International Journal of Computer Applications (0975 – 8887)
Volume 60– No.16, December 2012

SVM based Signature Verification by Fusing Global and Functional Features

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ABSTRACT
On-line signature verification can be used in real time applications like credit card transactions or resource accesses because of its popularity in regular authentication. In signature verification number of signatures avalible to train a model is very limited, and therefore identification of the most suitable features which characterize the class is critical. Therefore feature selection is essential to minimize the classification error. The mRMR (minimum Redundancy Maximum Relevance) method is applied to select the features. Verification is based on global features and scores from functional features. The scores are generated by comparing the functional features of the test signature with the corresponding reference features. These scores are treated as additional features in a two-class classification problem solved with the ANN and SVM. Verification accuracy is enhanced by fusion of user specific global and functional features. The methods are tested with the database of SVC2004.

Keywords
Support vector machine, On-line signature verification, Feature selection, mRMR.

1. INTRODUCTION
Automatic signature verification is a commonly used form of biometric verification and identification, because of wide spread acceptance of static signature in the application of personal authentication, document certification for a very long time in manual verification [1]. It can be predicted that as the technology enhances online signature will be one of the important means of biometric in this field with good user acceptance. The online context is more desirable to prevent imitation. An impostor can imitate visible shape of the signature, but it is nearly impossible to achieve the imitation of dynamic content of the signature, which is embed in the gesture of signing and is very personal.

2. LITERATURE REVIEW
One of the first publications on on-line signature verification was by Herbst and Liu [2]. In this paper handwriting was modeled as ballistic motions that do not involve sensory feedback. Extensive literature is available in the field of online (dynamic) signature verification. A survey of signature verification can be found in [3-5].

Leclerc and Plamondon categorized the various signature verification methodologies into two types: functional approach and parametric approach [4]. In the function-based approach, online signatures are characterized and analyzed as time sequences (e.g., position trajectory, velocity, acceleration, pressure, direction of pen movement, and azimuth) [6].

In general, function-based features show better discriminating ability than the parameter-based features but they usually require time-consuming algorithm for comparison. However, the work by Aguilar et al. reported that the parametric approaches are equally competitive with the function based approaches [7]. In parametric approaches, the authenticity of a test signature is estimated by comparing test feature set against reference feature set. Each matching method is based on similarity (or dissimilarity) measurement. In the parameter based approach, one commonly used distance measure is Euclidean distance [6]. The verification methods are based on Neural Networks (NN) [8], Hidden Markov Model (HMM) [9], and Support vector machine (SVM) are mostly used [10-11].

Function-based approaches can be classified into local and regional methods. In local approaches, the time functions of different signatures are directly matched by using elastic matching technique such as dynamic time warping [12-16]. However, the time complexity of DTW is of $O(n^2)$. In the case of function-based approach, the matching methods must take care of the phase shift and non-linear distortion of functions.
A popular technique used for signature verification is the SVM. With the help of training examples from two classes, an SVM search the maximum separating hyperplane. In [11], comparison of SVM classifiers with HMM classifiers is carried out in terms of the number of samples used for training and verification using different types of forgeries. Under both conditions, SVM appears to produce better result. However, the main limitations of SVMs are high algorithmic complexity and extensive memory requirements in large-scale tasks.

Signature verification schemes based on Neural Network are also proposed [8]. Although, the neural network-based approaches have the capabilities in generalization, the drawback is the need for a large number of genuine and forgery signatures for training, which is not always practically viable.

In the verification system user data should be described in such a way that it will discriminate the user maximally. To fulfill this purpose the intra class variability is to be reduced and at the same time the inter class variability is to be preserved. To reduce the intra class variation and keeping the discriminatory feature, it is better to normalize the signature in the function domain before feature extraction and matching. The fusion of function and feature based verification score gives better accuracy. Selection of the consistent statistical feature is a great challenge in feature based verification [17].

3. ONLINE SIGNATURE VERIFICATION SYSTEM

A diagram of a general signature verification system is shown in Fig. 2.

