PREDICTIVE MOTION CONTROL OF A MIROSOT MOBILE ROBOT

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ABSTRACT

This paper discusses predictive motion control of a MiRoSoT robot. The dynamic model of the robot is deduced by taking into account the whole process – robot, vision, control and transmission systems. Based on the obtained dynamic model, an integrated predictive control algorithm is proposed to position precisely with either stationary or moving obstacle avoidance. This objective is achieved automatically by introducing distant constraints into the open-loop optimization of control inputs. Simulation results demonstrate the feasibility of such control strategy for the deduced dynamic model.

KEYWORDS: Predictive Control, MiRoSoT, Obstacle Avoidance.

1. INTRODUCTION

Robot soccer has attracted more and more interest as an intriguing test bed for intelligent control of dynamic systems in a multi-agent collaborative environment [1]. It is also a typical multidisciplinary project, which involves in-depth knowledge in the fields of motion control, radio communication, image processing and strategy programming. Nowadays the use of global vision has been increasing in robot soccer because of the emphasis on the co-ordination and co-operation of multiple robots [2]. In such scenario, playing robots are controlled by a centralised computing system through the visual information received from a camera mounted above the playground. The motion control of such configuration is usually difficult due to large time delays in the image processing stage and the lack of local sensors.

Various methods have been applied to control mobile robots [3]. Nowadays, predictive control has been used increasingly for their inherent capability of prediction for future states of time-delay systems in a straightforward way [4]. Messom etc. [5] and Pereira etc. [6] studied such predictive control methods for mobile robots with global vision. However, predictors were only used for predicting the state of the target or the robot and obstacle avoidance was not considered in their approaches.

In this paper, an integrated predictive control algorithm is proposed to control a MiRoSoT robot using global vision, where the stability of the time-delay system is to be guaranteed by incorporating contractive constraints and automatic obstacle avoidance is to be realized by incorporating distant constraints into the open-loop optimization of control inputs. The paper is organized as follows: first, in Section 2, the dynamic model of the robot is deduced by taking into account the whole process, which includes vision system, dynamic system and transmission system; then in Section 3, a predictive control algorithm with the inherent function of automatic obstacle avoidance is proposed for the control of the resulting time-delay nonlinear dynamic system; the simulation results of the proposed algorithm are provided in Section 4; finally, some conclusions are drawn in Section 5.

2. ROBOT MODELING

The variables measured by the global vision system are the position $(\mathbf{x},\mathbf{y})$ of the geometrical centre of the robot and the angle θ between the main axis of the robot and the axis $\mathbf{X}$ of the playing field, as shown in Figure 1.

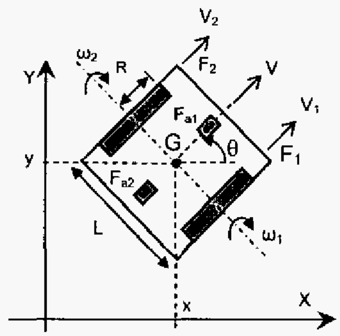


Figure 1. Model of the robot.

Based on Figure 1 and the Newton's second law, a dynamic model for the robot can be derived and written as

$$\begin{cases} \mathbf{x}_k = \mathbf{x}_{k-1} + \left[\mathbf{V}_{k-1}\mathbf{T} + (\mathbf{a}_1\mathbf{U}_{1k-d} + \mathbf{a}_2\mathbf{U}_{2k-d} + \mathbf{F}_{a1k-1} + \mathbf{F}_{a2k-1}) \dfrac{\mathbf{T}^2}{\mathbf{m}} \right] \cos(\theta_{k-1}) \\ \mathbf{y}_k = \mathbf{y}_{k-1} + \left[\mathbf{V}_{k-1}\mathbf{T} + (\mathbf{a}_1\mathbf{U}_{1k-d} + \mathbf{a}_2\mathbf{U}_{2k-d} + \mathbf{F}_{a1k-1} + \mathbf{F}_{a2k-1}) \dfrac{\mathbf{T}^2}{\mathbf{m}} \right] \sin(\theta_{k-1}) \\ \theta_k = \theta_{k-1} + \omega_{k-1}\mathbf{T} + (\mathbf{a}_1\mathbf{U}_{1k-d} - \mathbf{a}_2\mathbf{U}_{2k-d}) \dfrac{\mathbf{T}^2}{2\mathbf{I}} \end{cases} \tag{1}$$

