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Identification of Electric Steering Gear Based on Improved Particle Swarm Optimization

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Abstract: In this study, in order to identify the mathematical model of an electric steering gear which is very useful for simulation and design of control system, an improved particle swarm optimization algorithm is proposed. Advantages and disadvantages of particle swarm algorithm are been investigated and demonstrated. The improved algorithm focus on the problem of stagnation in model identification, to solve the problem that particle swarm optimization is easy to fall into local optimal solution, the possibility methods are analyzed and a feasible algorithm is given. Through different discriminating methods, result of arithmetic operation is better than using particle swarm optimization only. With the improved algorithm identification, an experiment is done, the results show that the improved algorithm is very effective, can be used to identify dynamic model the improved particle swarm optimization algorithm can be used for solving the mathematical model of electric steering gear.

Key words: PSO, electric steering gear, identification

INTRODUCTION

The Particle Swarm Optimization (PSO) Algorithm was initially introduced by Kennedy and Eberhart (1995). PSO is an algorithm to solve optimization problem based on the study on a swarm of birds' looking for food. The algorithm is developed rapidly because of its simple concept, easy to implement suitable for solving nonlinear, multi-peak problem (Eberhart and Shi, 2001). However, the basic PSO is very easily to stagnate, or fall into optima, many scholars have made a study and proposed different solutions. For example, change the particle' position with a certain probability, change the particle' velocity with a certain probability, the strategy of adaptive and dynamic adjustment of the inertia weight (Shi and Eberhart, 1998) imitation on adjacent (Dautenhahn, 2002) particles combined with other optimization algorithm and so on (Allahverdi and Al-Anzi, 2006). This study studies the identification process of PSO and analysis some method which can solve the stagnation of PSO algorithm. Improved PSO algorithm is been proposed.

Finally, the improved algorithm is applied to the identification of a model of electric steering gear.

METHODS

This section's main idea is about the basic PSO algorithm. Suppose S is a subspace in D-dimensional space non-empty. Define a real function f on S and N is the number of particles. For the i-th particle, $x_i = (x_{i1}, x_{i2}, ..., x_{iD})^T \in S$ is the location of particle i. $v_i = (v_{i1}, v_{i2}, ..., v_{iD})^T$ is the velocity of particle i. Also define $eval_i = f(x_i)$ as the function value of particle i. The value of i is 1 to N.

Define $pbest_i$ as the minimum function value, $X_i^{pbest} = (X_{i1}^{pbest}, X_{i2}^{pbest},..., X_{iD}^{pbest})^T$ as the corresponding position of particle i, $nbest_i$ as the minimum function value and $X_i^{pbest} = (X_{i1}^{pbest}, X_{i2}^{pbest},..., X_{iD}^{pbest})^T$ as the corresponding position of the adjacent particles. Define $P = \{p = (e_1, e_2,...,e_D)^T \in, e_d^{min} \le e_d \le e_d^{max}, d = 1, 2,..., D\}$ as a non-empty search space (Eberhart and Shi, 2001).

Above all, the basic PSO process can be summarized as follows:

Step 1: Randomly generate the initialization of location and velocity of each particle in the particle swarm based on the search space

Step 2: Evaluate the function value of each particle. $eval_i$ i = 1, 2, ..., N

Step 3: For i = 1, 2,..., N, compare $eval_i$ and $pbest_i$, if $eval_i$ is less than $pbest_i$, let $pbest_i$ equals $eval_i$, X_i^{pbest} equals x_i

Step 4: For i = 1, 2, ..., N, calculate the minimum function value $n\ min_i$ and the corresponding location X_i^{nmf} of adjacent particle i, if $n\ min_i$ is less than $nbest_i$, let $nbest_i$, equals $n\ min_i$, X_i^{nbest} equals X_i^{nmf}

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Step 5: Update the velocity and location of particles as follows:

$$v_{id} = K[v_{id} + C_1 * rand_1 * (X_{id}^{pbest} - x_{id}) + C_2 * rand_2 * (X_{id}^{nbest} - x_{id})]$$
$$x_{id} = x_{id} + v_{id}$$

Check whether the value of the x_{id} and v_{id} are out of given range or not, the range of v_{id} is as follows:

$$v_{id} = \begin{cases} V_d^{max}, & v_{id} > V_d^{max} \\ -V_d^{max}, & v_{id} < -V_d^{max} \end{cases}$$

where, i = 1, 2,.., N, d = 1, 2, ..., D. In the above equations, K, w, C_1, C_2 and $V^{max} = (V_1^{max}, V_2^{max}, ..., V_D^{max})^T$ is the design parameters and $rand_1$, $rand_2$ is independent random number range in [0, 1].

