OBJECT TRACKING BASED ON MACHINE VISION AND IMPROVED SVDD ALGORITHM

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

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Abstract- Object tracking is an important research topic in the applications of machine vision, and has made great progress in the past decades, among which the technique based on classification is a very efficient way to solve the tracking problem. The classifier classifies the objects and background into two different classes, where the tracking drift caused by noisy background can be effectively handled by one-class SVM. But the time and space complexities of traditional one-class SVM methods tend to be high, which makes it do not scale well with the number of training sample, and limits its wide applications. Based on the idea proposed by Support Vector Data Description, we present an improved SVDD algorithm to handle object tracking efficiently. The experimental results on synthetic data, tracking results on car and plane demonstrate the validity of the proposed algorithm.

Index terms: Object tracking, machine vision, Support Vector Data Description, one-class SVM, classification.

I. INTRODUCTION

Machine vision means utilizing computer to simulate the visual function of human eyes, identify the shape and movement of objects in the objective world by extract information from images or image sequences. Machine vision is a comprehensive technology, including digital processing technology, mechanical engineering technology, control technology, illumination technology, optical imaging technology, sensor technology, analog and digital video technology, computer software and hardware technology, man-machine interface technology, etc. Machine vision emphasizes practicality, such as high capability on fault-tolerant and security, strong versatility and portability, high performances on real-time, fast speed and high precision.

A typical industrial machine vision system includes light source, optical image system, image capturing system, image collection & digitalization module, image processing module, intelligent judgment decision module and mechanical control execution module (as shown in Figure l).

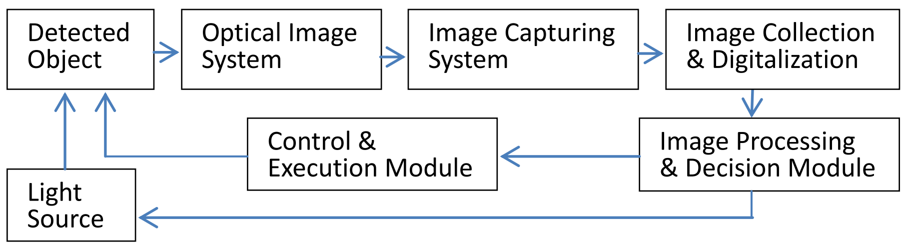

Figure 1. The flow diagram of typical industrial machine vision system

Firstly, the objects are converted into analog image signal by image capturing and collection systems, and then the digital signals processed by digitalization system are transmitted to the dedicated image processing system. According to the pixel distribution, brightness, and color information, a variety of operations will be calculated to extract target features, and finally outputs the decision results according to the preset permissibility and other conditions.

The machine vision technology is a combination of rapidity and repeatability of computer, high ability of intelligence and abstraction for the human vision. The final research goal of machine vision aims at making a computer or robot can understand the world by observing like people's doing through visual ability, which needs a long term efforts to reach the purpose.

We make a brief review about the fruitful achievements of machine vision during the past few decades in the subsection below.

a. Current research status on machine vision

The global research boom of machine vision began from the 1980's, and obtained vigorous development in the mid-1980s, new concepts, new methods and new theories are created in this period. For example, based on the cognitive features, the object recognition theoretical framework, active vision theoretical framework, and visual integrated theoretical framework, appeared.

The visual calculation theory proposed by D. Marr is by far the most perfect theory in visual research, whose computing theoretical fundamental is based on computer science, and systematically summarizes the important results which have been achieved in psychological physiology and neurophysiology. The visual calculation theory makes a clear theoretical system for the research of computer vision, and greatly promoted the development of computer vision research.

D. Marr claimed that vision is an information processing system, whose process can be divided into three phases, as shown in Figure 2.

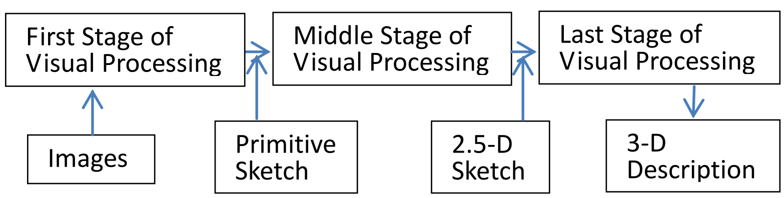

Figure 2. Three stages in the vision theory of D. Marr

In the first stage of visual processing, the inputted original images are processed by extraction of fundamental features, such as comers, edges, textures, lines, and boundaries. These characteristic sets called primitive sketch.

