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Identification of Nonlinear Time Lag Systems by Improved Genetic Algorithm and Its Application to Explosion-Proof Pneumatic Robots

Toshiyuki ASAKURA*　and　Qingzhi GUO*

In this paper, a new identification method is proposed which can obtain a good accuracy of identification of nonlinear time lag system on the basis of combination of genetic algorithm and sequence method.　The nonlinear system may be described as a discrete model of a polynomial type with unknown parameters using Kolmogorov-Gabor's method.　The task of system identification is to determine these parameters.　Though the system parameters can be obtained through the search of GA, there is a potential risk, in using a simple GA, that a solution is usually stuck at a local minimum.　In order to solve this problem, a new GA search method is proposed by adding a sequence search, which is carried out nearby the value of each estimated parameter coming from a simple GA.　By this method, the individual whose fitness is larger can be found.　As a result, the solution escapes from a local minimum and converges to the optimum one.　The effectiveness of the proposed method is demonstrated through simulation of the identification of nonlinear time lag systems. As an application, the proposed identification method is applied to explosion-proof pneumatic robots, which are modeled as nonlinear time lag systems because the controller links with an actuator by a long pneumatic tube to prevent explosion.

Key Words : Identification, Genetic Algorithm, Sequence Search, Local Minimum,
　　　　　　　Nonlinear, Time Lag

1. INTRODUCTION

In many model-based approaches, it is essential to build a good model. After the model structure is determined, the main task of the identification is to estimate model parameters. However, in a real nonlinear time lag system, the identification is very difficult [1,2]. For instance, an explosion-proof pneumatic robot as shown in Figure 1, often generates hunting due to a time lag of pneumatic pressure signal [3,4]. In order to prevent it and design the controller, it is necessary to derive the dynamical equation of the robot.

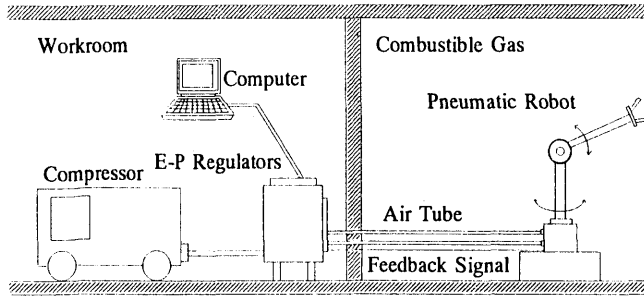*Department of Mechanical Engineering

FIGURE 1: Structure of Explosion-Proof Robot

In recent researches, it is known that genetic algorithm (GA) is a very powerful method and has many advantages through its multi-point search with population [5], [6]. As this method can perform robust search, it has been applied in many fields [7]. Using the search of GA, an identification method has been proposed for nonlinear time lag systems [8]. However, there is a potential risk in using simple GA search because the solution of loss function is usually blocked at a local minimum for a multimodal nonlinear time lag system, and thus results in a poorly identified model. In this paper, a hybrid method is proposed to prevent the local minimum problem [9], [10], [11]. This approach can be summarized as follows. First, GA carries out the search through all the space until a good initial value is obtained. Next, as the local search is conducted by a sequence method, a better value is renewed progressively and then the identification accuracy is increased.

To examine the usefulness of the proposed method, several examples are given for nonlinear vibration systems with time lag as simulation studies and also it is applied to an explosion-proof pneumatic robot. Through these studies, the possibility of the identification of nonlinear time lag systems is confirmed and the effectiveness of the proposed method is verified.

2. PROBLEM STATEMENT

A general model of nonlinear time lag system can be described as follows [12],

$$\frac{dy(t)}{dt} = f(y(t), y(t - h_1), \cdots, y(t - h_\gamma), u(t), u(t - k_1), \cdots, u(t - k_\upsilon), \phi(t), t) \tag{1}$$

where $y(t)$ is the solution, $u(t)$ the input, h_i (i =1,2,$\cdots\gamma$) time lag in system, k_j (j=1,2,$\cdots,\gamma$) time lag of input, $\phi(t)$ the noise and f nonlinear function. The nonlinear function can be expressed using Kolmogorov-Gabor 's method as a discrete model of polynomials with unknown coefficients.

$$y(k) = f(V_1, V_2, \cdots, V_s) = \sum_{i=1}^{s} a_i V_i + \sum_{i=1}^{s} \sum_{j=1}^{s} b_{ij} V_i V_j + \cdots + \underbrace{\sum_{i=1}^{s} \sum_{j=1}^{s} \cdots \sum_{n=1}^{s}}_{m} c_{ij\cdots n} V_i V_j \cdots V_n + \varepsilon(k) \tag{2}$$

