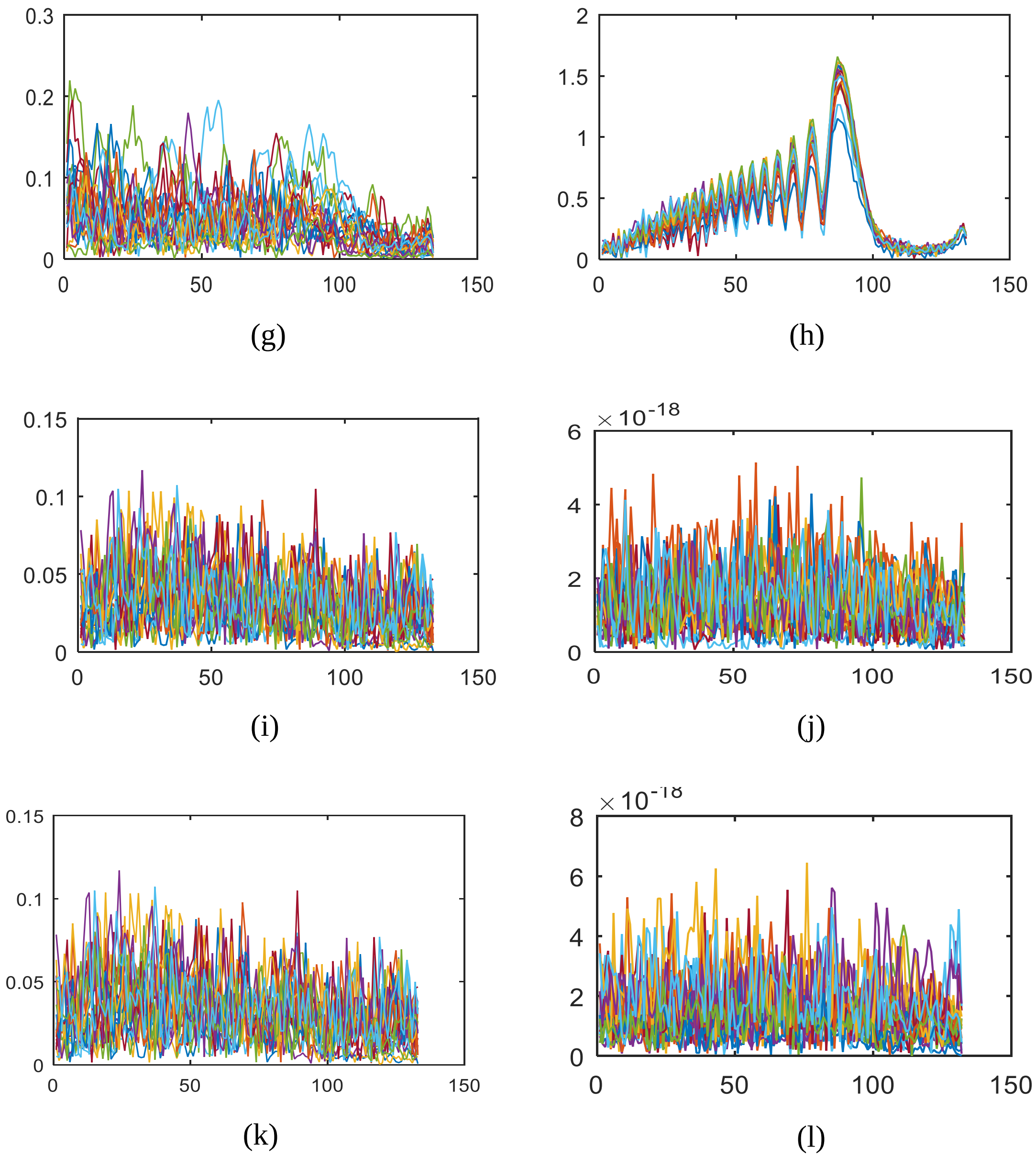


Figure 4.7: DFrCT's of Extracted Features of Forged Signature, (g) Area Pressure, (h) Motion Pressure, (i) Tangential Acceleration, (j) Centripetal Acceleration, (k) Tangential Jerk, and (l) Centripetal Jerk.

4.5 Experimental Results of Verification System

SVC2004 database consisting of 20 genuine and 20 forgery signatures was used for the experiment. 5 users were taken out of database to have 200 signatures for carrying out the experiment. Euclidean norm is calculated for each signature under test. Verification is performed by taking the difference between the Euclidean norm of reference and test signature. Verification system is provided with 5 genuine signatures for each user. Mean Euclidean norm of 5 signatures for each user is termed as reference norm. If this difference of norms is less than the threshold value, then it is a genuine signature otherwise forged. Different FAR and FRR combinations are obtained by varying the threshold value.

In the further sections, experimental results of signature verification using DCT, PCA with DCT, DFrCT and PCA with DFrCT are given. The tables in each section provide the Euclidean norm difference and number of false rejected and false accepted signatures. In the tables for false accepted and rejected signatures, the value accounting for least number of false acceptance and false rejection is highlighted. If there is same number of rejections or acceptances then, number resulting in lower EER is highlighted. Further with same EER, the rejection or acceptance value for lower threshold value is highlighted. The variations observed during signing cannot be properly defined by taking two or three features only. To improve the efficiency of the system, there is a need to consider more number of features that may prove helpful in signature verification. This is the main reason why the verification is done from five to ten numbers of features.

4.5.1 Signature Verification using DCT

DCT is applied on the features extracted from the pre-processed signature. These frequency domain features are given as input and output of the FIR filter in combinations of two. The impulse responses of FIR filters are combined to calculate Euclidean norm of test signature. In the Tables given in this section, verification done using DCT on the basis of difference between the Euclidean norm of reference and test signature is demonstrated along with their respective EERs. On the basis of threshold value applied by hit and trial, different genuine signatures are false rejected and forged signatures are false accepted.

Table 4.1: Difference in Euclidean Norm of Reference and Test Signature using DCT over 5 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-1.9421	-2.3094	-2.5258	-1.0414	-0.9063	-0.5582	-2.3824	-0.8363	9.9104	0.5826
2	-0.1043	-0.9345	-3.7617	0.2411	-0.6993	-0.6981	-1.8412	-1.2782	1.4829	0.6053
3	-0.9393	-1.8836	-1.3219	-0.2568	-1.6940	-1.7937	-1.0313	-1.8224	-7.6135	0.4052
4	-1.0406	-2.3727	-3.7234	0.3022	-0.6034	-0.5812	-1.0399	-0.4890	11.8434	-0.7168
5	-0.6257	-2.3625	-4.8118	0.3885	-0.5616	-0.5674	-0.7998	-0.6845	-2.9702	5.6048
6	-3.8513	-1.1287	0.915	-9.3767	-0.5005	-2.4522	-0.6228	-2.4992	-6.8742	-0.5989
7	-4.3978	-0.8234	-2.2930	0.1208	-0.5390	-1.0753	-0.7811	-18.5250	-3.8106	0.7053
8	-0.7307	-0.9148	0.2899	-0.1709	-0.5044	-1.1216	-0.7733	-2.6923	0.7030	-3.4053
9	-3.2673	-1.8206	-0.1670	0.6271	-0.6735	-0.6212	-2.6634	-17.5996	1.4442	0.8053
10	-5.6636	-3.2673	-3.2787	0.6231	-0.5649	-0.8161	-1.9907	-1.1711	3.3615	7.8053
11	-3.4897	-2.5119	-8.148	-2.6977	-0.6277	-0.5867	-1.3864	-0.5722	1.6946	0.3053
12	-0.6681	-1.2838	-2.7485	0.2119	-0.5659	-0.9732	-0.7896	-9.6068	-0.1020	0.8052
13	-0.8981	-11.122	-10.699	-0.301	-0.5972	-0.4847	-1.0186	-2.3251	-0.8458	1.1053
14	-2.2276	0.9937	0.1199	-11.061	-0.5571	-8.020	-0.7702	-1.2580	-0.1849	1.0053
15	-2.9792	-2.2113	-0.179	0.2468	-0.5562	-0.9457	-1.0366	-2.2463	-0.1274	0.7053
16	-0.7810	-0.4573	0.1834	-44.312	-0.5645	-4.2959	-0.6664	-2.5674	1.3109	1.0052
17	-0.6416	-0.6760	0.1803	-7.9421	-0.6178	-0.8234	-0.6445	-1.3795	-0.1127	-0.8053
18	-1.2316	-1.5089	0.298	0.4474	-0.7780	-1.5845	-1.9811	-3.3853	8.2768	4.5053
19	-0.7521	-1.1629	-2.3185	-0.637	-0.5527	-2.0300	-1.6194	-0.7102	-0.1433	2.3053
20	-2.3459	-2.1689	-3.1184	0.2797	-0.5854	-0.1691	-1.2925	-0.7276	-3.2322	0.1053

