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Learning Control of an Overhead Crane for Obstacle Avoidance

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Abstract

A control strategy is presented for a 3-dimensional overhead crane. Using the differential flatness of the crane and a parameterization method, we calculate the optimal trajectory of the payload that results in minimum transfer time when there exist obstacles in the direct moving path. A learning algorithm is then used to generate the desired feedforward input signal that can drive the system output to track the optimal trajectory exactly.

1. Introduction

Much research has been done on the crane modeling and control [2][4][5]. However, these methods consider only 2-dimensional crane trajectory planning. Here, we outline a control strategy for a 3-dimensional overhead crane. Detailed formulation and development are available upon request. This strategy can move the load to the desired place while avoiding obstacles. We approach the problem in two steps. First, we calculate the time-optimal trajectory for the payload to move from one place to another without colliding with obstacles. Next, we use a learning control algorithm to obtain the desired input signal which generates the desired output to track the optimal trajectory.

2. Model Description

We consider a 3-D overhead crane shown in Figure 1 with the following assumptions:

1. The payload is a point-mass.
2. The rope is massless and has no torsional stiffness.
3. The motion of the trolley and gantry is frictionless.
4. The control inputs to the system are the mechanical forces.

In Figure 1, x, y, l are the coordinates of trolley, girder and hoist. x_g, y_g, z_g are the coordinates of the load. α, β represents the swing angles. They have the following relationship

$$x_g = x + l \sin\alpha \sin\beta \tag{1}$$
$$y_g = y + l \sin\alpha \cos\beta \tag{2}$$
$$z_g = l \cos\alpha \tag{3}$$

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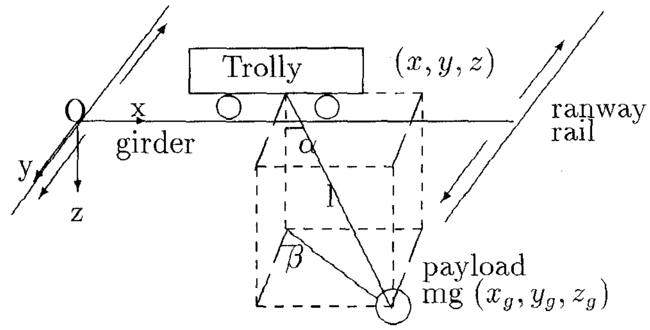

Figure 1: Overhead Crane

Using the Lagrangian method, the equations of motion are given by

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q_i}}\right) - \frac{\partial L}{\partial q_i} = u_i, \quad i = 1, \ldots 5 \tag{4}$$

where $[q_1 \ldots q_5] = [x \; y \; l \; x_g \; y_g], [u_1 \ldots u_5] = [F_1 \; F_2 \; F_3 \; 0 \; 0]$. F_1, F_2, F_3 are the mechanical forces applied to the trolley, girder and hoist, respectively. $L = T - U$, T, U represent the kinetic energy and potential energy, respectively, of the whole crane system and are given by

$$T = \frac{1}{2}m_1(\dot{x}^2 + \dot{y}^2) + \frac{1}{2}m_2\dot{y}^2 + \frac{1}{2}m(\dot{x_g}^2 + \dot{y_g}^2 + \dot{z_g}^2) \tag{5}$$

$$U = -mgz_g \tag{6}$$

where g is the gravitational acceleration. z_g is a nonlinear function of x, y, l, x_g, y_g. m_1 and m_2 are the masses of the trolley and girder, respectively. m is the mass of the load. Let $\bar{x} = [x \; y \; l \; x_g \; y_g \; \dot{x} \; \dot{y} \; \dot{l} \; \dot{x_g} \; \dot{y_g}]^T$, the state space model can be written as

$$\dot{\bar{x}} = f(\bar{x}, u) \tag{7}$$

3. Time-Optimal Load Trajectory

The optimal trajectory planning is to seek a load trajectory that will accomplish the required load transfer in minimum time while at the same time satisfy some constraints on obstacle avoidance.

In general, trajectory planing needs to be performed for all state variables of $\bar{x}$ in order to meet the dynamic constraints. However, the crane model can be shown to be a differentially flat system [1]. The state variables and their derivatives satisfy the following equations

$$x = x_g - \frac{\ddot{x}_g z_g}{\ddot{z}_g - g} \tag{8}$$

$$y = y_g - \frac{\ddot{y}_g z_g}{\ddot{z}_g - g} \tag{9}$$

$$l = \sqrt{(x_g - x)^2 + (y_g - y)^2 + z_g^2} \tag{10}$$

That is, x, y, l are functions of x_g, y_g, z_g and their derivatives. Therefore, we only need to perform trajectory planing for x_g, y_g, z_g. Then, all the other variables in $\bar{x}$ can be obtained from x_g, y_g, z_g and their derivatives.

