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Off-line signature verification based on grey level information using texture features

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ABSTRACT

A method for conducting off-line handwritten signature verification is described. It works at the global image level and measures the grey level variations in the image using statistical texture features. The co-occurrence matrix and local binary pattern are analysed and used as features. This method begins with a proposed background removal. A histogram is also processed to reduce the influence of different writing ink pens used by signers. Genuine samples and random forgeries have been used to train an SVM model and random and skilled forgeries have been used for testing it. Results are reasonable according to the state-of-the-art and approaches that use the same two databases: MCYT-75 and GPDS-100 Corpuses. The combination of the proposed features and those proposed by other authors, based on geometric information, also promises improvements in performance.

1. Introduction

The security requirements of today's society have placed biometrics at the centre of an ongoing debate concerning its key role in a multitude of applications [1–3]. Biometrics measure individuals' unique physical or behavioural characteristics with the aim of recognising or authenticating identity. Common physical biometrics include fingerprints, hand or palm geometry, retina, iris, or facial characteristics. Behavioural characteristics include signature, voice (which also has a physical component), keystroke pattern, and gait. Signature and voice technologies are examples of this class of biometrics and are the most developed [4].

The handwritten signature is recognised as one of the most widely accepted personal attributes for identity verification. This signature is a symbol of consent and authorisation, especially in the credit card and bank checks environment, and has been an attractive target for fraud for a long time. There is a growing demand for the processing of individual identification to be faster and more accurate, and the design of an automatic signature verification system is a real challenge. Plamondon and Srihari [5] noted that automatic signature verification systems occupy a very specific niche among other automatic identification systems: "On the one hand, they differ from systems based on the possession of something (key, card, etc.) or the knowledge of something (passwords, personal information, etc.), because they rely on a specific, well learned gesture. On the other hand, they also differ from systems based on the biometric properties of an individual (fingerprints, voice prints, retinal prints, etc.), because the signature is still the most socially and legally accepted means of personal identification."

A comparison of signature verification with other recognition technologies (fingerprint, face, voice, retina, and iris scanning) reveals that signature verification has several advantages as an identity verification mechanism. Firstly, signature analysis can only be applied when the person is/was conscious and willing to write in the usual manner, although it is possible that individuals may be forced to submit the handwriting sample. To give a counter example, a fingerprint may also be used when the person is in an unconscious (e.g. drugged) state. Forging a signature is deemed to be more difficult than forging a fingerprint, given the availability of sophisticated analyses [6]. Unfortunately, signature verification is a difficult discrimination problem since a handwritten signature is the result of a complex process depending on the physical and psychological conditions of the signer, as well as the conditions of the signing process [7]. The net result is that a signature is a strong variable entity and its verification, even for human experts, is not a trivial matter. The scientific challenges and the valuable applications of signature verification have

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attracted many researchers from universities and the private sector to signature verification. Undoubtedly, automatic signature verification plays an important role in the set of biometric techniques for personal verification [8,9].

In the present study, we focus on features based on grey level information from images containing handwritten signatures, especially those providing information about ink distribution along traces delineating the signature. Textural analysis methodologies are included for this purpose since they provide rotation and luminance invariance.

The paper is organised as follows: Section 2 presents the background to off-line signature verification. Section 3 provides an overview of statistical texture analysis. Section 4 describes the approach proposed. Section 5 presents details about the database. Section 6 is devoted to the classifiers. Section 7 presents the evaluation protocol and reports the experimental results. The paper ends with concluding remarks.

2. Background

There are two major methods of signature verification. One is an on-line method to measure sequential data, such as handwriting speed and pen pressure, with a special device. The other is an off-line method that uses an optical scanner to obtain handwriting data written on paper. There are two main approaches for off-line signature verification: the static approach and pseudo-dynamic approach. The static one involves geometric measures of the signature while the pseudo-dynamic one tries to estimate dynamic information from the static image [10]. On-line systems use special input devices such as tablets, while off-line approaches are much more difficult because the only available information is a static two-dimensional image obtained by scanning pre-written signatures on a paper; the dynamic information of the pen-tip (stylus) movement such as pen-tip coordinates, pressure, velocity, acceleration, and pen-up and pen-down can be captured by a tablet in real time but not by an image scanner. The off-line method, therefore, needs to apply complex image processing techniques to segments and analyse signature shape for feature extraction [11]. Hence, on-line signature verification is potentially more successful. Nevertheless, off-line systems have a significant advantage in that they do not require access to special processing devices when the signatures are produced. In fact, if the accuracy of verification systems is stressed, the off-line method has much more practical application areas than that of the on-line one. Consequently, an increase in amount of research has studied feature-extraction methodology for off-line signature recognition and verification [12].

