GA-Based Evolutionary Identification Algorithm for Unknown Structured Mechatronic Systems

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***Abstract*—Soft computing techniques, e.g., neural networks, fuzzy inference, evolutionary computation, and chaos theory, have been applied to a wide variety of control systems in industry because of their control capability and flexibility. They are also powerful to handle the complicated mechatronic systems with various nonlinearities which are difficult to model using mathematical formulas. In order to achieve the system identification of unknown structured mechatronic systems, this paper presents a novel evolutionary algorithm using genetic algorithms (GAs), where the optimal mathematical structure of plant mechanisms and the combination of parameters can be autonomously determined by means of the optimization ability of the GA. The effectiveness of the proposed identification has been verified by experiments with comparative studies, using the typical mechanical systems with velocity controller.**

***Index Terms*—Genetic algorithms (GAs), mechatronic systems, system identification, unknown structured system.**

I. Introduction

MOST of design strategies of motion controllers for various mechatronic systems are based on the control theory, where the compensators are generally designed using control CADs on the basis of mathematical plant models and are computationally processed using high-performance CPUs. In such strategies, the motion control accuracy is affected by both the structured and unstructured uncertainties [1] in the models, where, generally speaking, the structured uncertainties are caused by errors in the parameterization for exact mathematical models, and the unstructured uncertainties are due to the structural modeling errors. Although the structured uncertainties can be compensated by system identification algorithms and the unstructured uncertainties can also be compensated by robust control algorithms, these approaches are very computationally intensive and require the higher processing capability of CPUs. Recently, digital signal processors (DSPs) and/or reduced instruction set computers (RISCs) have gained the capability to perform such complicated control processing on line by means of their optimal hardware architecture and effective instruction sets [2]. However, as the control specifications become more severe, various nonlinearities in controller elements and mechanisms, e.g., the saturation of compensator outputs, the nonlinear friction, and the lost motion (backlash + torsional property) of gears, should be well handled. Recently, soft computing techniques have been attracting interest in industrial application fields [3], [4]. Since the soft computing algorithms are bio-mimetic-based strategies and can handle qualitative techniques with no mathematical model, they are easily applied to complex systems. In such diverse algorithms, the evolutionary computation techniques, e.g., genetic algorithms (GAs) [5], evolutionary programming (EP) [6], evolution strategy (ES) [7], and genetic programming (GP) [8], are particularly applied as the optimization strategies [9]. For example, the GA is suitable and is actively applicable to identify unknown plant systems [10] and/or to design a variety of control systems [11]–[13].

This paper presents an evolutionary algorithm for the identification of unknown structured mechatronic systems to assist the compensator design of motion control systems [14], [15]. In this research, under the assumption that the transfer characteristics of the linear time-invariant plant system can be modeled by a fractional expression, the GA assigns the optimal combination of modules for poles and zeros, and identifies those parameters to satisfy the specified system transfer characteristic, by evaluating the appropriate fitness in the genetic process. The proposed scheme has a distinctive feature in that the determination of the system structure (“structuring”) and the identification of parameters (“parameterization”) can be simultaneously attained, in contrast to the conventional identification algorithms, e.g., a linear regression technique under the given system structure. The effectiveness of the proposed identification has been verified by experiments, where a one-mass rigid system and a two-mass resonant system have been selected as the typical mechanisms in mechatronic systems.

II. Identification of Mechatronic System

A. Mechatronic System

The main objective of the research is to identify the unknown structured mechanism in mechatronic systems, based on a transfer characteristic of the motor velocity ω_M for the motor torque τ_M. The transfer function $G(s)$ can be generally formulated by the following fractional expression:

$$G(s) = \frac{\omega_M}{\tau_M} = K\frac{\prod_b (s+B_b)}{\prod_a (s+A_a)}. \tag{1}$$

In this research, in order to express a high-order proper transfer function as a combination of simple factors, the factor modules listed in Table I for gain ($K \in \boldsymbol{R}$), poles ($A \in \boldsymbol{C}$), and zeros ($B \in \boldsymbol{C}$) are utilized. By factorizing the transfer function of

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TABLE I
FACTOR MODULES FOR TRANSFER FUNCTION

module type	factor module	parameters
G_0	K	K (gain)
$G_1(s)$	$\frac{1}{s+A_{1i}}$	A_{1i} (poles)
$G_2(s)$	$\frac{s+B_{2j}}{s+A_{2j}}$	A_{2j} (poles), B_{2j} (zeros)

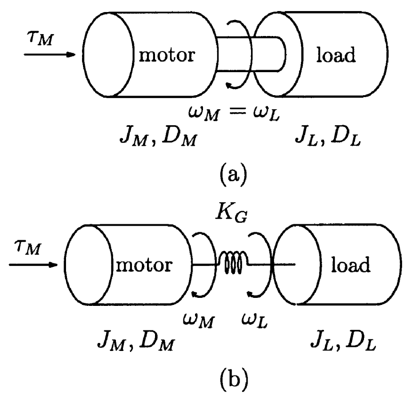

Fig. 1. Typical mechanical structure in motion control systems. (a) One-mass rigid system. (b) Two-mass resonant system.

