Advanced methods for two-class problem formulation for on-line signature verification

Loris Nanni*, Alessandra Lumini

DEIS, IEIIT—CNR, Università di Bologna, Viale Risorgimento 2, 40136 Bologna, Italy

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Abstract

We present several systems for on-line signature verification that approach the problem as a two-class pattern recognition problem. To our knowledge, this is the first work that solves the problem of on-line signature verification as a two-class problem using global (and not local) features. The feature vector obtained by global features is then classified into one of the two classes (genuine or impostor) by a support vector machine. Moreover, we show the combination of the systems introduced in this work permit a dramatic reduction of the equal error rate.

Keywords: Signature verification; Support vector machine

1. Introduction

Let us call such signatures for which we have only a static visual record, off-line, and let us call signatures during whose production the pen trajectory or dynamics is captured, on-line. Whereas attempts to automate the verification of off-line signatures have fallen well short of human performance to this point, it is demonstrated that automatic on-line signature verification is feasible [4]. The main approaches proposed in the literature in order to extract relevant information from on-line signature data [4,8] are: (i) feature-based approaches, in which a holistic vector representation consisting of global features is derived from the acquired signature trajectories, and (ii) function-based approaches, in which time sequences describing local properties of the signature are used for recognition (e.g., position trajectory, velocity, acceleration, force, or pressure). In [2] an on-line signature verification system based on fusion of local and global information is presented; in this paper we propose a new approach that extends the previous work with respect to the global feature-based machine expert. The results obtained by the subsystem exploiting global information in [2] were characterized by high variability of the performance changing the system parameter (number of features retained); in [7] the authors show that a random subspace-based ensemble of Parzen Window Classifiers makes the performance more stable with respect to system parameters.

Results using all the 5000 signatures from the 100 subjects of the SUBCORPUS-100 MCYT Bimodal Biometric Database [9] are presented, yielding remarkable performance improvement both with random and skilled forgeries. The machine experts based on global information are described in Section 2. Experimental procedure and results are given in Section 3. Finally, conclusions are drawn in Section 4.

2. Machine expert based on global information

The systems here proposed are based on the features proposed in a previous work [2], where the complete set of 100 global features is detailed (a \( d \)-dimensional feature vector, \( d = 100 \)).
In this paper we propose five methods:

- modified version of the classification method proposed by Kholmatov in [5] (KHA);
- our “base” classifier (BASE);
- random subspace ensemble of BASE (RS);
- random subspace ensemble with resampling of BASE (RSB);
- fusion (FUS).

2.1. KHA

For a reference set of an individual i, we compute average values over the reference set, for

- distances of reference signatures to their nearest-neighbor (d_{min,i}),
- distances of reference signatures to their farthest neighbor (d_{max,i}),
- distances of reference signatures to the template signature (d_{template,i}).

We select as the template the reference signature with the minimum average distance to all other supplied signatures. The computed average distance values describe the users variation to some extent and were selected so as to be used in normalizing signature’s min, max and template distances to its reference set. First, each training signature (Y) is compared to the signature’s in the reference set (RID) it is claimed to belong to, giving three distance values (d_{min,i}, (Y,RID), d_{max,i}, (Y,RID), and d_{template,i}, (Y,RID)). These distance values are normalized by the corresponding averages of the reference set, to give the three-dimensional feature vector. Note that the same normalization process is done both for training signatures during the training process and for testing signatures during the testing process. Using principal component analysis [1], we reduce the dimensionality from three to one while keeping most of the variance, as the three features are highly correlated. A linear classifier is trained on this feature space. Please note, in our tests we do not use the local features used in [5] but our set of global features. The system based on that proposed in [5] was ranked in first place, for skilled forgeries, in Signature Verification Competition 2004 [10].

2.2. BASE

Our first method is very simple, for each couple A and B of signatures of the training set the features extracted are used to create the vectors a and b, the difference c = a − b is a pattern of a new training set TR, the label of c is 1 if A and B belong to the same individual, else the label of c is 0. For each signature D of the test set the features extracted are used for creating the vector d; for each individual i of the training set we calculate the differences between d and each vectors e_{i,k} \( k = 1, \ldots, n \) extracted from the \( n \) signatures of the individual i. The vector \( c_{i,k} = d - e_{i,k} \) for which the 2-norm is minimum is used to calculate the score of the classes genuine and impostor. The feature vector \( (c_{i,k}) \) is classified into one of the two classes (genuine or impostor) by a radial basis function-support vector machine (RSVM) trained using TR (parameters: Gamma = 1, C = 1) [1]. Obviously, the label of \( c_{i,k} \) is 1 if the signature C belongs to individual i else the label of \( c_{i,k} \) is 0.

