GA-Based Practical Auto-Tuning Technique for Industrial Robot Controller with System Identification

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This paper presents a practical auto-tuning technique based on a genetic algorithm (GA) for servo controllers of multi-axis industrial robots. Compared to conventional manual tuning techniques, the auto-tuning technique can help save an engineers’ time and the cost of controller tuning, reduce performance deviation among products, and achieve higher control performance. The technique consists of two main processes. One is an autonomous system identification process involving the use of actual motion profiles of a typical robot. The other is an autonomous control gain tuning process in the frequency and time domains involving the use of a genetic algorithm, which satisfies the required tuning specifications, e.g., control performance, execution time, stability, and practical applicability in industries. The proposed technique has been validated through experiments performed with a six-axis industrial robot.

Keywords: industrial robot, auto-tuning, autonomous identification, genetic algorithm

1. Introduction

Industrial robots are versatile manufacturing machines for industry automation, while the performance requirements become more and more strict for various applications. A wide variety of control strategies have been continuously researched for the fast and precise motion control, which are also the main issues in the field of industrial robots. In order to achieve the desired performance in such control strategies, it is important to optimize all gains of the controller as well as to design suitable controllers. In general, the control gains of industrial robot controller can be manually determined by control engineers using trial-and-error method through simulation and experimental analyses. However, the manual tuning of multi-axis industrial robots unceasingly requires much time and cost consuming as well as performance deviations among products according to tuning persons.

Applications of auto-tuning techniques to the industrial robot controller should be one of the solutions to overcome these problems. Various attempts of intelligent optimization schemes, e.g. neural networks, fuzzy inference, and genetic algorithm (GA), have been already reported to provide the optimal control gains. Especially, the GA of a heuristic algorithm (GA), have been already reported to provide the schemes, e.g. neural networks, fuzzy inference, and genetic algorithm and so on. The whole autonomous tuning process to the industrial robot controller should be still a challenging task, where it is mightily important to keep the balance of servo bandwidth between each axis for trajectory tracking performance, and to operate stable enough during tuning processes even when the characteristics drastically change according to robot’s pose.

This paper presents a practical auto-tuning technique for servo controllers of multi-axis industrial robots. In this approach, the combination of system model identification and control gain tuning on the basis of GA optimization provides whole autonomous tuning process to the industrial robot controller. At first, mathematical model parameters for each axis of industrial robot can be autonomously identified by GA. Actual motion profiles of typical industrial robot are particularly adopted to this autonomous system identification process in consideration of practical applicability in industries. Next, the second optimization process using GA is accomplished to tune control gains based on the identified mathematical model. Two-step optimization algorithm in the frequency and time domains is proposed in the second optimization process to reduce execution time as well as...
to satisfy the required control specifications, e.g. overshoot, vibration, settling time, and position accuracy. In addition, appropriate fitness functions for each GA process are simultaneously presented, considering typical characteristics of industrial robots. The proposed auto-tuning technique has been verified through experiments using a 6-axis industrial robot of Hyundai Heavy Industries (HHI).

2. System Configuration

2.1 Manipulator Setup HA006 robot shown in Fig. 1, which is a typical 6-axis industrial robot used for arc welding, sealing, and material handling applications, is comprised of six links, AC motors with encoders, RV and harmonic drive gears, and payload. Inertia ratio between the actuator and the load in each axis changes from about 1:1 to 1:5 depending on the pose. Mechanical specifications of the robot are listed in Table 1. The robot is interfaced with rapid control prototyping (RCP) device for the fast prototyping and immediate implementation of the proposed algorithms. In this setup, each axis can be controlled by the motor torque command in the angular position feedback control manner using motor encoder with a sampling period of 500 $\mu$s.

2.2 Controller Structure The conventional cascade controller as shown in Fig. 2 is applied to the each axis, where $K_{pp}$ is position proportional gain, $K_{vp}$ is velocity proportional gain, $K_{vi}$ is velocity integral gain, $K_{vf}$ is velocity feedforward gain, $C_p(s)$ is position compensator, $C_v(s)$ is velocity compensator, $P(s)$ is plant system, $r$ is position reference, $\tau_{ref}$ is torque reference, and $\theta_m$ is motor angle, respectively. In this control framework, the gains $K_{pp}$, $K_{vp}$, $K_{vi}$, and $K_{vf}$ are free parameters to be auto-tuned.

