

## A SURVEY ON PATTERN RECOGNITION APPLICATIONS OF SUPPORT VECTOR MACHINES

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In this paper, we present a survey on pattern recognition applications of Support Vector Machines (SVMs). Since SVMs show good generalization performance on many real-life data and the approach is properly motivated theoretically, it has been applied to wide range of applications. This paper describes a brief introduction of SVMs and summarizes its various pattern recognition applications.

*Keywords:* Support Vector Machines; pattern recognition; face detection; face recognition; object recognition; handwritten character recognition; speech recognition.

### 1. Introduction

The SVM is a new type of pattern classifier based on a novel statistical learning technique that has been recently proposed by Vapnik and his co-workers.<sup>13,19,101</sup> Unlike traditional methods such as neural networks, which minimize the empirical training error, SVMs aim at minimizing an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data.<sup>3</sup> Since SVMs are known to generalize well even in high dimensional spaces under small training sample conditions<sup>48</sup> and have been shown to be superior to the traditional empirical risk minimization principle employed by most of neural networks,<sup>65</sup> SVMs have been successfully applied to a number of pattern recognition applications involving face detection, verification, and recognition,<sup>1,2,10,15,24,33,38,40,44,48,53,58,59,61,62,64,65,67,68,75–77,79,84,87,92,97,99,104,106–108</sup> object detection and recognition,<sup>26,49,63,73,80,83,89,90</sup> handwritten digit and character recognition,<sup>9,18,30,74,98,116</sup> speech and speaker verification, and

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recognition,<sup>11,22,29,66,102</sup> information and image retrieval,<sup>21,34,41,100,115</sup> gender classification,<sup>71,103,110</sup> prediction,<sup>23,25,27,69,96</sup> text detection and categorization,<sup>6,45,46,47,93</sup> and so on.<sup>4,7,8,20,36,39,51,56,70,85,109,112–114</sup>

This paper is organized as follows. We give a brief explanation on SVMs in Sec. 2 and a survey on pattern recognition applications of support vector machines in Sec. 3. Section 4 describes the limitations of SVMs and conclusion is given in Sec. 5.

## 2. Support Vector Machines

Classical learning approaches are designed to minimize error on the training dataset and it is called the Empirical Risk Minimization (ERM). Those learning methods follow the ERM principle and neural networks are the most common example of ERM. On the other hand, the SVMs are based on the Structural Risk Minimization (SRM) principle rooted in the statistical learning theory. The SVM has better generalization abilities for unseen test data and achieves SRM through a minimization of the upper bound which is the sum of the training error rate and a term that depends on VC dimension of the generalization error.<sup>13,16,19,35,101,116</sup>

### 2.1. Linear support vector machines for linearly separable case

The basic idea of the SVMs is to construct a hyperplane as the decision plane, which separates the positive (+1) and negative (−1) classes with the largest margin, which is related to minimizing the VC dimension of SVM. In a binary classification problem where feature extraction is initially performed, let us label the training data  $\mathbf{x}_i \in \mathbf{R}^d$  with a label  $y_i \in \{-1, +1\}$ , for all  $i = 1, \dots, l$ , where  $l$  is the number of data, and  $d$  is the dimension of the problem. When the two classes are linearly separable in  $\mathbf{R}^d$ , we wish to find a separating hyperplane which gives the smallest generalization error among the infinite number of possible hyperplanes. Such an optimal hyperplane is the one with the maximum margin of separation between the two classes, where the margin is the sum of the distances from the hyperplane to the closest data points of each of the two classes. These closest data points are called Support Vectors (SVs). The solid line on Fig. 1(a) represents the optimal separating hyperplane.

Let us suppose they are completely separated by a  $d$ -dimensional hyperplane described by

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \quad (1)$$

The separation problem is to determine the hyperplane such that  $\mathbf{w} \cdot \mathbf{x}_i + b \geq +1$  for positive examples and  $\mathbf{w} \cdot \mathbf{x}_i + b \leq -1$  for negative examples. Since the SVM finds the hyperplane which has the largest margin, it can be found by maximizing  $1/||\mathbf{w}||$ . The optimal separating hyperplane can thus be found by minimizing Eq. (2) under the constraint (3) to correctly separate the training data.

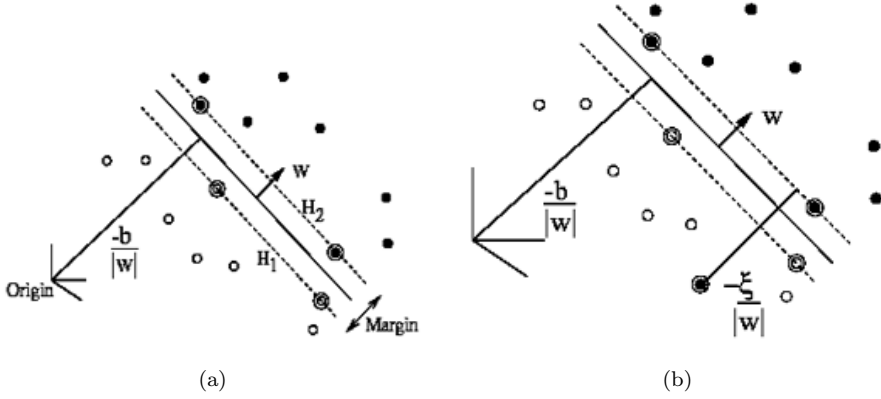


Fig. 1. (a) Linear separating hyperplanes for the separable case. (b) Linear separating hyperplane for the nonseparable case. The support vectors are circled.<sup>16</sup>

$$\min_{\mathbf{w}} \tau(\mathbf{w}) = \frac{1}{2} \|\mathbf{w}\|^2 \quad (2)$$

$$y_i(\mathbf{x}_i \cdot \mathbf{w} + b) - 1 \geq 0, \quad \forall i \quad (3)$$

This is a Quadratic Programming (QP) problem for which standard techniques (Lagrange Multipliers, Wolfe dual) can be used.<sup>35,50,77,81</sup> The detailed explanation on QP problems and alternative researches are described in Sec. 2.4.