2.3. RS

The random subspace method is the combining technique proposed by Ho [3]. This method modifies the training data set (generating K new training sets), builds classifiers on these modified training sets, and then combines them into a final decision rule. The new training sets contain only a subset of all the features. The percentage of features retained in each training set is denoted by NFe (NFe = 50%). In our experiments, we set K = 10, and we combine the classifiers using the “max rule” [6]. Considering the similarity matching score estimated by each of the K RSVM [1] between an input signature s and its claimed identity c, the “max rule” selects as final score the maximum score of the pool of K classifiers. Please note, in this paper the similarity matching score is the class confidence value [1] obtained by RSVM.

2.4. RSB

In this method from each random subspace we build different training sets, each training set is built using a subset of D (D = 4) signatures of the entire training set. We combine the classifiers using the “max rule” [6].

2.5. FUS

This combination uses the “sum rule” [6] between RSB and KHA. Before the fusion the scores of each classifier are normalized to mean 0 and variance 1. Considering the similarity matching score estimated by RSB and KHA between an input signature s and its claimed identity c, the “sum rule” selects as final score the sum of the score of RSB and KHA.

3. Experiments

The 100 signers of the SUBCORPUS-100 MCYT database are used for the experiments (100 signers with 25 genuine signatures and 25 skilled forgeries per signer— forgers are provided the signature images of the clients to be forged and after training with them several times, they are asked to imitate the shape with natural dynamics, i.e., without breaks or slowdowns). The signature corpus is divided into the training and the test sets. In case of considering Skilled Forgeries, the training set comprises the first five genuine signatures of each individual and the
skilled forgeries of the first 20 individuals. The test set consists of the remaining samples (i.e., $80 \times 20$ client, respectively, and $80 \times 25$ impostor similarity test scores). In case of considering Random Forgeries (i.e., impostors are claiming other’s identities using their own signatures), client similarity scores are as above and we use one signature of every other user as impostor data so the number of impostor similarity scores is $80 \times 79$.

Please note, in our tests the reference set in KHA coincides with the training set. Moreover, for both KHA and BASE the example of the class 0 (impostors) are obtained considering for each individual only the forgery of that individual. We compare each forgery of an individual $i$ with each genuine of the individual $i$, we do not compare a forgery of an individual $i$ with a genuine of an individual $j$.

We compare our method with the approach based on Global Information proposed in [7] (GI), which to our knowledge is the state-of-the-art method for signature verification. Please note that GI outperforms [2,7] the local system based on a hidden Markov model that was ranked in first and second place, for random and skilled forgeries, respectively, in Signature Verification Competition 2004 [10]. For the performance evaluation we adopt the equal error rate (EER) [4], that is the error rate when the frequency of fraudulent accesses (false acceptance rate, FAR), and the frequency of rejections of people who should be correctly verified (false rejection rate, FRR) assume the same value; it can be adopted as a unique measure for characterizing the security level of a biometric system. In Figs. 1 and 2, we show that our system (FUS) permits improvement in comparison to the state-of-the-art work [2] (RPWC) of signature matcher.

The experimental results show that:

1. The global features can be used for solving the problem of on-line signature verification as a two-class problem.
2. The EERs obtained by the ensembles are lower than that obtained by BASE.
3. The fusion between KHA and RSB drastically outperforms the state-of-the-art (RPWC).

4. Conclusions

We introduced a new on-line signature matcher that dramatically outperforms the state-of-the-art [7]. The main contribution of our work is to propose and validate new algorithms based on global features that consider the signature verification problem as a two-class pattern recognition problem. It is shown experimentally that the machine expert (RS) based on the two-class classifier outperforms (skilled forgery) the system based on the one-class classifier (RPWC). We also studied the effects on the performance of combining different methods. The two proposed systems (RS and KHA) are also shown to give complementary recognition information which has been exploited with simple rules. The fusion between KHA and RSB drastically outperforms the state-of-the-art (RPWC). Our system could be used for each biometric problem, when it is possible to extract numerical features (i.e., face). Please note that random subspace works well for large sets of features with redundant features. For this reason the method proposed in this paper is well suited for a on-line signature verification method based on global features. We plan in the future to study different classifiers (i.e., adaboost) to classify between genuine and impostor.

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References


Loris Nanni is a Ph.D. Candidate in Computer Engineering at the University of Bologna, Italy. He received his Master Degree cum laude in 2002 from the University of Bologna. In 2002, he started his Ph.D. in Computer Engineering at DEIS, University of Bologna. His research interests include pattern recognition, and biometric systems (fingerprint classification and recognition, signature verification, face recognition).

Alessandra Lumini received her degree in Computer Science from the University of Bologna, Italy, on March 26, 1996. In 1998, she started her Ph.D. studies at DEIS—University of Bologna and in 2001 she received her Ph.D. degree for her work on "Image Databases". Now she is an Associate Researcher at the University of Bologna. She is a member of the BIAS Research Group at the Department of Computer Science of the University of Bologna (Cesena). She is interested in biometric systems (particularly fingerprint classification), multidimensional data structures, digital image watermarking and image generation.