2.3 Mathematical Model In order to describe the characteristics of each axis that include several significant vibration modes, a modal plant model $P(s)$ with delay time component can be formulated by Eq. (1).

$$P(s) = \frac{K_0}{s^2 + \sum_{i=1}^{N} \frac{K_i}{s^2 + 2\zeta_i\omega_i s + \omega_i^2}} e^{-T_d s}$$

where $K_0$ is rigid mode constant, $K_i$ is modal constant, $\omega_i$ is natural angular frequency, $\zeta_i$ is modal damping coefficient, $N$ is number of vibration modes, and $T_d$ is delay time component.

2.4 Outline of Whole Auto-tuning Process In this research, the whole auto-tuning process is performed as a flowchart shown in Fig. 3, with the combination of the autonomous system identification explained in Sect. 3 and the autonomous control gain tuning process explained in Sect. 4. Both processes are individually optimized by GA. At first, mathematical model parameters for each axis and pose are autonomously identified by GA. Next, the second GA-based optimization process divided into two steps in the frequency and time domains is accomplished to tune control gains for each axis based on the identified models. Since it is physically impossible to tune for all pose of robot, three significant poses (high, middle and low) that can represent characteristics of multi-axis robot are selected according to the inertia of load side in common with the manual tuning case.

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Table 1. Mechanical specifications of HA006

<table>
<thead>
<tr>
<th>Degree of freedom</th>
<th>6</th>
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<tr>
<td>Maximum load capacity</td>
<td>6kg</td>
</tr>
<tr>
<td>Reach at wrist</td>
<td>1600 mm</td>
</tr>
<tr>
<td>Weight</td>
<td>155 kg</td>
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Fig. 1. HA006, 6-axis industrial robot from HHI

Fig. 2. Block diagram of feedback compensator for each axis

Fig. 3. Flowchart of whole auto-tuning algorithm
3. Autonomous System Identification

Mathematical models for each axis and pose are required to evaluate system characteristics in the control gain tuning process, while the model parameters should be autonomously identified during the whole auto-tuning process. In this research, nonparametric frequency-domain identification method is applied as an intermediate step for the parametric identification of mathematical model\(^{[13]}\), where frequency response function (FRF) is estimated without using a certain model set.

Motion profiles of typical industrial robots are used for exciting the system, considering stability and practical applicability in industries. The frequency characteristic of system is calculated by transforming the measured time domain signals into frequency domain data. GA optimization is then applied to autonomously identify the parameters of mathematical models in Eq. (1) by minimizing the discrepancy between the model and the estimated FRF.

3.1 Measurement Method of Frequency Characteristics

System should be excited by external input signal to measure the frequency characteristics. Choice of the input signal substantially influences observed output data as well as estimated models. One of possible choice can be to use a sinusoidal excitation, consisting of a series of sine measurements with specified frequencies. Fast fourier transform (FFT), on the other hands, allows users to process more complex input signals which include broadband spectrums instead of the single signal with specified frequency. This gives considerable reduction in the measurement time.

There exist various kinds of complex input signals, e.g., random noise, pseudo-random binary sequence, swept sine, and sum of sinusoids. The measurement approach of frequency responses using the actual robot motion is adopted to measure the frequency characteristics. Choice of the input signal substantially influences observed output data as well as estimated models. One of possible choice can be to use a sinusoidal excitation, consisting of a series of sine measurements with specified frequencies. Fast fourier transform (FFT), on the other hands, allows users to process more complex input signals which include broadband spectrums instead of the single signal with specified frequency. This gives considerable reduction in the measurement time.

The selected weight values are adjusted according to the purpose of optimization.

This fitness evaluation is applied to each axis and pose with the specifications of the GA as the population of 100, generation of 50, crossover rate of 0.7, mutation of 0.04, and bit length of 12. Furthermore, the process for determining the weight values \(W_1\) and \(W_2\) is as follows:

1) The weight values are selected to make each term of the fitness function to be equal ratio.

2) The selected weight values are adjusted according to the purpose of optimization.

In detail, the ratio of \(\sum_{k=1}^{N} [G_x(k) - G_m(k)]^2\) and \(\sum_{k=1}^{N} |zG_x(k) - zG_m(k)|^2\) in Eq. (3) is nearly 1 : 10 at the trial in advance. Therefore, the weight values are selected as \(W_1 : W_2 = 10 : 1\) to make each term to be equal ratio. Finally, \(W_1\) is multiplied by the specifications of the GA as the population of 100, generation of 50, crossover rate of 0.7, mutation of 0.04, and bit length of 12. Furthermore, the process for determining the weight values \(W_1\) and \(W_2\) is as follows:

\[ F_{id} = W_1 \sum_{k=1}^{N} |G_x(k) - G_m(k)|^2 \]
\[ + W_2 \sum_{k=1}^{N} |zG_x(k) - zG_m(k)|^2 \]  

where \(W_1\) and \(W_2\) are weights, \(G_x(k)\) is frequency response measured by experiment, \(G_m(k)\) is frequency response calculated by model, \(k\) is sampling number, and \(N\) is number of evaluated data. The first term of the right-hand side in Eq. (3) is a penalty for the gain characteristics, while the second term is for the phase characteristics in frequency responses. Both of the term are calculated by an integral of squared error as determined in Fig. 6.

