Design of Human Works Model for Gantry Crane System

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ABSTRACT

In this paper, we propose a human model for analysis for human work pattern or human fault, where a gantry crane simulator is used to survey the property of human operation. From the input and output of gantry crane response, we make a human operation model by using conventional ARX identification method. For identify the human model, we assume the eight inputs and two outputs. By using the input/output data, we estimate the parameters of ARX of the human system model. For verify the proposed method, we compared the real data with the modeled data, where three kinds of work trajectory path are used.

1. Introduction

The accidents such as at Chernobyl and Bhopal have demonstrated unequivocally the importance of considering human error in higher risk systems. For any existing plant, or new one being designed, it is importance to try to assess the likelihood of such accidents and prevent them from occurring. This requires the assessment of the impact of human errors on system safety and, if warranted, the specification of ways to reduce human error impact and/or frequency. For generic approach for assessment of human error, there are three goals, namely: the human error identification is first step to reduce human error in higher risk systems. The second step can provide quantification of error which might be needed to construct a safety case. The final step will develop error data-bases to reduce human error.

Interest in modeling the behavior of a human as an active feedback control device began during Word War II, when engineers and psychologists attempted to improve the performance of pilots, gunners, and bombardiers. To design satisfactory manually controlled systems these researchers began analyzing the neuro-muscular characteristics of the human operator . For instances, we can find a solution to this problem as in (Malek 1988, Shinners 1947, Martens 1999, Yehia 1995, Charles 1980 and Kim 2003). Their approach was to consider the human as an inanimate servomechanism with a well-defined input and output.

Over the years, the evolution of the control-theory paradigm for the human controller or operator paralleled the development of new synthesis techniques in feedback control. Thus, "optimal control models" (OCMs) of the human operator appeared as linear quadratic Gaussian (LQG) control system design techniques were being developed. "Fuzzy controller" models and "H infinity" models of the human operator closely followed the appearance of these design techniques (Bryson 1975, Franklin 1998, Levine 1996, Zhou 1998, Antsaklis 1998, Skogestad 1996).

Recently, Malek and Marmarelis (1988) have been proposed to describe quantitatively the human operator (HO) dynamics in manual tracking tasks. These models have been derived through the application of classical and modern control theory or time-series analysis. Structural isomorphic models were the result of applying classical control theory. These models seek to account for many of subsystem characteristics of the human operator by assigning transfer functions to the different subsystems involved. These subsystems and their interconnections are postulated on the basis of physiologically isomorphic considerations.

Especially, the application of the time-series analysis to this problem was first introduced by Shinners (Shinners 1947 and Malek 1988) who developed autoregressive moving-average (ARMA) models of data collected from human operators involved in compensatory tracking experiments using bandlimited white noise inputs (bandwidth=1.5Hz). His results showed that all operators exhibited a time delay 0.2s and the discrete transfer functions that represent their dynamics had one zero and two poles. Based on the analysis of model residuals, he concluded that the human operator is a generator of seasonal (rhythmic) characteristics during tracking of random inputs.

For instances, Charles 1980 and Malek 1988 developed a transfer function model from input-output data collected from a HO during both compensatory and pursuit manual tracking experiments. In their experiment, two unpredictable inputs, formed by the addition of five sinusoids, were used. The first had a low-frequency range (0.04-0.8 Hz) and the second had a high-frequency range (0.08-1.48 Hz). For the low frequency range, they were able to fit a transfer function with two poles and no zeros, while a transfer function with two poles and one zero adequately fitted the high-frequency range input-output data. Analysis of model residuals showed no sign of rhythmic characteristics that were observed earlier by Shinners.

Generally, an importance step in the modeling of HO dynamics using the time-series approach is to identify the model order (i.e., the number of poles and zeros in the model). Several model order determination criteria, commonly used in systems identification were critically evaluated in their ability to estimate the order of a simulated autoregressive model (AR) with parameters obtained from input-output data of an HO during a compensatory tracking experiment (Efe 1999, Glass 1988, Ljung 1999, Sinha 1983).

In our model, HO acts as a position feedback control system, where the system obtains an estimate of target position and position error through both visual and proprioceptive feed back loop.