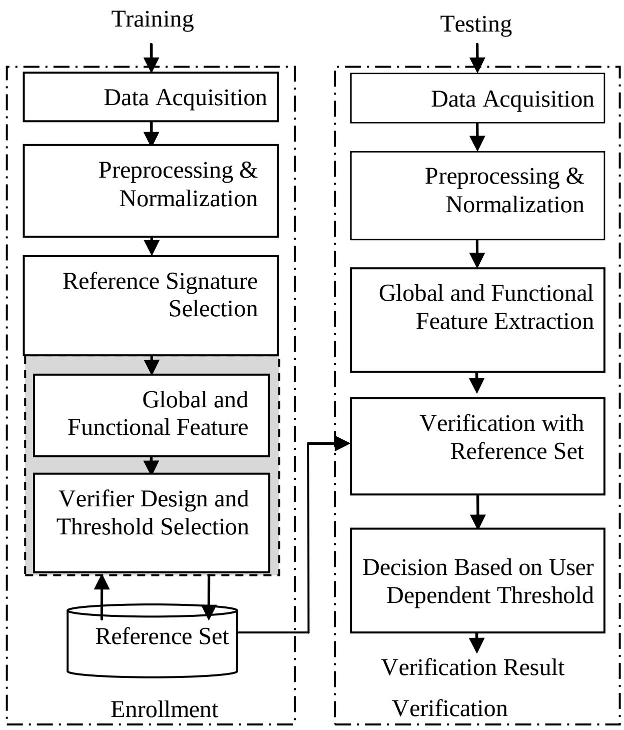

Figure 2: General model of online signature verification

Signature verification systems are generally divided into two modules: Signature enrollment or training module and signature verification or testing module. A signature verification system must provide a solution to the problems of data acquisition, preprocessing and normalization, reference signature selection, feature extraction, matching, and performance evaluation. Out of these feature selection and verification methods have been considered in this paper. Detail discussion of other modules is beyond the scope of this paper.

4. DATABASE

First international signature verification competition (SVC2004) was held as a step towards establishing common benchmark databases and benchmarking rules [18]. For each of the two tasks of the competition, a signature database involving 40 sets of signature data was created, with 20 genuine signatures and 20 skilled forgeries for each set. Experimental results have been conducted using the Task 1 SVC2004 database. Shape of online signature and its associated function are shown in Fig, 1.

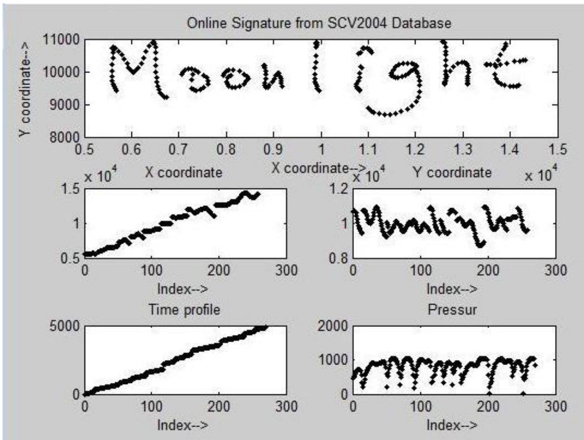

Figure 1: On-line signature shape and its associated functions from SVC2004 database

5. FEATURE EXTRACTION

Both global feature and functional feature are used here for verification.

5.1 Global Feature Extraction

In the global parametric approach, a fixed set of parameter is extracted to describe a signature pattern. More importantly, this approach is expected to be more stable against the variations in local regions, which are common in signatures. The difficulty with this approach lies in selecting the salient parameters that can distinguish between the classes and are consistent among the same set. The major limitation of this approach lies in its discriminative ability [19-20]. An averaging effect arises in calculating the parameters over the whole pattern. Although this effect is obviously the reason for the above-mentioned stability, the parameters selected from a small set of signers may not work well on a larger set of signers [19].

However, verification with global features of a signature has several advantages. It is simple to compute and address the concerns related to privacy because it does not need to retain the original signature once the features are extracted. In total 48 global features are calculated here for every signature.

5.2 Functional Feature Extraction

In the functional approach, complete signals [$x(i)$, $y(i)$, $p(i)$, $t(i)$ etc, where, i is index of the signature samples] directly or indirectly constitute the feature set. The two signals, one from the reference signature and the other from the test signature, are then compared point-to-point or segment-to-segment basis [21]. The challenge within this approach is that two signals are likely to have different durations and also undergo non-linear distortions.

Seventeen signature functions (local features) are taken for score generation. Three measures are estimated for comparison, namely 1) correlation coefficient 2) DTW distance 3) Euclidean distance. From the outputs of three measures total $17 \times 3 = 51$ scores are estimated.

