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Safe Distance Prediction for Braking Control of Bridge Cranes Considering Anti-Swing

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Abstract

Cranes are widely deployed for lifting and moving heavy objects in dynamic environments with human coexistence. Suddenly appeared workers, vehicles and robots can affect the safety of the cranes. To avoid possible collisions, cranes must have the prediction ability to know how dangerous the situation is. In this paper, we address the safety issues of a bridge crane based on its online physical states and control model. Due to the dynamic nature of the swinging payload, the safe braking distance cannot be a constant value. Therefore, we here propose a model prediction control (MPC) based anti-swing method for cranes with non-zero initial states, where a new reference trajectory and a new cost function for optimization are proposed, such that the proposed MPC method can control the crane to follow the proposed reference trajectory and achieve a stable stop state without swinging. Furthermore, an offline learning mechanism is introduced to learn a statistical model between the velocity of the crane and the safe braking distance achieved by using the proposed MPC braking control method. In this way, we can predict how far the crane would require to safely stop without swinging based on its current velocity, which is the safe distance prediction to evaluate the dangerous level of the dynamic obstacle. Experiments using both a simulated crane and a real crane demonstrate that the proposed safe braking distance prediction method is effective for the safe braking control of the bridge crane.

KEYWORDS:
Bridge crane, safe distance, safe braking, model prediction control, anti-swing.

1 | INTRODUCTION

Cranes can help people lift and move large, heavy, dirty and dangerous objects, and have been widely used in many industrial fields[1], e.g., building construction, transportation, logistics, etc. For these application scenarios, cranes often work with human workers, robot arms, or vehicles, such that the working environments of the crane are usually highly dynamic and dangerous. Therefore, the safety problem of cranes is very important and has attracted considerable attention from both industry and academia. With the rapid advancement of laser and vision sensing technologies in recent years, detection of static and dynamic obstacles is not considered challenging nowadays. However, as shown in Fig.1 , the trolley of the crane is connected with a payload using a rope, which can swing during launching, moving and braking. The payload cannot stop immediately to avoid collisions due to the unpredictable swinging motions. Because of this special physical structure, it is difficult and challenge

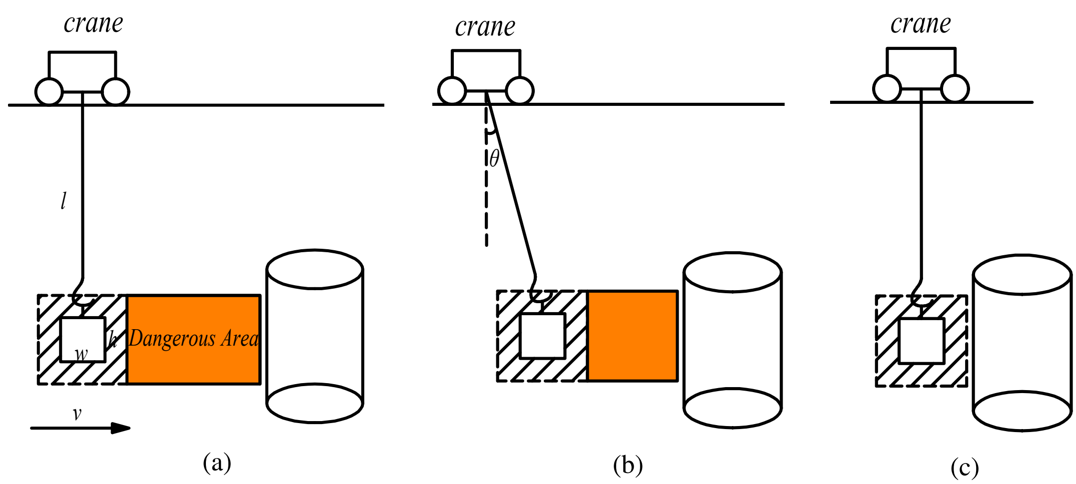


FIGURE 1 As the crane system is an underactuated system, the safe braking distance is a variable and can not be directly controlled. This paper tries to study on the safe braking control method and learn the statistical relation between the safe braking distance and the velocity, while the swing angle is constrained. In this way, the crane can define a dangerous area using the learned braking distance as shown in the orange area of (a), and use the proposed braking control method to stop with anti-swing as shown in (b) and (c).

to design crane controllers [2,3,4,5,6,7] with robust anti-swing performance. The safety standards require the crane to stop quickly and the swing angle of the payload to be constrained within a small range. This means that the crane must consider the anti-swing with non-zero initial states. Previous works have mostly use human experiences as references to achieve safe braking performance, but have not considered safe braking distance prediction and anti-swing control with non-zero initial state.

When an emergency stop is required, the non-zero initial state of the crane can introduce strong residual vibrations to the payload, i.e., velocity, swing angle or angular velocity are not zero. Although many works have been proposed to solve the stable control problem of the overhead crane, most of them assume that the cranes have zero initial states, e.g., proportional–integral–derivative (PID) control [8], [9], fuzzy control [10,11,12], optimal control [13,14,15], sliding-mode control [16,17,18,19], model predictive control [20,21,22,23], trajectory planning control [24,25], and command shaping control [26,27,28]. To handle the non-zero initial velocity issue, Joaquim Maria Veciana et al. [29] introduced a method that considered the initial states for the control inputs, which were obtained from a feedback sensor and this method could be processed with a reasonable time delay. Although their method can minimize the residual oscillation at the final stop, it can introduce a large load swing angle during the emergency stop. To solve the anti-swing problem, a new swing elimination control approach is introduced in [30] and can achieve smooth transferring of payloads with a zero initial velocity state. However, this method cannot guarantee the swing angle to be constrained within the expected range. In [31], a minimum time online motion planning method is introduced for under-actuated overhead crane systems by considering both physical constraints and safety. Fang and Sun [32] convert the swing constraint into the control input constraint, such that the anti-swing becomes an optimization problem. However, their anti-swing methods only consider the situation that the load has a zero initial state [33,34,35,36].

The safety problem of cranes is very important for the human coexistence environment. For instance, Chi and Caldas [37] established a set of safety rules based on three fundamental risks: (1) excessive work speeds, (2) access to dangerous areas, and (3) close proximity between objects, such as crane and workers. Zhen Yang et al. [38] calculate the safety distance of the crane using visual images to warn workers to avoid risks. We can see that the safety issues are very important since the workers often work with cranes closely. However, previous works use fixed distances for danger detection which presents limitations, since the crane can have varying swing angles as its initial states that would require different braking distances correspondingly due to the dynamic environments. Therefore, it is necessary to be able to predict the distance that the crane require to safely stop under different initial states while anti-swing must be concerned, and this is the main goal of this paper.

In this paper, we propose an adaptive safe braking distance prediction method considering anti-swing with non-zero initial states, which mainly includes two parts: First, we introduce an Model Predictive Control (MPC) based control scheme to stop the moving load in a short period while the swing angle is constrained. The MPC algorithm is employed for planning a velocity

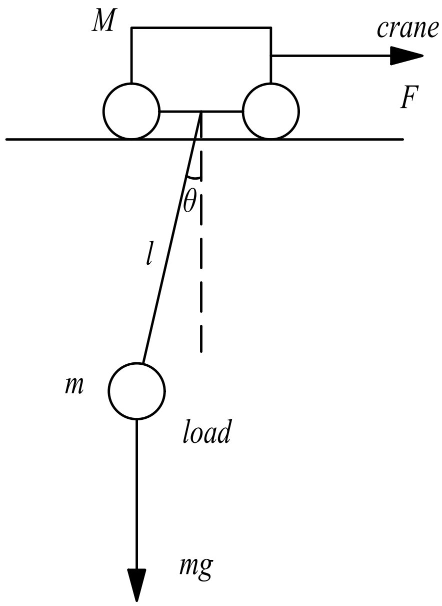


FIGURE 2 A simplified model of a bridge crane.

reference trajectory, which stops the crane and payload quickly and stably. Second, the safe braking distance is predicted according to the performance of the MPC braking control method and the relative velocity between the obstacle and the payload. The statistical model of the safe braking distance prediction function is derived by an offline learning method. In this way, we can estimate the safe braking distance at runtime according to the relative velocity between the payload and the obstacle, such that the crane can predict possible collisions, and take safe control decisions in advance according to the situation of the dynamic environment. This work extends our earlier version[39] by adding real-world experiments on the crane and giving more details of the proposed algorithm. The contributions of this paper can be summarized as follows:

(1) To the best knowledge of the authors, this is the first attempt to introduce an online safe braking distance prediction method for an overhead crane based on the current velocity, in order to ensure the crane to stop quickly and stably without swinging.

