Automatic Person Identification and Verification using Online Handwriting

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CERTIFICATE

It is certified that the work contained in this thesis, titled "*Automatic Person Identification and Verification using Online Handwriting*" by Sachin Gupta, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Advisor: Dr. Anoop Namboodiri

To my family, and friends.

Acknowledgement

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Abstract

Automatic person identification is one of the major concerns in this era of automation. However, this is not a new problem and our society has adopted several different ways to authenticate the identity of a person such as signature and possessing a document. With the advent of electronic communication media (Internet), the interactions are becoming more and more automatic and thus the problem of identity theft has became even more severe. Even, the traditional modes of person authentication systems such as *Possessions* and *Knowledge* are not able to solve this problem. *Possessions* include physical possessions such as keys, passports, and smart cards. *Knowledge* is a piece of information that is memorized, such as a password and is supposed to be kept a secret. *Knowledge* and *possession* based methods are more focused on "what you know" or "what you possess" rather than "who you are". Due to inability of knowledge and possession based authentication methods to handle the security concerns, biometrics research have gained significant momentum in the last decade as the security concerns are increasing due to increasing automation of every field. *Biometrics* refers to authentication of a person using a physiological and behavioral trait of the individual that distinguish him from others. Biometric authentication has various advantages over knowledge and possession based identification methods including ease of use and non repudiation. In this thesis, we address the problem of handwriting biometrics. Handwriting is a behavioral biometric as it is generated as the consequence of an action performed by a person. Handwriting identification also has a long history. Signature (a specific instance of handwriting) has been used for authentication of legal documents for a long time.

This thesis addresses the various problems related to automatic handwriting identification. Most of the writer identification work is being done manually till date as a lot of context dependent information, such as, source of documents, nature of handwriting, etc. is difficult to model mathematically. However, they can be easily analyzed by human experts. Still, an automatic handwriting analysis system is useful as it can remove subjectivity from the process of handwriting identification and can be used for expert advice in various court cases. The final aim of this research is to design efficient algorithms for automatic feature extraction and recognition of the writer from a given handwritten document with as less human intervention as possible.

Specifically, we propose efficient solutions to three different applications of handwriting identification. First we look at the problem of determining the authorship of an arbitrary piece of online handwritten text. We then analyze the discriminative information from online handwriting to propose an efficient and accurate approach for text-dependent writer verification for practical and low security applications. We also look at the problem of repudiation in handwritten

documents for forensic document examination. After introducing the problem of repudiation in handwritten documents, we propose an algorithm for repudiation detection in the handwritten documents.

Handwriting identification is quite different from handwriting recognition; the other popular sub-field of automatic handwriting analysis. Handwriting recognition tries to identify the content of a handwritten text and tries to minimize variations due to writing style. On the other hand, in the case of handwriting identification, variations due to style is sought out.

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Chapter 1

Introduction

With the ease and speed of interactions, electronic media is extremely popular these days, in the form of e-mails, chats and phone calls. With the advances in electronic and communication technologies, traditional inter-personal interactions are getting replaced with interactions over a communication medium (emails, chat etc.) or human machine interactions: ATM machines, digital libraries etc. Knowledge of identity of your peer was taken for granted in traditional interactions. However as digital data replaces the vision and sound in traditional interactions, the individual's claimed identity must be authenticated by more rigorous means rather than just being assumed. Fraudulent use of false identity is one of the most undesirable aspects of automation. Use of a fast and robust person authentication system can deter crime, help in maintaining social cohesion as well as save a lot of critical resources from being wasted. Person authentication is not a new problem and our society had adopted various ways to verify the identity of a person, i.e., to authenticate the person. The traditional modes of person authentication are *Possessions*, *Knowledge* and *Biometrics*. *Possessions* include physical possessions such as keys, passports, and smart cards. *Knowledge* is a piece of information that is memorized, such as a password and is supposed to be kept a secret. According to a survey by CyberSource Corp. [1], the cost of credit card fraud reaches into billions of dollars annually and increasing each year. In 2006 only, fraud in the United-states alone was estimated at $\$3$ billion(an increase of 7% over 2005). According to NTA survey [2] in 2002, individual user have average 21 different passwords and they either select easy-to-guess passwords or write them down, which makes passwords based authentication more prone to forgery. Biometrics solves the problems posed by knowledge and possession based methods and provides the forgery robust and fast person authentication methods. *Biometrics* refers to the authentication of a person using a physiological or behavioral trait of individuals that distinguish one person from another. These three modes of authentication can be used either individually or in combination with others. *Knowledge* and *possession* based methods are more focused on "what you know" or "what you possess" rather than "who you are". At the same time, possessions such as identity cards can be lost or stolen and passwords can be guessed, this makes the use of such authentication methods prone to forgery attacks. Since, the personal biometrics traits like face, fingerprints, voice, etc. can not be stolen or easily copied so biometrics traits can replace current identification methods to identify a person uniquely.

This thesis addresses the specific problem of person identification using handwriting: a behavioral biometric trait. Writer identification has many applications in various forensic and civilian applications. Person authentication using signature, which is being used extensively for person authentication in banks and documents authentication in general, is a specific instance of writer identification. With the increase in usage of mobile devices based on pen-based input such as PDA and Tablet PC, the amount of data created in the handwriting form also increases. However, the use of such documents for various forensic and legal purposes depends on our ability to assign authorship/writership to the document. Most of the writer identification work is being done manually as a lot of context dependent information like source of documents, nature of handwriting, etc. are difficult to model mathematically, while being easier to analyze manually. The main objective of this work is to design efficient algorithms for automatic feature extraction and pattern recognition to identify the writer of a given document with as less human intervention as possible. Connected to the authorship of a document, there are many other interesting research problems, such as:

1. *Personalized handwriting recognition system*: Automatic handwriting recognition is one of the most challenging problem of automatic pattern analysis owing to the within class variations due to different handwriting styles. It is very difficult to design automatic handwriting recognition system for all handwriting styles with high accuracy. However, at the same time, there are less variations within each writer. This problem is being addressed as the problem of writer adaptation in handwriting literature. The main objective of a writer adaptation system is to learn the writer specific details from the handwriting of the writer and adapt those changes to increase the accuracy of the recognition system itself.

2. *Quantitative analysis of individuality of handwriting*: How much amount of data do we require to model the writer with significantly high accuracy and how much accuracy for person identification, we can gain with handwriting as the biometrics.

Specifically, we propose efficient solutions to three different applications of handwriting identification. First we look at the problem of determining the authorship of an arbitrary piece of online handwritten text. We then analyze the discriminative information from online handwriting to propose an efficient and accurate approach for text-dependent writer verification for practical and low security applications. We also look at the problem of repudiation in handwritten documents for forensic document examination. After introducing the problem of repudiation in handwritten documents, we propose an algorithm for repudiation detection in the handwritten documents. Before describing the comprehensive details of the work, we briefly introduce some of the commonly used terms in the field of the writer identification.

1.1 Handwriting: a Behavioral Biometric

Biometrics (origin: Greek, bios =”life”, metron =”measure”) is the study of methods for uniquely recognizing humans based upon one or more intrinsic physiological or behavioral traits, such as face, iris, hand, hand veins, ear, handwriting, speech, keystroke dynamics, gait patterns, etc. Physical modalities like face, iris, hand, hand-veins, ear etc. are more invasive and need cooperative subjects. Behavioral modalities such as, handwriting, speech, gait, etc. are less invasive. However, high within class variations make them less accurate. Handwriting is a behavioral biometric trait, as handwriting is generated as the result of an action accomplished by the person.

Handwriting identification is the study of differences and similarities of the handwriting of individuals in order to identify the writer of a given document. Handwriting identification can be defined as the study of discriminating elements (characteristics or writing habits), which are simply the manifestations of the habits of an individual. Handwriting identification is based on the hypothesis that handwriting of each individual is unique and an individual's handwriting can be modeled mathematically. However, there still exists a lot of challenges that make handwriting identification a hard task.

Handwriting identification, like other biometrics such as fingerprint identification, DNA analysis and face identification, is a discriminatory process. However, it is subject to larger variations from one occasion to another and even the range of variations vary between the individuals. According to Huber and Headrick [3]:

"In case of handwriting, no two samples of the same text, by the same individual, with the same writing instrument, on the same date, and under the same writing and writer circumstances will be identical in all aspects."

Some of the factors (as recognized by handwriting experts) that affects the handwriting of a person includes: Adequacy of standards, accidental occupancies, alternative styles, ambidexterity, carelessness or negligence, changes in health conditions of writer, changes in physical conditions like fractures, fatigue, weakness etc. of writer, changes in mental condition or state of the writer, concentration on the act of writing, disguise or deliberate change, drugs of alcohol, influence of medications, intentional changes for later denial, nervous tension, natural variations - beyond those of standards, writing conditions - place or circumstances(moving vehicles), writing instrument, writing position - include stance, writing surface and writing under stress.

Another major difference between handwriting and other physical biometrics traits is that the handwriting should be readable. It is not free (like fingerprints) to vary from one subject to another without imparting recognition. It must be written clearly in order to be readable. Thus there are more chances that two writers duplicate the same style when they are writing the same text. Thus extraction of writer information from handwriting is challenging compared to verification based on physical biometrics traits, due to the large intra-class variation (between handwriting samples of the same person), and the high inter-class similarity (same words being written by different people). Further, the handwriting of a particular writer may also be affected by the nature of the pen, writing surface, and the writer's mental state.

In addition to the above, challenges in handwriting identification increase further when user is not cooperating. Two major problems arise usually due to uncooperative users. **Repudiation**, also called negative biometrics in biometrics literature, comes in to light when person tries to disguise himself from the system by not revealing his identity. The problem of **Forgery**, also called positive biometrics, arises when a person tries to copy someone else's identity(handwriting). Forgeries have been focus area in other fields like signature identification. However, the problem of *repudiation* in context of handwriting has not been addressed before. In short, challenges of traditional handwriting identification can be summarized as follows:

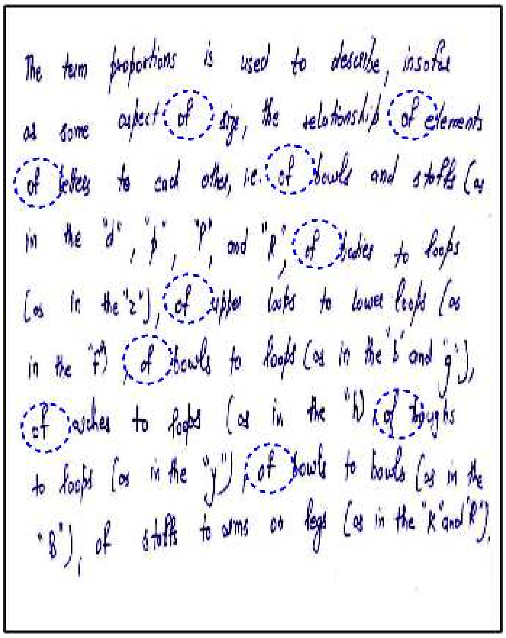
- *High within writer variations*: Documents written by the same writer are also quite different at different times based on mood and conditions, which adds to high intra-class variations of the handwriting.
- *Low between writer variation*: Each writer is basically trying to write the same word or character. At the same time, there is not much scope for variation, as handwriting must also be readable. This makes the variations between handwriting of different writers, low.
- *Repudiation and Forgery*: These problems of handwriting are caused by non-cooperative individuals. The result of repudiation is increase in within writer variations, as the writer essentially is trying to alter his handwriting. However, in the case of forgery, the between writer variations become less, as a writer is deliberately trying to copy someone else's handwriting.

Based on the above discussions, it can be concluded that the problems in writer identification is quite different from other biometrics and thus needs different attention and methods as compared to other physical biometrics. Another major difference in writer identification is that some part of the handwriting can be more informative and more discriminating than other text for a particular writer.

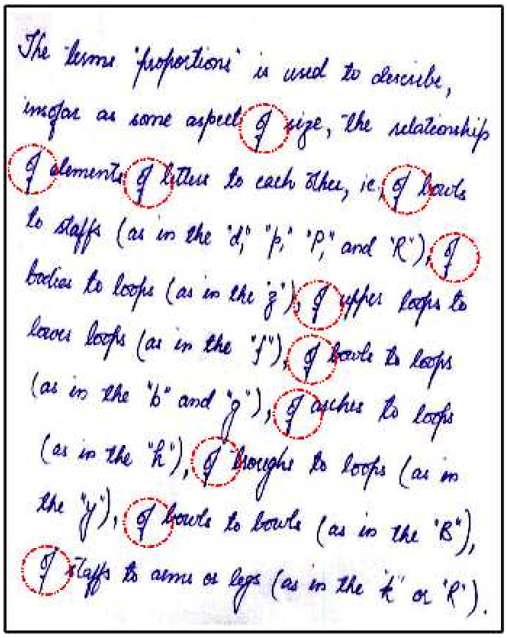
In spite of all these problems, it has been shown by the forensic experts, that handwriting identification is possible. They have shown that even repudiation and forgery detection can be done, if the examination is carried out at an appropriate level of precision. From the principle of *exclusion* and *inclusion*, inferred by the document examiners from their experience in the field, *one can't exclude from one's own writing, those discriminating elements of which he/she is not aware, or include those elements of another's writing of which he/she is not cognizant* [3]. Next section will explain in detail what makes handwriting identification possible. We also describes various individuality features of the handwriting.

1.1.1 Individual Features of Handwriting

Challenges and variations posed by the handwriting makes us to think whether the writer of a document is uniquely determinable with sufficient confidence. We have discussed various factors which do influence handwriting of the individuals. In this section, we will discuss the factors which make handwriting individuality possible. The major goal of handwriting identification systems is to find out whether the difference between the documents is significant enough and overtake the similarities between the documents. Handwriting identification is possible based on two accepted premises or principles:



(a)



(b)

Figure 1.1 Within-writer consistency and between-writer variations of handwriting (a) Writer1, (b) Writer2

- *Habituation:* People are primarily creatures of habits and writing is the collection of those habits. Writing habits are considered neither instinctive nor hereditary but are complex processes that are developed gradually.

- *Individuality or heterogeneity of handwriting:* Each individual had his own style of writing. Nature has not given the same style to any two writers. In short, no two individuals can have the same handwriting.

Numerous elements of writing become habitual with practise, and the execution becomes more automatic as the writing process separates itself from the thought process. The individual is being more concerned about what is being written rather than how it is being written. Due to complexity of writing process, the individual develops his/her own idiosyncracies in both the shape or form of letter and fashion in which they are combined, all of which become habitual gradually. All these habits make the handwriting of the individuals different from one another. See Figure 1.1 for within writer consistency and between writer variations while writing same document.

Based on the handwriting experts [3], the discriminating elements of handwriting can be segregated into two main categories (Elements of style and execution) and two minor categories (consistency and lateral expansion):

1. *Elements of style*: Consists mainly of arrangement, connections, construction, design, dimensions, slant or slope, spacings, class and choice of allograph(s). With the exception,

perhaps, of construction, these are the aspects of writing that play a significant role in creating pictorial, general or overall effect. Differences in the construction, of course, do not necessarily alter the overall effects.

2. *Elements of execution*: Consists of abbreviations, alignments, commencements and terminations, diacritic and punctuation, embellishments, line continuity, line quality or fluency(speed), pen control(includes pen hold, pen position, and pen pressure), writing moment, (including angularity) and legibility or writing quality (which includes letter shapes or letter forms for any given allograph).

3. *Consistency or natural variations and persistency*

4. *Lateral expansion:* Horizontal dimension of a group of successive letters and words and word proportions (Vertical Dimension Vs Horizontal Dimension and the Product of size and spacing).

All these features are used by the handwriting experts during handwriting analysis. It may not always be possible to compute all these features mathematically either due to the absence of sufficient data needed for statistically stable computations or due to the absence of efficient algorithms to compute this.

In addition to the above features, which can be computed from the handwritten documents, logical and analytical features are also being used by handwriting experts for the final conclusion during manual inspection. The fact that such determination is possible and done by experts make automatic handwriting identification possible even if it is not an easy one. We now look at various categories of problems in handwriting analysis.

1.1.2 Handwriting Recognition Vs Writer Identification

Handwriting has received much attention from the time human-beings started writing. The ease and individuality of handwriting made it to expand as a major communication medium. With the advent of easy to use and fast electronic communication and storage mediums, the focus starts shifting from handwriting. However, still handwriting is one of the major modes of expression and data storage, for example, there are specific situations such as classrooms, one-to-one discussions, meeting, etc. where handwriting is still the major medium for note taking. At the same time, with the advent of electronic handwriting devices such as PDA, Tablet PC, research interests in the field of automatic handwriting analysis have gain significant increase in the last two decades. Researchers are always attracted by non-intrusive nature of handwriting data entry methods as compared to keyboards and speech. At the same time, keyboards can not be used for data entry in all languages that can be done easily using handwriting. This makes automatic handwriting recognition even more popular.

At the same time, the complexity of handwriting generation process have always attracted many researchers to explore the field of automatic handwriting analyst. The study of handwriting has been done from various perspectives, based on the information content to be extracted from the handwriting. The information that is present in the handwriting can be categorized as text level information (what has been written), person style information (who has written it), and noise (due to external factors like pen, paper, etc). The extraction of the former is addressed as handwriting recognition and latter is known as writer identification in literature. Both the forms of handwriting analysis look quite similar, which essentially is not the case.

- **Handwriting recognition**: Handwriting recognition is a process to extract the style invariant features to eliminate variations added due to different handwriting styles. The major goal of handwriting recognition is to extract the underlying text, automatically. This will enable us to use many automatic systems that are controlled using handwritten query. The handwriting recognition systems look for style invariant features, so that the variations added due to different handwriting styles can be eliminated. Thus, handwriting recognition require eliminations of variations due to different writers.

- **Handwriting identification**: Writer identification is a process to identify the writer of the documents. In writer identification systems, features are extracted that can discriminate between different writers i.e., features based on the style of the writer. In short, writer identification requires enhancement of the variations due to style.

Based on the above arguments, it can be concluded that both handwriting recognition and handwriting individuality are two opposite facets of handwriting analysis. Another major field that is closely related to handwriting individuality is *Graphology [4] (Study of handwriting to analyze the personality of the person).*

1.1.3 Text independent Vs Text dependent systems

Automatic handwriting analysis is more constrained and challenging than manual analysis of documents. From the point of view of pattern recognition, techniques for writer identification can be categorized as text independent and text dependent. *Text-dependent systems* are more constrained and require similar verification and enrollment text. Text dependent systems are closer to signature verification systems and thus inherit the problems associated with signature verification, such as, forgery. Text dependent methods are more general in approach than the signature identification. These methods, therefore, require prior localization and segmentation of the relevant information, which can be performed interactively by the human user or by an automatic segmentation algorithm. *Text independent systems*, on the other hand do not make any assumption about the underlying data. Text independent methods for writer identification and verification use statistical features, extracted from an entire block of handwriting. A minimum amount of handwritten data is needed to ensure the stability and consistency of characteristics extracted from the data.

Both the text-dependent and the text-independent systems have their pros and cons. Text dependent systems provide high accuracy and confidence with small amount of data, which is not

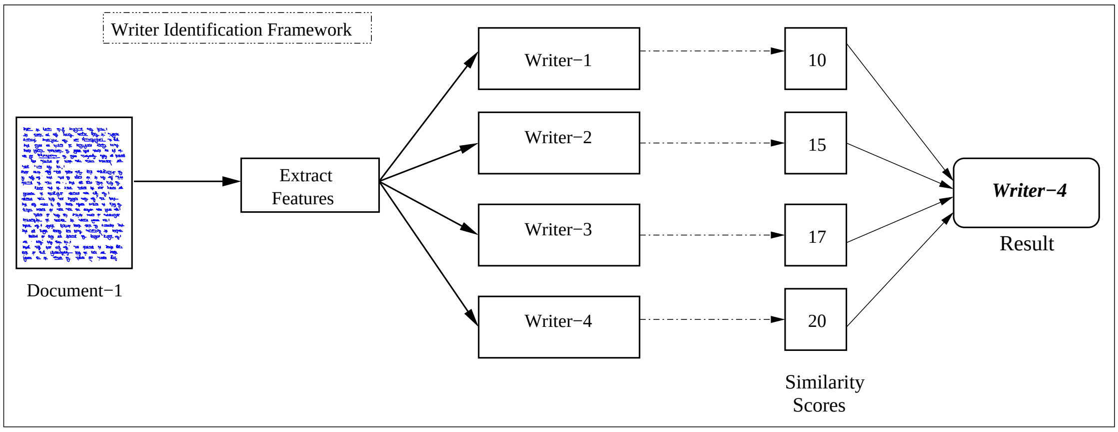


Figure 1.2 Identification framework: Who is the writer of the document among the pool of writers?

possible for text independent systems. However, they are more prone to forgery, as the verification text is known in advance. In case of text independent systems forgery is not a major problem as the text-independent systems extract less frequent properties from the handwritten document that are difficult to forge. The major problem with text-dependent system is of annotation of data prior to training. Automatic annotation can be done using either a handwriting-recognition engine or an alignment engine. However, the state-of-art in handwriting recognition systems in not such that it can be used prior to writer identification. Moreover, handwriting recognition systems are not available for all languages and at the same time it is an expensive operation. Since text-independent systems generally do not require annotated text, they are better from a practical point of view.