In the present approach, the time-series analysis, specifically ARX modeling, our approach is applied to input-output data of human operator involved in transport of container. Our aim is to provide a simple model capable of quantifying variations in the HO dynamical behavior in transport of container following paths given, this is a kind of manual tracking tasks. The input data of human operator are reference path, and the state of gantry crane(the position of trolley, the sway angle, and the length of cable; and also the first order and the second order of differentiating of these states). The output data of human operator are two angles in horizontal and vertical handles in the joystick which proportionate with the forces on trolley and cable, in respect.

In this paper, we propose a human model for analysis for human work pattern or human fault, where a gantry crane simulator is used to survey the property of human operation. From the input and output of gantry crane response, we make a human operation model by using conventional ARX identification method. For identify the human model, we assume the eight inputs and two outputs. By using the input/output data, we estimate the parameters of ARX of the human system model. For verify the proposed method, we compared the real data with the modeled data, where three kinds of work trajectory path are used.

2. System Models

2.1 Gantry Crane System Model

The gantry crane system is divided into two systems: trolley system and hoist system. These two systems can move the container in horizontal axis and vertical axis by adjusting the trolley motor torques and hoist motor torques, respectively. The standard gantry crane system is modeled as in Fig. 1.

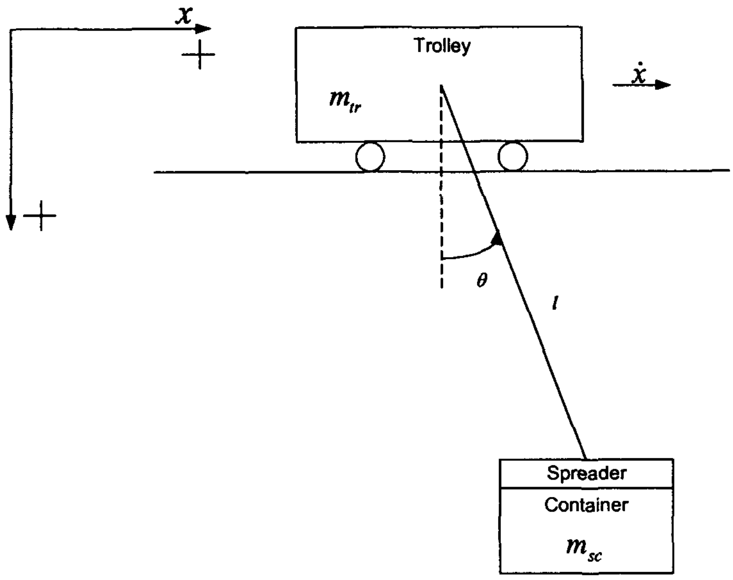

Fig. 1 Gantry Crane Dynamics

where m_{tr} and m_{sc} denote the trolley mass and spreader mass with container respectively, and x, l, and θ denote the trolley position, cable length, and sway angle, respectively.

Let us define the gantry crane state variable as (x, l, θ). By using Lagrangian equation, the gantry crane equations are obtained as

$$\ddot{x} = \frac{m_{sc}}{2m_{tr}}\dot{x}\sin(2\theta)\left(\dot{\theta}-1\right)+\frac{F_{hox}-c_x\dot{x}-(F_{hol}-c_l\dot{l}-m_{sc}g\cos(\theta))\sin(\theta)+\frac{c_\theta\dot{\theta}}{l}\cos(\theta)}{m_{tr}} \tag{1a}$$

$$\ddot{l} = -\ddot{x}\sin(\theta)+l\dot{\theta}^2+g\cos(\theta)+\frac{(F_{hol}-c_l\dot{l}-m_{sc}g\cos(\theta))}{m_{sc}} \tag{1b}$$

$$\ddot{\theta} = \frac{-\ddot{x}\cos(\theta)-2\dot{l}\dot{\theta}-\dot{x}\dot{\theta}\sin(\theta)+\dot{x}\sin(\theta)-g\sin(\theta)}{l}+\frac{-c_\theta\dot{\theta}}{m_{sc}l^2} \tag{1c}$$

Define the joystick angular values for trolley and hoist operation as $\alpha_x(t)$ and $\alpha_l(t)$ respectively, then the forces of trolley and hoist can be transformed as

$$\begin{bmatrix} F_{hox}(t) \\ F_{hol}(t) \end{bmatrix} = \begin{bmatrix} p_x & 0 \\ 0 & p_l \end{bmatrix}\begin{bmatrix} \alpha_x(t) \\ \alpha_l(t) \end{bmatrix} \tag{2}$$

where $F_{hox}(t)$ and $F_{hol}(t)$ denote the trolley force and hoist force, respectively.