where i.e. $\mathbf{x}_k$ indicates the value of $\mathbf{x}$ at time instant $\mathbf{kT}$; $\mathbf{V}$ and ω are the linear and angular velocity components of the robot and the terms $\mathbf{F}_{a1}$ and $\mathbf{F}_{a2}$ are the friction forces at the contact line between the bearing and the floor; $\mathbf{m}$ represents the robot mass and $\mathbf{I}$ is the inertia moment around the robot's centre of mass $\mathbf{G}$; the robot is commanded by two signals, $\mathbf{U}_1$ and $\mathbf{U}_2$, which represent the magnitudes of the voltage at the right and left motors, respectively; the time delay between the time of the action of these signals and the visualisation of its effects is denoted by $\mathbf{d}$.

The model of Eq. (1) is a physically motivated approximate description of the system. One of the problems in the model is that some terms such as friction forces, are difficult to obtain; another relevant problem is that the velocity terms are not directly measured by the vision system. This can be circumvented by an adequate parameterization of the model followed by consistent parameter estimation. Thus the physical model can be rewritten as

$$\begin{cases} \mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{c}_1\mathbf{V}_{Xk-1}\mathbf{T} + (\mathbf{c}_2\mathbf{U}_{1k-d} + \mathbf{c}_3\mathbf{U}_{2k-d})\cos(\theta_{k-1}) \\ \mathbf{y}_k = \mathbf{y}_{k-1} + \mathbf{c}_4\mathbf{V}_{Yk-1}\mathbf{T} + (\mathbf{c}_5\mathbf{U}_{1k-d} + \mathbf{c}_6\mathbf{U}_{2k-d})\sin(\theta_{k-1}) \\ \theta_k = \theta_{k-1} + \mathbf{c}_7\omega_{k-1} + \mathbf{c}_8\mathbf{U}_{1k-d} + \mathbf{c}_9\mathbf{U}_{2k-d} \end{cases} \tag{2}$$

where V_X and V_Y are the projections of the linear velocity V on the axis X and Y, respectively. It is important to note that the mass m, sampling time T and friction forces F_{a1}, F_{a2} are grouped together in parameters $c_i (i = 1, \cdots, 9)$. The velocity components in V_X, V_Y and θ can be roughly approximated by

$$\left\{ V_{Xk-1} = \frac{x_{k-1} - x_{k-2}}{T}, \quad V_{Yk-1} = \frac{y_{k-1} - y_{k-2}}{T}, \quad \theta_{k-1} = \frac{\omega_{k-1} - \omega_{k-2}}{T} \right. \tag{3}$$

Then Eq. (2) can be represented as an auto-regressive model with exogenous inputs of the form:

$$\begin{cases} x_k = a_{1X} x_{k-1} + a_{2X} x_{k-2} + (b_{1X} U_{1k-d} + b_{2X} U_{2k-d}) \cos(\theta_{k-1}) \\ y_k = a_{1Y} y_{k-1} + a_{2Y} y_{k-2} + (b_{1Y} U_{1k-d} + b_{2Y} U_{2k-d}) \sin(\theta_{k-1}) \\ \theta_k = a_{1\theta} \theta_{k-1} + a_{2\theta} \theta_{k-2} + b_{1\theta} U_{1k-d} + b_{2\theta} U_{2k-d} \end{cases} \tag{4}$$

In order to estimate the parameters of the model in Eq. (4) through a general least-square method, experimental data from the control inputs, U_1 and U_2, and the system output, x, y and θ are needed. The acquisition process of these variables demands a few considerations: dynamical testing should be performed in open loop to avoid correlation between input signal and measurement noise; the system must be properly excited to allow parameter estimation and since the model in Eq. (4) was derived considering basic physical laws and assuming some approximations, a number of real observed phenomena might not be well represented by it [2]. In order to reduce the effect of unmodeled phenomena, it is better to excite the robot, whenever possible, within a limited range around the operating point.