(2) We propose an MPC based anti-swing method for a bridge crane with a non-zero initial state, meaning that, at least, the velocity, the swing angle or the angular velocity is not zero, in order to ensure the swing angle to be constrained in a desired range during braking.

(3) The statistical function of the safe braking distance prediction is derived by analyzing the anti-swing performance of the MPC, which can be used to calculate the safe distance at runtime, such that possible collisions can be evaluated in advance.

(4) The safe braking control algorithm can be applied to the crane system, with different control algorithms, such as uniform acceleration (UA) control, MPC control, PID control etc.

The rest of the paper is organized as follows. In section 2, the crane dynamic system and model transformations are introduced. Section 3 presents the details of the MPC controller for anti-swing with a non-zero initial state, and section 4 explains the safe braking distance function derived by a statistical analysis method. Then the proposed method is demonstrated using the simulated crane and real crane described in section 5. Finally, section 6 concludes the work of this paper.

2 | MODEL

A simplified model of the bridge crane is shown in Fig.2 , which has a point mass and a cable. The cable is assumed to have no bending moment and elasticity. The physical models of the trolley and the payload can be derived from the dynamic equation and the control input, e.g., the displacement and velocity of the crane, the swing angle of the payload and the angular acceleration.

2.1 | Dynamic system

The two-dimensional dynamic characteristics of the bridge crane are described as follows[32]:

$$(M + m)\ddot{x} + ml\ddot{\theta}\cos\theta - ml\dot{\theta}^2\sin\theta = F \tag{1}$$

$$ml^2\ddot{\theta} + ml\cos\theta\ddot{x} + mgl\sin\theta = 0 \tag{2}$$

where M and m represent the mass of the trolley and the payload respectively, x denotes the displacement of trolley, l is the length of the rope, θ is the swing angle of the payload, F represents the force acting on the trolley, and g is the gravity acceleration. The force F can be regarded as the control input of the system. For safe braking with a non-zero initial state that at least one of the velocity, swing angle and angular velocity is not zero. The velocity and swing angle are the key factors, so we define the state vector as $x_m(t) = [\,\theta \;\; v \;\; \dot{\theta}\,]^T$, where v is the linear speed of the trolley and $\dot{\theta}$ represents the angular speed of the payload. We can further simplify (1) and (2) to the following equations:

$$\dot{v} = \ddot{x} = \frac{mg\sin\theta\cos\theta + ml\dot{\theta}^2\sin\theta + F}{M + m\sin^2\theta} \tag{3}$$

$$\ddot{\theta} = \frac{-\cos\theta\dot{v} - g\sin\theta}{l}. \tag{4}$$

2.2 | System Linearization

We linearize (3) and (4) around the equilibrium point $x_m(t_\infty) = [\,0 \;\; 0 \;\; 0\,]^T$ and derive two linearized equations as

$$\dot{v} = \frac{mg}{M}\theta + \frac{1}{M}F \tag{5}$$

$$\ddot{\theta} = -\frac{(m+M)g}{lM}\theta + \left(-\frac{1}{lM}\right)F. \tag{6}$$

According to equations (5) and (6), we can further derive the state space expression of the system as follows:

$$\dot{x}_m = \begin{bmatrix} 0 & 0 & 1 \\ \frac{mg}{M} & 0 & 0 \\ -\frac{(m+M)g}{lM} & 0 & 0 \end{bmatrix} x_m + \begin{bmatrix} 0 \\ \frac{1}{M} \\ -\frac{1}{lM} \end{bmatrix} u, u(t) \in \mathbb{R} \tag{7}$$

$$y = x_m. \tag{8}$$

2.3 | Discrete system

By discretizing the spatial state equations (7) and (8), which are in the continuous time domain, we can obtain the discrete state space equations as

$$\begin{cases} x_m(k+1) = A_m x_m(k) + B_m u(k) \\ y(k) = C_m x_m(k), C_m = I_{4\times4} \end{cases} \tag{9}$$

Furthermore, the state variables at the next step can be expressed as follows:

$$\begin{cases} x_m(k_i + N_p|k_i) = A_m^{N_p} x_m(k_i) + A_m^{N_p-1} B_m u(k_i) \\ \qquad + \cdots + A_m^{N_p-N_c} B_m u(k_i + N_c - 1) \\ y(k_i + N_p|k_i) = C_m x_m(k_i + N_p|k_i), C_m = I_{4\times4} \end{cases} \tag{10}$$

where N_p represents the prediction time horizon, and N_c represents the time step of control u that is lower than N_p. The sampling time is expressed by k_i. When the information $x_m(k_i)$ is given, the future state variables can be predicted from time $k_i + 1$ until time $k_i + N_p$.

We can further write equation (10) in a compact matrix form as follows:

$$\begin{aligned} Y &= PX_m(k_i) + \Psi U, \\ \Psi &= \begin{bmatrix} C_m B_m & \mathbf{0} & \cdots & \mathbf{0} \\ C_m A_m B_m & C_m B_m & \cdots & \mathbf{0} \\ \vdots & & & \\ C_m A_m^{N_p-1} B_m & C_m A_m^{N_p-2} B_m & \cdots & \cdots \end{bmatrix} \\ P &= \begin{bmatrix} C_m A_m \\ C_m A_m^2 \\ \vdots \\ C_m A_m^{N_p} \end{bmatrix}, P \in \mathbb{R}^{3N_p \times 3}, \Psi \in \mathbb{R}^{3N_p \times N_c}. \end{aligned} \tag{11}$$

3 | METHOD FOR BRAKING

In this section, we introduce an MPC based anti-swing control method to stop a crane with a non-zero initial state. The overall principle of this work is to find different required braking distances for varying predefined reference trajectories with different initial states. The overall goal of the MPC algorithm is to control the crane to follow the reference trajectories while aiming to reduce the final velocity, swing angle and angular velocity towards zero. In other words, the crane tracks the given reference trajectory and finally achieves a stable stop state, with the swing angle constrained to a certain range. The flowchart of the algorithm is shown in Fig.3 .

3.1 | Reference trajectory

The reference trajectory used in MPC to control the crane with a non-zero initial state is defined as

$$r_v(k) = y(t_0) \times (1 - \tanh(\lambda k T)) \tag{12}$$

where T is the control period, $\lambda > 0$ denotes the convergence time coefficient, and $y(t_0)$ represents the initial state of the crane, defined as $y(t_0) = [\,\theta(t_0)\;\; v(t_0)\;\; \dot{\theta}(t_0)\,]^T$, where $v(t_0)$, $\theta(t_0)$ and $\dot{\theta}(t_0)$ represent the initial velocity, initial angle and angular velocity respectively. According to equations (11) and (12), the tracking objective state reference trajectory $R_v(k_i)$ of Y at k_i can be represented as

$$R_v(k_i) = \begin{bmatrix} r_v^T(k_i) \\ r_v^T(k_i+1) \\ \vdots \\ r_v^T(k_i + N_p - 1) \end{bmatrix}. \tag{13}$$

3.2 | Optimal solution

The goal of the MPC is to minimize the difference between the real velocity trajectory Y and the velocity reference trajectory R_v, so we can define the cost function as

$$J(U) = (R_v - Y)^T (R_v - Y). \tag{14}$$

We can substitute equations (11) and (13) into (14), and leave the polynomial with the variable U to be optimized. The cost function becomes

$$J(U) = U^T(\Psi^T Q \Psi)U - 2U^T \Psi^T (R_v - PX_m(k_i)) \tag{15}$$

where $Q \in \mathbb{R}^{3N_p \times 3N_p}$ denotes the weight coefficients of the three state variables.

