Proceedings of the 2007 IEEE
International Conference on Mechatronics and Automation
August 5 - 8, 2007, Harbin, China

Dynamic Collision Avoidance Path Planning for Mobile Robot Based on Multi-sensor Data Fusion by Support Vector Machine

Jingwen Tian and Meijuan Gao
Department of Automatic Control
Beijing Union University
Beijing, China
ttjjww999@163.com

Erhong Lu
Department of Electronic Information Engineering
Beijing Electronic Science and Technology Institute
Beijing, China
ttgg500@163.com

Abstract **- Statistical learning theory is introduced to movement planning of intelligent robot, considering the issues that the dynamic collision avoidance planning of mobile robot is a complicated and nonlinear system, and combine the advantages of the support vector machine (SVM) possessed, a method of mobile robot dynamic collision avoidance planning based on multi-sensor data fusion by SVM is presented in this paper. We utilize 5 ultrasonic sensors and an image sensor get environmental information in this method, and the SVM is used to do multi-sensor data fusion to compute these information, in order to achieve the purpose that dynamic control the mobile robot's next action. The method fully utilizes the potential of the SVM and the multi-sensor data fusion to solve dynamic path planning problem of mobile robot. The simulation result shows that this method is feasible and effective.**

Index Terms - Mobile robot, Path planning, Dynamic collision avoidance, Support vector machine, Multi-sensor data fusion.

I. INTRODUCTION

The path planning technology is an important branch of robot research field. The so called path planning of mobile robot is that the robot searches an optimum or approximate optimum non-collision path from start state to goal state according to a certain performance objective. A lot of research work had been done in the mobile robot path planning [1]-[6]. According to difference of the robot know the environment information extent, the path planning is divided two types: the global path planning that the environment information is known completely and the local path planning that the environment information is not known completely or partially, the local path planning is called the dynamic collision avoidance planning, it uses the global path planning as guidance, and detects the operating environment of robot on-line by sensors, as to obtains the information that of the position, shape and size of obstacle et al. So the local path planning is a process which avoids the arisen unknown obstacle at as short time as possible using the local environmental information of obtained on-line.

The dynamic collision avoidance planning is a kind of mapping that from the perception space to the action space. The mapping relation can realize using different methods, but it is difficult to express using an exact arithmetic formula. The artificial neural network is an information processing algorithm that emulate biologic nervous system, it has the ability of strong nonlinear function approach and the ability of strong data fusion. So the neural network has a bigger application potential for the mobile robot's local path planning in dynamic environment. But the neural network system is affected by the learning sample significantly, it is very difficult to select the sample set which has stronger representativeness, and it is not actual to let the sample set cover the whole sample space, so the selection and design of the sample is a difficult problem. On the other hand, the neural network has some problems such as converge to local minimum, the over learning and the structure of ANN is always decided by experience because it doesn't have a good guiding theory. Especially, when the number of the training sample is not enough, the predicting accuracy will be influenced.

Support Vector Machine (SVM) proposed by Vapnik is a newly developed technique which based on statistical learning theory [7]. SVM adopts Structure Risk Minimization principle which avoids local minimum and effective solves the overfitting and assures good generalization ability and better classify accuracy. The special predominance of SVM in resolve limited samples, non-linear function and multidimensional pattern recognition make it become a kind of excellent machine learning method. Considering the issues that the dynamic collision avoidance planning of mobile robot is a complicated and nonlinear system, and combine the feature that the support vector machine has the ability of strong nonlinear function approach and the ability of strong generalization and the ability of strong data fusion and the global optimization, in this paper, a method of mobile robot dynamic collision avoidance planning based on the classify support vector machine is presented.

II. PRINCIPLE

A. *The Principle of SVM*

SVM is proposed which is based on the idea of optimal classify hyperplane of linearly separability. Suppose we have two classes samples of linearly separability, H is the class line which divide the two classes without mistake, H_1 and H_2 are the line that pass through the points which are the nearest to the class line in each classes samples and parallel to the class line. The distance between H_1 and H_2 is called the separating margin of the two classes. We want the optimal class line not only can separate the two classes correctly which ensure the experience risk minimization, but also can have the maximum separating margin of the two classes which ensure the real risk minimization. For the high dimension, the optimal class line is the optimal classify hyperplane.