The middle stage means recovering the depths, normal directions, outlines of visible parts of scenes by outputted images and primitive sketch in coordinate system centered on the observer, where the information includes the depth, but it is not the real 3-Dimensional description, called 2.5-Dimensional sketch.

The last stage refers to the process of recovering, representing, and identifying 3-Dimensional objects by inputted images, primitive sketch, and 2.5-Dimensional sketch in the object-centered coordinate system.

b. Machine vision applications

Except for the absence of human eye's fatigue, machine vision has higher precision and processing speed than the human eye. By utilizing of infrared-ray, ultraviolet-ray, X-ray, ultrasound and other advanced detection techniques, machine vision has the significant advantages in detecting invisible object and high dangerous scene, machine vision technology has been widely used.

b.i Application of machine vision in industrial detection

Nowadays, machine vision 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.

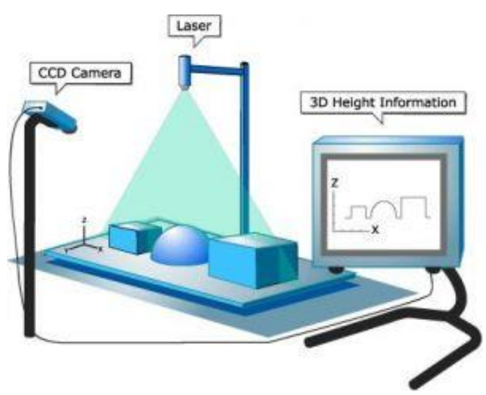

Figure 3. Scheme of machine vision in industry detection

b.ii Application of machine vision in aviation and remote sensing

Machine vision 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.

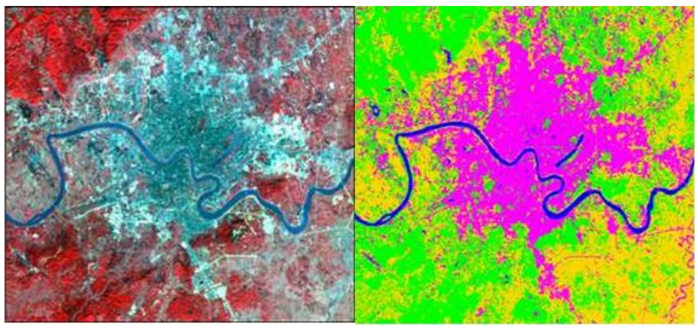

Figure 4. Remote sensing image classification: Original image (left) V.S. Classified image (right)

b.iii Application of machine vision in biomedicine

In the field of biomedicine, machine vision 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. 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.

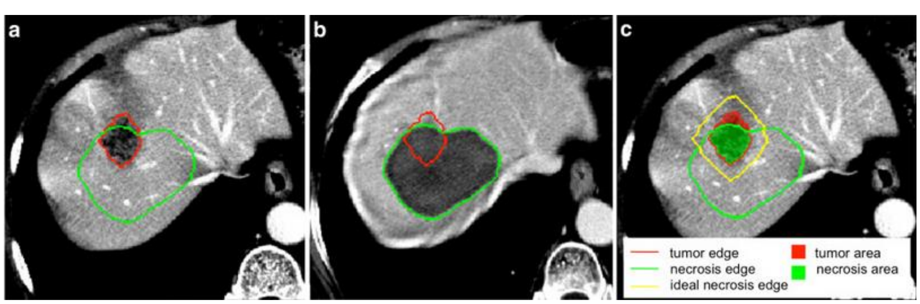

Figure 5. The lesion area detection

b.iv Application of machine vision in military and public security

Military security: the cruise missile terrain recognition, the object recognition and tracking (seen in Figure 6), 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 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.

The topic we discussed in this article is related to object tracking.