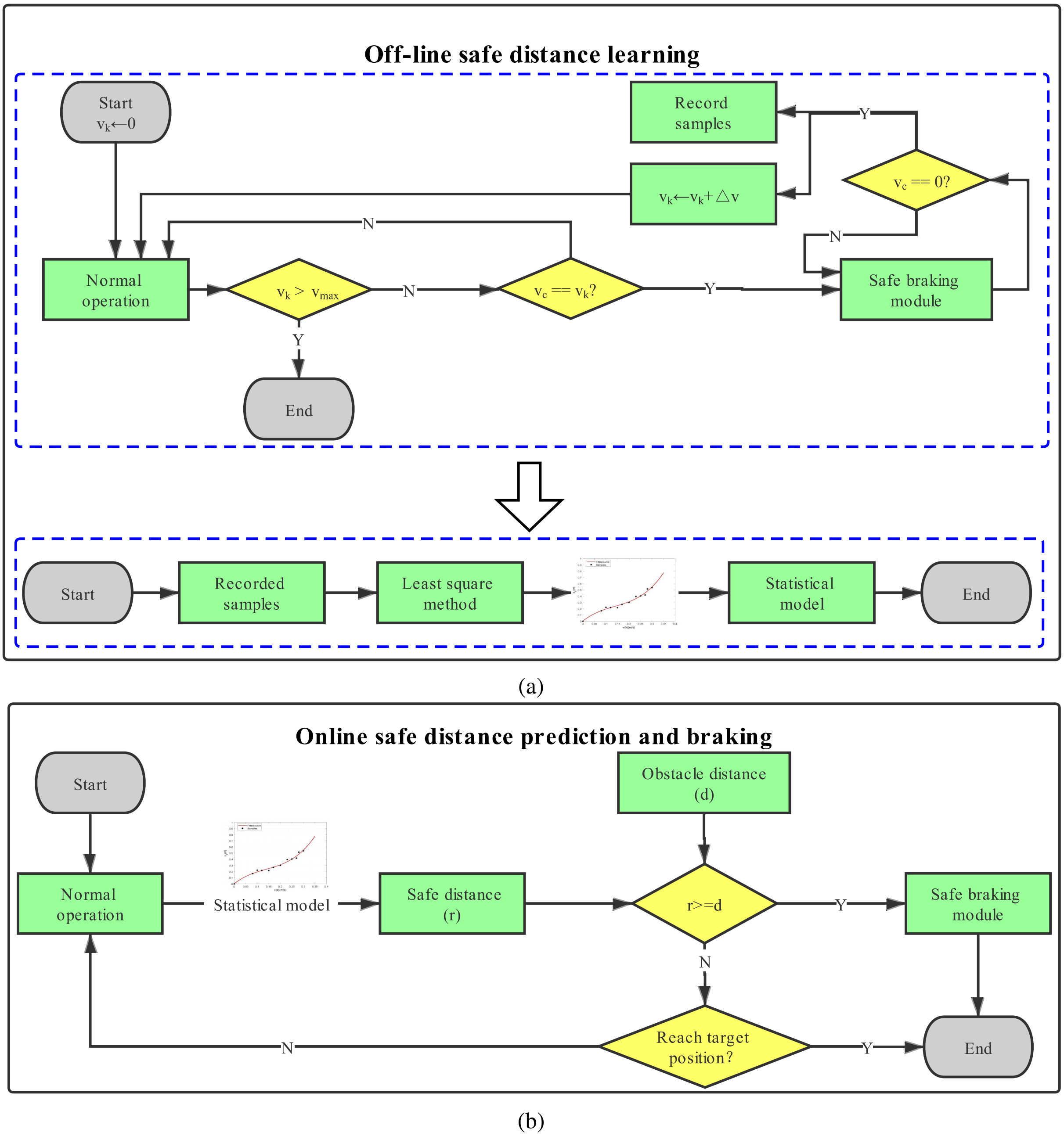


FIGURE 3 The flow chart of model prediction control (MPC) method for safe distance learning (a) and braking with anti-swing (b). For off-line safe distance learning, we try to find different braking distances with different initial velocities using the proposed MPC anti-swing control algorithm, where υ_c represents the current velocity, υ_k is a predefined velocity sample and υ_{max} is the maximum limitation of the crane. In each iteration, the crane starts from zero velocity and accelerates (normal operation) until the current speed υ_c is equal to υ_k. Then, the safe braking module starts to work until the crane stops. The braking distance is then recorded with respect to different υ_k, which is updated with a step size of $\Delta\upsilon$. After these samples are recorded, the least square method is used to find the statistical model between the initial velocities and safe braking distances. For online safe distance prediction and braking, we compare the safe braking distance and the distance to the obstacle to decide whether the crane is safe to continues or not.

Considering the upper and lower limits of the input force and swing angle constraints, the boundary inequalities of the control input are introduced as

$$minimize\ J(U) \tag{16}$$

subject to

$$-u_{max} \le u_{k_i} \le u_{max} \tag{17}$$

$$-Ma_{max} - mg\theta \le u_{k_i} \le Ma_{max} - mg\theta \tag{18}$$

where $a_{max} = \frac{\sqrt{lg}}{T}\left(\theta_{max} - \sqrt{\theta^2(0) + \frac{l}{g}\dot{\theta}^2(0)}\right)$ is the maximum acceleration[19], θ_{max} denotes the maximum swing angle, and $\theta(0)$ and $\dot{\theta}(0)$ are the initial values of $\theta(t)$ and $\dot{\theta}(t)$ respectively. For each control period, the initial values are equal to the final values of the previous control period.

The Lagrangian function for the optimization problem of (16) , (17) and (18) is defined as

$$\begin{aligned} L(U,\mu) = J(U) + \mu^1(U - U_{max}) + \mu^2(-U_{max} - U) \\ +\mu^3(U - A_{max}) + \mu^4(A_{min} - U) \end{aligned} \tag{19}$$

where μ^1 and μ^2 are the Lagrange multipliers of constraints (17), μ^3 and μ^4 are the Lagrange multipliers of constraints (18), $U = [\ u_{k_i}\ \overbrace{0\ \cdots\ 0}^{N_p-1}\ ]$, $U_{max} = [\ u_{max}\ \overbrace{0\ \cdots\ 0}^{N_p-1}\ ]$, $A_{min} = [-Ma_{max} - mg\theta\ \overbrace{0\ \cdots\ 0}^{N_p-1}\ ]$, and $A_{max} = [Ma_{max} - mg\theta\ \overbrace{0\ \cdots\ 0}^{N_p-1}\ ]$. The corresponding Karush-Kuhn-Tucker conditions (KKT) are given by

$$\begin{aligned} &\nabla_U L(U^*,\mu^*) = 2(\Psi^T Q\Psi)U^* - 2\Psi^T(R_v - PX_m(k_i)) \\ &\qquad + \mu^{1,*} - \mu^{2,*} + \mu^{3,*} - \mu^{4,*} \\ &0 \le \mu^{1,*}, \mu^{2,*}, \mu^{3,*}, \mu^{4,*}, \\ &0 = \mu^{1,*}(U^* - U_{max}), \\ &0 = \mu^{2,*}(-U_{max} - U^*), \\ &0 = \mu^{3,*}(U^* - A_{max}), \\ &0 = \mu^{4,*}(A_{min} - U^*). \end{aligned} \tag{20}$$

We can calculate the optimal solution by the Lagrange multiplier method to ensure $\theta \le \theta_{max}$, which is the input driving force of each control period. With this driving force, the crane can run according to the trajectory of reference to realize the anti-swing crane braking.

4 | METHOD FOR SAFE DISTANCE PREDICTION

In this section, we propose to use an off-line data learning method to build the model between relative velocity and safe braking distance with a constrained swing angle. This model can help calculate the safe distance online according to the current relative velocity of the crane.

4.1 | Off-line learning

According to equations (19) and (20), a safe braking distance can be derived based on the initial velocity of the crane. Therefore, if multiple initial velocities are given, we can obtain a group of safe braking distances. Furthermore, a statistical model $f(v)$ can be estimated using this pairwise dataset, which is the safe braking distance estimation function. By using this statistical model, we can estimate the safe braking distance in real time according to the current velocity of the crane. Thus, we construct an analytical function of $f(v)$ for safe braking distance estimation employing a least square polynomial curve fitting method.