Table 4.2: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 5 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
-0.341	1	4	0.092	**1**	8	0.084	**1**	3	-1.133	0	4	0.044	**2**	4	**5**	23
-0.340	**1**	3	0.091	2	5	-0.819	2	2	-.0256	**0**	2	0.041	2	3	7	15
-0.205	2	**2**	0.090	2	4	-1.024	2	1	-3.656	1	**1**	0.247	4	2	11	10
-0.512	6	2	-0.065	5	**2**	-1.041	2	**0**	-3.854	2	1	-1.813	5	**1**	20	**6**

Table 4.3: Difference in Euclidean Norm of Reference and Test Signature using DCT over 6 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-17.618	-21.291	-29.8301	-14.9862	-8.3737	-4.8927	-20.658	-5.1984	-9.8378	-8.9693
2	-1.0433	-7.5420	-42.1895	-2.1609	-6.3042	-6.2924	-15.247	-9.6171	-13.416	-5.4031
3	-7.590	-17.033	-17.7916	-7.1402	-16.251	-17.248	-7.1479	-15.0595	-10.160	-23.963
4	-4.184	-21.924	-41.8064	-1.5500	-5.3455	-5.1229	-7.2337	-1.7255	-10.981	-6.1933
5	-8.603	-21.822	-52.6908	-0.6865	-4.9268	-4.9848	-4.8327	-3.6804	-8.1839	-3.0271
6	-6.2556	-9.484	-3.6565	-98.3401	-4.3162	-23.833	-3.0635	-21.8276	-15.465	-40.283
7	-36.710	-6.431	-27.5027	-3.3634	-4.7013	-10.064	-4.6458	-182.085	-15.430	-26.755
8	-42.170	-7.345	-1.6726	-21.6654	-4.3550	-10.526	-4.5686	-23.7578	-9.0628	-5.0995
9	-5.504	-16.403	-6.2421	1.6997	-6.0463	-5.3318	-23.469	-172.831	-9.9415	-5.4334
10	-30.87	-30.870	-37.3600	1.6592	-4.9603	-7.5268	-16.742	-8.5465	-8.4953	-6.0854
11	-54.833	-23.316	-12.7204	-31.5497	-5.5881	-5.1873	-10.699	-2.5576	-10.191	-5.0423
12	-33.094	-11.035	-32.0579	-2.4530	-4.9699	-9.0448	-4.7316	-92.9036	-9.9994	-6.3238
13	-4.8780	-109.423	-111.568	-4.8733	-5.2830	-4.1577	-7.0215	-20.0864	-10.699	-9.9716
14	-7.1780	-8.1348	-3.3729	-115.184	-4.8818	-7.3307	-4.5371	-9.4155	-8.0663	-28.353
15	-20.473	-20.310	-4.7520	-2.1035	-4.8733	-8.7678	-7.2011	-19.2986	-7.3663	-6.3809
16	-27.989	-2.770	-2.7373	-447.694	-4.9565	-42.270	-3.4995	-22.5094	-12.294	-6.0200
17	-6.007	-4.957	-2.7689	-83.9934	-5.4894	-7.5452	-3.2805	-10.6304	-8.4942	-4.7313
18	-4.613	-13.286	-4.2738	-0.0980	-7.0910	-15.156	-16.645	-30.6884	-8.5820	-4.4203
19	-10.513	-9.826	-27.7580	-5.2095	-4.8384	-19.611	-13.029	-3.9369	-12.273	-4.7038
20	-5.718	-19.886	-35.7570	-1.7745	-5.1653	-1.6912	-9.7601	-4.1116	-9.9402	-3.8536

Table 4.4: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 6 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.101	15	**1**	1.050	15	**1**	-0.251	14	**2**	-.030	15	**2**	1.471	5	**0**	63	**8**
1.640	11	8	1.033	8	4	-0.082	12	4	1.05	10	5	1.445	4	3	47	24
1.778	5	13	1.076	8	3	0.001	11	9	4.560	5	12	1.337	2	6	31	41
1.821	**1**	16	0.20	**2**	13	0.088	**3**	15	5.055	**1**	14	-0.571	**0**	17	**7**	76

Table 4.5: Difference in Euclidean Norm of Reference and Test Signature using DCT over 7 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.1132	0.1999	-1.6319	0.0534	0.44405	0.4410	-0.0071	0.0019	0.5163	0.4588
2	0.2082	0.1648	-0.0746	0.0761	0.41492	0.3728	0.0016	-0.7957	-0.0073	0.0323
3	0.0150	0.2294	0.0652	-0.3005	0.44708	0.3881	-0.0024	-0.0062	0.5237	-0.0354
4	0.0416	0.0317	0.0726	-0.1305	0.068794	0.3558	0.0007	-0.2903	0.5086	0.4527
5	0.1419	-0.0351	0.0747	-0.7294	0.32755	-1.474	-1.1442	-0.2687	0.4806	0.2405
6	0.0645	0.2174	0.0773	-39.778	0.44600	0.4443	0.0010	0.0051	0.5039	0.4919
7	0.1774	0.1704	0.0739	-1.2069	0.43185	0.4364	0.0018	0.0005	0.5243	0.5274
8	-0.1149	0.2273	0.0771	0.7752	-6.0174	0.3125	0.0039	-0.0296	0.4947	0.2277
9	-0.2256	0.2309	-0.3695	-0.2067	0.43369	-19.471	-0.0172	-0.0071	0.4997	0.5104
10	0.0528	0.0527	-4.8639	-0.0974	0.13442	-0.3669	-0.0028	-0.0049	-0.9159	0.4734
11	0.1999	0.2306	0.0701	0.0765	0.29938	0.3847	-0.0007	-0.0313	0.5120	0.5118
12	0.0839	-0.1247	0.0754	0.0752	0.22702	0.4394	-0.0015	-0.0628	0.4655	0.4577
13	0.2229	0.2294	0.0617	0.0485	0.15790	0.4295	0.0021	0.0053	0.5087	0.3532
14	-0.1348	0.2275	0.0693	-0.0018	-79.324	0.2396	0.0026	0.0042	-10.838	-4.6910
15	-1.0706	0.2170	-0.0543	0.0464	0.38584	0.1968	0.0010	-1.4670	0.5137	0.5244
16	-0.2686	0.1792	0.0739	0.0752	-6.7655	-4.781	-0.0126	-0.2430	0.1646	0.5029
17	-0.3286	0.2145	-0.0780	-0.1960	-83.838	-4.436	-0.0375	-6.8220	0.0986	0.5244
18	-1.3283	0.1014	-3.2656	0.0538	0.42562	0.3191	-4.1842	-0.0025	-0.0509	-41.140
19	-6.4115	0.1558	0.0059	0.0746	0.43912	0.3959	-3.7168	-0.2395	-1.5262	0.5073
20	0.1490	0.2307	-1.1540	0.0756	0.44510	0.1436	-0.4703	-0.1759	-6.9183	0.2413

Table 4.6: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 7 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.030	**3**	8	-0.30	4	10	-5.286	**3**	11	-0.388	**4**	11	0.028	3	10	**17**	50
01002	4	4	-.042	**4**	6	0.167	5	5	-0.037	6	6	0.210	**3**	4	22	25
0.170	6	3	0.074	5	4	0.339	5	4	-0.006	7	4	0.501	7	3	30	18
0.200	6	**2**	0.755	7	**1**	0.385	6	**2**	0.001	9	**2**	0.509	8	**2**	36	**9**