It is also true that the track of the pen shows a great deal of variability. No two genuine signatures are ever exactly the same. Actually, two identical signatures would constitute legal evidence of forgery by tracing. The normal variability of signatures constitutes the greatest obstacle to be met in achieving automatic verification. Signatures vary in their complexity, duration, and vulnerability to forgery. Signers vary in their coordination and consistency. Thus, the security of the system varies from user to user. A short, common name is no doubt easier to forge than a long, carefully written name, no matter what technique is employed. Therefore, a system must be capable of ‘‘degrading’’ gracefully when supplied with inconsistent signatures, and the security risks must be kept to acceptable levels [13].

Problems of signature verification are addressed by taking into account three different types of forgeries: random forgeries, produced without knowing either the name of the signer nor the shape of its signature; simple forgeries, produced knowing the name of the signer but without having an example of his signature; and skilled forgeries, produced by people who, after studying an original instance of the signature, attempt to imitate it as closely as possible. Clearly, the problem of signature verification becomes more and more difficult when passing from random to simple and skilled forgeries, the latter being so difficult a task that even human beings make errors in several cases. Indeed, exercises in imitating a signature often allow us to produce forgeries so similar to the originals that discrimination is practically impossible; in many cases, the distinction is complicated even more by the large variability introduced by some signers when writing their own signatures [14]. For instance, studies on signature shape found that North American signatures are typically more stylistic in contrast to the highly personalised and ‘‘variable in shape’’ European ones [15].

2.1. Off-line signature verification based on pseudo-dynamic features

Dynamic information cannot be derived directly from static signature images. Instead, some features can be derived that partly represent dynamic information. These special characteristics are referred to as pseudo-dynamic information. The term ‘‘pseudo-dynamic’’ is used to distinguish real dynamic data, recorded during the writing process, from information, which can be reconstructed from the static image [15].

There are different approaches to the reconstruction of dynamic information from static handwriting records. Techniques from the field of forensic document examination are mainly based on the microscopic inspection of the writing trace and assumptions about the underlying writing process [16]. Another paper from the same author [17] describes their studies on the influence of physical and bio-mechanical processes on the ink trace and aims at providing a solid foundation for enhanced signature analysis procedures. Simulated human handwriting movements are considered by means of a writing robot to study the relationship between writing process characteristics and ink deposit on paper. Approaches from the field of image processing and pattern recognition can be divided into: methods for estimating the temporal order of stroke production [18,19]; methods inspired by motor control theory, which recover temporal features on the basis of stroke geometries such as curvature [20]; and finally, methods analysing stroke thickness and/or stroke intensity variations [21–25]. An analysis of mainly grey level distribution, in accordance with methods of the last group, is reported in this paper. A grey level image of a scanned handwritten signature indicates that some pixels may represent shapes written with high pressure, which appear as darker zones. High pressure points (HPPs) can be defined as those signature pixels which have grey level values greater than a suitable threshold. The study of high pressure features was proposed by Ammar et al. [21] to indicate regions where more physical effort was made by the signer. This idea of calculating a threshold to find the HPP was adopted and developed by others researchers [26,14]. Lv et al. [27] set two thresholds to store only the foreground points and edge points. They analyse only the remaining points whose grey level value is between the two thresholds and divide them into 12 segments. The percentage of the points whose grey level value falls in the corresponding segment is one of the values of the feature vector that reflects the grey level distribution. Lv and co-workers also consider stroke width distribution. In order to analyse not only HPPs but also low pressure points (LPP) a complementary threshold has been proposed by Mitra et al. [28]. In a previous work, we use a radial and angular partition (RAP) for a local analysis to determine the ratio, over each cell, between HPPs and all points conforming the