where, $V_1 = y(k - 1), \cdots, V_{\gamma+1} = y(k - 1 - d_{h\gamma}), V_{\gamma+2} = u(k - 1), \cdots, V_s = u(k - 1 - d_{k_\upsilon})$ and $s = \gamma + \upsilon + 2$, Also, $\varepsilon(k)$ is the surplus part in finite terms. The estimated value of $y(k)$ is expressed in Eq.(3), where
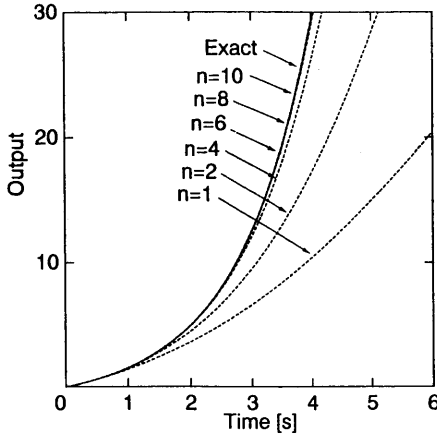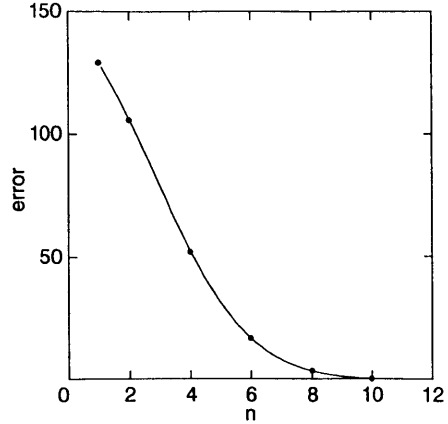
FIGURE 2: Output $y(t), \hat{y}(kT+1)$ FIGURE 3: Relation of n and ε (kT)

$p=1,2,\cdots,\gamma$ and $q=1,2,\cdots,\upsilon$. Then, the system identification is to determine the unknown parameters $\hat{a}_i, \hat{b}_{ij}, \hat{c}_{ij\cdots n}, \hat{d}_{hp}$ and $\hat{d}_{kq}$ of Eq.(3).

$$\hat{y}(k) = \sum_{i=1}^{s} \hat{a}_i V^*_i(\hat{d}_{hp}, \hat{d}_{kq}) + \sum_{i=1}^{s} \sum_{j=1}^{s} \hat{b}_{ij} V^*_i(\hat{d}_{hp}, \hat{d}_{kq}) V^*_j(\hat{d}_{hp}, \hat{d}_{kq}), \cdots,$$
$$+ \underbrace{\sum_{i=1}^{s} \sum_{j=1}^{s} \cdots \sum_{n=1}^{s}}_{m} \hat{c}_{ij\cdots n} V^*_i(\hat{d}_{hp}, \hat{d}_{kq}) V^*_j(\hat{d}_{hp}, \hat{d}_{kq}) \cdots V^*_n(\hat{d}_{hp}, \hat{d}_{kq}) \tag{3}$$

Example: In order to verify the accuracy of the approximately estimated value, an example is given as described by

$$\frac{dy(t)}{dt} = e^{Lt} \tag{4}$$

After being sampled with a period of T, the Eq. (4) can be expressed as a discrete-time system of polynomials

$$y(kT+1) = y(kT) + T(1 + LkT + \frac{(LkT)^2}{2!} + \cdots + \frac{(LkT)^n}{n!} + \varepsilon(kT)) \tag{5}$$

where $\varepsilon(kT)$ is an approximate model error, written as

$$\varepsilon(kT) = \frac{(LkT)^{n+1}}{(n+1)!} e^{\theta LkT} \qquad 0 < \theta < 1, \tag{6}$$

n is the number of polynomial.

The estimated $\hat{y}(kT+1)$ is deduced to be

$$\hat{y}(kT+1) = \hat{y}(kT) + T(1 + \hat{L}kT + \frac{(\hat{L}kT)^2}{2!} + \cdots + \frac{(\hat{L}kT)^n}{n!}) \tag{7}$$

The results of numerical calculation are showed in Figures 2 and 3. Figure 2 shows the solutions of Eq.(4) and Eq.(7). The broken lines indicate the estimated volume, and the solid line is exact solution. In this case, the time lag $L = \hat{L} = 0.8$. Figure 3 is the errors between the exact solution and estimated values. It can be

seen that, when n is big, the errors become small. Then, by selecting the terms finely, the model with high accuracy can be obtained.

3. IDENTIFICATION BY IMPROVED GA

The identification method based on the search of both GA and sequence method can be described as two stage processes, in which a good initial value is searched out using GA, and then the identification is performed by the search of sequence method.

Genetic Algorithms, which are modeled on genetic processes occurring in nature, are adaptive methods that may be used to solve search and optimization problems. They work with a population of individuals (also known as chromosomes), which represent possible solutions to a given problem. Each individuals are assigned a fit score according to how good a solution to the problem it is. The highly fit individuals are given opportunities to be reproduced by cross breeding with individuals in the population. Over several generations, individuals tend to identity and the solution is converged.