Table 4.7: Difference in Euclidean Norm of Reference and Test Signature using DCT over 8 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-6.4839	0.3405	0.1053	0.0453	-1.0419	-8.925	0.4531	-9.1799	0.1955	0.1905
2	0.4116	-0.5854	0.1148	-2.3341	0.197	-24.086	-1.1339	-14.308	0.1929	0.1905
3	0.4236	-2.3235	-1.1786	-0.0658	0.1702	-11.691	0.6221	-16.961	0.1705	-1.947
4	0.3418	-1.8158	0.0913	-0.064	0.1963	-15.832	0.7202	-11.502	0.1022	-6.302
5	0.3412	-5.1189	0.0997	0.1049	0.1888	-27.610	0.5518	-5.7588	0.0413	-2.4324
6	-0.7057	-4.8678	0.1143	-0.066	-0.8192	-4.9626	0.616	-20.048	-0.2466	-5.1425
7	0.4373	-1.7452	0.1126	0.0246	-1.0246	-34.193	0.7395	-10.676	0.0445	-21.459
8	0.4545	-0.42	0.0656	0.0841	0.1972	-5.588	0.7443	-17.572	0.1745	-7.9945
9	0.3829	-1.4163	0.0673	0.0985	0.1974	-4.0789	0.7334	-7.3223	0.0845	-2.1727
10	0.3948	0.3948	0.0926	0.0535	0.1954	-12.517	-3.8534	-64.187	0.1018	-15.574
11	0.2752	-3.9684	0.0991	0.0289	0.1955	-24.045	0.7178	-22.004	0.1917	-17.214
12	0.4366	-2.0277	0.1079	-0.1395	0.1973	-1.6014	0.6659	-26.890	0.1228	-9.5119
13	0.4541	-3.222	0.1057	0.0645	0.1963	-1.5869	0.6834	-28.530	-1.8134	-5.5129
14	0.4523	-1.6865	-0.6175	-0.0822	0.1957	-7.0599	-0.1182	-8.8903	0.1567	-2.4035
15	0.3552	-5.4898	0.107	0.0549	0.0857	-9.6345	0.6465	-14.716	0.1942	-14.505
16	0.4505	-0.4331	0.1071	0.0527	0.1945	-5.3474	0.3727	-50.847	0.1557	-1.4667
17	0.4539	-0.736	0.0908	0.0621	0.1974	-1.3396	0.7539	-3.3252	-0.2477	-1.2801
18	0.3999	-1.4079	0.0975	-0.2132	0.0843	0.1154	-3.6592	-15.924	0.1887	-5.8708
19	0.3536	-1.1168	0.1092	0.0689	0.1966	-1.8787	-0.256	-11.812	0.1903	-3.1843
20	0.3706	-5.2555	0.1085	0.0825	0.1936	-0.1044	0.5786	-7.836	0.1438	0.0252

Table 4.8: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 8 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.341	1	4	0.092	**1**	8	0.084	**1**	3	-1.133	0	4	0.044	2	4	**5**	23
0.340	**1**	3	0.091	2	5	-0.819	2	2	-.0256	**0**	2	0.041	**2**	3	7	15
0.205	2	**2**	0.090	2	4	-1.024	2	1	-3.656	1	**1**	0.247	4	2	11	10
-0.512	6	2	0.065	5	**2**	-1.041	2	**0**	-3.854	2	1	-1.813	5	**1**	20	**6**

Table 4.9: Difference in Euclidean Norm of Reference and Test Signature using DCT over 9 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.5579	-0.5926	0.3961	-2.9729	0.0891	-0.5941	1.3918	-1.3776	0.6859	-0.9364
2	0.5735	-0.9791	-2.0495	-2.8301	0.1128	-0.3231	1.2112	-4.1415	0.755	-2.5099
3	0.3435	-2.6932	-0.36	-1.4651	0.1127	-0.2595	-1.9126	-0.222	0.7605	-0.3793
4	0.0479	-1.3433	0.4477	-0.9331	0.4113	-0.4085	1.5277	-4.6914	0.718	-1.5532
5	6.7799	-3.1699	0.4363	-0.4208	0.111	-0.2234	1.5379	-1.1476	0.7604	-0.13
6	-0.5924	-1.9493	0.5601	-2.1791	0.0996	-1.5057	1.5404	-0.7321	-0.0807	-0.8319
7	0.4593	-8.2102	-3.1115	-0.473	0.1122	-0.3513	1.5414	-0.3986	-6.479	-0.5219
8	0.3005	-4.4139	-1.1034	-0.9647	0.1111	-0.4848	1.5313	-1.2057	0.7599	-0.1839
9	0.5938	-1.3167	-0.2196	-1.1429	0.1129	-0.4965	-8.3266	-1.3813	0.716	-0.6182
10	0.5722	-2.1194	0.6929	-1.2579	0.7028	-0.4169	-0.3466	-5.4325	0.7573	-1.3195
11	0.4983	-1.7541	0.6402	-1.1164	0.0996	-1.4258	-1.2189	-1.4481	0.7417	-1.1306
12	0.4686	-2.8248	0.6249	-0.9249	0.0811	-1.2755	1.5378	-1.342	0.76	-2.3978
13	1.1821	-1.4538	-0.3782	-1.9457	0.1036	-2.3682	1.324	-3.2573	0.7054	-3.8393
14	0.3248	-1.234	0.6097	-1.0295	0.111	-1.3191	0.9259	-6.683	0.7216	-7.3975
15	0.4814	-2.359	0.6265	-3.5121	0.0856	-1.0026	0.9188	-2.6439	0.7605	-1.5992
16	0.4596	-4.0608	0.6194	-1.2652	0.1089	-0.2378	15387	-2.3217	0.7605	-0.1368
17	0.5472	-1.2288	0.585	-0.6783	0.1088	-2.0094	1.5401	-1.2867	0.7488	-0.4034
18	0.4998	-7.4873	0.7413	-4.8308	-1.9969	-0.5689	-2.2888	-1.7715	0.7599	-4.8198
19	0.4757	-1.0128	-0.0129	-1.1242	0.113	-1.0718	-5.4617	-0.5586	0.7062	-0.6794
20	-0.0139	-7.5903	0.255	-0.5898	0.1098	-0.1649	1.4881	-1.1592	-6.0183	-1.0884

Table 4.10: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 9 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.578	0	2	0.741	2	2	1.545	1	3	0.702	2	2	0.767	0	2	5	11
0.557	**0**	1	0.619	**1**	**1**	1.391	2	2	0.112	1	**1**	0.741	2	2	6	7
0.498	2	**0**	0.560	2	1	0.925	2	**1**	-1.997	**0**	2	0.721	1	**1**	7	**5**
0.572	0	2	0.741	2	2	1.541	**1**	3	0.702	2	2	0.760	**0**	2	**4**	11

Table 4.11: Difference in Euclidean Norm of Reference and Test Signature using DCT over 10 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.0888	-2.3001	-4.2286	1.0140	-0.0826	0.0014	-9.5697	-18.514	1.4560	-13.345
2	1.5954	-0.4591	1.0561	-1.2409	-0.1094	0.846	-5.3993	-0.116	1.4691	-506.73
3	0.8084	61.803	1.0342	0.9389	0.0951	0.0116	5.2875	4.079	1.4459	-260.39
4	-2.5722	1.2141	1.0516	1.0764	0.0958	0.1026	4.8885	-3.686	1.2403	-19.033
5	0.0796	59.102	1.0862	1.0841	0.0011	0.1027	4.4594	1.503	-5.6113	-1374.8
6	1.5888	1.4429	1.0763	0.1116	0.0139	0.0992	1.9220	0.223	1.4258	-13.137
7	1.3430	-0.1151	1.0614	-0.3768	0.1005	0.0846	3.3999	4.976	1.4654	1.4712
8	0.9824	-0.0010	1.0839	0.8248	0.0665	-3.3287	5.3632	4.357	1.4523	0.9366
9	1.5863	1.5346	1.0768	0.8696	0.1000	0.0526	4.9846	4.173	1.4567	1.3274
10	0.5846	1.0557	0.2234	1.0781	-0.0512	-0.1480	4.5610	2.197	1.4414	0.8883
11	1.3338	-2.6370	1.0771	-3.8003	0.0781	-0.1854	0.5386	4.287	1.4728	1.4723
12	1.5930	1.4696	1.0831	1.0870	-0.2256	0.0870	2.3739	5.105	1.3923	1.4431
13	-0.2149	-0.0034	0.9876	1.0616	-0.4852	-0.2743	5.0755	5.221	1.4705	1.4118
14	1.5938	1.5548	1.0760	1.0032	0.890	0.0666	3.4999	0.124	1.4647	-91.991
15	-0.8765	-0.0001	1.0588	0.7737	-6.7672	0.0867	-8.6267	2.737	1.4633	-35.479
16	1.6009	1.2761	1.0797	1.0321	-0.0421	0.0445	3.3856	-2.705	1.4496	-114.96
17	1.5887	-0.5413	1.0770	1.0845	0.0831	-0.5739	-0.9281	4.971	1.4380	-37.025
18	1.5768	1.5982	1.0781	1.0726	0.0956	-6.583	1.1751	5.042	1.4720	-1631.7
19	-0.6940	-0.4461	1.0849	-2.5530	-.03070	-2.2852	4.9560	0.828	1.4741	0.9632
20	1.5643	1.2632	1.0777	1.0863	0.0973	-1.4379	4.8562	4.965	1.2693	16.649