Step 6: If the termination condition has been satisfied, as min ($pbest_1$, $pbest_2$, ..., $pbest_N$) is less than a threshold value or has reached the maximum number of iteration, the calculation is terminated. Otherwise, algorithmic process jumps to step 2

The basic PSO has five design parameters, K, w, C_1, C_2 and V^{max}.

STAGNATION PROCESS

In this section, basic particle Swarm identification algorithm is analyzed in order to find the reasons that may affect the stagnation.

Generally while using particle swarm algorithm for identifying a mathematical model, the initial position and velocity of the particles were assigned by the random number, the initial state of the particle is random.

Since, the algorithm is convergence, therefore, the position and speed of the particles will be convergent with the identify process. In the whole search process, the particles which have excellent location and search speed are always updated to the current value.

Whether the particle's position and particle's earch speed update or not, depending on calculating for each particle's current fitness. Each particle's fitness, needs to be compared with the best fitness' history records. If the calculated fitness is smaller, it was recorded as the best fitness. If the calculated fitness is greater, remains the best historical position of fitness. Therefore, with the increase of the iterative process, particles' fitness may no longer be reduced which will result in stagnation.

Algorithm is no longer going on. Based on the above analysis, the stagnation in the identification process of the basic PSO algorithm is due to the way of updating the optimal fitness. For this, the study improves the basic PSO.

In essence, the concept of fitness and variance are approximate, in practice solving process, the algorithm can determine whether the current location is the optical location by taking advantage of both fitness value and variance.

MODIFICATION ON PSO

Discussion in the previous section has set out the possible improvements to improve the PSO. The stagnation and optimization inaccurate can be improved in several respects. This section focuses on the major improvements of improved particle swarm. A flowchart of improved particle swarm algorithm is drawn.

Application of particle swarm algorithm for model identification, first, the need to solve the problem is that how to determine the particle solver has stalled. Based on the above analysis, some definitions are as follows:

- **Index:** Used to describe the optimal position of the particle in the population in the process of solving the result. Optimal location of the particle at each identification process needs to be recorded
- **Width_indx:** Used to describe the number of the recording position. Particle's position which is been recorded should be the latest. Similarly, identification by the improved PSO algorithm should record the latest real recognition system output and model output, to figure out the variance
- **K_Variance:** Used to describe the relationship between current calculated variance and the minimum variance given in multiples. The minimum variance can be given by experience, or rely on statistics
- **K_Pbest:** Used to describe the relationship between fitness of the current calculated and history optimal fitness given in multiples. Figure 1 shows the flowchart of Improved Particle Swarm Optimization

Improved Particle Swarm Optimization first determines whether the optimal particles positions in record are the same or not.

If all the optimal particles positions in record are consistent with the current value, judgment is that the algorithm is in stagnation, enter restart judgment. Otherwise, enter the next optimization judge.

Judging whether the algorithm is in the restart status or not, if it is, the current variance should be figure out. A minimum variance K_Variance times is given to make sure the current variance is bigger enough. While the current variance value is appropriate, the current fitness is used

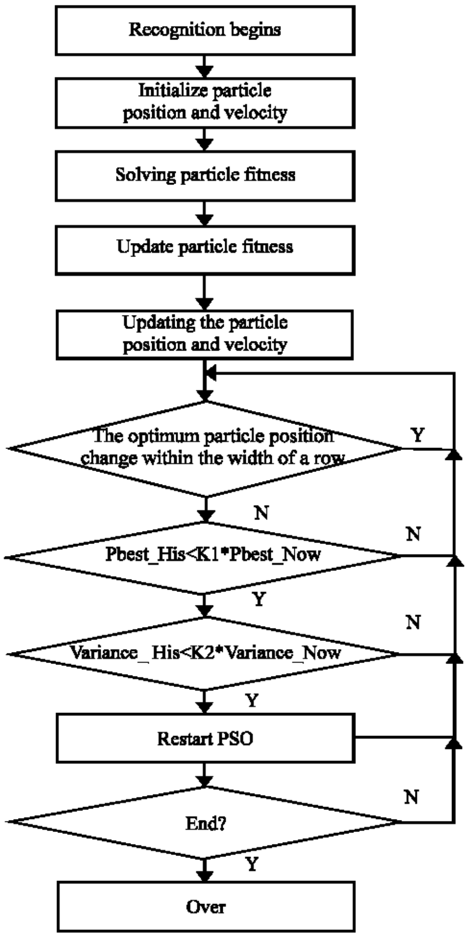

Fig. 1: Flowchart of improved particle swarm optimization

to compare with the optimal fitness in history. K_Pbest is a value for the current fitness and the optimal fitness in history like K_Variance. Based on the above analysis, in this study, the improvement of particle swarm optimization algorithm for identification, focused on particle swarm identify whether in stagnation or not a judgment on whether restart or not.