In this research, the estimated parameters in Eq. (3) can be encoded as a chromosome, which is a string of binary bits written as Eq.(8). When the search is finished, the genetic information in binary numbers is returned to the parameters in decimal numbers by the transformation equation expressing in Eq. (9) and the estimated values of the parameters can be obtained.

$$G_p = \overbrace{01\cdots1}^{\hat{a}^{*}_{1}}\cdots\overbrace{01\cdots0}^{\hat{a}^{*}_{s}}\overbrace{00\cdots1}^{\hat{b}^{*}_{11}}\cdots\overbrace{11\cdots1}^{\hat{b}^{*}_{ss}}\cdots\overbrace{11\cdots0}^{\hat{c}^{*}_{11\cdots1}}\cdots\overbrace{10\cdots1}^{\hat{c}^{*}_{ss\cdots s}}\overbrace{01\cdots0}^{\hat{d}^{*}_{h1}}\cdots\overbrace{11\cdots0}^{\hat{d}^{*}_{h\gamma}}\overbrace{00\cdots1}^{\hat{d}^{*}_{k1}}\cdots\overbrace{10\cdots0}^{\hat{d}^{*}_{k\upsilon}}_{(s+s^2+\cdots+s^m+\gamma+\upsilon)^*p \ \ bits} \tag{8}$$

$$\hat{a}_i(\hat{b}_{ij},\cdots,\hat{c}_{ij\cdots n},\hat{d}_{hp},\hat{d}_{kq}) = \hat{a}^{*}_i(\hat{b}^{*}_{ij},\cdots,\hat{c}^{*}_{ij\cdots n},\hat{d}^{*}_{hp},\hat{d}^{*}_{kq})/(2^l-1)*E_k \tag{9}$$

where E_k is a constant showing the upper limit of every estimated parameters. The procedure of GA operation is given in Figure 4, where the individuals of the population in first generation may be given as random values. Then, the selection is performed depending on the fitness of each individual. In this study,
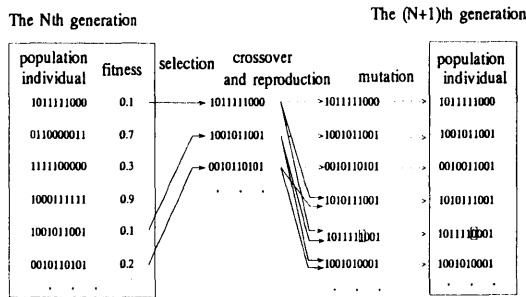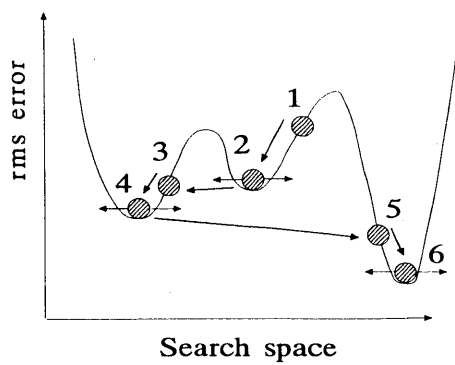

FIGURE 4: GA Operation

FIGURE 5: Sequence Method

the fitness function is expressed as a loss function of rms error in Eq.(10) and the smaller the rms error the better.

$$J = \sqrt{\frac{1}{z}\sum_{k=1}^{z}(y(k) - \hat{y}(k))^2} \qquad (10)$$

where z is a number of data.

Although a good initial value can be obtained by repeating such a kind of evolution showing in Figure 4, it should be noticed that, when a simple GA is used to multimodal nonlinear systems, it is easy to be blocked at a local minimum and the solution at this point will be much different from the finally close one.

In order to solve this problem, a sequence method is introduced to local search to make the solution escape from the local minimum by renewing the initial value. The approach is shown in Figure 5: in the first, the rms error of individuals generated at random is on position 1, and through the process of GA search, the rms error is converged to position 2 which stands for a local minimum solution. To escape from this position, the sequence search is carried out subsequently. By adjusting the parameter values finely, the individual whose fitness is larger is generated. As a result, the solution escapes from the local minimum and converges to the optimum one whose rms error is on position 3. After escaping from the local minimum, the search is returned to GA. Then, such searches are done again and again.

$$1 \to 2 \qquad \to \qquad 3 \to 4 \qquad \to \qquad 5 \to 6$$

$$GA \Rightarrow Sequence\ search \Rightarrow GA \Rightarrow Sequence\ search \Rightarrow \cdots$$

The renewal of the parameters with sequence method is expressed as follows,

$$\hat{a}_i(\hat{b}_{ij}, \cdots, \hat{c}_{ij\cdots n}, \hat{d}_{hp}, \hat{d}_{kq})_{times\ T+1} = \hat{a}_i(\hat{b}_{ij}, \cdots, \hat{c}_{ij\cdots n}, \hat{d}_{hp}, \hat{d}_{kq})_{times\ T} \pm \beta_k \qquad (11)$$

$$\beta_k = \delta * \hat{a}_i(\hat{b}_{ij}, \cdots, \hat{c}_{ij\cdots n}, \hat{d}_{hp}, \hat{d}_{kq})_{times\ T} \qquad (12)$$

where $\hat{a}_i(\hat{b}_{ij}, \cdots, \hat{c}_{ij\cdots n}, \hat{d}_{hp}, \hat{d}_{kq})_{times\ T}$ is the estimated parameters of the Tth generation, β_k the coefficient of sequence search which is determined by Eq.(12) and δ a small positive value. It is supposed that the

parameters obtained by GA at the Tth generation time are

$$\hat{a}_{T1},\cdots,\hat{a}_{Ti},\cdots,\hat{a}_{Ts},\hat{b}_{T11},\cdots,\hat{b}_{Tij},\cdots\hat{b}_{Tss},\cdots,\hat{c}_{T11\cdots1},\cdots\hat{c}_{Tij\cdots n},\cdots\hat{c}_{Tss\cdots s},\hat{d}_{Th1},\cdots,\hat{d}_{Thp},\cdots,\hat{d}_{Th\gamma},\cdots,\hat{d}_{Tk1},\cdots,\hat{d}_{Tkq},\cdots,\hat{d}_{Tk\upsilon}$$