Table 4.12: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DCT over 10 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.101	15	**1**	1.050	15	**1**	-.251	14	**2**	-.030	15	**2**	1.471	5	**0**	63	**8**
1.640	11	8	1.033	8	4	-.082	12	4	1.050	10	5	1.445	4	3	47	24
1.778	5	13	1.076	8	3	.001	11	9	4.560	5	12	1.337	2	6	31	41
1.821	**1**	16	0.200	**2**	13	.088	**3**	15	5.055	**1**	14	-0.571	**0**	17	**7**	76

Using DCT as a verification technique, following combinations of different features out of twelve extracted features resulted in minimum EER as provided below.

Five Features: With the combination of five features, it is observed that Horizontal Direction, Displacement, Centripetal Acceleration, Tangential Acceleration, and Centripetal Jerk resulted in minimum EER of 8.25%.

Six Features: With the combination of six features, it is observed that Horizontal Direction, Displacement, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 7.25%.

Seven Features: With the combination of seven features, it is observed that Horizontal Direction, Displacement, Areal Velocity, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 6%.

Eight Features: With the combination of eight features, it is observed that Horizontal Direction, Displacement, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 5.5%.

Nine Features: With the combination of nine features, it is observed that Horizontal Direction, Displacement, Areal Velocity, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 5.25%.

Ten Features: With the combination of ten features, it is observed that Horizontal Direction, Displacement, Direction, Areal Velocity, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 5%. This EER is minimum among all the verifications done using DCT.

4.5.2 Signature Verification using PCA with DCT

Firstly, PCA is applied over different combinations of the extracted features. Then principal components obtained are processed using DCT. These frequency domain components are given as input and output of the FIR filter in combinations of two. The impulse responses of FIR filters are combined to calculate Euclidean norm of test signature.

Table 4.13: Difference in Euclidean Norm of Reference and Test Signature using PCA over DCT over 8 features resulting in Minimum EER

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.1132	0.1999	-1.6319	0.0534	0.4440	0.4410	-0.0071	0.0019	0.5163	0.4588
2	0.2082	0.1648	-0.0746	0.061	0.4149	0.3728	0.0016	-0.7957	-0.0073	0.0323
3	0.0150	0.2294	0.0652	-0.3005	0.4470	0.3881	-0.0024	-0.0062	0.5237	-0.0354
4	0.0416	0.0317	0.0726	-0.1305	0.0687	0.3558	0.0007	0.2903	0.5086	0.4527
5	0.1419	-0.0351	0.0747	-0.7294	0.3275	-1.4741	-1.1442	-0.2687	0.4806	0.2403
6	0.0645	0.2174	0.0773	-39.778	0.4460	0.4443	0.0010	0.0051	0.5039	0.4921
7	0.1774	0.1704	0.0739	-1.2069	0.4318	0.4364	0.0018	0.0005	0.5243	0.5127
8	-0.1149	0.2273	0.0771	0.0775	-6.0174	0.3125	0.0039	-0.0296	0.4947	0.2247
9	-0.2256	0.2309	-0.3695	-0.2067	0.4336	-19.471	-0.0172	-0.0071	0.4997	0.5150
10	0.0528	0.0527	-4.8639	-0.0974	0.1344	-0.3669	-0.0028	-0.0049	-0.9159	0.4734
11	0.1999	0.2306	0.0701	0.0766	0.2993	0.3847	-0.0007	-0.0313	0.5120	0.5118
12	0.0839	-0.1247	0.0754	0.0752	0.2270	0.4394	-0.0015	-0.0628	0.4655	0.4577
13	0.2229	0.2294	0.0617	0.0485	0.1579	0.4295	0.0021	0.0053	0.5087	0.3532
14	-0.1348	0.2275	0.0693	-0.0018	-79.324	0.2396	0.0026	0.0042	-10.838	-4.691
15	-1.0706	0.2170	-0.0543	0.0464	0.3858	0.1968	0.0010	-1.4670	0.5137	0.5244
16	-0.2686	0.1792	0.0739	0.0752	-6.7655	-4.7812	-0.0126	-0.2430	0.1646	0.5029
17	-0.3286	0.2145	-0.0780	-0.1960	-83.83	-4.4366	-0.0375	-6.8220	0.0986	0.5244
18	-1.3283	0.1014	-3.2656	0.0538	0.4256	0.3191	-4.1842	-0.0025	0.4588	-410.14
19	-6.4115	0.1558	0.0059	0.0746	0.4391	0.3959	-3.7168	-0.2395	-1.5262	0.5073
20	0.1490	0.2307	-1.1540	0.0756	0.4451	0.1436	-0.4703	-0.1759	-6.9183	0.2413

Table 4.14: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using PCA with DCT over 8 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.03	**3**	8	-0.300	**4**	10	-5.286	**3**	11	-0.388	**4**	11	0.028	3	10	**17**	50
0.10	4	4	-0.042	4	6	0.167	5	5	-0.037	6	6	0.210	**3**	4	22	25
0.17	6	3	0.074	5	4	0.339	5	4	-0.006	7	4	0.501	7	3	30	18
0.20	6	**2**	0.755	7	**1**	0.385	6	**2**	0.001	9	**2**	0.509	8	**2**	36	**9**

In the Table 4.13 and 4.14, verification done on the basis of difference between the Euclidean norm of reference and test signature is demonstrated. By applying PCA with DCT minimum EER of 3.5% is achieved when 8 features Horizontal Direction, Displacement, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk are extracted.

4.5.3 Signature Verification using DFrCT

DFrCT is applied on the features extracted from the pre-processed signature. These frequency domain features are given as input and output of the FIR filter in combinations of two. The impulse responses of FIR filters are combined to calculate Euclidean norm of test signature. In the Tables given in this section, verification done using DFrCT on the basis of difference between the Euclidean norm of reference and test signature is demonstrated along with their respective EERs. On the basis of threshold value applied by hit and trial, different genuine signatures are false rejected and forged signatures are false accepted.

Table 4.15: Difference in Euclidean Norm of Reference and Test Signature using DRrCT over 5 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge)

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	1.132	1.9996	-1.6319	0.0534	0.0444	0.0441	-0.0071	0.0019	5.1635	4.5881
2	2.082	1.6482	-0.0746	0.0761	0.0415	0.0373	0.0016	-0.7957	-733.34	32.394
3	0.150	2.2949	0.0652	-0.3005	0.0447	0.0388	-0.0024	-0.0062	5.2375	-35.438
4	0.416	0.3172	0.0726	-0.1305	0.0069	0.0356	0.0007	-0.2903	5.0867	4.5276
5	1.419	-0.3519	0.0747	-0.7294	0.0328	-0.1474	-1.1442	-0.2687	4.8067	2.4035
6	0.645	2.1741	0.0773	-397.78	0.0446	0.0444	0.0010	0.0051	5.0397	4.9219
7	1.774	1.7047	0.0739	-1.206	0.0432	0.0436	0.0018	0.0005	5.2438	5.1274
8	-1.149	2.2732	0.0771	0.7752	-0.6017	0.0313	0.0039	-0.0296	4.9474	2.2477
9	-2.256	2.3090	-0.3695	-0.2067	0.0434	-1.9471	-0.0172	-0.0071	4.9979	5.1504
10	0.528	0.5276	-4.8639	-0.0974	0.0134	-0.0367	-0.0028	-0.0049	-9.1591	4.7344
11	1.999	2.3069	0.0701	0.0766	0.0299	0.0385	-0.0007	-0.0313	5.1201	5.1183
12	0.839	-1.2474	0.0754	0.0752	0.0227	0.0439	-0.0015	-0.0628	4.6558	4.5773
13	2.229	2.2948	0.0617	0.0485	0.0158	0.0430	0.0021	0.0053	5.0870	3.5325
14	-1.348	2.2757	0.0693	-0.0018	-7.9324	0.0240	0.0026	0.0042	-0.0108	-0.4691
15	-10.706	2.1702	-0.0543	0.0464	0.0386	0.0197	0.0010	-1.4670	5.1377	5.2443
16	-2.686	1.7924	0.0739	0.0752	-0.6765	-0.4781	-0.0126	-0.2430	1.6469	5.0292
17	-3.286	2.1458	-0.0780	-0.1960	-8.3838	-0.4437	-0.0375	-6.8220	98.627	5.2440
18	-13.283	1.0141	-3.2656	0.0538	0.0426	0.0319	-4.1842	-0.0025	-50.984	-0.0041
19	-64.115	1.5589	0.0059	0.0746	0.0439	0.0396	-3.7168	-0.2395	-0.1526	5.0734
20	1.490	2.3078	-1.1540	0.0756	0.0445	0.0144	-0.4703	-0.1759	-0.6918	2.4137