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by five times as $W_1 : W_2 = 50 : 1$ because the characteristics of gain are more important than those of phase during the autonomous control gain tuning process in Sect. 4. This process is also used to determine all of the weight values in this paper. The comparative result between the identified model and the experiment in the frequency response for a pose of the 1st axis is shown in Fig. 7.

4. Autonomous Control Gain Tuning

The other main purpose in this auto-tuning technique is to autonomously optimize the control gains. In this research, the GA-based two-step optimization algorithm is proposed to reduce the executing time as well as to optimize control performances. The descriptions of each step are as follows.

**Step 1:**
The control gains are optimized in off-line, to take account of the closed loop characteristics and the robust stability on the evaluation in frequency domain using the identified mathematical model.

**Step 2:**
The control gains are optimized in on-line, to achieve better control performance using actual motion responses in time domain with considerations of the stability and the balanced servo bandwidth in axes.

Two different stroke motions (5deg, 60deg) are used for performance evaluation at each pose, where the population of 40, generation of 10, crossover rate of 0.7, mutation of 0.04, and bit length of 12 are adopted as the specifications of GA. In the following sections, the process of “Step 1” and “Step 2” are explained in detail.

4.1 Off-line Optimization in Step 1

Even in the case of auto-tuning, execution time is important for control engineers. Performance evaluation in time domain is the most time consuming processing because it should include actual motions of robot. The execution time can be reduced by the performance evaluation in off-line using the identified mathematical models, even though the models may include some modeling errors. This off-line optimization, as the first step of autonomous control gain tuning, is performed in frequency domain taking account of the closed loop characteristics and the robust stability. The evaluation indexes in GA are as follows:

1) Stability:

Sensitivity function $S(s)$ determined by Eq. (4) is evaluated as the stability index.

$$S(s) = \frac{1}{1 + L(s)} = \frac{1}{1 + C(s)P(s)}$$  \hspace{3cm} (4)

where $C(s)$ is feedback controller ($= C_{ss}(s) \cdot (s + C_p(s))$, and $P(s)$ is identified model. Suppression of the gain in $S(s)$ leads to the good performance and stability.

2) Closed-loop characteristics:

Peak gain for overshoot and phase delay are evaluated as the closed loop characteristic index by the following $G_{cm}(s)$.

$$G_{cm}(s) = \frac{(K_{ps} + K_{pp})C_{ss}(s)P(s)}{1 + L(s)}$$  \hspace{3cm} (5)

Suppression of peak gain of $G_{cm}(s)$ in low frequency range achieves the small overshoot in motion. Suppression of phase delay of $G_{cm}(s)$, on the other hand, leads to the fast response.

3) Robust stability and noise:

Complementary sensitivity function $T(s)$ determined by Eq. (6) is evaluated as the noise suppression and the robust stability.

$$T(s) = 1 - S(s)$$  \hspace{3cm} (6)

Suppression of gain in $T(s)$ in high frequency range achieves enough robust stability and good noise suppression characteristics.

Fitness function for the first step in the frequency domain, therefore, can be determined as Eq. (7). Here, $W_S$, $W_T$, $W_{C_s}$, $W_{C_p}$ are weight constants, $S_d$, $T_d$, $G_{cm}$, are desired values, $\omega_S$, $\omega_T$, $\omega_{C_s}$, and $\omega_{C_p}$ are search ranges for each index.

$$F_{step1} = W_S \sum_{pose} \max(|S(s)| - S_d)$$

$$+ W_T \sum_{pose} \max(|T(s)| - T_d)$$

$$+ W_{C_s} \sum_{pose} \max(|G_{cm}(s)| - G_{cm})$$

$$+ W_{C_p} \sum_{pose} \min(G_{cm}(s))$$  \hspace{3cm} (7)

where

1. $\omega_S \{ \omega_{S_{min}} < \omega_S < \omega_{S_{max}} \}$.
2. $\omega_T \{ \omega_{T_{min}} < \omega_T < \omega_{T_{max}} \}$.
3. $\omega_{C_s} \{ \omega_{C_{s_{min}}} < \omega_{C_s} < \omega_{C_{s_{max}}} \}$.
4. $\omega_{C_p} \{ \omega_{C_{p_{min}}} = \omega_{G_{cm}} \}$.