The load swing angles can also be represented as functions of x_g, y_g, z_g and their derivatives by following equations

$$m\ddot{x}_g = -T \sin\alpha \sin\beta \tag{11}$$

$$m\ddot{y}_g = -T \sin\alpha \cos\beta \tag{12}$$

$$m\ddot{z}_g = -T \cos\alpha + mg \tag{13}$$

where T is the tension of the rope. From these equations, α, β can be represented as

$$\alpha = \arctan \frac{\sqrt{\ddot{x}_g^2 + \ddot{y}_g^2}}{\ddot{z}_g - g} \tag{14}$$

$$\beta = \arctan \frac{\ddot{x}_g}{\ddot{y}_g} \tag{15}$$

The trajectory planning is solved by a parameterization method. For simplicity, the desired trajectories of x_{gd}, y_{gd}, z_{gd} are parameterized as linear combinations of sinusoidal functions

$$x_{gd} = x_{dg0} + x_{gdf}\frac{t}{t_f} + \sum_{i=1}^{n} c_{1i} \sin i\pi \frac{t}{t_f} \tag{16}$$

$$y_{gd} = y_{dg0} + y_{gdf}\frac{t}{t_f} + \sum_{i=1}^{n} c_{2i} \sin i\pi \frac{t}{t_f} \tag{17}$$

$$z_{gd} = z_{dg0} + z_{gdf} + \sum_{i=1}^{n} c_{3i} \sin(2i-1)\pi \frac{t}{t_f} \tag{18}$$

where,$(x_{gd0}, y_{gd0}, z_{gd0})$ is the initial position and $(x_{gdf}, y_{gdf}, z_{gdf})$ is the final position of the load. Some extra conditions at the initial and final time also need to be satisfied. Thus, given the load initial position and final position, the time optimal trajectory planning problem is to find c_{ji} such that

$$\min_{c_{ji}} t_f$$

subject to:

$$g_k(c_{ji}) \leq r_k \quad k = 1, 2, \ldots n$$

$$|\alpha(c_{ji})| \leq \alpha_0$$

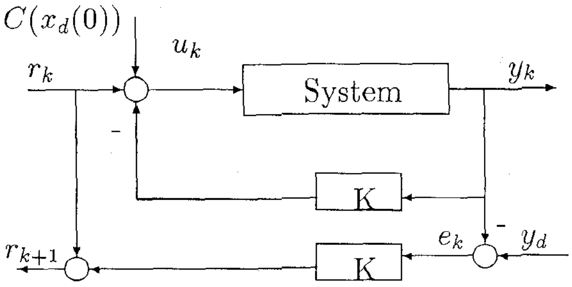

Figure 2: Learning control scheme with full state feedback

where t_f is the final time. j=1,2,3, i=1,...n. $g_k(\bar{c_{ji}}) \leq r_k$, $k = 1, 2, \ldots, n$, represent geometric constraints needed for obstacle avoidance. $|\alpha(c_{ji})| \leq \alpha_0$ is the constraint for the maximum swing angle.

The problem can then be solved using MATLAB.

4. Learning Control Algorithm

The purpose of learning control is to design a control input such that this input can drive the system output to track the desired trajectory. We use a learning algorithm similar to [3]. Their paper assumes that the number of actuators is the same as the number of degrees of freedom. However, in our 3-D crane system, the degrees of freedom are more than the number of actuators. Fortunately, we can show that their method is still useful in our system.

Suppose the linearized system of nonlinear system (7) is given by

$$\begin{aligned} \dot{\bar{x}} &= A\bar{x} + Bu \\ y &= C\bar{x} \end{aligned} \tag{19}$$

If $u = r - K\bar{x}$ is used to stabilize the system, where K is a feedback control gain obtained from, say, pole placement method, then the learning algorithm is given by

$$r_{k+1} = r_k + K(\bar{x} - \bar{x}_d) \tag{20}$$

where $\bar{x}_d$ is the given optimal path for $\bar{x}$. The control scheme is shown in Figure 2. Simulation results demonstrate the efficiency of our learning algorithm.

5. Conclusions

The dynamic model of a 3-dimensional overhead crane is developed. In case there exist obstacles in the load moving path, the time-optimal load trajectory is obtained under the constraints of no swing at the end of the movement and bounded load swing angle in the process of the movement. Such a trajectory corresponds to minimum transfer time and at the same time it avoids the obstacles. Using the learning algorithm, a desired reference input signal is calculated which assures the system output to track the optimal trajectory exactly.

Reference and simulation results are available upon request.