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Optimal Suppression Control of Load Swing with Disturbance for Rotary Crane System Using Neuro-controller

Kunihiko Nakazono†, Kosuke Tamanoi‡, Keijiro Ozaki‡, and Kouhei Ohnishi§

† Faculty of Engineering, University of the Ryukyus.
‡ Graduate School of Engineering and Science, University of the Ryukyus.
§ Faculty of Science and Techonology, Keio University
†,‡ 1 Senbaru, Nishihara, Okinawa JAPAN 903–0213
§ 3–14–1 Hiyoshi, Yokohama JAPAN 222–8522
{nakazono,tamanoi,ozaki}@mibai.tec.u-ryukyu.ac.jp, ohnishi@sd.keio.ac.jp

Abstract: In the paper, we propose a neuro-controller (NC) for suppression of load swing in a crane system rotating around the vertical axis. As in a nonholonomic system, the traditional control method using a static continuous state feedback law cannot stabilize the load swing. It is necessary to design a time-varying feedback controller or a discontinuous feedback controller. We propose a simple three-layered neural network as a controller in order to have control performance even if the load of the rotary crane system swings suddenly (disturbance). The NC is trained by a simple GA. The validity of the proposed NC is verified through computer simulation.

Keyword: neuro-controller, genetic algorithm, load swing suppression, disturbace

1 Introduction

A rotary crane system is used to move a load mass to a desired position through rotating, raising, and lowering the jib arm. These operations are accompanied by oscillation of the load, or load swing. Rotary crane systems are usually operated using both the rotation angle and the lean angle in order to suppress such a load swing. Operation of the rotary crane system rotating around the vertical axis results in a nonholonomic system for which the control problem is complex and necessary to design a time-varying feedback control method or a discontinuous feedback control method [1]. In this paper, we propose a neuro-controller (NC) [2] trained by a genetic algorithm (GA)[3, 4, 5, 6, 7]. It is easy to apply the NC which has simple layered structure and has generalized ability as a controller.

Many control methods for load swing suppression in a rotary crane system have been researched[8, 9, 10, 11, 12]. An example is a control method in which the control law follows the most suitable trajectory along which the load swing will be smallest[8]. The theory of the optimal regulator for linear systems fuzzy reasoning, and feedback law for nonlinear systems are examples of such control methods. These control methods can fundamentally stabilize the load swing in the circumferential direction, but cannot suppress the swing in the radial direction. Some vibration control methods for the crane system with only controllable rotation operation have been reported [10, 11, 12]. Anti-sway control method of the crane system based on a skillful operator's knowledge has been proposed[10]. Load swing suppression based on a linear feedback law by switching two modes in the radial and circumferential directions has been reported[11, 12]. However, all of these control methods require knowledge of difficult control theories. In contrast, a neuro-controller trained by an evolutionary computation technique, such as a genetic algorithm, is substantially simpler to realize than conventional control methods.

In general, the load of the rotary crane system has swung due to disturbance, that is, a gust of wind, a constant wind, and so on. In this paper, we propose the NC which has optimal control performance even if the load swings suddenly. And the performance of the resulting controller is compared with that of a controller without disturbance using computer simulations. The training algorithm of the neural network is a bit-string GA.

2 Model of rotary crane system

Figure 1 shows the crane system rotating around the z axis. x, y, z denote the coordinates of the load mass position, θ denotes the rotation angle. r is the radius of rotation, h is the height from the tip of the jib arm, m is the load mass, and ℓ is the wire length. The control purpose is to suppress load swing from the arbitrary position to the reference position by controlling the rotation motion.

If the swing of the load mass is sufficiently small, we have only to think about three-dimensional space

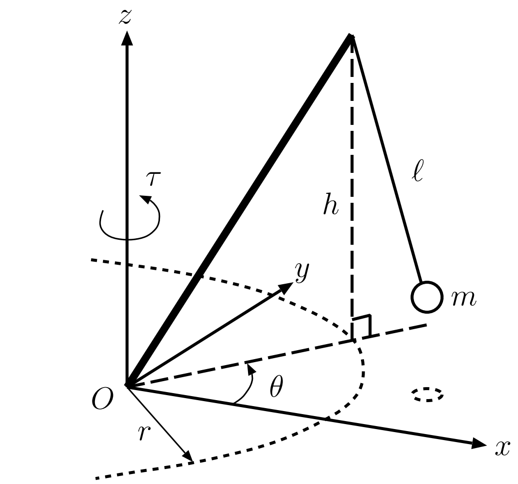


Fig. 1: Rotary crane system

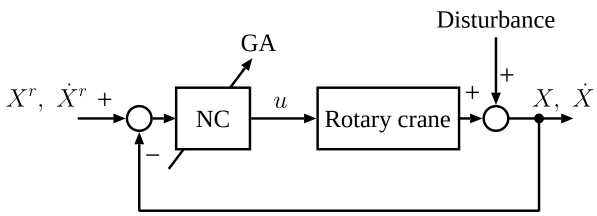


Fig. 2: Control system for rotary crane

but a two-dimensional plane. Using Lagrange equation for the constraint system, the dynamics of the rotary crane system can approximately be described in terms of the following equations:

$$\begin{cases} \ddot{x}(t) &= \omega^2(r\cos\theta(t) - x(t)) \\ \ddot{y}(t) &= \omega^2(r\sin\theta(t) - y(t)) \\ \ddot{\theta}(t) &= Ku \end{cases} \quad (1)$$

where $\omega = \sqrt{g/\ell}$ is natural frequency and K is constant value.