Suppose the linearly separability sample set (x_i, y_i), $i = 1, \cdots, n$, $x \in R^d$, $y \in \{+1, -1\}$ is the classes number. The commonly form of the linear distinguish function of d-dimension is $g(x) = w \cdot x + b$, the hyperplane equation is:

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

Where, w is the normal of the hyperplane, b decides the place which relative the origin point. We normalized the distinguish function, make all the samples of the two classes satisfy $|g(x)| \geq 1$, namely make the closest sample to the hyperplane satisfy $|g(x)| = 1$. In this way, the separating margin is $2/\|w\|$, So, in order to maximize the separating margin, we should minimize the $\|w\|$ (also the $\|w\|^2$). If the hyperplane can classes all the sample correctly, it need satisfy:

$$y_i[(w \cdot x_i) + b] - 1 \geq 0, \ i = 1, 2, \cdots, n \quad (2)$$

Therefore, the hyperplane that satisfies formula (2) and minimizes the $\|w\|^2$ is the optimal hyperplane. The training samples on the hyperplane H_1 and H_2 which satisfier the equal sign of the formula (2) are called Support Vectors, because they support the optimal classify hyperplane.

So our problem can be formulated as

$$\min \phi(w) = \frac{1}{2}\|w\|^2 = \frac{1}{2}(w \cdot w) \quad (3)$$

$$\text{subject to } y_i[(w \cdot x_i) + b] - 1 \geq 0 \quad i = 1, 2, \cdots, n$$

This is a convex quadratic programming problem. We use Lagrange function to translate the upper problem to its dual problem:

$$\max \ Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \quad (4)$$

$$\text{subject to } \sum_{i=1}^{n} y_i \alpha_i = 0 \quad i = 1, \cdots, n$$

$$\alpha_i \geq 0 \ \text{(linearly separability)}$$

$$0 \leq \alpha_i \leq C \ \text{(linearly impartibility)}$$

Where, C is the punish factor that decide the punish degree for the wrongly separating sample.

By solving α_i, we can get the optimal classify function is:

$$f(x) = \mathrm{sgn}\{(w^* \cdot x) + b^*\} = \mathrm{sgn}\{\sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^*\} \quad (5)$$

From the formula (5), we can see that the optimal classify function only contains dot product operation between the need classify sample and the Support Vector of training samples. It is obvious that if we want to solve the optimal linear classify problem in a characteristic space, we only need know the dot product operation in the space. For the optimal non-linear classify problem, we can transform it to another high dimensional space such that the problem will be linear problem. If the dot product $(x \cdot x_i)$ is replaced by the kernel function $K(x, x')$, equal that transforms the original characteristic space to a new characteristic space, then the optimal function as follow:

$$Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad (6)$$

While the corresponding classify function is

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{n} \alpha_i^* y_i K(x_i \cdot x) + b^*) \quad (7)$$

The rest condition of the algorithmic keep changelessness, this is Support Vector Machine.

The basic thought of the SVM could be generalized as following: at first, transform the input space to a high dimensional space by non-linear transformation, then we work out the optimal classify hyperplane in the new space, while the non-linear transformation is achieved by defining a proper kernel function.

The classify function obtained by the support vector machine is analogous to a neural network in formally, it's output is a linear combination of numbers of middle layer nodes, and the every node of the middle layer corresponds to the inner product of the input sample and a support vector, so it is also called as the support vector network, the sketch map of support vector machine is shown as follow Fig.1.