The use of text independent or text dependent system fully depends on the application and availability of data. For example, in the case of forensic applications, we can not control the proceedings, i.e., we can not make sure the data that is available for verification is same as that of reference handwriting, thus the only option is to use text-independent system. However, as data is less manual alignment can be done easily and a text-dependent algorithm can be used. We will be using these two terms frequently and the difference will become more prominent and clear.

1.1.4 Verification Vs Identification

The problem of resolving the identity of a person can be categorized into two fundamentally distinct types of problems with different inherent complexities: (i) Verification problems and (ii) Recognition (Identification) problems. Verification refers to the problem of confirming or denying any identity claim (am I who I claim I am?). Verification is generally a two class problem. Identification, on the other hand is the problem of establishing the identity of a person from a group of people (close identification problem) or otherwise (open identification problem). Writer identification systems make one-to-many comparisons with a given database of writers

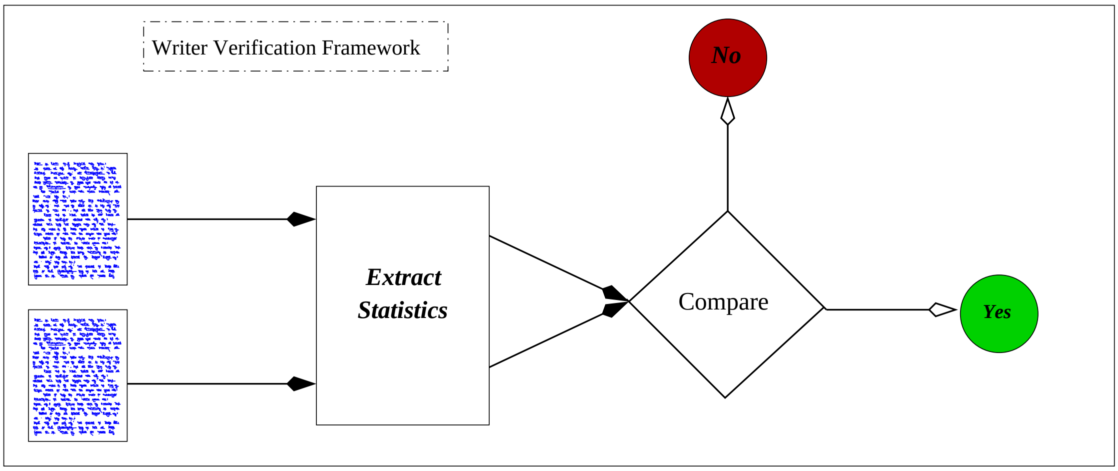


Figure 1.3 Verification framework: Are the given two documents written by same person?

and returns a writer or a list of probable writers. Writer identification system essentially can be thought of as information extraction system from a given pool of database of writers, where features are specific to the writer of the document. The identification problem can be formally posed as: given a input feature vector X_Q, determine the writer W_i, $i \in 1, 2, \ldots, N, N+1$. Here N is the number of writers enrolled in the system and $N+1$ is the case for rejection option where no suitable identity is determined for the input. Assume that $S(.,.)$ is the similarity function between two feature vectors.

$$X_q \in \begin{cases} W_k & \text{if}(k = \max_k S(X_q, X_{w_k}) \text{ and } S(X_q, X_{w_k}) > \eta) \\ W_{k+1} & \text{otherwise} \end{cases} \tag{1.1}$$

In the case of document analysis, the verification systems work in two different modes. In the first mode, the system verifies the claim made by a person previously enrolled in the system. The given problem can either be solved using one-to-one comparison or using one-to-many comparisons. In one-to-one comparison, the questioned sample is compared with the reference sample of the claimed identity stored in the database. Identity is then established using similarity score and within writer distance threshold (calculated during training phase). The case of one-to-many comparison is essentially same as the writer identification, as the questioned sample is compared with all the samples from the database and the writer with the minimum distance is compared with the claimed identity. The one-to-one problem in case of verification can be posed as: given as database of writers, questioned document X_q and the claim K,

$$Y = \begin{cases} 1(\text{Accept Claim}) & \text{if}(Dis(X_q, X_{w_k}) < \eta) \\ 0(\text{Reject Claim}) & \text{otherwise} \end{cases}, \tag{1.2}$$

Here, η is the threshold of between-class and within-class distance, calculated during training stage.

In second mode, verification problem verifies whether two given documents, *Questioned document*, whose identity need to be verified and *Reference document*, which is collected from the writer for comparison, belong to the same writer or not. The writer of the reference document may or may not be known. This is the major problem in case of forensic documents, where usually two documents need to be compared. This problem can be thought of as the more general instance of one-one verification problem. The difference between the two is that in this case no database of writers is available and thus, a threshold can not be computed. In order to solve the problem, some statistical measure is needed to compute the significance of the score. The problem of *repudiation* and *forgery* detection comes under this category. The generic problem of writer verification can be stated as follows: given two documents D_Q and D_R, we need to find out whether two documents belongs to same writer or different writers.

$$Y = \begin{cases} 1(\text{Same Writer}) & \text{if}(H(Dis(X_q, X_r)) > \eta) \\ 0(\text{Different Writers}) & \text{otherwise} \end{cases}, \tag{1.3}$$

Here $H(.)$ calculates the statistical significance of the distance measure.

1.2 Applications

Handwriting biometrics, can be applied in a lot of fields. However, based on security and other aspects, applications of any biometric systems can be broadly divided into following categories:

- *Personalized handwriting recognition systems:* A general handwriting recognition system can not perform as accurate as is required, since it is difficult to learn the variations due to the different handwriting styles. However, an adaptive (handwriting recognition) system for an individuals' needs to learn the personal handwriting traits of a writer. Since the writing style of an individual is consistent, recognition performance will be better. Automatic writer identification system can be used as the preprocessing step to recognition that can identify the handwriting style and perform the handwriting recognition specific to the writer. To this end, we have developed an automatic writer identification algorithm that can learn the discriminative features in a individual's handwriting.

- *Low security access control systems:* Handwriting is considered as a weak biometric trait based on amount of discriminating power it posses, however it can be used for low security access control applications, where the cost due to false accept is quite low. Low security applications, such as access to personal computer can be done using writer identification system rather than a password, which is the common practice these days. Our aim in this context was to enhance the verification accuracy and propose a forgery resistant handwriting verification algorithm.

- *Automatic forensic document examination:* The field of forensic handwritten document examination is concerned with issues such as determining whether the writer of a document (say a Ransom Letter) is the same as the known writer of sample documents, whether the given piece of handwriting is genuine or forgery, whether the writer of the documents is trying to conceal his identity, etc. We have specifically addressed the problem of detecting repudiation with a statistical framework.

Forensic applications are the major applications of handwritten documents examination. The major issue in any forensic document examination is the high risk associated with the result. Civilian applications require less security. However the main concern in civilian applications is the ease of use.

1.2.1 Online Vs Offline Handwriting

Based on the nature of data availability, handwriting analysis systems can be categorized as online or offline handwriting systems. Offline handwriting refers to scanned images of handwritten documents. Online documents contain temporal information of the pen movement such as stroke order information together with pen up-down events. Since, online documents have more information as compared to offline documents, systems working on online data are supposed to provide more accurate results. However, both online and offline documents are associated with different set of problems and challenges. Even though, online documents have more information, their within writer variations is also more, that makes modeling and recognition tasks difficult. In the case of offline documents the temporal information is lost. In a lot of practical applications, online data is not available, such as forensic applications. However, in the case of access control applications, a user can be asked to provide online data. Since, online and offline handwriting documents have different set of problems and information and thus require different processing methods and need to be studied differently than offline handwriting based approaches.

1.3 Contributions of the thesis

The key contributions of this work are:

1. Proposed a method for identification of discriminating features for text-independent writer identification [5]. The key characteristics of the system are:
   - (a) Presents an algorithm for automatic extraction of consistent features for writer identification.
   - (b) Robust to forgery and
   - (c) Provides a script-and text-independent framework.
2. A framework for repudiation detection in forensic documents [6]. Key insights are:
   - (a) We introduce the problem of repudiation for handwriting for the first time, and
   - (b) Presents a hypothesis testing based framework for writer verification in forensic applications.

3. Text dependent writer verification for civilian applications [7]. The key contributions of the work are:
   (a) An algorithm to generate writer-specific test sentences for individual writers.
   (b) Forgery resistant framework by implanting randomness into the generation process, and
   (c) Applicable to low security access control and civilian applications.

1.4 Thesis overview

This thesis is organized as follows. Chapter-2 presents the overview of the work that has been done previously and describes features and pattern recognition techniques that has been applied to the online and offline handwriting identification. The next chapter presents the framework for text-independent writer identification using online handwriting. The framework presents the code book designing algorithm together with the empirical results to prove the applicability of the proposed algorithm. Chapter-4 explains a text-dependent technique for practical and low security applications of writer verification. The system presents a boosting based approach for text-selection specific to a writer. Chapter-5 presents a framework for repudiation detection in handwritten documents. The problem of repudiation have not been studied before in context of handwritten documents. We, first introduce the problem of repudiation and then presents a solution for repudiation detection, together with empirical results. The conclusion and future work is presented at the end.

Chapter 2

Background and Related Work

Owing to the need and applications of handwriting analysis in various forensic and civilian domains, many researchers have been attracted towards the field. The security of documents always has been a major concern, however due to advances in electronics and digital media, as traditional interactions are being replaced by electronic interactions, these concerns have become more vital. Need for automatic document analysis and the complexity of handwriting generation process have always attracted researchers towards it. Signature verification systems had been used previously to authenticate handwritten documents. However, handwriting itself contain individuality information about the writer that can easily be used for writer identification. Writer identification system also have various advantages over traditional signature based verification systems. Moreover, signature identification is the specific sub-field of handwriting identification, in which a writer is to be verified based on some specific predefined text chosen by the writers themselves, i.e.signature of the writer. This chapter will present the insight in to the related work and various approaches used by different researchers for writer identification. Comprehensive survey of work until 1989 has been published in [8]. With the advent of new technologies, a variety of new approaches have been proposed for the problem of writer identification and verification. We will try to include most of the known approaches that have significant impact on this field.

Chapter is organized as follows. First two sections present the details about text-dependent and text-independent systems. Section following that will list out the remaining pen input approaches which are not described in previous two sections. Next section will present the details about various machine learning and pattern recognition methods for writer identification and verification. Analysis of the field based on features, classifiers and results is included at the end.

2.1 Text-dependent approaches

Text dependent approaches assume the similar text to be used for enrollment and authentication. Signature identification is a specific instance of text dependent writer identification. In case of signature identification, writer himself choose the text that will be later used for verification, i.e. signature of the writer. The major difference between general text dependent handwriting

	Feature-Level	Handwriting Type	Feature Description
Text-Dependent	Character	Offline	GSC features [9, 10] Structural features [11–14] Directional features [15]
		Online	Pen-input features [16]
	Word	Offline	GSC, WMR, SC, SCON [17, 18] Morphological features [19]
Text-independent	Line Features	Offline	Connected Components Enclose regions, Lower and upper profiles, Fractal features [20, 21]
	Paragraph	Offline	Gabor, GSCM [22, 23], GGD, contourlet GGD [24, 25] Directional features [26–28] Code-book generation [29–31]
		Online	Code-book Generation [5, 32]
Image Processing	Document	Offline	Grey scale features [33, 34] Grey scale Histogram [35, 36] Run length coding [37]
Pen Input Feature	Document	Online	Pen Pressure, Velocity, Azimuth [38] Velocity bary center [39] Point Distribution model [40] Continuous Dynamic programming [41]

Table 2.1 Feature extraction methods used for writer identification.

identification system and signature verification system is that in case of general text dependent system user may not have enough freedom to choose verification text. User can be asked to write some predefined text for verification, which is not known before. Moreover general text dependent writer identification system are more complex than normal signature verification, as the signature of a person can be a scribble that may or may not be readable. However, in case of general text dependent writer identification words are mostly written to be readable and as the other person is also trying to write the same word, difference between-writers and within-writer distances will reduce more.

Text dependent systems suffer from the major drawback of vulnerability to forgery. Since the verification text is known in advance, the system sometimes become prone to forgery. The comparison of similar text may look easier on the first instance, however, since no two handwriting pieces of the same individual are exactly the same, contains a lot of within-writer variations, it sometimes becomes difficult to verify whether the distance between handwritten documents is due to within- writer variability or words are actually written by different writers. Analyzing the handwriting variations between two documents, Harrison [3] once expounds that:

"... it is not surprising that when specimens of the handwriting of one person written under different conditions are compared, there should be a doubt expressed that one individual was responsible for writ-

ing all the scripts, so different they appear."

However challenging may be the text-dependent systems, but since the text-dependent systems rely on similar text comparisons, they can provide high accuracy as compared to text-independent systems with small amount of data. The text-independent systems, on the other hand, use less frequent properties of handwriting that can not be extracted from lesser data. Based on above arguments, major challenge of text-dependent systems is to classify the distance between similar pieces of text as the within-writer and between-writers distances. Various researchers have studied the problem of the text-dependent writer identification for both online and offline handwriting. In this section, we discuss the details of various feature extraction methods used for text dependent systems. One should note the point here that for the practical text-dependent systems, the features extraction should be done at lower level, i.e., sub-character, character or word level. Since paragraph or line-based feature may not be practically feasible. We categorize the feature extraction methods according to document level hierarchy, i.e., character, word, line and paragraph.

2.1.1 Sub-character and character level features

Huber and Headrick [3] have identified some features (refer to section 1.1.1) those are used by forensic experts for manual or semiautomatic document examination. According to handwriting experts size and shape of the characters have large amount of individuality information associated. Researchers have tried to design computational algorithms to extract the shape and size based individuality of the characters.

Srihari et al. have studied the problem of individuality of characters [9] and numerals [10] for offline handwritten documents. Srihari have proposed computational algorithms for size and shape estimation of characters, called micro-features. Micro features are 512 bit features corresponding to gradient(192 bit), structure(192 bit) and concavity(128 bits) and are computed locally from the character image. Micro features have extensively been used previously for handwriting recognition purposes. Gradient features are the distribution of the directions of gradient elements extracted from the image using 3X3 Sobel operators and represent shape of the characters. Structural feature extractor takes gradient map and looks in the neighborhood for certain combinations of gradient values that are used to represent the strokes and corner of the image. Concavity features is extracted by applying a star like operator in eight directions at each of the white pixels to extract the strokes, holes and concavities. More information about micro features can be found in [42].

In the study, micro features(GSC) are found to be discriminating for the writers. Nearest neighbor classifier is used for identification and Aritifical Neural Network (ANN) for verification to classify the dichotomy of within-writer and between-writer distances. Srihari analyzed that the numeral '1' and '0' are least discriminating. According to the study, 'G', 'b', 'N', 'I', 'K', 'J', 'W', 'D', 'h', 'f' are the 10 most discriminating characters.

Leedham et al. [11–13] have also proposed 11 different binary features those correspond closely to the conventional features extracted by forensic experts. Leedham essentially tried to design exact algorithm for conventional Features. Feature include aspect ratio, number of end points, number of junctions, shape size and number of loops, width and height distributions, slant, shape, average curvature, and gradient features. Leedham et al. [14] also proposed a method based on 25 structural features extracted from the skeleton of word ’th’, in order to establish the individuality power of each of the 25 structural features, such as, height, width, aspect ratio, presence of loop, structure of t-bar, structure of h-stem, stroke width, number of strokes etc. The height of the character is found to be relevant (more discriminating), while width and pseudo-pressure information was not found as relevant(less discriminating). Wang et al. have analyzed the strength of the directional features for the offline character images. Feature computations had been done by dividing the image into sub-regions and calculating different values. Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA) is used to reduce the dimensionality of the feature vector and to make it more discriminating. More information about the feature extraction process is given by Wang [15].

Except these set of features, which are extracted from character image(binary or grey level), researchers have also designed algorithm for features extraction for online handwriting. Online handwriting has extra temporal information about the sequence and the structure of the strokes in the character [43] and thus possess more individuality information about the writer. Yoshikaju [16] has done analysis on the individuality power of the characters (Kanji) from online handwriting. He extracted the features such as writing duration, pen-up and pen-down duration, pen pressure, pen azimuth, bounding box, the aspect ratio, centroid, the length of stroke etc., for each character, stroke and sub-stroke. Features have been evaluated with one-way Analysis of Variance (ANOVA) and the Kruskal-Walls tests. Some of the features such as, relative position of terminations and commencements, pen inclination, absolute starting position and length were found to be more discriminating than other features. These features directly correspond to the conventional features such as terminations, beginning, pen pressure and pen inclinations and can also be used for forensic analysis such as repudiations and forgery detections.

2.1.2 Word level features

According to the handwriting experts also the handwritten words possess a lot of individuality information in the form of character-spacing and connections. Handwriting experts have been using these properties since a long time manually. In case of automatic handwriting analysis, the word based features have a long history, starting with the work of Steinke’s work [44].

For establishing the discriminating power of the words [17, 18], the micro features together with the other word comparison features(segmentation free and segmentation based) are used. Tomai et al. have used four different type of feature extraction methods: (i) GSC(Gradient, Structural and Concavity features) [42], (ii) WMR (Word Model Recognition) [45], (iii) SC (Shape curvature) and (iv) Shape context [46]. The WMR features capture the distribution of the directions in the each segment of the word. Shape Curvature represent the complexity of the character through curvature information. The Shape-context has been demonstrated by Belongie et al. [46] as the robust object recognition method using shape based comparison. The Shape-context establishes the similarity between objects using critical points of the contour. Results have been published for 1000 writers that is the largest database used by any expert in the field. According to the study, larger words are more discriminating. However, the words which contain higher discriminating characters (e.g. 'G','F' [9]) are also more discriminating. For about 10 words, the highest accuracy (GSC features) of 62% and 82% have been reported for identification and verification, respectively.

Another set of features which has also been considered is morphological operations. Morphological operations extract information about geometrical and structural properties of the words. Zois and Anastassopoulos [19] has performed writer identification and verification using morphological operations on thinned word images. The word image is processed with horizontal opening operator of increasing size to estimate the area distribution under the function $p(x)$ (vertical projection profile). Another set of features is obtained using central moments. Classification is performed using Bayesian classifier and multi-layer perception (ANN). Accuracies around 95 percent are obtained for both Greek and English scripts.

In case of online handwriting, Nakamura et al. [16] has analyzed the individuality power of the handwriting words using features similar to the character together with space between subsequent characters(or strokes). Bunke et al. [20] have also analyzed some of the character spacing based features for text independent offline handwriting. However the method has been used for the text-independent comparisons.

2.1.3 Line and paragraph level features

In case of the text-dependent handwriting identification, it is impractical to expect same line to be written (by the writer) for authentication. We as such are not aware of any system(text-dependent) based on the line and paragraph level features. However, many line and paragraph level approaches have been discussed in text-independent context.

2.2 Text Independent Methods

Text-independent methods as opposed to text-dependent do not make any assumptions about verification text. At the same time these systems do not generally require any recognition or segmentation engine prior to authentication which is the major advantage of these systems over text dependent systems. Since state-of-the-art in handwriting recognition is not such that they can be used as automatic annotation systems, most of the annotation work has to be done manually that makes annotation a very difficult task. Moreover, for most of the languages in the world, recognition engines are even not available. Also the assumption about the verification text is also infeasible in a lot of circumstances. For example in case of forensic document examination task, we do not have any control over the proceedings.

However, text independent systems require large amount of text for training, in order to learn the less frequent user specific properties of the writers with high statistical stability. Most of the text independent approaches assume each writer as a stochastic generator of the ink-blob shapes and graphemes. According to these approaches handwriting generation is a neuromuscular process and human being a consistent generator of similar invariant shapes or graphemes. Each individual's handwriting is considered as a different combination of smaller number of graphemes, with only difference in distribution and shape of these invariants. As these invariants can not be learned using characters or words only, most of the text independent systems are based on line, document level features. As such we are not aware of any system (text- independent) just based on character or word level entities.

2.2.1 Text Line Features

Conventional features, used by forensic experts include line level features such as, word-spacing, line slant and line slope etc. These features are not dependent on the text and thus can be used for text independent approaches. Bunke et al. [20] has analyzed some of the line-level features for offline documents and can be categorized into different categories, as follows:

1. *Connected components:* Spacing between the characters within the word is one of the major individuality components. However, in case of non-annotated data it is very difficult to segment words at character-level. Character level segmentation [47] is still a very difficult problem in document analysis. Thus in order to Analyze spacing between characters, Bunke segmented the words into smaller units based on some predefined heuristics. Spacing between bounding box of connected components is calculated and average, variance, distribution of spacing are used as features. This feature directly correspond to character and word spacing parameters.