## 2.2. Linear support vector machines for nonseparable case

In practical applications for real-life data, the two classes are not completely separable, but a hyperplane that maximizes the margin while minimizing a quantity proportional to the misclassification errors can still be determined. This can be done by introducing positive slack variables  $\xi_i$  in constraint (3), which then becomes

$$y_i(\mathbf{x}_i \cdot \mathbf{w} + b) \geq 1 - \xi_i, \quad \forall i \quad (4)$$

If an error occurs, the corresponding  $\xi_i$  must exceed unity, so  $\sum_i \xi_i$  is an upper bound for the number of misclassification errors. Hence the objective function  $\tau(\cdot)$  in (2) to be minimized can be changed into

$$\tau(\mathbf{w}, \xi) = \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^l \xi_i \quad (5)$$

where  $C$  is a parameter chosen by the user that controls the tradeoff between the margin and the misclassification errors  $\xi = (\xi_1, \dots, \xi_l)$ . A larger  $C$  means that a higher penalty to misclassification errors is assigned. Minimizing Eq. (5) under constraint (4) gives the *Generalized Separating Hyperplane*. This still remains a QP problem. The nonseparable case is illustrated in Fig. 1(b).

### 2.3. Nonlinear support vector machines and kernels

#### 2.3.1. Nonlinear support vector machines

An extension to nonlinear decision surfaces is necessary since real-life classification problems are hard to be solved by a linear classifier.<sup>96</sup> When the decision function is not a linear function of the data, the data will be mapped from the input space into a high dimensional feature space by a nonlinear transformation. In this high dimensional featured space, the generalized optimal separating hyperplane shown in Fig. 2 is constructed.<sup>35</sup> Cover's theorem states that if the transformation is nonlinear and the dimensionality of the feature space is high enough, then input space may be transformed into a new feature space where the patterns are linearly separable with high probability.<sup>37</sup> This nonlinear transformation is performed in implicit way through so-called kernel functions.

#### 2.3.2. Inner-product kernels

In order to accomplish nonlinear decision function, an initial mapping  $\Phi$  of the data into an (usually significantly higher dimensional) Euclidean space  $H$  is performed as  $\Phi : \mathbf{R}^n \rightarrow H$ , and the linear classification problem is formulated in the new space with dimension  $d$ . The training algorithm then only depends on the data through dot product in  $H$  of the form  $\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$ . Since the computation of the dot products is prohibitive if the dimension of transformed training vectors  $\Phi(\mathbf{x}_i)$  is very large, and since  $\Phi$  is not known *a priori*, the Mercer's theorem<sup>16</sup> for positive definite functions allows to replace  $\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$  by a positive definite symmetric kernel function  $k(\mathbf{x}_i, \mathbf{x}_j)$ , that is,  $k(\mathbf{x}_i, \mathbf{x}_j) = \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$ . In training phase, we need only kernel function and  $\Phi$  does not need to be known since it is implicitly defined by the choice of kernel. The data can become linearly separable in feature space although original input is not linearly separable in the input space. Hence kernel substitution provides a route for obtaining nonlinear algorithms from algorithms previously restricted to handling linear separable datasets.<sup>17</sup> The use of

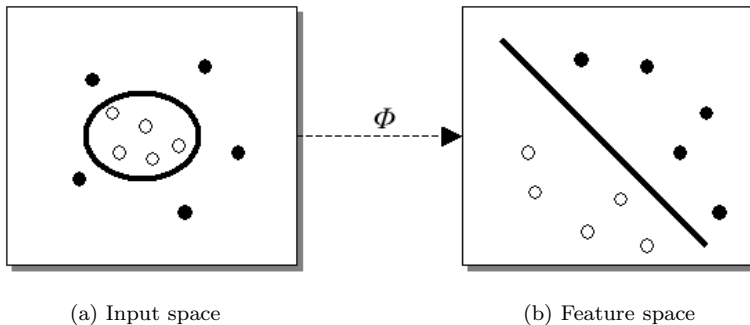


Fig. 2. Feature space is related to input space via a nonlinear map, causing the decision surface to be nonlinear in the input space.<sup>34</sup>

Table 1. Summary of inner-product kernels.<sup>37</sup>

Kernel Function	Inner Product Kernel $K(\mathbf{x}, \mathbf{x}_i), i = 1, 2, \dots, N$
Polynomial kernel	$K(\mathbf{x}, \mathbf{x}_i) = (\mathbf{x}^T \mathbf{x}_i + 1)^d$
Gaussian kernel	$K(\mathbf{x}, \mathbf{x}_i) = \exp(-\ \mathbf{x} - \mathbf{x}_i\ ^2 / 2\sigma^2)$
Multi-layer perceptron (sigmoid)	$K(\mathbf{x}, \mathbf{x}_i) = \tanh(\beta_0 \mathbf{x}^T \mathbf{x}_i + \beta_1),$ $\beta_0$ and $\beta_1$ are decided by the user

implicit kernels allows reducing the dimension of the problem and overcoming the so-called “dimension curse”.<sup>101</sup> Variant learning machines are constructed according to the different kernel function  $k(\mathbf{x}_i, \mathbf{x}_j)$  and thus construct different hyperplanes in feature space. Table 1 shows three typical kernel functions.

## 2.4. Quadratic programming problem of SVMs

### 2.4.1. Dual problem

In Eqs. (2) and (3), the optimization goal  $\tau(\mathbf{w})$  is quadratic and the constraints are linear, so it is a typical QP. Given such a constrained optimization problem, it is possible to construct another problem called the dual problem. We may now state the dual problem: *given the training sample  $\{(\mathbf{x}_i, d_i)\}_{i=1}^N$ , find the Lagrange multipliers  $\{\alpha_i\}_{i=1}^N$  that maximize the objective function*

$$Q(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j d_i d_j \mathbf{x}_i^T \mathbf{x}_j \quad (6)$$

subject to the constraints

$$\sum_{i=1}^N \alpha_i d_i = 0, \quad (7)$$

$$\alpha_i \geq 0, \quad \text{for all } i = 1, \dots, N. \quad (8)$$

We may also formulate the dual problem for nonseparable patterns using the method of Lagrange multipliers. Given the training sample  $\{(\mathbf{x}_i, d_i)\}_{i=1}^N$ , *find the Lagrange multipliers  $\{\alpha_i\}_{i=1}^N$  that maximize the objective function*

$$Q(\alpha) = \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j d_i d_j \mathbf{x}_i^T \mathbf{x}_j \quad (9)$$

subject to the constraints

$$\sum_{i=1}^N \alpha_i d_i = 0, \quad (10)$$

$$0 \leq \alpha_i \leq C, \quad \text{for all } i = 1, \dots, N, \quad (11)$$

where  $C$  is a user-chosen positive parameter. The objective function  $Q(\alpha)$  to be maximized for the case of nonseparable problems in the dual problem is the same as the case for the separable problems except for a minor but important difference. The difference is that the constraints  $\alpha_i \geq 0$  for the separable case is replaced with the more stringent constraint  $0 \leq \alpha_i \leq C$  for the nonseparable case.<sup>37</sup>

#### 2.4.2. How to solve the quadratic problem

A number of algorithms have been suggested for solving the dual problems. Traditional QP algorithms<sup>91,95</sup> are not suitable for large size problems because of the following reasons<sup>50</sup>:

- They require that the kernel matrix is computed and stored in memory, so it requires extremely large memory.
- These methods involve expensive matrix operations such as the Cholesky decomposition of a large submatrix of the kernel matrix.
- For practitioners who would like to develop their own implementation of an SVM classifier, coding these algorithms is very difficult.

