Identification And Verification of Handwritten Signatures Using Digital Image Processing Techniques in An Offline Setting

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Abstract— This study provides a writer-independent signature verification system. To classify the data, the system uses K-Nearest Neighbours (KNN) while Fourier Descriptors (FD) are used for feature extraction. In this case, to obtain reliable and steady features we were gathering, scanning and preparing signatures of ten people. As for the performance of the system, it achieved a 95% recognition rate on both the local and MCYT datasets where K=1. There is a need to develop something in this regards because it was shown that the misclassifications were due to having different signature limits. The findings reveal that both FD and KNN function well in writer independent model and provide a reliable solution to the problem of automated signature verification.

Index Terms- Signature verification, writer-independent, Fourier Descriptors, K-Nearest Neighbors, feature extraction, classification, image processing.

I. INTRODUCTION

Biometrics, the identification of individuals through the use of technologies that measure their physiological and behavioral traits, is now a critical tool in numerous fields that range from security to law enforcement and identification. This means that among all the available biometric systems, the signature verification is more preferred because of its contactless nature and acceptance in legal and financial processes. The following thesis focuses on the area of offline handwritten signature identification and verification with the aid of digital image processing technology.

The word 'biometrics' is derived from two Greek roots, bios meaning life and metron meaning measure, and it refers to identification methods that include physiological or behavioral characteristics. Physiological biometrics comprises of fingerprints, scanning of the retina and DNA whereas behavioral biometrics entails voice recognition and signature verification. Compared to other forms of identification, for instance, passwords or PIN numbers, biometric systems provide better security because the characteristics being used are unique features that cannot be easily mimicked or otherwise appropriated. Handwriting identification and recognition has been in practice for many years due to its reliability in matters such as authentication of documents, contracts and financial transactions. However, unlike other biometric systems, signature verification does not require special equipment, and thus is much more efficient. Nevertheless, the process of verifying handwritten signatures is not as straightforward as with other biometric data, especially the offline collection where signatures are taken on paper and then scanned.

The importance of signature verification is that it creates a sense of security while at the same time not causing much inconvenience. Biometric signatures are accepted in the society and among legal systems for identification thus making them useful in different fields such as in banking and in contracts. Moreover, signatures are fairly unobtrusive and can be fairly easily collected with out the need for specialized equipment unlike other methods such as iris scans or finger printing. That is why signature verification is desirable for many organizations and individuals.

Signature verification systems can operate in two primary modes: The two major categories of biometric systems are identification and verification. Identification mode is used to compare the signature to a large database of signatures in an effort to find the identity of the signer while verification mode is employed to compare the signature to a known sample in order to verify the identity of the signer. The former is a 1:N matching process where a record is matched with one record from another data source while the second type of record linkage is where a record from a database is matched with another record from the same database. Each mode of estimation is not without its specific difficulties and both need to be equipped with powerful algorithms that ensure the accuracy of the calculated results.

The given study proposes to improve the performance and effectiveness of offline handwritten signature verification systems with the help of modern methods for image analysis of digital data. By employing high-quality feature extraction techniques and advanced classification models, the research is expected to make a meaningful contribution to the field of biometric authentication, thus providing a safe and efficient means of identity validation in a wide range of contexts. This contribution is very significant when considering the current trends, where there is growing demand for safe and efficient biometric systems due to frequent cases of identity theft and security violations.

- Statement of Problem

Currently, most of the fingerprint databases or any kind of verification techniques used are developed from non-Indian population, hence, yielding lower results for Indian signatures commonly written in regional language. To fill this gap, this research aims to compile a comprehensive local database for signatures in India and design the most effective verification processes. The aim is to increase recognition efficiency and stability of the signature images with the help of digital image processing that operates with the data which has the distinctive features of Indian signature.

- Research Gap

There can be low identification accuracy in Indian signatures, because their regional scripts and mnemonics used are not included in the existing data sets; some stylistic features. Translation of signatures may be very difficult and traditional verification algorithms may not capture features that are exclusive to Indian signatures hence the need for special techniques. This paper reveals that the feature extraction and classification algorithms can be improved to increase the precision and efficiency of the Indian signature verification system by implementing the models according to the Indian signature characteristics. This contribution fills the gap in the existing research and sets the foundation for further research on CLD biometric data which in turn contributes to the overall growth of biometric authentication.

