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Intelligent 3D Obstacles Recognition Technique Based on Support Vector Machines for Autonomous Underwater Vehicles

Zhen-Shu Mi and Yong-Gi Kim

Department of Computer Science, Research Institute of Computer and Information Communication, Gyeongsang National University.
Jinju, Kyungnam 660-701, Republic of Korea

Abstract

This paper describes a classical algorithm carrying out dynamic 3D obstacle recognition for autonomous underwater vehicles (AUVs), Support Vector Machines (SVMs). SVM is an efficient algorithm that was developed for recognizing 3D object in recent years. A recognition system is designed using Support Vector Machines for applying the capabilities on appearance-based 3D obstacle recognition. All of the test data are taken from OpenGL Simulation. The OpenGL which draws dynamic obstacles environment is used to carry out the experiment for the situation of three-dimension. In order to verify the performance of proposed SVMs, it compares with Back-Propagation algorithm through OpenGL simulation in view of the obstacle recognition accuracy and the time efficiency.

Key Words : SVM, Obstacle Recognition, AUV, BP Algorithm, OpenGL

1. Introduction

Object recognition attracts a great deal of attention and it has been an important subject in machine learning and computer vision. Appearance-based object recognition methods have recently demonstrated good performance on a variety of problems. However, many of these methods either require good whole-object segmentation, which severely limits their performance in the presence of clutter, occlusion, or background changes; or utilize simple conjunctions of low-level features, which cause crosstalk problems as the number of objects is increased [1]. In this paper we are investigating an appearance-based obstacle recognition using SVM that solves many of these problems for AUVs navigation safety.

Support vector machine is a kind of research algorithms in this area. In here, appearance-based recognition methods are described. SVM is a new generation learning system based on recent advances in statistical learning theory. SVMs deliver state-of–the-art performance in real-world applications such text categorization, hand-written character recognition, image classification, etc. Their first introduction in the early 1990s lead to a recent explosion of applications and deepening theoretical analysis, that has now established Support Vector Machines along with neural networks as one of the standard tools for machine learning and data mining. It is considered as a very effective method of learning and classification [2-4].

Autonomous Underwater Vehicles (AUVs) have become a hot topic of research in ocean sciences because of their commercial and military potential and the technological challenge in developing them. There are two main reasons to keep navigation security for AUVs. First, safe AUVs can search, rescue, and facilitate exploration in the scientific field. Second, it can save a lot of money because of AUVs expensive cost. So AUVs safety problem have become an exciting and hotspot research topic. But the complex nature underwater environment makes the research work become a difficult task. Thereby, development of an intelligent 3D obstacle recognition system becomes necessary for AUVs safe navigation.

As far as we known, most of AUVs use sonar instead of good quality camera to recognize obstacles. Because underwater situation is very dark and in shallow water AUV cannot see even several meters ahead since the water is usually not clear in deep ocean. But in some special environment and situation cameras are used to instead of sonar. For an example, when a ship need be cleaned or repaired for some malfunction, good quality camera is very high priorities choice to solve this problem. There are a lot of applications for taking some valuable pictures using camera including underwater resource exploration, bridge survey, and business diving.

In this paper we build an obstacle recognition testing system for appearance-based 3D object recognition using SVM [3], [5], [6]. The aim of this paper is to prove that SVM has better performance than BP Algorithm in 3D obstacle recognition. And the dynamic 3D obstacle simulation designed by OpenGL will provide some test data for getting the better experiment result. So the SVM will help in varieties way to recognize the underwater obstacle, mission planning and intelligent control of AUV.

This paper is organized as follows. In section 2, we review of SVM. Section 3 presents 3D obstacle recognition system. Section 4 is about the obstacle recognition experiments based on OpenGL simulation. Finally, the conclusion sums up this paper.

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2. Overview of Theoretic Background

Support Vector Machines (SVM) foundation was developed by Vapnikand and his colleagues [7]. SVM is a method for creating functions from a set of labeled training data. The function can be a classification function or the function can be a general regression function. For classification, SVMs operate by finding a hypersurface in the space of possible inputs. This hypersurface will attempt to split the positive examples from the negative examples. The split will be chosen to have the largest distance from the hypersurface to the nearest of the positive and negative examples. Intuitively, this makes the classification correct for testing data that is near, but not identical to the training data. The goal of SVM is to find out an optimal separable hyperplane to solve the classification task. The optimal hyperplane has maximal distance between two classes and the hyperplane.