(1), $G(s)$ can be handled as the combination of factor modules as follows:

$$G(s) = K\prod_{p}\left(\frac{1}{s+A_{1i}}\right)\prod_{q}\left(\frac{s+B_{2j}}{s+A_{2j}}\right) \tag{2}$$

$$= G_0\prod_{p} G_{1i}\prod_{q} G_{2j}. \tag{3}$$

Let us consider examples in the industrial mechatronic systems. The typical mechanisms can be generally classified into two: one is a one-mass rigid system and the other is a two-mass resonant system with a low stiff component as shown in Fig. 1, where ω_M is motor angular velocity, τ_M is motor torque, ω_L is load angular velocity, J_M is motor moment of inertia, D_M is motor viscous damping coefficient, J_L is load moment of inertia, D_L is load viscous damping coefficient, and K_G is torsional constant.

In the one-mass system [Fig. 1(a)], the motor and load are considered to be rigidly coupled, resulting in $\omega_M = \omega_L$, $J = J_M + J_L$, and $D = D_M + D_L$. Therefore, the transfer function can be given in (4), using two factor modules for the gain and the pole

$$G(s) = K \times \frac{1}{s+A_{11}}. \tag{4}$$

In the case of the two-mass system [Fig. 1(b)], on the other hand, the following fractional expression with four factor modules can be obtained:

$$G(s) = K \times \frac{1}{s+A_{11}} \times \frac{s+B_{21}}{s+A_{21}} \times \frac{s+B_{22}}{s+A_{22}}. \tag{5}$$

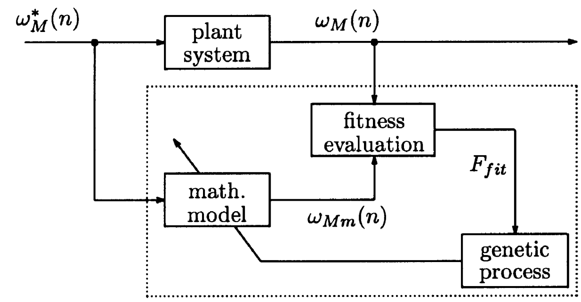

Fig. 2. Identification system using GA.

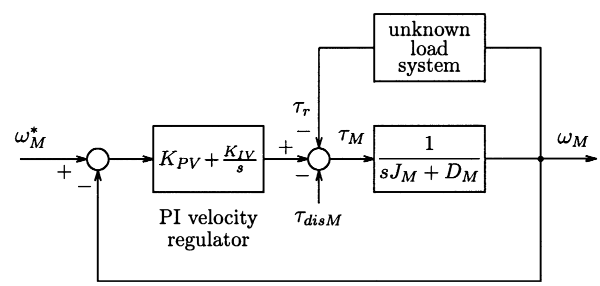

Fig. 3. Block diagram of plant system with PI velocity regulator.

That is, the structure of each mechanical system can be characterized by $(p = 1, q = 0)$ for the one-mass system or $(p = 1, q = 2)$ for the two-mass system, using the structural parameters p and q in (2).

These examples show that the simple factor modules can easily synthesize arbitrary higher order systems, and the identification of the mechatronic systems results in the determination of the order p and q, gain K, poles A, and zeros B for each module.

B. Principle of System Identification Using GA

Fig. 2 shows the proposed identification system. The "plant system" consists of an objective mechanical system to be identified and a proportional and integral (PI) motor velocity regulator, which is indicated in Fig. 3. The "mathematical model" is given by the fractional expression in (2) and the same velocity regulator as of the plant system. The same time-series motor velocity command $\omega_M^*(n)$ is given to both plant and mathematical models. The time-series actual motor velocity $\omega_M(n)$ is supposed to be detected from the plant system. On the other hand, the output response $\omega_{Mm}(n)$ of the mathematical model can be calculated by the recurrence formula converted from each factor module using the bilinear transformation.