6. FEATURE SELECTION

In signature verification number of sample signature avalible to train a verifier model is very limited [22], whereas number of avalible features (or attributes) are very large compared to the sample data. Feature vector with very large dimensionality leads to th curse of dimensionality problem [23]. Identification of the most suitable features of the oserved data which characterize the class is also critical. Therefore feature selection is very essetial to minimize the inconsistancy in classification.

6.1 Feature Selection by mRMR Method

In an unsupervised situation minimal error usually requires the maximal statistical dependency of the target class, say C, on the data distribution [22, 24]. The method of Minimum Redundancy Maximum Relevance (mRMR) has been proposed by Peng et al. [22].

One of the most popular approaches to realize maximum dependency is maximum relevance feature selection, i.e., selecting the features with the highest relevance to the target class C. Relevance is usually characterized in terms of correlation or mutual information. Results of global feature selection by mRMR method are shown in Table 1. Out of 48 features, 10 best selected features using mRMR method is shown in Table 1.

Table 1: 10 common selected features

Average Rank	**Symbol used**	**Name and description.**
9.45	μ_{ax}	x-directional average absolute acceleration
13.85	μ_{ay}	y-directional average absolute acceleration
15.1	σ_{ax}	Standard deviation of x-directional acceleration
15.7	μ_{axy}	Average absolute acceleration
16.625	μ_p	Average pen pressure $= mean\{p\}$
18.075	σ_{ph}	Standard deviation of the phase $= std\{Ph\}$
18.45	p_{med}	Median of writing pen pressure $= median\{p\}$
18.575	E_{SS}	Entropy of shape signature function
18.65	σ_{axy}	Standard deviation of acceleration
18.775	T_t	Duration of the complete writing process in ms

Out of 51 scores, 10 common selected scores using mRMR method is shown in Table 2.

Table 2: 10 common selected functional scores

Average Rank	**Feature Name and Description.**	**Matching Method**
13.325	X directional	Correlation efficient
13.675	Pressure Function	Euclidean Distance
13.875	Absolute acceleration	Correlation Coefficient
13.875	Pressure function	DTW Distance
15.575	Y directional	Correlation Coefficient
16.4	Absolute acceleration	Euclidean Distance
17.075	Pressure function	Correlation Coefficient
17.55	Time function	DTW Distance
17.6	Time function	Euclidean Distance
19.375	Magnitude of change in XY coordinate	Euclidean Distance

In global feature and functional score concatenated$(48 + 51 = 99)$. First 48 features are global features and rest 51 features are scores as explain above. Feature number 63 corresponds to score feature number 15 $i.e.$ Magnitude of overall acceleration with correlation score. Feature number 61 corresponds to X directional acceleration with correlation score. Similarly feature number 97 corresponds to score feature number 49 $i.e.$ Magnitude of acceleration with Euclidean distance score. Out of 99 (global features and scores respectively concatenated), 10 best selected features and scores method are shown in Table 3 using mRMR method.

Table 3: 10 common selected features and functional scores (jointly selected). G means global feature and S means score from local feature.

Average Rank	Feature No	Feature Name	G/S
17.2	22	$\boldsymbol{x}$-directional average absolute acceleration	G
24.65	23	$\boldsymbol{y}$-directional average absolute acceleration	G
25.9	63	Magnitude acceleration	S
27.075	61	X directional acceleration	S
29.45	25	Standard deviation of x-directional acceleration	G
30.1	24	Average absolute acceleration	G
30.875	62	Y directional acceleration	S
31.325	86	Pressure Function	S
32.55	69	Pressure Function	S
34.425	97	Magnitude of acceleration	S

Average rank has been computed as the mean of ranks corresponding to all 40 users in SVC2004 database.

7. SUPPORT VECTOR MACHINE

Online signature verification problem can be put as a two class classification problem. In this problem the goal is to separate the two classes by a function which is induced from the training data. Consider the example in Fig. 3. There are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin (maximizes the distance between the nearest data point of each class) as shown by bold line in Fig. 3. This is termed as the optimal separating hyperplane.

