Intelligent PID Controller using Modified PSO Algorithm for Ultrasonic Motor

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Abstract: The ultrasonic motor (USM) is an important actuator which has excellent features and several advantages over the common electromagnetic motor. However, it is hard to control USM because of no-accurate mathematical model and its dynamic characteristics. This paper presents an intelligent PID controller using modified particle swarm optimization (MPSO) for USM. MPSO algorithm is used to determine the gains of PID controller automatically according to USM’s characteristic behavior. The standard PSO (SPSO) has shortcoming, namely premature convergence and easy to fall into local optima. In the proposed MPSO, an inertia weight, one of the parameters in PSO, is decreased nonlinearly from maximum value to minimum value based on iteration to overcome the shortcoming of SPSO. The effectiveness of the proposed method is verified by numerical simulation and experimental investigation. The results demonstrate that the proposed method has shown a satisfactory performance.

Keywords: Intelligent PID controller, Particle swarm optimization (PSO), Electromagnetic motor, Ultrasonic motor (USM)

1. Introduction

The ultrasonic motor (USM) is a new type motor that is driven by the ultrasonic vibration of piezoelectric parts. USM has excellent features and several advantages over the common electromagnetic motor, such as compactness, light-weight, high position accuracy, high torque, EMC compliance, quick response and silence. Recently, USM has become quite popular and can be applied in various fields, such as for auto-focus of camera, spacecraft planetary instruments, MRI (magnetic resonance imaging), micro-robot, etc. [1][2]. However, it is difficult to control USM because of no-accurate model of USM. Moreover, the characteristic of USM is easy to change during operation due to temperature, loading, input frequency, disturbances, etc. [3]. Since PID controller can be designed without using a mathematical model of plant, PID controller has been widely used in USM applications [4][5]. However, the conventional fixed gain PID controller has limitation and cannot compensate the characteristic changes of USM.

To overcome those problems, self-tuning using intelligent computation such as GA, NN, fuzzy, BFO and PSO, was developed. Among them, PSO is used because of its superior excellent such as simple algorithm, faster convergence and efficient in time-calculation [6][7][8][9][10]. By using this method, the gains of PID controller can be adjusted automatically according to plant behavior. Thus, the characteristic changes of USM can be compensated. However, the standard PSO that is used for self-tuning PID has a shortcoming, namely premature convergence and fall into local optima. Due to this shortcoming, the accuracy of USM isn’t optimal, especially in loading condition.

In this work, a modified PSO which employs nonlinear decreasing of inertia weight was applied to optimize the PID parameters for USM servo system. To show the effectiveness of our proposed method, the numerical simulation and the experiment in real system were compared with that of the previous methods (fixed-gain type PID and standard PSO based PID).

2. Particle Swarm Optimization

PSO is a population based stochastic optimization method using the concept of cooperation inspired by the behavior of organism, such as birds flocking, in search for food [10]. The outline for PSO is marked as follows. Let consider the optimization problem of maximizing the evaluation function \( f: M \rightarrow M^* \subset R \) for variable \( x \in M \subset R^n \). Let there be \( N \) particles (mass point) on \( M \) dimensional space, where the position vector and velocity vector of \( i=1,2,3,\ldots,N \)th particle for \( k \) searching number are \( x_i^k \) and \( v_i^k \). The best position for each particle in the evaluation function \( f(x) \) of \( x_1^k, x_2^k, \ldots, x_N^k \) searching point is represented as \( Phi(Pbest) \), while the best position of \( f(x) \) in the searching point for the whole particle is represented as \( gPhi(gbest) \). The parti-
pbest

Figure 1: Search example of PSO.