2. *Enclosed regions:* Enclose regions represents the holes, blobs and loops present in the character. Srihari [9] has identified character 'G' as the most discriminating character due to the presence of loop. Enclosed regions(blobs) are calculated using standard region growing algorithms [48, 49]. Size and shape of these regions are being calculated using formulas given in [20]. Bunke later found this feature not much discriminating as the number of blobs are quite small for each text line that may not be able to model the individual's handwriting style.

3. *Lower and upper profiles:* A number of features have been extracted using upper and lower profiles of text lines. Profiles are calculated as upper and lower points from each column. Gaps between the words are eliminated shifting columns to the left. Slope of lines is calculated using linear regression analysis on upper and lower profile. Mean square error of upper and lower profiles are also used as a feature. frequency of minima and maxima are also used for writer classification. All the above features that correspond to the profiles are the measure of slant and slope of the line that has been used frequently by the handwriting experts.

4. *Fractal features:* [50, 51], showed previously that fractal geometry is useful to derive features that can characterize handwriting styles. The basic idea behind fractal feature is to measure how the area A (i.e. number of pixels) of a handwritten text grows when we apply a dilation operation on the binary image. In the study, line images are dilated using disk-shape and ellipsoidal- kernels of increasing radius. Disk shape kernel results in an evolution graph that is invariant under rotation of the original image. Three slope parameters related to this evolution graph was used to characterize the writer. Fractal features extract the direction of individual strokes and stroke segments. More information about fractal feature can be found in the paper [20].

5. *Basic features:* Other features such as height of three main writing zones (upper, middle and lower), width of writing have also been used. More information about computational algorithms of these features can be found in [21]. .

Classification experiments for 50 writers were performed using 5-nearest neighbor based classifiers. Out of all the features blob features have the lowest classification rates as the number of blobs are quite small in the line and thus could not be modeled accurately. Best performance was provided by fractal features of around 86.2% accuracy. With all the lines and all the features taken together 99.6% accuracy was reported

2.2.2 Paragraph/document level features

In case of forensic applications of handwriting one strives for 100% accuracy from a list of 100 available writers. Methods defined above are not able to get up to that level. Some methods are required that can automatically generate the features from the document without much human intervention. Next few sections will describe some methods based on that.

2.2.2.1 Texture Analysis

Texture analysis based methods assume handwriting of the individual having discriminating and consistent texture. Various texture analysis based approaches have been proposed that includes *2-D multi-channel Gabor filters (MGF), gray scale co-occurrence matrix (GSCM) [52], wavelet based generalized Gaussian density(GGD) models, and contour-let based GGD models*. Texture components essentially capture the directional components from the handwritten document image that are very essential for writer identification.

Multichannel Gabor [22] filter technique is inspired by the psycho-physical findings that the processing of pictorial information in the human visual cortex involves a set of parallel and quasi-independent mechanisms or cortical channels which can be modeled by bandpass filters. Using MGF and GSCM, accuracy of 96% are reported for 40 writers with 1000 documents. [53–55] also proposed other Gabor filter based approaches.

2-D Gabor filter is an effective writer identification method. Usefulness of 2-D Gabor filter together with GSCM features has been demonstrated in [23, 56–58].However, it still suffers from some inherent disadvantages. One of the most serious disadvantages is the intensive computational cost, because the 2-D Gabor filter has to convolute the whole image for each orientation and each frequency. Compared with the Gabor filter, 2-D wavelet GGD [25] can decompose the image into sub-bands with different frequencies and orientations. So, we only need to deal with the specified wavelet sub-bands according to the selected values of frequency and orientation. Wavelet-based GGD not only improves the identification accuracy but also greatly reduces the computational cost as well.

Wavelet-based GGD [25] is good at catching separate edge points of image, however it can not notice the contour along these edge points, that actually means that the wavelet fails to represent the geometric structure of image. However, contourlet [59] is an image representation scheme which owns a powerful ability to efficiently capture the smooth contours of image. Contourlets not only possesses the main features of wavelets (namely, multi-scale and time-frequency localization), but also specially decompose the sub-band at each scale into different directional parts with flexible number. Contour-let based GGD method for texture analysis perform better as well as faster than both Gabor filter and wavelet-based GGD. Information about implementation and usage of contourlet based GGD can be found in [24].

2.2.3 Directional features

Handwriting modeling approaches [60–64] have shown that distribution of directions of the strokes while represented in the polar system have ability to characterize the writer. Schomaker et al. [26, 27] proposed an approach using edge based directional features. They have proposed a new feature: edge hinge distribution, that can characterize the changes in direction undertaken during writing. The hinge is being placed on each edge pixels, with its legs aligned along the edges. The joint probability of the angles that legs of the hinge makes with the horizontal was used as a feature in polar coordinates space. Run length of these directional features are also used as second feature. The joint PDF of ”hinged” edge-angle combinations outperformed all the other evaluated features. Further improvements are obtained through incorporating location information by extracting separate PDFs for the upper are lower halves of the text lines and then adjoining the feature vectors [28].

2.2.4 Code-book Generation

According to handwriting modeling papers [65, 66], handwriting consists of concatenation of ballistic strokes, which are bound by the points of high curvature. Curve shapes are realized by the differential timing of movement of the wrist and finger subsystem. In spatial domain, a natural coding therefore is expressed by angular information of the curve [67].

This subsection presents some of the techniques used to generate codebook of strokes from online as well as from offline handwriting which was used later for identification and verification. In case of offline documents, Bensefia et al. [29, 68–70] used distributions of graphemes generated by a handwriting segmentation method to encode the individual characteristic of handwriting independent of the textual content. Handwriting characters are divided into graphemes using some segmentation method. Experimental results are reported on three data sets containing 88 writers, 39 writers and 150 writers, with two samples (text blocks) per writer. Writer identification is performed as an information retrieval framework while writer verification is based on the mutual information of the grapheme distribution in given two documents using hypothesis testing based framework. Yoon et al. [71] have described a method to classify profiles of the writers based on handwriting style codebook. They have used features like gradient (slant) etc to classify the handwriting style.

Another work related to graphemes based approach is proposed by Balacu et al. [28, 30, 72, 73]. They proposed an autograph based approach to identify various connected components contour from offline handwriting of individual. Code book of these connected components was constructed using various clustering algorithms. Results are reported on the data set of 150 writers, with top-10 performance of 97 percent.

In an another approach [31,74] the reference code-book is generated using fractal based image compression techniques. Fractal compression is a technique that has been developed [75] and mostly used in the field of image compression. Fractal based feature extraction methods consider a given image I, as the fixed point (or attractor) of a geometrical transform T defined on the set of all images with same size. It is deduced from one of the usual ways some synthetic images are generated, fractal images.

In case of online documents, we [5] proposed a work to construct the code-book of handwriting styles from online handwriting. We proposed a method to extract writer specific curves using the velocity profile the strokes. Velocity profile is used to segment the strokes into different units. The size and shape of the curves together with distribution of these curves was used as the discriminating features. Major difference in previous two approaches and our approach is in feature space since the feature corresponding to previous two approaches uses only distribution of the curve. However, shape and size of these curves also make some impact on the individuality information. In another approach for online documents [32, 76–78] proposed a method to cluster the strokes based on some previous designed clusters of stroke type and then used the distribution of properties on these strokes for the writer characterization.

The major difference between all these approaches is in the method of segmentation and clustering. The common point of all these approaches is that the first reference strokes are segmented from the handwriting and then using some clustering methods common code-book of each writer is constructed. Writer is identified/verified based on this code-book. [79] also provides the clustering comparison for stroke clustering.

2.2.4.1 Image processing features

Except all these features lots of other features based primarily on the image processing techniques are also being analyzed and studied. Some of these features have been described and used by Srihari [33,34], called macro features. Macro features are extracted at the document level or at paragraph level. Macro features are classified into three groups: pen pressure (entropy of Grey Level, Grey level threshold, number of black pixels), writing movement(interior contour and exterior curves), and stroke information(vertical, horizontal, positive and negative slope components). Macro features correspond closely with conventional features extracted by experts. [80] have also used Grey level histogram for writer profiling. [35,36] have used run length histogram for writer authentication. [37] have analyzed timing information contained in the on/off paper motions of handwriting for its applicability to the problem of handwriting identification.

2.3 Online Handwriting

With the advent of PDA and Tablet PC, pen input devices are becoming more common in practice. The major advantage of online devices is the extra temporal information together with pressure information associated with the devices. This information has been used for the purpose of writer identification. [38, 81] proposes writer identification framework based on pen input based features like pen pressure, velocity, pen azimuth etc..

Velocity information is the major part that is associated with the input devices. Absolute velocity information may not be associated with the device. However, as devices used to capture stroke points with equal intervals, relative velocity of strokes can be used. Pitak et al. [39,82,83] proposes an approach based on velocity of Bary center of pen input. Bary center is the center of curve between two consecutive points on the stroke. Finite Impulse Response (FIR) of velocity of Bary center is taken as feature. Type I accuracies of 1.5 percent and type II accuracies of 0.5 percent are being reported for database containing 81 writers.

Tsai et al. [40] proposed a writer identification approach based on point distribution model. Tsai proposes an approach to identify the point distribution models for each characters for the writer and then used dimensionality reduction methods to reduce the complexity as well as to generate discriminating features. [41, 84] have given a continuous dynamic programming based approach for figure based writer identification. A writer can write any portion of the figure(enrolled into the system), for the verification. Extensive experiments are proposed to support the algorithm.

Yashushi et al. [85, 86] has proposed a writer specific text selection method for verification using Hidden Markov Models (HMM). Different data is used for multiple authentications and the data is generated using discriminating information available about the data(characters) for the specific writer. Yashushi et al. have used the P-type fourier descriptor as the features of the strokes.

2.4 Machine Learning for writer Identification

Except from feature extraction process, different analysis has been done for analyzing the applicability of various classifiers for the problem of writer identification. In this section we will describe different machine learning and pattern recognition methods used for writer identification and verification.

Bunke et al. [87–90] have proposed an algorithm for writer identification using HMM based recognizer with text line based features [20, 21] proposed above. Each writer's handwriting style is modeled using single HMM. Hundreds of different features are extracted for the purpose. Log likelihood scores of HMMs are used to identify the writer on separate text lines of variable contents. Results of 96 percent are reported for identification with 2.5 percent equal error rate (EER) for writer verification. [91] presents the variant of above system using Gaussian mixture models(GMMs), instead of HMMs. HMM is used to model time series data and GMM model data as the mixture of various Gaussian. [92] also presents the comparison between GMMs and HMMs for writer identification task. Schalpbach et al [93] presented a feature selection based framework with nearest neighbor classifiers for text line, wavelet and other texture based features described in [20].

Long Zuo et al. [94] proposed a new approach for writer identification using Principle component analysis (PCA). Zuo calculated the discriminatory power of each word for each writer using PCA based method for handwritten word images. Words with higher discriminating power was used for identification. Images are scaled to equal size and used as feature vectors. Results are shown for 16000 Chinese words, written by 40 different writers. Accuracies of 97.5 percent is reported for 10 combined words.

[95] have discussed methods to improve statistical and model-based approaches used in [28]. Matten analyzed wavelet based multi resolution approaches over single scale approach used for statistical edge-hinge feature extraction. In case of model based approaches, Matten et al. have analyzed that generating code-books using self-organized feature map (SOFM) is quite unnecessary and random draw of curves from the codebook is performing with similar accuracy.

Hypothesis testing based framework have been extensively used for the purpose of writer verification. Hypothesis testing with Nayman Pearson paradigm provides the better way to prove the truthness of the hypothesis. [96, 97] presented a method based on Neyman Pearson paradigm for decision level fusion using handwriting words. [29, 68] have also proposed a framework for writer verification using hypothesis testing on distribution of connected components in the handwritten documents.

One of the major problem in case of writer verification is the fusion of heterogeneous features and distances. [98, 99] have proposed a framework for fusion of different distance coming from heterogeneous sources using a dichotomy transformation. Dichotomy transformation is the transformation of feature space into feature distance space. The problem of writer verification after transformation will become the problem of identifying whether distance belongs to within writer category or between writer category. [100] has proposed a binary vector dissimilarity method for comparison of GSC features explained in [9]. For writer verification in case of forensic documents, Srihari [101] have proposed a statistical framework using log likelihood similarity between documents. Results was provided on a 9-point scale used by forensic experts.

In case of forensic documents, [102] have done some work using wrinkleness factors. According to cha et al. genuine documents have more smoother than forgery documents. They have derived wrinkleness factor from offline handwritten document in order to capture forgery. [103]

has discussed the use of forensic knowledge i.e. handwriting formulation (used by handwriting experts) for forensic document examination. Other documents and projects related to forensic documents can be found in [104–108].

2.5 Our contribution

This thesis addresses various problems associated with automatic writer verification and identification for online handwriting. In the next chapter we proposed a framework for writer identification using online handwriting. We proposed an algorithm for designing the code-book of individual writers. In the next chapter, we proposed framework for text-dependent writer verification from online handwriting. We proposed boosting based algorithm to identify discriminating elements of handwriting for each individual handwriting. In case of forensic approaches, we introduced the problem of repudiation detection from handwritten documents for the first time. We proposed a hypothesis testing based approach to detect repudiated documents.

Chapter 3

Text Independent Writer Identification

In the previous chapter, we have introduced several text-dependent and text-independent approaches used previously for writer identification. In this chapter, we present a text-independent framework for writer identification using online handwriting. Text independency is an important aspect of a writer identification system. Text independence essentially means that the system does not make any assumption about the data available for identification. In other words, the system need not have any prior knowledge about the data written for identification or verification. Text independent system do have various advantages over text dependent systems. Some of the major advantages are listed below:

- *Less Manual Labor*: For text dependent systems, data need be annotated which is the major problem of these systems. Text-independent systems extract features/statistics that are not directly dependent on specific text and extract the global features of the writer's handwriting style. Annotation is considered as major problem since, the state-of-art in automatic handwriting annotation or recognition systems is not satisfactory enough to be used it directly. Moreover, for most of the languages, the recognition systems are not even available. Thus most of the annotation work has to be done manually that includes cost and very difficult to be used in practice.

- *Robust to forgery*: Forgery is the major concern for any writer identification and verification system. Forgery essentially means that unauthorized users are able to access the system by copying the handwriting style of the genuine writer. Text dependent systems, usually rely on text specific comparisons for authentication. On the other hand, text-independent systems do extract features that are not frequent and hence difficult to forge. Sometimes even writers are not aware of his own handwriting features and thus are difficult to forge. At the same time, as a specific and predetermined text is not written for authentication, the chances of forgery are further minimized.

In this chapter, we propose an algorithm for text-independent writer identification. We present a framework for automatic identification and extraction of consistent features from individual's handwriting. The system constructs a codebook of handwriting style of each individual, which is later used as the reference base for identification. Codebook for each writer do model the handwriting style of the writer. Codebook is basically constructed using sub-strokes of individual handwriting. Various handwriting modeling approaches [65, 66] consider handwriting generation process as a neuromuscular process and consistent generator of sub-curves called graphemes. Handwriting of each individual is considered to be a collection of these graphemes. Graphemes are usually dependent on the script under consideration and the shape, size and distributions of graphemes vary from individual to individual. In the present approach, our major contribution is to construct a database of grapheme for the specific script and to use size, shape and distributions of these sub-curves(graphemes) to identify writers. The proposed approach presents algorithms for graphemes identification and extraction from online handwritten document. Even user is unaware about the features being extracted by system and thus have less chance to be forged. Automatic extraction of features make the system applicable to different scripts as the approach itself, is not dependent on a particular script. Framework is easily expendable and more robust representation and clustering algorithms can always replace the algorithms used here, without much changes in the entire framework itself. There is no major assumption about the data or the constituent algorithms. The only assumption is that the online data is provided to the system. Framework proposes a text independent method for writer identification using online handwriting. In case of online handwriting [43], usually methods based on pen usage characteristics such as pressure, tilt, etc. have been proposed. However, methods based on codebook of graphemes have been discussed in case of offline handwriting [28, 30]. More information about literature survey can be found in chapter 2.

The remainder of the chapter is organized as follows. The next section introduces the challenges of text-independent handwriting identifications. The section following that explains comprehensive framework of the system. Section 3.3 provides the details of feature extraction methods used for experimentation. Section 3.4 provides the details about the experimental setup and analysis of the empirical results. Conclusion and future directions in which work can be proceeded, are covered in the last section.

3.1 Challenges due to Text independency

The text independent systems are more general and do not require annotated data for comparison. However, this generality adds more complexity to the system. The challenges posed by text-independent systems can be categorized as follows:

- *Less Accurate*: The text-independent systems are less accurate as compared to the text-dependent systems. Since it is always easier to compare to similar words for differences or similarities as in the case of text-dependent system (for example signature verification) which is not the case with text independent systems. Text-independent system, on the other hand, rely on less frequent properties of handwriting of an individual those became consistent due to long form habits [3].

- *More amount of data is required*: Text independent systems require more data for comparison as with small amount of data less frequent properties can not be extracted consistently.

Text independent algorithms usually extract features which user write with consistency. In order to capture consistency from user's handwriting more amount of data will be needed.

In spite of all challenges, text independent systems are needed to design forgery free security systems. The next section will explain the complete framework of text-independent system using online handwriting.

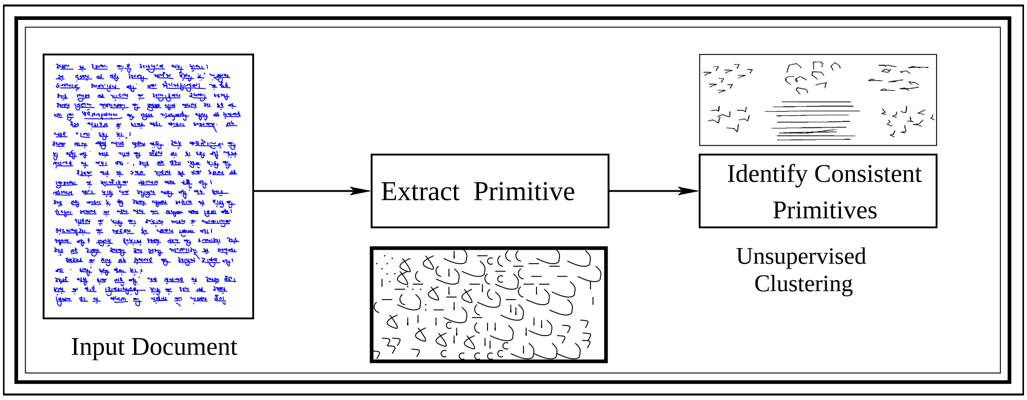


Figure 3.1 Training phase: Given documents the main goal is to identify and extract consistent primitives.

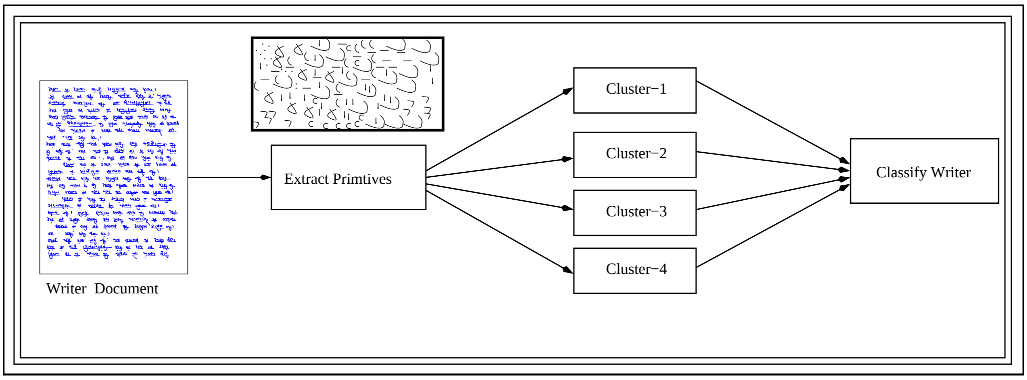


Figure 3.2 Writer Identification: Given writer-document; extract primitives; cluster into various groups and finally classify the writer.

