A New Parameter Identification Method for Industrial Robots with Friction

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Abstract: Commonly used intelligent algorithms that are used to identify the parameters of friction of industrial robots have poor accuracy or involve complex coding, which is not conducive to their use in engineering. This paper uses the random wandering simulated annealing-based variable-step beetle antennae search (RWSAVSBAS) algorithm to identify the parameters of friction of industrial robots. The moment of friction of the third joint of the robot is experimentally obtained and used to establish a Stribeck friction model. Following this, the RWSAVSBAS algorithm is used to identify the frictional parameters of the industrial robot. These parameters can be used to accurately predict the friction-induced torque of the robot.

Keywords: industrial robot; friction force; random wandering simulated annealing variable step beetle antennae search algorithm; beetle antennae search algorithm

1. Introduction

Frictional forces in industrial robots can cause tracking errors as large as 50% to degrade the accuracy of their trajectories of motion [1]. Models of friction of the industrial robot have thus been widely developed to compensate for this [2–4]. Currently used empirical models of friction for the joints of robot can be divided into two categories: static and dynamic models. Dynamic models can better reflect the dynamic frictional characteristics of the joints of the robot during its motion but have complex structures and are difficult to measure. The Stribeck friction model is representative of static friction models, which can provide better predictions of the frictional force than dynamic models for the section of the robot moving at low speed. This study thus uses the Stribeck model to examine friction in industrial robots [5].

Chao Chen used the differential evolution (DE) algorithm to identify the parameters of a continuous and static friction model for industrial robots, and the experimental results showed that it can adequately respond to the frictional characteristics of such robots [6]. Zhang Jing used the genetic algorithm (GA) to identify the parameters of the Stribeck friction model for industrial robots, and the experimental results demonstrated that this method can adequately identify the parameters of friction [7]. However, coding for the DE algorithm and GA is complicated and unsuitable for use in engineering [8,9]. Wu et al. proposed an improved Stribeck model and then used the Levenberg–Marquardt (L–M) algorithm to identify the frictional parameters of the industrial robot [10]. However, the solution process of the L–M method is susceptible to the initial solution, and it requires a large memory to solve complex problems [11]. Therefore, an algorithm that is simple to code and is highly accurate is needed to identify the appropriate model of friction for industrial robots.
In our previous work, we proposed a random wandering simulated annealing variable step beetle antennae search algorithm (RWSAVSBAS) algorithm. The results of verification showed that it has a higher accuracy than commonly used affine algorithms [12–14]. Because this algorithm was based on the BAS algorithm, which has the advantage of simple coding, we use RWSAVSBAS in this paper to identify the frictional parameters of industrial robots.

The remainder of this paper is structured as follows: The principle of measuring frictional torque in an industrial robot is first introduced in Section 2 and is used to obtain the frictional torque in joint 3 of the robot. Following this, the principle of the RWSAVSBAS algorithm is introduced in Section 3. The performance of the algorithm in terms of identifying the parameters of friction of the robot is compared with that of commonly used improved BAS algorithms in Section 4. The conclusions of this study are summarized in Section 5.

2. Experimental Data Acquisition

2.1. Friction Torque Sampling Principle

To identify the frictional force of an industrial robot, we need to first obtain data on the speed of a certain joint of the robot and the frictional force in it. To this end, the robot joint was made to move at a uniform speed. Its inertial force, Koch force, and centrifugal force can be neglected when they are small [7]. Then, we get

\[ \tau = G(q) + F(q) \]  

(1)

When measuring the frictional force in joint \( i \) of the industrial robot, the other joints are locked. The joint of the robot was then made to move from angle \( \theta_1 \) to \( \theta_2 \) at a uniform speed. The moment of the joint consisted only of friction and gravity at this time, i.e.,

\[ \tau_1 = G(q) + F(q) \]  

(2)

Making the robot joint move from angle \( \theta_2 \) to \( \theta_1 \) with uniform speed, we have:

\[ \tau_2 = G(q) - F(-\dot{q}) \]  

(3)

The frictional forces in the forward and reverse directions of the robot at the same speed are approximately equal. Then, we have:

\[ F(q) = -F(-\dot{q}) \]  

(4)

Then, after eliminating gravity from the above equation, the robot friction moment can be obtained as:

\[ F(\dot{q}) = 0.5 \times (\tau_1 - \tau_2) \]  

(5)

