www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

NOVEL MULTI-CLASS SVM ALGORITHM FOR MULTIPLE OBJECT RECOGNITION

Yongqing Wang[1,2*] and Yanzhou Zhang[3]

[1] Department of Computer Science and Applications, Zhengzhou Institute of Aeronautical Industry Management, Zhengzhou 450015, China

[2] Henan aviation economics research center, aviation economic development & aeronautic materials technology collaborative innovation center

[3] Basic Course Department, Henan Polytechnic, Zhengzhou 450046, China

*Email: wyq-yongqing@163.com

Submitted: Feb. 16, 2015 ***Accepted: Apr. 22, 2015*** ***Published: June 1, 2015***

Abstract- Object recognition is a fundamental task in applications of computer vision, which aims at detecting and locating the interested objects out of the backgrounds in images or videos, and can be originally formulated as a binary classification problem that can be effectively handled by binary SVM. Although the binary technique can be naturally extended to solve the multiple object recognition, which are known as one-vs.-one and one-vs.-all techniques, but the scalability of traditional methods tend to be poor, and limits the wide applications. Inspired by the idea presented by Multi-class Core Vector Machine, we propose a novel Multi-class SVM algorithm, which achieves excellent performance on dealing with multiple object recognition. The simulation results on synthetic numerical data and recognition results on real-world pictures demonstrate the validity of the proposed algorithm.

Index terms: Object recognition, computer vision, multi-class, SVM algorithm, classification problem.

I. INTRODUCTION

Object recognition refers to a process of distinguishing a specific object from other objects, or objects of one type from other types. It includes not only the recognition of two very similar objects, but also the recognition of objects which belong to different types.

a. The principle and procedure of object recognition

The basic principle of object recognition is the usage of object's characteristics information in radar echo, such as amplitude, phase, frequency spectrum and polarization, through the various multidimensional space transformation of mathematics to estimate the object's size, shape, weight and surface physical properties parameters, and finally accomplishing the identification in the classifier according to the identification functions, which determined by a large number of training samples.

The whole procedure of object recognition includes four steps as follows, whose logical relationship can be listed in Figure l.

Step 1: Extracting the features from known objects.

Step 2: Creating the feature database of known objects.

Step 3: Extracting the features from unknown objects.

Step 4: Comparing the features of unknown objects with the ones existed in feature database and making decision.

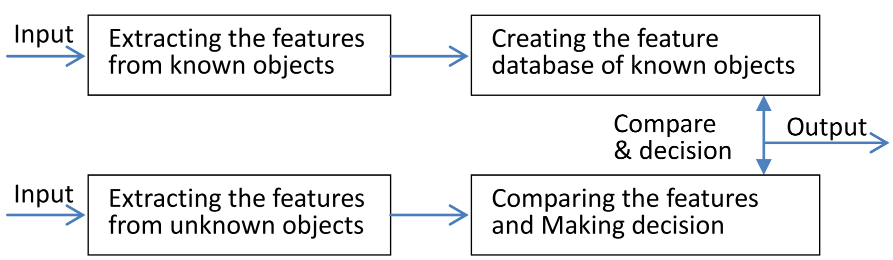


Figure 1. The flow diagram of object recognition

b. Object recognition applications

Object recognition had made great progress in the last few decades, during which it had achieved great successful applications in diverse areas, such as biometric recognition, industrial detection, aviation and remote sensing, biomedicine, military and public security, etc.

b.i Application in biometric recognition

Biometric recognition refers to the use of inherent physiological or behavioral characteristics of human body for personal identification in computer technology. Inherent physiological characteristics, many of which are congenital, consist of face, fingerprint, palm print, iris, etc. Behavior habits, many of which are acquired, include speech, gait, handwriting, and keystroke action, etc. (seen in Figure 2).

Figure 2. Application of object recognition in biometric recognition

The biometric features for identity authentication should involve the following three aspects.

(1) Accuracy: the biometric features can improve the accuracy of the identification.

(2) Reliability: forging of the biological characteristics is difficult.

(3) Applicability: the biometric features are feasible to application.

An ideal biometric recognition system should consist of various biological characteristics, such as gait, fingerprint, gesture, face, Iris, keystroke action, handwriting, speech, palm print, etc.

b.ii Application in industrial detection

Nowadays, object recognition has been successfully applied in the field of industrial detection (seen in Figure 3), and greatly improves the quality and reliability of the product, which guarantees the speed of production. For example, the quality detection in packaging and printing for products, quality detection for containers, drink filling, and bottle cap sealing in beverage industry, timber wood detection, semiconductor integrated packaging quality detection, coil quality detection, the industrial computed tomography of key mechanical parts, etc. At the customs, the application of X-ray and the machine vision technology can inspect the cargo without opening the package, which can greatly improve the speed of customs clearance, and saves a large amount of manpower and material resources. In the pharmaceutical production line, machine vision technology can be used to test the drug packaging, which can guarantee the package quality of drags.

Figure 3. Application of object recognition in industry detection

b.iii Application in aviation and remote sensing

Object recognition can be used in diverse scenes of aviation and remote sensing (seen in Figure 4), which can be listed but not limited to the following applications.

The reconnaissance, positioning and navigation in military scenes. Automatic cartography, satellite images and topographic map alignment, automatic surveying and mapping. Management of land and resources, such as the management of the forest, water, soil, etc. Synthetic analysis and prediction to weather forecast, automatic environment and fire alarm monitoring. Detection and analysis of astronomy and space objects, transportation and air lines management, etc.

Collecting satellite remote sensing images, automatic identifying and classifying the ground targets according to the characteristics of image and graphics topography, etc.