Table 4.16: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 5 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.345	1	4	0.092	1	8	0.084	**1**	3	-1.133	0	4	0.044	2	4	**5**	23
0.340	**1**	3	0.091	2	5	-0.819	2	2	-.0256	**0**	2	0.041	**2**	3	7	15
0.208	2	**2**	0.090	**2**	4	-1.024	2	1	-3.656	1	**1**	0.247	4	2	11	10
-0.514	6	2	0.065	5	**2**	-1.041	2	**0**	-3.854	2	1	-1.81	5	**1**	20	**6**

Table 4.17: Difference in Euclidean Norm of Reference and Test Signature using DRrCT over 6 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge)

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-64.115	-1.2474	-4.8639	-397.78	-8.3838	-1.9471	-4.1842	-6.822	-733.34	-35.438
2	-13.283	-0.3519	-3.2656	-1.2069	-7.9324	-0.4781	-3.7168	-1.467	-50.984	-0.4691
3	-10.706	0.3172	-1.6319	-0.7294	-0.6765	-0.4437	-1.1442	-0.7957	-9.1591	-0.0041
4	-3.286	0.5276	-1.154	-0.3001	-0.6017	-0.1474	-0.4703	-0.2903	-0.6918	2.2477
5	-2.686	1.0141	-0.3695	-0.2073	0.0069	-0.0367	-0.0375	-0.2687	-0.1526	2.4035
6	-2.256	1.5589	-0.078	-0.1901	0.0134	0.0144	-0.0172	-0.243	-0.0108	2.4137
7	-1.348	1.6482	-0.0746	-0.1301	0.0158	0.0197	-0.0126	-0.2395	1.6469	3.5325
8	-1.149	1.7047	-0.0543	-0.0416	0.0227	0.024	-0.0071	-0.1759	4.6558	4.5276
9	0.15	1.7924	0.0059	-0.0057	0.0299	0.0313	-0.0028	-0.0628	4.8067	4.5773
10	0.416	1.9996	0.0617	0.0464	0.0328	0.0319	-0.0024	-0.0313	4.9474	4.5881
11	0.528	2.1458	0.0652	0.0485	0.0386	0.0356	-0.0015	-0.0296	4.9979	4.7344
12	0.645	2.1702	0.0693	0.0534	0.0415	0.0373	-0.0007	-0.0071	5.0397	4.9219
13	0.839	2.1741	0.0701	0.0538	0.0426	0.0385	0.0007	-0.0062	5.0867	5.0292
14	1.132	2.2732	0.0726	0.0746	0.0432	0.0388	0.001	-0.0049	5.087	5.0734
15	1.419	2.2757	0.0739	0.0752	0.0434	0.0396	0.001	-0.0025	5.1201	5.1183
16	1.496	2.2948	0.0739	0.0752	0.0439	0.043	0.0016	0.0005	5.1377	5.1274
17	1.774	2.2949	0.0747	0.0756	0.0444	0.0436	0.0018	0.0019	5.1635	5.1504
18	1.999	2.3069	0.0754	0.0761	0.0445	0.0439	0.0021	0.0042	5.2375	5.244
19	2.082	2.3078	0.0771	0.0766	0.0446	0.0441	0.0026	0.0051	5.2438	5.2443
20	2.229	2.309	0.0773	0.7752	0.0447	0.0444	0.0039	0.0053	98.627	32.394

Table 4.18: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 6 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.101	15	**1**	1.050	15	**1**	-0.251	14	**2**	-.030	15	**2**	1.471	5	**0**	63	**8**
1.640	11	8	1.033	8	4	-0.082	12	4	1.050	10	5	1.445	4	3	47	24
1.778	5	13	1.076	8	3	0.001	11	9	4.560	5	12	1.337	2	6	31	41
1.821	**1**	16	0.200	**2**	13	0.088	**3**	15	5.055	**1**	14	-0.571	**0**	17	**7**	76

Table 4.19: Difference in Euclidean Norm of Reference and Test Signature using DRrCT over 7 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge)

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.1132	0.19996	-1.6319	0.0534	0.44405	0.44100	-0.0071	0.0019	0.51635	0.45881
2	0.2082	0.16482	-0.0746	0.0761	0.41492	0.37288	0.0016	-0.7957	-0.0073	0.03239
3	0.0150	0.22949	0.0652	-0.3005	0.44708	0.38819	-0.0024	-0.0062	0.52375	-0.0354
4	0.0416	0.03172	0.0726	-0.1305	0.068794	0.35584	0.0007	-0.2903	0.50867	0.45276
5	0.1419	-0.03519	0.0747	-0.7294	0.32755	-1.4741	-1.1442	-0.2687	0.48067	0.24035
6	0.0645	0.21741	0.0773	-39.778	0.44600	0.44434	0.0010	0.0051	0.50397	0.49219
7	0.1774	0.17047	0.0739	-1.2069	0.43185	0.43648	0.0018	0.0005	0.52438	0.51274
8	-0.1149	0.22732	0.0771	0.0775	-6.0174	0.31254	0.0039	-0.0296	0.49474	0.22477
9	-0.2256	0.23090	-0.3695	-0.2067	0.43369	-19.471	-0.0172	-0.0071	0.49979	0.51504
10	0.0528	0.05276	-4.8639	-0.0974	0.13442	-0.3669	-0.0028	-0.0049	-0.9159	0.47344
11	0.1999	0.23069	0.0701	0.0766	0.29938	0.38472	-0.0007	-0.0313	0.51201	0.51183
12	0.0839	-0.12474	0.0754	0.0752	0.22702	0.43945	-0.0015	-0.0628	0.46558	0.45773
13	0.2229	0.22948	0.0617	0.0485	0.15790	0.42953	0.0021	0.0053	0.50870	0.35325
14	-0.1348	0.22757	0.0693	-0.0018	-79.324	0.23960	0.0026	0.0042	-10.838	-4.6910
15	-1.0706	0.21702	-0.0543	0.04640	0.38584	0.19687	0.0010	-1.4670	0.51377	0.52443
16	-0.2686	0.17924	0.0739	0.0752	-6.7655	-4.7812	-0.0126	-0.2430	0.16469	0.50292
17	-0.3286	0.21458	-0.0780	-0.1960	-83.838	-4.4366	-0.0375	-6.8220	0.0986	0.52440
18	-1.3283	0.10141	-3.2656	0.0538	0.42562	0.31915	-4.1842	-0.0025	-0.0509	-410.14
19	-6.4115	0.15589	0.0059	0.07463	0.43912	0.39596	-3.7168	-0.2395	-1.5262	0.50734
20	0.1490	0.23078	-1.1540	0.0756	0.44510	0.14365	-0.4703	-0.1759	-6.9183	0.24137

Table 4.20: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 7 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.030	**3**	8	-0.300	4	10	-5.286	**3**	11	-0.388	**4**	11	0.028	3	10	**17**	50
01002	4	4	-.0426	**4**	6	0.167	5	5	-0.037	6	6	0.210	**3**	4	22	25
0.170	6	3	0.074	5	4	0.339	5	4	-0.006	7	4	0.501	7	3	30	18
0.2000	6	**2**	0.755	7	**1**	0.385	6	**2**	0.001	9	**2**	0.509	8	**2**	36	**9**