In the proposed identification, the variable parameters in the mathematical model are evolutionally identified by the genetic process so that the actual velocity ω_M and the model velocity ω_{Mm} should coincide with each other. That is, the GA optimizes the combination of p, q, K, A, and B, which makes the

TABLE II
SPECIFICATIONS OF GA OPERATION

population size	50
tournament selection	
multi-point crossover	crossover rate: 0.9
bit mutation	mutation rate: 0.01

p	q	K	A_{11}	$\cdots$	A_{1i}	$\cdots$	A_{21}	B_{21}	$\cdots$	A_{2j}	B_{2j}	$\cdots$

Fig. 4. Individual expression for parameters.

fitness function F_{fit} in (6) minimum, using the time-series velocity response data $\omega_M(n)$ and $\omega_{Mm}(n)$ obtained from the plant system and the mathematical model, respectively

$$F_{\mathrm{fit}} = \sum_{n=1}^{S} \{W_{f1}(\omega_M(n) - \omega_{Mm}(n))\}^2 + W_{f2}k \qquad (6)$$

where S is the sampled number of the response data, $k = p + q$ i the total number of structural parameters, and W_{f1}, W_{f2} are weights. The second term on the right-hand side of (6) is a penalty term with a weight W_{f2} for the order of factors. In this fitness evaluation, the optimal identification for parameters, i.e., poles and zeros, can be attained under the minimum order of model structure since not only the integral of squared error but the order are evaluated considering the information criterion [16].

Specifications of the GA operation are listed in Table II, where guidelines to determine the genetic parameters are as follows.

- The size of the population should be selected considering the convergency under the appropriate/practical computation load,
- Crossover in a generation should be performed for almost every individual,
- Mutation rate should be 1%–3% to prevent the search from being a random one, with consideration of the population size and bit length of the individual.

The order, gain, poles, and zeros in (2) are expressed in binary chromosomes consisting of 2 bits each for p and q, 10 bits for K, and 20 bits for complex A and B with 10 bits each for real and imaginary parts. A set of the chromosomes composes an individual in the GA process as shown in Fig. 4. The genetic operations are individually processed for each corresponding chromosome because the parameters in (2) are independent of each other. In the following experimental studies, a 194-bit individual (2-bit $\times$ 2 + 10-bit $\times$ 1 + 20-bit $\times$ 9) is designed to handle a model whose order is $k \leq 6$ ($p \leq 3, q \leq 3$). This word length allows each individual in the population to express a mathematical model with arbitrary order, while only the part in A and B corresponding to p and q has effective information on the model. For example, in the case of $p = 1$ and $q = 2, A_{12} \sim A_{13}, A_{23}$, and B_{23} have no significant information, while those are indispensable to the GA operations, especially to the crossover with other chromosomes corresponding to $k > 3$.

All identification processing indicated in the dotted box in Fig. 2 is performed using a DSP TMS320C30 (33 MHz), where the computational processing for one generation in GA can be performed within 30 ms. The genetic process is iterated up to 1000 generations, i.e., the total processing time for the proposed approach is within 30 s. Although this processing time obliges the identification to be in an offline manner, it is practical enough for the offline identification in industrial applications.

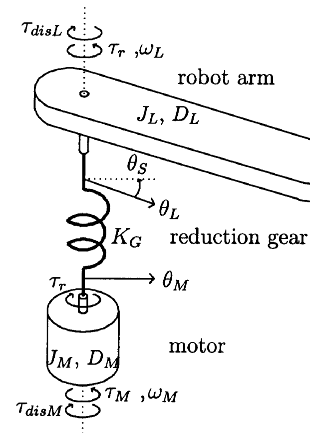

Fig. 5. Model of two-mass resonant system for robot arm.

TABLE III
SPECIFICATIONS OF PROTOTYPE

nominal mechanical parameters			control parameters		
J_M	1.02×10^{-4}	[kgm^2]	K_{PV}	0.0232	[Nm·s]
D_M	0.003	[kgm^2/s]	K_{IV}	1.367	[Nm]
J_L	5.815×10^{-4}	[kgm^2]	T_s	0.444	[ms]
D_L	0.008	[kgm^2/s]			
K_G	2.59	[Nm/rad]			

III. EXPERIMENTAL VERIFICATION

A. Configuration of Experimental Setup

The proposed identification scheme has been verified by experimental studies using a robot arm with a flexible joint as shown in Fig. 5, which is modeled by the two-mass resonant system. In the experiments, the one-mass rigid system can be also examined by removing the load arm of this mechanism. Specifications of the prototype are listed in Table III, where the nominal mechanical parameters are given by mechanical specification sheets and the PI motor velocity control is digitally performed with a sampling period of $T_s = 444$ μs.