4.2 | Online calculation of safe braking distance

For online safe braking distance estimation, we use the analytical function $x_d(v_i) = f(v_i)$ derived from the offline learning mechanism from the previous section. We assume that the payload of the crane has velocity v_i, length L, width w and height h. An expansion coefficient K is employed to expand the size of the load, such that the minimum safe braking distance in front of the crane can be derived as

$$S(v_i) = (w \times (1 + K) + x_d(v_i) + l sin\theta) \times h \times (1 + K). \tag{21}$$

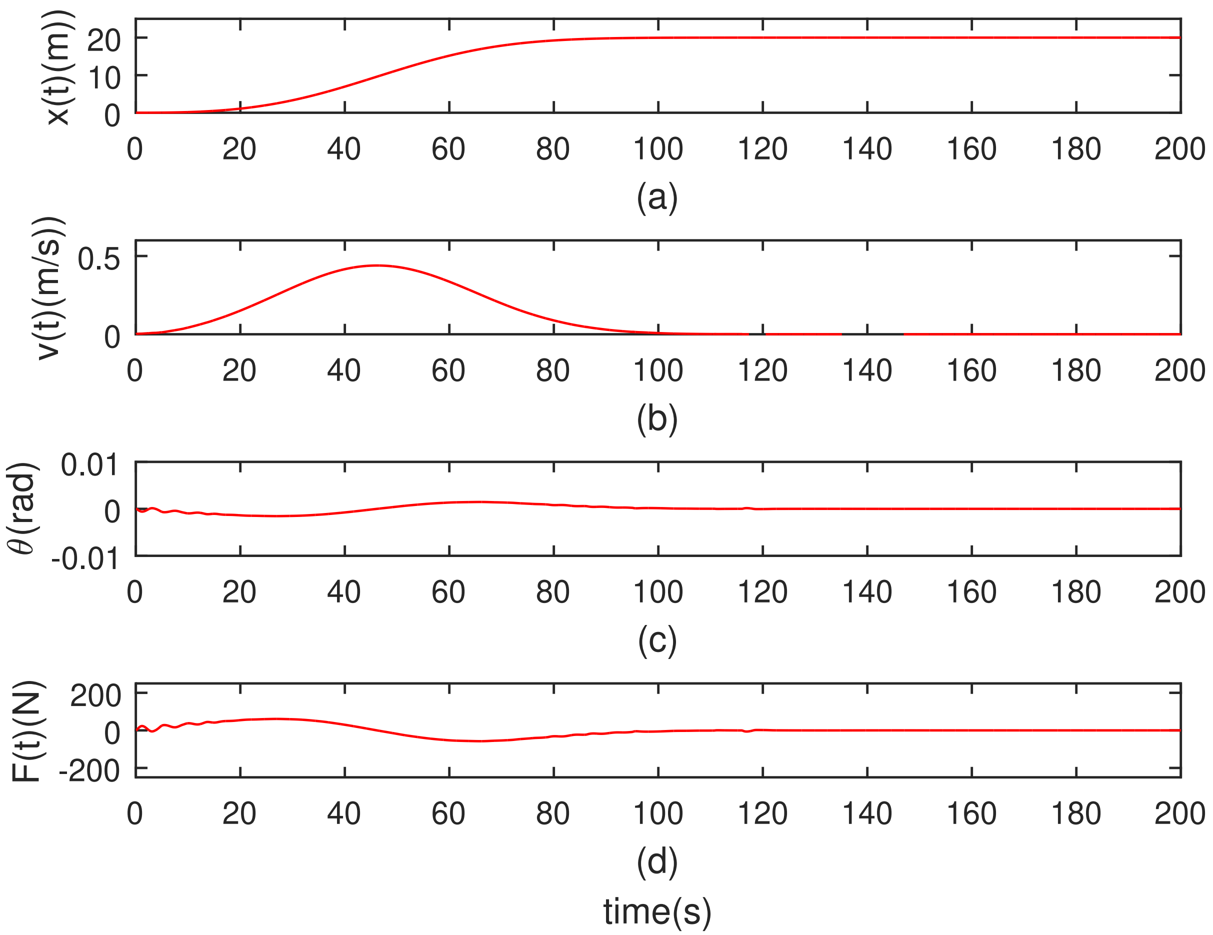


FIGURE 4 The simulation result of crane with the target position at $x = 20m$ controlled by a standard MPC algorithm with a zero initial state: (a) position, (b) velocity, (c) swing angle and (d) drive force. The swing angle is constrained at $\theta_{max} \leq 0.02\ rad$.

If dynamic obstacles enter this area, collisions can happen and hence negatively impact the safety level. Therefore, the crane has to predict such dangerous situations and make decision of emergency stops to ensure safe operations, calculated using the relative velocity and the distance to the obstacle.

5 | EXPERIMENT RESULTS

In this work, we demonstrate the proposed idea using both a simulated environment and a real-world crane. The MPC-based anti-swing control is first discussed, and then the offline learning and online prediction of safe braking distance are presented using a simulated crane in the Matlab development environment. Finally, a real crane is built and used for demonstrating the proposed methods.

5.1 | Simulation

5.1.1 | MPC for anti-swing with a zero initial velocity

We here discuss how the MPC-based anti-swing control can be used for a crane with a zero initial velocity to reach the target position. The crane parameters used in the simulation are $m = 5kg,\ M = 20kg,\ l = 1.6m,\ g = 9.8m/s^2$ and $T = 0.05s$. As

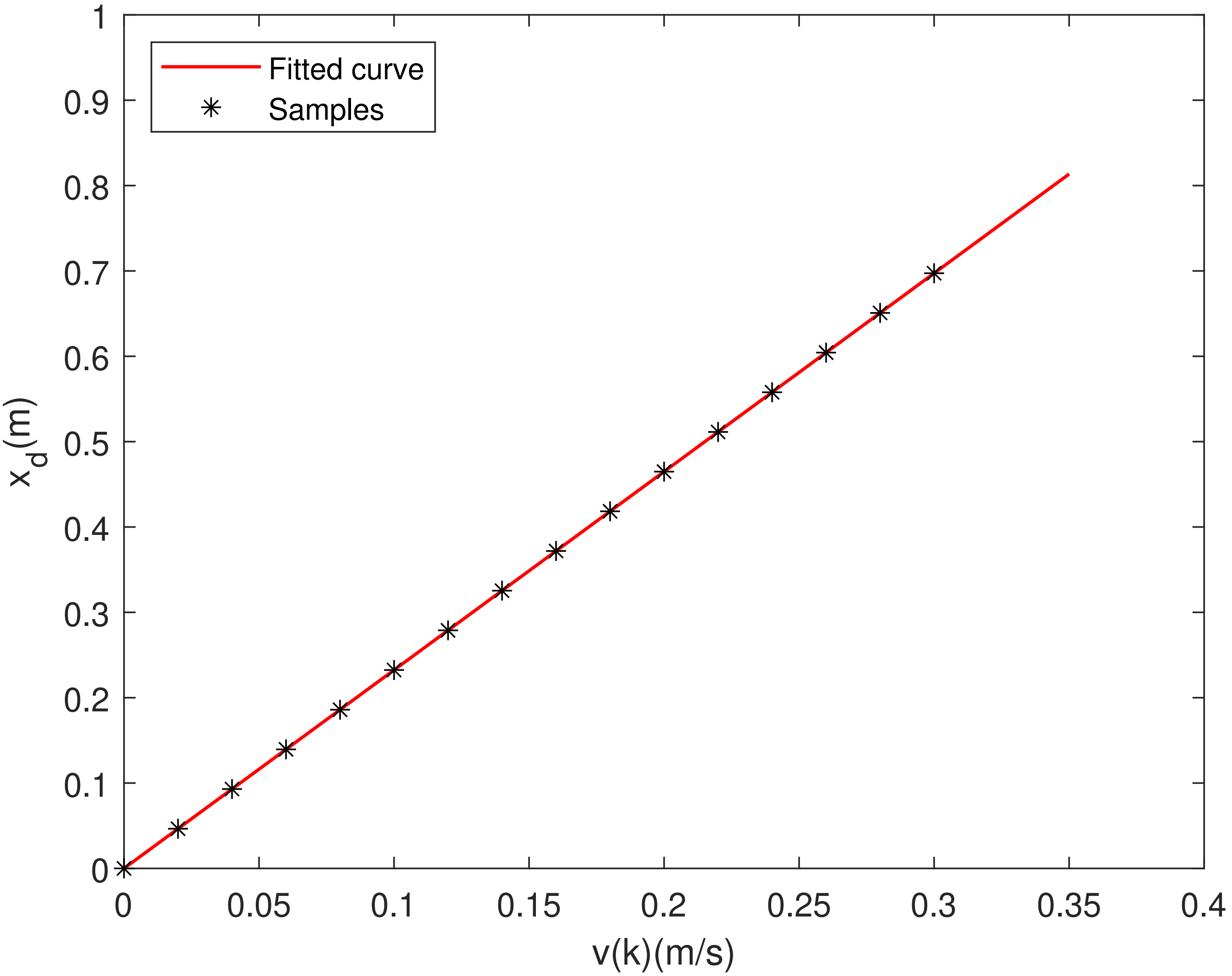


FIGURE 5 The statistical relationship fitted between the safe braking distance x_d and the relative velocity v between the crane and an obstacle. The relative velocity ranges from 0 m/s to 0.3 m/s. The mass of the payload is $m = 5$kg and the length of the rope is $l = 1.6$m. The fitted red curve is estimated using the least square method.