2.1 Linear Separable Case

Consider the problem of separating the set of training vectors belonging to two linearly separable classes,

$$(x_i, y_i), x \in R^d, y \in \{+1,-1\}, i = 1,...,n \tag{1}$$

with a hyperplane

$$w \cdot x + b = 0 \tag{2}$$

where the parameters w, b are constrained by

$$\min_i \left| w \cdot x_i + b \right| = 1 \tag{3}$$

The set of vectors is said to be optimally separated by a hyperplane if it is separated without error. The distance between the closest vector and the hyperplane is maximal. Hence, a separating hyperplane in canonical form must satisfy following constraints

$$y_i \cdot (w \cdot x_i + b) \geq 1, i = 1,2,...,n \tag{4}$$

Suppose that the following bound holds

$$\|w\|^2 \leq c. \tag{5}$$

The VC dimension h of the set of canonical hyperplanes in n dimensional space is bounded by

$$h \leq \min([R^2, c], d) + 1 \tag{6}$$

where, R is the radius of a hypersphere enclosing all training vectors. Hence the hyperplane that optimally separates the data is the one that minimizes Eq. (4).

$$\phi(w) = \frac{1}{2}(w \cdot w) \tag{7}$$

This is equivalent to minimizing an upper bound on the VC dimension. In practice, such a hyperplane does not exist. So we need to relax the constraints of Equation (4) by introducing slack variables $\xi \geq 0, i = 1, 2, ...n$

$$y_i \cdot (w \cdot x_i + b) \geq 1 - \xi, i = 1,2,...,n \tag{8}$$

In this case, the optimization problem becomes

$$\phi(w, \xi) = \frac{1}{2}(w \cdot w) + C\sum_{i=1}^{n} \xi_i \tag{9}$$

with a user defined positive finite constant C. The solution to optimization problem (9), under the constraints of Equation (8), could be obtained in the saddle point of Lagrangian function

$$L(w,b,\alpha,\xi,\gamma) = \frac{1}{2}(w \cdot w) + C\sum_{i=1}^{n} \xi_i$$
$$-\sum_{i=1}^{n} \alpha_i \left| y_i(w \cdot x_i + b) - 1 + \xi_i \right| - \sum_{i=1}^{n} \gamma_i \xi_i \tag{10}$$

where $\alpha_i \geq 0$, $\gamma \geq 0$, $i = 1, 2, ..., n$ are the Lagrange multipliers.

The Lagrangian function has to be minimized with respect to w, b, ξ_i . Classical Lagrangian dualityenables the primal problem, Equation (10), to be transformed to its dual problem, which is easier to solve. The dual problem is given by,

$$\max_{\alpha} [\sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)] \tag{11}$$

with constraints

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \tag{12}$$

$$0 \leq \alpha_i \leq C, i = 1,2,...,n \tag{13}$$

This is a classic quadratic optimization problem. There exists a unique solution. According to the Kuhn-Tucker theorem of optimization theory [8], the optimal solution satisfies

$$\alpha_i [y_i (w \cdot x_i + b) - 1] = 0, i = 1,2,...n \tag{14}$$

The equation (14) have non-zero Lagrange multipliers when and only when the points x, satisfy

$$y_i \cdot (w \cdot x_i + b) = 1 \tag{15}$$

These points are termed Support Vectors (SV). The hyperplane is determined by the SV, which is a small subset of the training vectors. Hence if α_i^* is the non-zero optimal solution, the classifier function can be expressed as

$$f(x) = \text{sgn}\{\sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^*\} \tag{16}$$

where b^* is the solution of Equation (14) for any the non-zero α_i^* .

2.2 Nonlinear Case

When a linear boundary is inappropriate SVM can map the input vector into a high dimensional feature space. By defining a non-linear mapping, the SVM constructs an optimal separating hyperplane in this higher dimensional space. Usually non-linear mapping is defined as following function

$$\phi(\cdot): R^d \rightarrow R^{dh} \tag{17}$$

In this case, optimal function (8) becomes (18) with the same constraints

$$\max_{\alpha}[\sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i, x_j)] \tag{18}$$

Where

$$K(x_i, x_j) = \phi(x_i)\cdot\phi(x_j) \tag{19}$$

is the kernel function performing the non-linear mapping into feature space. It may be any of the symmetric function that satisfies the Mercer conditions [9]. The following functions are kernel functions used commonly.