II. LITERATURE REVIEW

Alajrami et al. 2020

Altogether, the use of deep learning has improved the accuracy of verification of handwritten signatures as compared to offline techniques. Offline (static) verification techniques have been regarded as slow and having a very low rate to process files in relation to the volume of documents to process. Online verification, especially dynamic verification, uses parameters like pressure and speed to trace the production of signatures in real-time using digital devices. It also improves efficiency and reduces the risk of exposing sensitive information. Currently, it is also shifting towards quicker and more reliable verifications, where technologies like iris scans and fingerprint scanners are prominent examples. As stated in the paper by Alajrami et al. (2020), offline signature verification can benefit from the use of CNNs in terms of increasing the precision. In the evaluation with test data, the authors realised a precision rate of 99. 70% while differentiating genuine signatures from forged ones. This shows that the deep learning method has the ability to enhance the methods of verifying a signature. This is because CNNs' have proven to be capable of solving difficult pattern recognition problems and have the potential to vastly improve biometric authentication systems.

R.A Mohammed et al. 2015

There has been a recent explosion of activity in the field of handwritten signature verification (HSV). So far, we have accomplished a great deal in terms of precision and computing. Behavioural biometrics include things like signature verification and keystroke dynamics, whereas physiological biometrics include things like fingerprints and iris characteristics. Using both online and offline methods, signature verification is a topic of much research and discussion. In many regions of the globe, offline systems are preferable than online ones due to their greater applicability and user-friendliness. The absence of dynamic information, however, makes it more challenging than online verification. Current knowledge regarding both kinds of HSV systems is presented in this article. In this work, we showcase various pre-processing approaches and techniques, as well as new data collecting methods. Additionally, the state-of-the-art approaches to feature extraction and signature system verification are discussed. Lastly, we go over some examples of approaches and techniques that have been implemented. Finally, we suggest that future iterations integrate more of your suggestions.

S.Y Ooi et al. 2016
When a physical copy of a signature is required for a financial transaction, image-based handwritten signature verification is crucial. Because static signature photos don't provide any information about the subject's behaviour, we suggested a system that combines discrete Radon transform (DRT), principal component analysis (PCA), and probabilistic neural networks (PNN). At the picture level, the proposed framework seeks to differentiate between real and fake signatures. Both our private signature database and MYCT, a public database, are subjected to rigors testing. The reported error rates (EER) for random, casual, and competent forgeries of our own database are 1.51%, 3.23%, and 13.07%, respectively. Applying our suggested method to the MYCT signature database yields a 9.87% EER using only 10 training samples.

L.G. Hafemann et al. 2017
Verifying a person's identification using handwritten signatures becomes more challenging when a professional forger has access to their signature and attempts to duplicate it. It is not straightforward to create feature extractors that can distinguish between real signatures and ones that have been expertly faked since offline (static) signature verification does not maintain the dynamic information about the signature-writing process. Consequently, the performance is subpar, with verification errors of approximately 7% for the best systems reported in the literature. To tackle the issue of getting suitable features and boosting system performance, we propose learning signature photo representations using Writer-Independent Convolutional Neural Networks. To be more specific, we suggest a new way of looking at the problem—one that incorporates expert forgery information from some users into the feature learning process—with the goal of capturing visual cues that differentiate between real signatures and fakes, independent of the user. The GPDS, MCYT, CEDAR, and Brazilian PUC-PR datasets were the subjects of intensive experimental testing. With an Equal Error Rate of 1.72% on GPDS-160, we significantly outperformed the state-of-the-art, which was 6.97% in the literature. Furthermore, we confirmed that the features outperform state-of-the-art performance on different datasets, not only the GPDS dataset, and that this is achieved without fine-tuning the representation for each individual dataset.

