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Simulated Annealing Algorithm for Friction Parameters Identification

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Abstract

The present study is concerned with friction parameters identification in the pushing system of projectile of large caliber cannon howitzer. Coulomb model (CM) is adapted to build friction model in the process of pushing projectile. Random direction search algorithm (RDSA) is probably to get into the local best because of the large number of parameters to identify. So simulated annealing algorithm (SAA) based on continuous search space (CSAA) and based on discrete search space (DSAA) is applied to identify friction parameters. The identification results show that both CSAA and DSAA have better accuracy and convergence than RDSA, and CSAA has better accuracy than DSAA.

Keywords*: parameters identification, Coulomb model, simulated annealing algorithm*

1. Introduction

In the pushing system of projectile of large caliber cannon howitzer, dynamic performance of projectile is greatly affected due to the existence of friction. It's necessary that friction parameters are identified to develop control strategies in engineering design and analysis. Friction is a typical nonlinear process of mechanic system, which includes Static Friction, Coulomb Friction, Stribeck Effect and some other complex objects. In the process of pushing projectile, the impact of vibration and collision is inevitable, which increase the complex of parameters identification. The pushing system of projectile of large caliber cannon howitzer is a typical nonlinear system with complex friction parameters and interference terms, which sets forth more requirements for parameters identification methods.

It is very important to choose a suitable model in the process of model identification parameters. The dynamic process of the friction phenomenon can't be truly reflected by using the classical friction model including Coulomb friction and viscous friction in practice. At present, there are many friction models which have been proposed such as Karnopp [1] model, LuGre [2] model and integrated model. Canudas proposed LuGre model in 1995. It can accurately describe complex dynamic and static characteristics in the process of friction. Considering the impact of collision and vibration, Haonan Ye developed Augment Coulomb Model [3] (ACM) and brought a series of sine signal linear combination in Coulomb friction in order to get a more precise model.

For model parameters identification, many traditional optimization algorithms and tools have been widely used. Hartman [4] proposed randomly direction search algorithm (RDSA) in 1972. Later, Quan Zhen [5] developed RDSA to reduce the computational in 1978. But these methods have their own limitation such as local convergence, inefficient and easy to get into the local best. Many problems are effectively solved by modern optimization method. Some intelligent algorithm have been widely used to solve different kinds of problems [6-7]. Metropolis proposed the idea of simulated annealing in 1953, and Kirkpatrick applied it in combinatorial optimization problems.

In this paper, an important experiment is carried out to obtain the data of pushing projectile process. Velocity signal is calculated by differencing displacement signal. To get the proportion of the low frequency component, a low pass filter is designed to eliminate the high frequency component of the data. Simulated annealing algorithm (SAA) based on two kinds of neighborhood structure is proposed. SAA based on continuous search space (CSAA) and

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discrete search space (DSAA) is adapted to identify friction parameters. At the same time, error men square (EMS) is used as a criteria to compare the pros and cons of different methods.

2. Friction Model

2.1 Coulomb Model (CM)

When only friction is considered in system model, CM divides system friction in three main influence factors:
(1) Coulomb Friction (CF): The friction during the pushing process of the projectile
(2) Static Friction (SF): The friction which prevents the projectile from static to dynamic
(3) Viscous Friction (VF): The friction produced by viscous effect between interface materials
The general form of CM is as follows:

$$F_f = F_c \operatorname{sgn}(v) + (F_s - F_c)e^{-(\frac{v}{v_s})^{\delta}} + F_v v \quad (1)$$

where F_c is coulomb friction, F_v is viscous friction coefficient, F_s is static friction, v_s is Stribeck velocity, and δ is empirical parameter.
In general, Tustin model is chosen when δ =1. So CM can be modified as follows:

$$F_f = F_c \operatorname{sgn}(v) + (F_s - F_c)e^{-\frac{v}{v_s}} + F_v v \quad (2)$$

2.2 Modeling for the Process of Pushing Projectile

In the process of pushing projectile in Figure 1, the force of projectile F can be divided into two parts: F_p and F_f. F_p is the projectile force given by the feeding system. F_f is the projectile friction given by the channel. System model can be expressed as:

$$F = F_p - F_f \quad (3)$$

Considering the impact of vibration of the projectile and collision between projectile and channel, a series of sine signal linear combination are brought in modeling. F_p can be expressed as:

$$F_p = F_0 + \sum_{i=1}^{N} F_{pi} \sin(i\omega t + \varphi_i) \quad (4)$$

After substituting Eq. (4) to Eq. (3), the projectile force can be expressed as:

$$F = F_0 + \sum_{i=1}^{N} F_{pi} \sin(i\omega t + \varphi_i) - (F_c \operatorname{sgn}(v) + (F_s - F_c)e^{-(\frac{v}{v_s})^{\delta}} + F_v v) \quad (5)$$