(1) Polynomial Function

$$K(x_i, x_j) = (x_i \cdot x_j + 1)^q, q > 0 \tag{20}$$

(2) Radial Basis Function

$$K(x_i, x_j) = \exp\{-\frac{\left|x_i - x_j\right|^2}{\sigma^2}\} \tag{21}$$

(3) Sigmoid Function

$$K(x_i, x_j) = \tanh(\beta\cdot(x_i \cdot x_j) + c) \tag{22}$$

The classifier function can be defined as

$$f(x) = \mathrm{sgn}\{\sum_{i=1}^{n}\alpha_i^* y_i K(x_i, x) + b^*\} \tag{23}$$

where b^* is the solution of the following Equation for any the non-zero α_i^*.

$$\alpha_i[y_i\sum_{j=1}^{n}\alpha_j y_j K(x_j, x_i) + b - 1] = 0 \tag{24}$$

3. The 3D Obstacle Recognition System

In linear separable case, all the data of the same class are on the same side of the hyperplane. We illustrate an example to explain this problem, see figure 1.

We suppose a set of given data is that before describing 3D obstacle recognition detail. We first illustrate the main obstacles images like the COIL images database. The COIL (Columbia Object Image library) database are consists of 7,200 images of 100 objects. We select some simple and typical images like simulation obstacles by way of example test data (eg. Fig 2). The images are color images (24 bits for each of the RGB channels) of 128×128 pixels. For each object, the turntable is rotated of 5 degree per image. Tester can design and adjust rotation degree to get an optimal test image data. All the selected color images data are according to COIL image standard. Fig.1 and fig.2 show a selection of the objects in the database and one every three views of a specific objects, respectively [10].

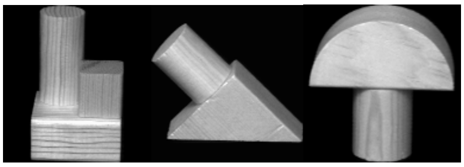

Fig. 1 Images of 3 objects of the COIL database

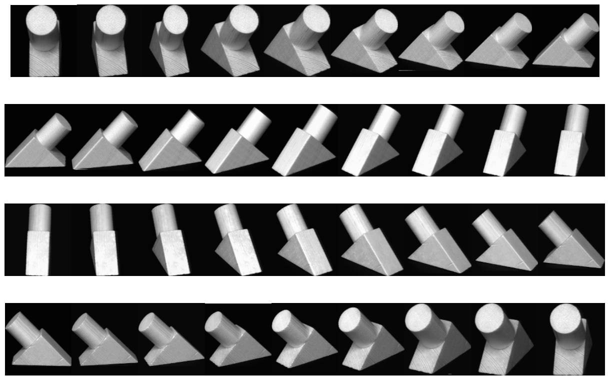

Fig. 2 36 images of all the 72 images of one COIL object

3.1 Obstacles Images Processing based on OpenGL Simulation

In the real research, the underwater environment is hazy and the surrounding information is difficult to be known. But the simulation using OpenGL is easy to be understood and we place some obstacles by random and create the virtual environment according to the real system. In this paper we will design a 3D obstacle environment space using OpenGL to get some test data more convenient for recognizing the obstacles.

Each image I = (R, G, B) was first transformed into a gray-level image through the conversion formula

Gray = Red * 30 + .Green * 59 + Blue * 11

rescaling the obtained gray-level from 0 to 255. The obstacles images spatial resolution was reduced to 32×32 by averaging the gray levels over 4×4 pixel patches. The purpose of preprocess is to identify the selected data for the image containing obstacles and make the obstacles images standardization [10], [11].

3.2 Training and Testing the Obstacles Images

It is a very important problem how to select kernel functions in the training phase. In our experiments three kernel parameters determine the dynamics of an SVM network including σ, c and q. We select the optimal parameters for optimizing and adjusting the SVM parameters. The Radial Basis function (RBF) kernel function nonlinearly maps samples into a higher dimensional space. The RBF kernel has less numerical difficulties; its computation is not as complex as the other kernel's. The RBF kernel is a better choose for training and testing. We use best variables σ and c based on statistical results of all the trainings.

In the SVM recognition system, we adjust the kernel parameters by training, until the optimal kernel parameters is found. Processed data are as the feature vector used in the test. To reduce the computational quantity, we use principal component analysis method generate 128-dimension feature vectors which can represent the characteristics of the image [7].

In one case, 20 objects, total 720 images are selected as samples in the training phase. All the 1440 images for 20 objects are the test data. Given a subset σ of the 20 objects and the associated training set of 36 images for each object in σ, the test set consists of the remaining 36 images for each object in σ.