III. METHODOLOGY

The method of this signature verification method is made up of the following processes; gathering of data, preparation, feature extraction and classification. The goal is to design a unique authentication method that would not require any human intervention and use KNN and FD classifiers for its efficient functioning.
Data Collection

To enhance diversity, the data for this study consisted of 10 different individuals who were selected randomly at different workplaces and asked to sign a document. Each subject signed on white A4 paper for sixteen times in cases whereby the next time would be at different intervals to capture variations. The signatures were scanned on a flatbed scanner set to greyscale at 300 dpi to digitise the signatures acquired. The photographs were then scanned, and with the help of the image processing tools of the computer, horizontal and vertical profile operations were done to extract the individual signatures and create a cropped signature image set.

Preprocessing
Preprocessing is very important in order to make the extracted signature fit for feature extraction since this stage defines the quality of the subsequent steps. Multiple preprocessing stages were conducted: Multiple preprocessing stages were conducted:

Binarization: To accomplish this goal, an appropriate thresholding method was used to transform the grayscale images into binarized images. Noise Removal: Additional processing that was used include morphological operations like erosion and dilation to remove any unwanted noise that might have existed in the binary images. Normalisation: As a result, the binary pictures were normalized to the same size of 40×60 in order to get constant input for feature extraction. Boundary Extraction: To maintain uniformity across the samples the boundaries were drawn round the 'signatures'.

Feature Extraction

To extract information from the signature, we employed Fourier Descriptors (FD), which are effective in capturing its shape aspects. The following is the sequence of steps that were taken:

The outlines of the binarized signature images were determined. Fourier Transform: The Fourier Descriptors were computed using these contours. The frequency domain representations were derived by translating the spatial domain representations, and the signatures were depicted as closed boundaries. Dimensionality Reduction: The Fourier Descriptors were reduced to 64 dimensions, retaining the significant form characteristics and eliminating redundant ones.

Classification

In the classifying process K-Nearest Neighbours (KNN) classifiers were used to classify and rate the signatures. First, the selection of the training set was done manually, when we chose ten signatures each of the sixteen collections of the given subjects. This resulted in a training sample total of one hundred as an outcome of it. Every training sample was described by 64-dimensional FD feature vector. Assembling the Test Set: The remaining 6 signatures from each participant was used in producing a grand total of 60 test samples. These samples were represented using 64-dimensional features vector. Moreover, the labels were utilized to recognize which of the participants' training samples the corresponding samples belonged to. Before going through the recognition process, the test samples are not categorized or given any identification. The extracted feature vectors from the training and test set were then used to train the KNN classifier. The classifier for each test signature calculated the distances to all the training samples and identified the nearest neighbor (K=1) to assign the label.

Performance Evaluation

The correct identification rates of the KNN classifier were used to assess the performance of the proposed approach. That is why we were able to calculate the mean recognition rate using the local dataset and the MCYT database at K=1. The proposed strategy has a great recognition rate of 95%, thus making the strategy seemed to have worked well.

Results Analysis

As for the variables, the results obtained for both datasets showed that the settings that produced the best outcomes were when K=1. However, the main reason for the misclassifications was the fluctuations in the values of bounding limits of the signatures. This feature extraction and preprocessing might be another area that could help improve the system's resilience if more work was put into it. This method has the advantage of using KNN for classification, as well as the FD for feature extraction, which makes it rather resistant to noise and has a high accuracy when using writer independent signature verification. Thus, for the purpose of achieving better results and reducing misclassification rates in the future, the utilization of a hybrid system, as well as the application of more normalisation methods may be considered.

IV. MODELLING AND ANALYSIS

This section is to introduce the model of the study and to explain the data used for signature verification. The most commonly used model is the writer-independent signature verification system where feature extraction is done by Fourier Descriptors (FD) and classification is done using KNN. The collection signatures were scanned in 300 dots per inch in shades of grey and came from ten different signers with varied occupations. Six signatures were used for testing and the remaining ten for training respectively from each person.

Fourier Descriptors from the outline of every signature were used to compute the 64-dimensional feature vectors. These feature vectors are then consumed by the K-Nearest Neighbors classifier. During the classification stage, the feature vectors of the test signatures are matched with the feature vectors of the training set if we use the best recognition rate when we used K=1.