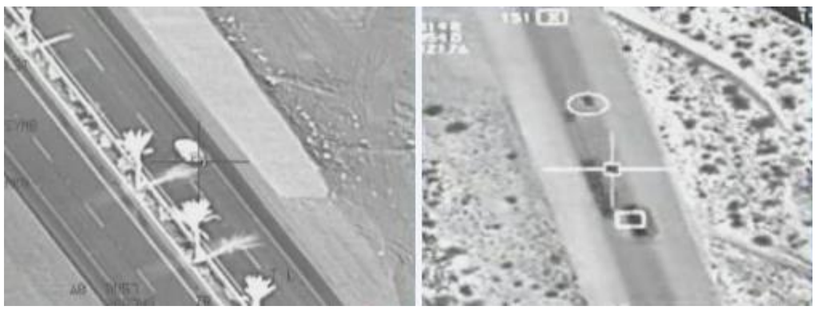

Figure 6. Military target recognition: Single target (left) V.S. Multi target (right)

The rest of this paper is organized as follows. We present a brief introduction to object tracking in Section II. Section III provides a review on Support Vector Data Description. We propose the detailed improved SVDD algorithm and experimental results in Section IV, and section V concludes this paper.

II. REVIEW ON OBJECT TRACKING

Object tracking is a challenging research topic in the field of computer vision, which has been widely used in the military reconnaissance, precise guidance, firefighting, battlefield assessment, and the security monitoring, etc. Tracking can be simply defined as the estimation for trajectory in the image plane of an object moving around a scene.

a. Mathematical description of object tracking

The object system can be regarded as a composition of dynamic system and observation system. The real state of the target system cannot be determined, so the target system can be identified as a black box, we can only through observations to estimate the state. And then, the object tracking problem can be transformed to the designing of state estimator [1], where the key point can be formulated as follows.

Given observations of $Z = \{z_i \mid i = 1,...,k\}$, the goal is to solve the posterior probability density distribution function of object state x_k. Aiming at solving this state estimation problem, we suppose the state function of object to be

$$x_k = f_k(x_{k-1}, v_{k-1}) \qquad (1)$$

where f_k is the nonlinear function of state vector x_{k-1}, and $\{v_{k-1}, k \in N\}$ is the system noise. The corresponding object observing function is

$$z_k = h_k(x_k, n_k) \qquad (2)$$

where h_k is the nonlinear function of state observing process, and $\{n_k, k \in N\}$ is the observing noise. According to the Bayesian Theory and Chapman-Kolmogorov function, the estimation of state prior probability density at the k^{th} moment is

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid z_{1:k-1}) dx_{k-1} \qquad (3)$$

The state posterior probability density at the k^{th} moment is

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k) p(x_k \mid z_{1:k-1})}{\int p(z_k \mid x_k) p(x_k \mid z_{1:k-1}) dx_k} \qquad (4)$$

where the value of equation (4) depends on the statistical properties of likelihood function $p(z_k \mid x_k)$ and observing noise n_k. Based on the criterion of minimum mean square error, the optimal estimation can be calculated as

$$\hat{x}_k = \int x_k p(x_k \mid z_{1:k}) dx_k \qquad （5）$$

The whole process of reasoning can be interpreted as two stages, prediction and update [2]. Prediction: Substituting the state probability density at the $k-1^{th}$ moment $p(x_{k-1} \mid z_{1:k-1})$ into the move equation of object to get the prior probability density distribution of current state $p(x_k \mid z_{1:k-1})$, as shown in equation (3). Update: using the similarity measure function $p(x_k \mid z_k)$ of current observation data, and the prior probability distribution $p(x_k \mid z_{1:k-1})$ of state to determine the posterior probability density distribution of current state, as shown in equation (4). The tracking to the process of state's changes can be finally achieved by the whole procedure stated above.

b. Object tracking methods

Object tracking aims at generating the trajectories of moving objects over time by locating their positions in every frame of the video. Object tracker may also provide the complete region in the image that is occupied by the object at every time instant. According to the different strategies adopted in related methods, A. Yilmaz [3] divided the common object tracking into three categories.

b.i Point tracking

Objects detected in consecutive frames are represented by points, and the association of the points is based on the previous object state which can include object position and motion. This approach requires an external mechanism to detect the objects in every frame.