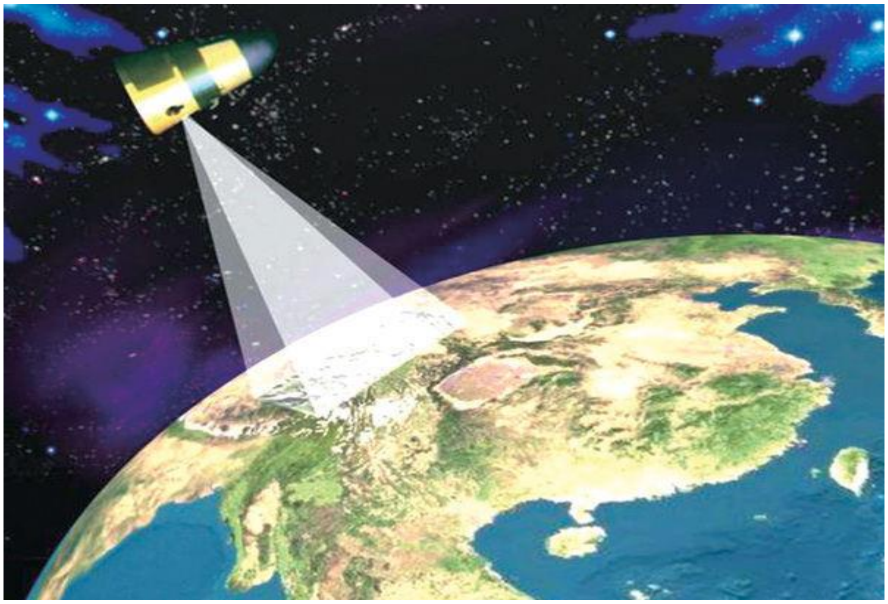


Figure 4. Application of object recognition in aviation and remote sensing

b.iv Application in biomedicine

In the field of biomedicine, object recognition is used to assist doctors in medical images analysis (seen in Figure 5), where digital image processing and information fusion technologies can be used for medical imaging data statistics and analysis in the scenes of X-ray perspective, nuclear magnetic resonance and CT images.

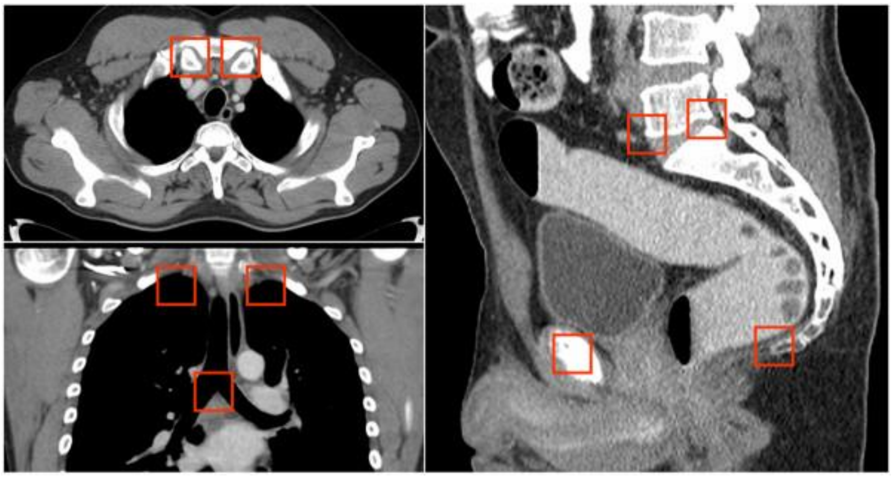


Figure 5. Application of object recognition in anatomical landmarks detection

For example, X-ray images reflect the bone tissue, nuclear magnetic resonance images reflect the organic organization, and doctors often need to consider the relationship between skeleton and organic organization, therefore the digital image processing technique is required to suitable superpose two kinds of images together to facilitate the medical analysis.

b.v Application in military and public security

Military security: the cruise missile terrain recognition, the object recognition and recognition, the radar terrain reconnaissance, the remote control aircraft guidance, the target identifying and guidance, the military alert system and automatic control of artillery, etc.

Public security: fingerprint, iris feature automatic recognition, the synthesis of criminals' face, the detection of suspect in public surrounding (seen in Figure 6), the automatic identification of handwriting, portrait, and seal, enhancing image quality to capture emergency in the monitoring system for closed circuit television, intelligent scheduling in traffic management system, etc.

Figure 6. Application of object recognition in suspect detection

The rest of this paper is organized as follows. We present a brief review on object recognition in Section II. Section III provides a review on Multi-class SVM. We propose the detailed improved Multi-class SVM algorithm and experimental results in Section IV, and section V concludes this paper.

II. REVIEW ON OBJECT RECOGNITION

Object recognition is a challenging research topic in the field of artificial intelligence, which has been widely used in the military reconnaissance, precise guidance, firefighting, battlefield assessment, and the security monitoring, etc.

In a recognition scenario, an object can be defined as anything that is of interest for further analysis. Objects can be represented by their shapes and appearances.

a. Object shape representations

A. Yilmaz [1] described the object shape representations commonly employed for object recognition as follows (Fig. 7).

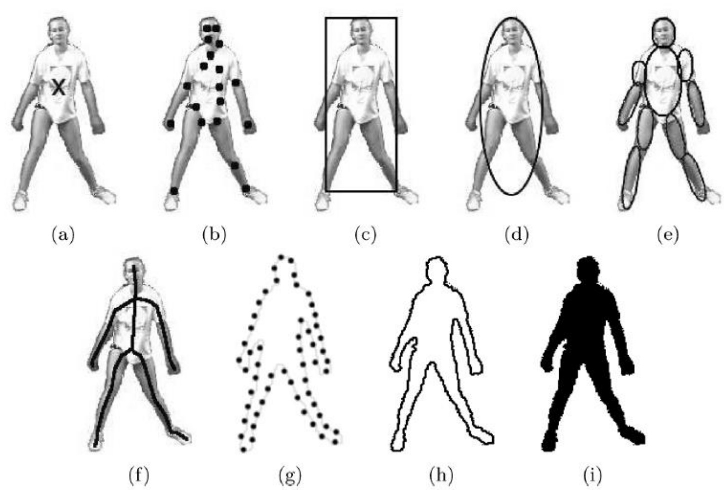


Figure 7. Object shape representations

a.i Points

The object is represented by a point, that is, the centroid (Figure 7(a)) [2] or by a set of points (Figure 7(b)) [3]. In general, the point representation is suitable for recognition objects that occupy small regions in an image.

a.ii Primitive geometric shapes

Object shape is represented by a rectangle, ellipse (Figure 7(c), (d)) [4], etc. Object motion for such representations is usually modeled by translation, affine, or projective transformation.