When the robot joint movement direction and gravity are perpendicular, the direction of movement of the robot is horizontal, its gravity is 0, and the measurement of the obtained moment is the friction moment. Then, there is:

\[ \tau = F(\dot{q}) \]  

(6)

2.2. Experimental Data Acquisition

This study used a six-joint industrial robot for experiments. This was a tandem robot consisting of a base, waist, large arm, small arm, and wrist. The third joint of the robot was “taught” to move at a uniform speed in the joint space, and information on its torque was obtained through a built-in current sensor in the servo driver. A schematic of the sampling site is shown in Figure 1.
was obtained through a built-in current sensor in the servo driver. A schematic of the sampling site is shown in Figure 1.

Figure 1. Schematic diagram of robot sampling site.

The sampling steps are as follows

1. Set the trajectory of the robot in the joint space through a demonstrator.
2. Move the robot at a uniform speed in the space according to instructions of the trainer while obtaining information on its frictional torque through the servo drive.
3. The sampled data on the robot’s joint and frictional torque in it are read by the controller.
4. Repeat the above steps by moving the robot in the space at different speeds.
5. Record and process the data.

Signals of the torque in the joint and the frictional torque obtained by sampling are shown in Figures 2 and 3, respectively:

Figure 2. Robot joint torque signal.
The related behavior of wolves has attracted the interest of many scholars. In the original Wandering Antennae base, add the main improvements:

2.3. Friction Modeling

The Stribeck model is the most widely used friction model, which can more accurately reflect the non-linear characteristics of friction, and can be expressed as follows:

$$f(w) = \tau_c + (\tau_s - \tau_c)e^{-\frac{w}{\delta}} + \tau_0 w$$  \hspace{1cm} (7)

where $w$ denotes the speed of rotation of the joint of the robot’s arm, $f(w)$ denotes the frictional moment of the arm, $\tau_c$ and $\tau_s$ denote Coulomb friction and static friction, respectively, $\tau_c$ denotes the coefficient of viscous friction, $\delta$ represents the empirical parameter, which was set to one here according to Tustin’s empirical model [10,15], and $w_s$ denotes the Stribeck model.

Figure 3 shows that when the speed of the robot’s joint was zero, the intersection of the Stribeck model and the vertical coordinate was the static friction $\tau_s$; when its speed was sufficiently high to form a tangent line along $w$, the intersection of the tangent line and the intercept of the $y$-axis was $\tau_c$, and the slope of the tangent line was $\tau_0$. The horizontal coordinate of the intersection of the tangent line at zero velocity and the line formed when $\tau_c$ was parallel to the $x$-axis was $w_s$.

![Figure 3. Friction torque of industrial robot.](image)

Figure 3. Friction torque of industrial robot.

Figure 3 shows that the sampled friction force increased in the low-speed section of the robot, as expected.

![Figure 4. Strubeck model.](image)

Figure 4. Strubeck model.
3. Related Work

The BAS is a single-particle optimization algorithm that has the advantage of a high efficiency of iteration but the disadvantage of easily falling into a local optimum for complex function optimization problems. In our previous work, we proposed the RWSAVSBAS algorithm and used it to identify geometric errors in the parameters of medical robots. This method is superior to the commonly used and improved BAS algorithm and the shuffled frog-leaping algorithm. We thus used RWSAVSBAS to identify the frictional parameters of the industrial robot [12].

3.1. RWSAVSBAS Algorithm Principle

Compared with the BAS algorithm, the RWSAVSBAS algorithm has the following main improvements:

3.1.1. “Wandering Antennae”

In the original bettle left and right Antennae base, add “Wandering Antennae”, “Wandering Antennae” iteration formula as follows:

\[ G_{\text{best new}} = G_{\text{best}} + \sin\left(\frac{2\pi \times P}{h}\right) \times \text{step} \] (8)

The related behavior of wolves has attracted the interest of many scholars [16,17]. \( G_{\text{best new}} \) denotes the global optimal solution of BAS after the wandering search of the wolf pack algorithm. The new solution obtained after the search is compared with the solution obtained by BAS to determine the subsequent direction of movement of the beetle. The accuracy of identification of the local optimum by BAS can thus be improved.

3.1.2. Metropolis Guidelines

The original BAS is prone to falling into local optimal solutions during the search process. Inspired by the metropolis criterion, RWSAVSBAS has an inner and outer double loop, and selectively accepts poor solutions through the metropolis criterion during iterations of the inner loop to improve the accuracy of global optimization of BAS [18].