On first we tested the recognition system on sets of 20 of the 100 COIL objects. The training sets consisted of 36 images (every 10 degree for each of the 20 objects) and the test sets of the remaining 36 images. For all the 12 random choices of 20 of the 100 objects, the system got perfect score. So we decided to select by hand the 20 objects more difficult to recognize.

To gain a better understanding of how an SVM actually perform recognition, it may be useful to look at the relative weights of the components of *w*. A gray-values encoded representation of the absolute value of the components of *w* relative to the optimal separating hyperplane [10]. Note that the background is essentially irrelevant, while the larger components can be found in the central portion of the image [7], [10].

3.3 System Overview

When AUV meets the problem of obstacles recognition in the underwater unknown environment, the main problem is how to preprocess, training and testing obstacles image data. The obstacles recognition system using SVM can summarize into five below steps and the flowchart of the obstacles recognition system overview using SVM is illustrated in the figure 3.

Obstacles Detect: If AUVs detects obstacle then go to next step, else to step 5

Input Obstacles Image: If AUV detects the obstacles, the cameras will take the obstacles images from the underwater environment and send these data to the computer for analyzing and computation continuously and dynamically.

Images Preprocessing: System selects and preprocesses some obstacles images for recognizing system. The purpose of preprocess is to identify the selected data for the image containing obstacles and make the obstacles images standardization for next step.

Training and Testing Data using SVMs: In this step, the Radial Basis Function kernel is chose for training and testing. SVMs adjust the kernel parameters by training, until the optimal kernel parameters is found.

Recognition Result and Mission Control: When AUVs computer gets the obstacles images recognition result, the AUVs mission controller will change the navigation plan follow the recognition result and obstacles position in the underwater environment. Finally AUVs will go to the goal safety based on SVM technology.

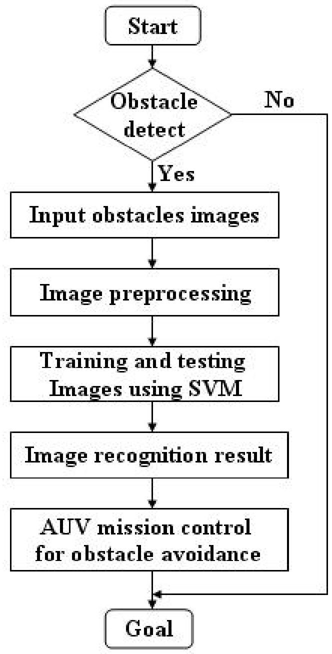

Fig. 3 System Overview

4. Experiment

In this section we built a real SVM test environment using OpenGL for 3D obstacle recognition. In the following 3D simulation environment the small black ball is defined as start point at the right side and the small red ball is defined as goal point at the left side. The AUV will navigate from the start point to the goal point to finish this exploration navigation. From the process of this navigation the AUV finds some virtual obstacles, it will pick up some test data using camera for processing the 3D obstacles recognition experiment. The using of OpenGL images data can guarantee that SVM recognizes the intelligent 3D obstacle more exact and more feasibility for real AUV safety navigation autonomously. Computer will get random images as test data in each second and each degree from the simulation. Figure 4 is describing the process and the scene of AUVs navigation at the 3D dynamic OpenGL simulation. Computer will see different kinds of obstacles around AUVs clearly and testers can get the 3D obstacles images data easily from this simulation.

One of the experiments is tested by MATLAB tool based on the OpenGL test images. OpenGL test images contain 720 images of 20 objects. For each object we got from OpenGL simulation was taken at every 10 degrees of rotation, total 36 images every obstacle.

The same sample data as the training input and the same test data as the test input are used in both BP and SVM tests. We make a large of experiments for training and testing this obstacles recognition system. SVM and BP algorithm will use these data to compare the validity for 3D obstacle recognition

[12], [13].

In the experimental environment using BP algorithm, we select the optimal parameters in the experiments, optimizing the neural network architectures and adjust the parameters. In the neural network system, back-propagation is used. A 3-layers back-propagation network is designed. We use tansig function in the hidden layer and logsig function in the output layer. It is trained for finding out the optimal neuron numbers using lots of time in the hidden layer, which can make the network output the best result [4], [14].

In the following, we design some simple and different obstacles as the dynamic simulation of how to get lots of test images for 3D obstacles recognition. The research purpose must keep effective 3D obstacles recognition for AUVs safe navigation when the AUVs work in a complex underwater environment obstacles space.