It is difficult for a designer to control the rotation angle of the rotary crane system by conventional methods because the dynamic model is a type of nonholonomic system. As in a nonholonomic system, the control method for the rotary crane system using a static continuous state feedback cannot stabilize the load swing. It is necessary to design a time-varying feedback controller or a discontinuous feedback controller. In this paper, the controller is instead designed using NC optimized by GA.

3 Control system for rotary crane

The control system using NC with GA is shown in Fig.2. In this figure, the state variable is $X = [x, y, \theta]$, and the reference is $X^r = [x^r, y^r, \theta^r]$, respectively. The training method uses a simple GA. The NC receives the position error, the velocity of the load mass, the rotation angle error, and the angular velocity as inputs. And it outputs the control input u. The NC is composed of three hierarchical layers, with 6–5–1 structure. A linear function is used at the input and output layers, and a sigmoid function in range $[-1, 1]$ is used for the hidden layer. The control purposes to suppress the load swing accompanying movement from an arbitrary initial position (x_0, y_0) to the reference position (x^r, y^r) by rotation control.

In general, the load of the rotary crane system has swung due to disturbance, that is, a gust of wind, a constant wind, and so on. In this paper, we propose the NC which has optimal control performance even if the load swings suddenly. The disturbance is as follows: When the control start, position (x, y) of the load suddenly move to position $(x+\Delta x, y+\Delta y)$ on the way. $\Delta x, \Delta y$ are determined by constant random numbers in range $[-\alpha, \alpha]$.

The NC is trained by the bit-string GA in an off-line process. The evolutionary algorithm for the NC is as follows:

STEP 1. Create initial NCs at random. The initial connection weights are set in the range $[-2.0, 2.0]$ and are transformed to the chromosome. The genetic code is transformed to the binary code (12 bit).

STEP 2. Calculate an error function E while demonstrating control simulation for all NCs.

STEP 3. Select the upper NCs by ranking selection in the individuals.

STEP 4. Perform a one-point crossover operation to produce new NCs.

STEP 5. Perform a mutation operation to produce additional new NCs.

STEP 6. Alternate the NCs including the new NCs to the next generation. Iterate from STEP 2 until the evolution process reaches generation 10000.

Table 1 shows further information regarding to the parameters of the GA.

During evolutionary process, an error function E is used to evaluate the performance of each NC. The error function E is defined as

$$E = (X^r - X)^T(X^r - X) + (\dot{X}^r - \dot{X})^T(\dot{X}^r - \dot{X}) \quad (2)$$

The error function is determined so as to settle the load swing at the desired position. In the GA evolution, the connection weights of the NC are modified in order to minimize the error function in Eq. (2).

Table 1: GA parameters

Parameter	Value/method
No. of initial NCs	40
No. of children	20
Selection	ranking selection
Crossover	one-point
Mutation	bit reverse
Mutation rate	0.1
Final generation	10000

Table 2: Parameters and initial conditions

Parameter/condition	Value
Load mass m [kg]	0.5
Rotation radius r [m]	1.0
Length of wire ℓ [m]	2.0
Acceleration of gravity g [m/s^2]	9.8
Initial rotation angle θ_0 [deg]	90
Reference position (x^r, y^r) [m]	(1, 0)
Constant value K	5.0
Control time [s]	10.0

4 Simulation results

The validity of the NC trained by GA is verified using computer simulations. Runge-Kutta method is used for the system dynamic model, and sampling time is 10 [ms]. The parameters of the rotary crane system and the initial conditions are listed in Table 2.

The aim of the evolution progressed by the GA is to obtain an NC that suppress the load swing of the rotary crane system upon movement from the initial position (x_0, y_0) to the reference position (x^r, y^r). When the initial rotation angle θ_0 is 90 [deg] and the initial position of the load is set $(x_0, y_0) = (\cos\theta_0, \sin\theta_0)$, the evolution process affording the best NC with GA-based training is shown in Fig. 3. The position (x, y) of the load suddenly move to position $(x + \Delta x, y + \Delta y)$ after the control time equals 1 [s]. When $\alpha = 0.03$, it means that the disturbance is set by constant random numbers in range $[-\alpha, \alpha] = [-0.03, 0.03]$. The training involved for 10000 iterations and the values of $\Delta x, \Delta y$ randomly change during each generation in evolutionary process.