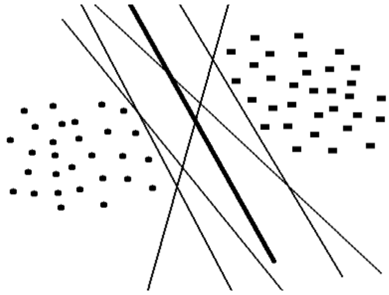

Figure 3: Optimal separating hyperplane

7.1 The Optimal Separating Hyperplane

Consider the problem of separating the set of training vectors belonging to two separate classes

$$x = \{x_1, x_2, \dots\dots, x_k\} \quad \in \mathcal{R}^n \tag{1}$$

$$y = \{y_1, y_2, \dots\dots, y_k\} \quad \in \{-1,1\} \tag{2}$$

with a hyperplane: $\quad w^T x + b = 0. \quad (3)$

The separating hyperplane is said to be optimum if the distance between the closest vectors to the hyperplane is maximal and the separation is without error. There is some redundancy in Eq. 3, and it is appropriate to consider a canonical hyperplane [25-26], where the parameters w, b are given by,

$$\min_{i} |w^T x_i + b| = 1 \tag{4}$$

A separating hyperplane in canonical form must satisfy the following constraints,

$$y_i[w^T x_i + b] \geq 1, \qquad i = 1, \dots\dots.., k \tag{5}$$

The distance $d(w, b; x)$ of a point x from the hyperplane (w, b) is,

$$d(w, b; x_i) = \frac{|w^T x_i + b|}{\|w\|} \tag{6}$$

The optimal hyperplane is given by maximizing the margin, ρ, subject to the constraints of Eq. 5. The margin is given by,

$$\rho(w, b) = \min_{x_i: y_i = -1} d(w, b; x_i) + \min_{x_i: y_i = 1} d(w, b; x_i)$$

$$= \min_{x_i: y_i = -1} \left[\frac{|w^T x_i + b|}{\|w\|}\right] + \min_{x_i: y_i = 1} \left[\frac{|w^T x_i + b|}{\|w\|}\right]$$

$$= \frac{1}{\|w\|}\left(\min_{x_i: y_i = -1} |w^T x_i + b| + \min_{x_i: y_i = 1} |w^T x_i + b|\right)$$

$$= \frac{2}{\|w\|} \tag{7}$$

The maximization of ρ can be implemented by minimizing a function $\phi(w)$, where

$$\phi(w) = \frac{1}{2}\|w\|^2 \tag{8}$$

It is independent of b because provided Eq. 5 is satisfied (i.e. it is a separating hyperplane) changing b will move it in the normal direction to itself. Accordingly the margin remains unchanged but the hyperplane is no longer optimal in that it will be nearer to one class than the other. The saddle point of the Lagrange functional gives the solution to the optimization problem of Eq. 8 under the constraints of Eq. 5 [27].

$$\phi(w, b, \alpha) = \frac{1}{2} w^T w - \sum_{i=1}^{k} \alpha_i \left(y_i[w^T x_i + b] - 1\right), \tag{9}$$

where α are the Lagrange multipliers. The Lagrangian has to be minimised with respect to w, b and maximised with respect to $\alpha \geq 0$. Lagrangian duality enables the primal problem, Eq. 9, to be transformed to its dual problem, which is easier to solve. The dual problem is given by

$$\max_{\alpha} W(\alpha) = \max_{\alpha}\left(\min_{w,b} \phi(w, b, \alpha)\right). \tag{10}$$

Thus, differentiating $\phi(w)$ with respect to w, b and setting the results equal to zero, we get the following two conditions of optimality:

Condition 1: $\quad \frac{\partial \phi}{\partial w} = 0 \ \Rightarrow w = \sum_{i=1}^{k} \alpha_i y_i x_i$

Condition 2: $\quad \frac{\partial \phi}{\partial b} = 0 \ \Rightarrow \sum_{i=1}^{k} \alpha_i y_i = 0 \quad (11)$

The solution vector w is defined in terms of an expansion that involves the k training examples. Although this solution is unique by virtue of the convexity of the Lagrangian, the same can not be said about the Lagrange coefficients, α_i.

It is also important to note that at the saddle point, for each Lagrange multiplier α_i, the product of that multiplier with its corresponding constant vanishes, as shown by

$$[\alpha_i y_i (w^T x_i + b) - 1] = 0 \ \ for\ i = 1,2, \dots., k \tag{12}$$

Therefore those multipliers exactly meeting Eq. 12 can assume nonzero values. This property follows from the Kuhn-Tucker conditions of optimization theory [28]. Hence only the points x_i which satisfy,

$$y_i(w^T x_i + b) = 1 \tag{13}$$

will have non-zero Lagrange multipliers. These points are termed Support Vectors (SV). If the data is linearly separable all the SV will lie on the margin and hence the number of SV can be very small. Consequently the hyperplane is determined by a small subset of the training set. The other points could be removed from the training set and recalculating the hyperplane would produce the same answer [25].