2.2 Human Works Model

For getting the human work model, first we have to construct the human operation model for gantry crane system. Fig. 2 shows the basic human work model which represents the container transportation from the initial position to the reference position, where the container should be avoid the given obstacles.

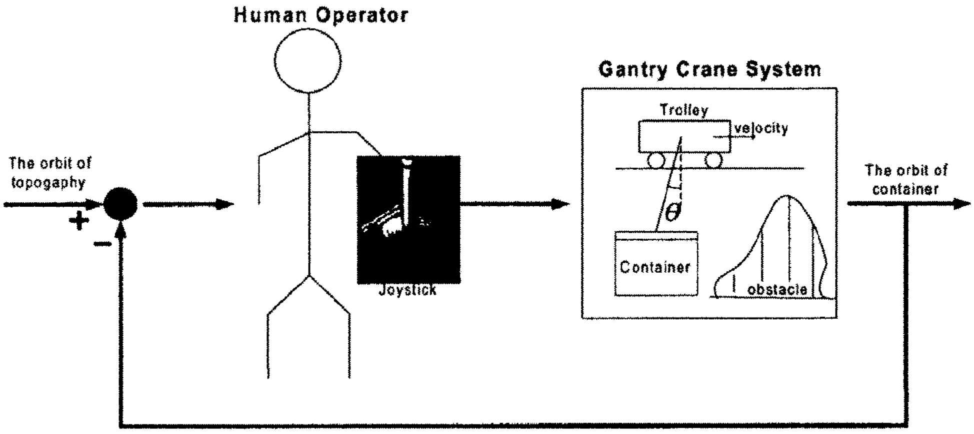

Fig. 2 Representation of human operation for gantry crane system

In Fig. 2, the human operator operate the joysticks to control the trolley position and hoist cable length by through the motor inverters, in respectively. In this case, the operator watch the container movement and its sway angle(also, the operator know the actual and desired position of trolley and container at each time), that is visual signals. The operator indicate error between desired and actual position of container, and the operator decide to control joystick in the way compensating the error. The signals from joystick, horizontal direction and vertical direction, are proportional rate of change of the forces on trolley and cable, in respectively.

2.3 Human Identification Model

By using the gantry crane operation, we have to achieve the human operation data such as joystick angular, gantry crane operations such as trolley position, container position, sway angle, cable length etc., and desired container transportation trajectory, respectively. For this, we can make a block diagram for human works model as in Fig. 3.

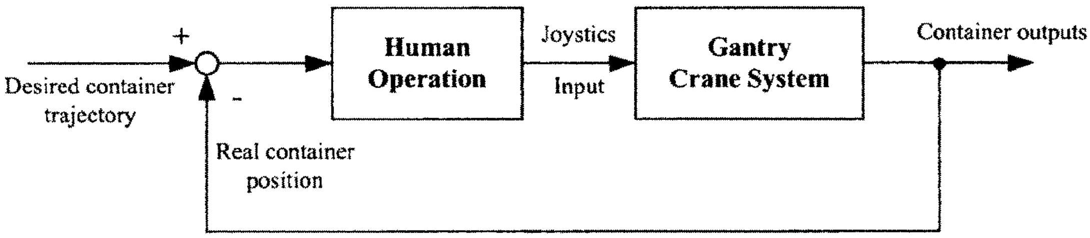

Fig. 3 A block diagram for human work model

For identify the human work model for gantry crane system, we have to divide the input and output factors from the above data. In here, we assume the desired container trajectory will be given by using optimal control method or other procedures. For human operation, the input term is given as desired container trajectory, real container position, trolley position, sway angle, and container cable length. And the joystick angles for trolley and hoist control are given as in input terms. From these input and output term, the above Fig. 3 can be represented as in Fig. 4.