A few attempts have been made to develop methods that overcome some or all of these problems. Osuna *et al.*<sup>77</sup> proved a theorem, which suggests a whole new set of QP problems for SVM. The theorem proves that the large QP problem can be broken down into a series of smaller QP subproblems. As long as at least one example that violate the Karush–Kuhn–Tucker (KKT) conditions is added to the examples for the previous subproblem, each step will reduce the cost of overall objective function and maintain a feasible point that obeys all of the constraints. Therefore, a sequence of QP subproblems that always add at least one violator will be guaranteed to converge.<sup>77</sup>

Platt proposed a Sequential Minimal Optimization (SMO) to quickly solve the SVM QP problem without any extra matrix storage and without using numerical QP optimization steps at all. Using Osuna's theorem to ensure convergence, SMO decomposes the overall QP problem into QP subproblems. The difference of the Osuna's method is that SMO chooses to solve the smallest possible optimization problem at every step. At each step, (1) SMO chooses two Lagrange multipliers to jointly optimize, (2) finds the optimal values for these multipliers, and (3) updates the SVMs to reflect the new optimal values. The advantage of SMO is that numerical QP optimization is avoided entirely since solving for two Lagrange multipliers can be done analytically. In addition, SMO requires no extra matrix storage at all. Thus, very large SVM training problems can fit inside the memory of a personal computer or workstation.<sup>81</sup> Keerthi *et al.*<sup>50</sup> pointed out an important source of confusion and inefficiency in Platt's SMO algorithm that is caused by the use of single threshold value. Using clues from the KKT conditions for the dual problem, two threshold parameters are employed to derive modifications of SMO.

## 2.5. SVMs applied to multiclass classification

The basic SVM is for two-class problem. However it should be extended to multi-class to apply to the multi-class problems. There are two basic strategies for solving  $q$ -class problems with SVMs : one-to-others and tree-structure (pairwise SVMs and DDAG).

### 2.5.1. One-to-others multiclass SVMs<sup>116</sup>

Take the training samples with the same label as one class and the others as the other class, then it becomes a two-class problem.<sup>116</sup> For the  $q$ -class problem ( $q > 2$ ),  $q$  classifiers are formed and denoted by  $\text{SVM}_i$ ,  $i = 1, 2, \dots, q$ . As for the testing sample  $\mathbf{x}$ ,  $d_i(\mathbf{x}) = \mathbf{w}_i^* \cdot \mathbf{x} + b_i^*$  can be obtained by using  $\text{SVM}_i$ . The testing sample  $\mathbf{x}$  belongs to the class  $j$  where

$$d_j(\mathbf{x}) = \max_{i=1, \dots, q} d_i(x) \quad (12)$$

### 2.5.2. Tree structured multiclass SVMs: pairwise SVMs and DDAG SVMs

In the pairwise approach, machines are trained for  $q^2$ -class problem.<sup>83</sup> All these SVM classifiers must be used for classifying the testing samples and the synthesizing result is gotten. The pairwise classifiers are arranged in trees, where each tree node represents a SVM. A bottom-up tree which is similar to the elimination tree used in tennis tournaments was originally proposed by Pontil and Verri<sup>83</sup> for recognition of 3D objects and was applied to face recognition by Guo *et al.*<sup>32,33</sup> A top-down tree structure called Decision Directed Acyclic Graph (DDAG) has been recently proposed in Platt *et al.*'s paper.<sup>82</sup> There is no theoretical analysis of the two strategies with respect to the classification performance.<sup>38</sup> Regarding the training effort, the one-to-others approach is preferable since only  $q$  binary SVMs in one-to-others have to be trained compared to  $q(q-1)/2$  binary SVMs in the pairwise approach. However, at runtime both strategies require the evaluation of  $q$  SVMs.<sup>38</sup> Recent experiments on person recognition show similar classification performance for the two strategies: one-to-others and tree-structured methods.<sup>73</sup>

Also Hsu and Lin<sup>42</sup> compared the above methods based on three types of binary classification: one-to-others, pairwise and DDAG SVM. Their experiments indicated that pairwise and DDAG SVM methods are more suitable for practical use than the one-to-others method.

## 3. Pattern Recognition Applications of SVMs

In this section, we survey applications of pattern recognition using SVMs. We classify existing methods into roughly five categories according to their aims. Some methods, which are not included in these categories, are summarized in Sec. 3.6. Osuna *et al.*<sup>77</sup> first demonstrated the applicability of SVM by embedding SVM in

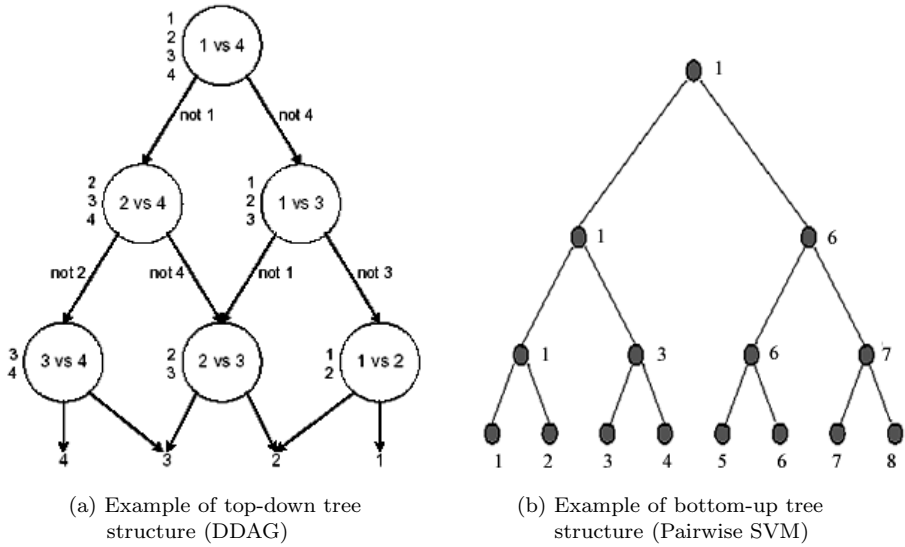


Fig. 3. Tree structure for multi-class SVMs. (a) The DDAG for finding the best class out of four classes. (b) The binary tree structure for eight classes. For a coming test image, it is compared with each two pairs, and the winner will be tested in an upper level until the top of the tree. The numbers 1–8 encode the classes.<sup>32,33</sup>

face detection system which performs comparable recognition results to the state-of-the-art system. The reason to investigate the use of SVM is the fact that (1) SVMs are very well founded from the mathematical point of view, being an approximate implementation of the Structural Risk Minimization induction rule and (2) the adjustable parameters are only  $C$  and the kernel functions.<sup>77</sup> There are many publicly available free software such as SVMFu, SVMLight, LIBSVM, SVMtorch, etc. and a brief summary of these software is described in Table 2.