Depending on Eq. (11), those of the (T+1) th generation time can be obtained as follows,

$$\hat{a}_{T1},\cdots,(\hat{a}_{Ti}+\beta_k),\cdots,\hat{a}_{Ts},\hat{b}_{T11},\cdots,\hat{b}_{Tij},\cdots\hat{b}_{Tss},\cdots,\hat{c}_{T11\cdots1},\cdots(\hat{c}_{Tij\cdots n}-\beta_{ij\cdots n}),\cdots\hat{c}_{Tss\cdots s},$$
$$\hat{d}_{Th1},\cdots,\hat{d}_{Thp},\cdots,\hat{d}_{Th\gamma},\cdots,\hat{d}_{Tk1},\cdots,\hat{d}_{Tkq},\cdots,\hat{d}_{Tk\upsilon}$$

$$\hat{a}_{T1},\cdots,\hat{a}_{Ti},\cdots,\hat{a}_{Ts},\hat{b}_{T11},\cdots,(\hat{b}_{Tij}-\beta_{ij}),\cdots\hat{b}_{Tss},\cdots,\hat{c}_{T11\cdots1},\cdots(\hat{c}_{Tij\cdots n}+\beta_{ij\cdots n}),\cdots\hat{c}_{Tss\cdots s},$$
$$\hat{d}_{Th1},\cdots,(\hat{d}_{Thp}+\beta_{hp}),\cdots,\hat{d}_{Th\gamma},\cdots,\hat{d}_{Tk1},\cdots,\hat{d}_{Tkq},\cdots,\hat{d}_{Tk\upsilon}$$

$$\bullet\ \bullet\ \bullet$$

$$\hat{a}_{T1},\cdots,(\hat{a}_{Ti}-\beta_i),\cdots,\hat{a}_{Ts},\hat{b}_{T11},\cdots,(\hat{b}_{Tij}-\beta_{ij}),\cdots\hat{b}_{Tss},\cdots,\hat{c}_{T11\cdots1},\cdots(\hat{c}_{Tij\cdots n}-\beta_{ij\cdots n}),\cdots\hat{c}_{Tss\cdots s},$$
$$\hat{d}_{Th1},\cdots,\hat{d}_{Thp},\cdots,\hat{d}_{Th\gamma},\cdots,\hat{d}_{Tk1},\cdots,(\hat{d}_{Tkq}+\beta_{kq}),\cdots,\hat{d}_{Tk\upsilon}$$

$$\bullet\ \bullet\ \bullet$$

By introducing a new GA operator named as development, we have proposed an improved GA, which is an effective combination of both genetic algorithm and sequence method. A hybrid identification algorithm based on this consideration is shown in Figure 6. Also, the principle of this improved GA is easy, but there are some important points in realizing it. First, if the fitness has no change in several generation times, the solution can be thought of having been stuck at local minimum. Then, the search is turned to the sequence
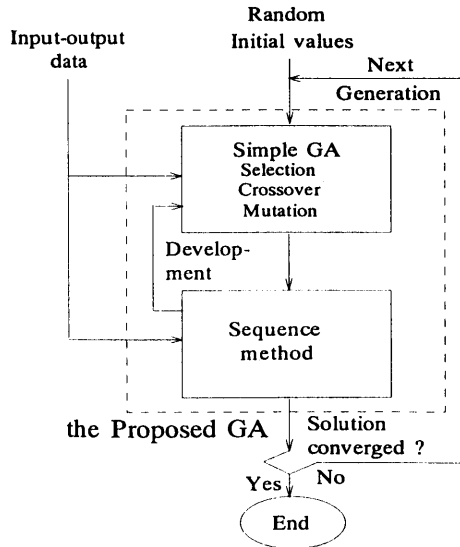

FIGURE 6: Image of Improved GA

method and the local search starts. The part in broken line of Figure 6 will be repeated and repeated and the system identification with high precision can be expected. Second, the end condition is designed to be generation times. Third, in order to protect the device, a safe limit of the rms error is set up in a real system and, if the fitness is over this limit, the parameters will be invalid.

4. SIMULATION STUDIES

In order to demonstrate the effectiveness of the proposed identification method, numerical simulations have been performed for the systems of *Duffing* type nonlinear equations. It's supposed each of the systems includes time lag and the results are compared with those using simple GA. Parameters used in GA are set as,

Total of individuals =50

Selection rate =50%

Mutation rate =20%, 80%

Generation times =400

Data numbers =300

The mutation rate in GA operation is 20% in the first 50 generations and 80% subsequently. The renewed coefficient of Eq.(11) in sequence method is assumed to be

$\beta_k = 0.01$

for the sake of convenience.