Step response data were used to perform preliminary tests and to aid in the dead time estimation. From the data shown in Figure 2, a dead time of approximately 126 ms was estimated. For parameter estimation, however, Pseudo Random Binary Signals (PRBS) were used as inputs

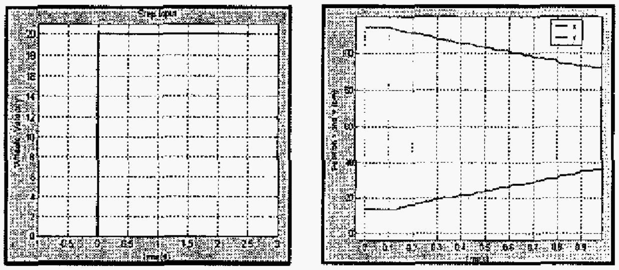
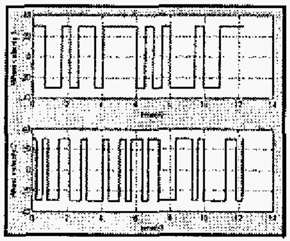


Figure 2. Step response of the system.

in order to guarantee that the system was properly excited, as shown in Figure 3. A typical response of such a test is shown in Figure 4. Cross-correlation between inputs and outputs was generally small and this was somewhat compensated by the use of sufficiently large number of points. The sampling time was initially chosen to be 18ms based on the characteristics of the vision, control and communication systems. With the time delay estimated and using the sampling time of the system, we have $d = 7$.



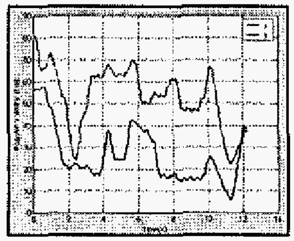


Figure 3. Pseudo Random Binary Signal. *Figure 4. Data used in parameter estimation.*

The Extended Least Squares Method was applied independently to estimate each sub-model of Eq. (4). The following model was obtained:

$$\begin{cases} x_k = 1.3724x_{k-1} - 0.3724x_{k-2} + (0.0096\,U_{1k-7} + 0.0119U_{2k-7})\cos(\theta_{k-1}) \\ y_k = 1.221y_{k-1} - 0.221y_{k-2} + (0.0117\,U_{1k-7} + 0.0121U_{2k-7})\sin(\theta_{k-1}) \\ \theta_k = 1.121\theta_{k-1} - 0.121\theta_{k-2} - 0.00396U_{1k-7} + 0.00422U_{2k-7} \end{cases} \quad (5)$$

3. PREDICTIVE CONTROL

Based on the obtained model in Eq. (5), the control task of robotic interception is to catch the target with a proper orientation; meanwhile, the robot will not collide with obstacles during its movement to the target. The position of all obstacles is denoted by $\{x_o, y_o\}$. Thus corresponding control problem to be solved is to compute a sequence of inputs $\{U_{1k+j}, U_{2k+j}\}$ that will take the robot from its current state $X_k = \{x_k, y_k, \theta_k\}$ to the desired state $X_d = \{x_d, y_d, \theta_d\}$ with additional constraints of keeping a distance from all obstacles. The desired state of the robot is to be determined by the position of the target and the angle of interception.

According to the principle of model predictive control (MPC) [7], the sequence of inputs $U_{k+j} = \{U_{1k+j}, U_{2k+j}\}$ is aimed to drive the robot to the target as soon as possible and meanwhile to guarantee the robot to keep a distance from all obstacles such as walls and opponent robots, i.e., the control sequence of every step is to be calculated through minimizing the following cost function on the basis of satisfying corresponding constraints

$$J_{(n,m)}(X_0) = \min_{\{U(k+j|k)\}_{j=0}^{m-1}} \left\{ \begin{aligned} &[X(k+n|k) - X_d]^T P_0 [X(k+n|k) - X_d] + \\ &\sum_{i=1}^{n-1}[X(k+i|k) - X_d]^T Q [X(k+n|k) - X_d] + \sum_{j=0}^{m-1} U^T(k+j|k) R U(k+j|k) \end{aligned} \right\} \quad (6)$$

subject to control, distant and contractive constraints

$$\begin{cases} |U(k+j|k)| \le G_1 \\ \|[x_{k+i} \quad y_{k+i}] - [x_o \quad y_o]\|_2 \ge G_2 \\ \|[x_{k+n} \quad y_{k+n}] - [x_d \quad y_d]\|_2 \le \alpha \|[x_k \quad y_k] - [x_d \quad y_d]\|_2, \alpha \in [0,1) \end{cases} \quad (7)$$

where n denotes the length of the prediction horizon; m denotes the length of the control horizon ($m \le n$); G_1 denotes the maximum absolute value of control signals; G_2 denotes the minimum distance between the robot and the obstacles; α determines the degree of state contraction for every open-loop optimization.

The control constraint corresponds to the limit of the speed of motors that drives the robot; the distant constraint corresponds to the obstacle avoidance by keeping a proper distance from all obstacles; the contractive constraint is to guarantee that the robot is approaching to the target by distance and thus ensures the stability of the closed-loop system since the constraint can be transformed to a decreasing Lyapunov function of the closed-loop system [7].