### 3.1. Face detection and recognition

Face detection, verification and recognition are one of the popular issues in biometrics, identity authentication, access control, video surveillance and human–computer interfaces. There are many active researches in this area for all these applications using different methodologies. However, it is very difficult to achieve a reliable performance. The reasons are due to the difficulty of distinguishing different persons who have approximately the same facial configuration and wide variations in the appearance of a particular face. These variations are because of changes in pose, illumination, facial makeup and facial expression.<sup>104</sup> Also glasses or a moustache makes difficult to detect and recognize faces. Recently many researchers applied SVMs to face detection, facial feature detection, face verification and recognition and compared their results with other methods. Each method used different input features, different databases, and different kernels for SVM classifier.



Table 2. Some examples of publicly available SVM software.

Software	Developer	Language	Environment	Algorithms	URL
SVMFu	R. Rifkin M. Nadermann (MIT)	C++	Unix-like system	Osuna <i>et al.</i> , SMO (Platt)	<a href="http://www.ai.mit.edu">http://www.ai. mit.edu</a>
LIBSVM	C. C. Chang, C.H. Lin (National Taiwan Univ.)	C++, Java	Python, R, Matlab, Perl	SMO (Platt), SVMLight (Joachims)	<a href="http://www.csie.ntu.edu.tw/~libsvm">http://www.csie. ntu.edu.tw/~ libsvm</a>
SVMLight	T. Joachims, (Univ. of Dortmund)	C	Solaris, Linux, IRIX, Windows NT	T. Joachims	<a href="http://www.svm-light.joachims.org">http://www.svm-light. joachims.org</a>
SVM Torch	R. Collobert, (IDIAP, Switzerland)	C, C++	Windows	R. Collobert	<a href="http://www.idap.ch/learning/SVMTorch.html">http://www.idap.ch /learning/SVMTorch. html</a>

**Face Detection:** A SVM can be used to distinguish face and non-face images since a face detection problem is a binary classification problem. The application of SVM for frontal face detection in image was first proposed by Osuna *et al.*<sup>77</sup> The proposed algorithm scanned input images with a  $19 \times 19$  window and a SVM with a second degree polynomial as a kernel function is trained with a novel decomposition algorithm, which guarantees global optimality. This system was able to handle up to a small degree of non-frontal views of faces.

Although non-face examples are abundant, non-face examples that are useful from a learning point of view are very difficult to characterize and define.<sup>77</sup> To solve this problem, bootstrap was the most popular method and also hierarchical linear SVMs were used to exclude non-face images step by step and more complex non-linear SVM verified the face in the last step.<sup>2,67,68</sup> By Ma *et al.*,<sup>68</sup> five hierarchical linear SVMs to exclude non-face used different  $C$ 's with  $C_{\text{face}}$  being 100, 50, 10, 5, 5 times of  $C_{\text{non-face}}$  indicating different cost-sensitivity.

To avoid the scanning of the whole image to decide face or non-face, many papers applied their methods on the skin-color segmented region.<sup>58,79,84,99</sup> Kumar and Poggio<sup>58</sup> recently incorporated Osuna *et al.*'s SVM algorithm in a system for real-time tracking and analysis of faces on skin region and also to detect eyes. In Qi *et al.*'s paper,<sup>84</sup> SVMs used the ICA features as an input after applying skin color filter for face detection and they showed that the used ICA features gave better generalization capacity than by training SVM directly on the whole image data. In Terrillon *et al.*,<sup>99</sup> they applied SVM to invariant Orthogonal Fourier–Mellin Moments as features for binary face or non-face classification on skin color-based segmented image and compared the performance of SVM face detector to multi-layer perceptron in terms of Correct Face Detector (CD) and Correct Face Rejection

(CR). In Xi and Lee's paper,<sup>108</sup> LH and HL subimages of wavelet decomposition are used as a feature vector for face detection. Also, in order to speed up the face detection, Ai *et al.*<sup>1</sup> have used two templates of eyes-in-whole and face in filtering out face candidates for SVMs to classify face and non-face classes. Another method to improve the speed of the SVM algorithm found a set of reduced support vectors (RVs) which are calculated from support vectors.<sup>87</sup> RVs are used to speed up the calculation sequentially.

For the input feature vectors to SVMs, Xi *et al.*<sup>106–108</sup> and Huang *et al.*<sup>44</sup> used component-based feature vectors such as eye brows, eyes, mouth as an input to SVMs and showed their component-based face detection performed well to the whole input image. In order to extract the 14 facial components by SVMs, Bileschi and Heisele<sup>12</sup> trained each facial component only on positive examples of face images. The negative training data for each component is extracted from four random crops to overlap the component by no more than 35% of the area of each component in face images. The performance of complete system using SVM classifiers trained on facial negatives for each facial component detection outperformed.

SVMs have also been used for multi-view face detection by constructing separate SVMs specific to different views based on the pose estimation. For face recognition, frontal view SVM-based face recognizer is used if the detected face is in frontal view after head pose estimation.<sup>62,75,76</sup> Also combined methods are tried to improve the performance for face detection. Li *et al.*<sup>61</sup> tested the performance of three face detection algorithms, eigenface method, SVM method and combined method in terms of both speed and accuracy for multi-view face detection. The combined method consisted of a coarse detection phase by eigenface method, and then the ambiguous outputs of eigenface methods are tested by a fine SVM phase so that an improved performance could be achieved by speeding up the computation and keeping the accuracy. Buciu *et al.*<sup>15</sup> attempted to improve the performance of face detection by majority voting on the outputs of five different kernels of SVM. Papageorgio *et al.*<sup>79</sup> applied SVM to overcomplete wavelet representation as input data to detect faces and people and Richman *et al.*<sup>86</sup> applied SVMs to find nose cross-section for face detection. The summary of face detection using SVM is given in Table 3 in terms of feature vectors, different databases, detection rate, different kernels, and SVM software used. The benchmark test sets<sup>111</sup> for face detection are MIT data set, CMU-set A, CMU-set B, Kodak Data Set, M2VTS, etc. The descriptions are followings:

- **MIT data set:** two sets of high (301 frontal and near frontal mugshots of 71 different people) and low (23 images with 149 faces) gray-scale images with multiple faces in complex background.
- **CMU frontal face (set A, B, C, D):** 130 gray scale images with a total of 507 frontal faces.
- **CMU profile face set:** 208 gray-scale images with faces in profile views.
- **CMU-PIE database:** pose, illumination, expression face database.

