LS-SVM based motion control of a mobile robot in dynamic environment

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Abstract: In this paper, least squares support vector machine (LS-SVM) based motion control of a mobile robot in dynamic environment is proposed under the measured data with uncertainties. The proposed scheme can control the robot by consideration of local minima, where the controller is based on Lyapunov function candidate and considers virtual forces information. Comparing with standard support vector machine (SVM) method, LS-SVM method is used for estimating the control parameters from the measured data with uncertainties. Simulation results are presented to show the effectiveness of the proposed scheme.

1. INTRODUCTION

For motion planning and controller design of the mobile robot, the artificial potential field method is popular used (Ge and Cui, 2002; Deng et al., 2007; Jiang et al., 2007; Jiang et al., 2008), because it can unify path planning, trajectory and control into one problem. The basic concept of the potential field is to fill the robot's workspace with an artificial potential field, it includes a repulsive artificial potential in which the robot is repulsed away from the obstacles and an attractive artificial potential in which the robot is attracted to its target position without colliding with obstacles. The issue of obstacle avoidance in a known environment has been addressed by many researchers. For example, Lyapunov function based potential field methods are considered for obstacle avoidance (Jiang et al., 2007). Ge and Cui, (2002) introduced an artificial potential method in a dynamic environment which consists of moving target and obstacle. Deng et al., (2007) gave a direct control scheme to make the robot avoiding the obstacles. However, in real application, the measured data is with unknown noises. The desired control result is difficult to obtain in the above environments. Recently, Jiang et al., (2007), Jiang et al., (2008) considered a method based on standard SVM, where the method is used for estimating the controller parameters. However, in Jiang et al., (2007), the Lyapunov compensation function is difficult to design with the moving obstacle and target.

In this paper, a new control scheme under dynamic environment is discussed. The parameters in the proposed controller are obtained from LS-SVM method, which simplifies the required computation to the standard SVM method. The rest of this paper is organized as follows. Model of two wheeled mobile robot is given in Section 2. In Section 3, the LS-SVM based design of controller is given. A scheme to eliminate the uncertainties of the observation information is proposed. Compared results by simulation are shown in Section 4 to illustrate the effectiveness of the proposed control scheme. Conclusion is drawn in section 5.

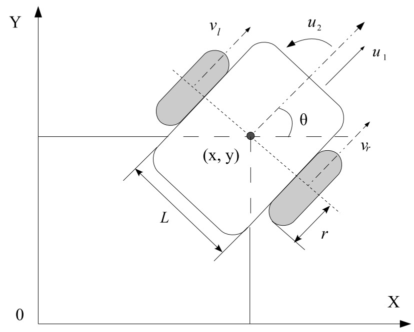

Fig. 1. Model of two wheeled mobile robot

2. MODEL OF TWO WHEELED MOBILE ROBOT

The controlled system is considered as a two wheeled mobile robot which is shown in Fig. 1, where, (x, y) is the position and θ is the heading angle of the mobile robot on two dimensional Cartesian workspace, in which global coordinates is defined. For the controlled system, the control inputs are translational velocity u_1 and angular velocity u_2 of the mobile robot, the kinematics model of the robot are given by

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{1}$$

Equation (1) can be transformed as follows

$$\frac{dz}{dt} = Bu \tag{2}$$

where

$$z = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix}, B = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix}, u = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

For the robot, velocity of the left and the right wheel v_l, v_r are described as equation (3) with r, L, which are radius of a wheel and distance between both wheels respectively.

$$\begin{bmatrix} v_l \\ v_r \end{bmatrix} = \begin{bmatrix} \frac{1}{r} & \frac{L}{2r} \\ \frac{1}{r} & -\frac{L}{2r} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{3}$$

The objective of this paper is to propose a method for eliminating the uncertainties of the observation information by using LS-SVM in the navigation of the robot.

3. LS-SVM BASED DESIGN OF PROPOSED CONTROLLER

Based on the model of the mobile robot, the objective is to design a new controller under the uncertainties of the observation information. That is, the parameters in the proposed controller are obtained by using LS-SVM. Assuming that all of the position information could be measured, such as the robot position, the obstacle position and the target position. The measured position always accompanies noise. The noise would affect the motion and the control accuracy of the robot. In this paper, the LS-SVM method for function estimation is selected to eliminate the noise from the measured data. LS-SVM (Suykens et al., 2002) is regularized for supervised approximators, which is efficient for function estimation. Only solving linear equations instead of a quadratic programming problem is needed in the optimization process, which simplifies the process to the standard SVM. Consider a given regression data set $(\tilde{x}_i, \tilde{y}_i)_{i=1}^{N}$, where the N is the total number of training data pairs, $\tilde{x}_i \in R^n$ is the regression vector and $\tilde{y}_i \in R$ is the output. According to SVM (Schölkopf and Smola, 2005), the input space R^n is mapped into a feature space $\mathcal{H}$ with the nonlinear function $\Phi(\tilde{x}_i)$. In the feature space,