3.2 Text-independent framework

This section explains a generic text-independent framework for writer identification. The basic idea of our framework is to automatically identify repetitive and consistent primitives from handwritten script, and use variations in the captured primitives to discriminate between writers. Since framework does not make any assumption about the script and extract features independent of the underlying script, framework is applicable to any script. Figures 3.1 and 3.2 displays the stepwise implementation of text-independent writer identification system. The identification framework consists of the following major components:

1. **Defining Primitives:**

   The major goal of any identification system is to extract the primitives that can be used to model the handwriting of an individual and afterward can establish the identity of writers. Any handwriting identification system essentially can be thought of as an information extraction process in which the information pertaining to writer is to be extracted. The first stage of information extraction system is to identify the information that is to be extracted. In the context of handwriting identification system, we will refer to the information as primitives. The primitive can be defined as any component of handwriting which posses individuality information about the writer. Consistent definition of primitive will make feature extraction process easier. Various primitives of handwriting can be sub-character, character, word, line, paragraph and documents. Handwriting experts [3] also identified features pertaining to these components only. They divided various features in different categories such as character based, sub-character based, word based and document-level global features. Major problem of character and word level features are that they are dependent on the specific text. However, since the present work concentrate on text independent systems, primitive should not be varying with the varying text. Any primitives that is consistent in the handwriting for the individual and doesn't depend on the text can be used for text-independent identification. Examples include shape primitives, which defined the shape of various sub-characters; allograph types, connections between parts of handwriting such as characters and sub-characters, etc. Section 1.1.1 presents the details for primitive selection and extraction algorithms.

2. **Extraction and Representation:**

   Once the primitives to be used are defined, a mechanism to extract them from the data need to be identified. A consistent mechanism for primitive extraction is essential for ensuring consistency in the statistics derived from them, and hence the overall accuracy of the system. A clear definition of the primitive will lead to a simple extraction scheme. Extraction essentially means to automatically extract the primitive from the handwriting. let the primitive be certain type of characters, extraction method will define the process to extract all the present character from the handwriting automatically. *Representation* essentially means feature extraction. Any automatic pattern classification system use numbers to classify any pattern. hence, in order to classify the pattern, pattern need to be represented automatically. This phase is referred to as *feature extraction* process in context of pattern recognition. Feature extraction is the bottleneck of any classification system. A consistent method of feature extraction directly impact the accuracy and efficiency of final system.

3. **Similarity Measure:**

A similarity or distance measure between two primitives need to be defined for comparison, based on the representation chosen in the previous step. Distance essentially means a method to compare two given patterns and represents the similarity between two patterns. The less the distance, the more the patterns are similar. Based on the feature space various similarity and distance measures can be used such as Euclidean distance, Manhattan Distance etc. Distance measure should be such that within-class distances can be discriminated from between-class distances.

4. **Identifying Consistent Primitives:**

   Depending on the script under consideration, certain type of primitives repeat more often than other in various allographs. These primitives can be used directly for writer identification. These primitives can be automatically identified using some unsupervised clustering algorithm. Pair-wise distances are computed for each pair of primitives extracted from the training samples and a distance-based clustering method, such as k-means clustering is used. The clusters thus formed are referred to as consistent primitives of the script. For each script consistent primitives are being identified automatically during training phase.

5. **Writer Identification:** The final step is to use the between-writer variations within consistent primitives to determine the identity of the writer. This involves the design of a classifier for each of the consistent primitives (clusters) and then combining the results to get the most likely identity.

   Let S_j be the j^{th} primitive that was extracted from the data and C_k be the k^{th} cluster in the script. The data likelihood of the primitive S_j, given a particular writer W_i can be computed as:

$$p(S_j/W_i) = \sum_{k=1}^{N} p(S_j/W_i, C_k) * \alpha_{i,k}, \tag{3.1}$$

   where $\alpha_{i,k}$ is the weight of the kth cluster for the ith writer that quantifies the discriminability of the kth cluster for the ith writer.

   Now the complete data likelihood (for the document D), given writer W_i, can be computed from equation 3.1 as:

$$p(D/W_i) = \prod_{S_j \in D} p(S_j/W_i), \tag{3.2}$$

   The probability that the given document belongs to a writer can now be computed using Baye's rule from equation 3.2.

$$P(W_i/D) = \frac{p(D/W_i) * P(W_i)}{\sum_{i=1}^{n} p(D/W_i) * P(W_i)}. \tag{3.3}$$

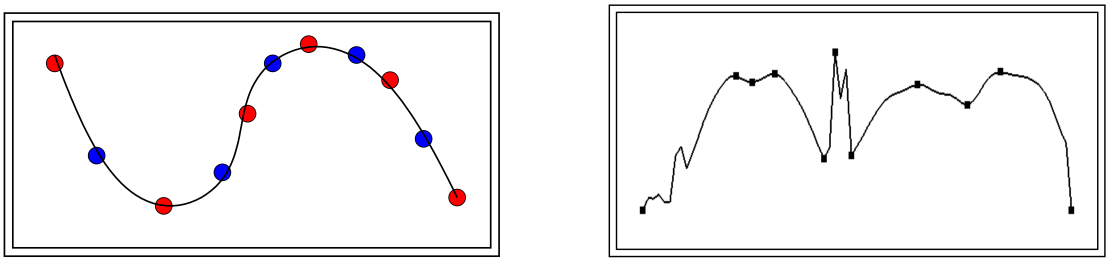
Note : Equal prior probabilities are assigned to all writers.

3.3 Feature Extraction

As discussed earlier, five different levels of individuality information: sub-character level, character level, word level, line level and paragraph level, is present in handwritten data. Based on the requirement different individuality information will be extracted from handwriting samples. For any practical purpose, individuality information present at paragraphs or lines level will be very difficult to capture as person may not be willing to give so much data each time to verify identity. Also, for text independent systems, we need some features which are independent of the text. In the previous literature of handwriting modeling, handwriting generation process have been modeled as neuromuscular process, which generate ink-blob(curves) continuously. These curves are considered to posses a lot of individuality information with them in the form of shape, size and distribution. Since the writer usually writes sub-characters unconsciously, due to long formed habituation, writer tends to write consistently.

In this framework, sub-character level information is used to model the writer as sub-character level information is independent of the text. Sub-character level information includes design, construction and spatial distribution of curves present in the script. We can use different sub-character level information like size, shape, style for extracting writer-specific information. We demonstrate the effectiveness of the proposed framework using curve shapes as the basic primitive. The curve shape and size captures only part of the individuality information present at sub-character level. However, the results suggest that even the partial information can effectively distinguish between writers. Our framework allows for extension to multiple primitives for writer identification. This sub-character level information will be referred to as the shape curve in our discussions.

In this work, shape primitive is defined using the velocity profile of handwriting. It has been analyzed in various previous studies that relative velocity of an individual remains the same, inspite of changes in absolute velocity. According to kinematic theory of human hand movements, presented by Plamondon [8, 67], human movements are combination of different forces and transition between these forces. In case of handwriting, a single force can be defined as the equi-curvature portion of handwritten stroke (Portion of handwriting between one pen-down and corresponding pen-up events). Stroke is also defined as the combination of different forces. Based on the above, portion of stroke between two minimum velocity points can represent the basic primitive, *shape curve*. Figure 3.3 shows dominant (maximum and minimum velocity) points, extracted using velocity profile of the stroke shown in Figure 3.3. According to our empirical findings also, the dominant points of the stroke remains the same, in-spite of changes of velocity on different occasions. This reason behind this consistency can be the habituation while writing these small curves. In order to exploit the individuality information present in the transition, two consecutive shape curves are used as basic primitive.



(a) (b)

Figure 3.3 (a) Stroke and velocity based dominant points(Red Points represents minimum velocity points and Blue points the corresponding maximum velocity points.) (b)Velocity profile of the stroke

The consistent and clear definition of the primitive, enable us to extract the primitive easily as follows. For each stroke from the handwriting samples of the individual, find the dominant velocity points. The portion of curve between three consecutive velocity points is used as the basic shape primitive.

The third step is to devise consistent representation for shape primitive. A curve of constant curvature can be uniquely represented using three parameters: the incident direction, the curvature and size or length of the curve [67]. Based on this principle, curve shapes are represented using angle of incidence, angle between corresponding vectors and size of the vectors. Figure 3.4 shows all the elements, used for representation of a particular shape-based primitive curve. Features 1–4 represent the incident angles and the curvature of each portion of the curve, while the other features represent the length of the curve. Thus each shape primitive is represented using an 8-dimensional feature vector. The representation constitutes an abstraction of the curve that is both direction and scale dependent. Another shape representation techniques such as shape context [46] geometric moments and zernike moments [109, 110] can also be used to represent curves together with directional features defined above.

Since, the shape curve is represented using a fixed sized feature vector, a distance measure between two curves can be defined using Euclidean distance. To account for the variations in scales of the angular features and the length feature, we use a weighted Euclidean distance. Another distance measure can be easily used based on the feature extraction method. Dynamic Time Warping (DTW) based distance measure can be used to provide distance which is not usually affected by small changes in the curve shape. The distribution of shape primitive curves varies in different scripts. To identify repetitive shape primitives present in the script, unsupervised k-means clustering algorithm is used. Ratio of within-cluster variance to between-cluster variance is used as cluster validation criteria. Figure 3.5 shows six major primitive shape clusters extracted from Devanagari script.

To calculate the between-writer variation for consistent primitives, we design a classifier using the labeled training samples that falls in each of the k clusters. In this experiment, we have used Neural Network based classifier for classifying each curve primitive. The output of the classifier

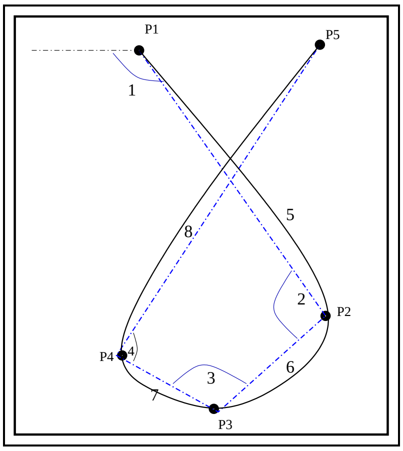


Figure 3.4 curve representation: angles represents shape of the curves and size of vectors represents the size of the curve.

for each of the classes is used as the probability of observation of the curve, given the cluster and the writer. For each consistent primitive cluster different classifier is used. Equation 3.1 and equation 3.2 are used to calculate the log-likelihood of shape based primitives. Equation 3.3 is used to find out the probability of the writer given the document. One could replace the classifier in each node with any other technique such as Gaussian models or k- nearest neighbor (KNN), as long as the classifier returns a confidence measure for the given curve. Next section will describe the experimental set up with complete results.

3.4 Experimental Results

Experiments were performed on 5 different scripts; Devanagari, English, Cyrillic, Arabic and Hebrew. For each script, experiments were performed for 10 to 12 writers. Data was collected using IBM CrossPad. Each user was asked to write out any text in particular script on a letter sized paper, that was captured electronically by the CrossPad. Data was divided randomly into four parts and at every step, three parts of the data were used for training and the remaining part for testing.

The data was smoothened using a Gaussian low-pass filter prior to training and testing, to remove any noise added due to pen vibration. Around 700 instances of basic shape primitives are extracted from the training data of each writer.

Three different sets of experiments were performed to determine the variation in accuracy of the identification scheme: i) variation as data size varies ii) variation as number of writers increase and iii) variation with different scripts under consideration. First two set of experiments were performed only for Devanagari script as we had more data available for it.

For the first two experiments, around 700 curves were extracted from Devanagari data collected from 10 different writers. The data was clustered into 16 clusters (experimentally chosen) and the classifiers were trained on each of these clusters. Ratio of within cluster variance to

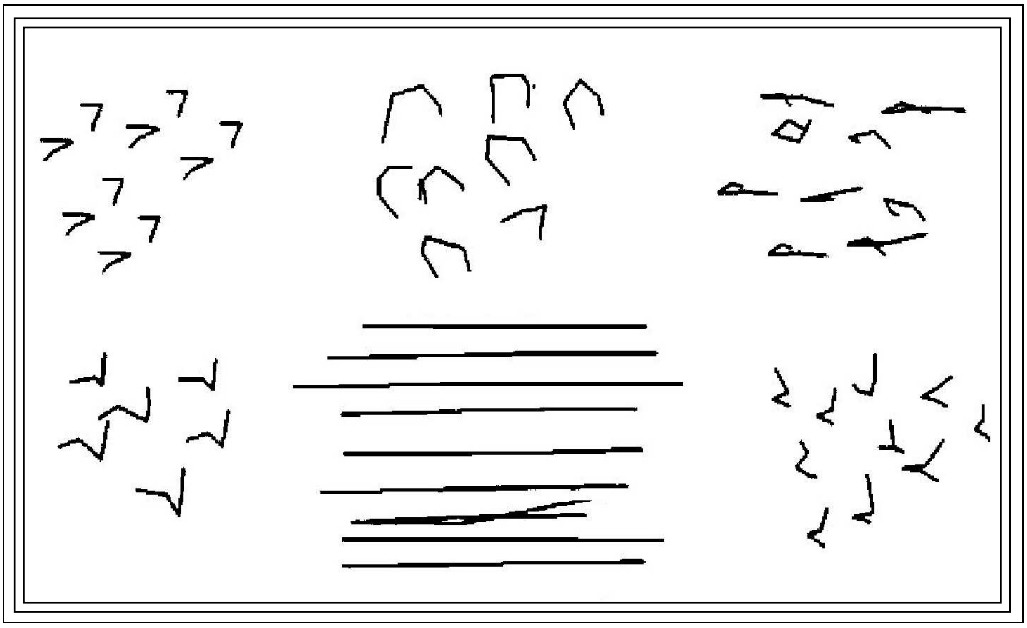


Figure 3.5 Different Clusters extracted from Devanagari script using unsupervised K-mean clustering

between cluster variance was used as cluster validity criterion. Data was varied starting from 10 curves (approx. 1 word) to 300 curves (approx. 25 words). With around 200 curves, accuracy of 80% is achieved. Experiments are performed 30 times for each data size with different set of data. figure 3.6 shows the accuracy variation with variation in test data size.

As seen from the figure 3.6 accuracy of classifier increases, as more test data is available. Only $20-30$ curves (approx. $2-3$ words) are required to identify 60% of the samples correctly, and with 220 curves (approximately 12 words) probability of correct classification increased up to 87%. Accuracy of 87% is reported using only single primitive, as more and more primitives will be used accuracy will increase.

Second set of experiments were performed to determine the effectiveness of our algorithm to classify handwritten data from multiple scripts. For each script, the set of primitive clusters are usually different and hence need to be trained separately. However, the overall procedure remains the same for all scripts. Table 3.1 shows the accuracy of each script with number of writer. For all the scripts, the Top-2 accuracy approaches 100%. For all the scripts other than Roman approximate 700-800 curves are used for training and approx 100 curves (approx. 10 words) for testing. For Roman script around 400 curves are used for training.

Third set of experiments were performed to determine the effect of the different number of writers on accuracy. This set of experiments were also performed using Devanagari data set. Table 3.2 shows the variation in accuracy as number of writers increased from 2 to 10. From each writer approx. 700 curves were taken as training data and 100 (approx. 10 words) were taken as testing data.

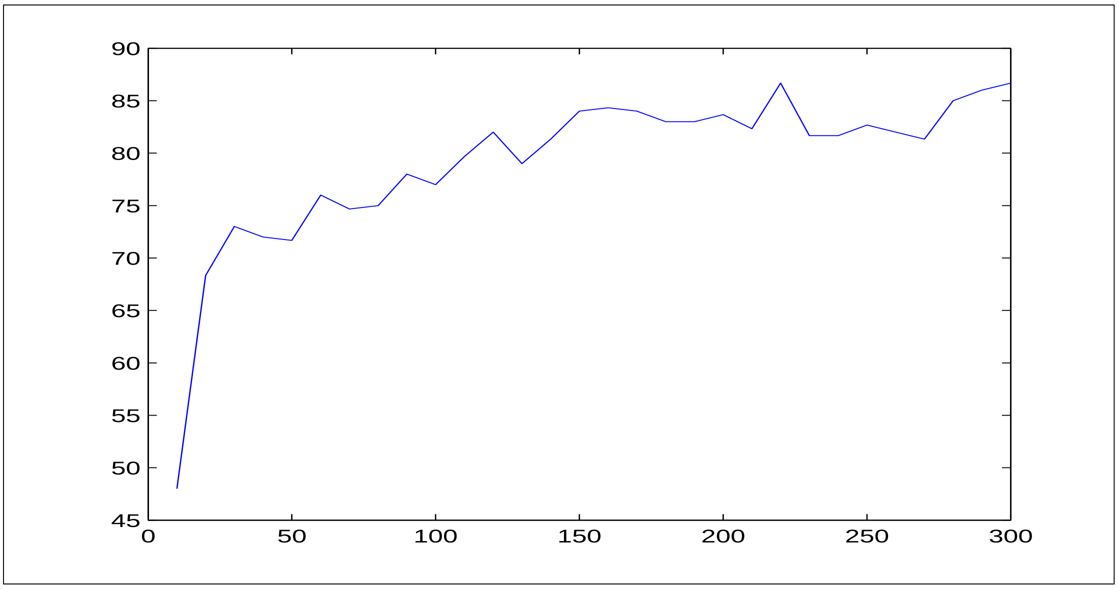


Figure 3.6 Test data size Vs Accuracy: Test data is represented as the number of curves. Each word on an average have 10-12 curves.

Script	No. of Writer	Top-1 Accuracy	Top-2 Accuracy
Devanagari	10	87	100
Roman	6	83	88
Cyrillic	10	80	100
Arabic	15	85	97
Hebrew	10	90	100

Table 3.1 Script Vs Accuracy

No of Writers	Accuracy
2	100
3	99.8
4	99.6
5	98.8
6	98.0
7	98.3
8	97.0
9	92
10	87

Table 3.2 Accuracy Vs Different Number of Writers

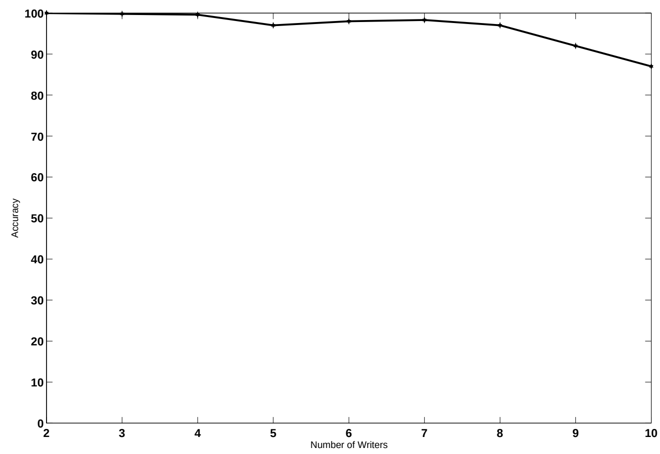


Figure 3.7 Number of Writers Vs Accuracy

Shape based primitive proved a bad choice for Chinese Script, as most of the shapes extracted were straight lines, that do not contain much individuality information. Only 50% accuracy could be achieved. However, one could identify a different set of primitives and different representation scheme to rectify this problem. For Chinese and Roman scripts, in which lots of shape based primitives are straight lines, size based primitive, like ratio of size between consecutive primitive curves can be used. Experiments are being performed to check the confidence measure of size based primitives for different scripts.

3.5 Analysis and Conclusion

In this chapter, we proposed a text independent writer identification system for online documents. The advantage of this method include the need of small amount of test data in addition to being text independent. The classification is fast and we can improve our confidence in the results as the data size increases (evidence accumulation). Even with one line of data we can get a high confidence about the identity of the writer. We have used sub character level features for writer identification.

To improve on the accuracy and robustness of the system, for the script like Chinese and Roman, in future we can use other high level primitives based on character,word, line and paragraph. Different primitives like shape, size and other higher level features can also be used in combination to improve the system. More robust representation, like spline, can be used for shape primitives. More robust cluster validity criteria can be used for generating the clusters.

Chapter 4

Text Dependent Writer Identification

In the previous chapter, we have presented a text-independent writer identification system. However, the applicability of the text-independent identification is still doubtful in the practical scenario, owing to the need for large amount of data for writer authentication. In this chapter, we address the problem of automatic text-dependent writer verification using online handwriting. Text-dependent systems require that the enrollment and verification text be similar for authentication. Automatic signature verification [111] is a specific instance of the text-dependent systems, in which the writer is verified based on the text chosen by the writer himself, i.e., his signature. Since text-dependent writer verification systems are based on similar text comparison, the amount of data required for authentication is quite less as compared to text-independent approaches. However, text-dependent systems are more prone to forgery as compared to text-independent approaches. This chapter presents a verification system for practical low security access control applications using online handwriting. For the verification system based on handwriting to be applicable in practical scenarios, it should have some specific characteristics described below:

1. *Robust to forgery:*

   Forgery is a major problem with every biometric system. In order for a biometric system to be applicable to any practical purpose, the false accept rates should be as low as possible, i.e., system should be able to identify impostors efficiently. Since the handwriting is a behavioral biometric, and can be learned by rigorous and continuous practice, the problem of forgery is even bigger. In case of text-independent handwriting identification systems, the problem is not severe since text-independent systems extract features that can not be forged easily. However, in case of text-dependent verification as the verification text is known in advance, risk due to forgery is even bigger. This risk can be minimized using varying and writer-specific text for verification.