The system is a computer platform that conducts the FD and KNN algorithms and image processing software to facilitate pre-processing tasks, such as binarization and noise removal, and a flatbed scanner for inputting the signatures. Recognition rates and the comparison of the system's performance based on accuracy were studied and results reflected accuracy of 95% for local dataset and MCYT dataset In addition to the detailed Notation Table 6.1, and feature extraction method Figure 6.3 in this section, reporting appropriately the dataset composition and a clear structure regarding the feature extraction and recognition system block diagram aims to provide the necessary information to be able to reproduce the results in the described format.

V. RESULTS

6.1 Writer-independent Offline Signature Recognition based upon Fourier Descriptors

Authentic signatures are denoted as positive instances in writer-dependent signature verification, whereas signatures from different users are denoted as negative instances. Each user's signature verification is performed using a model that is specifically trained for that user. As more users are added, the complexity and cost of this approach increase due to the need for a binary classifier for each user. Writer-independent systems, on the other hand, utilise a single model created by supervised classifiers on a limited number of training samples that accurately represent all users in the dataset. Subsequently, this model categorises signatures from any user inside the dataset.

Several writer-independent feature extraction methods for verification have been proposed. Rivard et al. employed a combination of boosting feature selection, dichotomy transformation, and other feature extraction techniques. Bertolini et al. utilised graphometric properties along with a cluster of classifiers to enhance the difficulty of detecting forgeries. Victor L. F. Souza et al. obtained superior outcomes compared to other methods on the Brazilian and GPDS datasets by utilising SVM classifiers and deep convolution neural network features. The utilisation of Fourier Descriptors (FD) enables the outcome to concentrate on a recognition approach that is not influenced by the writer's identity. Features are derived from a continuous curve that fits the signature, and these features are used as input for KNN classifiers. Each of the ten participants had their signatures converted into grayscale and digitised at a resolution of 300 dots per inch (dpi). The dataset consisted of 100 training signatures and 60 testing signatures. Each individual had 10 signatures used for training and 6 signatures used for testing. The training data were utilised to compute and assign FDs with 64 dimensions; however, the test samples were employed to calculate FDs without any assigned labels.

When K was set to 1, the KNN classifier performed better than the local counterpart on the MCYT database. Consistent preprocessing is essential due to misclassifications resulting from variations in the enclosing boundaries of certain signatures.

The results of the classifier are presented in Table 6.1

Table 6.1: Recognition results using KNN classifier

Subjects	No. of train/test	Recognition Local Database		Recognition MCYT	
		K=1	K=3	K=1	K=3
1	10/6	6	6	5	6
2	10/6	6	6	6	5
3	10/6	4	5	5	4
4	10/6	5	6	6	6
5	10/6	4	4	5	4
6	10/6	6	2	5	3
7	10/6	3	4	4	4
8	10/6	5	5	5	5
9	10/6	6	5	6	5
10	10/6	5	4	5	4
Recognition accuracy in %		83.33	78.33	86.66	76.66

A biometric security system's false acceptance rate (FAR) indicates how often it will mistakenly approve an unauthorized user's access attempt. The false acceptance rate (FAR) of a system is usually defined as the ratio of the total number of identifications attempts to the number of erroneous acceptances. The accuracy and FAR is shown in table 6.2

Table 6.2: Accuracy and FAR value of classifier

Classifier	Accuracy	FAR
KNN for K=1	83.33%	0.1667
KNN for K=3	78.33%	0.2167

6.2 Writer-independent Offline Signature Recognition based upon Histogram of oriented gradients (HOGs) feature

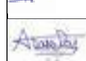
The Histogram of Oriented Gradients (HOG) is one feature descriptor used often in computer vision and image processing for object recognition. Using techniques similar to shape contexts, edge orientation histograms, and scale-invariant feature transform descriptors, one can quantify the frequency of gradient orientations in particular sections of an image. HOG is worth investigating if you want an algorithm that raises accuracy. It executes calculations on a dense grid of routinely spaced cells using overlapping local contrast normalisation.