Though primitive geometric shapes are more suitable for representing simple rigid objects, they are also used for recognition non-rigid objects.

a.iii Articulated shape models

Articulated objects are composed of body parts that are held together with joints. For example, the human body is an articulated object with torso, legs, hands, head, and feet connected by joints. The relationships between the parts are governed by kinematic motion models, for example, joint angle, etc. In order to represent an articulated object, one can model the constituent parts using cylinders or ellipses as shown in Figure 7(e).

a.iv Skeletal models

Object skeleton can be extracted by applying medial axis transform to the object silhouette. This model is commonly used as a shape representation for recognizing objects [5]. Skeleton representation can be used to model both articulated and rigid objects (see Figure 7(f).

a.v Object silhouette and contour

Contour representation defines the boundary of an object (Figure 7(g), (h). The region inside the contour is called the silhouette of the object (see Figure 7(i)). Silhouette and contour representations are suitable for recognition complex non-rigid shapes [6].

b. Object appearance representations

There are a number of ways to represent the appearance features of objects. Note that shape representations can also be combined with the appearance representations [7] for recognition. Some common appearance representations in the context of object recognition can be summed up as follows.

b.i Probability densities of object appearance

The probability density estimates of the object appearance can either be parametric, such as Gaussian and a mixture of Gaussians [8], or nonparametric, such as Parzen windows [9] and histograms [4]. The probability densities of object appearance features (color, texture) can be computed from the image regions specified by the shape models (interior region of an ellipse or a contour).

b.ii Templates

Templates are formed using simple geometric shapes or silhouettes [10]. An advantage of a template is that it carries both spatial and appearance information. Templates, however, only encode the object appearance generated from a single view. Thus, they are only suitable for recognition objects whose poses do not vary considerably during the course of recognition.

b.iii Active appearance models

Active appearance models are generated by simultaneously modeling the object shape and appearance [11]. In general, the object shape is defined by a set of landmarks. Similar to the contour-based representation, the landmarks can reside on the object boundary or, alternatively, they can reside inside the object region. For each landmark, an appearance vector is stored which is in the form of color, texture, or gradient magnitude. Active appearance models require a training phase where both the shape and its associated appearance is learned from a set of samples using, for instance, the principal component analysis.

b.iv Multi-view appearance models

These models encode different views of an object. One approach to represent the different object views is to generate a subspace from the given views. Subspace approaches, for example, Principal Component Analysis (PCA) and Independent Component Analysis (ICA), have been used for both shape and appearance representation. Another approach to learn the different views of an object is by training a set of classifiers, for example, the support vector machines [12] or Bayesian networks [13]. One limitation of multi-view appearance models is that the appearances in all views are required ahead of time.

In general, there is a strong relationship between the object representations and the recognition algorithms. Object representations are usually chosen according to the application domain. For recognition objects, which appear very small in an image, point representation is usually appropriate. For instance, Veenman et al. [2] use the point representation to recognize the seeds in a moving dish sequence. Similarly, Shafique and Shah [14] use the point representation to recognize distant birds. For the objects whose shapes can be approximated by rectangles or ellipses, primitive geometric shape representations are more appropriate. Comaniciu et al. [4] use an elliptical shape representation and employ a color histogram computed from the elliptical region for modeling the appearance. In 1998, Black and Jepson used eigenvectors to represent the appearance. The eigenvectors were generated from rectangular object templates. For recognition objects with complex shapes, for example, humans, a contour or a silhouette-based representation is appropriate. Haritaoglu et al. [15] use silhouettes for object recognition in a surveillance application.

III. MULTI-CLASS SUPPORT VECTOR MACHINE

Based on Statistical Learning Theory (SLT), Vapnik et al. proposed the Support Vector Machine (SVM) method. Compared with the traditional statistical learning methods, SVM method has more solid mathematics theory foundation, which can effectively dealing with high-dimensional data under the condition of limited samples, and has the merits of strong generalization ability, convergence to the global optimal, non-sensitive to dimension, etc. Based on these merits, SVM has become one of the most popular research direction in the field of machine learning, and achieved widely research and application successfully in many fields, such as pattern classification, regression analysis, and estimation of density function, and so on.

a. Binary SVM

SVM was originally proposed to handle binary classification, and can be formulated as a QP to maximize the margin between two classes (seen in Figure 8), whose consequent generalization ability is always better than the other machine learning methods.

Given a training data sets $S=\{(x_i,y_i)\,|\,i=1,\dots,m\}$, where $x_i \in R^d$ and $y_i \in \{+1,-1\}$, the primal for the Binary SVM problem can be formulated as

$$\begin{aligned} &\min_{w,\rho,b,\xi_i} \ ||w||^2 + b^2 - 2\rho + C\sum_{i=1}^{m}\xi_i^{\,2} \\ &s.t. \quad y_i(w'\phi(x_i)+b) \ge \rho - \xi_i,\ i=1,\dots,m. \end{aligned} \qquad (1)$$

The corresponding dual is

$$\begin{aligned}\min_{\alpha_i}\ & \sum_{i,j=1}^{m}\alpha_i\alpha_j(y_iy_jk(x_i,x_j)+y_iy_j+\frac{\delta_{ij}}{C}) \\ s.t.\ & \sum_{i=1}^{m}\alpha_i=1,\ \alpha_i\geq 0,\ \ i=1,\ldots,m,\end{aligned} \tag{2}$$

Where δ_{ij} is the Kronecker delta function, defined as

$$\delta_{ij}=\begin{cases}1, & if\ i=j,\\ 0, & if\ i\neq j.\end{cases} \tag{3}$$