   - *Varying verification text:*

     Fixed predefined text is the major problem of text-dependent systems that leads to the problem of forgery. To make systems robust to forgery, the verification text should not be revealed beforehand, and be varied with time. The verification stage should itself be able to generate different text for verification, each time a user tries to access the system. Since the system is well aware of the text written by the writer, it can still use text dependent comparison for higher accuracy. Also, since it is difficult and not even possible to learn every aspect of individual's handwriting, the problem of forgery can be minimized through text variation.

2. **Minimum amount of text for verification**

   Ease of use is a major concern for any authentication system. In the era of automation, no-one has much time and asking a writer to write large amount of data for verification can adversely affect the utility of the system. A user can not be asked to write long sentences for comparison which is a major problem for text-independent systems. However, if we choose specific text that is more discriminating for a particular user, one can minimize the amount of data required for authentication.

   - *Writer-specific text and threshold:*

     Writer-specific text for a person is the combination of primitives (sub-characters, characters, words, etc) that can easily discriminate the individual from other individuals. Signature verification is a good example of writer-specific verification. Writer-specific text can also make the system robust to forgery with less amount of text since it is difficult to copy the information that the writer writes consistently and discriminating from other writers.

     Write-specific text generation will also solve our problem of identification of an appropriate threshold. Traditional verification systems use the threshold of within and between-writer distances for verification which is calculated using training data. However, it is sometimes difficult to specify a global threshold for all writers (or the respective text) that perform efficiently. This is due to the fact that different primitives(characters, words etc.) of handwriting possess different discriminating power for different individuals and single primitive of handwriting can not be discriminating enough to discriminate between different pair of writers [3]. Thus thresholds should be selected based on the underlined text and the writer. If one can generate text; specific to the writer, he can simultaneously identify a writer-specific threshold also.

3. Adaptiveness to the handwriting changes:

   Handwriting is a behavioral biometric and the handwriting of an individual changes with time. However, these changes will not be abrupt and will be continuous. Any verification system should be able to adapt to these changes in handwriting and should learn the changes from the test samples itself. Adaptiveness can increase the lifespan of a system, as if a system is not adaptive, it may start rejecting genuine writers and the users will get frustrated by repeated rejections.

In short, a system that combines the above features can take advantage of both text-independent (*robust to forgery)* and text-dependent systems *(high accuracy with less data)* to verify the writer of the system. Beside all the above mentioned advantages such a system will be faster and more suited for practical purposes.

The major theme of this work is to design a practical verification system for low security and access control applications. The requirements of low security civilian applications are quite different from that of forensic document examination(or other high security applications). In case of low security civilian applications, the major requirements are ease of use and low false rejection rate, i.e., genuine user should not be rejected frequently. Another major factor that arise from the domain of use is the control over data collection. In case of low security access control applications, the user can be asked to provide online data, which may not be possible in case of high security and forensic applications. In this chapter, we present a framework for text-dependent writer verification that is quite different from traditional approaches. Traditional text dependent approaches require some predefined text, to be written for verification, that makes the system more prone to forgery. We propose a method to generate writer specific test data at verification stage, which also suits the requirements of the practical verification system.

4.0.1 Challenges

Handwriting based person authentication systems pose several challenges due to: i) High within-writer variations and ii) Low between-writer variations. However, in case of text-dependent comparisons, the between-writer distances become even smaller; as the writers are essentially writing the same text and trying to make it readable. Thus the variations are limited and not similar to other biometrics, such as iris, face, DNA, etc. At the same time, verification using online data poses more challenges due to high variations within writers. Major sources of variations in the case of online handwriting are:

1. *Overwriting:* Writers tend to overwrite whenever they make a mistake. Overwriting may not be a major problem in the case of offline handwriting, as it can just increase the stroke width for a single stroke. However, in case of online handwriting, overwriting is captured as a different stroke. Since in the case of online handwriting, the number and order of strokes is the part of the information and overwriting will lead to increase in within-writer distances.

2. *Quality of capturing devices:* In case of online handwriting, data capturing devices are not very accurate and sometimes they do introduce noise, which is usually not present in the actual stroke. This tends to increase within-writer distance.

4.1 Framework of the system:

Based on our discussion on practical writer verification systems, varying the verification text is an important requirement. However, if this text is specific to the writer as well, and if we can generate writer-and text-specific threshold that would add to the performance of the system. However, the text can not be varied as such since text-dependent systems do require similar text written by the writer beforehand, for text-dependent comparisons. This limits the scope of the text variations only to the text collected at the time of enrollments. In order to solve this problem, the text generation phase is delayed till the authentication phase, accompanied by the text synthesis phase. The text synthesis [112] phase will synthesize the handwriting of the writer based on handwriting samples provided by the individual during enrollment. For example, assume that the character level data is collected from the users during enrollment phase and stored in the database. During authentication phase, the text generation unit will generate the text and display it on the screen and synthesis phase will generate the corresponding handwriting text specific to the user which will be compared with the test data provided by the user at the time of authentication. Distance between test sample (written by user for verification) and training (generated by synthesis phase) samples will be used to verify the authenticity of the claim based on the thresholds generated by the text-generation phase. Figure 4.1 displays an example of text-dependent authentication system. Given six primitive characters, text generation unit has selected three characters (based on discriminating power of the characters for the writer). Language unit, then generate a meaningful word from the combination of these characters. Writer is asked to write the word and is compared with the training template generated by synthesis unit. Distance between two templates is compared with threshold for final decision.

4.1.1 Authentication phase:

Writer verification or authentication phase is divided into text generation and verification phases. The following subsections will explain in detail each of them.

4.1.1.1 Text generation

Text generation (see Figure 4.2) is the major requirement for the writer verification framework. The generated text should be specific to the writer that can discriminate the writer from the other writers. This will make verification engine forgery resistant and at the same time will reduce the amount of text for verification.

Given a set of primitives, i.e. sub-characters, characters, words, etc. none of which is individually efficient enough to discriminate the writer from other writers (i.e. are weak classifier), the problem of text generation is to design most discriminating and compact text for a specific writer. Given a set of primitives and features, for the purpose of text selection, an automatic feature selection method can be used. Since the major requirement of the verification system is text variation, thus different text should be generated for multiple authentication and at the same time at each stage primitives should be selected based on the selected in the previous stages. Bunke et al. have proposed a feature selection for offline writer verification in [93]. In this chapter, we present a Boosting based feature selection framework for writer verification system. Boosting [113] is a method to combine different sets of weak classifiers, to boost the performance of

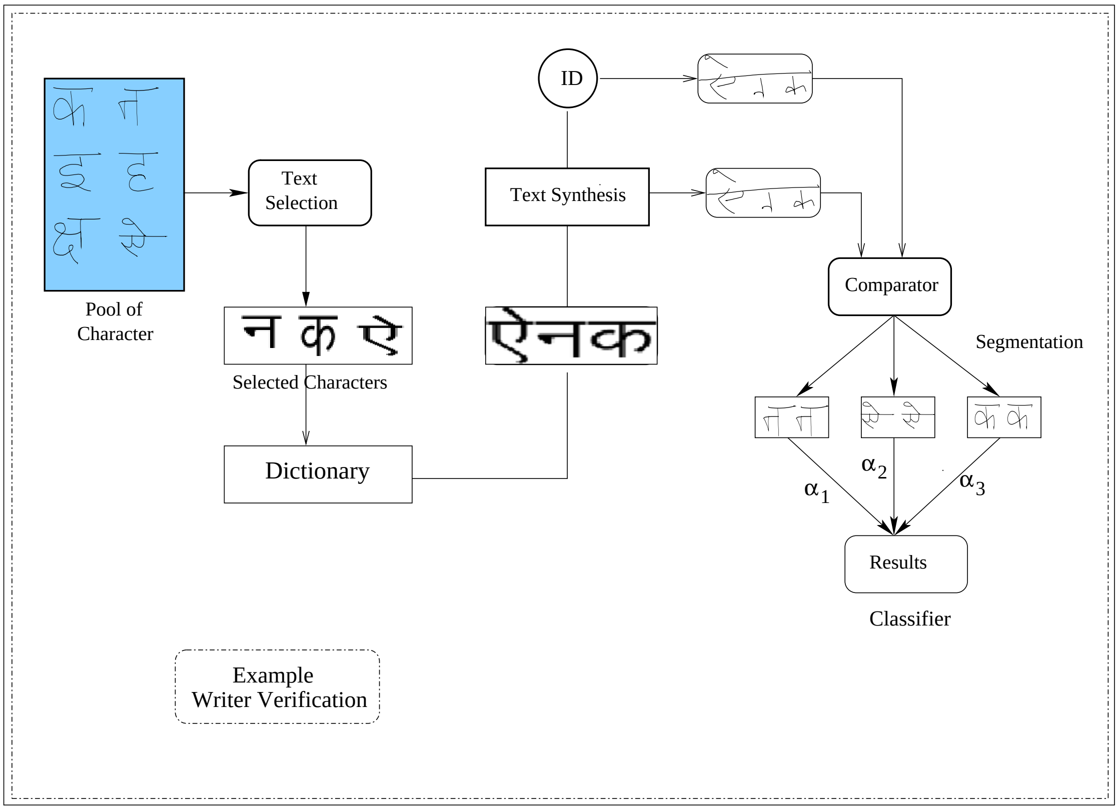


Figure 4.1 Example of text generation based verification system.

the final hypothesis. Adaboost (an efficient boosting algorithm) is a greedy algorithm, which at each stage selects the most efficient classifier from a bag of weak classifiers depending on the previously selected hypothesis. Adaboost can be efficiently used as feature and text selection method, by cleverly designing base classifiers.

In case of writer verification, in order to enable text generation, each weak classifier is based on the primitives and features. The number of base classifiers will be number of primitive times the number of different features. The complete discussion on discriminating features has been given in section 1.1.1. Adaboost has also been used before as a feature selection method in other domains (for example face detection [114]).As the text-selection, in case of verification system, is sequential and also dependent on previous selection, Adaboost provides a dynamic framework to fulfill these requirements. At the same time, since individual features and primitive based classifiers are not discriminating enough, Adaboost can also select and combine the feature based weak classifiers such that accuracy of final classifier is high. In our case, as the classifiers are dependent both on text as well as different features extracted from this text, the feature selection method can effectively be used for the purpose of text selection also. In the next section, we will introduce the Adaboost algorithm for boosting and its applicability to writer verification.

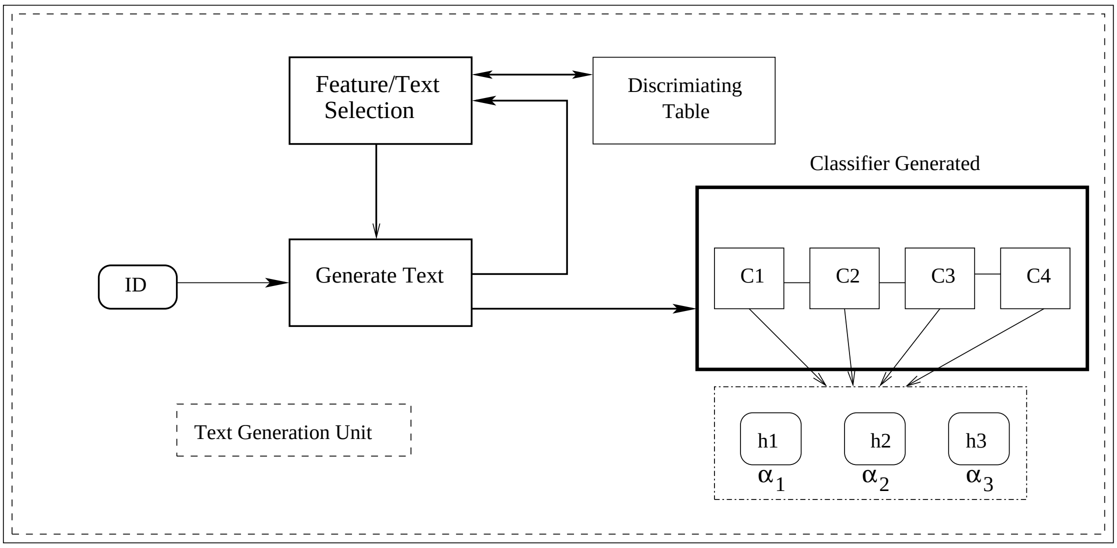


Figure 4.2 Text generation unit for writer verification

4.1.1.2 Boosting and text generation

Algorithm: Adaboost algorithm for boosting

Require: $(x_1, y_1), \ldots, (x_m, y_m)$, where $x_i \in X$, $y_i \in Y = -1, +1$ and the list of weak learners, h_j

1: Initialize $D_1(i) = 1/m$
2: **for** each $t = 1, \ldots, T$ **do**
3: Select weak learner, h_t, such that $\epsilon_k = Pr_{i \sim D_t}[h_t(x_i) \neq y_i]$ is minimum
4: Calculate: $\alpha_t = \log\left(\frac{1-\epsilon_k}{\epsilon_k}\right)$
5: Update: $D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$ where Z_t is a normalization factor (chosen so that D_{t+1} will be distribution).
6: **end for**
7: Final hypothesis: $H(x) = \sum_t \alpha_t h_t(x)$

For complete reference on boosting refer to [115]. Boosting is a general method for improving the accuracy of any given weak learning algorithm. It combines ”weak” learning algorithms that perform slightly better than random guessing into one with arbitrarily high accuracy. The Adaboost algorithm for boosting weak classifiers have been explained above 4.1.1.2. The algorithm takes as input a training set, $(x_1, y_1) \ldots (x_m, y_m)$, where each x_i belongs to some domain or instance space, $\mathbb{X}$ and each label, y_i is in some label set, $\mathbb{Y}$. Adaboost calls a given weak or base learning algorithm repeatedly in the series of rounds, $t = 1, 2, \ldots, T$. The algorithm maintains the distribution or set of weights over the training set. The weights of this distribution on training sample i on round t is denoted as $D_t(i)$. Initially all weights are set equally, and on the subsequent rounds, the weights of the incorrectly classified examples are increased so that the weak learner is forced to focus on the hard examples in the training set. The weak learner's job is to find a weak hypothesis $h_t : \mathbb{X} \to \mathbb{R}$ appropriate for the distribution, D_t of weights. In the simplest case, the range of each h_t is binary, i.e. restricted to $\{-1, +1\}$; the weak learner's job is to minimize the error due to misclassification. Once the weak hypothesis, h_t has been received, Adaboost chooses the parameter, α_t belongs to $\mathbb{R}$, which intuitively measure the importance that it assigns to h_t or in other words, the weight of the classifier.

The verification problem can be posed as the two-class classification problem of *"One vs Rest"*. The samples for the specific writer will be considered as the positive samples and rest all writers as negative samples. For each writer different set of classifiers will be combined by repeatedly calling weak learning algorithm (feature/text selection). In the case of writer verification, a set of weights will be maintained for the writers and not for the individual training sample. Initially equal weights is given to each writer and after each stage weights will be reassigned such that the writers who are more discriminated by the selected primitive, get lesser weights. The more discriminating a writer is from the given writer based on the selected primitive, the less will be the weight and vice versa. This is done to make sure the next primitive is selected based on hard samples. The next weak hypothesis will be chosen based on the set of weights, thus giving more importance to classes that are less discriminated. Final hypothesis will be such that negative samples are nicely discriminated from the positive samples.

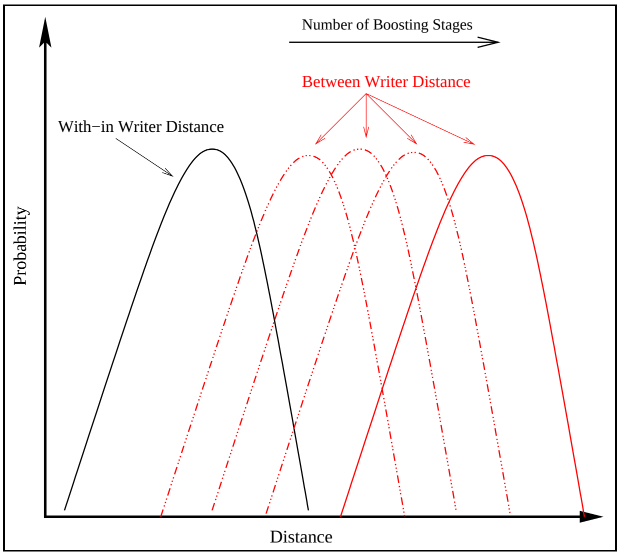


Figure 4.3 Effect of number of stages on the Margin between positive and negative samples.

Weak learning algorithms will be based on different primitives and features of handwriting. Different primitives of the handwriting can be sub-character, characters, words, etc. Since, primitives are not discriminating enough to individually discriminate positive samples from negative samples with high accuracy thus they will perform as weak classifiers. Essentially Adaboost based algorithm will behave as a primitive selection mechanism such that primitive with high discrimination get more importance than the others. Since, Adaboost algorithm selects primitives dynamically, primitive selection will be specific to each writer and will vary from writer to writer. Relative importance(weights) of each primitive will be calculated using Adaboost algorithm. In some sense, boosting can also be seen as the process of increasing the margin between positive and negative samples (see Figure 4.1.1.2), selecting the primitive classifier that is the most discriminating for the certain distribution of the weights of the writers. Another main advantage of Adaboost algorithm is that it provides better generalization than other classifier combination mechanisms. The key insight is that generalization error is related to margin of the examples and the Adaboost achieves large margins rapidly. Schapire et al [115] bound the generalization error of the Adaboost as:

$$P_D\big(yf(x) \leq 0\big) \;\leq\; P_S\big(yf(x) \leq \theta\big) + O\left(\frac{1}{\sqrt{m}}\left[\frac{\log(m)\,\log|H|}{\theta^2} + \log(\frac{1}{\delta})\right]\right) \tag{4.1}$$

Here the term, m, refers to the margin of the examples. T is the number of iterations and $|H|$ represents the cardinality of the classifier subspace.

Since, generalization error is directly proportional to the margin and as more and more weak classifiers are combined, the margin will also increase. As at each stage, we select the classifier that is most discriminating for the writer, given the list of writers to compare with, essentially the classifier is selected will increases the margin between positive and negative samples. However, the generalization error is also dependent on the cardinality of the classifier space. As the number of classifiers are quite large, generalization error will also be large. In order to overcome that problem, a cascaded structure of classifiers have been proposed in the next section.

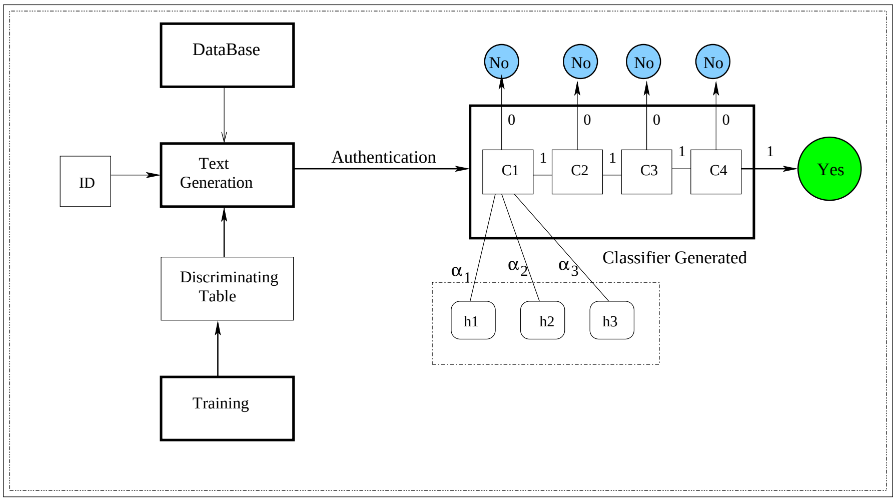


Figure 4.4 Writer verification framework for low security access control applications.

4.1.1.3 Cascaded Classifier

As seen from the framework in Figure 4.4, classifiers are combined in the cascade. At each stage in the cascade, some of the writers are rejected, thus pruning the list of writers at each stage.

Each cascaded classifier is a combination of different boosted classifiers. Cascaded structure of the classifiers is employed to reject the writers those are quite discriminating from the writer to be verified and about which we are more confident. One can now spend more effort for the hard samples in the following stages. Essentially the writers with smaller weights are removed from consideration. If any cascaded classifier rejects some writer from the consideration, then no further processing is done for that writer. The structure of the cascaded classifiers is essentially that of a ”degenerate decision tree” and is related to the work of Fleuret & Geman [116] and Amit & Geman [117].