7.2 Gamma and C in SVM

In signature verification number of observation is very less compared to number of features. It is better to use the linear SVM rather than nonlinear kernel SVM. Because the number of features is already much larger than the number of observations, non linear mapping is not essential which map the data into a higher dimensional features space. If linear SVM is used then only parameter C is needed to search for the better accuracy.

As conjectured in [29] a small C yields a high error rate on the training patterns, whereas a large C is bound to result in a high error rate on future patterns. In this signature verification problem training accuracy is achieving 100% with large C but testing accuracy is not able to reach near 100%. So to get better testing accuracy and thereby a more reliable SVM classifier it is needed to restrict the value of parameter C within a limited range.

8. NUMERICAL EXPERIMENT

Six numerical set up has been consider for verification using SVM as shown in Table 4.

Table 4: Six numerical setups.

Setup 1:	Global Feature Based Verification Using Nonlinear (RBF kernel) SVM
Setup 2:	Global Feature Based Verification Using Linear SVM
Setup 3:	Local Score Based Verification Using Nonlinear (RBF kernel) SVM
Setup 4:	Local Score Based Verification Using Linear SVM
Setup 5:	Global Feature and Local Score Based Verification Using Nonlinear (RBF kernel) SVM
Setup 6:	Global Feature and Local Score Based Verification Using Linear SVM

The LIBSVM- A Library for Support Vector Machines toolbox is used for experiment [30]. Since version 1.2, it implements an SMO-type algorithm proposed in [31]. All the algorithms proposed in this thesis are implemented in MATLAB 7.7 [32]. Two class SVM parameters and their ranges are shown in Table 5.

Table 5: Parameter for the two class SVM classifier

Parameter Name	Value
Kernel Type	Radial basis function (RBF) $K(x_i, x) = e^{-\gamma\|x_i - x\|^2}$
Degree	0
Gamma($\boldsymbol{\gamma}$)	$2^{-60}: 2^{-0.5}: 2^{10}$
Coefficient	0
C	$2^{-50}: 2^{-0.5}: 2^{30}$
Cache size	50
epsilon	0.001
SVM type	Two Class c SVM

9. RESULTS

The results from the final stage of signature verification using SVM is shown in Table 6. User specific ranked features are used in this experiment. Summary of results using SVM with common ranked features is shown in Table 7.

Table 6: Summary of results using SVM technique and user specific ranked feature

Setup	% Training Accuracy	% Testing Accuracy	$log_2\gamma$	log_2C	Time (s)
1	100	95.75	-52.05	-27.3	0.39
2	99.88	95.94	NA	-25.33	0.34
3	100	91.75	-45.91	-22.25	0.47
4	100	91.5	NA	-16.2	0.22
5	100	96	-55.91	-40.98	0.41
6	100	97.69	NA	-34.58	0.22

Table 7: Results using SVM and common ranked features

Setup	% Training Accuracy	% Testing Accuracy	$log_2\gamma$	log_2C	Time (s)
1	100	91.57	-27.88	-7.83	0.39
2	99.63	90.69	NA	-23.79	0.74
3	100	90.75	-27.8	-8.62	0.36
4	100	89.5	NA	-17.11	0.26
5	100	92.13	-28.95	-26.9	0.37
6	100	92.38	NA	-22.39	0.26

Time indicated in Table 6 and 7 is the average time required to train 20 signatures and to test 40 signatures.ANN classifier model is formed with one hidden layer consist of five neuron feed-forward back propagation network. Average Testing accuracy is 96.125% for user specific best selected 5 features. Average Testing accuracy drops down to 87.25% for best selected common 5 features.

10. DISCUSSION AND CONCLUSION

Acceleration and pressure related features are mostly selected in all the ranking processes. By observing the performance of linear and nonlinear SVM it is found that linear SVM with only six number of features gives better result than non linear SVM (with RBF kernel function). Training accuracy is 100% in the case of nonlinear SVM but testing accuracy is not close to training accuracy. But in the case of linear SVM testing accuracy is closer to the training accuracy. It implies that linear SVM is more reliable in global feature based verification. Time taken in linear SVM is also less. All these results indicate that linear SVM outperforms the nonlinear (RBF kernel) SVM for this particular case. Combination of global features and functional scores is proven to be fruitful giving better verification accuracy (97.69%).

11. ACKNOWLEDGMENTS
The authors would like to thank the authorities of IIT Kharagpur and EU-India CultureTech Project under ECCP for their support to carry out this research work.

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