At the fitness evaluation in the genetic process, the integral number S in (6) is 250, i.e., the actual motor velocity is stored for 0.111 s ($=S \times T_s$) to prepare the time-series data $\omega_M(n)$ which are detected by a step response. Notice here that the stepwise motor velocity command corresponding to the actual motion condition should be applied, in order to reflect the actual effects of uncertainties on the velocity response and the identified parameters. The weights, on the other hand, are selected as $W_{f1} = 1.0$ and $W_{f2} = 2.0$ with trial and error so that the initial ratio of the integral of squared error to the order of model structure in (6) should be about 1 to 1, in order to equally evaluate both terms.

It is indispensable to determine the appropriate search spaces of identified parameters in the genetic operations, in order to

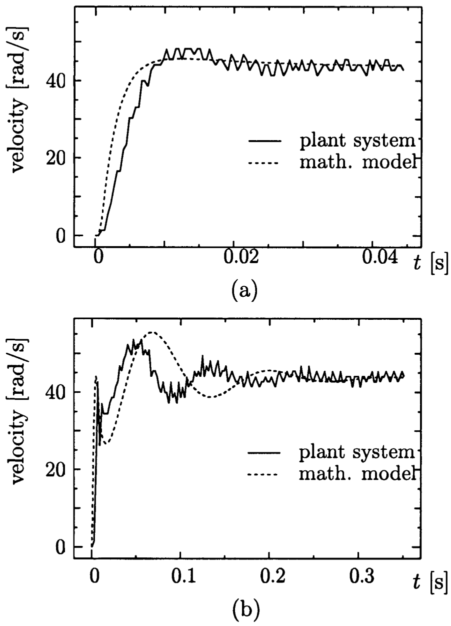

Fig. 6. Motor velocity responses for step command with nominal parameters. (a) One-mass system. (b) Two-mass system.

TABLE IV
IDENTIFICATION RESULTS

	one-mass rigid system		two-mass resonant system	
	nominal	identified	nominal	identified
p	1	1	1	1
q	0	0	2	2
K	9813.54	6278.26	9813.54	6545.29
A_{11}	29.44	34.13	16.11	15.41
$A_{21,22}$	-	-	$13.54 \pm 172.2i$	$10.30 \pm 150.9i$
$B_{21,22}$	-	-	$6.88 \pm 66.35i$	$4.26 \pm 93.98i$
J_M	1.02×10^{-4}	1.59×10^{-4}	1.02×10^{-4}	1.53×10^{-4}
D_M	0.30×10^{-2}	0.54×10^{-2}	0.30×10^{-2}	0.42×10^{-2}
K_G	-	-	2.59	1.96
J_L	-	-	5.82×10^{-4}	2.21×10^{-4}
D_L	-	-	0.80×10^{-2}	0.19×10^{-2}
fitness	124.6	58.7	215.2	102.8

provide accurate and efficient identification. The search range for parameters is selected under the assumption that the perturbation range of the system total moment of inertia and the frequencies of vibration modes are known in advance.

B. Experimental Results

Fig. 6 shows the motor velocity responses for a step motor velocity command whose amplitude is 43.6 rad/s. In the figure, the plant response is detected from the real plant system and the model response is calculated using the mathematical model whose parameters are set by the nominal mechanical ones in Table III. Two responses do not show good agreement in both cases of one- and two-mass systems. This disagreement is due to the existence of unstructured uncertainties, e.g., nonlinear friction in the real plant system.

Table IV lists the identification results by the proposed scheme and Fig. 7 shows the averaged fitness-generation characteristics for 20 trials of the identification process, both for one- and two-mass systems. Notice here that no prior knowledge of the plant structure is given before the identification, i.e., the initial population in the GA system is composed of individuals with the arbitrary order of model $(p \leq 3, q \leq 3)$. From both results in the table, although the orders of modules in the identified model can be determined correctly, the converted mechanical parameters (J, D, K_G) by the identified poles and zeros do not coincide with the corresponding nominal ones. However, it is apparent that the identified combinations make the fitness smaller. This means that the poles and zeros have been determined to make the fitness in (6) minimum by compensating for the effects of unstructured uncertainties on the actual plant velocity response.