According to the above problem description, the nonlinear MPC control steps are as follows:

1. Get the current state $\mathbf{X(k)}$;
2. Solve the optimization in Eq. (6) by corresponding optimization algorithm and get the optimal control sequence $\{\mathbf{U}^*(\mathbf{k}+\mathbf{j}|\mathbf{k})\}_{\mathbf{j}=0}^{\mathbf{j}=\mathbf{m}-1}$;
3. Apply the first control signal $\mathbf{U(k)} = \mathbf{U}^*(\mathbf{k}|\mathbf{k})$ in the resulting optimal control sequence;
4. $\mathbf{k}+1 \to \mathbf{k}$, Return to 1.

It can be seen that a characteristic of the proposed algorithm is that it has integrated the control task of interception, the task of path planning and the task of obstacle avoidance, which will avoid heavy computation for extra path planning and obstacle avoidance such as in [8]. Thus it is especially useful for those cases where online path planning and obstacle avoidance become very hard due to the lack of global information on the environments around the robot or rapid change of the environments around the robot.

4. SIMULATION RESULTS

Based on the above predictive control algorithm and the deduced robotic model, two cases are simulated: robotic interception with stationary obstacle avoidance and robotic interception with moving obstacle avoidance. In all simulations, the cost function is set to be $\mathbf{J}_{(\mathbf{n},\mathbf{m})}(\mathbf{X}_0) = \min\limits_{\{\mathbf{U}(\mathbf{k}+\mathbf{j}|\mathbf{k})\}_{\mathbf{j}=0}^{\mathbf{j}=\mathbf{m}}} 2\sum_{\mathbf{i}=1}^{\mathbf{n}}\left[\mathbf{X}(\mathbf{k}+\mathbf{i}|\mathbf{k})-\mathbf{X}_\mathbf{d}\right]^\mathbf{T}\left[\mathbf{X}(\mathbf{k}+\mathbf{n}|\mathbf{k})-\mathbf{X}_\mathbf{d}\right]$ and the other parameters are set to be $\mathbf{m}=\mathbf{n}=17, \mathbf{G}_1=100, \mathbf{G}_2=12\mathbf{cm}, \alpha=0.95$. Figure 5 shows the first case, where there are five stationary obstacles in the environments and the control task is to drive the robot to the target with the desired orientation. The trajectory of the control result shows that the robot can arrive to the target precisely without collision with all obstacles. Figure 6 shows the moving case, where five obstacles are moving and the control task is also to intercept the target with a proper orientation. The trajectory of the control results also shows that the robot can intercept the target with the desired orientation and without collision with the moving obstacles.

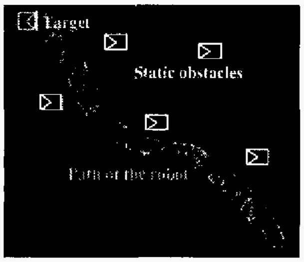


Figure 5. Robotic interception with stationary obstacle avoidance.

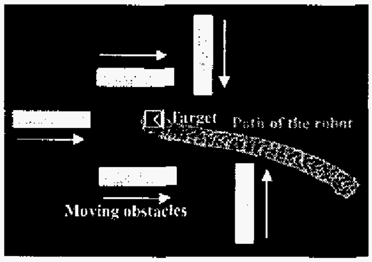


Figure 6. Robotic interception with moving obstacle avoidance.

Simulation results demonstrate the feasibility of the proposed predictive control algorithm based on the deduced robotic model. However, the trajectories of the moving obstacles and the target are assumed to be known in advance in these two cases in order to simplify the test of the algorithm proposed. In practice, these trajectories should be predicted as well while corresponding predictive control algorithm is similar [5].

5. CONCLUSIONS

This paper discussed predictive motion control of a MiRoSoT robot. The dynamic model of the robot has been deduced with the consideration of the whole process including robot, vision, control and transmission systems. Model predictive control has been proposed to control such complex dynamic system with nonlinearities and time-delay. Additional constraints such as contractive constraint and distant constraint have been integrated into the algorithm for guaranteeing the stability of the close-loop system and realizing obstacle avoidance simultaneously. However, as illustrated in [9], the computation of open-loop optimizations in predictive control is heavy and more efficient algorithms should be explored further for real-time application in the future.

6. ACKNOWLEDGEMENTS

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