Table 4.21: Difference in Euclidean Norm of Reference and Test Signature using DRrCT over 8 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge)

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-6.4115	-0.12474	-4.8639	-39.778	-83.838	-19.471	-4.1842	-6.822	-10.838	-410.14
2	-1.3283	-0.03519	-3.2656	-1.2069	-79.324	-4.7812	-3.7168	-1.467	-6.9183	-4.691
3	-1.0706	0.03172	-1.6319	-0.7294	-6.7655	-4.4366	-1.1442	-0.7957	-1.5262	-0.0354
4	-0.3286	0.05276	-1.154	-0.3005	-6.0174	-1.4741	-0.4703	-0.2903	-0.91591	0.03239
5	-0.2686	0.10141	-0.3695	-0.2067	0.068794	-0.3669	-0.0375	-0.2687	-0.05098	0.22477
6	-0.2256	0.15589	-0.078	-0.1960	0.13442	0.14365	-0.0172	-0.243	-0.00733	0.24035
7	-0.1348	0.16482	-0.0746	-0.1305	0.1579	0.19687	-0.0126	-0.2395	0.098627	0.24137
8	-0.1149	0.17047	-0.0543	-0.0974	0.22702	0.2396	-0.0071	-0.1759	0.16469	0.35325
9	0.015	0.17924	0.0059	-0.0018	0.29938	0.31254	-0.0028	-0.0628	0.46558	0.45276
10	0.0416	0.19996	0.0617	0.0464	0.32755	0.31915	-0.0024	-0.0313	0.48067	0.45773
11	0.0528	0.21458	0.0652	0.0485	0.38584	0.35584	-0.0015	-0.0296	0.49474	0.45881
12	0.0645	0.21702	0.0693	0.0534	0.41492	0.37288	-0.0007	-0.0071	0.49979	0.47344
13	0.0839	0.21741	0.0701	0.0538	0.42562	0.38472	0.0007	-0.0062	0.50397	0.49219
14	0.1132	0.22732	0.0726	0.0746	0.43185	0.38819	0.001	-0.0049	0.50867	0.50292
15	0.1419	0.22757	0.0739	0.0752	0.43369	0.39596	0.001	-0.0025	0.5087	0.50734
16	0.149	0.22948	0.0739	0.0752	0.43912	0.42953	0.0016	0.0005	0.51201	0.51183
17	0.1774	0.22949	0.0747	0.0756	0.44405	0.43648	0.0018	0.0019	0.51377	0.51274
18	0.1999	0.23069	0.0754	0.0761	0.4451	0.43945	0.0021	0.0042	0.51635	0.51504
19	0.2082	0.23078	0.0771	0.0766	0.446	0.4415	0.0026	0.0051	0.52375	0.5244
20	0.2229	0.2309	0.0773	0.0775	0.44708	0.44434	0.0039	0.0053	0.52438	0.52443

Table 4.22: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 8 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.347	1	4	0.092	**1**	8	0.084	**1**	3	-1.133	0	4	0.044	2	4	**5**	23
0.333	**1**	3	0.091	2	5	-0.819	2	2	-.0256	**0**	2	0.041	**2**	3	7	15
0.205	2	**2**	0.090	2	4	-1.024	2	1	-3.656	1	**1**	0.247	4	2	11	10
-0.513	6	2	0.065	5	**2**	-1.041	2	**0**	-3.854	2	1	-1.81	5	**1**	20	**6**

Table 4.23: Difference in Euclidean Norm of Reference and Test Signature using DRrCT over 9 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge)

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	1.1113	-0.27887	-31.365	-3.2744	-94.564	-17.421	-0.5121	-0.50322	-0.0871	-0.8086
2	-0.2346	-0.12761	-1081.9	-3.0749	-25.679	-0.8211	-0.2787	-0.03426	-0.0002	-0.6369
3	-0.2152	-0.09988	-32.945	-0.7489	-20.897	-0.4939	-0.1738	0.09544	0.09109	-0.5081
4	-0.0783	-0.02796	-75.137	0.9583	-11.501	-0.2033	0.00834	0.11702	0.10821	-0.1331
5	0.0512	-0.0269	-28.446	2.3508	-6.3552	-0.0332	0.06284	0.1199	0.11561	-0.0118
6	0.1184	-0.01262	-27.368	2.4203	-4.1553	0.04975	0.09995	0.12539	0.11993	0.10465
7	0.1207	0.00997	-25.717	2.4285	-2.3919	0.15895	0.10413	0.12612	0.12709	0.11241
8	0.121	0.03852	-11.611	2.563	-1.1078	0.19692	0.12072	0.12659	0.13632	0.13153
9	0.1246	0.05016	-0.6568	2.9186	-0.6744	0.25171	0.12167	0.1275	0.15499	0.16609
10	0.1408	0.0565	1.8619	2.9545	-0.5516	0.27076	0.12299	0.12801	0.15511	0.1671
11	0.148	0.06785	1.9629	2.9903	-0.0878	0.27972	0.12631	0.12811	0.16042	0.16744
12	0.1521	0.1076	2.0777	3.0401	-0.0968	0.27989	0.12675	0.12817	0.16262	0.16775
13	0.1577	0.12152	2.4166	3.0492	0.01585	0.28296	0.12696	0.12823	0.16639	0.16832
14	0.1584	0.13232	2.4853	3.0497	0.16362	0.28457	0.12784	0.12879	0.16664	0.17117
15	0.1594	0.13399	2.5295	3.0513	0.2308	0.28645	0.12836	0.12885	0.16995	0.17127
16	0.1601	0.13483	2.9245	3.0562	0.2441	0.28704	0.12865	0.12893	0.1709	0.17141
17	0.1636	0.15213	2.9735	3.0617	0.24787	0.28707	0.12874	0.12898	0.17149	0.17224
18	0.1684	0.15509	3.047	3.0632	0.25141	0.28731	0.12881	0.12906	0.17225	0.17236
19	0.1702	0.15941	3.0654	3.0645	0.27297	0.28742	0.1289	0.12917	0.17274	0.17238
20	0.1709	0.17261	3.0698	3.0665	0.28746	0.28761	0.12926	0.12923	0.17274	0.17269

Table 4.24: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 9 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.589	0	2	0.741	2	2	1.541	1	3	0.702	2	2	0.760	**0**	2	**5**	11
0.554	**0**	1	0.619	**1**	**1**	1.391	2	2	0.112	1	**1**	0.741	2	2	6	7
0.492	2	**0**	0.560	2	1	0.925	2	**1**	-1.997	**0**	2	0.721	1	**1**	7	**5**
0.512	0	2	0.741	2	2	1.545	**1**	3	0.702	2	2	0.767	0	2	5	14

Table 4.25: Difference in Euclidean Norm of Reference and Test Signature using DFrCT over 10 features resulting in Minimum EER (Gen.=Genuine, Forg.=Forge).

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	-6.4839	0.3405	0.1053	0.0453	-1.0419	-8.925	0.4531	-9.1799	0.1955	0.1905
2	0.4116	-0.5854	0.1148	-2.3341	0.197	-24.086	-1.133	-14.308	0.1929	0.1905
3	0.4236	-2.3235	-1.1786	-0.0658	0.1702	-11.691	0.6221	-16.961	0.1705	-1.947
4	0.3418	-1.8158	0.0913	-0.064	0.1963	-15.832	0.7202	-11.502	0.1022	-6.302
5	0.3412	-5.1189	0.0997	0.1049	0.1888	-27.610	0.5518	-5.7588	0.0413	-2.4324
6	-0.7057	-4.8678	0.1143	-0.066	-0.8192	-4.9622	0.616	-20.048	-0.2466	-5.1425
7	0.4373	-1.7452	0.1126	0.0246	-1.0246	-34.193	0.7395	-10.676	0.0445	-21.459
8	0.4545	-0.42	0.0656	0.0841	0.1972	-5.588	0.7443	-17.572	0.1745	-7.9945
9	0.3829	-1.4163	0.0673	0.0985	0.1974	-4.078	0.7334	-7.3223	0.0845	-2.1727
10	0.3948	0.3948	0.0926	0.0535	0.1954	-12.517	-3.8534	-64.187	0.1018	-15.574
11	0.2752	-3.9684	0.0991	0.0289	0.1955	-24.045	0.7178	-22.004	0.1917	-17.214
12	0.4366	-2.0277	0.1079	-0.1395	0.1973	-1.6014	0.6659	-26.890	0.1228	-9.5119
13	0.4541	-3.222	0.1057	0.0645	0.1963	-1.5869	0.6834	-28.530	-1.8134	-5.5129
14	0.4523	-1.6865	-0.6175	-0.0822	0.1957	-7.0599	-0.1182	-8.8903	0.1567	-2.4035
15	0.3552	-5.4898	0.107	0.0549	0.0857	-9.6345	0.6465	-14.716	0.1942	-14.505
16	0.4505	-0.4331	0.1071	0.0527	0.1945	-5.3474	0.3727	-50.847	0.1557	-1.4667
17	0.4539	-0.736	0.0908	0.0621	0.1974	-1.3396	0.7539	-3.3252	-0.2477	-1.2801
18	0.3999	-1.4079	0.0975	-0.2132	0.0843	0.1154	-3.6592	-15.924	0.1887	-5.8708
19	0.3536	-1.1168	0.1092	0.0689	0.1966	-1.8787	-0.256	-11.812	0.1903	-3.1843
20	0.3706	-5.2555	0.1085	0.0825	0.1936	-0.1044	0.5786	-7.836	0.1438	0.0252