In this research, we will adopt the nonlinear decreasing inertia weight method to enhance the ability of PSO and the convergence and fall into local optima in SPSO is still occurred frequently. However, the risk of premature exploitation (local search) ability of PSO. This balancing is a key to improve the performances of PSO. However, the adjusting of inertia weight is still unclear and more need investigation. In previous research, a standard PSO was applied to solve the optimization problem. In this method, the value of inertia weight is adjusted of inertia weight is still unclear and more need investigation. However, the risk of premature convergence and fall into local optima in SPSO is still occurs frequently.

In this research, we will adopt the nonlinear decreasing inertia weight method to enhance the ability of PSO and the adjustment of inertia weight is given as:

\[ w = w_{\text{min}} + (w_{\text{max}} - w_{\text{min}}) \cdot \left( \frac{\text{iter}_{\text{max}} - \text{iter}}{\text{iter}_{\text{max}} - 1} \right)^x \]

where \( x \) is the nonlinear modulation index. The value of \( x \) will determine the degree of non-linearity function of inertia weight. This method is known as PSO with nonlinear decreasing inertia weight (PSO-NDW). The effectiveness of the proposed PSO-NDW will be compared to the previous methods in both numerical simulations and experiments.

4. Numerical Simulation

To evaluate the performance of the proposed PSO-NDW and compare to the previous methods, we herein take a 2-D Sphere function:

\[ f(x, y) = (x - 15)^2 + (y - 20)^2 \]

where the global best solution for the above problem is zero which is achieved when \( x = 15 \) and \( y = 20 \). We decided to use 2-D Sphere function in order to display particle’s “flying” process on the computer screen to get a visual understanding of the PSO performances.

For the purpose of comparison, all the simulation deploy the same parameter settings in both PSO-LDW and PSO-NDW, such as the maximum number of iterations, \( \text{iter}_{\text{max}} = 50 \); cognitive constant, \( c_1 = 1.0 \); social constant, \( c_2 = 1.0 \); and the dynamic range for all elements of a particle is defined as \( (0, 50) \), that is, the particles cannot move out of this range in each dimension. For the Sphere function, the dimension is 2. The nonlinear modulation index of PSO-NDW was varied as follows: 1.2, 1.5, 2, 5, and 10. Since PSO is a stochastic algorithm that randomly searches the best solution, so for testing we have done as much as 100 runs.

The influence of the different value of inertia weights for PSO with number of particles, \( n = 5 \) and 10, is listed in Table 1. In Table 1, the \( \text{Err}_{\text{mean}} \) shows an average error in 100 runs. In order to better see the influence of the inertia weight and number of particles, the data of Table 1 can be converted into Fig. 2. In the event that the number of particles is 5, the error becomes smallest when the inertia weight is 0.7. Other event that the number of particles is 10, the error becomes smallest when the inertia weight is 0.5. The value of inertia weight that causes the smallest error is called as the optimal inertia weight. The simulation

Table 1: Error over inertia weight.

<table>
<thead>
<tr>
<th>Inertia weight</th>
<th>( n = 5 )</th>
<th>( n = 10 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>3.3535</td>
<td>1.5454-01</td>
</tr>
<tr>
<td>0.2</td>
<td>1.5988</td>
<td>2.56-02</td>
</tr>
<tr>
<td>0.3</td>
<td>4.024-01</td>
<td>9.97E-04</td>
</tr>
<tr>
<td>0.4</td>
<td>5.01E-02</td>
<td>1.14E-11</td>
</tr>
<tr>
<td>0.5</td>
<td>3.6E-03</td>
<td>9.18E-13</td>
</tr>
<tr>
<td>0.6</td>
<td>3.03E-04</td>
<td>1.13E-09</td>
</tr>
<tr>
<td>0.7</td>
<td>7.67E-05</td>
<td>8.90E-07</td>
</tr>
<tr>
<td>0.8</td>
<td>2.7E-03</td>
<td>4.72E-04</td>
</tr>
<tr>
<td>0.9</td>
<td>6.596E-01</td>
<td>1.44E-01</td>
</tr>
</tbody>
</table>

results show that the inertia weight has significant effect to the performance of PSO. PSO with many particles is better because the ability of searching and the probability to find the solution is greater. Consequently, the time calculation is longer. We can conclude that for PSO with a few particles, we should use the high inertia weight and vice versa.