4.2 On-line Optimization in Step 2

Through the first step of the optimization in frequency domain, the optimized control gains can be roughly obtained in each axis and pose. However, the final aim of control gain tuning is to improve the control performance in time domain, not only for the individual axis motion but also for the multi-axis trajectory motion.
In the second step of autonomous control gain tuning, the control gains are optimized by GA in on-line manner by actual motion responses under the analyses of system stability and servo bandwidth balance. The settling, overshoot and vibration in response are adopted as performance evaluation indexes for this second GA process. The each of them can be evaluated by the following indexes.

\[ I_{stb} = S_{res} - S_{ref} \]
\[ I_{oos} = \max(|\theta_m(t) - r(\infty)|) \quad \{r|S_{res} < t < T\} \]
\[ I_{vib} = \int_{S_{res}}^{T} t \cdot (\theta_m(t) - r(\infty))^2 dt \]

Here, the settling index \( I_{stb} \) is the difference between settling time of reference \( S_{ref} \) and settling time of response \( S_{res} \), the overshoot index \( I_{oos} \) is a maximum position error multiplied by time after the settling within the required accuracy, and the vibration index \( I_{vib} \) is an integral of squared error multiplied by time. Fig. 8 shows each value in the indexes using an example waveform of position error. Therefore, fitness function for the second step optimization in the time domain can be determines as Eq. (11) using these evaluation indexes.

\[ F_{step2} = W_{stb} \sum_{stroke} \left( \sum_{stroke} (W_{stroke} \cdot I_{stb}) \right) + W_{oos} \sum_{stroke} \left( \sum_{stroke} (W_{stroke} \cdot I_{oos}) \right) + W_{vib} \sum_{stroke} \left( \sum_{stroke} (W_{stroke} \cdot I_{vib}) \right) \]

where \( W_{stb}, W_{oos}, \) and \( W_{vib} \) are weights for each index, and \( W_{stroke} \) is a weight for each motion stroke. In addition, this fitness function has two important constraints as follows:

**Constraint 1:** The stability of feedback loop is simultaneously evaluated by a nyquist stability criterion in frequency domain. Equations (12), (13) and (14) are constraints for the stability.

\[ \max(S(s)) \leq W_{sen} \]
\[ GM \geq W_{GM} \]
\[ PM \geq W_{PM} \]

where \( W_{sen} \) is a worst sensitivity gain, \( W_{GM} \) is a worst gain margin, \( W_{PM} \) is a worst phase margin, \( S(s) \) is a sensitivity function, \( L(s) \) is an open-loop transfer function, \( GM \) is the gain margin in \( L(s) \), and \( PM \) is the phase margin in \( L(s) \) of system. If some control gains generated by GA cannot satisfy any these constraints, positioning trials with the control gains are excluded for maintaining the system stability.

**Constraint 2:** Balanced servo bandwidth among the axes, which means how synchronously controllers of each axis can respond the input references, is important to achieve the required trajectory tracking performance. Therefore, the balanced servo bandwidth is adopted as the other constraint by Eq. (15).

\[ \int_{\theta_m=0}^{\theta_m} (\theta_m - \hat{\theta}_m)^2 \, dt \leq W_{BW} \]
Performance evaluation criterion is defined using the score in area of robot as shown in Fig. 12, are used in the experiment. Responses, 3D trajectory tracking performance of the robot end effector is examined using multi-axis motion profiles. The standard motion profiles referenced by ISO9283 standards \((17)\), such as rectangular and line motions considering the working area of robot as shown in Fig. 12, are used in the experiment. Performance evaluation criterion is defined using the score in off-line process and the rest for on-line process) for whole auto-tuning with no unstable motion. Through the several auto-tuning trials, almost similar optimization results for control gains are obtained at all time. One control gains set is adopted among them to evaluate the performance. The auto-tuned control gains for 6 axes are as listed in Table 4, comparing with the manual-tuned gains by a skilled engineer.

Figs. 10 and 11 show comparative example waveforms of the motor position response for three poses of the 1st axis between two control gains. From these figures, the control performance, especially in steady state error, is improved with the auto-tuned control gains.