Tracking can be formulated as the correspondence of detected objects represented by points across frames. Point correspondence is a complicated problem, especially in the presence of occlusions, misdetections, entries, and exits of objects.

Overall, point correspondence methods can be divided into two broad categories, namely, deterministic method [4-7] and statistical method [8-10]. The deterministic methods use qualitative motion heuristics [4] to constrain the correspondence problem. On the other hand, probabilistic methods explicitly take the object measurement and take uncertainties into account to establish correspondence.

b.ii Kernel tracking

Kernel refers to the object shape and appearance. For example, the kernel can be a rectangular template or an elliptical shape with an associated histogram. Objects are tracked by computing the motion of the kernel in consecutive frames. This motion is usually in the form of a parametric transformation such as translation, rotation, and affine.

Kernel tracking is typically performed by computing the motion of the object, which is represented by a primitive object region, from one frame to the next. The object motion is generally in the form of parametric motion (translation, conformal, affine, etc.) or the dense flow field computed in subsequent frames. These algorithms differ in terms of the appearance representation used, the number of objects tracked, and the method used to estimate the object motion. A. Yilmaz [3] divided these tracking methods into two subcategories based on the appearance representation used, namely, templates and density-based appearance models [11-15], and multi-view appearance models [16, 17].

b.iii Silhouette tracking

Tracking is performed by estimating the object region in each frame. Silhouette tracking methods use the information encoded inside the object region. This information can be in the form of appearance density and shape models which are usually in the form of edge maps. Given the object models, silhouettes are tracked by either shape matching or contour evolution. Both of these methods can essentially be considered as object segmentation applied in the temporal domain using the priors generated from the previous frames.

Objects may have complex shapes, for example, hands, head, and shoulders that cannot be well described by simple geometric shapes. Silhouette-based methods provide an accurate shape description for these objects. The goal of a silhouette-based object tracker is to find the object region in each frame by means of an object model generated using the previous frames. This model can be in the form of a color histogram, object edges or the object contour. A. Yilmaz [3] divided silhouette trackers into two categories, namely, shape matching and contour tracking. Shape matching approaches [18-20] search for the object silhouette in the current frame. Contour tracking approaches [21-25], on the other hand, evolve an initial contour to its new position in the current frame by either using the state space models or direct minimization of some energy functional.

c. Existing problems in object tracking

Object tracking has made significant progress during the last few decades, some robust trackers have been developed to track objects in real time in simple scenarios. However, the assumptions to validate tracking techniques tend to be unpractical in real world. For example, smoothness of motion, minimal amount of occlusion, illumination constancy, high contrast with respect to background, etc., are violated in many realistic scenarios and therefore limit a tracker's usefulness in applications. We list the potential challenging problems as follows.

(1) The target's appearance changes with time, such as the variation and revolve of scale, the rotation of hyper-plane, the severe and non-uniform variation of target color caused by illumination change, non-rigid deformation, appearance variation cause by the perspective changes, etc.

(2) The various and complex changes in background, increases the difficulty in modeling and submerges the objects into the noisy background.

(3) The processing of occlusion and block phenomenon occurred in multiple targets.

(4) The blurring of high-speed motion target caused by the instability or inferior frame frequency of camera, etc.

(5) The reoccurrence of target after being totally covered or even loss.

The method proposed in this article can efficiently handle problem (2) mentioned above.

III. SUPPORT VECTOR DATA DESCRIPTION

The tracking technique based on classification is a very efficient way to solve the object tracking problem. The classifier classifies the objects and background into two different classes, where the tracking drift caused by noisy background can be effectively handled by one-class SVM.

From the angle of mathematics, one-class SVM has the identical mathematical formulation in duality space, i.e., the Minimum Enclosing Ball (MEB) problem, under which relationship appears the Support Vector Data Description (SVDD) [26] method.

a. Mathematical formulation of MEB

Given a set of data points $S=\{x_i \mid i=1,\ldots,m\}$, 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., $B(c,R)=\{x_i \in R^d \mid \|x_i - c\| \le R\}$.