Table 3. Summary of face detection by SVMs.

Method	Feature Vectors	Database	Detection Rate/ False Alarms	SVM Software	Kernel
(baseline)	System 5	CMU-set A	90.5% (570)	– Neural Network Methods	
Rowley <i>et al.</i> <sup>88</sup>	System 11	CMU-set B	86.2% (23)	– Used for baseline algorithm	
Osuna <i>et al.</i> <sup>77</sup>	19×19 gray image	313: single face 23: multi-faces with a total of 155 faces	97.4% (4) 74.2% (20)	decomposition algorithm	2nd polynomial (C = 200)
Qi <i>et al.</i> <sup>84</sup>	ICA features	820 face images: LAMP (Univ. of Maryland) and Essex face database	92.5% (54)	N/A	N/A (C = 230)
Terrillon <i>et al.</i> <sup>99</sup>	Invariant Orthogonal Fourier- Mellin Moments	Own database 100 images with 144 face images	CD: 93.1% CR: 72.8%	N/A	RBF
Romdhani <i>et al.</i> <sup>87</sup>	20×20 gray image	CMU-set A	81.9% (465)	SMO	RBF (2207 SVs, C = 200)
Bassiou <i>et al.</i> <sup>10</sup>	mosaic image (multireolution images)	M2VTS best case (set 4)	FAR: 0% FRR: 0%	N/A	Polynomial, RBF, Linear, Sigmoid (C = 1000)
Xi and Lee <sup>108</sup>	Wavelet LH, HL sub-images	Own database, Set A: 325 images (one face per image) Set B: 136 images (with more than 2 faces)	Set A: 98.1% (0.3% FR) Set B: 75.4% (13.4% FR)	N/A N/A	N/A
Ma and Ding <sup>68</sup>	20×20 gray images	CMU face data	88.9% (23)	N/A	5 linear SVMs 2nd polynomial
Ma and Ding <sup>67</sup>	20×20 gray images	Nokia test set CMU face data	90.1% (148) 87.2% (156)	N/A 5 linear SVMs (C = 10) Nonlinear SVM (C = 200)	

- **Kodak data set:** faces of multiple size, pose and various illumination in color images.
- **M2VTS:** video sequences of 37 different subjects in four different shots.
- **XM2VTS:** video sequences of 295 different subjects taken over a period of four months.

**Face Recognition and Authentication:** The recognition of a face is a well-established field of research and a large number of algorithms have been proposed in the literature. Machine recognition of faces yields problems that belong to the following categories whose objectives are briefly outlined<sup>97</sup>:

- **Face Recognition:** Given a test face and a set of reference faces in a database, find the  $N$  most similar reference faces to the test face.
- **Face Authentication:** Given a test face and a reference one, decide if the test face is identical to the reference face.

Guo *et al.*<sup>32,33</sup> proposed multi-class SVM with pairwise bottom-up tree strategy for face recognition and compared SVM result with Nearest Center (NC), Hidden Markov Model (HMM), Conventional Neural Network (CNN), and Nearest Feature Line (NFL). Normalized feature extracted by PCA was the input of the SVM classifier. Error rates of NC, HMM, CNN, NFL, and SVM are 5.25%, 5%, 3.83%, 3.125%, and 3.0% respectively on ORL face database.

Heisele *et al.*<sup>38,44</sup> proposed a component-based method and compared the performance with two global methods for face recognition by one-to-others SVMs. Huang *et al.*<sup>44</sup> generated a large number of synthetic face images to train the system by rendering the 3D models under various poses and illumination. In component-based system, they extracted facial components and combined them into a single feature vector, which is classified by SVMs. The global systems used SVMs to recognize faces by classifying a single feature vector consisting of the gray values of the whole face image. One global method used single SVM and the other used view-based SVMs. Their results showed that the component-based method outperformed the global methods.

Kim *et al.*<sup>53</sup> used modified SVM local correlation kernel to explore spatial relationships among potential eye, nose, and mouth objects and compared their kernel with existing kernels with error rate of 2% on ORL database. Wang *et al.*<sup>104</sup> proposed a face recognition algorithm based on both 3D range and 2D gray-level facial images. 2D texture (Gabor Coefficient) and 3D shape features (Point Signature) are projected onto PCA subspace and then integrated 2D and 3D features are as an input of SVM to recognize faces.

For face authentication and recognition, Jonsson *et al.*<sup>48</sup> presented that SVMs could extract the relevant discriminative information from the training data and the performance of SVMs was relatively insensitive to the representation space and preprocessing steps. To prove this, they performed a number of experiments with different decision rules (Euclidean distance, normalized correlation, SVMs), subspaces (PC, LD), and preprocessing (no preprocessing, zero-mean and unit variance, histogram equalization). A SVM with histogram equalization and LD subspace showed the best performance of EER = 1.00, FAR = 1.37, FRR = 0.75. Tefas *et al.*<sup>97</sup> reformulated Fisher's discriminant ratio to a quadratic optimization problem subject to a set of inequality constraints to enhance the performance of morphological elastic graph matching (MEGM) for frontal face authentication. SVMs which find the optimal separating hyperplane are constructed to solve the reformulated quadratic optimization problem for face authentication. These optimal coefficients by SVMs are used to weigh the raw similarity vectors that are provided by the MEGM and the best performance of the frontal face verification on M2VTS face database is EER = 2.4. The summary of face verification and recognition performance is given in Table 4.

Table 4. Summary of face verification and recognition by SVMs.