After each stage in cascaded structure, a threshold is selected which decides which writer is to be rejected. Since we are approaching the problem of writer verification for low security applications, where false rejection rate is the major concern, thus the threshold is selected such that verification system is biased towards the writer to be verified. The insight of the cascaded structure is that writers who are discriminated easily from the writer(to be verified) need not go through complex computations. Only the writers who are hard to discriminate need to be analyzed with complex computations. Moreover, as the number of writers decrease over the stages, the number of computations that are required for each classifier will also decrease, that, in turn, will make system fast. Writers are rejected based on threshold calculated during the text generation phase. Classifier stages are biased towards the writer in order to keep false rejection rate as small as possible. False acceptance rates are controlled with every new stages added. Stages are added until all the writers except the writer to be verified are not rejected. For any writer to verify claim, he/she should pass through each stage of cascade. Once the writer is rejected by any one of the stages, it will not be tested through any of the subsequent stages.

4.1.2 Writer Verification

The previous section explained the boosting based feature selection algorithm for text generation. Feature/text selection method removes the major hurdle of designing writer specific text. However, the problem of forgery in text-dependent system will still remain the same as the text will be the same each time user tries to verify identity, although the text is selected specific to the writer. In order to overcome this limitation of the system, the text generated should be different each time the user tries to verify his identity. At the same time, it is the requirement of the system to be aware of the text written by the writer to take the advantage of text-dependent comparison. Thus the system should itself design random text based on feature selection method and the user is asked to write that text to verify his identity. However, here our feature selection based method is limited as for each writer all different combinations of primitives need to be written beforehand by the writer, in order to allow text-dependent comparison, which is practically impossible. This problem is solved by text synthesis.

In order to vary text across multiple authentications, randomization is introduced at the weak hypothesis/classifier selection phase. In the modified selection process the hypothesis is selected not just based on discriminating power. We add an option that classifier can be rejected or accepted, each time the classifier selection routine is called. Other processing is done as before as

Algorithm: Boosting based text generation algorithm

Require: ID of the writer to be verified, weak hypothesis h_j

Initialize $D_1(i) = 1/n$, where $i = 1, \ldots, m$,
where n is the number of writers in the system

writer-List = $\{1, \ldots, n\}$

while $|writer - List| > 1$ **do**

  while $Nowriterisrejected$ **do**

    Select weak learner, h_t^k, such that
    $\epsilon_k = \sum_i D_t(i)\theta_i^{ID}$ is maximum.
    θ_i^{ID} represents the pairwise discriminating power of the classifier h^k for and calculated during the enrollment stage

    Calculate:
    $\alpha_t = \log\left(\frac{1-\epsilon_k}{\epsilon_k}\right)$

    Update:

    $$D_{t+1}(i) = \frac{D_t(i)exp\left(\alpha_t\theta_i^{ID}\right)}{Z_t}$$

    where Z_t is a normalization factor (chosen so that D_{t+1} will be distribution).

    Compute threshold Th for the stage using within-writer distance.

    if ($\xi_i > \mathrm{Th}$) Reject the writer

  end while

end while

in the basic version of classifier selection. Acceptance or rejection is based on a random number generator. The random number generator is also designed using discriminating distribution of the primitives. The weak classifiers are accepted or rejected based on their discriminating power. Classifier with more discriminating power has more chances of being selected.

Let each stage in the cascaded classifier denoted by C_i, where $i = 1, \ldots n$. n is the number of cascaded stages in the classifier. Final hypothesis, H is given by:

$$H(x) = \prod_i (W_i < \vartheta_i) \tag{4.2}$$

W_i is the score of i^{th} cascade and ϑ_j is the threshold for i^{th} cascade calculated during text generation phase. Threshold will be fixed such that the classifier is biased towards the writer to be verified and false rejection rate (FRR) is minimized. During the authentication stage, a writer is rejected if $W_i > \vartheta_i$, otherwise accepted. In order for a writer to be authenticated, he/she should be able to pass through all the stages. Rejection at any stage will also reject his claim. Score W_i of each cascaded classifier is calculated as the combination of various weak hypotheses selected at each selection stage. let h_j be the j^{th}weak hypothesis. Then W_i is given by:

$$W_i = \sum_j \alpha_j h_j \tag{4.3}$$

where α_j is the relative importance or weight given to j^{th} weak classifier computed during Adaboost based text generation phase and $h_j(X)$ is the hypothesis generated by j^{th} classifier within a single stage.

In order to vary text, as randomness is introduced in the framework. Each weak classifier can be rejected with probability of $P(1 - D_i(w))$. Where, $D_i(k)$ is the discriminating power of k^{th} primitive for i^{th}writer. Method to calculate discrimination power has been explained in next section.

It is always more natural to write words and sentences as compared to individual characters or sub-characters. Primitives of handwriting may be sub-character, character or any larger unit and the writer still can be asked to write a single sentence. This is done using a language-unit inside the system. The system supports language unit such that given a list of characters (or sub-character) and dictionary (or mapping sub-character to character), the language unit will generate meaningful words. The words can further be combined to form different sentences. Randomness can be incorporated at word level as well as sentence generation level. More the randomness, less will be chances of forgery. As this is always difficult to forge an arbitrary handwriting of any individual. Some of the simple rules that have been used for the purpose of experimentation has been given below. More complex rules can be easily incorporated.

- *SUBJECT* + *VERB* + *OBJECT*
- *SUBJECT* + *HELPING-VERB* + *MAIN-VERB* + *OBJECT*

4.1.3 Enrollment Phase

In traditional writer verification process, enrollment phase is to identify the threshold of between-writer distances to within-writer distances. In our framework, text generation phase and the threshold calculation phases are delayed till authentication phase (defined above). Thus only, the calculation of discriminating power and training of synthesis phase is done during the enrollment phase.

4.1.3.1 Discriminating information extraction

Discrimination is defined as the degree of separation of within-and between-writer distances between a pair of writers. The discriminating power for a primitive (for the writer) against the world population is approximated as the level of discrimination of that component against the writers in the training set.

Discriminatory power of primitive is defined as

$$D_{ij}(w) = 1 - \left(\int_{X_1}^{X} g(x) + \int_{X}^{X_2} f(x) \right), \tag{4.4}$$

where $D_{ij}(w)$ is the discriminatory power of word w for writers W_i and W_j and $f(x)$ and $g(x)$ are the distributions of within writer and between writer distances. So, the discriminating power

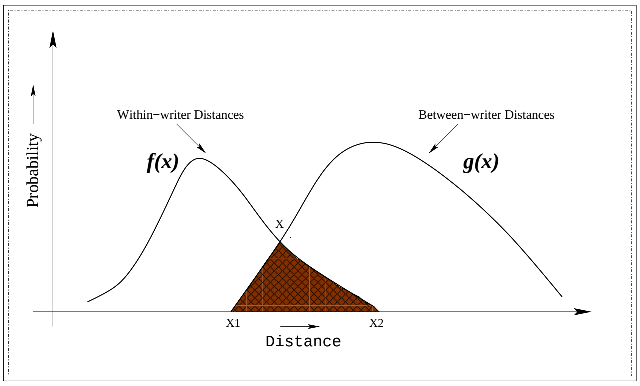


Figure 4.5 Discriminating power of words is inversely proportional to the area of intersection.

of words, essentially, is proportional to the overlap between distribution(see Figure 4.5). The more the overlap between distributions, The less the discriminating power and vice versa. Figure 4.6 lists the discriminating power of different words for different writer pairs.

W1 Vs	Word−1	Word−2	Word−3	Word−4	Word−5
W2	lemon	Indonesia	france	Queen	Afghanistan
	0.01	0.03	0.09	0.21	0.25
W3	california	woman	Afghanistan	Victory	Doctor
	0.05	0.09	0.12	0.25	0.35
W4	Queen	Victory	Lemon	France	Umbrella
	0.00	0.00	0.10	0.22	0.23
W5	Timetable	banana	River	Zimbabwe	Shuttle
	0.03	0.09	0.12	0.25	0.35

Figure 4.6 Discriminating table of the characters for pair of Writers. Discriminating table list five words with highest discriminating power for the 4-writer pairs.

4.2 Feature extraction

For the purpose of the experiments, words are used as basic unit of handwriting. Online word is the set of strokes which in turn is the sequence of points. Thus the distance between words can be calculated using distance between corresponding strokes of the words as the order, number and the shape of strokes do possess a lot of individuality information about the writer. For the experiments two different methods are used for strokes comparison, Dynamic time warping(DTW [118]) and directional features. DTW matching is the natural choice for the stroke distance as the number of points in the strokes are not same and DTW provides us an efficient method to compare different length feature vectors. Two approaches used to calculate stroke distances are:

- *DTW Matching:* As the number of points on the strokes are different even for same writers. DTW matching provides the method to compare two strokes.

- *Directional features:* As discussed in chapter-2 direction based features have lots of individuality information associated with them. The curvature of the strokes are calculated at each point and grouped into 12 bins. Euclidean distance between these fixed dimension feature vectors is used for distance calculations.

Once the distance between all pairs of strokes are calculated, dynamic time warping is used to calculate the distance between words. In this case, dynamic time warping will take care of order and number of strokes in the word while calculating distance between two words.

4.3 Experimental setup and results

As there is currently no available online handwriting databases with writer information, for the purpose of experiments, data is collected from different writers using Genius tablet. Data is collected from 30 writers in both Hindi and English scripts. Hindi data is collected from 10 users and English data is collected from 20 users. Each person have written 20 word, $10 - 12$ times each. Experiments are performed using 3-fold cross validation. The data is randomly divided into three sets. Two out of the three sets are used for training and remaining one for testing. The process is repeated for all possible combination of sets. Two different feature extraction methods are used for the experiments. Within and between class distances for each pair of writers is considered as the representative of true global distribution of the distances. The discriminating power of the words has been defined as the proportion of the samples that comes in the region between these two distributions. Discriminating power can also be defined as the measure of similarity between these two curves.

The boosting based framework described above, is essentially a feature/text selection based framework. In order to test the applicability and accuracy of the algorithm for writer verification task, results are compared with other feature/text selection approaches such as random selection and discrimination based selection. In the case of random selection, the primitives are selected randomly from the given database and given equal weights. In the second case of discriminating power based selection methods, words are selected based on their discriminating power for the given set of writers. Two variants of discrimination based methods are used differently for the purpose of experiments. In the first case, discriminating power of the primitives is determined taking all the writer taken together called as global discriminating power. In second case, discriminating power of the words can also be calculated for an individual writer. Global discriminating power can be affected by outliers as it is the average of all the individual discrimination (average is sensitive to outliers).

Figure 4.7 and Figure 4.8, shows the comparison of accuracies of different primitive selection methods. It is evident from the graph that accuracies of boosting based randomized method are quite comparable to discriminating power based primitive selection and quite higher than random selection. Effectiveness of the verification systems are quantitatively represented in terms of false acceptance rates(FAR) and false rejection rates(FRR). The false acceptance rates represents the percentage of impostors accepted by the systems and the false rejection rates is the percentage of the genuine user rejected by the system. False acceptance and false rejection rates are inversely proportional to each other as these two are related to the threshold selected for verification. The more the threshold, lesser will be the false rejection rates. However, the system will tend to accept a lot of impostors also, thus leading to high false acceptance rates and vice versa. Figure 4.7, 4.8 below shows the FAR, FRR rates of the boosting based selection in comparison to the other selection methods.

It is evident from the FRR graph (Figure 4.7 and Figure 4.8) that the performance of individual discrimination based selection is better than global discrimination based selection method. The main reason for this is that in the case of individual discriminating power, the threshold is selected based on the single classifier and thus it performs better for the individual writer and provide lower FRR. Boosting based method described in this chapter, performs better than all other methods. as this method selects primitives dynamically, based on the individual writers and give more weighage to the hard samples which are being misclassified in the previous stages. Performance of the boosting based classifier is much more dependent on the threshold that is chosen. In case of false acceptance rates, as seen from the diagram that false rejection rates are quite higher initially and decreases rapidly as the number of words increases. Boosting provides better generalization performance and as the number of stages increases, the margin between positive and negative samples increases. It has been empirically proved that boosting decreases the generalization error even long after training error becomes zero.

In the case of the cascaded-boosted classifiers described above, the threshold plays a major role in deciding the performance of the system. Traditional writer verification system uses single threshold of within and between-writer distances for the authentication. However, the text generation phase of the algorithm proposed in the chapter, enable us to decide the threshold specific to the writer and the text. In the case of the cascaded classifiers, the two thresholds are being selected which affects the performance of the system. The thresholds are decided based on both the positive and negative samples (see Figure 4.9). Threshold that is calculated based on the positive samples effects the false rejection rates of the system since if threshold is decided such that all the positive samples from training data are accepted then false rejection rates will be lower and vice versa. However, this also effects the false acceptance rates as the threshold is higher, impostors will also be accepted. The second threshold is chosen based on the negative samples and effectively controls false acceptance rates. It decides when to reject writer for consideration from the next cascade. Both thresholds are not independent and affects each other. For the sake

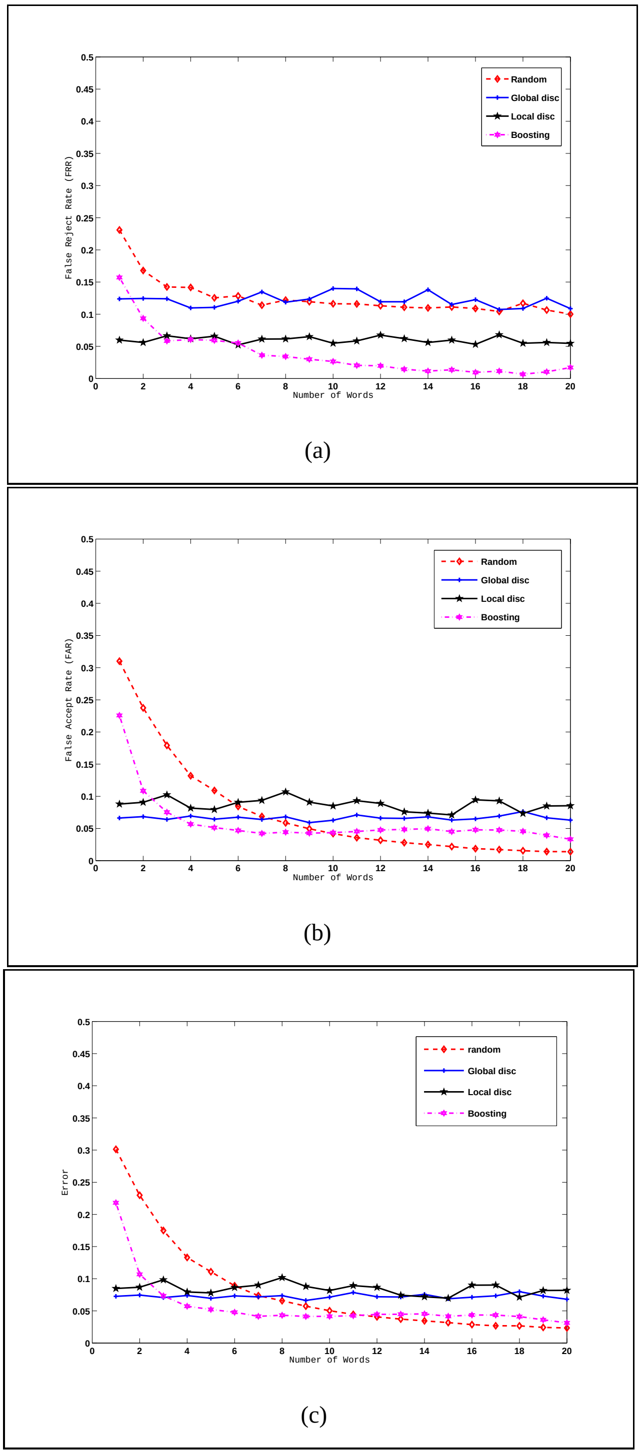


Figure 4.7 Comparison of (a) False Rejection Rates(FRR), (b) False Acceptance Rates (FAR) and (c) Total Error for different text selection methods for Hindi script using DTW

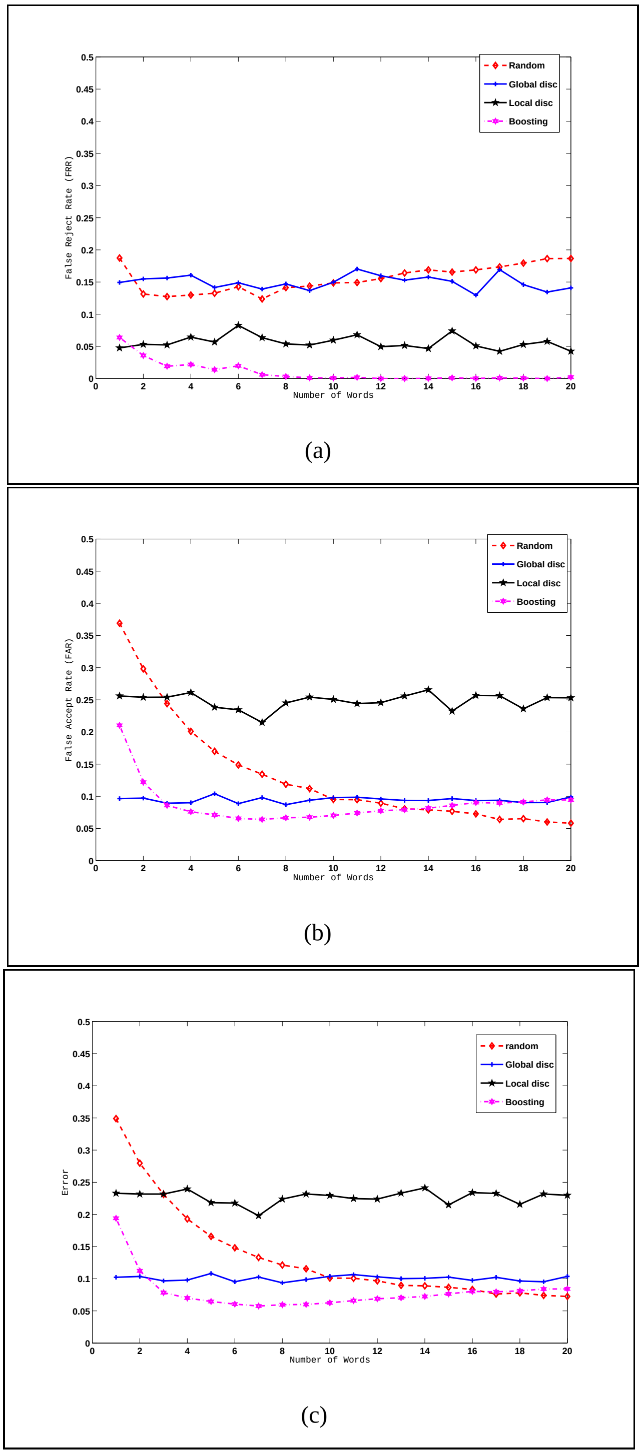


Figure 4.8 Comparison of (a) False Rejection Rates(FRR), (b) False Acceptance Rates (FAR) and (c) Total Error for different text selection methods for Hindi script using Directional features

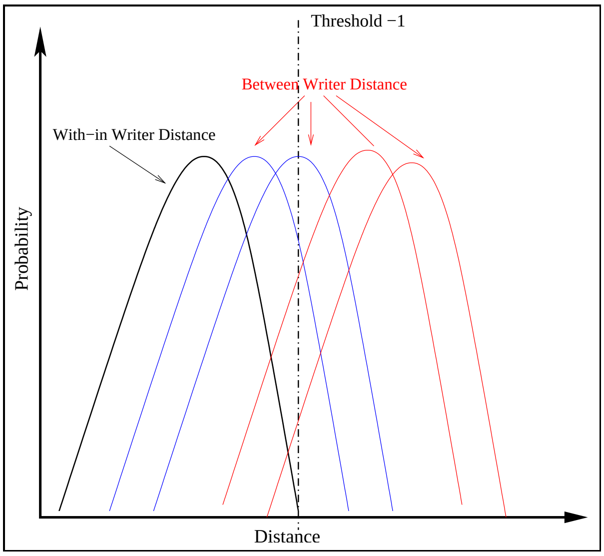
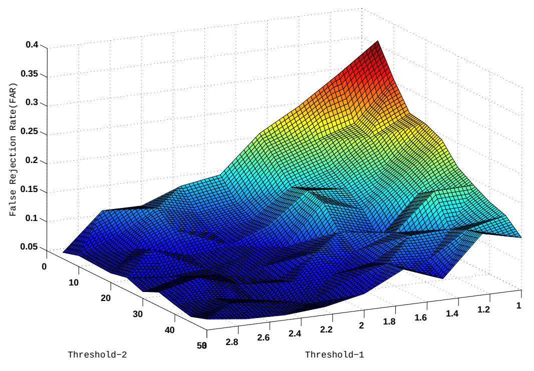


Figure 4.9 Description of Threshold-1 and Threshold-2. In the figure Threshold-2 is taken at 20 percentile and Threshold-1 as max of within writer distances. Writers W4,W5 will be rejected at the shown stage.