We denote the pair (x_i, y_i) as z_i to simplify the notation. Introducing a modified feature map $\tilde{\phi}(z_i)=[y_i\phi'(x_i)\ \ y_i\ \ \frac{e'_i}{\sqrt{C}}]'$ and the associated kernel function $\tilde{k}(z_i,z_j)=y_iy_jk(x_i,x_j)+y_iy_j+\frac{\delta_{ij}}{C}$, then the dual of Binary SVM with form (2) can be rewritten as

$$\begin{aligned}\min_{\alpha_i}\ & \sum_{i,j=1}^{m}\alpha_i\alpha_j\tilde{k}(z_i,z_j) \\ s.t.\ & \sum_{i=1}^{m}\alpha_i=1,\ \alpha_i\geq 0,\ \ i=1,\ldots,m.\end{aligned} \tag{4}$$

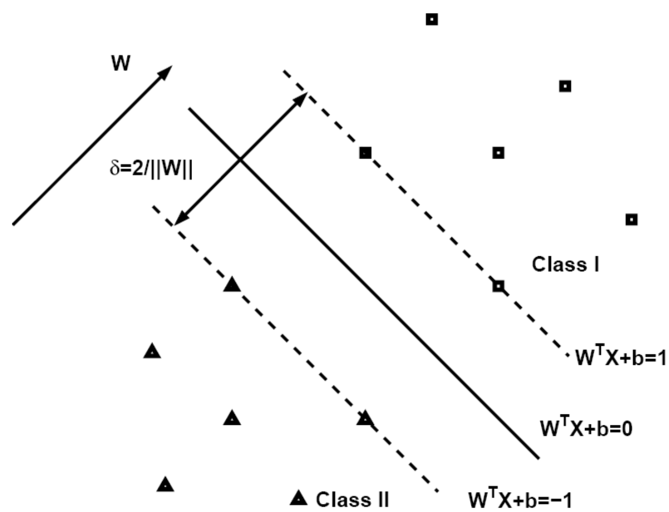


Figure 8. SVM with the maximal margin between two classes

b. Multi-class SVM

With the successful applications of binary-SVM in diverse areas, many efforts have been made to extend binary-SVM to tackle multi-class problems, among which there are two approaches.

The first approach is decomposing the multi-class problem into a number of binary classification problems, solving the consequent binary-class problems with binary-SVMs and output training results to formulate the final decision function. The prediction procedure is based on a voting scheme among all the binary classifiers to derive the winning class. Currently, the prevalent methods are 'one vs. all' and 'one vs. one'. The former compares each class with the rest and hence achieving *k* binary-SVMs for *k*-classification, which could unbalance the training sets, whether or not the primary data sets are balanced. The latter constructs a combination of arbitrary pair of classes and achieves c_k^2 binary-SVMs for *k*-classification, which could be computationally expensive for large class number *k*.

The second approach is utilizing all the available data and classes directly, formulating and solving an optimization problem to handle the multiple classification problems. The training procedures involved in these methods are fairly complicated and hence are computationally expensive. Asharaf [16] claimed that, even though the decomposition or data-sampling techniques [17-20] can help to reduce the complexity of the optimization problem, they are still expensive for use in applications involving large data sets [21-25].

With the idea of a reinterpretation of the normal vector of the separating hyper-plane, Szedmak and Shawe-Taylor formulated multi-SVM as an SVM with vector output, where the vector can be seen as a projection operator of the feature vectors into a one-dimensional subspace.

Given a set of data points $S = \{(x_i, y_i) \mid i = 1,\dots,m\}$, where $x_i \in R^d$, $y_i \in R^T$, i.e., we have *m* training data whose labels are vector valued. Obviously there are many choices of the vector labels, the simplest is the indicator vectors of the classes following the rule

$$(y_i)_t = \begin{cases} 1, & \text{item i belongs to category t, t} = 1,\dots,\text{T}, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Then the primal of the multi-SVM can be formulated as

$$\begin{aligned} \min_{w,\rho,b,\xi_i} \ & trace(w'w) + \|b\|^2 - 2\rho + C\sum_{i=1}^{m} \xi_i^{\ 2} \\ s.t. \quad & y_i'(w\phi(x_i) + b) \geq \rho - \xi_i, \ i = 1,\dots,m. \end{aligned} \tag{6}$$

The corresponding dual is

$$\begin{aligned} \min_{\alpha_i} \ & \sum_{i,j=1}^{m} \alpha_i \alpha_j (y_i' y_j k(x_i, x_j) + y_i' y_j + \frac{\delta_{ij}}{C}) \\ s.t. \ & \sum_{i=1}^{m} \alpha_i = 1, \ \alpha_i \geq 0, \ \ i = 1,\dots,m. \end{aligned} \tag{7}$$

From the KKT conditions on form (6) we can get $w=\sum_{i=1}^{m}\alpha_i y_i \phi(x_i)'$, $b=\sum_{i=1}^{m}\alpha_i y_i$. So the decision function predicting one of the labels from $\{(y_i)\,|\,i=1,\ldots,m\}$ for any test pattern xj can be descried as

$$\arg\max_{t=1,\ldots,T} \; y_t'(w\phi(x_j)+b)=\arg\max_{t=1,\ldots,T} \; (\sum_{i=1}^{m}\alpha_i y_i' y_t (k(x_i,x_j)+1)) \,. \qquad (8)$$

We denote the pair (x_i, y_i) as z_i to simplify the notation. Introducing a modified feature map $\tilde{\phi}(z_i)=[y_i'\phi'(x_i) \;\; y_i' \;\; \frac{e'_i}{\sqrt{C}}]'$ and associated kernel function $\tilde{k}(z_i,z_j)=y_i' y_j k(x_i,x_j)+y_i' y_j+\frac{\delta_{ij}}{C}$, then the dual of multi-SVM with form (7) can be rewritten as

$$\begin{aligned} &\min_{\alpha_i} \; \sum_{i,j=1}^{m}\alpha_i\alpha_j\tilde{k}(z_i,z_j) \\ &s.t. \; \sum_{i=1}^{m}\alpha_i=1, \; \alpha_i\geq 0, \;\; i=1,\ldots,m. \end{aligned} \qquad (9)$$

c. Multi-class Core Vector Machine

Utilizing the idea proposed by Core Vector Machine and the duality formulation presented by Minimum Enclosing Ball, Multi-class Core Vector Machine [16] can efficiently handle multi-class classification.

c.i Minimum Enclosing Ball

Given a set of data points $S=\{x_i\,|\,i=1,\ldots,m\}$, where $x_i\in R^d$, the Minimum Enclosing Ball (MEB) of S (denoted as MEB(S)) is defined as the smallest ball $B(c,R)$ that contains all the points in S, i.e., $B(c,R)=\{x_i\in R^d \,|\, \|x_i-c\|\leq R\}$.

