Target Detection and Navigation System for a mobile Robot

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Abstract: This paper presents the target detection method using Support Vector Machines(SVMs) and the navigation system using behavior-based fuzzy controller. SVM is a machine-learning method based on the principle of structural risk minimization, which performs well when applied to data outside the training set. We formulate detection of target objects as a supervised-learning problem and apply SVM to detect at each location in the image whether a target object is present or not. The behavior-based fuzzy controller is implemented as an individual priority behavior: the highest level behavior is target-seeking, the middle level behavior is obstacle-avoidance, the lowest level is an emergency behavior. We have implemented and tested the proposed method in our mobile robot "Pioneer2-AT". Comparing with a neural-network based detection method, a SVM illustrate the excellence of the proposed method.

Keywords: target detection, SVM, behavior-based fuzzy controller, mobile robot

1. INTRODUCTION

In recent years, various types of robots have been used in human assistance, welfare, amusement and the others. An intelligent robot should make decision behavior according to the facing environment and also should require its perceptual system and action system. There are various kinds of actions that a mobile robot must achieve basically in order to achieve a big task in indoor environment. In order to reach a target point, a mobile robot must be able to react to different situations that it can meet. Since a mobile robot must move various positions, it must find the exact coordinates.

The target detection was researched with various methods using a feature and a color. However, most techniques run into problems if the illumination source varies not only in intensity but also in spectral and a target is variously oriented In order to solute this problems we propose the use of support vector machine(SVM) learning in this paper. SVM is a learning tool originated in statistical learning theory [1]. In recent years, SVM learning has found a wide range of real-world applications, including handwritten digit recognition [2], speaker identification [3], face detection in images [4] and text categorization[5]. The formulation of SVM learning is based on the principle of structural risk minimization. Instead of minimizing an objective function based on the training samples[such as mean square error], the SVM attempts to minimize a bound on the error. As a result, a SVM tends to perform well when applied to data outside the training set. Indeed, it has been reported that SVM-based approaches are able to significantly outperform competing methods in many applications[6]-[8]. SVM achieves this advantage by focusing on the training examples that are most difficult to classify. These "borderline" training examples are called support vectors. In this paper we investigate the potential benefit of using a SVM-based approach of object detection.

The application of fuzzy control to a sonar-based obstacle avoidance has been implemented successfully[9]. All sonar sensors send data to the inputs of fuzzy controllers. Each fuzzy controller for obstacle avoidance has eight inputs and two outputs. Each membership function is considered as a Gaussian function. In this paper the fuzzy controller for the middle behavior is described. Fuzzy controllers are implemented under the behavior-based approach.

Behavior-based approaches have been established as a main alternative to conventional robot control in recent years. These approaches can be implemented and tested independently. The system architecture, in this application implemented in the Pioneer2-AT, has three levels. The highest level behavior is the target seeking. The middle level behavior is obstacle-avoiding behavior. The lowest is an emergency behavior.

In the section 2, we describe the target detection of a mobile robot, in the section 3 designs navigation controller, in the section 4 deals with the obtained experimental results. Finally, conclusions are drawn in the section 5.

2. TARGET DETECTION

In this section, we present a supervised SVM learning framework for detection vertically oriented of a target in grey level images. It handles targets over a wide range of scales and works under different lighting conditions, even with moderately strong shadows. In this paper targets are chosen electric sockets.

2.1 Training a target ob ect

Individual targets are localized in images from CCD camera on the robot head. Therefore, to detect whether a target is present at a giver location, it is sufficient to examine the image content within a small neighborhood around that location. Thus we define the input pattern to the SVM classifier to be a small $M \times M$ pixel window centered at the location of interest. The window should be chosen large enough to contain a target. In this paper we chose M=15.