3.1.3. Variable Step Length

The step size \( \text{step} \) is constant in the original BAS, which has better global search capability when the step size is large but can easily miss the local optimal solution. The RWSAVSBAS algorithm uses a variable step size to update the sizes of the steps of BAS. The initial step size of the RWSAVSBAS algorithm is large as it focuses on a global search, and then decreases gradually in later stages when it performs local search through dynamic adjustments to the step size of BAS. This helps to improve the search capability of the RWSAVSBAS algorithm [19].

The formula for updating the step size in RWSAVSBAS is as follows:

\[ \text{step} = \text{step} \times \text{eta} \] (9)

where \( \text{eta} \) denotes the step adjustment factor, and \( \text{eta} \) takes a value between 0 and 1.

3.2. RWSAVSBAS Algorithm Flow

The flow chart is as follows:

Then, the flow of RWSAVSBAS algorithm can be obtained from Figure 5 as follows [12]:

- A: Initialize the relevant parameters.
- B: Obtain the fitness values of the three antennae of the algorithm.
- C: Search for the optimal solution of the algorithm in the inner loop and select it according to the metropolis criterion \( Q \) times.
- D: Once the iteration of the inner loop is complete, use the outer loop to update the step size of the algorithm as well as the optimal solution.
• E: If the algorithm does not satisfy the termination condition, go to step B. Otherwise, stop the iterations, and use the obtained parameters to identify frictional parameters of the industrial robot.

![Flowchart of RWSAVSBAS Algorithm](image)

**Figure 5.** RWSAVSBAS algorithm flow.

4. *Experimental Results and Analysis*

4.1. *Experimental Parameter Setting*

We set the number of iterations of all algorithms to 1000. The initial step size of the RWSAVSBAS algorithm was set to 0.1, the temperature for simulated annealing $T$ was set
to 10,000 [20], the scale of decay of the annealing coefficient was 0.95, the inner loop Q of the RWSAVSBAS algorithm was 100, the h-value of the “wandering antennae” of the inner loop was 100, the h-value of the “wandering antennae” of the outer loop was 1000, the rate of change in step size $\alpha$ was 0.98, the number of instances of detection of the step and antennae of the beetle was set to 0.98, the antennae of the inner loop were set to 100, the ratio of the step of the beetle to the distance $d_0$ between the antennae was set to three, and $c$ was set to three. The parameters of the variable-step beetle antennae search (VSBAS) algorithm were the same as those of the RWSAVSBAS algorithm, 0.1 and 0.98, respectively [19]. Values of step$_{max}$ and step$_{min}$ for the improved beetle antennae search (IBAS) algorithm were set to 0.3 and 0.1, respectively, and the remaining values were the same as those of the RWSAVSBAS algorithm [21].

4.2. Adaptation Function

In this paper, the error between the friction torque predicted by the Stribeck model and the actual measured torque is defined as:

$$Y_i = F_i - \vec{F}_i$$  \hspace{1cm} (10)

In the above Equation (10), $F_i$ denotes the friction moment value predicted by the Strubeck model, $\vec{F}_i$ denotes the actual sampled friction moment value, $i$ denotes the $i$th sampling point, and $Y_i$ denotes the friction moment error predicted by the Strubeck model for the $i$th time. Then, the objective function is defined as:

$$\min \left( \sum_{i=1}^{N} Y_i^2 \right)$$  \hspace{1cm} (11)

In this paper, there are 17 actual sampling points, i.e., $N = 17$, and the objective function is the sum of the squared errors of all sampling points [8].

4.3. Experimental Results

4.3.1. Iterative Optimization Curve Comparison

Owing to the stochastic nature of intelligent algorithms, we ran each of the VSBAS, IBAS and RWSAVSBAS algorithms eight times to obtain their average curves of adaptation of the iterations eight times, as shown in Figure 6.

![Figure 6. Comparison of the average adaptation curves of each algorithm optimized for 8 iterations.](image-url)
The RWSAVSBAS algorithm was the most efficient on average, and converged quickly to close to the optimal solution early on. The VSBAS was the slowest to converge in the early stages. Table 1 shows the average fitness, maximum fitness, and minimum fitness of each algorithm.