Let k be a kernel function with the associated feature map ϕ, i.e. $k(x_i,x_j)=\langle\phi(x_i),\phi(x_j)\rangle$, where $\langle\cdot,\cdot\rangle$ denotes the inner product. Then the primal MEB problem in the kernel-induced feature space to find the MEB(S) with center c and radius R can be formulated as

$$\begin{aligned} &\min_{R,c} \; R^2 \\ &s.t. \; ||c-\phi(x_i)||^2\leq R^2, i=1,\ldots,m. \end{aligned} \qquad (10)$$

The corresponding dual is

$$\begin{aligned} \max_{\alpha_i} \quad & \sum_{i=1}^{m} \alpha_i k(x_i, x_i) - \sum_{i,j=1}^{m} \alpha_i \alpha_j k(x_i, x_j) \\ s.t. \quad & \sum_{i=1}^{m} \alpha_i = 1,\ \alpha_i \geq 0,\ i = 1, \dots, m. \end{aligned} \tag{11}$$

c.ii Core Vector Machine and Multi-class Core Vector Machine

Core Vector Machine (CVM) [26] is a promising technique for scaling up a Binary SVM to handle large data sets with the greedy-expansion strategy, where the kernels are required to be normalized to ensure the equivalence between the kernel-induced spaces of SVM and Minimum Enclosing Ball (MEB).

Considering only the situation where the kernel *k* satisfies $k(x, x) = \kappa$, a constant. This holds true for kernels like Gaussian, polynomial kernel with normalized inputs, and any normalized kernels [26]. Then the dual of the MEB problem (11) can be rewritten as

$$\begin{aligned} \min_{\alpha_i} \quad & \sum_{i,j=1}^{m} \alpha_i \alpha_j k(x_i, x_j) \\ s.t. \quad & \sum_{i=1}^{m} \alpha_i = 1,\ \alpha_i \geq 0,\ i = 1, \dots, m. \end{aligned} \tag{12}$$

When the involved kernels fulfill the requirements mentioned above, any Quadratic Programming (QP) of form (12) can be identified as an MEB problem, and so the formulation of Binary SVM with form (4) does.

Similarly, with the same requirement on kernel *k*, the Multi-class Core Vector Machine [16] presented that the Multi-class SVM with form (9) can be identified as an MEB problem, as well. The identical relationship provides the theoretical fundamental for introducing the MEB algorithm to solve SVM problem in dual space.

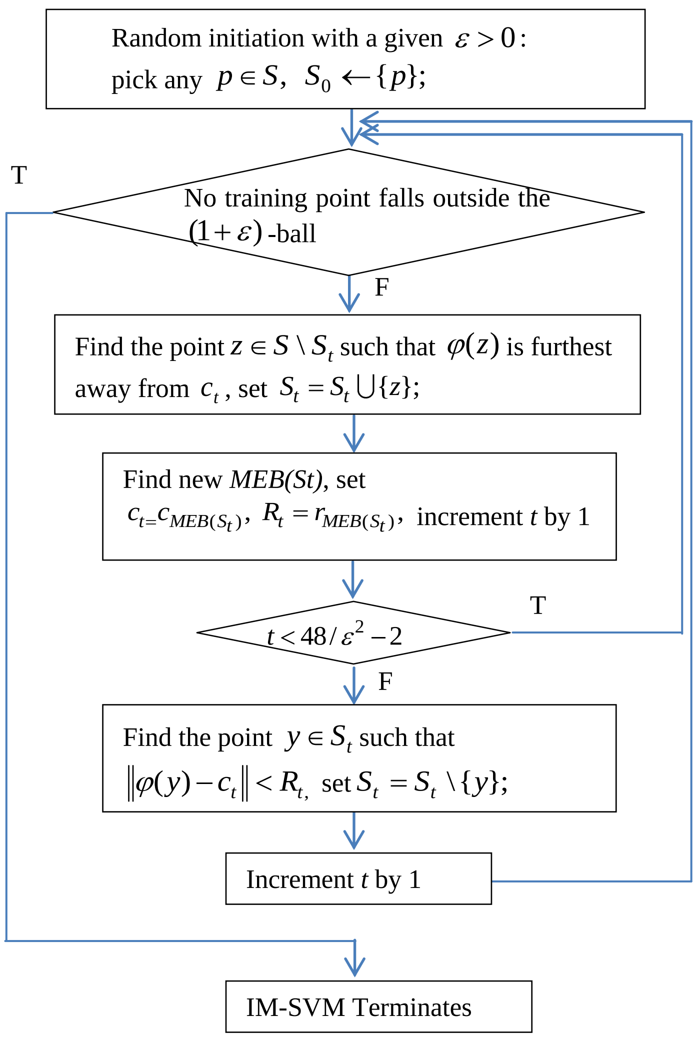
IV. IMPROVED MULTI-CLASS SVM ALGORITHM

The methods of CVM and Multi-class CVM can efficiently scale the SVM method to handle binary or multi-class classification problems. But we found that there always exist some redundancies in the implications, which limits the scalability of these two methods to deal with large scale data sets. In this paper, we propose an improved multi-class SVM (IM-SVM) algorithm, whose time and space complexities of $O(d^4 + d^2 m + \frac{d^3}{\varepsilon^2} + \frac{dm}{\varepsilon^2})$ and $O(\min\{\frac{1}{\varepsilon^4}, d^2\})$, respectively, and can handle large scale data set more effectively.

a. IM-SVM algorithm

We formulate the IM-SVM algorithm in Table 1 below.

Table 1. The improved multi-class SVM algorithm



b. The analysis on time and space complexities

We conclude the analysis on time and space complexities in Theorems 1 to 4 below.