Table 4.26: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using DFrCT over 10 features. (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.378	1	4	0.092	**1**	8	0.084	**1**	3	-1.133	0	4	0.044	2	4	**5**	23
0.348	**1**	3	0.091	2	5	-0.819	2	2	-.0256	**0**	2	0.041	**2**	3	7	15
0.234	2	**2**	0.090	2	4	-1.024	2	1	-3.656	1	1	0.247	4	2	11	10
-0.511	6	2	0.065	5	**2**	-1.041	2	**0**	-3.854	2	**1**	-1.813	5	**1**	20	**6**

Using DFrCT as a verification technique, following combinations of different features out of twelve extracted features resulted in minimum EER as provided below.

Five Features: With the combination of five features, it is observed that Horizontal Direction, Displacement, Centripetal Acceleration, Tangential Acceleration, and Centripetal Jerk resulted in minimum EER of 5.75%.

Six Features: With the combination of six features, it is observed that Horizontal Direction, Displacement, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 5%.

Seven Features: With the combination of seven features, it is observed that Horizontal Direction, Displacement, Areal Velocity, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 4.25%.

Eight Features: With the combination of eight features, it is observed that Horizontal Direction, Displacement, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 3.75%.

Nine Features: With the combination of nine features, it is observed that Horizontal Direction, Displacement, Areal Velocity, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 3.5%.

Ten Features: With the combination of ten features, it is observed that Horizontal Direction, Displacement, Direction, Areal Velocity, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk resulted in minimum EER of 3.25%. This EER is minimum among all the verifications done using DFrCT.

4.5.4 Signature Verification using PCA with DFrCT

Firstly, PCA is applied over different combinations of the extracted features. Then principal components obtained are processed using DFrCT. These frequency domain components are given as input and output of the FIR filter in combinations of two. The impulse responses of FIR filters are combined to calculate Euclidean norm of test signature. In this Table 4.27 and 4.28, verification done on the basis of difference between the Euclidean norm of reference and test signature is demonstrated.

Table 4.27: Difference in Euclidean Norm of Reference and Test Signature using PCA with DFrCT with 8 features resulting in Minimum EER

Sig.	USER 1		USER 2		USER 3		USER 4		USER 5	
	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.	Gen.	Forg.
1	0.5579	-0.5926	0.3961	-2.9729	0.0891	-0.5941	1.3918	-1.3776	0.6859	-0.9364
2	0.5735	-0.9791	-2.0495	-2.8301	0.1128	-0.3231	1.2112	-4.1415	0.755	-2.5099
3	0.3435	-2.6932	-0.36	-1.4651	0.1127	-0.2595	-1.9126	-0.222	0.7605	-0.3793
4	0.0479	-1.3433	0.4477	-0.9331	0.4113	-0.4085	1.5277	-4.6914	0.718	-1.5532
5	6.7799	-3.1699	0.4363	-0.4208	0.111	-0.2234	1.5379	-1.1476	0.7604	-0.13
6	-0.5924	-1.9493	0.5601	-2.1791	0.0996	-1.5057	1.5404	-0.7321	-0.0807	-0.8319
7	0.4593	-8.2102	-3.1115	-0.473	0.1122	-0.3513	1.5414	-0.3986	-6.479	-0.5219
8	0.3005	-4.4139	-1.1034	-0.9647	0.1111	-0.4848	1.5313	-1.2057	0.7599	-0.1839
9	0.5938	-1.3167	-0.2196	-1.1429	0.1129	-0.4965	-8.3266	-1.3813	0.716	-0.6182
10	0.5722	-2.1194	0.6929	-1.2579	0.7028	-0.4169	-0.3466	-5.4325	0.7573	-1.3195
11	0.4983	-1.7541	0.6402	-1.1164	0.0996	-1.4258	-1.2189	-1.4481	0.7417	-1.1306
12	0.4686	-2.8248	0.6249	-0.9249	0.0811	-1.2755	1.5378	-1.342	0.76	-2.3978
13	1.1821	-1.4538	-0.3782	-1.9457	0.1036	-2.3682	1.324	-3.2573	0.7054	-3.8393
14	0.3248	-1.234	0.6097	-1.0295	0.111	-1.3191	0.9259	-6.683	0.7216	-7.3975
15	0.4814	-2.359	0.6265	-3.5121	0.0856	-1.0026	0.9188	-2.6439	0.7605	-1.5992
16	0.4596	-4.0608	0.6194	-1.2652	0.1089	-0.2378	15387	-2.3217	0.7605	-0.1368
17	0.5472	-1.2288	0.585	-0.6783	0.1088	-2.0094	1.5401	-1.2867	0.7488	-0.4034
18	0.4998	-7.4873	0.7413	-4.8308	-1.996	-0.5689	-2.2888	-1.7715	0.7599	-4.8198
19	0.4757	-1.0128	-0.0129	-1.1242	0.113	-1.0718	-5.4617	-0.5586	0.7062	-0.6794
20	-0.0139	-7.5903	0.255	-0.5898	0.1098	-0.1649	1.4881	-1.1592	-6.0183	-1.0884

Table 4.28: Number of False Accepted and False Rejected Signatures Corresponding to Various Threshold Levels using PCA with DFrCT (Thd.=Threshold, FA=False Accepted, FR=False Rejected).

Thd.	USER1		Thd.	USER2		Thd.	USER3		Thd.	USER4		Thd.	USER5		SUM	
	FA	FR		FA	FR		FA	FR		FA	FR		FA	FR		
0.567	0	2	0.741	2	2	1.589	1	3	0.702	2	2	0.760	**0**	2	**5**	5
0.512	**0**	1	0.619	**1**	**1**	1.391	2	2	0.112	1	**1**	0.741	2	2	6	7
0.473	2	**0**	0.560	2	1	0.925	2	**1**	-1.997	**0**	2	0.721	1	**1**	7	**5**
0.579	0	2	0.741	2	2	1.541	**1**	3	0.702	2	2	0.782	0	2	5	11

By applying PCA with DFrCT minimum EER of 3% is achieved when 8 features Horizontal Direction, Displacement, Area Pressure, Motion Pressure, Centripetal Acceleration, Tangential Acceleration, Tangential jerk, and Centripetal Jerk are extracted.

It is obvious that with DCT/DFrCT the error rate reduces as number of features is increased. In the case of DFrCT, by increasing the number of features the time consumption and complexity goes on increasing, but the EER is reduced in comparison with the DCT. To avoid the complexity, PCA technique is used for feature selection which combines number of correlated variables to smaller uncorrelated ones. Thus, data dimension gets reduced due to redundancy removal. It is easy to apply verification over smaller number of principal components and thus, time consumption reduces. Moreover, due to use of direction and areal velocity further in derivation of accelerations and jerks, it is not required to take them in account during verification. Hence, eight features results in minimum EER instead of more.

The number of false accepted and false rejected signatures is more in case when only DCT is employed for signature verification. The scenario is improved when PCA is introduced for feature selection. The signature verification method further improves when DFrCT is used instead of DCT. The best results of false accepted and false rejected signatures are recorded when PCA is applied for feature selection in DFrCT based signature verification method.