Category	Feature Vectors	Database	Recognition Rate	Type of Multi-Class (Kernel)	Remarks
Face verification <sup>48</sup>	LDA	M2VTS	EER = 1.00 FAR = 1.37 FRR = 0.75	N/A (RBF kernel)	SVM is relatively insensitive to the representations space and preprocessing steps
	PCA	M2VTS	EER = 1.50 FAR = 2.19 FRR = 1.50	N/A (RBF kernel)	
Face verification <sup>97</sup>	Weighted MEGM	M2VTS	EER = 2.4	N/A (Nonlinear kernel)	
Face recognition <sup>33</sup>	PCA	ORL database	97%	Pairwise (N/A)	NC (94.75%), CNN (96.17%) HMM (95%), NFL (96.88%)
Face recognition <sup>38,44</sup>	Component based	Own database	ROC curve	One-to-others (linear kernel)	Component based method (outperformed) global based method
	Whole image	Own database	ROC curve	One-to-others (2nd order polynomial)	
Face recognition <sup>53</sup>	Feature-based (component based)	ORL database	98%	One-to-others (N/A)	Eigenface (90%)
Face recognition <sup>104</sup>	PCA of PS + GC	Own database	about 90%	DDAG (N/A)	

### 3.2. Object detection and recognition

Object detection or recognition aims to find and track moving people or traffic situation for surveillance or traffic control. Nakajima *et al.*<sup>73</sup> developed people recognition and pose estimation as a multi-class classification problem. This paper used pairwise and DDAG multi-class SVMs with linear kernel and the two types of SVM classifiers showed very similar performance. They recognized four people and four poses (left, right, front, back side) with 640 images of 40 images per each person at each pose of their own data. Two features (color histogram and local shape) are tested for people and pose recognition and local shape feature gave better performance. 3D object recognition was developed by Roobaert and Van Hulle,<sup>89</sup> and Pontil and Verri.<sup>83</sup> Both of them used COIL object database, which contained 7200 images of 100 objects with 72 different views per each object. Roobaert and Van Hulle<sup>89</sup> proposed 3D object recognition with SVMs to illustrate the potential of SVMs in terms of the number of training views per object. Their result showed that the performance was decreased much when the number of training views was less than 18 views. Pontil and Verri<sup>83</sup> used linear SVMs for aspect-based 3D object recognition from a single view without feature extraction, data reduction and estimating pose. They tested SVM method on the synthesized images of COIL database with noise, occlusion, and pixel shifts and got very good performance. The result showed that SVMs are well-suited for aspect-based recog-

Table 5. Summary of object detection and recognition by SVMs.

Category	Input	Database	Recognition Rate	Type of Multi-Class	Remarks
People recognition <sup>73</sup>	Color feature	Own Database	91.6%	Pairwise	Shape feature is better No performance difference between pairwise and DDAG SVMs
	Shape feature		99.5%	linear SVMs	
	Color feature		91.4%	DDAG	
	Shape feature		99.5%	linear SVMs	
Pose estimation <sup>73</sup>	Color feature	Own Database	68.2%	Pairwise	
	Shape feature		84.3%	linear SVMs	
	Color feature		68.0%	DDAG	
	Shape feature		84.5%	linear SVMs	
3D object recognition <sup>83,89</sup>	32×32 image	COIL database	99.7% (plain images)	Pairwise linear SVMs	Tested on the most difficult 32 objects out of 72 objects
			99.7% (with noise)		
			99.4%		
			(3 pixel shift)		
Pedestrian detection <sup>49</sup>	32×32 vertical edges	Own database	100% with FD = 0.01%	3rd order polynomial	

dition. Pittore *et al.*<sup>80</sup> developed VIDERE (VIsual Dynamic Event REcognition) system. They proposed a system that was able to detect the presence of moving people, represented the event by using a SVM for regression, and recognized trajectory of visual dynamic events from an image sequence by SVM classifier. Gao *et al.*<sup>26</sup> proposed a shadow and head-lights elimination algorithm by considering this problem as a two-class problem. That is, the SVM classifier was used to detect real moving vehicles from shadows. Some other object recognitions were on radar target recognition,<sup>63</sup> pedestrian detection<sup>49</sup> and recognition.<sup>105</sup> Kang *et al.*<sup>49</sup> used  $32 \times 64$  size of vertical edges as features to detect pedestrians by a SVM. Their system could detect pedestrians in different size, pose, gait, clothing and occlusions. The brief summary of object detection and recognition is given in Table 5.

3.3. Handwritten character recognition

Among the SVM-based applications, SVMs have shown to largely outperform all other learning algorithms for handwritten digit and character recognition problem. A major problem in handwriting recognition is the huge variability and distortions of patterns. To absorb these problems, Choisy and Belaid<sup>18</sup> used NSPH-HMM for local view and SVM for global view to recognize French bank check words. For handwritten digit recognition, SVMs are used by Gorgevik *et al.*,<sup>30</sup> Teow *et al.*<sup>98</sup> and Zhao *et al.*<sup>116</sup> Gorgevik *et al.*<sup>30</sup> used two different feature families (structural features and statistical features) for handwritten digit recognition using SVM classifier. They tested single SVM classifier applied on both feature families as one set. Also two feature sets are forwarded to two different SVM classifiers and the obtained results are combined by rule-based reasoning. The paper showed

that the single SVM classifier gave better performance than rule-based reasoning which combined two individual SVM classifiers. Teow and Loe<sup>98</sup> had developed a vision-based handwritten digit recognition system, which extracts features that are biologically plausible, linearly separable and semantically clear. In this system, they showed that their extracted features were linearly separable features over a large set of training data in a highly nonlinear domain by using linear SVM classifier. Zhao *et al.*<sup>116</sup> showed the recognition performance of handwritten digits according to (1) the effect of input dimension, (2) effect of kernel functions, (3) comparison of different classifiers (ML, MLP, SOM+LVQ, RBF, SVM) and (4) comparison of three types of multi-class SVMs (one-to-others, pair-wise, DDAG).

To recognize hand-printed Hiragana, Naruyama *et al.*<sup>74</sup> proposed the combination of two multi-class SVM methods which are one-to-others SVMs with max-win and DDAG for cumulative recognition rate. They found some pairs which are difficult to discriminate and then combined these pairs into the same group. They first applied DDAG and then one-to-others SVMs. If the result of DDAG was in the same group, then they applied one-to-others with majority voting for the pairs of the same group. The result showed that the proposed modified DDAG is 30 times faster than one-to-others and almost equivalent to one-to-others with max-win in terms of the cumulative recognition rate. The brief summary of handwritten digit and character recognition is given in Table 6.

### 3.4. Speaker recognition and speech recognition

In speaker or speech recognition problem, the two most popular techniques are discriminative classifiers and generative model classifiers. The methods using discriminative classifiers consist of decision tree, neural network, SVMs, etc. The well-known generative model classification approaches include Hidden Markov models (HMM) and Gaussian Mixture models (GMM).<sup>22</sup> For training and testing data, there are text dependent and text independent data. Bengio and Mariethoz,<sup>11</sup>

Table 6. Summary of handwritten character recognition by SVMs.