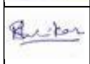
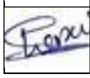
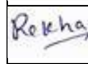
The HOG descriptor is primarily based on properly capturing and representing the local object's appearance and shape by distributing intensity gradients or edge directions. Within each cell, a histogram of gradient directions is created. A cell refers to a small connected piece of a picture. Combining these histograms results in the final metric. In order to enhance precision, the local histograms are subjected to contrast normalisation. This involves calculating the intensity of a larger area, or block, and applying it uniformly to all the cells within that block. Through the process of standardisation, we enhance its resilience against fluctuations in lighting and shadows. Utilising Histogram of Oriented Gradients (HOG) descriptors offers a multitude of substantial advantages. Except for object orientation, these entities remain geometrically and photometrically invariant, allowing them to tolerate localised alterations in appearance caused by shadows and illumination. The HOG algorithm was able to disregard the specific body motions of pedestrians as long as they remained standing, due to its use of rough spatial sampling, precise orientation sampling, and robust local photometric normalisation, as described by Dalal and Triggs in 2005. Due to its characteristics, HOG was well-suited for identifying signatures.

HOG utilises a grid matrix to overlay on the signature image, enabling the extraction of features. Subsequently, K-Nearest Neighbours (KNN) classifiers are employed to detect and recognise the signature. They accomplish this by conducting a comparison between the inputted features and the existing features stored in a database.

Out of the 16 signatures available, 10 were used for training and 6 were used for testing. This resulted in a training set of 100 signatures and a testing set of 60 signatures. The goal of this was to evaluate the performance. 81-dimensional Histogram of Oriented Gradient (HOG) features were computed and correctly labelled for each training set. We generated features for the test samples without any corresponding labels. The KNN classifier was fed with the feature vectors that were produced. When using an image size of 40x60 pixels that has been normalised, the results show that the HOG features accurately identified signatures with an average recognition rate of 95% for both KNN and Support Vector Machine (SVM) classifiers.

Table 6.3: Recognition results using KNN classifier

<table>
<tr><th rowspan="3">Subjects</th><th rowspan="3">No. of train/test</th><th colspan="5">Recognition</th></tr>
<tr><th colspan="2">Image size 128x256</th><th colspan="3">Image size 40 x 60</th></tr>
<tr><th>K=1</th><th>K=3</th><th>K=1</th><th>K=3</th><th>SVM</th></tr>
<tr><td></td><td>10/6</td><td>6</td><td>6</td><td>5</td><td>5</td><td>5</td></tr>
<tr><td></td><td>10/6</td><td>6</td><td>6</td><td>6</td><td>6</td><td>6</td></tr>
</table>

	10/6	6	6	6	6	6
	10/6	6	6	6	5	6
	10/6	5	5	6	5	6
	10/6	4	5	6	6	6
	10/6	6	5	5	5	6
	10/6	6	6	6	5	5
	10/6	6	6	6	6	6
	10/6	2	2	5	4	5
Average Recognition %		88.33	88.33	95.00	88.33	95.00

The confusion matrix is presented in table 6.4.

Table 6.4.: Confusion matrix with size normalization of 40x60 pixels and 128x256 pixels, respectively

K=1

Subjects	1	2	3	4	5	6	7	8	9	10
1	5	*	*	*	1	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	*	*	*	*	6	*	*	*	*	*
6	*	*	*	*	*	6	*	*	*	*
7	*	1	*	*	*	*	5	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	*	*	*	1	*	*	*	5

K=3

Subjects	1	2	3	4	5	6	7	8	9	10
1	5	*	*	*	1	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	5	*	*	1	*	*	*
5	*	*	*	*	5	*	1	*	*	*
6	*	*	*	*	*	6	*	*	*	*
7	*	1	*	*	*	*	5	*	*	*
8	*	*	*	*	*	1	*	5	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	*	*	*	*	4

K=1

Subjects	1	2	3	4	5	6	7	8	9	10
1	6	*	*	*	*	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	1	*	*	*	5	*	*	*	*	*
6	*	*	1	*	*	4	*	*	*	1
7	*	*	*	*	*	*	6	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	2	*	*	*	2

K=3

Subjects	1	2	3	4	5	6	7	8	9	10
1	6	*	*	*	*	*	*	*	*	*
2	*	6	*	*	*	*	*	*	*	*
3	*	*	6	*	*	*	*	*	*	*
4	*	*	*	6	*	*	*	*	*	*
5	1	*	*	*	5	*	*	*	*	*
6	*	*	3	*	*	3	*	*	*	*
7	*	*	*	1	*	*	5	*	*	*
8	*	*	*	*	*	*	*	6	*	*
9	*	*	*	*	*	*	*	*	6	*
10	*	*	2	*	*	2	*	*	*	2

The accuracy and FAR is shown in table 6.5.