Fig. 1 Target images(electric socket images)

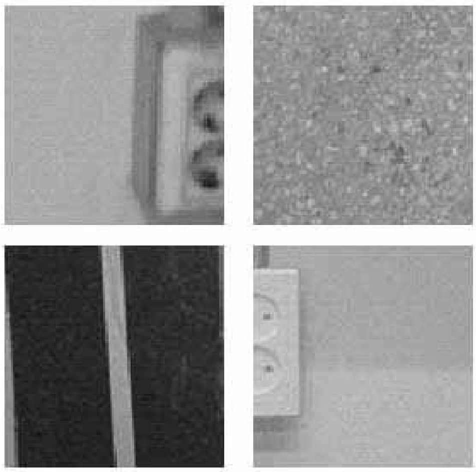

Fig. 2 Non-target images

We treat target detection as a two-class pattern classification problem. At each location in input images, we apply a classifier to determine whether a target is present or not. We refer to these two classes throughout as "target present" and "target absent". The procedure for extraction training data from the training image set is as follows. For each target location in a training-set image, a window of 15×15 image pixels centered at its center of mass is extracted; the vector formed by this window of pixels, denoted by x_i, is then treated as an input pattern for the "target present" class; y_i=+1. "target absent" samples are collected; y_i =-1. Fig 1 and fig 2 are example of target images and non-target images.

The problem is how to construct a classifier, a decision function f(x), that can correctly classify an input patter x that is not necessarily from the training set. The SVM classifier is defined as

$$f(x) = w^T\Phi(x) + b \qquad (1)$$

which is linear in terms of the transformed data Φ(x), but non-linear in terms of the original data x$\in$R^n. The function yields f(x)$\geq$ 0 for =+1, and f(x)<0 for =-1. In other words, training examples from the two different classes are separated by the hyperplane $f\ x$ 0.

For a given training set, while there may exist many hyperplanes that separate the two classes, the SVM classifier is based on the hyperplane that maximizes the separation margin between the two class. In other words, SVM finds the hyperplane that causes the largest separation between the decision fuction values for the "borderline" examples from the two classes. Mathematically, this hyperplane can be found by minimizing the following cost function.

$$\min J(w) = \frac{1}{2} w^T w = \frac{1}{2}\|w\|^2 \qquad (2)$$

subject to the separability constraints

$$y_i(w^T x_i + b) \geq 1; \qquad i = 1, 2, \cdots, l \qquad (3)$$

This specific problem formulation may not be useful in practice because the training data may not be completely separable by a hyperplane. In this case the cost function in (2) and the separability constraints in (3) can be modified as follows :

$$\min J(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\xi_i \qquad (4)$$

subject to

$$y_i(w^T\Phi(x_i) + b) \geq 1 - \xi_i \quad \xi_i \geq 0; \quad i = 1, 2, \cdots, l \quad (5)$$

where C is a user-specified, positive, regulation parameter. The variable ξ_i is a vector containing all the slack variables.

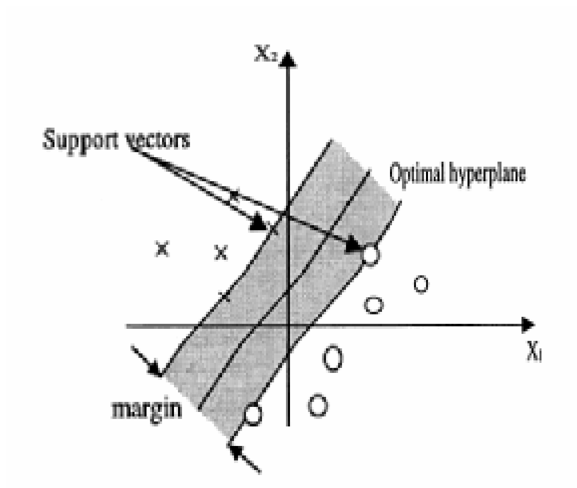

Fig. 3 SVM classification with a hyperplane that maximizes the separating margin between the two classes

The modified cost function in (5) constitutes the so-called structural risk, which balances the empirical risk with a model complexity. The regularization parameter C controls this trade-off. The purpose using the complex model to constrain the optimization of empirical risk is to avoid overfitting, a situation in which the decision boundary too precisely corresponds to the training data, and thereby fails to perform well on data outside the training set.