Example 1: A nonlinear time lag system of *Duffing* type with the following dynamics is considered,

$$m\ddot{x}(t) + c\dot{x}(t-L) + P(t) = q(t) + \phi(t) \tag{13}$$

where $m=1$ is the mass of the object, $\phi(t) \in N(0, 0.01)$ a white gaussion noise, c damping coefficient. Here, it is thought that there is a time lag L in the damper. The characteristics of spring $P(t)$ and the force $q(t)$ are

$$P(t) = bx(t) + a(x(t))^3 \tag{14}$$

$$q(t) = Q\cos(\omega t) \tag{15}$$

In order to obtain the data concerning the solution behavior of Eq.(13), the Eqs.(13)~(15) are expressed as a discrete model by,

$$x(k+2) = 2x(k+1) - \lambda_1(x(k+1-d) - x(k-d)) - \lambda_2 x(k) - \lambda_3(x(k))^3 + \lambda_4\cos(\omega k) + \phi(k) \tag{16}$$

where $\lambda_1 = ch/m$, $\lambda_2 = 1 + h^2 b/m$, $\lambda_3 = h^2 a/m$, $\lambda_4 = h^2 Q/m$ and $d = L/h$

The parameters of Eq.(13) are set as

$c=0.2, L=0.5, b=5.0$ and $a=1.0.$

The input parameters are given as $Q=10.0, \omega=5.0,$ and sampling period of time $h=0.02$ sec.

The results are shown in Figures 7~10 and Table 1. Figures 7 and 8 give the converging processes of parameters. Also, Figures 9 and 10 show the output response and rms error, respectively. It can be seen from Figure 9 that the solution sank into local minimum at about 54th generation point when using simple GA and the parameters stopped converging to the desired ones. Thus, it's hard to increase identification accuracy any

longer. The output responses are shown in Figure 10, in which the dotted line indicates the exact solution, the broken line is the identification result by simple GA and the solid line is that by proposed GA. It can be seen that there is a big residual error between the exact solution and the identified value, which was obtained by simple GA. On the other hand, in the searching by proposed GA, if rms error has not been improved at every 30 generations, the solution will be thought to have sunk into local minimum and the sequence method starts working. As a result, the estimated parameters get closer and closer to true ones and the identification
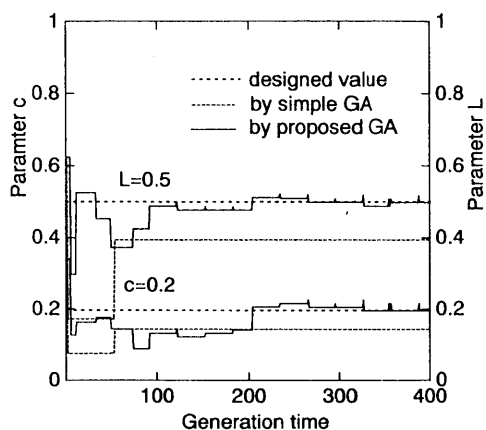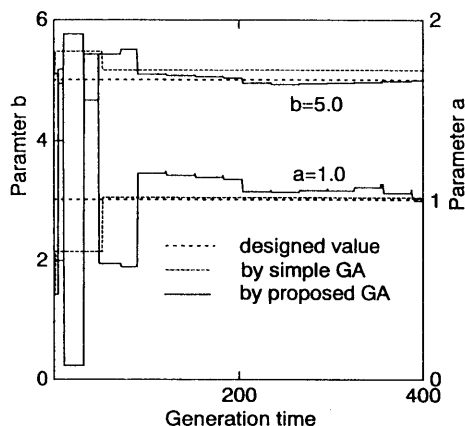
FIGURE 7: Estimated Parameters c , L
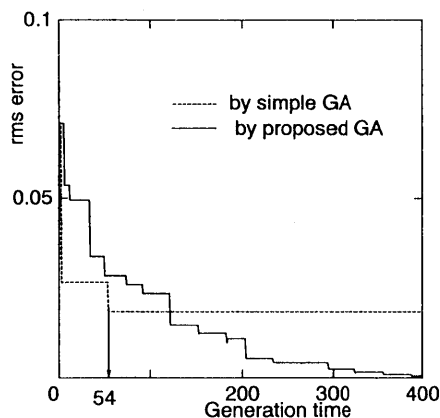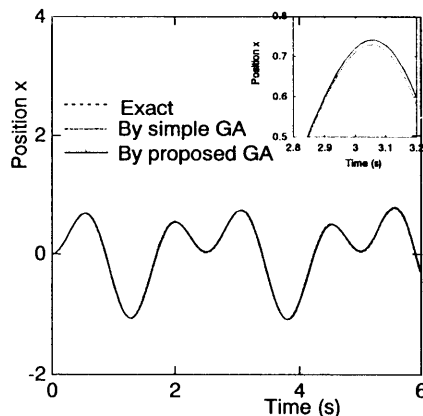
FIGURE 8: Estimated Parameters a, b

FIGURE 9: RMS Error

FIGURE 10: Output Rsponses

TABLE 1 :   Results of Estimated Parameters

Reference Value ①	Estimated values of parameters			
	Simple GA ②	Error | ①-② |	Proposed GA ③	Error | ①-③ |
c=0.2	0.143109	0.0569	0.195112	0.0049
L=0.5	0.393939	0.1061	0.497556	0.0024
b=5.0	5.171065	0.1711	5.004888	0.0049
a=1.0	1.018573	0.0186	1.012708	0.0127

with high accuracy has been performed. Table 1 shows the identified results of the estimated values of parameters. Datum file ① is the true values of the parameters, file ② the identified results using simple GA and ③ those of improved GA. It can be seen that the identification accuracy of each parameter is higher in the case of proposed GA.