Table 6.5: Accuracy and FAR value of classifier

Image Size	Classifier	Accuracy	FAR
128X256	KNN for K=1	83.33%	0.1667
	KNN for K=3	88.33%	0.1667
40X60	KNN for K=1	95.00%	0.0500
	KNN for K=3	88.33%	0.1667
	SVM	95.00%	0.0500

6.3 Offline Signature Recognition based upon LBP features

In computer vision and image processing for object detection, the histogram of oriented gradients (HOG) is a somewhat often used feature descriptor. This approach quantifies the frequency of gradient orientations in particular sections of an image, therefore it is comparable to shape contexts, scale-invariant feature transform descriptors, and edge orientation histograms. HOG uses overlapping local contrast normalisation to boost precision and computes on a dense grid of evenly distributed cells, unlike previous techniques.

Underlying HOG is the basic idea that the local visual qualities and form of objects inside an image can be defined by the arrangement of intensity gradients or edge orientations. For the pixels within every cell, a histogram of gradient directions is produced to show a limited linked section of the image. The best description is obtained from combining the histograms. We can achieve normalisation by computing the intensity across a wider area known as a block and then applying it to all the cells therein, hence improving the accuracy of these local histograms. This stage helps the description to be more resistant to changes in shadow and illumination.

HOG descriptors offer some advantages as compared to other descriptors. None of the geometric and photometric modifications have any impact on them, except for object orientation. Dalal and Triggs discovered that HOG (Histogram of Oriented Gradients) is highly effective in detecting signatures since it disregards the precise bodily movements of pedestrians, as long as they maintain an upright position. This discovery emphasises promising areas for further research, specifically focusing on issues related to automatic signature verification. HOG is employed to extract features from the signature image using a grid matrix. These characteristics are subsequently utilised as input for K-Nearest Neighbours (KNN) classifiers to facilitate recognition. The technique was evaluated using a total of 16 signatures, with 10 signatures utilised for training and 6 for testing. This resulted in a training set of 100 signatures and a testing set of 60 signatures. We computed and labelled 81-dimensional Histogram of Oriented Gradient (HOG) features for the training sets. Subsequently, the KNN classifier was provided with these features as input. Using a standardised image size of 40x60 pixels, the results indicate that the average accuracy rate for K=1 was 95% for both KNN and Support Vector Machine (SVM) classifiers. This demonstrates the effectiveness of using HOG features for signature recognition.

Table 6.6: Results using KNN and SVM classifier for local database

Subjects	No of Train/Test	Verification results		
		KNN		SVM
		K=1	K=3	
1	8/8	8	7	8
2	8/8	8	7	8
3	8/8	7	4	7
4	8/8	8	6	8
5	8/8	8	8	8
6	8/8	8	7	8
7	8/8	8	7	8
8	8/8	8	5	8
9	8/8	8	8	8
10	8/8	8	6	8

Average Recognition %	98.75	81.25	98.75

Table 6.7: Accuracy and FAR value for local database

Classifier	Accuracy	FAT
KNN for K=1	98.75	0.0125
KNN for K=3	81.25	0.1875
SVM	98.75	0.0125

Table 6.8: Results using KNN classification for K=1

Signature	Original	Forgery	True Acceptance	False Rejection	Accuracy
Original	100%	0	100%	0	90%
Forgery	20%	80%	80%	20%	

Table 6.9: Results using KNN classification for K=3

Signature	Original	Forgery	True Acceptance	False Rejection	Accuracy
Original	88%	12%	88%	12%	86%
Forgery	16%	84%	84%	16%	