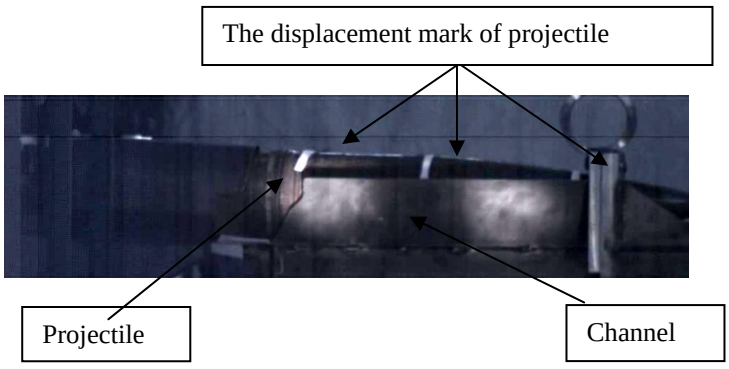


Figure 1. The Pushing System of Projectile

In Eq. (5), a precise model is got if N→∞. Considering the feasibility of calculation, set N as 10. There are twenty six parameters $(B_1, B_2 \ldots B_{26})$ need to be identified in Eq. (5).

3. Parameter Identification Methods

3.1 Random Direction Search Algorithm (RDSA)

Random direction search algorithm [8] is a method to constrain optimization problems. It's widely used in optimization of mechanical design. The iteration scheme of RDSA is written as follows:

$$x^{(k+1)} = x^{(k)} + \alpha s^{(k)}, k = 0,1,\ldots \quad (6)$$

where $s^{(k)}$ is random search direction of k times iterations, α is step factor.

RDSA has advantages such as simple principle, strong applicability and lower requirements of the behavior of objective function. But it has limitation such as local convergence, inefficient and easy to get into the local best.

3.2 Simulated Annealing Algorithm (SAA)

SAA is a generic probabilistic algorithm. It's used to find the optimal solution of the optimization problem with a large search space.

3.2.1 The Basic Principles of SAA

Annealing is a physical process[9]. A metal solid is heated to a certain temperature, and all molecules move freely in the state space D. As the temperature dropped, these molecules gradually stay in a different state. At the lowest temperature, molecules re-arrange in certain structure. Statistical mechanics studies show that molecules meet Boltzmann probability distributions when molecules stay in the state r and at a temperature T. It's expressed as:

$$\Pr\{\overline{E} = E(r)\} = \frac{1}{Z(T)} \exp(-\frac{E(r)}{k_B T}) \quad (7)$$

where $E(r)$ is the energy of state r. k_B is Boltzmann's constant. $Z(T)$ is the normalization factor of probability distributions:

$$Z(T) = \sum_{s \in D} \exp\{-\frac{E(r)}{k_B T}\} \quad (8)$$

If T trends to 0

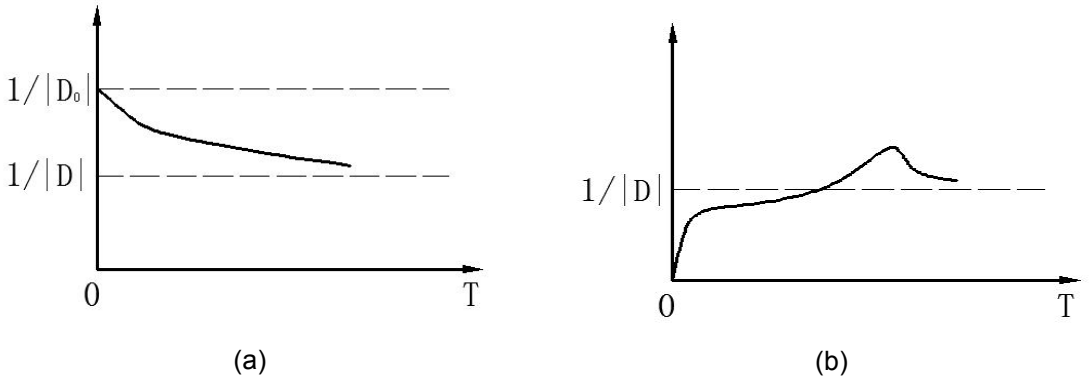
$$\Pr\{\overline{E} = E(r_{\min})\} \to \frac{1}{|D_0|}, T \to 0 \quad (9)$$

where $r_{\min}$ is the lowest energy state. $|D_0|$ is the set of lowest energy states. So it's concluded that the probability of the molecules staying in the lowest energy state trends to 1. The changing trend of probability which the molecules stay in the lowest energy state is shown in Figure 2(a).