Category	Database	Features	Recognition rate	SVM software
Handwritten digit recognition <sup>30</sup>	NIST; 16×16	54 structural features +	97.53% (Gaussian)	SVM Torch
	binary image	62 statistical features	95.06% (linear)	
Handwritten digit recognition <sup>116</sup>	NIST; various input resolutions	Whole image	97.21% (best case)	pairwise SVM
Handwritten digit recognition <sup>98</sup>	NIST; 36×36 gray image	Biologically motivated features	99.18%	SVMLight; pairwise linear SVM
Handwritten Hiragana recognition <sup>74</sup>	JEITA-HP; 64×64 gray image	256 directional features	94.00%	SMO

and Wan and Campbell<sup>102</sup> used SVMs for speaker verification on different data sets. They experimented on text dependent and text independent data and replaced the classical thresholding rule with SVMs to decide accept or reject. Text independent tasks gave significant performance improvements. Wan and Campbell<sup>102</sup> proposed a new technique for normalizing the polynomial kernel to use with SVMs and tested on YOHO database. Dong and Zhaohui<sup>22</sup> reported on the development of a natural way of achieving combination of discriminative classifier and generative model classifiers by embedding GMM in SVM outputs, and thus created a continuous density support vector machine (CDSVM) for text independent speaker verification. For utterance verification which is essential to accept keywords and reject non-keywords on spontaneous speech recognition, Ma *et al.*<sup>66</sup> trained and tested SVM classifier as the confidence measurement problem in speech recognition.

SVM is also applied to the visual speech recognition which recognizes speech by their lipreading. Viseme is defined by a mouth shape and mouth dynamics corresponding to the production of a phone or a group of phones indistinguishable in the visual domain. Each viseme is described by SVM and Vitterbi algorithm used SVMs as nodes for modeling the temporal character of speech. To evaluate the performance, they experimented on audio-visual data Tuplip 1 to solve the task of recognizing the first four digits in English.<sup>28,29</sup> The brief summary of speaker and speech recognition is given in Table 7.

Table 7. Summary of speaker and speech recognition by SVMs.

Category	Database	Input	Recognition rate	Remarks
Speaker verification <sup>11</sup> — text independent	PolyVar telephone database	39 coefficient	HTER = 1/2 (% FA+%FR)	
		features:	4.73% (RBF kernel)	SVM
		12LPC + deltas (HMM: generative model)	5.55 % (Bayes decision)	Torch
Speaker verification <sup>11</sup> — text dependent	CAVE	39 coefficient	HTER	
		features:	3.34 % (RBF kernel)	SVM
		12LPC + deltas (GMM: generative model)	3.40 % (Bayes decision)	Torch
Speaker verification <sup>102</sup> — text independent	YOHO	24 coefficient	EER: 0.34% (seen)	
		features:	EER: 0.59% (unseen);	
		12th order LPC + deltas	normalized 10th order polynomial kernel EER: 1.86% (unseen); unnormalized RBF kernel	N/A
Utterance verification <sup>66</sup>	Own data	4 features: normalized score, score per frame, word duration, speech rate	ER: 1% with 7% rejection rate	N/A
Visual speech recognition (lipreading) <sup>29</sup>	Tulips1	16×16 mouth region gray image and delta features	Word recognition rate: 90.6% (3rd order polynomial kernel)	SVM Light



3.5. Information and image retrieval

Content-based image retrieval is emerging as an important research area with applications to digital libraries and multimedia databases.<sup>34</sup> Guo *et al.*<sup>34</sup> proposed a new metric, distance-from-boundary to retrieve the texture image. The boundaries between classes are obtained by SVM. To retrieve more images or information relevant to the query image, SVM classifier is used to separate two classes of relevant images and irrelevant images.<sup>21,100,115</sup> Drucker *et al.*<sup>21</sup>, Tian *et al.*<sup>100</sup> and Zhang *et al.*<sup>115</sup> proposed that SVMs automatically generated preference weights for relevant images or information. The weights were determined by the distance of the two separating hyperplanes, which was trained by SVMs using positive examples (+1) and negative examples (−1). The brief summary of image and information retrieval is given in Table 8.

3.6. Other applications

There are many more other applications of SVMs for pattern recognition problems. Moghaddam and Yang<sup>71,110</sup> used nonlinear SVM implemented by SVMFu software to classify gender on FERET face database with 1496 training images (793 males and 713 females) and 259 test images (133 males and 126 females). Then they trained and tested each classifier with the face images using five-fold cross-validation. The performance of SVM (3.4% error rate) was shown to be superior to traditional pattern classifiers (linear, quadratic, FLD, RBF, ensemble-RBF). They experimented from  $21 \times 12$  low resolution images to  $84 \times 48$  high reso-

Table 8. Summary of information and image retrieval by SVMs.

Category	Database	Input	Recognition Rate	Remarks
Image retrieval <sup>34</sup>	Bordatz texture database	Mean and variance of 24 garbor filter banks (3 scales, 4 orientations)	87.61% retrieval performance in top 5 images	GRBF kernel (sigma = 0.3, C = 200)
Information retrieval with relevance feedback <sup>21</sup>	Reuters corpus of news articles	TF-IDF	100% (Topic: Earn)	SVMLight
		TF	100% (Topic: Earn)	
		TF-IDF	95% (Topic: Grain)	
		TF	87% (Topic: Grain) on 10 iterations	
Image retrieval with relevance feedback <sup>41,100</sup>	Correl database	Color, texture, structure	90% (Category 5) in top 20	Linear kernel
Image retrieval with relevance feedback <sup>115</sup>	Correl database	Autocorrelogram of $4 \times 4 \times 4$ quantized, R,G,B color images	0.75 recall after 5 iterations	Gaussian Kernel

lution images with various different kernels. From the experiments, female gave more errors because they have less significant features.<sup>71</sup> Also gender classification is done by gait data analysis using a SVM. Human body is segmented by adaptive background elimination and the body is divided into seven parts. Ellipse was fitted to these seven regions and centroid, aspect ratio of major and minor axes of the ellipse, the orientation of major axis of the ellipse are the feature vectors. They experimented with the best six features selected using ANOVA out of full 57 features. They experimented under the random-sequence and the random-person test and showed that the linear kernel performed at least as well as the polynomial and Gaussian kernels.<sup>60</sup> Walawalkar *et al.*<sup>103</sup> performed gender classification using visual and audio cues. The feature vectors of the visual cue were (1)  $20 \times 20$  whole images of recognition rate with 95.31% and (2) top 50 PCs with recognition rate of 90.94% implemented by SVMLight software using Gaussian RBF kernel. Their own data was used for their experiments with 1640 images (883 males and 757 females). The feature vectors of the audio cues was Cepstral feature with recognition rate of 100% on ISOLET Speech Corpus data with total of 447 utterances (255 males and 192 females).

