# 온라인 서명 검증을 위한 SVM의 커널 함수와 결정 계수 선택

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Selection of Kernels and its Parameters in Applying SVM to ASV

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### ABSTRACT

When using the Support Vector Machine in the online signature verification, SVM kernel function should be chosen to use non-linear SVM and the constant parameters in the kernel functions should be adjusted to appropriate values to reduce the error rate of signature verification. Non-linear SVM which is built on a strong mathematical basis shows better performance of classification with the higher discrimination power. However, choosing the kernel function and adjusting constant parameter values depend on the heuristics of the problem domain. In the signature verification, this paper deals with the problems of selecting the correct kernel function and constant parameter's values, and shows the kernel function and coefficient parameter's values with the minimum error rate. As a result of this research, we expect the average error rate to be less than 1%.

키워드

Automatic Signature Verification, SVM, Kernel Functions, Constant Parameters

### I. Introduction

In present, the verification problem of users become more and more important in smart computing environment with smart terminal equipments being widely used in our lives. Passwords are often used by the touch-screen pattern and path ways, but there are likely to be disadvantageous for users, because it is easy to be divulged. In smart equipments there are various inputting methods , such as pressure methods, electrostatic methods. electromagnetic methods and so on. Even though there exists various algorithms for ASV, the reliable verification method have rarely been studied for smart environment.

In ASV(Automatic Signature Verification), this paper mainly deals with the problems of selecting the correct kernel function and constant parameters' values, and shows the kernel function and coefficient parameter's values with the minimum error rate.

## II. SVM for ASV

#### 1. SVM Overview

SVM(support vector machine) is supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis.

It is supposed that the N D-dimensional feature vector  $x_i$  and the  $y_i$  which has the value of 1 and -1 was given. The SVM look for a classification boundary between the two classes that are the same as another classifier. That minimizes the objective function in the SVM is the same as equation (1).

$$\frac{1}{2}||w||^2 + C\sum_{i=1}^N \xi_i \tag{1}$$

## 2. Kernel Functions

 $K(x_i, x_i) = \Phi(x_i)^T \Phi(x_i)$  is called the kernel function. Through new kernels are being proposed by researchers, there are following four basic kernels:

Table 1. Four Kernel Functions

Туре		Function		
Linear		$K\!\left(x_i, x_j\right) = x_i^T x_j$		
Polynom	ial	$K\!\!\left(\boldsymbol{x}_{i}, \boldsymbol{x}_{j}\right) \!= (\boldsymbol{\gamma} \boldsymbol{x}_{i}^{T} \boldsymbol{x}_{j} + r)^{d}, \boldsymbol{\gamma} \! > \! 0$		
RBF		$K\!\!\left(x_i, x_j\right) \!= \exp\!\left(-\gamma \parallel x_i - x_j \parallel^2\right), \gamma \!>\! 0.$		
Sigmoid	1	$K\!\left(x_i, x_j\right) = \tanh\left(\gamma x_i^T x_j + r\right)$		

Here,  $\gamma$ , r and d are kernel parameters.

### III. Experimental Results

For each signer, it shows the results of analyzing the performance in terms of the FRR (False Reject Rate), the FAR (False Accept Rate) and the average error rates in Table 4.. It is worthy to notice that there are significant differences according to the signer, and the performance of FAR is better than the FRR, and the excellent for the discrimination of the forgery signature can be seen.

Kernel Function	(pres	ieature u ssure-re res excl	lated	76 features used (pressure-related features included)		
	FRR	FAR	AVG	FRR	FAR	AVG
Linear	1.96	0.65	1.31	1.16	0.47	0.82
Polynomial	33.6	10.7	22.2	41.6	4.42	23.0
RBF	3.88	1.03	2.45	2.48	1.14	1.81
Sigmoid	4.15	1.17	2.66	3.29	1.25	2.27

Table 2.	Performance	of Each Ke	rnel Func	tion
(with 25	samples for	positive and	negative	class)

## **IV.** Conclusions

The aim of this research was to derive an online signature verification algorithm for smart devices. For which, in the signature verification algorithm, the learning method was employed using all the data of the forgery signature and the true signature, by applying this learning method for the SVM in the signature verification, and presents the learning algorithm and the signature verification algorithm.

### References

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