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Online signature verification based on writer dependent features and classifiers☆

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ABSTRACT

In this work, an approach for online signature verification based on writer specific features and classifier is investigated. Existing models for online signatures are generally writer independent, as a common classifier or fusion of classifier is used on a common set of features for all writers during verification. In contrast, our approach is based on the usage writer dependent features as well as writer dependent classifier. The two decisions namely optimal features suitable for a writer and a classifier to be used for authenticating the writer are taken based on the error rate achieved with the training samples. The performance of our model is tested on both MCYT-100 (DB1), a sub corpus of MCYT data set, consisting of signatures of 100 writers, MCYT-330 (DB2) consisting of signatures of all 330 writers and visual subcorpus of SUSIG dataset. Experimental results confirm the effectiveness of writer dependent characteristics for online signature verification. The error rate that we achieved is lower when compared to many existing contemporary works on online signature verification especially when the number of training samples available for each writer is sufficient enough.

1. Introduction

Signature has been the most commonly adapted behavioral biometric trait for human identity establishment in many applications. Depending on the acquisition mode, signature verification can be categorized as offline and online [21]. In an offline mode, verification is done based on the information extracted from the hard copy of the signature image captured from a paper document. In an online mode, signature is captured using special devices such as smart pens, pressure sensitive tablets etc., which can record dynamic features of a writer such as velocity, pressure, acceleration etc., and verification is done considering both static and dynamic features. As these dynamic features are unique for an individual writer and also difficult to forge, online signature verification is more reliable than an offline mode.

Based on the representation schemes and matching techniques, online signature verification methods can be categorized as parametric and function based approaches [34]. A parametric based approach results in more compact representation as the entire signature is represented by means of a few parameters [25,36,38]. During verification, corresponding parameters of a test signature and a reference signature are compared. Parameters are further classified as global and local parameters depending on whether they correspond to the whole signature or to a specific point in the signature [20]. In a function based approach, a signature is represented by means of time functions of various dynamic properties such as pressure, velocity, acceleration etc., and verification is done by comparing the time functions of a test signature and a reference signature [22,33,39,40]. A function based approach generally takes a longer matching time compared to a parametric based approach yet resulted in lower error rate.

In literature we can see the application of various classifiers for online signature such as SVM [15,32], neural networks [1,5], HMM [2,3,12], Parzen window [29,30,43], distance based [4,35], random forest [16] and symbolic classifier [17,32]. Further, fusion based approaches are also proposed. Fusion may be either at the feature level or at the score level. In [28], the effect of different dynamic features such as pen pressure, azimuth and pen altitude on the verification performance is investigated. Rohilla et al. [37] proposed an approach where the various online signature features are categorized and are fused in different combinations for verification. Aguiliar et al. [1,2] proposed an approach where the matching scores obtained from two classifiers trained on different categories of features are fused to obtain a combined score for authenticating a signature. Nanni [29] proposed an approach where the matching

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score of various single class classifiers are fused using sum rule. In these works, it has been well established that the fusion based approaches result in a considerable improvement in the performance of the system when compared to the performance of an individual classifier. Cordella et al. [9] proposed a multi-expert approach where the decision on a test signature is taken based on combined decision of the individual experts. Zhang et al. [42] proposed a three stage verification system considering global, local and function features. Verification is done in stages considering these categories of features and a test signature is accepted as genuine if it passes through all the three stages. In multi expert approach [6], a signature is segmented into different strokes and each stroke is represented in different domains. Each stroke is authenticated individually and the final decision is taken based on the weighted average of the decisions of individual strokes. Approaches based on ensemble of classifiers also have been attempted [26,30].

As a signature of a writer depends on his/her physical and mental state, the effectiveness of a verification system depends on how best the writer dependent characteristics are considered. Generally, in a signature, writer dependent characteristics include writer dependent threshold, writer dependent features and writer dependent classifiers. Most of the existing works on online signature verification exploit writer dependency at the threshold level where different similarity thresholds are used for different writers [1,2,17,21]. It has been well argued in these works that the usage of writer dependent threshold resulted in lower error rate compared to the usage of a common threshold for all writers.

