Off-Line Signature Recognition

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INTRODUCTION

The most commonly used protection mechanisms today are based on either what a person possesses (e.g. an ID card) or what the person remembers (like passwords and PIN numbers). However, there is always a risk of passwords being cracked by unauthenticated users and ID cards being stolen, in addition to shortcomings like forgotten passwords and lost ID cards (Huang & Yan, 1997). To avoid such inconveniences, one may opt for the new methodology of Biometrics, which though expensive will be almost infallible as it uses some unique physiological and/or behavioral (Huang & Yan, 1997) characteristics possessed by an individual for identity verification. Examples include signature, iris, face, and fingerprint recognition based systems.

The most widespread and legally accepted biometric among the ones mentioned, especially in the monetary transactions related identity verification areas is carried out through handwritten signatures, which belong to behavioral biometrics (Huang & Yan,1997). This technique, referred to as signature verification, can be classified into two broad categories - online and off-line. While online deals with both static (for example: number of black pixels, length and height of the signature) and dynamic features (such as acceleration and velocity of signing, pen tilt, pressure applied) for verification, the latter extracts and utilizes only the static features (Ramesh and Murty, 1999). Consequently, online is much more efficient in terms of accuracy of detection as well as time than off-line. But, since online methods are quite expensive to implement, and also because many other applications still require the use of off-line verification methods, the latter, though less effective, is still used in many institutions.

BACKGROUND

Starting from banks, signature verification is used in many other financial exchanges, where an organization's main concern is not only to give quality services to its customers, but also to protect their accounts from being illegally manipulated by forgers.

Forgeries can be classified into four types—random, simple, skilled and traced (Ammar, Fukumura & Yoshida, 1988; Drouhard, Sabourin, & Godbout, 1996). Generally online signature verification methods display a higher accuracy rate (closer to 99%) than off-line methods (90-95%) in case of all the forgeries. This is because, in off-line verification methods, the forger has to copy only the shape (Jain & Griess, 2000) of the signature. On the other hand, in case of online verification methods, since the hardware used captures the dynamic features of the signature as well, the forger has to not only copy the shape of the signature, but also the temporal characteristics (pen tilt, pressure applied, velocity of signing etc.) of the person whose signature is to be forged. In addition, he has to simultaneously hide his own inherent style of writing the signature, thus making it extremely difficult to deceive the device in case of online signature verification.

Despite greater accuracy, online signature recognition is not encountered generally in many parts of the world compared to off-line signature recognition, because it cannot be used everywhere, especially where signatures have to be written in ink, e.g. on cheques, where only off-line methods will work. Moreover, it requires some extra and special hardware (e.g. pressure sensitive signature pads in online methods vs. optical scanners in off-line methods), which are not only expensive but also have a fixed and short life span.

MAIN THRUST

In general, all the current off-line signature verification systems can be divided into the following sub-modules:

- Data Acquisition
- Preprocessing and Noise Removal
- Feature Extraction and Parameter Calculations
- Learning and Verification (or Identification)

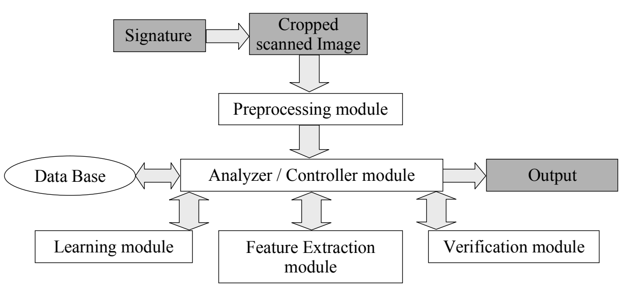
Data Acquisition

Off-line signatures do not consider the time related aspects of the signature such as velocity, acceleration and pressure. Therefore, they are often termed as "static" signatures, and are captured from the source (i.e. paper) using a camera or a high resolution scanner, in comparison to online signatures (in which data is captured using a digitizer or an instrumented pen generating signals) (Tappert, Suen, & Wakahara, 1990; Wessels & Omlin, 2000), which do consider the time related or dynamic aspects besides the static features.

Preprocessing

The preprocessing techniques that are generally performed in off-line signature verification methods comprise of noise removal, smoothening, space standardization and normalization, thinning or skeletonization, converting a gray scale image to a binary image, extraction of the high pressure region images, etc.

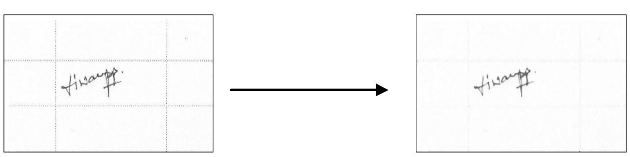
Figure 1. Modular structure of an off-line verification system



- **Noise Removal:** Signature images, like any other image may contain noises like extra dots or pixels (Ismail & Gad, 2000), which originally do not belong to the signature, but get included in the image because of possible hardware problems or the presence of background noises like dirt. To recognize the signature correctly, these noise elements have to be removed from the background in order to get the accurate feature matrices in the feature extraction phase. A number of filters have been used as preprocessors (Ismail & Gad, 2000) by researchers to obtain the noise free image. Examples include the mean filter, median filter, filter based on merging overlapped run lengths in one rectangle (Ismail & Gad, 2000) etc. Among all the filtering techniques mentioned above, average and median filtering are considered to be standard noise reduction and isolated peak noise removal techniques(Huang & Yan, 1997). However, median filter is preferred more because of its ability to remove noises without blurring the edges of the signature instance unlike the mean filter.
- **Space Standardization and Normalization:** In Space standardization, the distance between the horizontal components of the same signature is standardized, by removing blank columns, so that it does not interfere with the calculation of global and local features of the signature image (Baltzakis & Papamarkos, 2001; Qi & Hunt, 1994). In normalization, the signature image is scaled to a standard size which is the average size of all training samples, keeping the width to height ratio constant (Baltzakis & Papamarkos, 2001; Ismail & Gad, 2000; Ramesh & Murty, 1999).
- **Extracting the Binary Image from Grayscale Image:** Using the Otsu's method a threshold is calculated to obtain a binary version of the grayscale image (Ammar, Fukumura, & Yoshida, 1988; Ismail & Gad, 2000; Qi & Hunt, 1994). The algorithm is as follows:

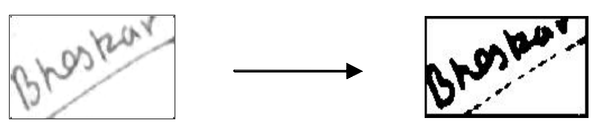
$$S(x,y) = \begin{cases} 1 & R(x,y) > threshold, \\ 0 & R(x,y) < threshold, \end{cases}$$

Figure 2. Noise removal using median filter



(a) Gray scale (b) Noise free

Figure 3. Converting grayscale image into binary image



(a) Gray scale (b) Binary

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