In addition to verifying the performance in motor responses, 3D trajectory tracking performance of the robot end effector is examined using multi-axis motion profiles. The standard motion profiles referenced by ISO9283 standards \((17)\), such as rectangular and line motions considering the working area of robot as shown in Fig. 12, are used in the experiment. Performance evaluation criterion is defined using the score in

\[
\text{Score} = C_1 \times \text{POA}/\text{TPOA} + C_2 \times \text{PAA}/\text{TPAA} + C_3 \times \text{OV}/\text{TOV} + C_4 \times \text{VI}/\text{TVI} + C_5 \times \text{CT}/\text{TCT} \quad (16)
\]

where

\[
\text{POA} = \frac{1}{n} \sum_{i=1}^{n} e_{yi}
\]

\[
\text{PAA} = \frac{1}{\int_{0}^{t_e}} \int_{0}^{t_e} (e_{2i}(t) \, dt)
\]

\[
\text{OV} = \frac{1}{n} \sum_{i=1}^{n} \max(|e_{3i}(t) - \text{POA}_i|) \cdot |t|_{S_{ref} < t < t_e}
\]

\[
\text{VI} = \frac{1}{n} \sum_{i=1}^{n} \left( \int_{S_{ref}} e_{3i}(t) - \text{POA}_i \, dt \right)
\]

\[
\text{CT} = \sum_{i=1}^{n} S_{res}
\]

\[
e_{1i} = \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (z_i - \hat{z}_i)^2}
\]

\[
e_{2i}(t) = \sqrt{(x_i(t) - \hat{x}(t))^2 + (y_i(t) - \hat{y}(t))^2 + (z_i(t) - \hat{z}(t))^2}
\]

\[
e_{3i}(t) = \sqrt{(x_i(t) - \hat{x}_i)^2 + (y_i(t) - \hat{y}_i)^2 + (z_i(t) - \hat{z}_i)^2}
\]

Here, POA is averaged position accuracy, PAA is averaged path accuracy, OV is averaged overshoot, VI is averaged vibration, CT is sum of cycle time, TPOA, TPAA, TOV, TVI, and TCT are desired specifications for each index, coefficients with under line are weights for each index, \(x(t), y(t), \) and \(z(t)\) are coordinated position responses, \(\hat{x}(t), \hat{y}(t), \) and \(\hat{z}(t)\) are coordinated absolute settling position, \(\hat{x}_i, \hat{y}_i, \) and \(\hat{z}_i\) are coordinated

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### Table 3. Parameters for GA of 2nd step

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<tr>
<th></th>
<th>(W_{\text{pp}})</th>
<th>(W_{\text{oml}})</th>
<th>(W_{\text{wav}})</th>
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<td>(K_{pp})</td>
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<td>(K_{oml})</td>
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<td>(K_{wav3})</td>
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### Table 4. Auto-tuned control gains and comparison with manual tuning

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<tr>
<th>Axes</th>
<th>Auto-tuned</th>
<th>Manual-tuned</th>
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<td>(K_{pp})</td>
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<td>(K_{oml})</td>
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<td>(K_{wav})</td>
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<td>(K_{oml2})</td>
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</tr>
<tr>
<td>(K_{oml3})</td>
<td>0.037</td>
<td>0.7</td>
</tr>
<tr>
<td>(K_{wav3})</td>
<td>0.072</td>
<td>0.7</td>
</tr>
<tr>
<td>(K_{oml4})</td>
<td>0.0079</td>
<td>1.0</td>
</tr>
<tr>
<td>(K_{wav4})</td>
<td>0.0039</td>
<td>0.1</td>
</tr>
</tbody>
</table>

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Fig. 10. Motor position responses using manual-tuned gains

Fig. 11. Motor position responses using auto-tuned gains
settling position reference, $e_1$, $e_2(t)$, and $e_3(t)$ are several types of position error in 3D space, $S_{rez}$ is settling time of reference, $S_{ref}$ is settling time of response as determined in Fig. 8, and $n$ is number of motion profiles, respectively. In this criterion, low score corresponds to the high performance in this evaluation.

Fig. 13 shows the result of performance evaluation with the criterion. Even though the indexes on path accuracy and overshoot are nearly similar between auto-tuning and manual-tuning, the indexes are fairly decreased in the case of vibration, cycle time, and especially position accuracy, resulting in the decrease in the total evaluation criterion “Score”.

6. Conclusion

In this paper, the development of practical auto-tuning techniques including the autonomous system identification and the autonomous control gain tuning for the servo controller of multi-axis industrial robot was presented. System models were autonomously identified by the GA optimization using typical robot motion profiles to guarantee the stability, while control gains were also automatically optimized to satisfy the required control specifications using GA. Finally, the experimental results with the specified performance criteria verified effectiveness of the proposed auto-tuning technique.

References

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