Example 2: The real system with the existence of coulomb friction is not always smoothly nonlinear. As an example of such kind of models, the selected system model is shown in Eq. (13) and the nonlinear term is

$$P(t) = bx(t) + \mu \, \text{sgn}(\dot{x}) \tag{17}$$

$$\text{sgn}(\dot{x}) = \begin{cases} 1 & (\dot{x} > 0) \\ -1 & (\dot{x} < 0) \end{cases} \tag{18}$$

where μ is the coefficient of coulomb friction. The parameters are given as

$$c = 0.2, \ L = 0.5, \ b = 5.0 \text{ and } \mu = 0.5$$
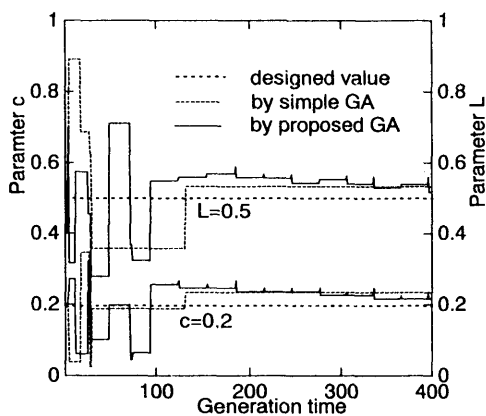

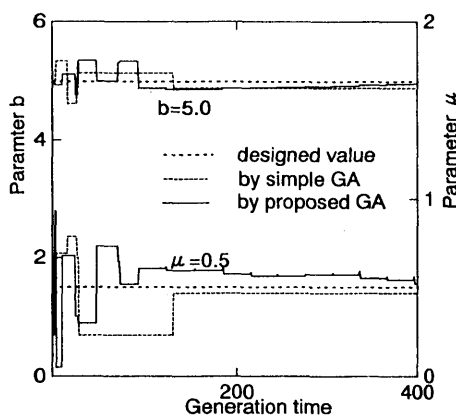FIGURE 11: Estimated Parameters c,L
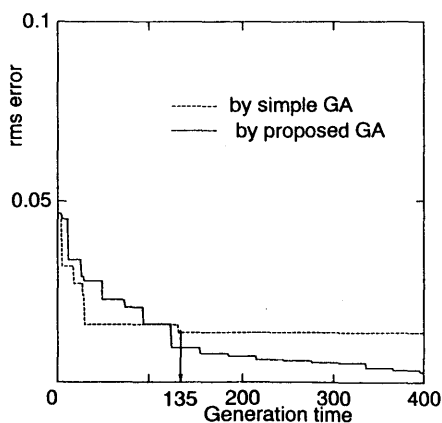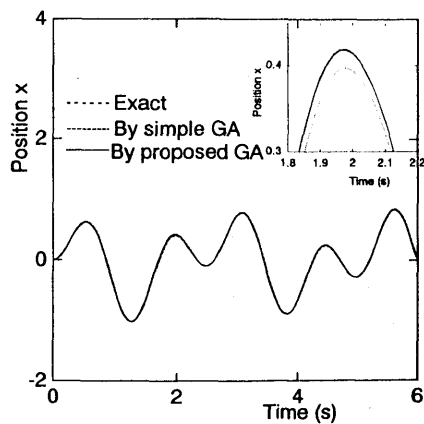

FIGURE 12: Estimated Parameters b, μ

FIGURE 13: RMS Error

FIGURE 14: Output Responses

TABLE 2:   Results of Estimated Parameters

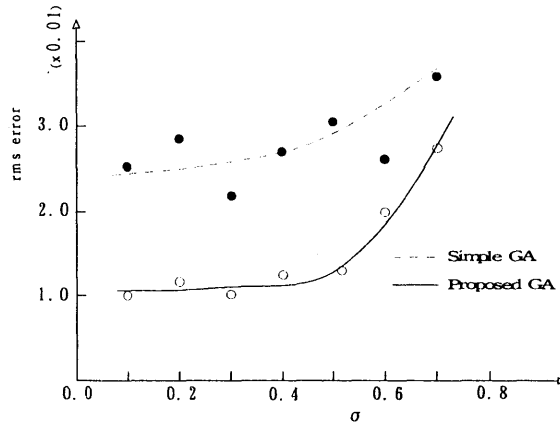| Reference Value ①	Estimated values of parameters			
	Simple GA ②	Error | ①-② |	Proposed GA ③	Error | ①-③ |
c=0.2	0.233822	0.0382	0.215445	0.0154
L=0.5	0.532747	0.0327	0.517107	0.0171
b=5.0	4.877810	0.1222	4.956012	0.0440
μ =0.5	0.466276	0.0337	0.520039	0.0200

FIGURE 15: Relation between Noise and RMS Error

The identified results are illustrated in Figures 11~14 and Table 2. It is the same as the results of *Example 1*, the identification parameters have converged to the desired ones by the proposed GA. As shown in Figure 13, because the rms error can not become smaller in the case of simple GA, the identified model is not better than that by the proposed GA shown in Figure 14 and Table 2. From these results, it can be clarified that the proposed identification method can identify even *piece wise* type nonlinear system with a good accuracy.