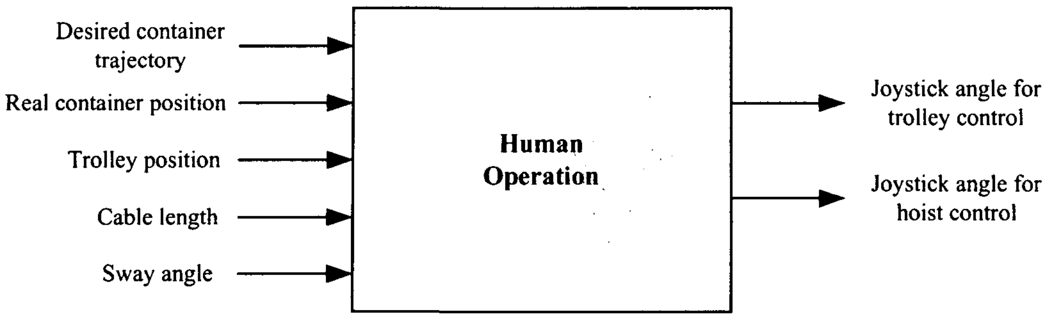

Fig. 4 A block diagram for human operation with input/output terms

By using the achieved input and output data for human modeling as in Fig. 4, the human operation model can be given by using ARX identification method. The brief identification method will be given the following procedures.

The standard ARX model is described by using linear difference equation in multivariable case as

$$y(t)+A_1y(t-1)+\ldots+A_ny(t-n)=B_0u(t)+B_1u(t-1)+\ldots+B_mu(t-m)+e(t) \tag{3}$$

where the input $u(t)$ is an k-dimensional vector and the output $y(t)$ is a p-dimensional vector. The term $e(t)$ denotes a white noise entered into system as an external disturbance. The A_i and B_i are $p\times p$ and $p\times k$ matrices, respectively.

Let us define a polynomial as

$$A(q)=I+A_1q^{-1}+\ldots+A_nq^{-n} \tag{4}$$

$$B(q)=B_0+B_1q^{-1}+\ldots+B_mq^{-m} \tag{5}$$

where q^{-1} denotes delay operator.

By using the above polynomial, Eq. (3) can be rewritten as

$$y(t)=A^{-1}(q)B(q)u(t)+A^{-1}(q)e(t) \tag{6}$$

Define the parameter vector as

$$\Theta=[A_1 \quad A_2 \quad \cdots \quad A_n \quad B_0 \quad \cdots \quad B_m]^T \tag{7}$$

where Θ is a matrix with $[p\times n+k\times(m+1)]\times p$

Then, Eq. (6) can be transformed as a matrix form easily:

$$y^T(t)=\Phi^T(t)\Theta+e^T(t) \tag{8}$$

where,

$$\Phi(t)=\begin{bmatrix}-y(t-1)\\ M\\ -y(t-n)\\ u(t)\\ M\\ u(t-m))\end{bmatrix}$$

To make the error model more compactly, let us introduce another matrix as:

$$Y(N)=[y(n+1)\quad \Lambda \quad y(N)]^T \tag{9}$$

$$\Psi(N)=\begin{bmatrix}\Phi^T(n+1)\\ M\\ \Phi^T(N)\end{bmatrix}=[\Phi(n+1)\quad \Lambda \quad \Phi(N)]^T \tag{10}$$

$$E(N,\Theta)=[e(n+1)\quad \Lambda \quad e(N)]^T \tag{11}$$

$$Y(N)=\Psi(N)\Theta+E(N,\Theta) \tag{12}$$

The ordinary least-squares estimator $\hat{\Theta}$ of the parameter vector is given by [B7]

$$\hat{\Theta}_{LS}=(\Psi^T\Psi)^{-1}\Psi^T Y \tag{13}$$

In the human operation systems, we have six signal inputs and two signal outputs. The signal inputs are the reference position of container in the given path, the controlled position of container, the trolley position, the cable length, and the sway angle. And defines these values as $u_1(t)$, $u_2(t)$, $u_3(t)$, $u_4(t)$, $u_5(t)$, $u_6(t)$ respectively. The output signals are given as the horizontal angle and vertical angle of the joysticks which control the trolley and the hoist for gantry crane systems. And define as $\alpha_1(t)$ and $\alpha_2(t)$ respectively.