shown in [12], a reference trajectory can be generated by

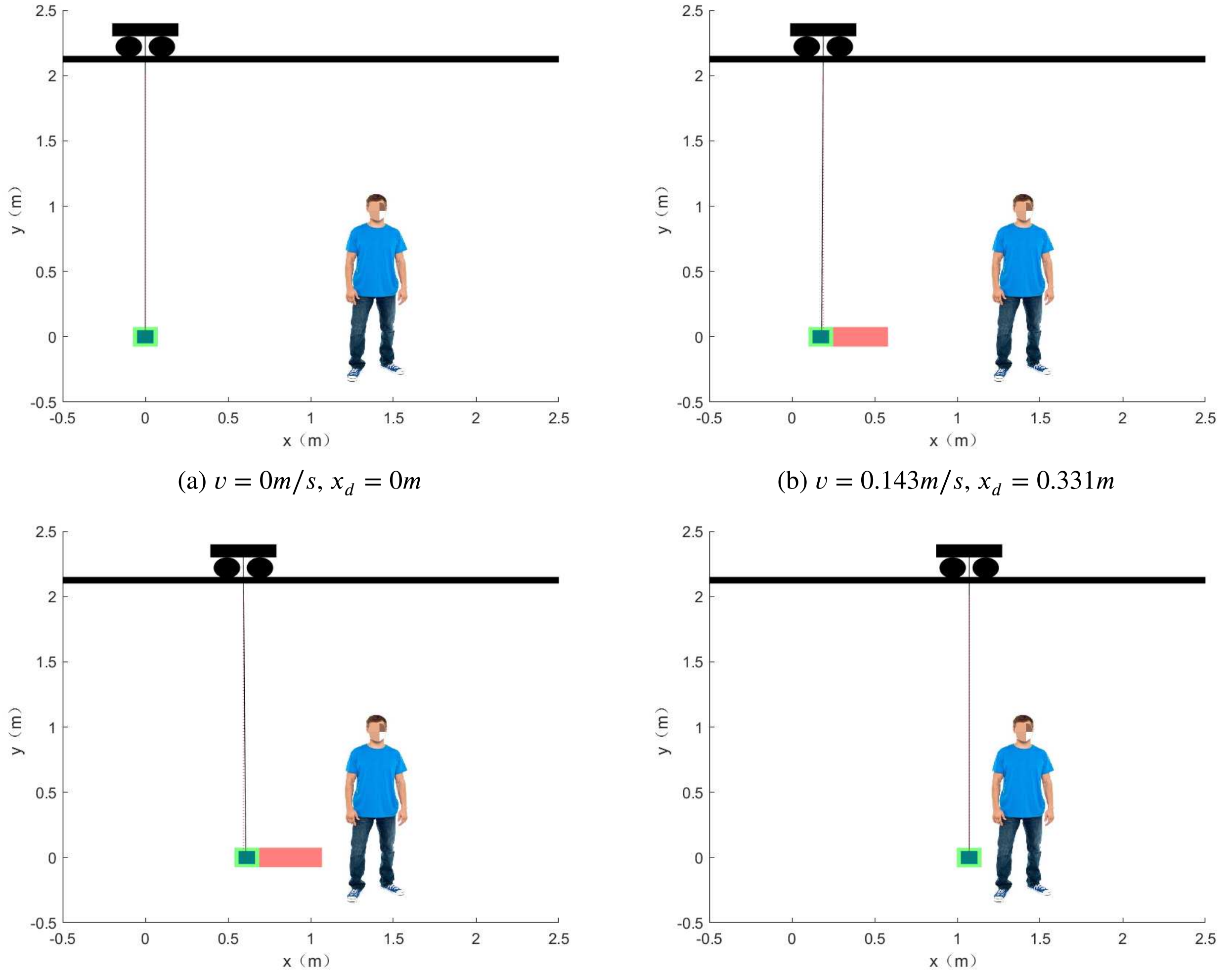
$$r(k) = cy(k-1) + (1-c)y_f \tag{22}$$

$$c = c_0 exp(-\beta(kT)^2) \tag{23}$$

where $r(k)$ represents the reference trajectory of $y(k)$ at time k, and y_f is the final target state. $c \in [0, 1]$ denotes the soften factor at the k_{th} step and c_0 is the initial soften factor value. β stands for the exponential convergence time factor and T is control period. The crane is controlled to follow this reference trajectory by the optimal driving force while the swing angle is constrained within the desired range. Fig.4 is the simulated results of controlling a crane to reach the target position $y_d = 1.8m$. It can be seen that the maximum swing angle is controlled to be constrained within 0.02 rad. The maximum driving force does not exceed 10N, which means that the control scheme meets the input saturation conditions.

5.1.2 | Off-line learning for safe braking distance estimation

The statistical relationship between the safe braking distance and the relative velocity is estimated by a curving fitting method in an off-line manner. We calculate the optimal safe braking distance for each relative velocity by using the MPC-based braking



(a) $v = 0m/s$, $x_d = 0m$

(b) $v = 0.143m/s$, $x_d = 0.331m$

(c) $v = 0.163m/s$, $x_d = 0.380m$

(d) $v = 0m/s$, $x_d = 0m$

FIGURE 6 This figure shows our online safe braking distance prediction for a heavy load. A human stands at $x = 1.2m$ ahead of the crane as an obstacle. The blue part is the area of the payload, the green part is the expansion area of the load, and the shallow red part is the safe braking range. When the distance to the obstacle is less than the safe braking distance, the crane takes the braking decision and starts to decrease its velocity until stop using the MPC-based anti-swing braking control method with the non-zero initial velocity, such that the swing angle during the braking process is constrained.

control method with non-zero initial velocities as described in Section 4. A total number of 16 different relative velocity samples with corresponding safe braking distances are collected as shown in Fig.5 , where the least square-based curve fitting method is used to find a function expression as $x_d = 0.0005x^3 - 0.0002x^2 + 2.3243x$.

5.1.3 | Online safe distance prediction and collision avoidance

In this section, a collision scenario is simulated where an obstacle is located $1.2m$ ahead of the crane with a heavy load $m = 5kg$ as shown in Fig.6 . During the whole process of crane movement, the safe braking distance will increase correspondingly as the relative velocity between the crane and the obstacle increases. while the swing angle is still within a small range as expected, attributed to the MPC method employed for anti-swing behaviours with non-zero initial velocities. For the heavy load, its dimension is defined by the width $w = 0.1m$ and height $h = 0.1m$ with an expansion coefficient $K = 0.8$. The length of the rope is $1.6m$. The crane continuously calculates its safe braking distance using the estimated function $x_d = 0.0005x^3$-$0.0002x^2$+$2.3243x$. For example, here it finds a possible collision at time $t = 4.55s$ with the corresponding velocity of $0.204m/s$.