Example 3: The effectiveness of the proposed method has been examined by real systems, which are subjected to big random disturbances. The object system is shown in Eq.(13) and ϕ *(t)* is obtained as the following [13],

$$\phi(t) = \chi + \sigma^2 \xi \tag{19}$$

$$\xi = (\sum_{i=1}^{N} \Psi(i) - \frac{N}{2}) / \sqrt{N/12} \qquad N \geq 3 \tag{20}$$

The mean value χ of Eq.(19) is considered as 0.0, and $\psi(i)$ of Eq.(20) is determined at random to the range of -1.0~1.0.

In order to examine the effect of noise on the identification accuracy, simulations of the relation between the standard deviation of noise σ and rms error are performed. Figure 15 gives the result, where the round

marks indicate experimental values. From this result, it can be seen that the identification accuracy can be improved even in the existence of great noise. Also, the rms error will become large as the standard deviation of noise turns to above 0.5, the identification will become worse even if the proposed improved GA is used.

5. APPLICATION TO EXPLOSION-PROOF PNEUMATIC ROBOT

5.1 Experimental Equipment

As shown in Figure 16, the principle of the explosion-proof pneumatic robot is summarized as follows. The displacement of the manipulator is detected using linear potentiometer, and given to computer by A/D converter. According to the calculation of the software in the computer, the voltage input to E-P regulator is determined and the air pressure from the E-P regulator is controlled. After transmitting the pressure through the long pneumatic tube to the air actuator, the manipulator turns to move.
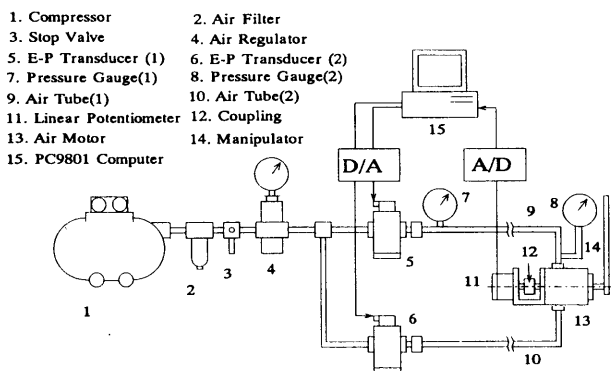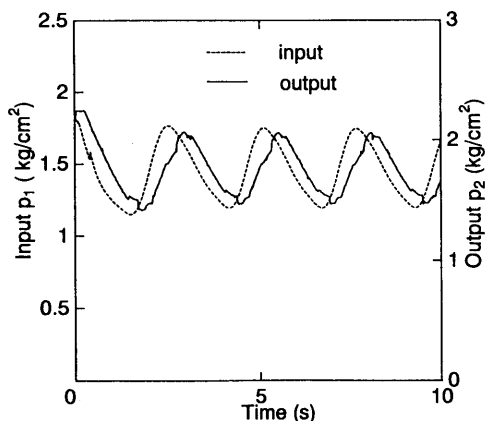

FIGURE 16: Experiment Equipment
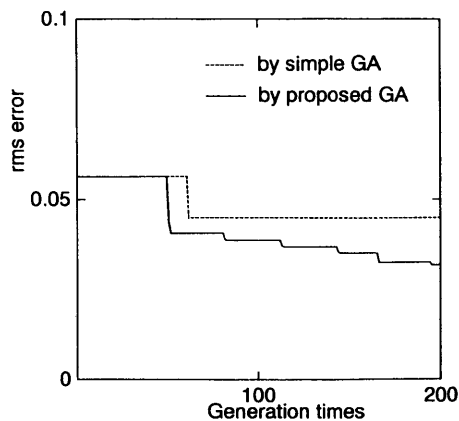

FIGURE 17 Input and Output

FIGURE 18: RMS Error

TABLE 3: Estimated Air Tube Parameters

Parameter	Simple GA		Proposed GA	
	Pattern 1	Pattern 2	Pattern 1	Pattern 2
K_L (Kg/cm^2)	0.9892	0.9902	0.9902	1.0000
T_L (s)	0.2854	0.4985	0.3402	0.3617
L (s)	0.2385	0.0753	0.1193	0.1349

The internal diameter of the air tube is 8mm, the supply of air pressure to the E-P regulator is 0.6 Mpa, and the output 0~0.51 Mpa and the air motor is vane type with a round angle of 270°. The range of air pressure used is 0.1~0.99 Mpa.

5.2 Identification of Air Tube

When the diameter of the long air tube is small, the time lag can not be negligible. By Brown's low-dimensional model, the transfer function of the air tube can be described as follows [14), 15)],

$$G_L(s) = \frac{K_L}{T_L s + 1} e^{-Ls} \tag{21}$$

where K_L is the gain, T_L the time constant and L the time lag.

In this experiment, the length of the air tube is 40 m, the data of both input and output shown in Figure 17 are obtained by the pressure gauges (1) and (2) in Figure 16. The results are summarized by Figure 18 and Table 3. It can be noted that the rms error shown in Figure 18 is small when using the proposed method. In Table 3, pattern 1 and pattern 2 are the identified results by input and output data of two sets obtained separately. When using simple GA, the identified parameters from two patterns are dispersive, while in the case of proposed GA, every parameters converge to close values. For a example, the estimated parameters of L by simple GA are the values of 0.2385 and 0.0753 which are very dispersive, in the case of proposed GA, they are 0.1193 and 0.1349, closely. Thus they can be considered as the real parameters of the equipment.