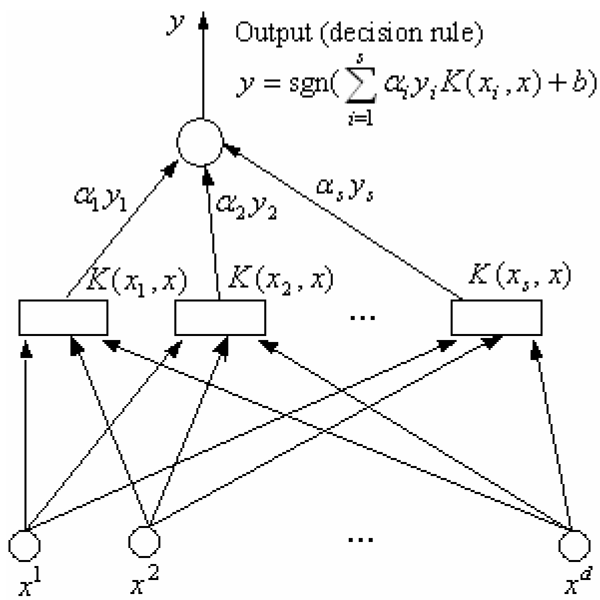

Fig. 1 The sketch map of support vector machine

For the final discriminant function actually only include the inner product of the input sample and support vector and the summation, so the computation complexity of identification is dependent on the number of the support vector.

Presently there are three kinds kernel function which commonly used.

(1) The multinomial form, $K(x, x_i) = [(x \cdot x_i) + 1]^q$

(2) The radial basis function, $K(x,x_i)=\exp\left\{-\frac{|x-x_i|^2}{\sigma^2}\right\}$

(3) S-sharp kernel function, $K(x,x_i)=\tanh(\nu(x\cdot x_i)+c)$

B. Multi-classify SVM

In above classify problem, we only consider two classify problem. In this paper, we will resolve the dynamic collision avoidance problem of mobile robot. According to the input vector of multi-sensor information, the SVM is used to do multi-sensor data fusion to compute the next rotation angle of mobile robot. In order to make the path that obtained by robot study smoothing and satisfactory of actual robot motion, the action space of robot is divided into 7 discrete action angles, that are -40^o, -20^o, -5^o, 0^o, 5^o, 20^o, 40^o, this is a multi-classify problem, so the system needs combination multi-SVM to classify. In this paper, we adopt "one to one" method of multi-SVM.

In this method, we will construct all the possible two classes classifier for the seven kinds training samples, every classifier only executes training on two kinds training samples of those seven kinds, in this way we will need $7\times(7-1)/2=21$ SVM two classes classifier, we use the "ballot" fashion to decide the finally classify result.

III. Dynamic Collision Avoidance Path Planning

A. Obtain Environmental Information

The environmental information includes the unknown static obstacle information and the unknown dynamic obstacle information. The collision avoidance path planning of mobile robot is first to solve the collision avoidance of static obstacle, here the environmental information primarily is the distances information, namely realize the relative positioning. In order to obtain the information which robot lies in environment timely and accurately, the robot apperceives the static obstacle information using the ultrasonic sensor, the range of these sensors lie in is shown as follow Fig.2. There are 5 range finding ultrasonic sensors dispersed over the robot forepart uniformly, for the robot has not the retrograde action, so the robot backside don't install the sensor. The search coverage of every sensor is a sector, the robot can apperceive that whether or not the obstacle exist in every sector range and corresponding distance information by the model.

Through continuous detecting the echo that reflected by the obstacle after the ultrasonic wave transmit, the supersonic sounding can detect the time difference T which from the shooting to the reception echo, then the distance $S=\frac{1}{2}VT$, here the V is the supersonic wave speed. For the supersonic is a kind of sound wave, the acoustic velocity relate to the temperature, when in use, if the temperature change is less, then it is reputed that the acoustic velocity is fundamental changeless. When the acoustic velocity is defined, we can compute the distance by detecting the round trip time of supersonic, then the obstacle distance of every supersonic sensor detecting is $d_{roi}=\frac{1}{2}VT_i$, $i=1,2,\cdots,5$, in this paper, the effective measuring range of supersonic sensor is 0.5-12m, the accuracy is 1cm.

The selected parameters must represent the environmental characteristic. According to the feature of robot dynamic path planning, an image sensor which can apperceive dynamic obstacle in 360^o was installed in the robot, it can detect the distance that between the robot and the dynamic obstacle, the motion velocity and the motion direction of the obstacle by the sensor information. The chart of the robot apperceive dynamic obstacle parameters is shown as follow Fig.3. Suppose anytime the robot can obtain these parameters by specific sensor, these parameters are shown as follow: d_{ro} is the distance that between the robot and the nearest dynamic obstacle; v_o is the speed of the nearest dynamic obstacle; θ_o is the angle that the nearest dynamic obstacle motion direction relative to the robot motion direction.