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 $\langle .,. \rangle$ 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

$$\begin{aligned} &\min_{R,c} \; R^2 \\ &s.t. \;\; \|c-\phi(x_i)\|^2 \le R^2, i=1,\ldots,m. \end{aligned} \tag{6}$$

The corresponding dual is

$$\begin{aligned} &\max_{\alpha_i} \; \sum_{i=1}^{m}\alpha_i k(x_i,x_i)-\sum_{i,j=1}^{m}\alpha_i\alpha_j k(x_i,x_j) \\ &s.t. \;\; \sum_{i=1}^{m}\alpha_i=1, \; \alpha_i\ge 0, \; i=1,\ldots,m. \end{aligned} \tag{7}$$

b. Mathematical formulation of SVDD

The idea of SVDD [26] can be formulated as follows. Formulating Binary SVM as a QP to maximize the margin between two classes, and the consequent generalization ability is always better than the other machine learning methods.

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

$$\begin{aligned} &\min_{w,\rho,b,\xi_i} \; \|w\|^2+b^2-2\rho+C\sum_{i=1}^{m}\xi_i^2 \\ &s.t. \;\; y_i(w'\phi(x_i)+b)\ge\rho-\xi_i, i=1,\ldots,m. \end{aligned} \tag{8}$$

The corresponding dual is

$$\begin{aligned} &\min_{\alpha_i} \; \sum_{i,j=1}^{m}\alpha_i\alpha_j(y_iy_jk(x_i,x_j)+y_iy_j+\frac{\delta_{ij}}{C}) \\ &s.t. \;\; \sum_{i=1}^{m}\alpha_i=1, \; \alpha_i\ge 0, \; i=1,\ldots,m, \end{aligned} \tag{9}$$

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

$$\delta_{ij}=\begin{cases}1, & if\ i=j, \\ 0, & if\ i\ne j.\end{cases} \tag{10}$$

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 (9) can be rewritten as

$$\begin{aligned} &\min_{\alpha_i} \; \sum_{i,j=1}^{m}\alpha_i\alpha_j\tilde{k}(z_i,z_j) \\ &s.t. \;\; \sum_{i=1}^{m}\alpha_i=1, \; \alpha_i\ge 0, \; i=1,\ldots,m. \end{aligned} \tag{11}$$

c. Mathematical formulation of CVM

Core Vector Machine (CVM) [29] 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 [27]. Then the dual of the MEB problem (7) can be rewritten as

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

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 equation (11) does.

IV. IMPROVED SVDD ALGORITHM

The quadratic optimization problem involved in both SVDD and CVM methods has high time and space complexities. Asharaf [31] claimed that, even though the decomposition or data-sampling techniques [32-37] can help to reduce the complexity of the optimization problem, they are still expensive for use in applications involving large data sets. A practical technique to overcome the problem to a large extent is introducing a fast MEB algorithm, whose strategy is incrementally including the farthest point away from the current center of hypersphere, and has the time and space complexities of $O(\frac{m}{\varepsilon^2}+\frac{1}{\varepsilon^4})$ and $O(\frac{1}{\varepsilon^2})$, respectively.

However, we found that the final core vectors obtained for formulating the final decision function is always more than necessary in implementations, which results in some redundancies in the process of storing and training. So, we propose the improve SVDD (I-SVDD) algorithm by the strategy of inclusion-and-exclusion, which can reduce the redundancy as much as possible.

a. I-SVDD algorithm

We formulate the I-SVDD algorithm in Table 1 below.

Table 1. The improved SVDD algorithm

I-SVDD algorithm	
	Given an $\varepsilon > 0$, pick any $p \in S,\ S_0 \leftarrow \{p\}$;
1	Outputs S_0, c_0, R_0;
2	Terminate if there is no training point z such that $\varphi(z)$ falls outside the $(1+\varepsilon)$-ball $B(c_t,(1+\varepsilon)R_t)$;
3	Find $z \in S \setminus S_t$ such that $\varphi(z)$ is furthest away from c_t, set $S_t = S_t \cup \{z\}$;
4	Find new MEB(St), set $c_{t=}c_{MEB(S_t)}, R_t = r_{MEB(S_t)}$, and increment t by 1, if $t < 48/\varepsilon^2 - 2,$ go back to Step 2; otherwise go to Step 5;
5	Find $y \in S_t$ such that $\lVert\varphi(y) - c_t\rVert < R_{t,}$ set $S_t = S_t \setminus \{y\}$;
6	Increment t by 1 and go back to Step 2.