Using the technique of Lagrange multipliers, we can show that a necessary condition for minimizing (4) is that the vector w is formed by a linear combination of the mapped vectors,

$$w = \sum_{i=1}^{l}\alpha_i y_i \Phi(x_i) \qquad (6)$$

$\alpha_i \geq 0$, i=1,2,$\cdots$,l, are the Lagrange multipliers associated with the constraints in (5). ubsitituting (6) into (1) yields

$$f(x) = \sum_{i=1}^{l}\alpha_i y_i \Phi^T(x_i)\Phi(x) + b = \sum_{i=1}^{l}\alpha_i y_i K(x_i, x) + b \quad (7)$$

where the function K is defined as

$$K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j) \qquad (8)$$

The Lagrange multipliers α_i>0, i=1,2,$\cdots$,l, are solved from

the dual form of (4), which is expressed as

$$\max \quad (\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad (9)$$

subject to

$$0 \le \alpha_i \le C, \; i=1,2,\cdots,l \quad (10)$$

$$\sum_{i=1}^{l} \alpha_i y_i = 0 \quad (11)$$

Notice that the cost function W(α) is convex and quadratic in terms of the unknown parameters α_i. This is in fact a so called quadratic programming problem which in general is expressed as follows.

$$\max 1/2 * z' Hz + f' z (z \in R^n) \quad (12)$$

Subject to

$$Az \le c, \; A_{eq} z = c_{eq}, \text{ and } z_l \le z \le z_u. \quad (13)$$

Changing maximization to minimization by reversing the sign of the cost function we set z=α, H=$y_i y_j K\ x_i, x_j$, $i, j\ 1,2,\cdots, l$ and f = -[1,⋯,1]', A=[0,⋯,0], c=0(a dumm inequality constraint), Aeq=[y_1,⋯, y_l], ceq=0, zl=[0,⋯,0], and finally zu=[C,⋯,C]. The kernel function in an SVM use Gaussian RBF kernel as follow:

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (14)$$

we set C=500, σ = 2.5. After that, we can solute α by using upper method and can solute w substituting α in (6). Also we can solute b as the following equation.

$$b = 1/y_j - \sum_{i=1}^{l} y_i \alpha_i K(x_i, x_j) - \alpha_j /(C y_j) \quad (15)$$

Therefore we can get the SVM Classifier.

2.2 Detecting a target ob ect

We detect targets by using SVM classifier learned. First we acquire a test data set from CCD camera in the mobile robot. The quantity of an image data(640*480) per a frame is very large. So it is necessary to diminish the image data. If we should use this image, the mobile robot that has limited hardware resource could not operate in real time. In this paper 160*120 pixel image data is used. To simplify the reduced image, we used sobel filter.

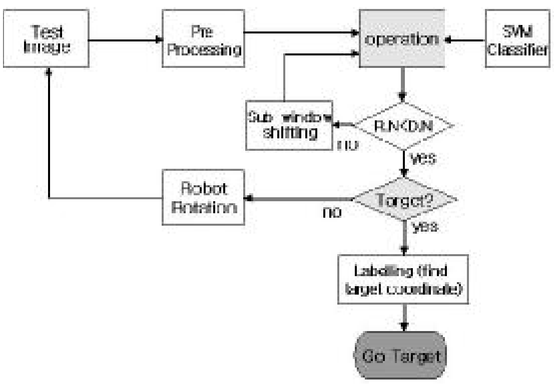

Fig. 4 The procedure of detection a target

(R.N : Reiteration Number., D.N : Default Number)

We extract a window of 15 × 15 image pixels centered at its center of mass. The vector formed by this window of pixels, denoted by *x*, is test input.

Therefore we detect a target as calculating equation

$$f(x) = \sum_{i=1}^{l} \alpha_i * y_i K(x_i, x) + b \quad (16)$$

where α_i* is values computed by learning method.

We set a target if f(x) > 0 and non-target if f(x) < 0. Also, to detect target objects in an image, we shift the detection window over all locations in the image. After that, we process the labeling and we acquire final target coordinates. The procedure of detection a target is presented fig 4

3. NAVIGATION CONTROLLER DESIGN

3.1 Fu y Controllers Design

Sonar sensors measure the time elapsed between the transmission of a signal and the receiving of an echo of the transmitted signal to determine the distance to an obstacle. The sonar sensors on mobile robots can be used to detect objects around the mobile robot and to avoid collision with unexpected obstacles.