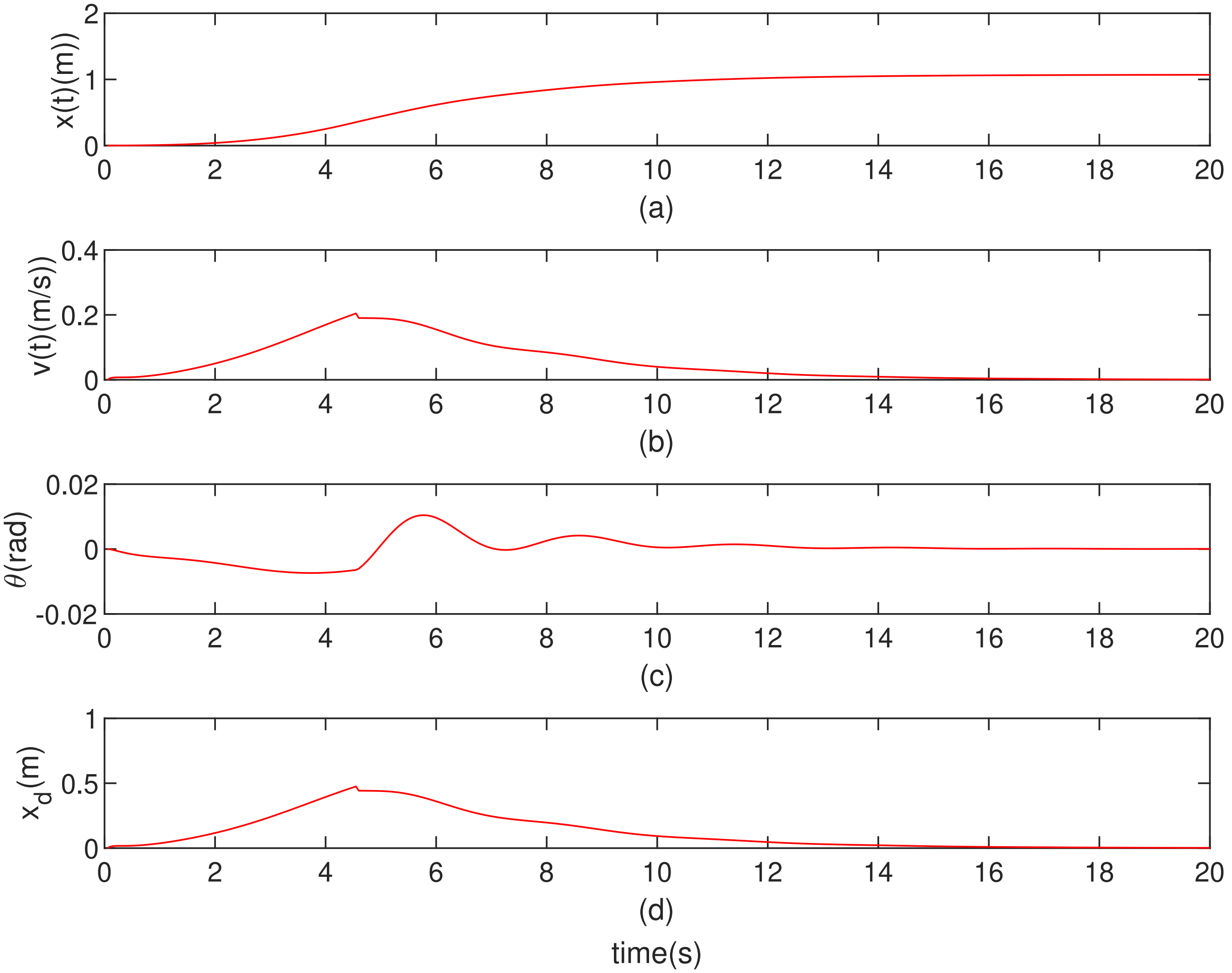


FIGURE 7 The figure shows the position (a), velocity (b), swing angle (c) and the safe braking distance (d) of the heavy load crane when the obstacle closes to the payload. The obstacle is at 1.2m ahead of the crane. The crane achieves the maximum velocity 0.204m/s before taking the brake decision and stops at 1.062m after braking, while the maximum swing angle is less than 0.02rad using the proposed safe braking method.

Then our MPC-based braking control will accordingly decrease the velocity until the crane stops at 1.062m, while the maximum swing angle of payload is less than 0.02rad as shown in Fig.7 .

5.2 | Real Crane

In order to prove the validity of the proposed method, we built an experimental crane platform, as shown in Fig.8 . The height of the crane platform is 2.2m, the width is 2m and the length is 3m. The trolley is driven by three servomotors and connected to the payload by a rope that passes through an angle sensor for measuring its swing angles. The sensor consists of two semi-rings with a rotating encoder placed vertically. An 8-axis motion control card is used to collect motor data and send control instructions. A 2D laser radar is used for obstacle detection. The proposed algorithm is implemented using the C++ programming language and runs on a general computer.

We first build the statistical learning model between the initial velocity and the safe braking distance as shown in Fig. 9 and Table 1 . 12 samples are recorded in our work. The least square method is used to find the nonlinear statistical function as $x_d = 21.68x^3$-$4.87x^2$+$1.06x$.

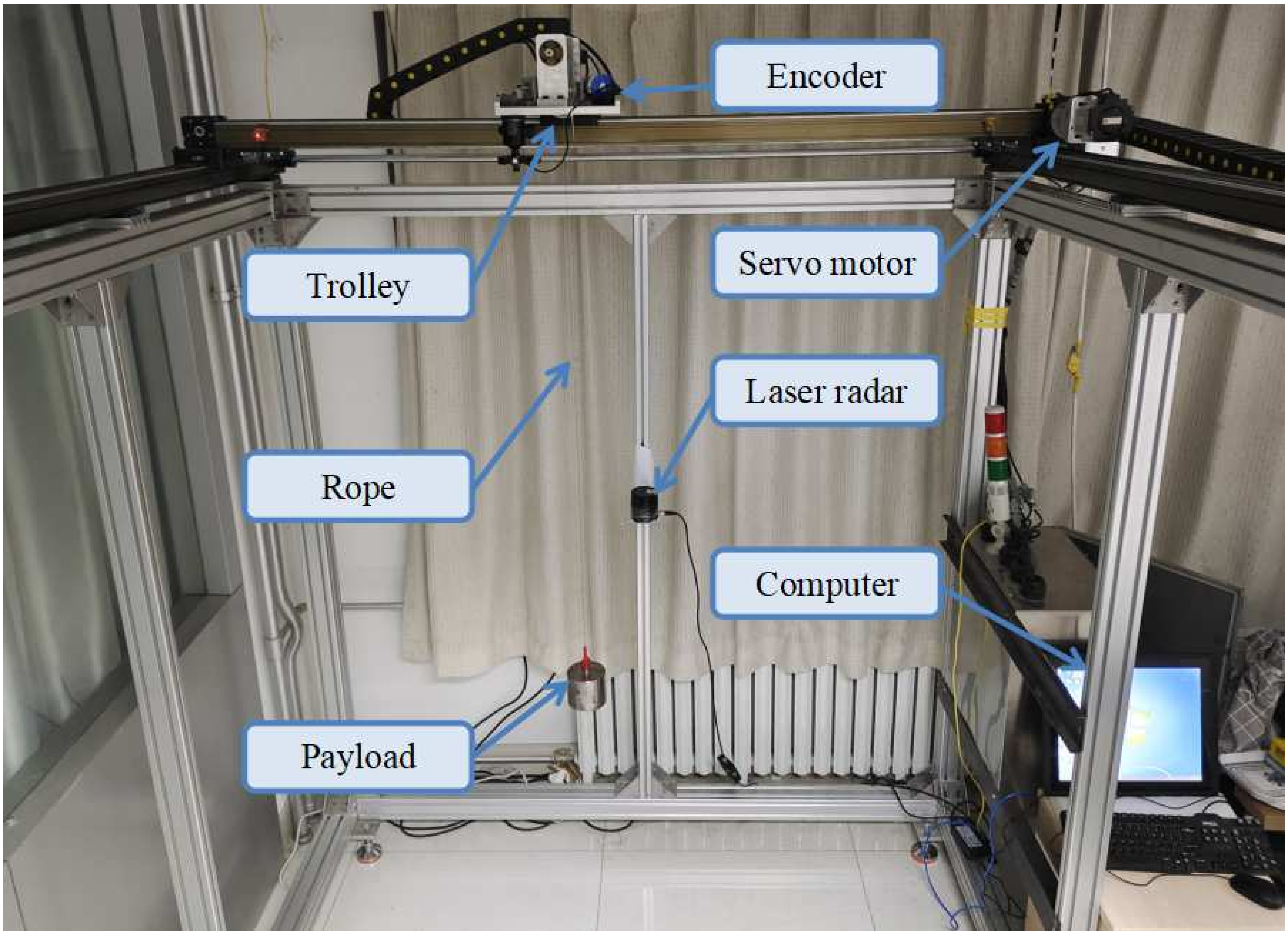


FIGURE 8 Main mechanical structure of the real crane. A 2D laser is used for obstacle detection.