$$y(\tilde{x}) = w^T \Phi(\tilde{x}) + b \quad\quad w \in \mathcal{H}, b \in R \tag{4}$$

is taken to estimate the unknown function, where vector w and scalar b are the parameters of the model. The optimization problem is defined as follows

$$\min_{w,e} J(w, e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{n} \mathrm{e}_i^2 \quad\quad \gamma > 0 \tag{5}$$

$$\text{subject to} \quad \tilde{y}_i = w^T \Phi(\tilde{x}) + b + e_i, \quad i = 1, 2, \ldots, N$$

where e_i is the error between actual output and predictive output of the ith data. The LS-SVM model of the data set can be given by

$$y(\tilde{x}) = \sum_{i=1}^{n} \alpha_i K(\tilde{x}_i, \tilde{x}) + b \tag{6}$$

where $\alpha_i \in R$ and $K(\tilde{x}_i, \tilde{x})$ $(i = 1, 2, \ldots, N)$ are Lagrange multipliers and kernel functions satisfying the Mercer condition respectively.

As a result, the uncertainties of the observation information can be eliminated by using estimation results of the position information. That is, the desired position information could be estimated by using the measured position information. Let (x_r, y_r, θ_r) be the position which would be estimated and (x, y, θ) be the measured position. At first, estimated functions are designed as follows

$$\begin{cases} x_r = f(x, \theta, u_1, Dis(rob, obs), Dis(rob, tar)) \\ y_r = g(y, \theta, u_1, Dis(rob, obs), Dis(rob, tar)) \\ \theta_r = h(\theta, u_2, Dis(rob, obs), Dis(rob, tar)) \end{cases} \tag{7}$$

where, $Dis(rob, obs)$ is the shortest distance between the robot and the obstacle, $Dis(rob, tar)$ is the shortest distance between the robot and the target. x, y, θ, u_1, u_2, $Dis(rob, obs), Dis(rob, tar)$ are the features which are crucial factors for obtaining function estimation models. The features of the unknown estimated functions are selected respectively, which are of considerable influential. Then, according to these features, the desired position models of the robot can be obtained from training data. Finally, with the estimation models of position, the uncertainties of the observation information can be eliminated. The estimated x_r, y_r, θ_r are used for design of the controller.

For the robot shown in Fig. 1, the following controller is considered. The controller includes three kinds of virtual forces, attractive force, repulsive force and detouring force, where the potential function used for the design of the controller considers the Euclidean distance information and the magnitude information of the relative velocity between the robot and the target/obstacle. Stability of the control system can be guaranteed. The control input is designed by multiplying the gradient vector of the Lyapunov function candidate V.

$$u = -(\alpha \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \hat{\beta} \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}) B^T \nabla V \tag{8}$$

where,

$$\hat{\beta} = \frac{\beta}{||B^T \nabla V||} [-\sin\theta_r, \cos\theta_r, 0] \; \nabla V$$

and α, β are positive constants. ∇V is designed by

$$\nabla V = \begin{bmatrix} F_{total_x} \\ F_{total_y} \\ 0 \end{bmatrix} \tag{9}$$

where

$$F_{total} = F_{att} + F_{rep} + F_s \tag{10}$$

$F_{total} = [F_{total_x} \quad F_{total_y}]^T$ is integration virtual force. The definitions of attractive force F_{att} and repulsive force F_{rep} are constructed based on the method in Ge and Cui, (2002). F_s is defined as detouring force (Jiang et al., 2008) for the obstacle avoidance as follows

$$F_s = K_s(||F_{rep1}|| + ||F_{rep2}||)Ns \tag{11}$$

where, K_s is positive constant, N_s is the unit vector in the tangential direction of the ellipse which the obstacle is approximately expressed. The expression of approximating the obstacle is omitted here. Figs. 2 and 3 show two cases that the robot runs into the local minima, the robot