After the improvement, the first to fifth steps are the same between the improved particle swarm identification algorithm and the particle swarm algorithm. After calculating the particle swarm first five steps, there are width_indx historic optimal particle's positions being recorded. Algorithm enters the improved algorithm. Step 6:

Step 6: Determine the best locations in history records are the same or not. If yes, go to step 7, otherwise, to step 9

Step 7: Judge the current variance is greater than the given minimum variance K_Variance times or not. If so, re-random position and velocity of a given particle, skip to step 9, otherwise go to step 8

Step 8: Determine if the current fitness is greater than the historical optimal fitness K_Pbest times, if so, re-random position and velocity of a given particle, skip to step 2. Otherwise, skip to the step 9

Step 9: Determine whether the algorithm needs to be terminated, if so, end of the algorithm, otherwise skip to step 2

IDENFICATION OF ELECTRIC STEERING GEAR BASED ON PSO AND IMPROVED PSO

In the previous sections, analysis of the improved PSO is been done. In this section, for a certain type of electric steering gear, an experiment was done to verify the improved reliability of the algorithm. First, the approximate mathematical model of electric steering gear is as follows:

$$G(sec) = \begin{cases} 0 \le t < 5sec & \dfrac{220.4}{0.01sec^2 + sec + 110.2} \\ 5sec \le t \le 10sec & \dfrac{330.6}{0.01sec^2 + sec + 110.2} \end{cases}$$

In practical applications, during operation, the model there may be greater changes in parameter values. The former 5 sec, the system' parameters are constant while in the latter 5 sec, the gain of the system becomes large. This model is used to verify the performance of improved particle swarm optimization algorithm for identification process. By comparing the identification results of simple PSO algorithm and improved PSO algorithm, demonstrate the better properties of improved algorithm in stagnation during the identification progress.

During the identification, the system needs to be discrete; identification algorithm is based on the differential equation. The above formula discrete model is given below:

$$y(k) = a_1y(k-1)+a_2y(k-2)+b_0u(k)+b_1u(k-1)+b_2u(k-2)+v(k)$$

b_0, b_1, b_2, a_1, a_2, are the parameters need to identify, $b_0 = b_2$ so this identification parameters is 4, v is white noise the variance is 0.01, u is the input signal for the system, y is the system's output signal.

In order to verify the superiority of the improved algorithm and make the results more apparent, identification results are obtained for comparison in the case of the same input, the electric steering gear model is same.

The input signal of model shown in Fig. 2, is a sinusoidal signal, frequency is 1.6 Hz, amplitude is 6 V.

Identification results figure out by basic particle swarm optimization algorithm are shown in Fig. 3.

Obviously, the identification results are constant. Stable value of each parameters are:

$$a_1 \approx -0.9977,\ a_2 \approx 0.4942,\ b_0 \approx b_2 \approx 0.09,\ b_1 \approx 0.8944$$

Using basic particle swarm optimization algorithm, the electric steering gear model's output and the real output is shown in Fig. 4.

As can be seen from the Fig. 4, when the system's parameters have changed after 5 sec, the system will change the output while the estimating of the output from identification using particle swarm algorithm cannot follow the system output tightly.

The results of identification using improved algorithm is shown in Fig. 5.

Before the model' parameters are changing, the constant parameters are:

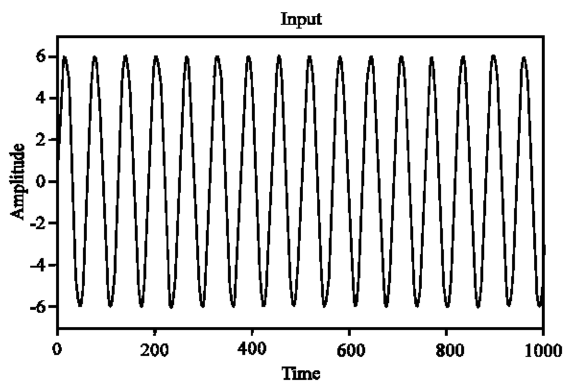

Fig. 2: Input sinusoidal signal of electric steering gear model

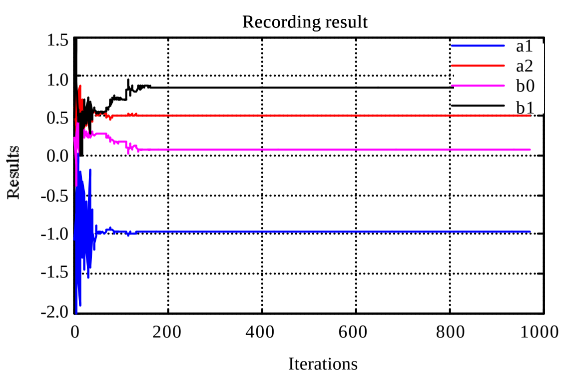

Fig. 3: Electric steering gear model identification's results, using basic particle swarm optimization algorithm

$$a_1 \approx -1.0007,\ a_2 \approx 0.5012,\ b_0 \approx b_2 \approx 0.18,\ b_1 \approx 0.7544$$