TABLE 1 Samples of initial velocity and corresponding braking distance

Sample	Initial velocity (m/s)	Braking distance (m)
1	0	0
2	0.08	0.051142
3	0.10	0.057208
4	0.12	0.102379
5	0.15	0.119768
6	0.17	0.157508
7	0.20	0.226850
8	0.23	0.253211
9	0.25	0.244853
10	0.27	0.361999
11	0.28	0.416513
12	0.30	0.487209

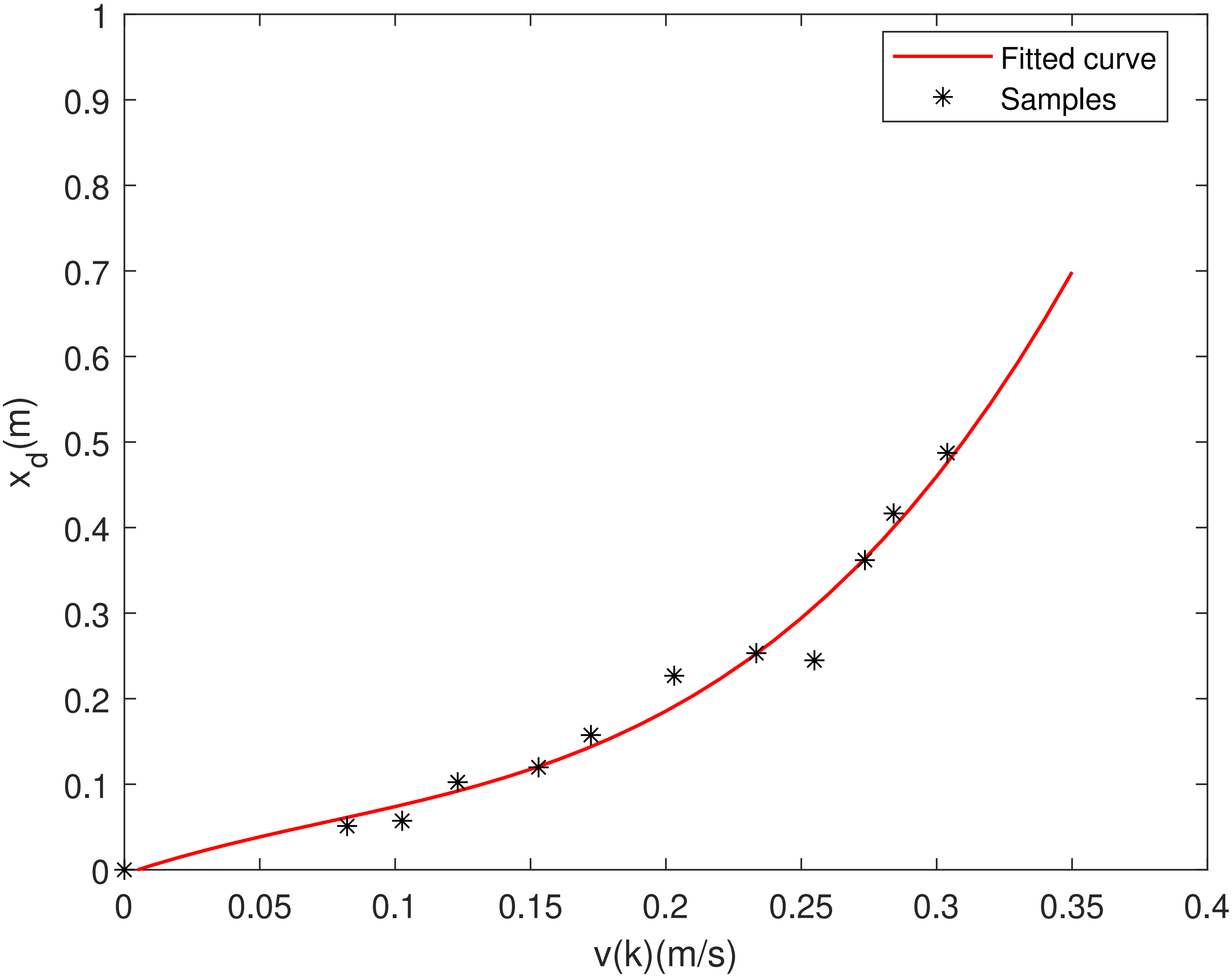


FIGURE 9 Off-line statistical learning of the relationship between the safe braking distance x_d and its initial velocity v with mass $m = 5kg$ and rope length $l = 1.6m$. Here we calculated 12 velocity samples from $0m/s$ to $0.3m/s$ represented by the black asterisks. The fitted curve function is estimated using the least square method depicted by the red curve.

To show the performance of the proposed safe braking mechanism, we use two control schemes: MPC and uniform acceleration (UA). First, the crane is controlled to reach the target position using the MPC or UA with a zero initial velocity. Then, an obstacle is placed in front of the crane, and the controller will calculate the difference between the distance to the obstacle and the safe braking distance. As the obstacle distance is getting close to the safe braking distance, the crane will start to change its control strategy, i.e, the proposed MPC-based braking method with non-zero initial velocities will be used. The experiment results show that the proposed safe braking method can be successfully used in both control schemes, as shown in Fig.10 and Fig.11 .

The crane parameters used in the experiment are $m = 5kg$, $M = 20kg$, $l = 1.6m$ and $T = 0.05s$. The target position is $1.8m$ and the obstacle position is $1.2m$ away from the start position of the crane. Fig. 10 shows the safe braking experiment with the MPC based control scheme. The braking action is taken at $4.185s$, and the crane takes about $4.06s$ to stop at the final position $1.094m$, which is safe. In addition, the maximum swing angle is constrained within $0.02rad$ in the whole process and $0.003rad$ in the braking process. For simplicity, the maximum swing angle in the braking process is abbreviated as MSAB in the rest of this article. Fig.11 shows the safe braking experiment with a UA control scheme with a constant acceleration of $0.2m/s^2$. The braking action is taken at $2.145s$, and the crane takes $6.43s$ to stop at the final position $(1.079m)$, which is safe. The maximum swing angle reaches $0.03rad$ in the whole process and $0.003rad$ in the braking process (MSAB).