From these input and output signal, we define input vector $u(t)$ and output vectors $\alpha(t)$ as

$$u(t)=\begin{bmatrix}u_1(t)\\ u_2(t)\\ u_3(t)\\ u_4(t)\\ u_5(t)\\ u_6(t)\end{bmatrix}, \text{ and } \alpha(t)=\begin{bmatrix}\alpha_1(t)\\ \alpha_2(t)\end{bmatrix} \tag{14}$$

To define ARX model for modeling the human operation, we assume the operating of human in the low frequency area and propose a model as:

$$\alpha(t)+A\alpha(t-1)+B\alpha(t-2)=Cu(t)+Du(t-1)+Eu(t-2)+e(t) \tag{15}$$

where A and B are 2×2 dimensional matrices, and C , D and E are 2×6 dimensional matrices. Thus, we have $2\times 2\times 2+2\times 6\times 3=44$ parameters need to be estimated. For simplicity, we assume that all of these parameters are time-invariant.

From Eq. (7) we define the parameter vector as:

$$\Theta = \begin{bmatrix} A & B & C & D & E \end{bmatrix}^T \tag{16}$$

$$\Phi(t) = \begin{bmatrix} -\alpha(t-1) \\ -\alpha(t-2) \\ u(t) \\ u(t-1) \\ u(t-2)) \end{bmatrix} \tag{17}$$

$$\alpha^T(t) = \Phi^T(t)\Theta + e^T(t) \tag{18}$$

From the measured data by using gantry crane simulator, we constructs a set of input and output data as:

$$\left\{ \begin{bmatrix} u_1(1) \\ u_2(1) \\ u_3(1) \\ u_4(1) \\ u_5(1) \\ u_6(1) \end{bmatrix}, \begin{bmatrix} u_1(2) \\ u_2(2) \\ u_3(2) \\ u_4(2) \\ u_5(2) \\ u_6(2) \end{bmatrix}, \ldots, \begin{bmatrix} u_1(N) \\ u_2(N) \\ u_3(N) \\ u_4(N) \\ u_5(N) \\ u_6(N) \end{bmatrix} \right\} \tag{19}$$

$$\left\{ \begin{bmatrix} \alpha_1(1) \\ \alpha_2(1) \end{bmatrix}, \begin{bmatrix} \alpha_1(2) \\ \alpha_2(2) \end{bmatrix} \ldots \begin{bmatrix} \alpha_1(N) \\ \alpha_2(N) \end{bmatrix} \right\} \tag{20}$$

with related matrices :

$$Y(N) = \begin{bmatrix} \alpha_1(3) & \alpha_2(3) \\ & \vdots \\ \alpha_1(N) & \alpha_2(N) \end{bmatrix} = [\alpha(3) \;\; \cdots \;\; \alpha(N)]^T \tag{21}$$

$$\Psi(N) = \begin{bmatrix} -\alpha^T(2) & -\alpha^T(1) & u^T(3) & u^T(2) & u^T(1) \\ & & \vdots & & \\ -\alpha^T(N-1) & -\alpha^T(N-2) & u^T(N) & u^T(N-1) & u^T(N-2) \end{bmatrix}$$

$$= \begin{bmatrix} \Phi^T(3) \\ \vdots \\ \Phi^T(N) \end{bmatrix} = [\Phi(3) \;\; \cdots \;\; \Phi(N)]^T \tag{22}$$

$$E(N,\Theta) = [e(3) \;\; \cdots \;\; e(N)]^T \tag{23}$$

$$Y(N) = \Psi(N)\Theta + E(N,\Theta) \tag{24}$$

The ordinary least-squares estimator $\hat{\Theta}$ of the parameter vector is given by (Franklin1988)

$$\hat{\Theta}_{LS} = (\Psi^T\Psi)^{-1}\Psi^T Y \tag{25}$$

To verify the fitness of the estimated model, the general expressions for the expected model fit, that are independent of the model structure. We have measured the fit between the model and the true system as:

$$fit = 100\left(1 - \frac{\|y - \hat{y}\|}{\|y - \bar{y}\|}\right)_{measured-data:y,estimated-data:\hat{y}} \tag{26}$$