In addition, considering the relative angle θ_{re} that between the robot motion direction and the object, so the state vector of robot lie in environment $S=[d_{roi},d_{ro},v_o,\theta_o,\theta_{re}]^T$ $i=1,2,\cdots,5$.

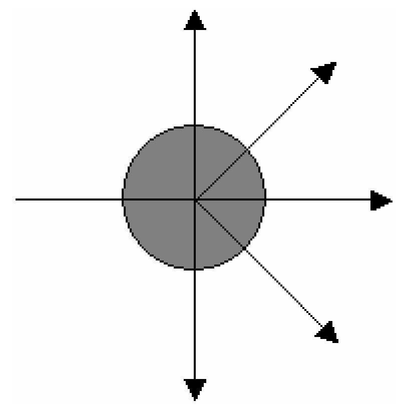

Fig. 2 The ranging sensors setting of robot

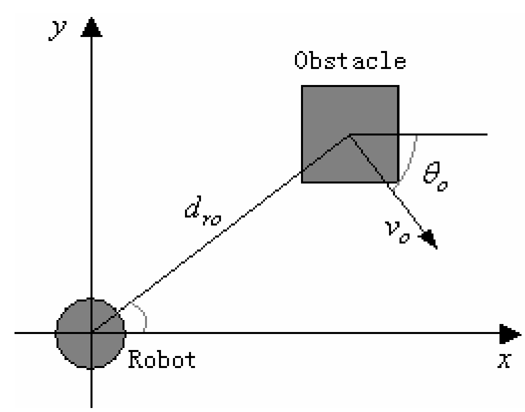

Fig. 3 The environmental state parameters of dynamic obstacle

In order to make the path that obtained by robot study smoothing and satisfactory of actual robot motion, so the action space of robot is divided into 7 discrete action angles, that are -40°, -20°, -5°, 0°, 5°, 20°, 40°, then the robot make way a certain distance along these discrete action angles.

B. *Multi-sensor Data Fusion*

For the single sensor signal is difficult to prove that the input information is accurate and reliable, and it can not satisfy that the intelligent robot system obtains the environmental information and the capability of system decision making. The purpose of data fusion technology is to generalize multi information source, add the complementarity of all kinds of sensors information and the adaptability for the environmental change by definite technical fusion method, and to make the mobile robot can obtain the allsided information that accomplish a certain task requisite and realize the autonomy at all sorts of complicated, dynamic and uncertain environment. The degree of reliability is higher than the single sensor. In addition, to make multi-sensor data fusion can obtain a consistency descriptive procedure and correct comprehension for environment, and make the robot system has fault tolerance, guarantee the rapidity and accuracy of systems information, enhance the correctness of decision making.

Firstly defined the parameters of SVM according to system demand and the fusion form in the multi-sensor data fusion based on support vector machine, and define the number of support vector and weights value by system learning. When the model of SVM is defined, the SVM model is used to do multi-sensor data fusion, make the path planning system has stronger fault tolerance and robustness.

C. *Local Path Planning Based on Multi-sensor Data Fusion by Support Vector Machine*

Owing to the SVM is a convex quadratic optimization problem, so it can assure the extremum result is the global optimum result, and it can effectively solve the overfitting problem of ANN, it has good generalization ability and better classification accuracy. Combine the advantages of multi-sensor data fusion, the method of multi-sensor data fusion based on SVM can enhance the real time controlled speed and recognition accuracy in the local path planning run procedure.