Theorem 1. In the process of IM-SVM Algorithm, when the iteration satisfies $i \geq \frac{48}{\varepsilon^2} - 2$, if one point q falls into the interior of current MEB, i.e., $\|q - c_i\| < r_i$, it will fall into the interior of subsequence MEBs, i.e., $\|q - c_{i+j}\| < r_{i+j}$, $j \in Z^+$.

Theorem 2. IM-SVM Algorithm can achieve a $(1+\varepsilon)$-approximate MEB for training data set S within $O(\frac{1}{\varepsilon^2})$ iterations.

Theorem 3. In the iterations of IM-SVM Algorithm, there exists a subset $P \subset S$, whose points are at distance at most $(1+\varepsilon)r_{B(S)}$ from center $c_{B(S)}$, and the size of P is $O(\min\{\frac{1}{\varepsilon^2}, d\})$.

Theorem 4. The time and space complexities of IM-SVM Algorithm are $O(d^4 + d^2 m + \frac{d^3}{\varepsilon^2} + \frac{dm}{\varepsilon^2})$ and $O(\min\{\frac{1}{\varepsilon^4}, d^2\})$.

The detailed proofs of these theorems are omitted here for conciseness, the interested readers can refer to Wang [27, 28].

c. Experiments on synthetic data

Experiments are performed on five synthetic data sets, which follow a uniform distribution on the interval (0, 10) (Table 2). We use Matlab 7.0 on a PC with Pentium-4 3.20 GHz CPU, 1GB of RAM running Windows XP to implement our experiments.

Table 2. Synthetic data sets in detail

Data set	**Sy. 1**	**Sy. 2**	**Sy. 3**	**Sy. 4**	**Sy. 5**	**Sy. 6**
# Class	**4**	**4**	**4**	**4**	**4**	**4**
# Dim.	**2**	**2**	**2**	**2**	**2**	**2**
# Point	**20**	**100**	**200**	**1000**	**2000**	**10000**

We denote the algorithms One-Vs.-One Multi-class SVM, One-Vs.-All Multi-class SVM, Multi-class CVM, and Improved Multi-class SVM as OVO-MSVM, OVA-MSVM, M-CVM and IM-SVM, respectively. The number of support vector, number of core vector and training time for all the algorithms, which vary with data size for the synthetic data under the best choice of ε are given in Figure 9 to Figure 11. We can see that the proposed IM-SVM is of the smallest core vectors' number and the shortest training time, expect for the training time of OVO-MSVM, which is of the lowest accuracy. The experimental results digitally demonstrate the superiority of IM-SVM to other algorithms.

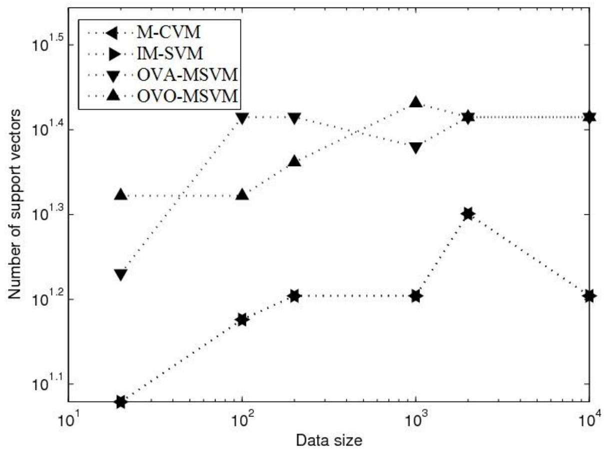


Figure 9. The numbers of support vector under the best choice of ε

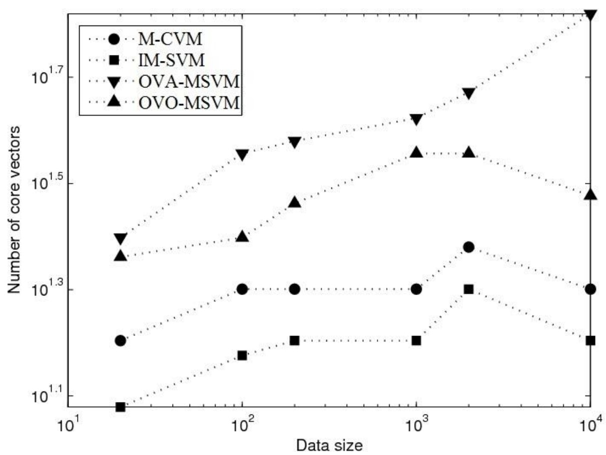


Figure 10. The numbers of core vector under the best choice of ε

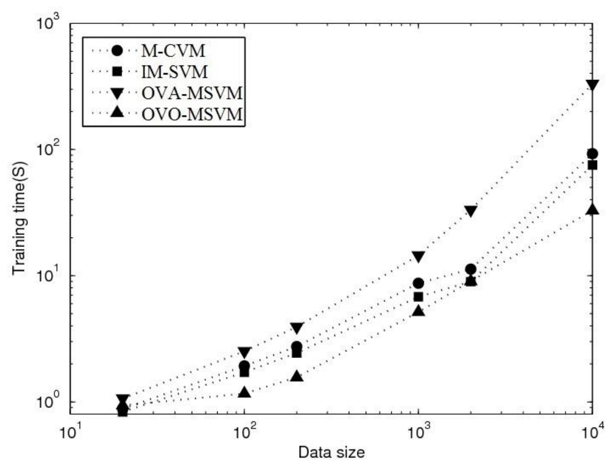


Figure 11. The training time under the best choice of ε

d. Experiments on object recognition

We implemented the proposed IM-SVM algorithm to handle object recognition problem, where the static recognition pictures are downloaded randomly from internet, which are related to aircrafts in flying or static status. We recognized flying aircrafts in low noisy background (see Figure 12), flying aircrafts in high noisy background (see Figure 13), static aircrafts with similar shapes in airport (see Figure 14), and static aircrafts with different shapes in airport (see Figure 15).

