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Dynamic Structural Statistical Model Based Online Signature Verification

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ABSTRACT

In this article, a new dynamic structural statistical model based online signature verification algorithm is proposed, in which a method for statistical modeling the signature's characteristic points is presented. Dynamic time warping is utilized to match two signature sequences so that correspondent characteristic point pair can be extracted from the matching result. Variations of a characteristic point are described by a multi-variable statistical probability distribution. Three methods for estimating the statistical distribution parameters are investigated. With this dynamic structural statistical model, a discriminant function can be derived to judges a signature to be genuine or forgery at the criterion of minimum potential risk. The proposed method takes advantage of both structure matching and statistical analysis. Tested in two signature databases, the proposed algorithm got much better signature verification performance than other results. [Article copies are available for purchase from InfoSci-on-Demand.com]

Keywords: *DTW; Handwriting Analysis; Pattern Matching; Pattern Recognition; Probability and Statistics; Signature Verification*

INTRODUCTION

Online handwritten signature verification (Vielhauer, 2005) is an open problem in the area of pattern recognition. The difficulty lies in big variances of genuine and forgery signatures and in detecting forgeries while allowing certain variability in genuine signatures, and also in the shortage of training samples which makes the verification problem even worse. Researchers made researches in this area and gave some solutions to it (Pirlo, 2003; Dimauro et al, 2004; Lei & Govindaraju, 2005; Deng et al, 2005). In general, there are two main approaches in dealing with this problem (Plamondon & Srihari, 2000; Parizeau & Plamondon, 1990; Gupta & McCabe, 1997): the function based approach and the parameter based approach.

The function based approach looks on the signature as time functions. Dynamic time warping (DTW) (Martens & Claesen, 1996; Jin & Liu, 1999; Jain et al, 2002; Tanabe et al, 2001), improved DTW (Munich & Perona, 1999; Feng & Wah, 2003) or Hidden Markov Model (Muramatsu & Matsumoto, 2003; Igarza et al, 2003) methods are used to reveal the local relationship between two time functions and give their differences to make a decision. For example, Yi et al. (2005) introduced a DTW based signature verification algorithm that uses the phase output of Gabor filter. Two signature dissimilarities are calculated from the feature profile and the phase profile. Fierrez et al. (2007) proposed a signature verification system using a set of time sequences and Hidden Markov Models. The best performance is achieved with seven discrete-time functions and 2 states with 32 Gaussian mixtures per state. The function based verification approach doesn't need many training samples, but the local difference values are given subjectively and lack of statistical basis in the DTW method and much computation power is required to train the model in the HMM method.

The parameter based approach does not use the signature's time-sample attributes directly, but extracting parameters from the signature (Kiran et al, 2001; Lee et al, 1996; Zhao & Li, 2003; Richiardi & Drygajlo, 2003). The parameters are supposed to follow some statistical distributions. Feature selection and feature transform are adopted (Kim et al, 1995; Brittan & Fairhurst, 1994). Statistical classifiers are utilized to make the decision. This method tries to give a statistical model to a signature. But the statistical distribution function can not be determined easily and a number of training samples are needed, thus constrain the efficiency of this method. Some more recent discussions on structural analysis, verification and synthesis of signatures can also be found in the study of Popel (2007) and Kamel et al. (2008).

In this article, a dynamic structural statistical model based online signature verification algorithm is proposed, which synthetically uses structural matching and statistical probability function estimation.

A signature sample is first resampled as a time sequence with fixed time interval (8 millisecond). All resampled points in the reference sequence are regarded as characteristic points of reference signature. Utilizing DTW method to get correspondence point pairs between a test signature sequence and a reference signature sequence, the characteristic points of the test signature are got. The variations of each characteristic point of the test signature sequence comparing with the corresponding characteristic point of the reference signature sequence are described by multi-variable statistical probability distribution functions, which compose the Dynamic Structural Statistical Model (abbreviated as DSSM). The same characteristic point pair in genuine and forgery signatures will get different statistical distributions. Thus a signature can be judged as genuine or forgery with different posterior probability estimation based on the DSSM.

To resolve the problem of estimating the statistical distribution parameters with

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