Table 6.10: Results using SVM classification

Signature	Original	Forgery	True Acceptance	False Rejection	Accuracy
Original	84%	16%	84%	16%	85%
Forgery	14%	86%	86%	14%	

Table 6.11: Accuracy and FAR value of classifier for MCYT database

Classifier	Accuracy	FAT
KNN for K=1	90%	0.1000
KNN for K=3	86%	0.1400
SVM	85%	0.1500

CONCLUSION

Signature recognition systems function by storing and comparing unique characteristics that depict the writer's patterns of conduct when creating a signature. The objective of a signature verification process is to authenticate or refute a given sample, while the objective of a signature recognition process is to ascertain the authorship of a certain sample. We have proposed effective methods for signature recognition by utilising Fourier Descriptors and HOG features. A proposed approach for signature verification utilises Local Binary Patterns (LBP) features. Presented below is a summary of the contents of this thesis.

A brief introduction on biometric systems is presented in Chapter 1. Significance of signature verification and the process involved has been discussed. Objective and methodology have been presented.

Database creation and pre-processing steps have been described. Literature survey briefly outlines the available methods for offline signature recognition and authentication. Database creation deals with the collection of handwritten signatures from persons of different age groups, professions and the pre-processing methods applied to the scanned signature images. Description about the standard database of signature images has also been presented in brief.

Offline Signature Recognition based upon Fourier Descriptors is presented in sub-heading I of result. A powerful method to recognize objects uses the Fourier Transform. FDs are derived from Fourier transform of shape signatures. A boundary tracing is performed on the signature image as follows. Using morphological operations, we enclose the entire signature in a closed curve that fits the signature. The curve so obtained is different for different signatures and hence can be used effectively to compute FDs for shape recognition. FAR measures and evaluates the efficiency and accuracy of a proposed system by determining the rate at which wrong patterns are verified on a particular system. In the present study performed on 60 test signature patterns from local dataset, ten patterns were wrongly accepted yielding an FAR of 0.166.

Based on HOG features, sub-heading II of the result shows offline signature recognition. The method measures gradients of orientation in localised areas of an image. Features are computed on a regularly spaced dense grid of cells. Using a KNN classifier, recognition is accomplished. 60 images were utilised for testing and 100 images were used for training in trials. With K=1 the FAR achieved for FDs and HOGs respectively is 0.1667 and 0.0500. HOG produced a good recognition accuracy when compared to results obtained using FD feature sets.

Result three presents an efficient method of signature verification. Ten genuine signatures and three forgery signatures for each subject are chosen at random among collection of the genuine and forgery signature set for training purpose. Test phase consists of verifying a given signature belongs to specific subject is genuine or forgery. The LBP operator, which is a measure of grayscale invariant texture based on a generic description of texture in a small neighbourhood, is used during feature extraction.

The LBP operator generates a 3x3 neighborhood's binary code by using the grey value of its centre as a threshold. One way to describe the texture is by looking at the histograms of the labels. The local dataset and the MCYT database are used as experimental subjects for the signature image analysis. For signature verification, KNN and SVM classifiers have been used.

In this thesis, identification of the signature as belonging to specific person has been carried out using Fourier Descriptors and Histogram of Oriented Gradient features. Signature authentication has been studied using LBP features. The offline signature image can be subjected to identification using any of the three approaches viz, FDs, HOG or LBP features, while for signature authentication the identified signature can be done using LBP approach.

The fact that various signature verification systems make use of distinct signature databases makes it extremely challenging to compare their respective performances. Here we compare our system's performance to that of other systems and databases.

FUTURE WORK

- The signature identification approach using FDs or HOG features can be extended to authentication of signatures.
- The methods suggested in this thesis can be expanded to study of signature recognition or verification for signature images written in other Indian and non-Indian scripts.
- The ability of the suggested system against all competent forgeries has been demonstrated by experimental findings. To improve performance, however, the different elements suggested could be merged. One could enhance the performance by means of an ensemble of classifiers.
- Other findings for conducting tests will be made available from the local data collection of images written in English, Kannada, Marathi, Telugu scripts.

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