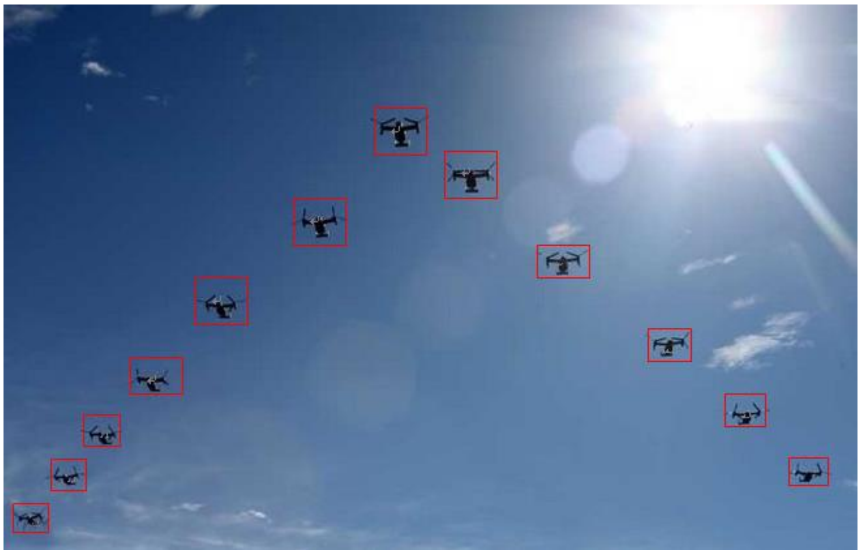


Figure 12. Recognition of flying aircrafts in low noisy background

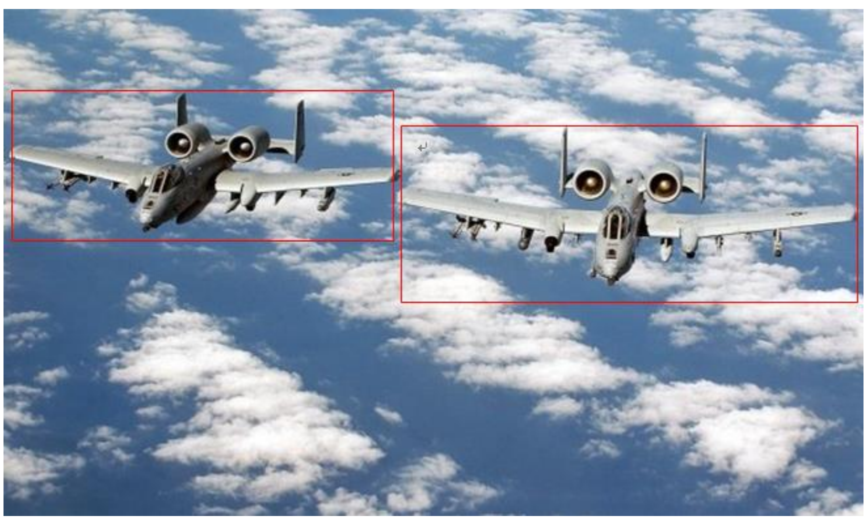


Figure 13. Recognition of flying aircrafts in high noisy background

Figure 14. Recognition of static aircrafts with similar shapes in airport

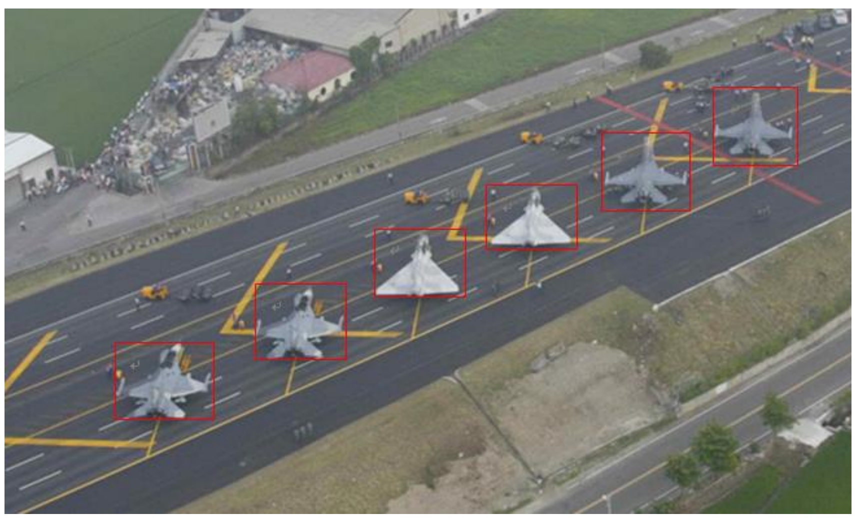


Figure 15. Recognition of static aircrafts with different shapes in airport

V. CONCLUSIONS

Based on the idea given by Cove Vector Machine and Multi-class Cove Vector Machine, and the dual formulation presented by Minimum Enclosing Ball, we proposed an Improved Multi-class SVM algorithm to handle object recognition efficiently. We prove theoretically that the proposed

IM-SVM algorithm has time complexity of $O(d^4 + d^2 m + \frac{d^3}{\varepsilon^2} + \frac{dm}{\varepsilon^2})$, which is linear in the number of training samples m for a fixed ε, and space complexity of $O(\min\{\frac{1}{\varepsilon^4}, d^2\})$, which is independent of m for a fixed ε. The experimental results on synthetic data, recognition results on aircrafts with different status demonstrate the validity of the proposed algorithm.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China (Grant No. 41001235), the Project of Henan Provincial Audit Office (Grant No. 20120922), the Scientific & Technological Research Key Project of Henan Provincial Education Office (Grant No. 13A520404), the Scientific & Technological Project of Henan Provincial Science & Technology Office (Grant No. 132102210468), the Project of Science and Technology Bureau of Zhengzhou (Grant No. 20120435 and 20130713).

The authors are grateful to the anonymous referees for their valuable comments and suggestions to improve the presentation of this paper.

REFERENCES

[1] Alper Yilmaz, Omar Javed, and Mubarak Shah, “Object tracking: A survey”, ACM Computing Surveys, Vol. 38, No. 4, 2006, pp. 1-45.