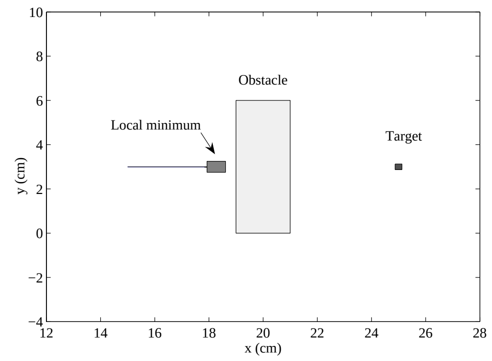

Fig. 2. An example of the situation with the local minimum

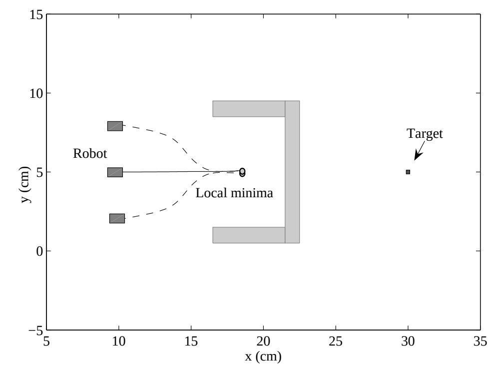

Fig. 3. An example of the situation with the local minima

could not reach the target. In the proposed method, F_s can drive the robot achieving local minima avoidance in dynamic environment. In the calculation of the F_{total} (F_{att}, F_{rep} and F_s), estimation results x_r, y_r and θ_r are of the parameters. Simulation results of the proposed scheme are demonstrated in the next section.

4. SIMULATION RESULTS

For evaluating the effectiveness of the proposed scheme to the existed methods in Deng et al., (2007), Jiang et al., (2007) and Jiang et al., (2008), local minima problem for one case is considered with static obstacle and target, one case is considered with moving obstacle and target. For using the proposed method, LS-SVMlab (Pelckmans et al., 2008) was selected to obtain the models of the estimated position and heading angle mixed with noises. The parameters were set as follows.
Virtual force parameters:
$a_p = 0.08$, $a_v = 0.4$, $m = 2$, $n = 2$, $\eta = 0.1$, $K_s = 0.1$, $\rho_0 = 5.0$, $a_{max} = 10$.
Controller parameters:
$\alpha = 0.8, \beta = 10.0, K(\tilde{x_i}, \tilde{x}) = exp(-\|\tilde{x_i} - \tilde{x}\|^2/(2\sigma^2)), \gamma = 100, \sigma^2 = 0.3$.

In order to simulate the measured data, random noise is introduced into x, y and θ. Namely, the noise brings uncertainties to the control system. In the simulation, local minima avoidance by using virtual force only are shown by solid line, which are reference results of the control system by using the method in Deng et al., (2007) (see Figs. 4-9),

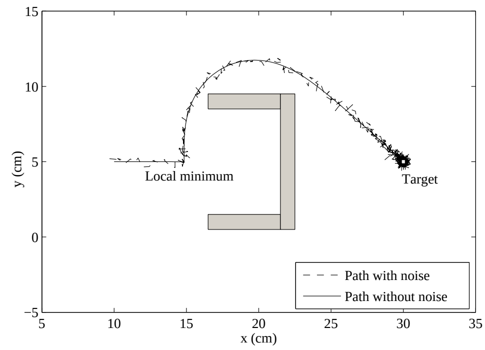

Fig. 4. LMA by using virtual force only

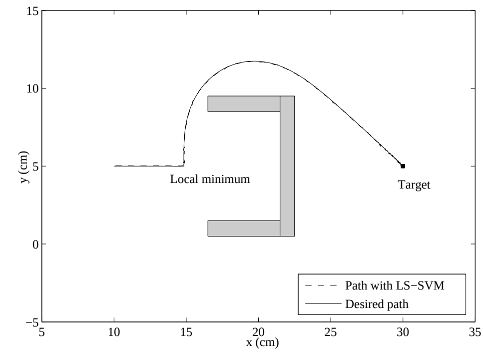

Fig. 5. LMA by using the proposed method

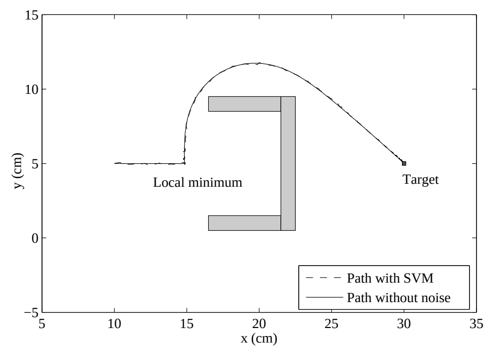

Fig. 6. LMA by using SVM

the control results with the proposed controller are shown by dashed line (see Figs. 5 and 8).