3. Experiments and Results

3.1 Experiments Conditions

In experiments by using gantry crane simulator, three kinds of trajectory path are assumed: rectangular path, circle path and ellipse path. In rectangular path, the operator pull the container up to the vertical axis by control the hoist motor, and move it to the reference position on horizontal axis by control the trolley motor, then drop it to the vertical axis by hoist on given final position. In this path, the container can be moved by control the hoist and trolley individually. In circle path and ellipse path, the container is moved by control the hoist and trolley at the same time. These operation trajectory paths are shown in Fig. 5

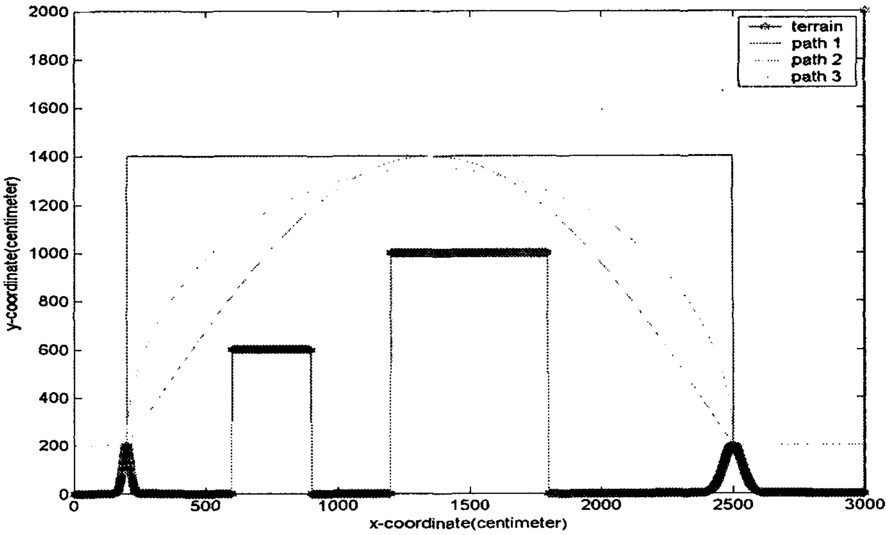

Fig. 5 Human operation task and its trajectory paths

For gantry crane simulator, we assume that trolley mass $m_{tr} = 1000[kg]$, spreader mass with container $m_{sc} = 1000[kg]$. And the damping coefficients of trolley, hoist and cable sway are given as $c_x = 1000\left[\frac{N}{m/s}\right]$, $c_l = 10000\left[\frac{N}{m/s}\right]$ and $c_\theta = 0.2 m_{sc} l^2 \left[\frac{kg.m^2}{s}\right]$, respectively. Also the work space for cable length is limited on 4 – 18 [m], the height of gantry crane is given as 20[m], and the trolley moving bound is given as 30[m]. For calculation and simulation, the sampling time is given 80[ms].

3.2 Results of Human Model

In simulation, we make three work trajectory paths for one person and take a human operation data with 80ms sampling time. The obtained human operation results are shown in Fig. 6 – 8. These results show the response of identified human work model with rectangular trajectory path, circle trajectory path, and ellipse trajectory path respectively. In figures, the first sub figure shows the container horizontal and vertical positions: solid line shows container horizontal position and dotted line shows the container vertical position. Second sub figure shows the controlled trolley motor force, where the solid line shows the original human operation data and dotted line shows the modeled human model output signal with same control input, respectively. Third sub figure shows the controlled hoist motor force, where the solid line and dotted line are same those of second sub figure.