5.3 Identification of Robot Actuator

The structure of the actuator is shown in Figure 19. Considering that the input is the pressure difference supplied to the air motor and the output is the displacement of arm angle, the identification method can be established for the robot manipulator. The state equation of the air in the chamber is given as follows,

$$W = \frac{1}{\kappa RT} (V \frac{dP}{dt} + \kappa P \frac{dV}{dt}) \tag{22}$$

where W is flow mass, κ specific heat, R gas constant, T absolute temperature of the air, V the volume and P the pressure of the air inside the chamber. The standard position is that when the vane is in the center of the actuator shown in the Figure 19. Letting the Eq.(22) be linearized under this state, we can obtain [16)],

$$\dot{P} + k_a P = k_b P_a - k_c \dot{\theta} \tag{23}$$

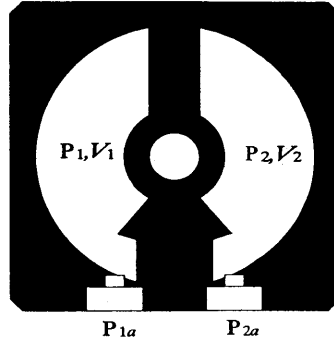where $P_a = P_{1a} - P_{2a}$, $P = P_1 - P_2$ and k_a, k_b, k_c the coefficients.

FIGURE 19: Structure of the Robot Actuator

TABLE 4: Estimated Robot Parameters

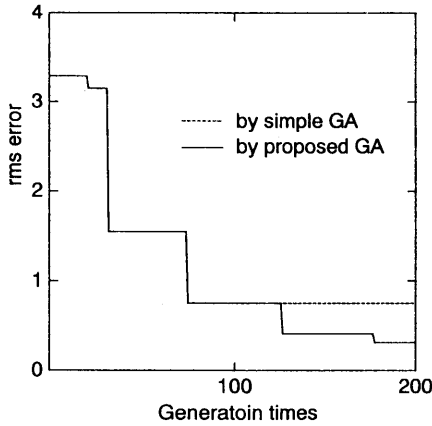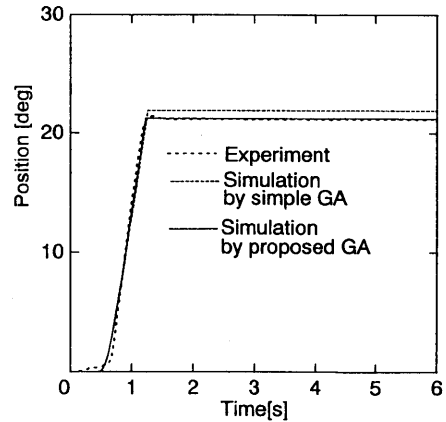| Parameter	Simple GA	Proposed GA
J (Kg•m^2)	3.6×10^{-4}	3.6×10^{-4}
F_c (N•m)	1.0068×10^{-2}	1.2317×10^{-2}
F_{max} (N•m)	3.5288×10^{-2}	3.3333×10^{-2}
K_a (N•m/Pa)	83.0890	83.0890
K_b (N•m/Pa)	121.7009	121.6784
K_c(N•m/Pa)	416.9110	456.9892

FIGURE 20: RMS Error

FIGURE 21: Output Responses

The solid friction in the motor is described in two states as follows,

Stick state: when the manipulator is static, the drive torque and the stick friction torque are in balance. Then, the following relation holds,

$$f = A_m(P_1 - P_2) \quad \dot{\theta} = \ddot{\theta} = 0 \quad (f < f_{max})$$
(24)

where A_m is the volume of a radian changed.

Slip state: the dynamical equation is represented by

$$J\ddot{\theta} + B\dot{\theta} + f_c \text{sgn}(\dot{\theta}) = A_m(P_1 - P_2) \tag{25}$$

Using the Eqs.(23) to (25), the identification is performed by a simple GA and the proposed GA. The results are shown in Table 4 and rms errors are shown in Figure 20. It can be seen that the rms error becomes smaller gradually by the applying of the proposed GA. Moreover, to evaluate the identification accuracy, the step response experiment by P control is performed and the results are shown in Figure 21. The broken line indicates the result of simulation using the parameters obtained by simple GA. The solid line is that by proposed GA and the dotted line stands for that coming from experiment. It can be verified from Figure 21 that the simulation results are identical with those of the experiment by using the proposed GA method and the identification accuracy can be improved.

6. CONCLUSIONS

An identification method using the search of GA to nonlinear time lag systems has been proposed. While only the traditional GA is used, the solution is usually sunk into local minimum. In order to solve this problem, a new identification method is constructed which has been combined the traditional GA with sequence method. For examining the usefulness of this method, several representative nonlinear time lag systems have been treated. Using the numerical data of *Duffing* type systems, which have been regarded as experimental ones, the identification experiments are performed. Furthermore, it has been applied to the identification of real systems of explosion-proof pneumatic robots. As a result, it has been verified that nonlinear time lag systems can be identified accurately by the proposed method and these results can be applied to the identification and control of nonlinear time lag systems and robots, especially to further development of explosion-proof pneumatic robots.

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