4.6 Comparative Analysis

The proposed scheme is based on the computation of the difference between the Euclidean norm of the test signature and reference signature for signature verification. To test the authenticity of the signature, different levels must be set which provides the binary hypothesis of the signature, i.e. genuine or forged. These levels may be demonstrated as different threshold values. For each signature a threshold value is set by hit and trial method. If the difference between the Euclidean norm of the two signatures lies above below the threshold value, it would correspond to genuine class of signatures otherwise to the forged class.

Table 4.29: Results using Various Techniques Applied and Different Features giving Minimum EER at Threshold Level 1.

Technique	No. of features	No of FIR filters	FAR(%)	FRR(%)	EER(%)
DCT	5	3	35	36.5	35.75
	6	3	31.5	35	33.25
	7	4	30.5	34.5	32.5
	8	4	30.5	32.5	31.5
	9	5	30	33	31.5
	10	5	28.5	33.5	**30.5**
PCA with DCT	5	3	20.5	28.5	24.5
	6	3	18	25	21.5
	7	4	18	24.5	21.25
	8	4	17.5	24.5	**21**
	9	5	18.5	24.5	21.5
	10	5	21.5	25.5	23.5
DFrCT	5	3	18	13.5	15.75
	6	3	10	11.5	10.75
	7	4	9.5	10	9.75
	8	4	8	9	8.5
	9	5	7.5	9	8.25
	10	5	7	8	**7.5**
PCA with DFrCT	5	3	11	10.5	10.75
	6	3	8	8.5	8.25
	7	4	5	6	5.5
	8	4	3.5	5.5	**4.5**
	9	5	3.5	6	4.75
	10	5	4	6.5	5.25

Table 4.30: Results using Various Techniques Applied and Different Features giving Minimum EER at Threshold Level 2.

Technique	No. of features	No of FIR filters	FAR(%)	FRR(%)	EER(%)
DCT	5	3	32.5	31	31.75
	6	3	28	30	29
	7	4	27.5	28.5	28
	8	4	26	27	26.5
	9	5	24.5	25.5	25
	10	5	23	24	**23.5**
PCA with DCT	5	3	18	25	21.5
	6	3	15.5	20	17.75
	7	4	14	18.5	16.25
	8	4	13.5	17	**15.25**
	9	5	15	17	16
	10	5	20.5	20	20.25
DFrCT	5	3	15	12	13.5
	6	3	9.5	10.5	10
	7	4	8	9.5	8.75
	8	4	7.5	8.5	8
	9	5	7	8.5	7.75
	10	5	6.5	8	**7.25**
PCA with DFrCT	5	3	8.5	8	8.25
	6	3	7	7.5	7.25
	7	4	5	5.5	5.25
	8	4	3	5	**4**
	9	5	3	5.5	8.25
	10	5	4	6	5

Table 4.31: Results using Various Techniques Applied and Different Features giving Minimum EER at Threshold Level 3.

Technique	No. of features	No of FIR filters	FAR(%)	FRR(%)	EER(%)
DCT	5	3	15.5	21	18.25
	6	3	18	20.5	19.25
	7	4	17.5	18.5	18
	8	4	15	17	16
	9	5	14	15.5	14.75
	10	5	12.5	14	**13.25**
PCA with DCT	5	3	10	12	11
	6	3	8.5	10	9.25
	7	4	7	8	7.5
	8	4	6.5	7	**6.75**
	9	5	7.5	7	7.25
	10	5	9	8	8.5
DFrCT	5	3	7	7.5	7.25
	6	3	6.5	6.5	6.5
	7	4	5	5	5
	8	4	4.5	4	4.25
	9	5	4	4	4
	10	5	3.5	3	**3.25**
PCA with DFrCT	5	3	6	7	6.5
	6	3	5.5	6.5	6
	7	4	4	5.5	4.75
	8	4	3.5	4	**3.75**
	9	5	3.5	5	4.25
	10	5	4	5	4.5

Table 4.32: Results using Various Techniques Applied and Different Features giving Minimum EER at Threshold Level 4.

Technique	No. of features	No of FIR filters	FAR(%)	FRR(%)	EER(%)
DCT	5	3	8.5	8	8.25
	6	3	7.5	5	7.25
	7	4	7	4	6
	8	4	7	4	5.5
	9	5	6.5	4	5.25
	10	5	6.5	3.5	**5**
PCA with DCT	5	3	6.5	6.5	6.5
	6	3	5.5	4	4.75
	7	4	4	4	4
	8	4	4	3	**3.5**
	9	5	4	4.5	4.25
	10	5	3.5	4.5	4
DFrCT	5	3	5	6.5	5.75
	6	3	4.5	5.5	5
	7	4	4	4.5	4.25
	8	4	3.5	4	3.75
	9	5	3.5	3.5	3.5
	10	5	3	3.5	**3.25**
PCA with DFrCT	5	3	4.5	4	4.25
	6	3	3.5	4	3.75
	7	4	3	3.5	3.25
	8	4	3	3	**3**
	9	5	3	3.5	3.25
	10	5	3.5	3.5	3.5

Table 4.29, Table 4.30, Table 4.31 and Table 4.32 shows the various parameters like FRR, FAR and EER for DCT, PCA with DFrCT, DFrCT and PCA with DFrCT techniques at different threshold levels. From these tables it is clear that minimum EER is achieved with all the techniques at threshold level 4 and maximum in the case of threshold level 1. EER at threshold level 2 and threshold level 3 lies in between the range of EERs calculated for threshold level1 and threshold level 4. It is depicted from these tables that PCA with DFrCT results for minimum EER% of 3% with 8 features.

Table 4.33: Comparison of Proposed Method with Existing Method.

Technique	EER (%)
PCA with DFrCT (Proposed Method)	3
DFrCT, M. Arora *et al.* [25]	5
DCT, P. Thumwarin *et al.* [19]	7.04

Online Signature verification using DCT done by P. Thumwarin *et al.* [19] achieved an EER of 7.04%. Further improvement in the method was done by M. Arora *et al.* [25] with the replacement of DCT technique by DFrCT. EER obtained with DFrCT was 5%. Better results are obtained with the proposed method having 3% EER. Thus, there is a 2% improvement in proposed work as compared to M. Arora *et al.* [25].

4.7 Chapter Summary

In this chapter, results obtained related to the methodology explained in chapter 3 are given. Detailed description of results is provided in form of graphs and tables for pre-processing, Features, and Features after DFrCT, best features out of PCA. Verification results are provided for DCT, PCA with DCT, DFrCT and PCA with DFrCT. Based upon the comparison with previous techniques it is concluded that proposed work employing PCA based feature selection of online signature verification system using DFrCT produces improvement in results. There is a 2% improvement in proposed work from the work done by M. Arora *et al.* [25] using DFrCT.

Chapter-5

Conclusions and Future Scope

5.1 Conclusions

Signature verification is classified in two groups i.e. offline signature which consist of an image of the signature and online signature having dynamic features which explains the signing process like acceleration, pressure etc., captured through a digital device such as tablet. With the increase in applications of identity check demand for more dynamic information is building. Identity proofs like ID cards already consists of image of the user's signature. Now a day's use of online signatures having more information is increasing.

The technique proposed by P. Thumwarin *et al.* [19] for online signature verification used DCT on six features and EER of 7.04% is recorded. Whereas, M. Arora *et al.* in [25] extended this approach by using DFrCT on six features and EER was reduced to 5%.

In this dissertation combination of features ranging from five to ten is developed and EER of 5% is observed in DCT and 3.25% in DFrCT using ten features. This is because of the fact that in DFrCT, a fractional order is present which can be varied to produce desirable results. Also, increasing the number of features, the variations in signature are more precisely described providing reduction in EER. In addition to this, the DFrCT has more computational complexity as compared to DCT.

The approach is further extended by employing PCA to both DCT and DFrCT. The introduction of PCA in the technique provides EERs of 3.5% for DCT and 3% for DFrCT, only considering eight features. As a result, the number of operations got reduced improving the efficiency of online signature verification system.

The main advantage of proposed methodology with respect to previous work is its ability to achieve 3% EER. This leads to improvement of 2% over the technique proposed by M. Arora *et al.* in [25].

5.2 Future Scope

Single value of fractional order (α) is used in this study for all the features. Different values of α's have been already optimized for different features using DFrCT. So, further performance improvement in work can be done by optimizing different values of α for different features using PCA with DFrCT. Further promising improvement in future can be expected by joint algorithms with other biometric modalities.

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