Table 1. Comparison of the average adaptation degree of each algorithm.

| Algorithms   | Average Fitness | Fitness (Max) | Fitness (Min) |
|--------------|-----------------|----------------|----------------|
| VSBAS        | 0.60            | 1.86           | 0.10           |
| IBAS         | 0.42            | 0.83           | 0.09           |
| RWSAVSBAS    | 0.00013         | 0.00014        | 0.00013        |

Table 1 shows that the average fitness of the RWSAVSBAS algorithm was 0.00013, and those of the VSBAS, IBAS were 0.60 and 0.42, respectively. Thus, the average fitness of the RWSAVSBAS algorithm was three orders of magnitude smaller than the other algorithms, and it was thus more stable. The maximum fitness of VSBAS was 1.86, which was the highest of all algorithms, followed by IBAS with 0.83, and RWSAVSBAS with only 0.00014. The RWSAVSBAS algorithm thus still delivered the best performance in terms of maximum fitness. The RWSAVSBAS algorithm had a value of 0.00013 for the minimum adaptation, which was 2–3 orders of magnitude smaller than the 0.10 recorded by VSBAS, and 0.09 by IBAS.

4.3.2. Frictional Torque Error Comparison

The frictional parameters of the four algorithms in case of minimum adaptation were selected and substituted into the above Stribeck model. Figure 7 shows the predicted errors in the minimum frictional moment for each algorithm.

![Figure 7. Comparison of minimum error of friction torque.](image)

It is clear from Figure 7 that the errors in the prediction of the IBAS and VSBAS algorithms were larger, with the maximum errors of VSBAS and IBAS at around 0.15 N.m and the overall errors at around 0.08 N.m. The RWSAVSBAS algorithm delivered the best performance in terms of errors in the high-speed and low-speed parts of the moving robot. Error of the frictional torque predicted by it was small and tended toward zero. Therefore, the RWSAVSBAS algorithm recorded the best performance overall.
4.3.3. Comparison of Predicted Friction Moments

A combination of the results in Table 1 and Figures 6 and 7 shows that the RWSAVSBAS algorithm could accurately predict the frictional torque of the robot. We thus chose the parameters corresponding to the minimum fitness value of this algorithm over eight iterations as ones to identify friction. The values of each parameter are shown in Table 2.

Table 2. Strubeck model identification parameter values.

| Parameters | τ_c | τ_s | w_s | τ_v |
|------------|-----|-----|------|-----|
| Identifying value | 0.084 | 0.641 | 0.066 | 0.0026 |

The curve of frictional moment predicted by the RWSAVSBAS algorithm, which was obtained by substituting the parameters of the Strubeck friction model from Table 2 and the measured velocity data into Equation (7), is shown by the red line in Figure 8. It is also compared with the empirically acquired curve of the frictional moment.

Figure 8. Friction torque prediction curves of RWSAVSBAS algorithm.

Figure 8 shows that the difference between the frictional torque predicted by the RWSAVSBAS algorithm and the empirically measured frictional torque was not significant, and the trend of the former was consistent with that of the latter in both the low-speed and the high-speed stages. This was expected. This verifies the accuracy of the frictional parameters identified by the RWSAVSBAS algorithm.

5. Conclusions

(1) In order to improve the accuracy of the friction parameter identification of industrial robots, this paper firstly establishes the friction moment of the robot by demonstration, and then uses the Strubeck model to establish the friction model of industrial robots. In this paper, a new Beetle Antennae search algorithm, RWSAVSBAS, is used to identify the friction model parameters of industrial robots. The experimental results show that the RWSAVSBAS algorithm maintains the advantage of BAS algorithm with fewer parameters, and at the same time has better recognition accuracy compared with other common improved Beetle Antennae search algorithm algorithms.

(2) This study did not consider the effects of temperature, load, and other factors when measuring the frictional force. Future work in this area should focus on the effects of
these external factors on the frictional force. Moreover, the RWSA VSBAS algorithm was used here only to identify the frictional parameters of industrial robots in series. Subsequent work should consider this task for industrial robots operating in parallel.

(3) The friction model identified by RWSA VSBAS will be written into the controller, and the torque feedforward is sent down from the software algorithm layer for control. The torque feedforward can effectively improve the following performance of the robot, and the theoretically derived robot dynamics generally ignore the effect of friction, so for the actual robot control, getting an accurate friction model can also improve the robot control performance, which includes dragging and dragging demonstration and collision detection of various human–robot collaboration functions that are inseparable from friction compensation.

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