The goal of navigation in this paper is that a mobile robot avoids an obstacle and goes a target. The motion of the mobile robot will be realized by the control of its linear velocity and heading angel. Therefore, the input fuzzy variables of the fuzzy controller are the forward distance of robot between mobile robot and obstacle. The output fuzzy variables are chosen as the heading angle and linear velocity. Own mobile robot and location of sonar sensors are presented in fig 4.

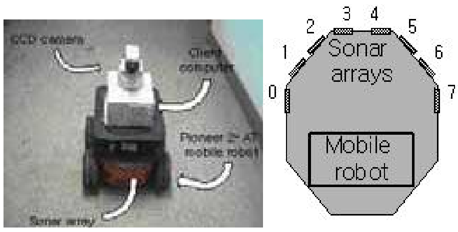

Fig. 4 Mobile robot system

There are 8 sonars in the robot. All sonar data must be adjusted. The fuzzy controllers for obstacle avoidance are designed as follows:

Read sonar data and construct three membership functions for input: All data from sonar sensors are received and displayed. Three membership functions for each input in its universe are constructed. Each membership function is considered as a Gaussian curve membership function.

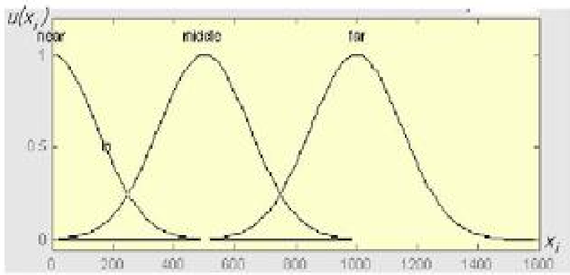

Fig. 6 Input membership function

Construct five membership functions for output : From our experiments, we construct five membership functions for angular velocity: positive(+30), small-positive(+15), zero(0), small-negative(-15), negative(-30) as given in fig 15. and two membership functions for linear velocity:speed1(5cm/sec), speed2(10cm/sec).

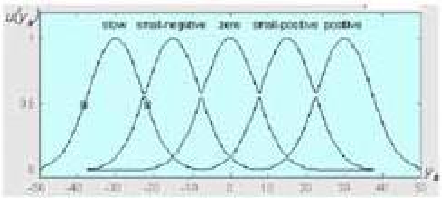

Fig. 7 Output membership function for angular velocity

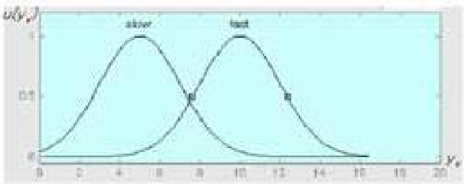

Fig. 8 Output membership function for linear velocity

Construct nine rules for angular velocity and linear velocity : The rules for avoiding frontal obstacles are shown in table 1. The results from Table 1 are obtained by nine rules. The sonar notations are the same as shown in table 1.

Left \ Right	near	medium	far
near	0/5	-15/5	-30/5
medium	15/5	0/5	-15/5
far	30/5	15/5	0/10

Table 1 Rules for obstacle avoidance

Defuzzification : In this step, we will defuzzify the membership function for the control action of angular velocity and linear velocity using the centroid method. We use the min-operation rule for fuzzy implication.

3.2 ehavior- ased Design

The behavioral architecture in this paper is based on fuzzy control. The behavior-based fuzzy control of Pioneer2-AT consists of several behavior. Each behavior represents a concern in mobile robot control and relates sonar sensor data, robot status data and goal information to control the robot The architecture is shown in figure 9.