For further simulation, we use the number of particles, \( n = 5 \). In the SPSO or PSO-LDW, we must determine the maximum and minimum value for inertia weight. The influence of the different range of inertia weight for PSO-LDW is listed in Table 2. In Table 2, the range of inertia weight from 0.9 to 0.4 shows the smaller error among other ranges. Moreover, the error of PSO-LDW in this range is smaller than the error of the PSO with the constant of inertia weight, \( w = 0.7 \).

Based on the Table 2, the proposed PSO-NDW also uses the range of inertia weight from 0.9 to 0.4. The influence of the different of nonlinear index number is listed in Table 3. It can be seen that the PSO-NDW with nonlinear index number, \( x = 1.5 \), has smaller error among other nonlinear index number. Also, the error of PSO-NDW is smaller than the PSO-LDW. It means that the solution accuracy of the proposed PSO-NDW is better than the PSO-LDW. The simulation results show that the nonlinear modulation index is a new important parameter in PSO-NDW and the proper adjustment of \( x \) can significantly improve the performance of PSO.

During searching process, all particles will try to approach a best solution with different velocity. Figure 3 shows the speed convergence of PSO, PSO-LDW and PSO-NDW. It is clear that the particles of PSO-NDW have more aggressive to find the best solution. At the 32\(^{th}\) iteration, PSO-NDW has reached error of \( 1 \times 10^{-2} \), while PSO and PSO-LDW reached the same error at 44\(^{th}\) and 34\(^{th}\) iteration, respectively.

The success rate (SR) shows the success of particles in reaching a predetermined solution value within 100 runs. If the particles can reach this value or smaller then we can say it as success. In this case, we used \( 1 \times 10^{-7} \) as a predetermined solution value. This facts show that the proposed PSO-NDW has higher success rate than other previous methods. Table 4 show the comparison of performance of each method.

5. Application of PSO-NDW in PID Controller

In this work, the PID controller was used as controller. It is comprised of three components: a proportional part, a derivative part and an integral part. The PID controller uses the following control equation:

\[
C(s) = K_p + \frac{K_i}{s} + K_d \cdot s
\]  

(5)

where the \( K_p \) is proportional constant, \( K_i \) is integral constant and \( K_d \) is derivative constant.

The main problem in PID controller is tuning process to determine the gains \( K_p, K_i \) and \( K_d \). The performances of system depend on this process. Improper tuning will lead to unexpected performances. The tuning process is
an optimization problem to obtain the best possible performance. The tuning process will be more complex for the plant which has nonlinear properties such as USM. The ability of PSO for solving the optimization problem can be applied to the case of determining the optimal PID parameters for a position control of USM.

Design of the PSO-NDW tuned PID controller for USM is shown in Fig.4. In this system, three PID parameters ($K_p$, $K_i$, $K_d$) will be tuned automatically by PSO-NDW algorithm. Because there are three parameters that should be adjusted, the PSO-NDW algorithm has three dimensions and each particle of the algorithm is candidate solution of the PID parameters. The signal $e(k)$ will be entered for PSO-NDW algorithm and subsequently evaluated in the fitness function to guide the particles during the optimization process. The fitness function for the proposed method is given as:

\[
Fitness = \frac{1}{1 + e(k)^2}
\]

Fitness shows the following-up of evaluation function for the object input. The purpose is to decrease the steady-state error by maximizing the function. The fitness is updated by each millisecond according to the value of $e(k)$.

The USM control for clockwise (CW) rotation and the counter clockwise (CCW) rotation use the different PSO in tracking the object input. Since the characteristics of USM is different depends on the rotation direction, we evaluate both rotations separately.