The table 1 and table 2 show the SVM optimal parameters and adjusting BP networks in the experiments. The table 3 shows the performance result of SVM and BP algorithm based on six group experiments. We will see the some advantages of SVM than BP algorithm clearly for testing data. SVM is the more effective than BP algorithm for 3D obstacle image recognition in three fields including training time, testing time and accuracy. So if we choose one algorithm from SVM and BP algorithm for recognizing the 3D obstacle in the complex underwater environment, SVM is the better algorithm than BP algorithm for AUV obstacle avoidance and navigation safety.

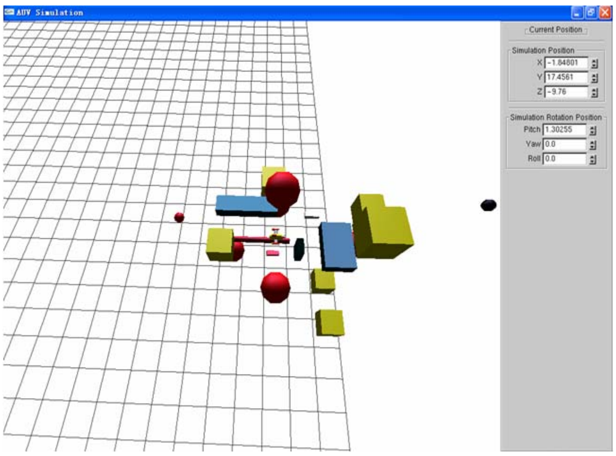

Fig. 4 The Obstacle Screen

Table 1. SVM optimal parameters.

arg	C	Training error	Training time
1	100	0.0106	48.09s
1	200	0.0127	41.45s
2	400	0.0171	39.52s
2	500	0.0062	63.15s

Table 2. Adjusting BP network.

Neurons in hidden layer	Training error	Training time
6	0.0148	631.17s
7	0.0136	683.52s
8	0.0127	495.76s
9	0.0112	451.23s

Table 3. The performance result of SVMs and BP algorithm

Classifier / Obstacles (Object-Sample)	BP Training time(s)	SVM Training time(s)	BP Testing time(s)	SVM Testing time(s)	BP Accuracy	SVM Accuracy
5-24	74.2	9.9	0.2	0.03	96.3%	97.8%
10-24	151.1	12.7	4.2	0.22	94.8%	96.4%
20-24	612.8	54.2	13.4	1.18	88.1%	91.2%
5-36	144.8	32.6	3.5	0.04	97.7%	98.9%
10-36	495.9	58.4	12.1	0.14	94.8%	97.3%
20-36	869.5	69.1	18.7	1.27	91.3%	94.7%

5. Conclusion

This paper discussed one widely used algorithm for the 3D obstacle recognition, and we designed a recognition system for displaying the capabilities of SVM.

BP algorithm is not a steady algorithm. In practical test, the training process is a long time and it takes up tremendous memory. In another word, the training process of SVM is rather faster than BP's. In the training phase of SVM, the algorithm only trained one time then the optimal separating hyperplane was found.

This paper takes large amount of tests on the recognition test. According to the testing result, it shows SVM has better recognition accuracy than BP algorithm. From the comparison, experiment results can conclude that SVM has the better performance than BP algorithm in appearance based on 3D obstacle recognition. So the AUV can use SVM to recognize the obstacles and reduce the collision danger for safety ocean navigation in the future research.

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Zhen-Shu Mi

He received the B.S degree in Computer Science from University of Liaoning Science and Technology, China in 2004. He received the M.S degree in Computer Science from Gyeongsang National University, Korea, 2006, and Ph.D. degree in Computer Science from Gyeongsang National University, Korea, 2009.

Research Area: Autonomous Underwater Vehicles, 3D Object Recognition, BK- Products, 3D OpenGL Simulation and Artificial Intelligence.

Yong-Gi Kim

He received the B.S degree from Seoul National University, 1978, and the M.S degree in Computer Science from University of Montana, U.S.A., 1987. He received the Ph.D. degree in Computer and Information Sciences from Florida State University, 1991. Since 1992, he has been a professor in Computer Science department of Gyeongsang National University, Korea.

Research Area: Artificial Intelligence, Knowledge-Based System, Fuzzy Application, and Autonomous Underwater Vehicles.

Email: ygkim@gsnu.ac.kr