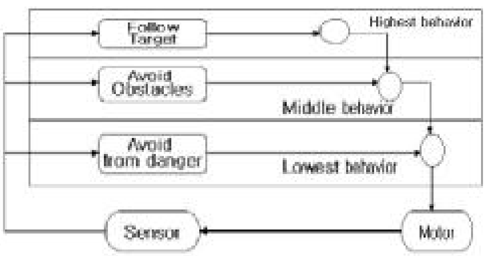

Fig. 9 Behavior-based fuzzy control architecture

3.2.1 Emergency ehavior

The first behavior is an emergency behavior, which has a higher priority than other behaviors. Since this behavior depends on the safety distance, the sonar sensor data is used directly to stop the robot. An emergency distance is defined for the emergency behavior. Therefore, the results of emergency behavior are shown as follows:

- **CHECK the objects using the sonar sensors.**
- **STOP moving if the objects are closer than the safety distance(20cm)**

3.2.2 Obstacle Avoidance ehavior

The obstacle avoidance behavior uses sonar sensor data to generate a fuzzy set that represents the distance relating to the robot's position. The eight sensors are used for obstacle avoidance behavior. The output is the avoiding rotation. The results of obstacle avoidance behavior are shown as follows:

- **TURN RIGHT : If the obstacle is located on the front-left side, then robot will turn right.**
- **TURN LEFT : If the obstacle is located on the front-right side, then robot will turn left.**

However, if there are obstacles located closer than an emergency distance, this behavior will be ignored.

3.2.3 Target-seeking ehavior

The target-seeking behavior is the desired target which will be acquired by the proposed target detection method. If there is no obstacle between the robot and the target, the target-seeking behavior is activated. With respect to the robot's position and orientation, robot turns and goes straight to the target. However, if there are obstacles located closer than an emergency distance and find obstacles in the way going a target, this behavior will be ignored.

4. EXPERIMENTAL RESULTS

The experiment of target detection was performed on 2500 frames with a size of 640*480 from CCD camera in the mobile robot. Of these frames, 2000 frames were used in the training phase and the others were used in the testing phase. For each frame, a set of rectangles representing target objects was drawn. Fig 11 shows example of the target detection in indoor environment.

Fig. 10 Example of a target detection

The proposed method detected 93.6% and 95.2% when we used set of 1000 and 2000 training data. To get a better understanding of the relevance of obtained results with SVMs, we performed the same experiment with neural networks. The network has hidden layers of sizes 500, 1000 respectively and was trained by backpropagation algorithm minimizing mean

squared error. To avoid the local minima, reported results with NN was obtained by training 10 networks with different initial weights and selecting the minimal error over all the results. Table 2 represents the results.

	Detection rate	
	Training data(1000)	Training data(2000)
NN	91.2%	92.4%
SVM	93.6%	95.2%

Table 2 Target detection results

The behavior-based fuzzy controller was implemented as follows. Emergency distance set 20cm and the velocity of the robot was given by 5cm/sec. Also there are many electric sockets in the wall. So we set a target coordinate again to avoid collision(30cm forward position). Fig 12 is experimental example of target detection in indoor environment and robot navigation.

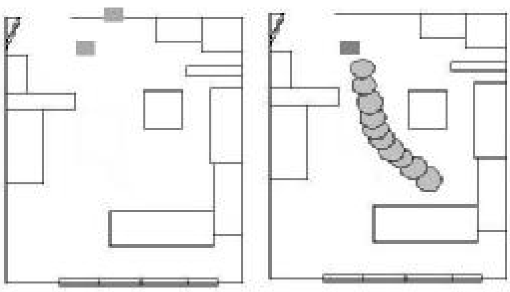

Fig. 11 Example of target detection and robot navigation

5. CONCLUSION

In this paper we proposed the use of a SVM for target detection in vision-based mobile robot. In the proposed method, a SVM classifier was trained through supervised learning to test at every location in a image whether a target is present or not. According to result of experiment, this SVM-based target detection method is more efficient than Neural Network ones. Occurred experimental error is due to a wide range of scales and works under different lighting conditions. Further training or utilization of domain-specific knowledge will help to overcome these problems. Moreover the behavior-based fuzzy controller can be navigated in the complex environment. Furthermore, the algorithm of target detection is very flexible and adaptable. It is very simple to increase the number of symbols in order to create a path to drive a mobile robot into indoor environments. The proposed method can be used for an intelligent mobile robot to in crease performance of a mobile root.

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