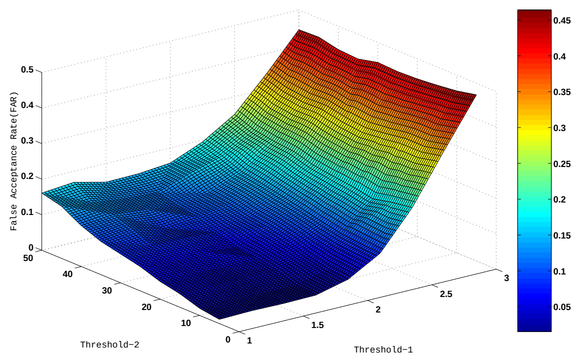
of experiments, second threshold is taken as the percentile of the negative samples below first threshold. For example, let the threshold-1 be Th and threshold-2 selected to be 20% (of number of total test samples for the class), then we reject all the writers for who have less than 20% of the samples below threshold-1. Essentially increasing threshold-2 means to make system more prone to rejecting writers and that directly affects the performance of the system on account of false rejection rates. For the experiments, threshold-2 is being varied from 5 to 50 with the step size of 5 and threshold-1 is varied as the multiple of the basic threshold from 1 to 3 with the step size of 0.25. Figure 4.10, 4.11 and 4.12 below shows the Performance of the system for different values of the threshold for different features.

As seen from the above graphs(see Figure 4.10, 4.11, 4.12), false acceptance rates of the classifiers increases with increasing threshold-1 and decreases with decreasing threshold-2. Explanation of this have been given in the previous paragraph. Also the system performs better in the case of the false rejection rates with higher values of threshold-1. As seen from the above graphs, direction based features perform slightly better than DTW distance based methods. The major reason behind this is the higher sensitivity of the DTW distance for small variations. On the other hand, direction based feature is not sensitive for small variations. Also, direction feature based comparison is faster than DTW based comparison, as the number of comparisons for each stroke is much more in DTW (of the order of n^2, n is the number of points on the stroke), whereas in case of directional feature based comparison, each stroke is just represented with 12-dimensional feature vector.

Threshold-1 and threshold-2 does not only affect the accuracy but they also affects the number of primitive comparison to be made for the decision. The number of comparisons are directly



(a)



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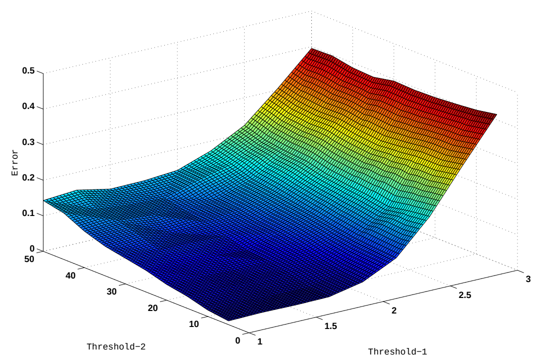


(c)

Figure 4.10 (a) FRR, (b) FAR and (c) Combined error rates for DTW distance for Hindi script

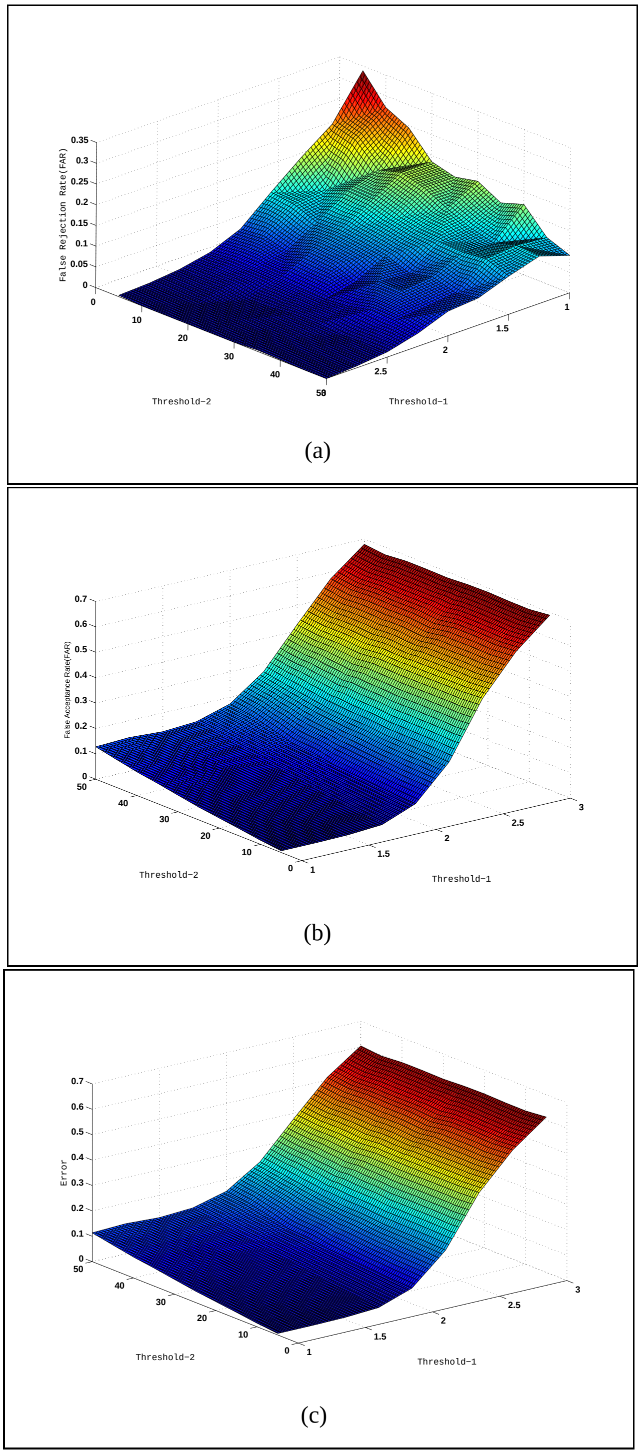


Figure 4.11 (a) FRR, (b) FAR and (c) Combined error rates for Direction features for Hindi script

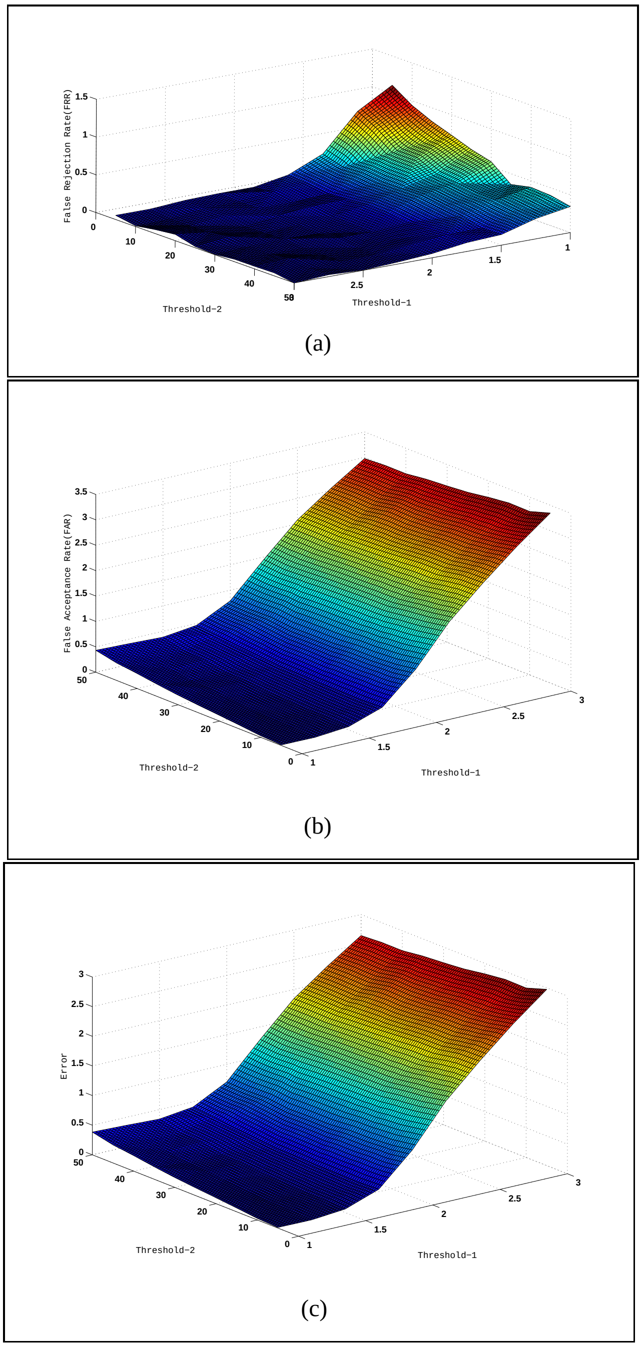


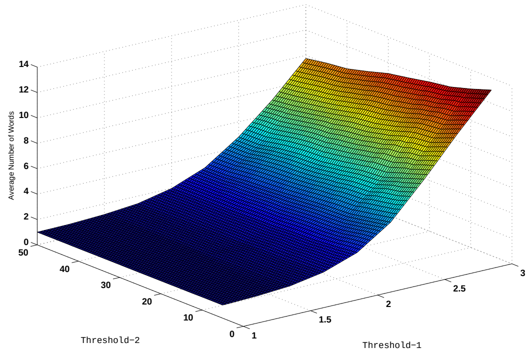
Figure 4.12 (a)FRR, (b)FAR and (c)combined error rates for Direction features for English Script

related to time taken for verification. Figure 4.13 below shows the variations in average number of comparison with the changes in values of threshold-1 and threshold-2. As seen from the diagram, as threshold-1 increases more number of words are needed for comparison. The main reason behind this is as the threshold-1 increases, more number of words will be needed to reject all the other writers(leaving only one writer, ID), for constant value of threshold-2. However, increase in threshold-2 effectively means that system is more prone to rejecting other writers and less number of words will be needed for comparison. As the number of comparison increases, more will be the accuracy because of increase in the number of stages of boosting based classifier.

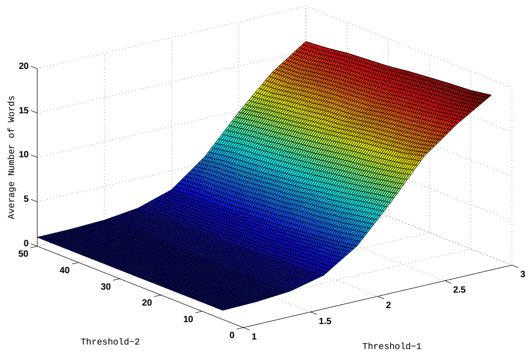
Major problem with different biometrics based verification systems is of scalability with the number of writers. As the number of writers increase the performance of the system decreases. However, in the cascaded boosting based method, performance of the system is not considerably affected by the increasing number of writers (see Figure 4.14). As evident from the graph 4.14, the error term is decreasing with the increase in the number of writers. This is due to the generalization capability of boosting based systems. At the same time, as the number of writers increases, the number of the cascaded stages also increases. More the number of stages, the writer have to pass through more rigorous testing. For small number of writers, number of stages will be lesser and since the system is biased towards accepting the writers rather than rejecting, the false acceptance rates will be higher. As the number of writer increases, effect due to biasing reduces and makes the system more accurate.

4.4 Conclusion and future work

Text-dependent writer verification framework for civilian applications has been proposed. System presented an algorithm to generate writer-specific test sentences for individual writers which makes the system forgery resistant (by implanting randomness into the generation process), and fast as the amount of text required for verification is low. System is being designed specifically for low security access control and civilian applications as false rejection rates are quite low can be controlled with varying thresholds. Experimental results show that boosting based text-generation system is better than different selection methods and also require small amount of data for verification.



(a)



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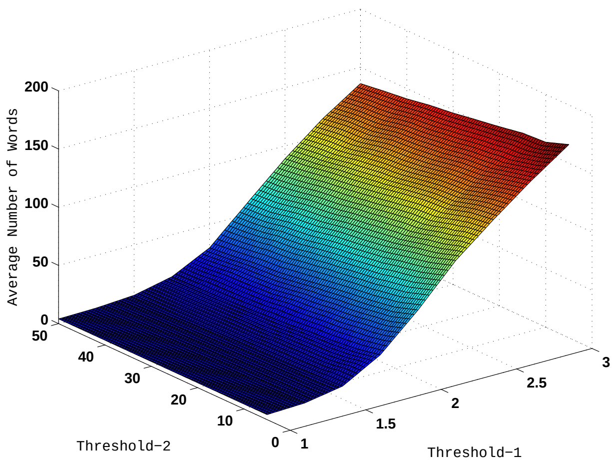
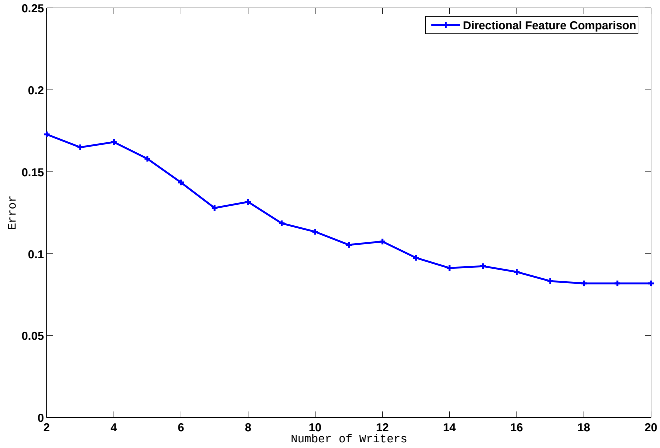
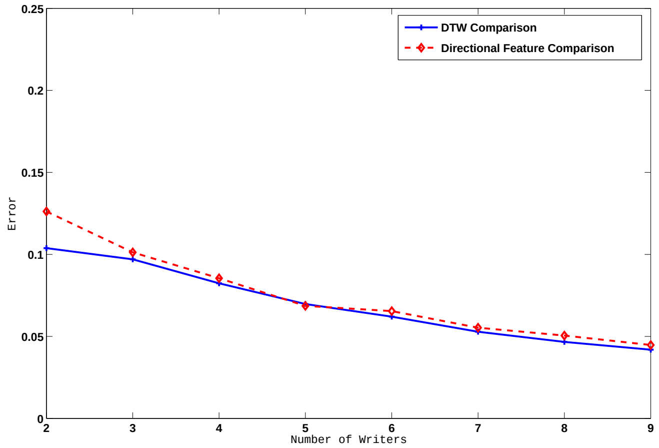


(c)

Figure 4.13 Number of words comparison as the function of Thresholds, (a) Hindi Script and DTW features, (b) Hindi Script and Direction features (c) English Script and Direction features



(a)



(b)

Figure 4.14 Error Rates as the function of Number of writers (a) English Script (b) Hindi Script

Chapter 5

Repudiation Detection in Handwritten Documents

In last two chapters, we have introduced the problems of traditional writer identification and verification in the context of text independent and text dependent scenario, respectively. In this chapter we will introduce the different set of problems that arise mainly in forensic documents. The problems that arise in forensic document examinations, are usually quite different from that of traditional writer identification and verification tasks, where the data is assumed to be natural handwriting. However, in case of forensic documents no such assumption can be made about data. This give rise to problems of forgery and repudiation detection. The problem of forgery detection has been studied in the context of signature verification. The second problem, repudiation, arise where a writer deliberately distorts his handwriting in order to avoid identification. Moreover, in case of forensic documents, we often have to arrive at a decision based on a single document pair. Thus learning writer specific models can also become difficult. Since the problem of repudiation is inherently different from that of writer identification or verification, the optimal way to handle them needs to be different. This chapter addresses the problem of repudiation in generic handwritten documents, and also proposes a framework to analyze such documents. The approach can further be extended for detection of forgeries as well.

In forensic science, the primary role of handwriting analysis is in the problem of Questioned Document Examination(QDE) [33,119]. Determination of authorship of a document is the main task in QDE, where one has to decide whether a pair of documents, the *questioned document* (one whose origin is unknown) and the *reference document* (one whose origin might be known), were written by the same writer or not. However, due to the circumstances under which the documents are generated, there is a motivation for the writer to deliberately alter his natural handwriting to avoid detection. We refer to this problem as *handwriting repudiation*, as the purpose of distortion is to deny someone's involvement in the case (repudiation [120]).

The problem of detection of repudiation in QDE is different from that of traditional writer identification and verification tasks. Writer identification is the problem of identifying writer of the document from given candidates and, writer verification is the process of verifying whether the claimed identity actually belongs to claimed writer. In both identification and verification problems, writer need to be enrolled into the system before hand. Also the data in case of traditional writer identification and verification is supposed to be naturally written. In case of

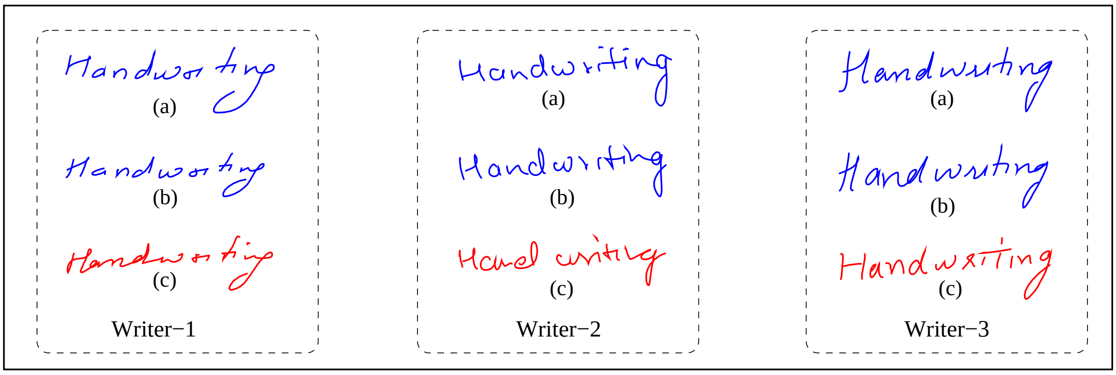


Figure 5.1 (a) and (b) Natural handwriting samples from 3 writers and (c) Repudiated samples from the writers.

forensic documents, as data can not be assumed to be natural handwriting, other problems arises, i.e. forgery and repudiation.

- *Forgery Detection*: The problem is identical to that of verification, except that there is an additional suspicion that the writer could be an impersonator.
- *Repudiation Detection*: Given two samples of handwriting (both could be deliberately distorted), verify the claim that they are from different writers.

Note that in both identification and verification tasks, the users are assumed to be cooperative, and one could build statistical models for each writer from their natural handwriting. However, in the case of forgery, the questioned document need not be natural, and in repudiation, both the questioned document and the reference document could be distorted, and we have to assume that the writer is non-cooperative. Figure 5.1 shows examples of words from three writers in their natural form, as well as when they distort their handwriting for repudiation.

In this chapter, we primarily deal with the problem of repudiation in generic handwritten documents. We propose a generic framework for automated analysis of handwritten documents to flag suspicious cases of repudiation.

5.0.1 Automatic Detection of Repudiation

Extraction of writer information from handwriting is more challenging as compared to verification based on physical biometrics traits, due to the large intra-class variation (between handwriting samples of the same person), and the large inter-class similarity (same words being written by different people). Moreover, the handwriting of a writer may also be affected by the nature of the pen, writing surface, and writers mental state. In addition, the problem of forensic document analysis is particularly difficult due to the additional problems posed by repudiation:

- During repudiation, a writer tries to change his handwriting style to be different from that of his natural handwriting. This introduces a large amount of intra-class variability that the system has to handle. Moreover, the writer need to be assumed non-cooperative, unlike in forgery, where the person who is being forged will be cooperative and provide their natural handwriting in the required manner and amount.

- The content of the handwriting that is available during forgery detection is not in our control, and is often small in quantity. This prevents us from using the less frequent statistical properties of the handwriting for the purpose of verification of the claims.

- The cost of false match is often very high in the case of forensic documents, as it might result in erroneous conviction of an innocent person. Moreover, to use such an evidence in the court, one needs to give a statistically valid confidence measure in the result that is generated.

In spite of all these problems, it has been shown by forensic experts, that repudiation detection is possible. From the principle of *exclusion* and *inclusion*, inferred by document examiners from their experience in the field, one can't exclude from one's own writing, those discriminating elements of which he/she is not aware, or include those elements of another's writing of which he/she is not cognizant [3]. Thus the task of repudiation detection comes down to finding the discriminating elements of which writer is not aware of. We propose a framework (see Figure 5.2) that exploits the statistical similarity between lower level feature distributions in two documents to detect possible cases of repudiation. One needs to add a line of caution here that many of the clues that are used by forensic experts comes from external sources (such as background of the suspect, examination of paper material, etc.) and are not available to an automatic writer verification system. Hence any such system can only be used as an aid to a forensic expert, and not a replacement.