Case 1 is given by multiple adjacent rectangle obstacles. The position of the obstacle is between the robot and the target. The robot can arrive to the target with local minimum avoidance (LMA) by making a detour with detouring force F_s nearby the local minimum, where the multiple obstacles are considered as complex one. From Figs. 4 and 5, the performance of the proposed method is desired.

Case 2 is given by considering the moving obstacle and the moving target. The robot converges to the moving target with the moving obstacle avoidance (MOA). The robot is assumed to do iteration movement. The motion control of the robot by using the proposed method is also stable and accurate than the one without using the proposed

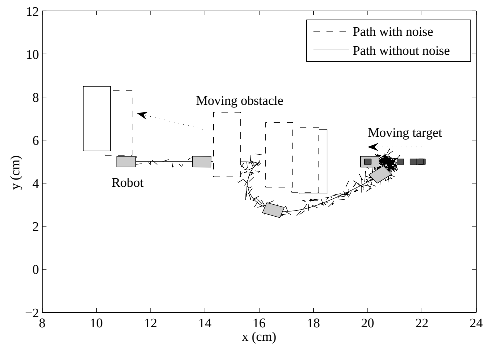

Fig. 7. Moving obstacle avoidance

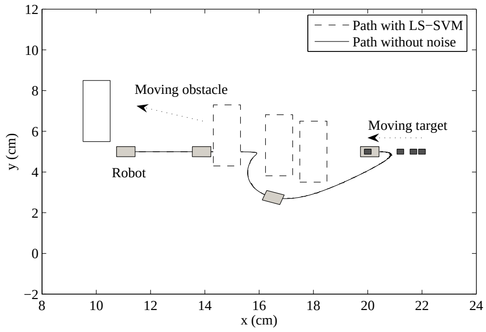

Fig. 8. MOA by using the proposed method

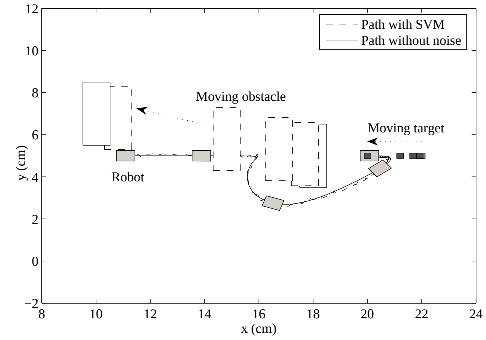

Fig. 9. MOA by using SVM

method. Local minima avoidance by using virtual force only is shown by solid line in Fig. 7, the proposed control results with noise are shown by dashed line in Fig. 8. The proposed result is closer to the reference control result without the noise.

For comparing with standard SVM method in Jiang et al., (2008), LibSVM (Chang and Lin, 2002) was chosen. The parameters were set by $\epsilon = 0.001$, $K(\tilde{x_i}, \tilde{x}) = exp(-\|\tilde{x_i} - \tilde{x}\|^2/(2\sigma^2))$, $\sigma^2 = 3$, $C = 1000$. The reference results of the robot system are shown by solid line (as Figs. 6 and 9 shown). The result with noise by using standard SVM is shown by dashed line in Figs. 6 and 9. The two kinds of SVM-based results with noise are shown by dashed line in Figs. 5-6 and 8-9. It can be seen that two kinds of SVM-based results are near results. In case 2, the result by using LS-SVM is closer to the reference one than the result by using standard SVM. However, the main difference between them is the training time of the estimated model. As shown in Table 1, in the similar simulation environment, we make 6 times training by standard SVM and LS-LSM in two cases respectively. Obviously, the training time of the standard SVM is longer than the LS-SVM. That is, LS-SVM simplifies the required computation.

Table 1. Training time of the estimation model

No.	Traning time(s)			
	Case 1		Case 2	
	Standard SVM	LS-SVM	Standard SVM	LS-SVM
1	5.530	3.935	11.001	7.829
2	5.359	3.697	10.875	7.703
3	4.975	3.758	11.811	7.875
4	5.297	3.691	10.955	7.859
5	5.563	3.740	11.873	7.907
6	5.515	3.762	11.071	7.938

5. CONCLUSION

In this paper, a new control scheme based on LS-SVM method was proposed under observation information with uncertainties. Local minima problem is solved by designing the detouring virtual force. LS-SVM is considered because of it's computationally more efficient than the standard SVM. As a result, LS-SVM method is used for the estimation of the control parameters. In simulation, the compared results with LS-SVM and standard SVM are presented by two kinds of cases to show the effectiveness of the proposed scheme.

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