Gutta *et al.*<sup>36</sup> have applied SVMs to face pose classification on FERET database and their results yielded 100% accuracy. Also Huang *et al.*<sup>43</sup> applied SVMs to classify face poses into three categories. Fingerprint type classification algorithms based on SVMs into five classes were proposed by Yao *et al.*<sup>112</sup> SVMs were trained on combining flat and structured representation and showed good performance and promising approach for fingerprint classification. Also, SVM is used to recognize intrusion detection and trained with 41 features to classify attack and normal patterns. The reason why SVM is used is the speed for real time performance and scalability: SVMs are relatively insensitive to the number of data points and the classification complexity does not depend on the dimensionality of the feature space. RBF kernel and SVM light are used.<sup>72</sup>

SVM for texture classification is designed to receive the raw gray-value pixels instead of feature extraction. This paper is not needed for a carefully designed feature extraction because the feature extraction is reduced to the problem of training the SVMs, and SVM has the capability of learning in high-dimensional spaces. For multi-class classification, one-to-others SVM is used with Neural Network arbitrator for the final decision. The experiments are done on Brodatz and MIT Vision Texture (VisTex) database with different kernels, fifth order polynomial, Gaussian, and Tangent Hyperbolic kernels.<sup>55</sup> SVM is also used to solve text detection and categorization problem.<sup>52,54</sup>

The aim of many nonlinear forecasting methods<sup>23,27,69,96</sup> is to predict next points of time series. Tay and Cao<sup>96</sup> proposed *C*-ascending SVMs by increasing the value of *C*, the relative importance of the empirical risk with respect to the growth of regularization term. This idea is based on the assumption that it is better to give more weights on recent data than distant data. Their results showed that *C*-ascending SVMs gave better performance than standard SVM in financial

time series forecasting. Fan and Palaniswami<sup>23</sup> had adopted SVM approach to the problem of predicting corporate distress from financial statements. For this problem, the choice of input variables (financial indicators) affects the performance of the system. This paper had suggested selecting suitable input variables that maximize the distance of vectors between different classes, and minimize the distance within the same class. Euclidean distance-based input selection provided a choice of variables that tends to discriminate within the SVM kernel used.

In addition, SVM had been applied to many other applications such as data condensation,<sup>70</sup> goal detection,<sup>4</sup> and bullet-hole image classification.<sup>109</sup> Data condensation<sup>70</sup> was to select a small subset from huge databases and the accuracy of a classifier trained on such reduced data set were comparable to results from training with the entire data sets. The paper extracted data points lying close to the class boundaries, SVs, which form a much reduced but critical set for classification using SVM. But the problem of large memory requirements for training SVM's in batch mode was solved so that the training would preserve only the SVs at each incremental step, and add them to the training set for the next step, called incremental learning. Goal detection for a particular event, ghost goals, using SVMs was proposed by Ancona *et al.*<sup>4</sup> Xie *et al.*<sup>109</sup> focused on the application of SVM for classification of bullet hole images in an auto-scoring system. The image was classified into one, two or more bullet-hole images by multi-class SVMs. Other applications are — white blood cells classification,<sup>78</sup> spam categorization,<sup>42</sup> cloud and Typhoon classification,<sup>8,56</sup> and soon.<sup>31,39</sup> There will be some more pattern recognition applications of SVMs which are not listed in this paper.

#### 4. Performance Issues

The performance of SVMs largely depends on the choice of kernels. SVMs have only one user-specified parameter  $C$ , which controls the error penalty when the kernel is fixed, but the choice of kernel functions, which are well suited to the specific problem is very difficult.<sup>16</sup> Smola *et al.*<sup>94</sup> explained the relation between the SVM kernel method and the standard regularization theory. However, there are no theories concerning how to choose good kernel functions in a data-dependent way.<sup>3</sup> Amari and Wu<sup>3</sup> proposed a modified kernel to improve the performance of SVMs classifier. It is based on information-geometric consideration of the structure of the Riemannian geometry induced by the kernel. The idea is to enlarge the spatial resolution around the boundary by a conformal transformation so that the separability of classes is increased.

Speed and size is another problem of SVM both in training and testing. In terms of running time, SVM is slower than other neural networks for a similar generalization performance.<sup>37</sup> Training for very large datasets with millions of SVs is an unsolved problem.<sup>16</sup> Recently, even though Platt<sup>81</sup> and Keerthi *et al.*<sup>50</sup> proposed SMO (Sequential Minimization Optimization) and modified SMO to solve the training problem, it is still an open problem to improve. The issue of how to control

the selection of SVs is another difficult problem, particularly when the patterns to be classified are nonseparable and the training data are noisy. In general, attempts to remove known errors from the data before training or to remove them from the expansion after training will not give the same optimal hyperplane because the errors are needed for penalizing nonseparability.<sup>37</sup> Lastly, although some researches have been done on training a multi-class SVM, the work for multi-class SVM classifiers is an area for further research.<sup>16</sup>

## 5. Conclusions

We have presented a brief introduction on SVMs and several applications of SVMs in pattern recognition problems. SVMs have been successfully applied to a number of applications ranging from face detection and recognition, object detection and recognition, handwritten character and digit recognition, speaker and speech recognition, information and image retrieval, prediction, etc. because they have yielded excellent generalization performance on many statistical problems without any prior knowledge and when the dimension of input space is very high. In this paper, we tried to summarize the comparison of the performance results for the same application as much as possible.

Some researches compared the performance of different kinds of SVM kernels to solve their problems and most results showed that RBF kernel was usually better than linear or polynomial kernels. RBF kernel performs usually better than others for several reasons such as (1) it has better boundary response as it allows extrapolation and (2) most high dimensional data sets can be approximated by Gaussian-like distributions similar to that used by RBFs.<sup>43</sup>

Among the application areas, the most popular research fields to apply SVMs are for face detection, verification and recognition. SVMs are binary class classifiers and it was first applied for verification or two-class classification problems. But SVMs had been used for multi-class classification problems since one-to-others and pairwise bottom-up, DDAG top-down multi-class classification methods were developed.

Most applications using SVMs showed SVMs-based problem solving outperformed other methods. Although SVMs do not have long histories, it has been applied to a wide range of machine learning tasks and used to generate many possible learning architectures through an appropriate choice of kernels. If some limitations related with the choice of kernels, training speed and size are solved, it can be applied to more real-life classification problems.

## Acknowledgments

This research was supported by the Brain Neuroinformatics Research Program and the Creative Research Initiative Program of the Ministry of Science and Technology, Korea.

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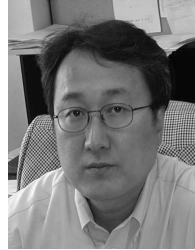
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