The prior work in this area primarily concentrates on the problems of natural handwritten documents. Comprehensive survey of work has been given in chapter-2.

5.0.2 Applications

The major applications of repudiation detection is in the field of forensic document only. Since, only in these scenario, writer would like to forcefully change his handwriting.

5.1 A Framework for Repudiation Detection

This section describes a generic framework for repudiation detection for questioned document examination. The primary goals of the framework are:

1. To develop a statistically significant matching score between two documents, without any additional information in the form of training data.

2. Utilize the online handwriting information that could be obtained from the reference document to improve the matching.

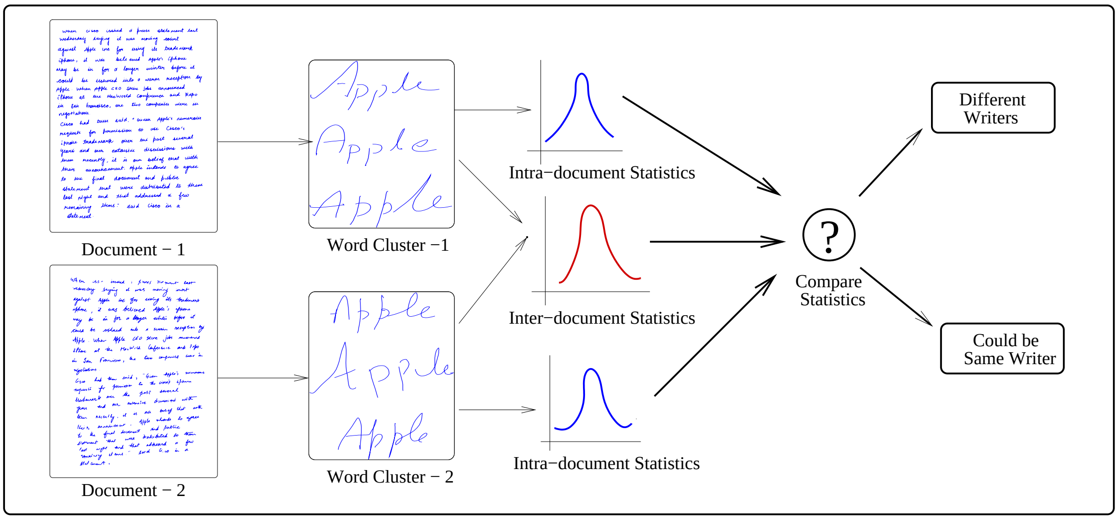


Figure 5.2 Framework for detecting repudiation from handwriting.

3. Allow the inclusion of additional features that might be extracted from the handwriting to enhance the results. This would also mean, we should not make specific assumptions about the distributions of the features, in the framework.

4. Allow the user to specify a confidence threshold, beyond which, the system will pass the documents for expert examination.

To make a generalized system is very difficult. We also make the certain assumptions in our approach. The assumptions, however, are practically sound and will not affect on the final system. The primary assumption is that the content of the questioned document and the reference document are either the same or has significant overlap at the word level. This allows us to use text-dependent approaches to compare the words in the two documents. Without this assumption, it will be difficult to identify consistent features of handwriting of individual, which is the bottleneck of the system. In case of repudiation, consistency is the major feature as it is difficult to change consistently written features from the individual's handwriting, even deliberately [3].

We also assume that the reference document is collected in the online mode (with temporal information). These assumptions are valid in the case of QDE, since the investigator can control the content and mode of the reference document being collected. Online data have more individuality information about the writer. This information can be used to compare the consistent features of reference document with same features from questioned document.

Let the two documents be denoted as $D_i = \{w^k\}, k = 1 \cdots n_i$ and $D_j = \{w^k\}, k = 1 \cdots n_j$. The words in each document are first partitioned into disjoint sets as follows:

$$
\begin{aligned}
D_i &= \bigcup_{k=1}^{N_i} C_i^k, \text{and} \\
C_i^k &= \{w^j | w^j \in D_i, \text{and denote the word } k\}
\end{aligned} \tag{5.1}
$$

where N_i is the number of distinct words in D_i. This partitioning can be done using recognition-based or ink-matching techniques. We then compute the correspondence between the sets C_i and C_j from the two documents. Once again, we can find the correspondence based on recognition results or ink matching. Without loss of generality, we assume that the corresponding sets are C_i^k and C_j^k, $k = 1 \cdots K$.

To compute the similarity between the two documents, we first define a distance measure between two corresponding words, W_i and W_j, as $d(W_i, W_j)$. This could be the distance between any set of features that are extracted from the word. Let $d_{i,j}$ denote the average distance between corresponding words in documents D_i and D_j. We compute two distributions of distances: i) p_w, coming from within document distances $d_{i,i}$ and $d_{j,j}$, and ii) p_b, from between document distances, $d_{i,j}$.

Now referring to the major requirements of the framework, one of the major problem with repudiation detection is to find out the significance of the score. After consistent features from reference document is being extracted and compared with similar features from questioned documents, we can easily arrive at some distance between documents.Now the problem of significant distance is posed as that of testing the hypothesis, whether the two distributions, p_w, and p_b, come from the same population or not. In other words, we can say that if intra-documentp_w and inter-document p_b, distance distribution came from same general distribution with high probability, then we can predict that these two documents are written by same writers with higher probability. One could assume that p_w and p_b are normal from central limit theorem and can be compared using parametric tests such as, t-test, z-test etc. However, no prior information about distributions is available in case of forensic documents verification. Any wrong assumption about data distribution can lead to misleading conclusions. Non-Parametric tests like KL-test and KS-test do not make any assumption about distance distributions and thus more fit for question document analysis. Complete analysis of non-parametric tests and hypothesis testing is given in next section.

5.1.1 Detecting Repudiation and Forgery

Major problem in case of verification is generating significance of distance between questioned pattern and known pattern. Traditionally, this is done using threshold, which in turn is calculated from training data. In case of one to one problems of verification, such as in forensic documents, where training data is not available, significance of distance need to be calculated using statistical methods such as Hypothesis testing. Hypothesis testing allows us to compute the significance of the distance and hence arrive at a confidence measure of the result in a meaningful and systematical manner. Hypothesis testing provides a formal means for distinguishing between probability distributions on the basis of random samples generated from the distributions. Two class hypothesis testing problem for forensic documents can be posed as:

$$\begin{aligned} H0 &= \text{Documents written by same writer} \\ H1 &= \text{Documents written by different writers} \end{aligned} \tag{5.2}$$

$$\Lambda = \frac{\text{Likelihood that documents written by same writer}}{\text{Likelihood that documents written by different writer}} \tag{5.3}$$

if $\Lambda > \alpha$, then documents are proved to be from same writer. Otherwise documents are declared to be written by different writers. Here, α is the threshold that is decided based on the problem.

Likelihood ratio, Λ, can be calculated as the probability whether two distributions p_w and p_b came from same universal probability distribution. Similarity of distributions can be calculated using different non-parametric tests, such as Kullback-Leibler(KL) divergence or Kolmogorov-Smirnov(KS) test. Kullback-Leibler divergence or relative entropy test is one of the tests that can be used to compare two hypothesis or distributions. Kullback-Leibler divergence test is the natural distance measure from a true probability distribution, P to an arbitrary distribution, Q. For probability distributions P and Q of a discrete variable, the KL divergence (or informally KL distance) of Q from P is given by equation 5.4.

$$\begin{aligned} D_{KL}(P||Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)} \\ P_{KL} = e^{-\xi D_{KL}} \end{aligned} \tag{5.4}$$

Distance D_{KL} can be converted into probability terms using 5.4. Kullback Leibler distance essentially calculates divergence between distributions, and is not a distance metric, as it is neither symmetric nor satisfies triangle inequality. On the other hand, KS test determines whether an underlying probability distribution differs from a hypothesized distribution, based on finite samples. The KS-test also has advantage of not making assumptions about the distribution of data and so, is a non parametric (parameter or distribution free method). Two parameter KS-test is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples. KS test computes a simple distance measure and mathematically can be represented by equation 5.5:

$$D_{KS}(P||Q) = max(P(i) - Q(i)), \forall i \tag{5.5}$$

Where P and Q are cumulative probability functions and $P(i)$ and $Q(i)$ are corresponding probability values. for two distributions. Distance D_{KS} can be interpreted as maximum absolute difference of cumulative probability on all potential values of i. Probability of similarity between two distributions is then calculated by:

$$\begin{aligned} P_{KS} &= Q_{KS}(\sqrt{N_e} + 0.12 + (\tfrac{0.11}{\sqrt{N_e}})D_{KS}) \\ Q_{KS}(\lambda) &= 2\textstyle\sum_{j=1}^{\infty}(-1)^{j-1}e^{-2j^2\lambda^2} \qquad |Q_{KS}(0) = 1, Q_{KS}(\infty) = 0, \end{aligned} \tag{5.6}$$

and N_e is effective number of data points, $N_e = N_1N_2(N_1 + N_2)^{-1}$, where N_1 and N_2 are number of data points in two distributions respectively. The major limitation of KS test is that it is more sensitive near the center of the distribution than at the tails. For experimentation purposes KS test is used as statistic. Distance metrics based on combination of KL test and KS test explained in [121] can also be used to get some improvement in the results. Any of these two tests can be used for our purpose. In this paper, experiments are performed using KS-test.

The formulation of the comparison using hypothesis test, makes an implicit assumption that two documents from the same writer will be exactly same. However, this is not true due to two factors: i) natural handwriting of two documents from a writer tends to be different due to environmental and physical conditions of the writer, and ii) In case of repudiation and forgery, the writer introduces some variation even if appropriate features are extracted. Hence we modify the hypothesis test result by looking at the confidence level of the result, and choosing a threshold, α, on the confidence to decide if we should involve an expert or not.

5.1.2 Feature Extraction

This section explains feature extraction and comparison details. In case of repudiated documents, feature extraction plays a major role. Based on the level of details discriminating features of handwriting can be divided as macro level or high level features and micro level or low level features. High level features, such as alignment, slope, slant of line and words can be repudiated, as the person is quite aware of these features and thus can be changed forcefully. However, lower-level features, such as shape and size of primitive curves and connection between these curves can not be changed easily, as the person is habituated of writing primitive curves for a long time. Moreover, various studies in the field had verified that people are more aware of words rather than individual characters present in those. Also, automatic segmentation of character from words is difficult task. Another major reason for choosing words as our primitive unit is same character is written quite differently (with respect to shape and size) within different words and this will introduce large intra-class variations at character level. Individual words are segmented and clustered into clusters of same words using automatic clustering and segmentation methods. Simple features like horizontal, vertical, lower and upper profiles of the word are used to cluster them into cluster of same words. Small errors in data clustering and segmentation

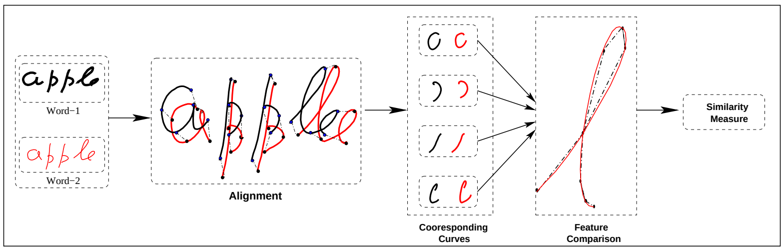


Figure 5.3 Comparison between two words '*apple*'

is removed using manual efforts. In case of forensic documents, manual segmentation is also possible as volume of data is small.

The distance between pair of words is calculated using lower level features like shape, size of size of the constituent primitive curves explained in [5]. Primitive curves from the words are calculated using dominant points. For online handwriting (reference document) dominant points are defined as maximum and minimum velocity points and for off-line words (questioned document) curvature points are used as dominant points. More rigorous method can be used to extract dominant points on the words. It can be argued that velocity of handwriting can change with change in environmental conditions and also be changed deliberately. However it can be shown that the critical points of velocity remains the same due to long form habits. Figure 5.3 describes the feature extraction and comparison process. It demonstrate two word *apple* written by same person from both normal and repudiated handwriting along with the corresponding critical points. Critical points were used to extract primitive curves from the words. Primitive curves are defined as the portion of curves between three consecutive minimum velocity points on the stroke. Note that in case both documents are off-line, critical points can be calculated using curvature.

Distance between a pair of words is calculated using dynamic time warping. Each word is represented as two dimensional feature vector of size mxn, where, m is the number if different curves in the word, w, and n is representation of each curve. Curves are represented using an n dimensional feature vector, comprising of curvature,size of connecting vectors, relative velocity and shape of each curve is represented using higher order moments to retain fine changes. Simple Euclidean distance can be used to calculate distance between two primitive curves. The proposed method is simple in nature, and could be replaced with a more comprehensive distance measure that uses various properties that are extracted from the curves. One could also employ distance measures based on *DTW* distance, between two primitives.

5.2 Experiments

The data used in our experiments was collected from 23 different writers. Each writer was asked to write three pages on A5 sized pages in his/her own natural handwriting. In addition, three pages of data was collected from each writer, while trying to masquerade his/her handwriting style. The data was collected using iball take-note, which collects the data in both on-line and off-line forms. The data is then segmented into words using inter-word distance and then clustered into groups of same words.

As noted before, the actual significance of the distance between two documents cannot be used directly. A threshold need to be identified, such that if the matching distance is below this, we use the services of an expert. To present the capabilities of the system, we plot the ROC curve of the system by varying the threshold. Figure 5.5 shows ROC curve and the corresponding distributions of within-writer and between-writer distance distributions. The document pairs that are written by same person is considered as genuine documents. Note that this includes repudiated documents from the same writer. The genuine accept rate is acceptance (or matching) of documents that are written by same person and false accept rate is percentage of documents that are accepted, when they actually belong to different writers. ROC curve shows that about 82% of documents which belong to different writers are rejected, while keeping the genuine acceptance rate at 100%. As discussed before, this step is considered as the preliminary step for the document screening before it goes to expert. All the documents, which are not rejected can be processed further by handwriting expert.

An alternate way of presenting the results of matching a particular document pair to an expert is on the traditional nine-point scale. Forensic experts use this scale to indicate the level of match between two documents under consideration. The scale consists of: *identification*, *strong probability of identification*, *probable*, *indications*, *no conclusion*, *indications did not*, *probably did not*, *strong probability did not* and *elimination*. We can present a similar result based on the densities in the corresponding histograms in figure 5.5. However, due to the bias introduced by hypothesis testing (tests are done under the assumption that null hypothesis is true), the results will be confined to the values of *no conclusion*, *indications did not*, *probably did not*, *strong probability did not* and *elimination*, in the case of repudiation.

We have introduced the problem of repudiation in handwritten documents, which is particularly relevant for forensic document examination. A statistical model for automatic repudiation (and forgery) detection , that uses the statistical significance of the distance between two distributions is presented. Preliminary results support the validity of the model. Such an automated system can act either as a screening mechanism for questioned documents, or could provide additional insights to an expert examiner of the documents.

Preliminary investigations into the use of the model for detecting forgeries seem to be promising. However, we need to conduct extensive experiments using expert forgeries to make any conclusive statements on the effectiveness. One can also experiment with a variety of features to compute the distance between two words, in order to improve the matching results.

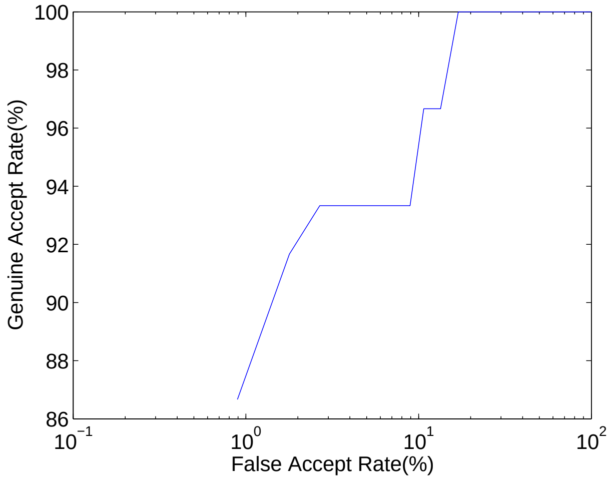
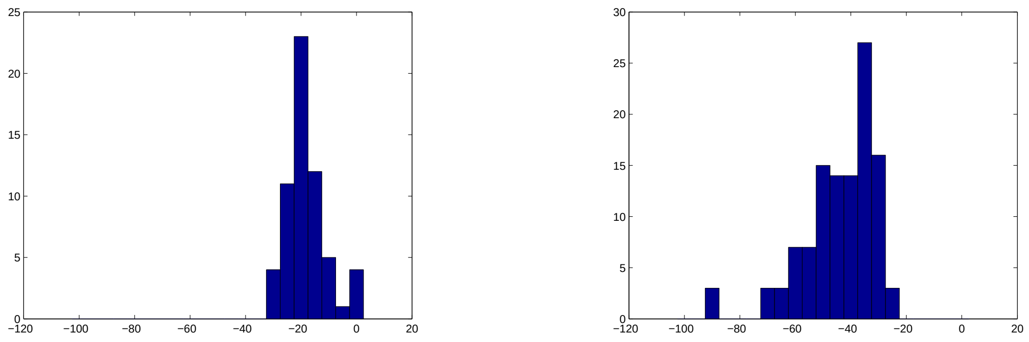


Figure 5.4 Roc Curve of False Acceptance and Genuine Acceptance rates for the proposed system.



(a) (b)

Figure 5.5 Histogram of (a) Inter-writer and (b) Intra-writer distances

Chapter 6

Conclusions and Future Work

Handwriting recognition and analysis is gaining popularity with the advent of pen-based devices, and the need for robust systems for recognition and writer identification is on the rise. In this thesis, we have explored the problem of writer identification. Due to habituation and the complex generation process, each individual develops his own style of handwriting which makes it different and discriminating from others. In this thesis, we discussed the problem of handwriting identification from different aspects such as text-independent and text-dependent. In the case of text-independent handwriting identification, the system learns writer's characteristics and style from the handwriting itself and uses that style information to identify the writer, later. The major problem of text-dependent systems is to classify the distance between handwriting samples as within and between-writer distance. High with-in writer variations and low between-writer variations due to same text, is the major problem in the case of text-dependent systems. We propose a method for text-selection based on boosting such that the margin between these distance distributions increases that in turn will improve the performance of the system.

The problems of forensic applications of handwriting is quite different than that of civilian applications. In the case of forensic analysis of the documents, handwriting can not be considered natural, which is a major assumption in the previous two problems. At the last, we have also presented an approach for repudiation detection in handwritten documents. Due to behavioral nature of handwriting, the repudiation is always possible. We have introduced the problem of repudiation for handwritten documents and also provided a framework to detect repudiation in handwritten documents.

6.1 Key contributions

We have explored three different, but important aspects of handwriting biometrics: text-independent, text-dependent and forensic document examinations in this thesis.

- A method is proposed for text-independent writer identification [5] using online handwriting. We presented an algorithm for automatic identification and extraction of consistent features that can be used to model an individual's handwriting style. Since the system extracts features at subcharacter level of which sometimes even the writer himself is not aware, the system becomes robust to forgery. As the features are not dependent on the script and are identified from different scripts individually, the framework can easily be applied to any script.

- A framework for repudiation detection in forensic documents [6] is proposed. We introduced the problem of repudiation for handwriting for the first time, and presented a hypothesis testing based framework for writer verification in forensic applications.

- A text-dependent writer verification framework for civilian applications [7] has been proposed. We presented an algorithm to generate writer-specific test sentences for individual writers which makes the system forgery resistant (by implanting randomness into the generation process), and fast as the amount of text required for verification is lower. The system is being designed specifically for low security access control and civilian applications where the false rejection rates needed to be low which can be controlled with varying thresholds in the system.

6.2 Future work

The problem of writer identification has been analyzed using online handwriting. However, it remains to be seen whether the system performance will be affected by using both online and offline features together. At the same time, quantitative analysis of handwriting individuality can be done, i.e., how much individuality does specific piece of a handwriting possess. In other words, can we confidently set upper and lower limits on the performance of the system?

Publications

The work in the thesis resulted in the following publications:

- **Anoop M. Namboodiri and Sachin Gupta**, *"Text-Independent writer identification for online handwriting"*, In Proceedings of "International Workshop on Frontiers in Handwriting Recognition", 23-26, Oct, 2006, Labarum, France.
- **Sachin Gupta and Anoop M. Namboodiri**, *"Repudiation Detection in Handwritten Documents*", In Proceedings of "International conference of Biometrics", 356-365, 2007, August, Seoul, Korea.
- **Sachin Gupta and Anoop M. Namboodiri**, *"Text-dependent writer verification"*, submitted to, "International Conference on Frontiers in Handwriting Recognition", Montreal, Canada.
- **Sachin Gupta and Anoop M. Namboodiri**, *"Text-dependent writer verification"*, To be submitted, "IEEE Transactions of Information Security and Forensics".

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