During the identify process, there is an obvious algorithm restart operation. After a period of Identify, the constant parameters are:

$$a_1 \approx -0.9893,\ a_2 \approx 0.5122,\ b_0 \approx b_2 \approx 0.245,\ b_1 \approx 1.2108$$

The improved PSO algorithm can make sure restart the identify process while model parameters have been constant.

The electric steering gear' model output and the real output using improved algorithm is shown in Fig. 6.

Comparing the identification results in Fig. 3 and 5, it is easily to find that the improved PSO has a restart process while parameters in the system are changed. Also, Fig. 4 and 6 show that while Particle swarm optimization algorithm has an obvious error between the model output and the real output, the improved PSO can make sure a precise follow.

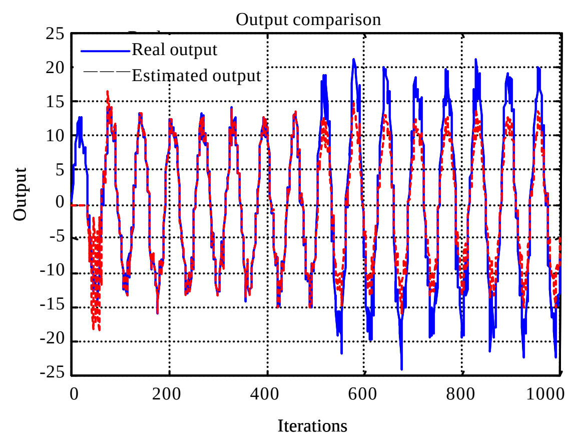

Fig. 4: Electric steering gear model (identified by basic PSO) output and the real output of electric steering gear

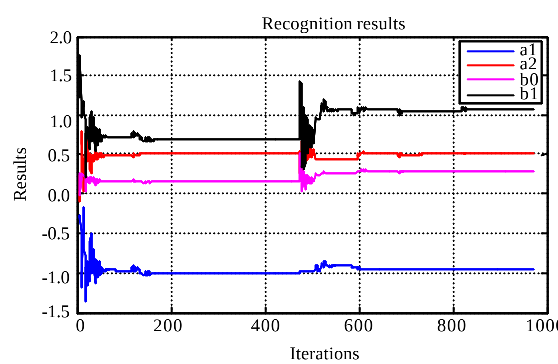

Fig. 5: Electric steering gear model identification's results, using improved particle swarm optimization algorithm

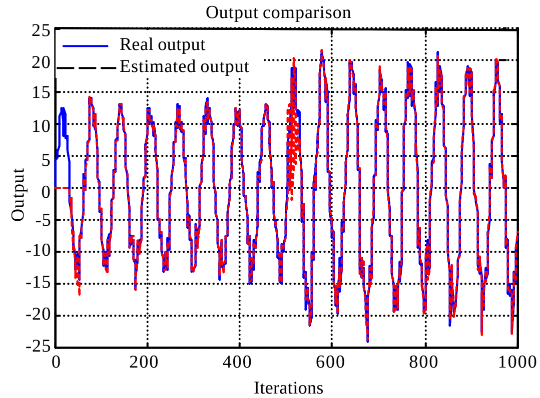

Fig. 6: Electric steering gear model (identified by improved PSO) output and the real output of electric steering gear

The improved PSO can achieve better identification results, model output followed the real output very tight. Also, the improved algorithm achieves to identify time-varying parameters.

CONCLUSION

This study implements an improved particle swarm algorithm which is better than the basic particle swarm algorithm for identification. In this study, two main strategies adapted for improvement is given out. The first is a method to determine whether identify process using particle swarm algorithm is entering the stagnation or not. Which can be achieved by means of recorded multiple times of the optimal position of the optimal particle. The second is a rule that strictly determine whether to restart or not. By programming algorithm, a model identification experiment is done, the result proves that the improved strategy is effective, can be used for Identify time-varying systems. The improved particle swarm algorithm in this study has a better characteristics compared with the original algorithm for electric steering gear identification experiments.

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