### 6. Experimental Result

The USM servo system constructed in this study is shown in Fig.5. USM, the electromagnetic brake and the encoder are connected on a same axis. The position information from an encoder is transmitted to the counter board embedded into a Personal Computer (PC). Meanwhile, according to error resulted from the comparison between the output and reference signal, the control input signal which is calculated in PC is transmitted to the driving circuit through the I/O board and oscillator. In each experiment, the load is added or not is discussed to observe the changes of the USM’s characteristics. While the voltage of 12 [V] is given, the force of 0.25 [N.m] could be loaded to the shaft of the USM. The specifications of USM servo system is shown in Table 5.

#### 6.1 A Conventional Hand-tuned PID Controller

Firstly, we used hand-tuned to determine the gains of PID controller. We found that $K_p = 0.3692$, $K_i = 12.175$ and $K_d = 0.000085$, for the best performance after many experiments. Then, we started on USM servo system with 10 runs of clockwise (CW) direction (i.e., $+45$ deg) and 10 runs of counter clockwise (CCW) direction (i.e., $-45$ deg) for unloaded condition. After that, we repeat again for loaded condition, i.e., 0.25 [N.m].

#### 6.2 Self-Tuning PID Controlling using PSO-NDW

The used parameters in PSO-NDW algorithm are as follows: particles number, $n = 5$; cognitive constant, $c_1 = 1.0$;
social constant, $c_2 = 1.0$; maximum inertia weight, $w_{\text{max}} = 0.9$; minimum inertia weight, $w_{\text{min}} = 0.4$. Using the same test condition as before, the PSO-NDW algorithm will tune automatically to determine the optimal gains of PID controller. For comparison, we also used the standard PSO or PSO-LDW with same parameters. According to Table 3, we used nonlinear index number, $x = 1.5$, for PSO-NDW.

Figures 8-11 show the position accuracy of USM in his-
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Figure 10: PSO-NDW PID (unloaded).

Figure 11: PSO-NDW PID (loaded).

Figure 12: Influence of nonlinear index number.

Figure 13: Convergence of fitness.

The influence of nonlinear index number in PSO-NDW based PID controller is shown in Fig.12. It is clear that the best value of this parameter that causes the smallest error is 1.5. This experiment result is similar with the numerical simulation result.

6.3 Comparison of the Mean of Steady-state Error

Table 5 shows the comparison of the proposed PSO-NDW and previous methods in term of average $E_{ss}$ and frequency of zero error (or error $< 0.0011$) in 20 runs. The self-tuned PID controllers (i.e., PSO-LDW, PSO-NDW) can outperform a hand-tuned PID or a fixed-gain PID. The average $E_{ss}$ of the PSO-NDW is smallest or 18.4% (unloaded condition) and 50.34% (loaded condition) lower than PSO-LDW (common strategy of PSO). Moreover, the frequency of zero $E_{ss}$ or error $< 0.0011$ (resolution of the encoder) of PSO-NDW is more often than the previous methods. It means that the ability of proposed method to avoid premature convergence and fall into local optima can be increased.
6.4 Comparison of the Convergence Speed

Figure 13 shows the fitness convergence characteristics of PSO-LDW and PSO-NDW. It is seen clearly that the particles PSO-NDW achieve faster convergence than the previous methods. The particles of PSO-NDW achieved convergence in 0.23 seconds, while the particles of PSO-LDW achieved convergence in 0.27 seconds.

7. Conclusion

The modified PSO using nonlinear decreased inertia weight has been successfully applied to intelligent PID controller for USM. The results are compared with the PSO with linear decreasing inertia weight based PID controller and the fixed-gain PID controller by experimenting on USM servo system. The proposed method has contributed to getting minimum fitness function and to quick convergence ability with better accuracy. According to result of success rate, this method can increase the ability to avoid premature convergence and fall into local optima. The experiment results show that the nonlinear modulation index (\(\alpha\)) plays an important role in searching for optimal solution in PSO-NDW.

References


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