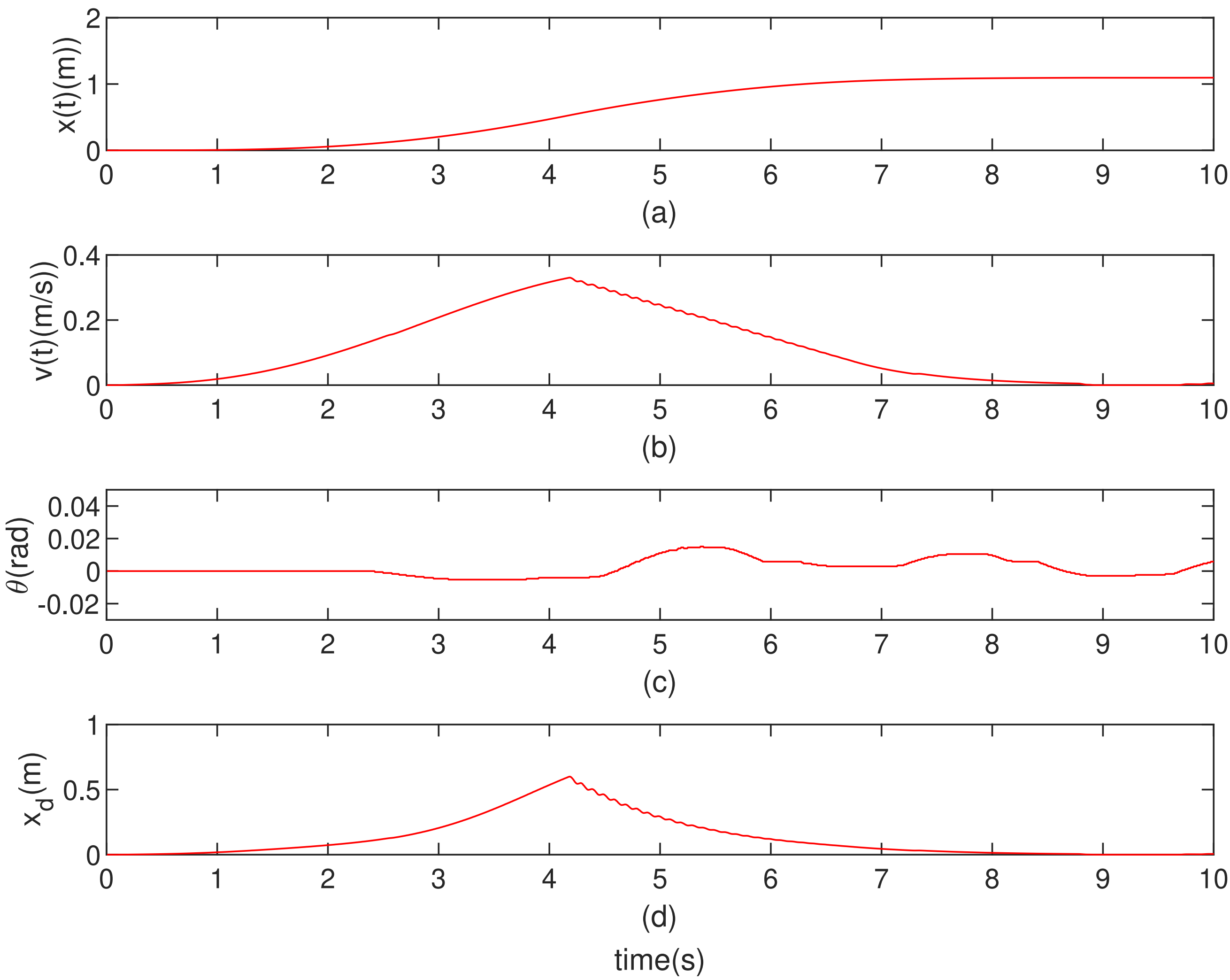


FIGURE 10 The crane starts its normal operation with the MPC algorithm (zero initial velocity). The proposed safe braking algorithm starts to work when the obstacle distance is less than the safe braking distance, and takes the safe braking decision at $t = 4.185s$. The final stop time is $8.795s$ and the stop position is $1.094m$. The swing angle is constrained within $0.02rad$ for the MPC control and within 0.003 rad for the safe braking process.

We can conclude that the MPC has an optimal solution for controlling the swing angle of the crane compared to the UA, i.e., $0.02rad$ vs. $0.03rad$. However, the proposed safe braking algorithm can work in both cases. From the experimental results, the crane successfully stops in front of the obstacle, and the swing angles are constrained within $0.02rad$.

In addition, through the MATLAB simulation experiment shown in Fig.7 and the real crane experiment shown in Fig. 10 , we can find that the angle changes for the simulation environment are smoother than in the real-world tests. This is reasonable as there are many other factors, such as complex resistance and motor characteristics, that the simulation environment has not considered thoroughly. Despite these, the conclusion of our work performs consistently well as expected that this proposed method can effectively guarantee safe braking for the crane.

6 | CONCLUSION

A crane is an equipment with a rope connected with payloads, which can unavoidably cause swinging during acceleration, e.g. start up or deceleration, e.g. braking. In this paper, we proposed a safe braking distance prediction method for evaluating

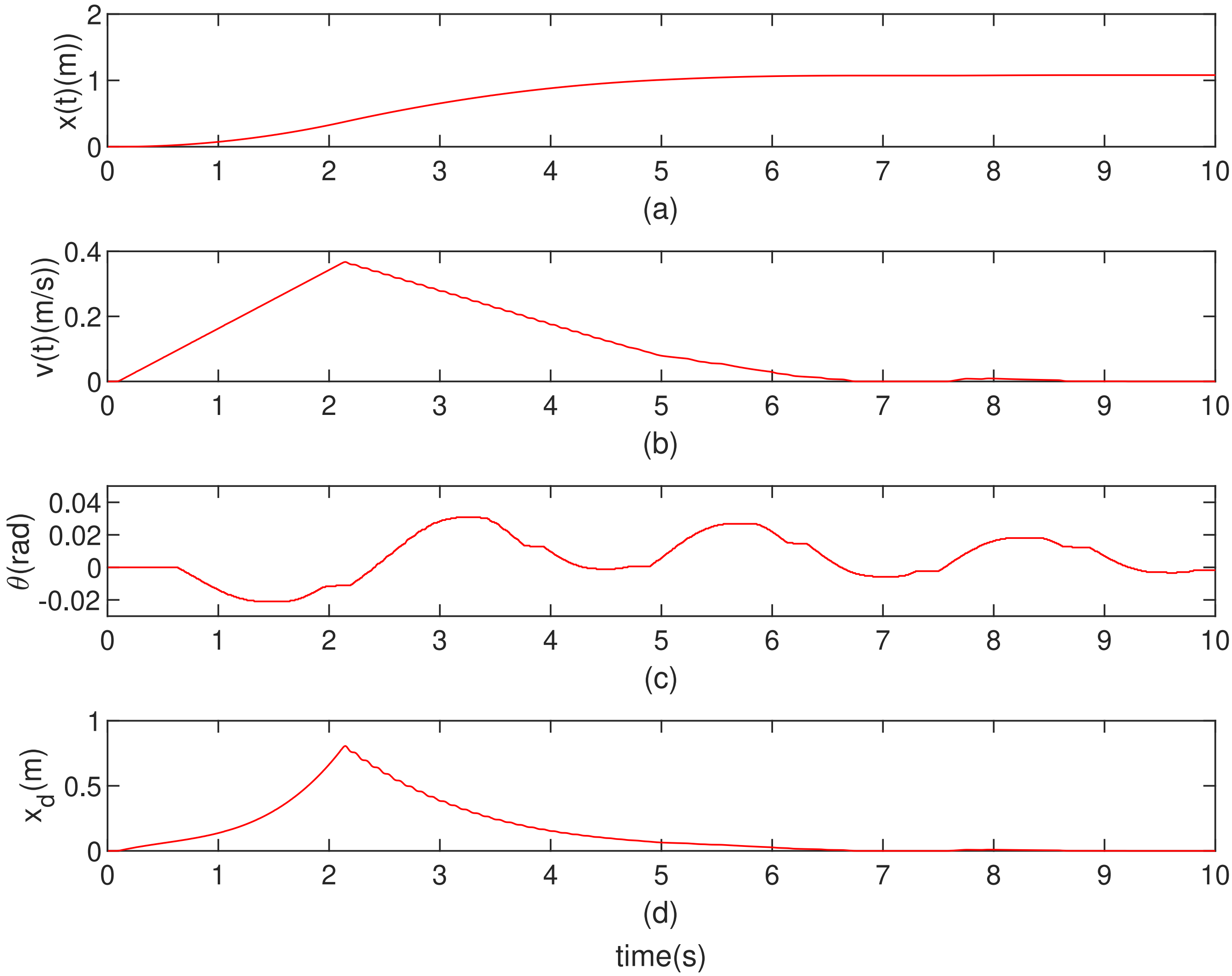


FIGURE 11 The crane starts its normal operation with the uniform acceleration (UA) of $0.2m/s^2$. The proposed safe braking algorithm starts to work when an obstacle is found in front of the crane. The start time of the braking is $2.145s$, the final stop time is $8.575s$ and the final stop position is $1.079m$. The maximum swing angle of the crane reached $0.031rad$ in the uniform acceleration period, but the maximum swing angle does not exceed $0.003rad$ for the safe braking process.

TABLE 2 Safe braking for different control schemes

Control schemes	Braking distance (m)	Braking time (s)	MSAB (rad)
MPC	0.5639	4.61	0.003
UA	0.7017	6.43	0.003

the dangerous level according to the relative distance and velocity between the crane and the obstacles, e.g., vehicles, human, and robots. To the best knowledge of the authors, this is the first time that the braking distance can be estimated according to the dynamic physical state of the crane, which can increase the safety of cranes in human-crane-coexistence environments. In this work, we here introduce an improved MPC control method to solve the anti-swing problem with non-zero initial states. Furthermore, the experiments using a simulated crane and a real crane show that the proposed safe braking distance prediction method can be combined with different control schemes, e.g., MPC or uniform acceleration. The results presented in this paper show that potential collisions can be effectively avoided, and the safety of dynamic workers and devices can be enhanced by predicting the safe braking distances. It is clear that the crane performance is greatly enhanced with this intelligent and predictive capability using our method since it can predict how long it requires to stop safely without any swinging. In future, a path planner will be used for obstacle avoidance, such that the crane can continue to work instead of a full stop, and the predicted braking distance can be used as a critical point for safety warning and obstacle avoidance.

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