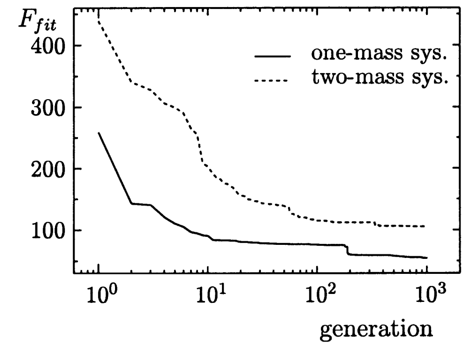

Fig. 7. Characteristics of averaged fitness generation in genetic operation.

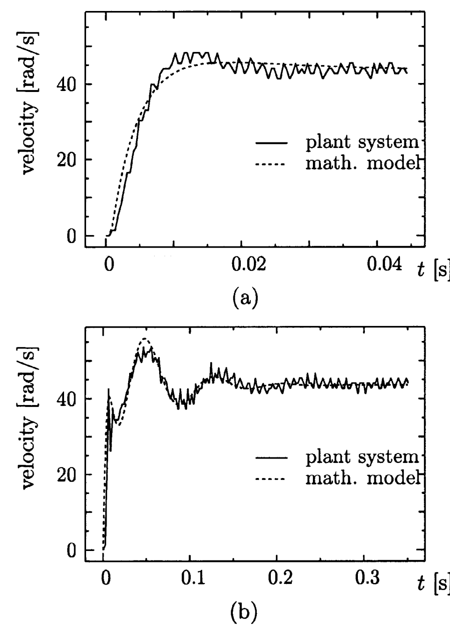

Fig. 8. Velocity responses for step command by identification result. (a) One-mass system. (b) Two-mass system.

Fig. 8 shows the velocity responses of the plant system and the identified mathematical model. In both cases, the plant and model responses show good agreement compared with those in Fig. 6 and, thus prove the effectiveness of the proposed identification.

C. Comparative Study to Conventional Identification

The identification results by the proposed scheme have been compared to the ones by the conventional identification

TABLE V
COMPARATIVE STUDY OF PROPOSED IDENTIFICATION RESULTS TO CONVENTIONAL LEAST-SQUARES METHOD

	one-mass rigid system		two-mass resonant system	
	conventional	proposed	conventional	proposed
α_0	0.056245	0.051627	0.166901	0.158765
α_1	0.001449	0.001330	-0.328939	-0.312558
α_2	-0.054796	-0.050297	-0.004631	-0.004672
α_3			0.328945	0.312565
α_4			-0.162264	-0.154086
β_1	1.868881	1.881221	3.644657	3.660535
β_2	-0.871779	-0.883881	-4.947453	-4.995487
β_3			2.960446	3.008738
β_4			-0.657661	-0.673800

approach. Here, the least-squares method has been applied as a typical conventional linear regression scheme under the assumption that the plant mathematical structure has been exactly given. In the least-squares method, the coefficients α_i and β_i in the following discrete polynomial can be determined by using the time-series data of $\omega_M^*(n)$ and $\omega_M(n)$, where the M-sequence signal is used as the motor velocity command:

$$\omega_M(n) = \sum_{i=0}^{N} \alpha_i \omega_M^*(n-i) + \sum_{i=1}^{N} \beta_i \omega_M(n-i). \quad (7)$$

Here, the polynomial structure is determined by the order N, i.e., $N = 2$ for the one-mass rigid system or $N = 4$ for the two-mass resonant system, where the total number of coefficients α_i and β_i to be parameterized is 5 or 9, respectively. In the comparative study, the identified transfer function in (2) by the proposed identification is converted into the same form as that of the discrete polynomial in (7).

The comparative results are shown in Table V. From the table, the coefficients by the proposed identification show good agreement with ones by the conventional method. This means that the proposed scheme can achieve the parameterization with the desired precision as well as the exact system structuring, without the prior knowledge of the system mechanical structure.

IV. CONCLUSION

In this paper, a novel evolutionary identification algorithm for mechatronic systems using a GA was presented. Unlike conventional identification techniques, the proposed scheme requires no preior knowledge of the mechanical system structure within range of the prospective order, thus allowing the process to be autonomous. The experimental results using the prototype and the comparative studies to the conventional scheme verify the effectiveness of the proposed identification.

Further work will be devoted to the expansion of the proposed GA-based identification approach to general mechatronic systems with nonlinear components [17]. Since a variety of approaches to the nonlinear system identification, e.g., a neural network approximation, have been proposed, it is indispensable to perform the comparative studies.

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