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 I-SVDD 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. I-SVDD 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 I-SVDD 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 I-SVDD 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, interested readers can refer to Wang [38].

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). All experiments do not adopt the probabilistic speedup method utilized in CVM for simplicity. 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: Data sets used in the experiments

data sets	**data 1**	**data 2**	**data 3**	**data 4**	**data 5**
dimension	2	2	2	2	2
number	10	100	1000	10000	100000

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 7 to Figure 9. We can see that the proposed I- SVDD is of the smallest core vectors' number and the shortest training time, expect for the training time of SVDD, which is of the lowest accuracy.

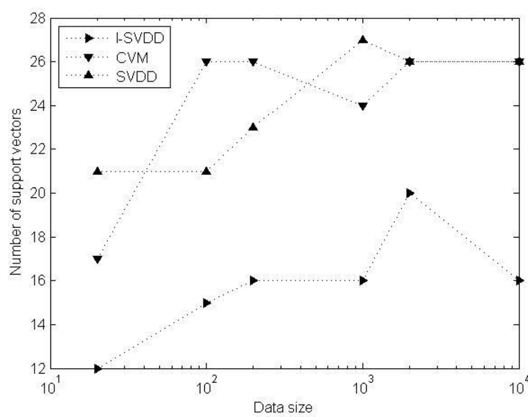

Figure 7. The numbers of support vector under the best choice of ε

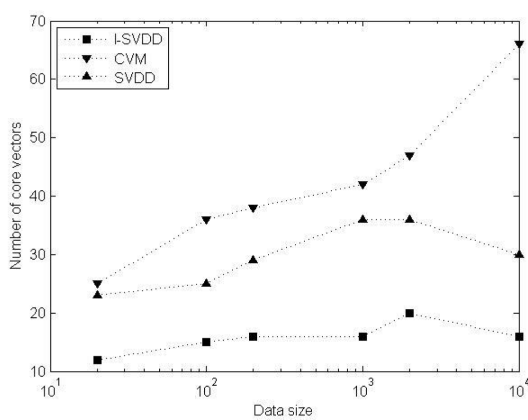

Figure 8. The numbers of core vector under the best choice of ε

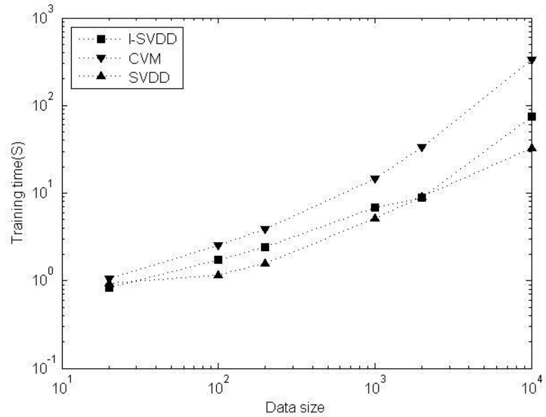

Figure 9. The training time under the best choice of ε

d. Experiments on object tracking

We implemented the proposed I-SVDD algorithm to handle object tracking problem, where the tracking videos are downloaded randomly from internet by personal interest. We tracked a car in highway with dynamic noisy background, a fade-out airplane in low noisy background, and a fade-in airplane in high noisy background. The results are given in Figure 10 to Figure 12 below.

Figure 10. Tracking a car in highway with dynamic noisy background

Figure 11. Tracking a fade-out airplane in low noisy background

Figure 12. Tracking a fade-in airplane in high noisy background

V. CONCLUSIONS

Based on the idea proposed by Support Vector Data Description, we present an improved SVDD algorithm to handle object tracking efficiently. We prove theoretically that the proposed I-SVDD algorithm has time complexity of $O(\frac{m}{\varepsilon^2}+\frac{1}{\varepsilon^3})$, which is linear in the number of training samples m for a fixed ε, and space complexity of $O(\frac{1}{\varepsilon^2})$, which is independent of m for a fixed ε. The experimental results on synthetic data, tracking results on car and plane demonstrate the validity of the proposed algorithm.

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