The support vector machine is used to do multi-sensor data fusion to realize the path planning in dynamic environment, first we need obtain the characteristic parameter of multi-sensors signal namely environmental state vector, the environmental state vector is used as the input vector of SVM. In this paper, we use the environmental state vector $S=[d_{roi}, d_{ro}, v_o, \theta_o, \theta_{re}]^T$ that obtained by 5 supersonic sensors and a image sensor as the input of the SVM system, use the next rotation angle of the mobile robot as the output of the SVM system, and the initial sample set is composed of a set of data of multi selected states, which represent the relationship between the environmental state vector and the robot's next rotation angle. The training sample is composed of nine input and one output. The SVM system which used for the path planning is trained off-line using all known samples, when the SVM model is defined, the SVM system can go in working process inline. The mobile robot from the current position starts, according the distance information between the static obstacle and the robot obtained by supersonic sensors, and the motion speed and motion direction of dynamic obstacle information obtained by the image sensor, the SVM network is used to do multi-sensor data fusion to compute these information, and obtain the next rotation angle of mobile robot, then the robot can make way a given step distance along the angle. In the system control process, using the error between the anticipant output and the real out of SVM system, the SVM system can be trained on-line and revised while the control system is running, so the SVM system can realize real time control for the local path planning of mobile robot.

IV. APPLICATION

A. *The Parameters Confirm of SVM*

The parameters of SVM have important influence for the classification capability, if the parameters do not enactment appropriate, we can't get the good classification result. The genetic algorithm (GA) is used to optimize SVM parameters in this paper, the forecast ability of SVM classifier is regarded as object function in order to optimization the capability of SVM. We adopt the classification SVM method based on the radial basis function, the steps of optimize the parameters as follow:

(1) First, construct the samples for pattern classification and get the training sample set.

(2) Decide the colony numbers of the GA, decide the initial value and scope of the penalty factor C and the width coefficient σ^2 of the radial basis function.

(3) Using SVM establish different classifier model for every class, estimate the forecast classification error of every classifier, if the forecast classification ability of classifier satisfy the request, then turn(5), if the forecast classification ability of classifier does not satisfy the request, then turn(4).

(4) Get the next generation parameters of SVM classifier using GA, then turn(3).

(5) Get the optimal SVM parameters and put out the result, then stop.

B. *Simulation Experiment*

In order to test the correctness and validity of the algorithm, we write some programmes of corresponding algorithm using C++, and do simulation experiment using the algorithm under the VC++ 6.0 environment. Here, the SVM uses radial basis function, the best parameters of SVM through the GA optimize are C=100, σ^2=2. The simulation result is shown as follow Fig. 4 and Fig.5. The block of figure express the static obstacle, the S represents the start point, the O represents the object point.

The Fig.4 shows the local path planning obtained by the trained SVM system in static environment, adding a dynamic obstacle in the environment, the robot can still arrive the object point, this is shown as Fig.5. The robot's current speed is 0.25m/s, the speed of dynamic obstacle is 0.3m/s. From the simulation result we can observe that the algorithm proposed in this paper is correctness and validity.

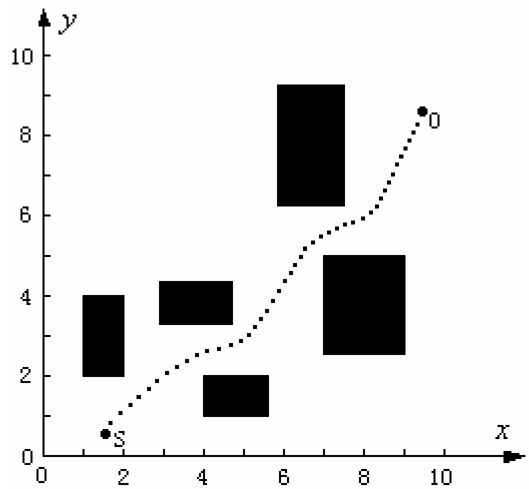

Fig. 4 Static environment path planning

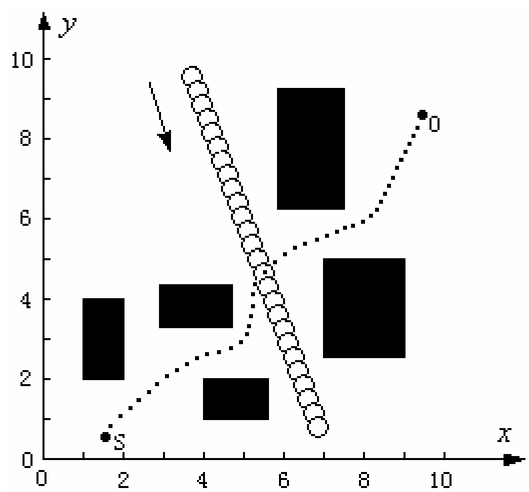

Fig. 5 Dynamic environment path planning

In order to show the further advantage and feasibility of SVM method, we adopt SVM and radial basis function neural network (RBFNN) to plan the path of mobile robot. For the RBFNN, the system error is 0.0001, the width of kernel function σ^2 is 2, equal to the width of kernel function of SVM. At the same environmental information, we select the different start point and object point, and obtain 4 paths, the experimental result is shown as table 1.