[2] C. VEENMAN, M. REINDERS, and E. BACKER, “Resolving motion correspondence for densely moving points”, IEEE Trans. Patt. Analy. Mach. Intell., Vol. 23, No. 1, 2001, pp. 54-72.

[3] D. SERBY, S. KOLLER-MEIER, and L. V. GOOL, “Probabilistic object tracking using multiple features”, In IEEE International Conference of Pattern Recognition, 2004, pp. 184-187.

[4] D. COMANICIU, V. RAMESH, and P. MEER, “Kernel-based object tracking”, IEEE Trans. Patt. Analy. Mach. Intell., Vol. 25, 2003, pp. 564-575.

[5] A. ALI, and J. AGGARWAL, “Segmentation and recognition of continuous human activity”, In IEEE Workshop on Detection and Recognition of Events in Video, 2001, pp. 28-35.

[6] A. YILMAZ, X. LI, and M. SHAH, "Contour based object tracking with occlusion handling in video acquired using mobile cameras", IEEE Trans. Patt. Analy. Mach. Intell., Vol. 26, No. 11, 2004, pp. 1531-1536.

[7] T. COOTES, and C. TAYLOR, "Robust real-time periodic motion detection, analysis, and applications", IEEE Trans. Patt. Analy. Mach. Intell., Vol. 23, No. 6, 2001, pp. 681-685.

[8] N. PARAGIOS, and R. DERICHE, "Geodesic active regions and level set methods for supervised texture segmentation", Int. J. Comput. Vision, Vol. 46, No. 3, 2002, pp. 223-247.

[9] A. ELGAMMAL, R. DURAISWAMI, and D. HARWOOD, "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance", Proceedings of IEEE, Vol. 90, No. 7, 2002, pp. 1151-1163.

[10] P. FIEGUTH, and D. TERZOPOULOS, "Color-based tracking of heads and other mobile objects at video frame rates", In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 1997, pp. 21-27.

[11] G. EDWARDS, C. TAYLOR, and T. COOTES, "Interpreting face images using active appearance models", In International Conference on Face and Gesture Recognition, 1998, pp. 300-305.

[12] S. AVIDAN, "Support vector tracking", In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2001, pp. 184-191.

[13] S. PARK and J. K. AGGARWAL, "A hierarchical bayesian network for event recognition of human actions and interactions", Multimed. Syst., Vol. 10, No. 2, 2004, pp. 164-179.

[14] K. SHAFIQUE and M. SHAH, "A non-iterative greedy algorithm for multi-frame point correspondence", In IEEE International Conference on Computer Vision, 2003, pp. 110-115.

[15] I. HARITAOGLU, D. HARWOOD, and L. DAVIS, "W4: real-time surveillance of people and their activities", IEEE Trans. Patt. Analy. Mach. Intell., Vol. 22, No. 8, 2000, pp. 809-830.

[16] S. Asharaf, M. N. Murty and S. K. Shevade, "Multiclass Core Vector Machine", Proc. the 24th International Conference on Machine Learning (ICML 2007), 2007, pp. 41-48.

[17] Francesco Orabona, "Better Algorithms for Selective Sampling", Proc. the 28th International Conference on Machine Learning (ICML 2011), 2011, pp. 433-440.

[18] Y. Liu, "Combining integrated sampling with SVM ensembles for learning from imbalanced datasets", Information Processing and Management, Vol. 47, No. 4, 2011.

[19] M. Volpi, “Memory-Based Cluster Sampling for Remote Sensing Image Classification”, IEEE Transactions on Geoscience and Remote Sensing, Vol. 50, No. 8, 2012.

[20] Abhimanyu Das and David Kempe, “Submodular meets Spectral: Greedy Algorithms for Subset Selection, Sparse Approximation and Dictionary Selection”, Proc. the 28th International Conference on Machine Learning (ICML 2011), 2011, pp. 1057-1064.

[21] G.Sengupta, T.A.Win, C.Messom, S.Demidenko and S.C.Mukhopadhyay, “Defect analysis of grit-blasted or spray printed surface using vision sensing technique”, Proceedings of Image and Vision Computing NZ, Nov. 26-28, 2003, Palmerston North, pp. 18-23.

[22] G. Sen Gupta, S.C. Mukhopadhyay and M Finnie, Wi-Fi Based Control of a Robotic Arm with Remote Vision, Proceedings of 2009 IEEE I2MTC Conference, Singapore, May 5-7, 2009, pp. 557-562.

[23] N.K. Suryadevara and S.C. Mukhopadhyay, “Wireless Sensor Network Based Home Monitoring System for Wellness Determination of Elderly”, IEEE Sensors Journal, Vol. 12, No. 6, June 2012, pp. 1965-1972.

[24] N. K. Suryadevara and S. C. Mukhopadhyay, “Determining Wellness Through An Ambient Assisted Living Environment”, IEEE Intelligent Systems, May/June 2014, pp. 30-37.

[25] N.K. Suryadevara, S.C. Mukhopadhyay, R. Wang, R.K. Rayudu, Forecasting the behavior of an elderly using wireless sensors data in a smart home, Engineering Applications of Artificial Intelligence, Volume 26, Issue 10, November 2013, Pages 2641-2652, ISSN 0952-1976, http://dx.doi.org/10.1016/j.engappai.2013.08.004.

[26] I. W. Tsang, J. T. Kwok and P. M. Cheung, “Core vector machines: Fast SVM training on very large data sets”, Journal of Machine Learning Research, Vol. 6, 2005, pp. 363-392.

[27] Y. Q. Wang, Y. Li, and L. Chang, “Approximate Minimum Enclosing Ball Algorithm with Smaller Core Sets for Binary Support Vector Machine”, Proc. the 2010 Chinese Control and Decision Conference (CCDC 2010), 2010, pp. 3404-3408.

[28] Y. Q. Wang, X. T. Niu, and L. Chang, “Multiclass Core Vector Machine with Smaller Core Sets”, Proc. the 2010 Chinese Control and Decision Conference (CCDC 2010), 2010, pp. 525-530.