Few attempts exploiting writer dependency at feature level can be traced where different set of features are used for different writers to effectively preserve the characteristics of the respective writer. In [41], optimal features for a writer are selected using genetic algorithm based on the discriminating power of the feature vector of the writer. But the main drawback of the genetic algorithm is the need for setting up of a number of parameters such as mutation probability, crossover probability, stop condition etc. Guru et al. [18,19] proposed a model based on writer dependent features which are selected based on a score computed for each feature of the respective writer, thereby resulting in selection of different set of features for different writers.

In the existing works, the utilization of writer dependency is limited to the usage of writer dependent thresholds and writer dependent features. Writer dependency has not been still exploited at classifier level especially for online signatures. Eskander et al. [11] proposed a hybrid approach for offline signatures where initially a writer independent classifier is built for each individual and later a writer dependent classifier is designed for each writer when enough number of samples are available. In spite of several approaches, still there is a difference in the way a human expert does verification when compared to a machine. Generally, a human expert looks for a different set of discriminating characteristics for different writers. Hence for a verification system to be effective, it requires considering writer dependent features rather than a common set of features for all writers. Further, the matching strategy adopted by a human expert will also be different for different writers. As the performance of any classifier depends on the nature of training samples, usage of same classifier for all writers is not effective. The reason for variations in the distribution of training signatures for different writer is due to variations in signing from a writer to a writer [24]. Hence, an automatic verification system based on the usage of writer dependent classifier is more effective when compared to the usage of a common classifier.

Considering these factors, in this work, we investigate an approach for online signature verification utilizing writer dependent characteristics. We exploit writer dependency both at feature level and at classifier level in two different stages. In the first stage, writer dependent features are selected to effectively preserve the characteristics of a particular writer. In the second stage, a classifier suitable for a writer is trained using the selected features. Even though a writer specific model requires a classifier to be trained each time when a new user is enrolled to the system, it is more secured than the writer independent system. Considering the security issues in most of the applications, it is necessary to build a verification system based on writer dependent characteristics. Overall, the major contributions of this work are:

- Exploration of writer dependent features and adaption of writer dependent classifier.
- A quantitative study on the relationships between writer dependent features and writer dependent classifiers on verification performance.

This paper is organized as follows. In Section 2, we discuss different stages of our proposed model. Details of training and testing data, experimental protocol along with the results are given in Section 3. A comparative study of our model with other existing models is reported in Section 4. Detailed critical discussion of the proposed model is presented in Section 5 and finally conclusions and future avenues are drawn in Section 6.

2. Proposed model

The proposed model has three stages; selection of writer dependent features, fixing up of a suitable classifier for a writer followed by signature verification based on the selected features and classifier.

2.1. Writer dependent feature selection

In this work, writer dependent features are selected using the feature selection algorithm proposed by Cai et al. [7]. It is a filter type feature selection algorithm which works on the principle of spectral clustering. Features selected indicate the ability of the feature in preserving the cluster structure. In our work, features for each writer are selected as follows. Given n number of signatures of a writer each characterized by P features, the feature selection algorithm computes the score for each of the P features and selects d features ($d < P$) out of P features with top scores. The steps in the adapted feature selection method are

- Define a graph with n vertices each corresponding to a data point x_i and a weight matrix representing the relationships between each data point and its nearest neighbor using heat-kernel weighting scheme.

$$W_{ij} = e^{-\frac{\|x_i - x_j\|}{\sigma}} \tag{1}$$

- Compute the graph Laplacian $L = D - W$ where W is the weight matrix and D is the diagonal matrix whose elements are the row sum or column sum of the weight matrix.
- Solve the generalized eigen problem $Ly = \lambda Dy$ where $Y = (y_1, y_2, y_3, \ldots, y_K)$ are the eigen vectors of the above eigen problem. Each row of Y is the flat embedding for each data points.
- After flat embedding for the data points are obtained, the contribution of each feature in differentiating each cluster is measured as follows; given y_k, a relevant subset of features is obtained by minimizing the fitting error as

$$\min_{a_k} \|y_k - X^T a_k\|^2 + \beta |a_k| \tag{2}$$

Each a_k contains the combination coefficients for different features in approximating y_i. $|a_i|$ is the $L-1$ norm of a_k. If the data set consists of K clusters, then after obtaining K sparse coefficient vectors as discussed, a subset containing non-zero coefficients in a_k