TABLE I
CONTRAST TABLE OF OPTIMAL PATH BY SVM AND RBFNN

serial number	path		SVM	RBFNN
	start point	object point	optimal path	optimal path
1	(1.5,0.5)	(9.5,8.5)	11.955	12.836
2	(1.5,0.5)	(4.5,9.5)	10.413	11.946
3	(7.0,1.0)	(1.0,5.0)	8.126	9.612
4	(10,3.0)	(3.0,10)	10.928	12.032

From the table 1, we can see the length of optimal path of SVM is shorter than the RBFNN. And the computing speed of SVM is enhanced about 1.0 times than the RBFNN with the same system error.

V. CONCLUSION

A method of multi-sensor data fusion based on SVM is applied to the mobile robot's dynamic collision avoidance path planning in this paper. It realizes the purpose of implementing the mobile robot's dynamic decision. This method has the feature of learning in-line in continuous state by using the classify support vector network, and also it makes the decision-making system has self adapting property. In the meantime using the SVM model, we can establish the directly nonlinear mapping from the environmental state to the control output by the self adapting learning, it can make the mobile robot effective avoid obstacle and arrive the target location with the shortest path in the unknown environment. The method fully utilizes the potential of the support vector machine and the multi-sensor data fusion to solve dynamic path planning problem of mobile robot. The simulation result shows that this method has good adaptability, it is an effective and feasible method to solve dynamic path planning problem of mobile robot.

ACKNOWLEDGMENT

This work was supported in part by the National High Technology Research and Development Program of China (863 Program) under Grant #2005AA420070-1.

REFERENCES

[1] C A lexopoulos, P M Griffin. Path planning for a Mobile Robot. IEEE Transactions on Systems, Man and Cybernetics, 1992, 22(2): 318-322.
[2] BORENSTEIN J, KOREN Y. The Vector Field Histogram-Fast Obstacle Avoidance for Mobile Robots [J]. IEEE Journal of Robotics and Automation, 1991, 7 (3): 278-288.
[3] FUJIMORI A, NIKIFORUK P N, GUPTA M M. Adaptive Navigation of Mobile Robots with Obstacle Avoidance [J]. IEEE Transcations on Robotics and Automation, 1997, 13 (4): 596-601.
[4] FIERRO R, L EWIS F L. Control of a Nonholonomic Mobile Robot Using Neural Networks [J]. IEEE Transcation on Neural Networks, 1998, 9 (4): 589-600.
[5] Zarate L E, Becker M, Garrido B D M, Rocha H S C. An artificial neural network structure able to obstacle avoidance behavior used in mobile robots [C]. In: IEEE 28th Annual Conference of the Industrial Electronics Society, 2002, (3): 2457-246.
[6] Yang S X, Luo C. A neural network approach to complete coverage path planning [J]. IEEE Transactions on Systems, Man and Cybernetics, 2004, 1(34): 718-724.
[7] V.Vapnik. Statistical Learning Theory.Wiley, 1998.
[8] J.Weston and C.Watkins. Support vector machines for multi-class pattern recognition. In Proceeding of the 6th European symposium on Artificial Neural Network (ESANN), 1999.
[9] Nello Cristianini, John Shawe-Taylor. An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods [M], Beijing: electronic industry publishing house, 2005.
[10]Sun zengxin. Intelligent control theory and technology [M], Beijing: Tsinghua university publishing house, 1997.
[11]Fang jianjun, He guangping. Intelligent robot [M], Beijing: Chemical industry publishing house, 2004.
[12]He you, Wang guohong. Multisensor information fusion with application [M]. Beijing: electronic industry publishing house, 2000.