The result demonstrates that the GA evolution process of NCs is successful. The error values of the GA initially decrease gradually, then decreases rapidly after 1000 generations until the evolution converges near generation 10000.

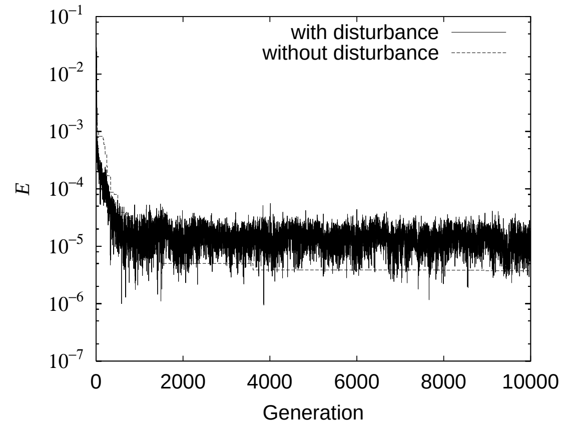


Fig. 3: Evolutionary process

Table 3: Rate of successful control (with disturbance)

Range	$\alpha = 0.03$	$\alpha = 0.04$	$\alpha = 0.05$
Rate[%]	100	93	71

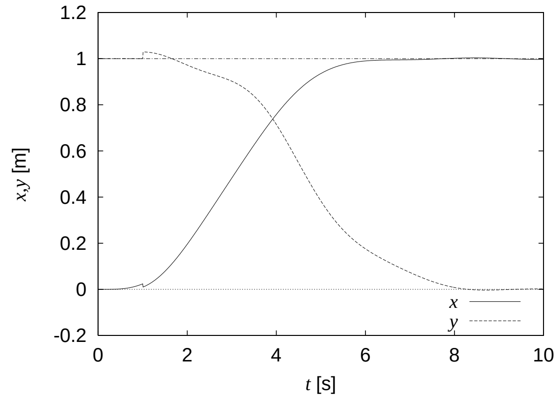
Table 3 shows the successful rate of control performance for the rotary crane system in 100 trials. The position $(x + \Delta x, y + \Delta y)$ of $t = 1$ [s] are randomly set in the ranges $[-\alpha, \alpha]$ at $\alpha = 0.03$. The criterion for success in control is when the squared errors less than 0.0001. It can be seen that the trained NC has good control performance and has generalized ability.

Figure 4 shows the control simulation results using the trained NC. Here, the disturbance is $(\Delta x, \Delta y)$ = $(0.0146, -0.0294)$. Control by the trained NC converges to the reference position on the x and y axes in approximately 8 [s]. The training is therefore effective for achieving good load swing suppression.

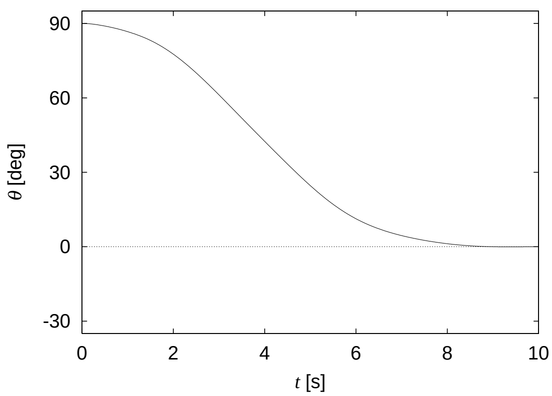
Figure 5 shows the trajectory of the load mass in the x–y plane using the trained NC. The load is transferred along the control trajectory with very little swing oscillation.

5 Conclusion

A simple GA was applied to optimeze a neuro-controller for load swing suppression in rotary crane systems involving only rotation about the vertical axis. Simulations confirmed that the bit-string GA training scheme is effective for generating a reliable



(a) Position



(b) Rotation angle

Fig. 4: Control results

NC with disturbance for the rotary crane system, with competitive performance to the trained NC without disturbance.

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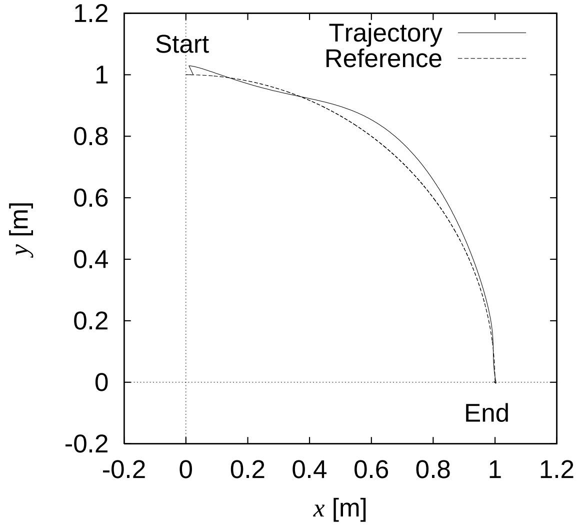

Fig. 5: Trajectory on x–y plane

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