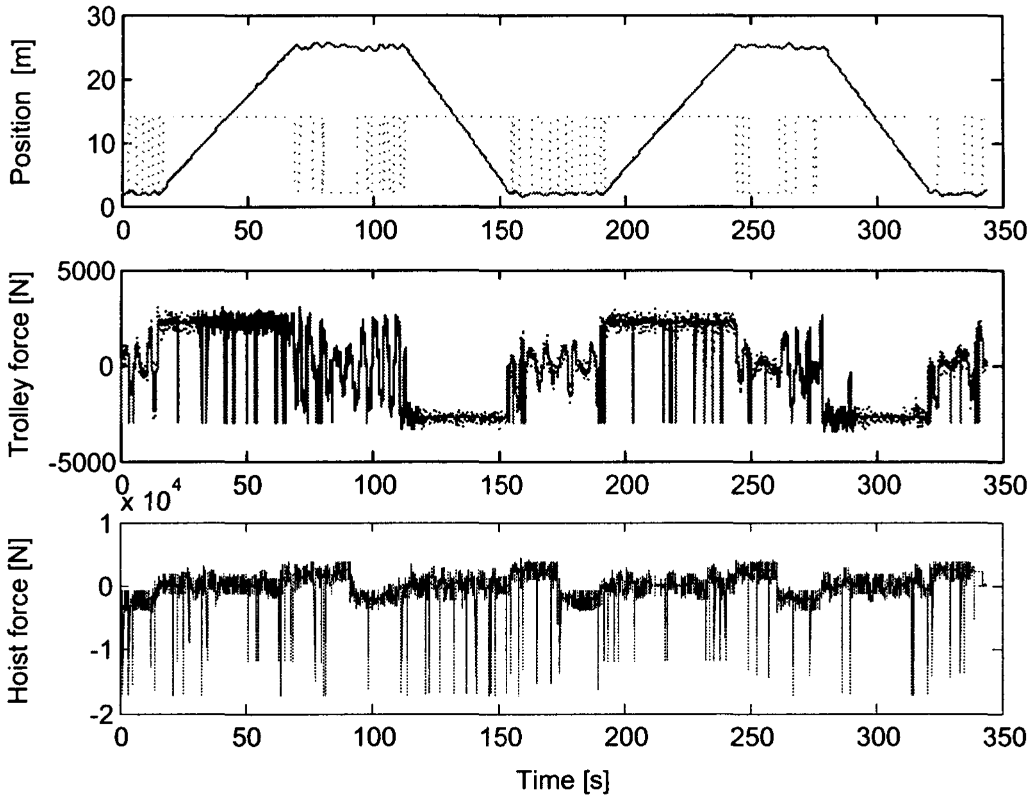

Fig. 6 Response of Human model for rectangular trajectory path

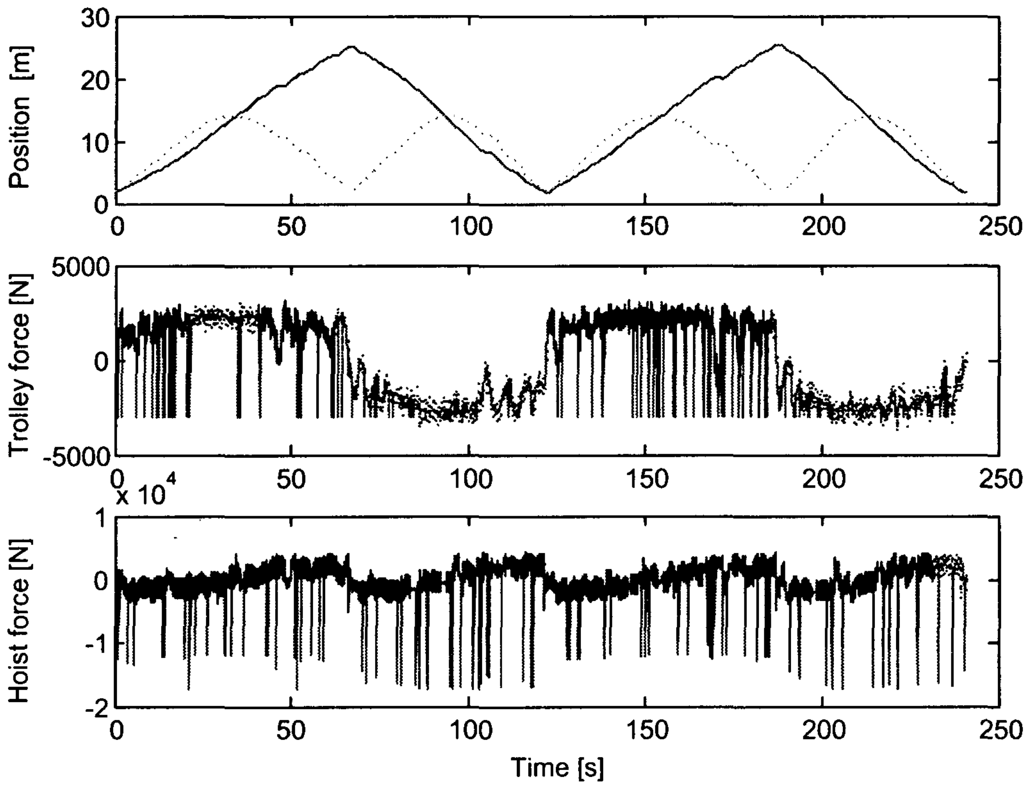

Fig. 7 Response of Human model for circle trajectory path

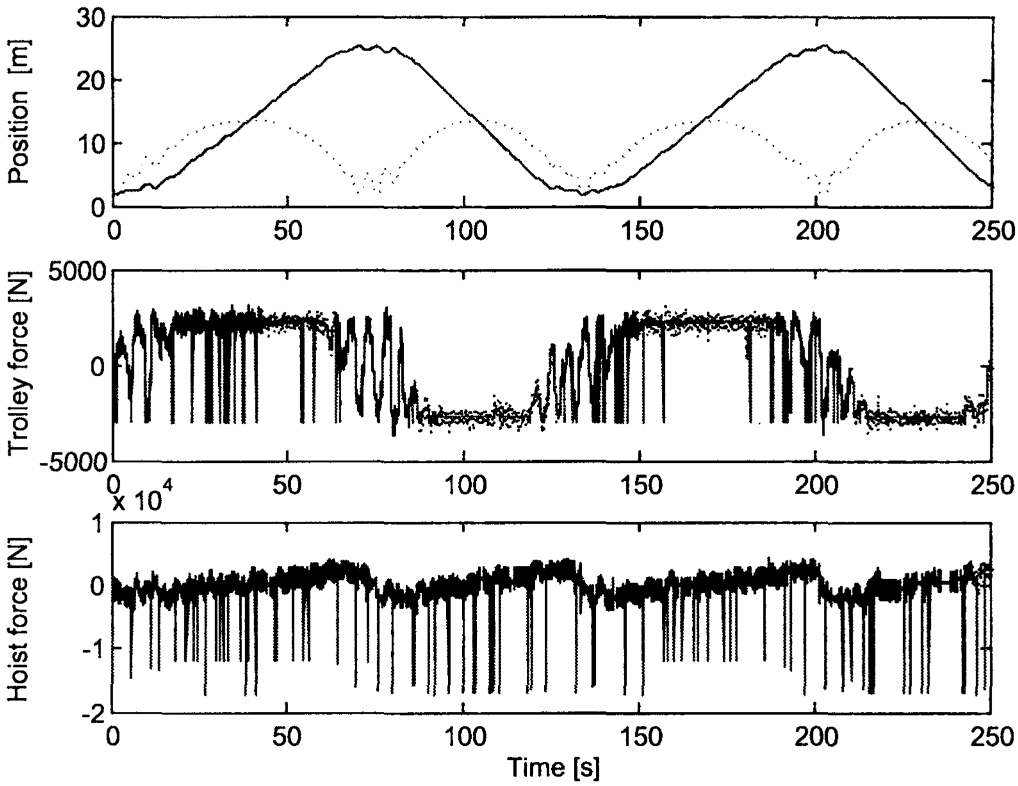

Fig. 8 Response of Human model for ellipse trajectory path

Table 1 Fitness of human work model by ARX identification method

	Case1		Case2	
	Trolley	**Hoist**	**Trolley**	**Hoist**
Rectangular path	**77.81%**	**46.69%**	**78.82%**	**45.04%**
Circle path	**72.91%**	**47.24%**	**77.81%**	**46.69%**
Ellipse path	**75.78%**	**47.74%**	**73.45%**	**43.70%**

Table 1 shows the fitness of the human work model with three trajectory paths. The average fitness of trolley control force and hoist control force are given as 76.10% and 46.18% respectively in given trajectory and other input data.

4. Conclusions

In this paper, we have proposed a human work model for gantry crane system by using the ARX identification method. For obtaining the human work model, we used a gantry crane simulator which controlled by crane operator using joystick with 2-D graphic motions. By using the obtained human work model, we have verified its efficiency with three work trajectory paths. Additionally, we needs to develop the gantry crane model which includes the non-linear dynamic term with 3D graphic motion and to design the human fault detection algorithm by using proposed human work model in future.

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