For molecules in non-lowest energy states, their probability is $1/|D|$. $|D|$ is the number of state space D. It may be above. When T trends to zero, the probability trends to zero. The changing trend of probability is shown in Figure 2(b).

From the above discussion, the lower temperature is, the higher the probability of the lower energy state is. In extreme conditions, only the probability of the lowest energy states is not zero. We can solve combinatorial optimization problems by analogy to metal objects annealing as follows:

Combinatorial Optimization	Metal Objects
Solution	State
Optimal Solution	Lowest Energy State
Cost Function	Energy



(a) (b)

Figure 2. The changing trend of probability; a) the lowest energy state, b) the non-lowest energy state

The optional solution of combinatorial optimization is by analogy to lowest energy in metal objects annealing. So the solving process of combinatorial optimization problem $z = \min\{ f(x) \mid g(x) \geq 0, x \in D \}$ is by analogy to annealing process:

$$\begin{aligned} &\min\ f(x) \\ &s.t. g(x) \geq 0 \\ &x \in D \end{aligned} \tag{10}$$

where $f(x)$ is cost function, $g(x)$ is constraint equation, D is domain.

3.2.2 The Process of SAA

STEP1 Choosing an initial solution x_0; $x_i := x_0$; $k := 0$; $t_0 := t_{\max}$ (initial temperature);

STEP2 If the temperature reaches within the loop stop condition, then jump to STEP3; else, x_j is randomly chosen from neighborhood $N(x_i)$, calculating $\Delta f_{ij} = f(x_j) - f(x_i)$; if $\Delta f_{ij} \leq 0$, then $x_i := x_j$, else if $\exp(-\Delta f_{ij} / t_k) > random(0,1)$, then $x_i := x_j$; repeat STEP2;

STEP3 $t_{k+1} := d(t_k)$; $k := k+1$; if meeting stop condition, end calculation; else, return STEP2

3.2.3 SAA for Model

1. Cost function of SAA

Cost function of SAA can be given as:

$$Cost = \sum_{i=1}^{n} (F(i) - F^*(i))^2, i = 1,2,\ldots n \tag{11}$$

Where F is actual force, F^* is theoretical force, and n is the length of data. When cost is smaller, it shows that parameters are better and the performance of identification is better.

2. Neighborhood structure of SAA

The range of optimal parameters $(B_1, B_2 \ldots B_{26})$ known by prior knowledge is $[a_i, b_i], i = 1,2,\ldots,26$. k - parameters are randomly selected from 26 parameters:

$$B_{m_j}, m_j \in \{1,2,\ldots,26\},\ j = 1,2,\ldots,k$$

CSAA:

N variables re-value randomly

$$B_{m_j} = rand \cdot (b_{m_j} - a_{m_j}) + a_{m_j} \tag{12}$$

DSAA:
N variables is encoded 0-1 code

$$S = \begin{pmatrix} 1,2,\ldots,n \\ *,*,\ldots,* \end{pmatrix} \tag{13}$$

where the first row of S represent ten positions, the second row of S represent ten 0-1 codes, which is binary code of B_{m_j}. The neighborhood of the solution is as below:

$$N(S^{'}) = \left\{ S \,||\, S - S^{'} |= \sum_{i=1}^{n} | S_i - S_i^{'} | \leq k, k \geq 1 \right\} \tag{14}$$

3. Control of the annealing
(1) Initial temperature:
According to the theory, initial temperature can be estimated as follow:

$$\begin{aligned} \delta &= \max\{ f(j) \mid j \in D \} - \min\{ f(j) \mid j \in D \} \\ t_0 &= K\delta \end{aligned} \tag{15}$$

where $K = 10$.
(2)The method of temperature dropping

$$t_{k+1} = \alpha t_k, k \geq 0, 0 < \alpha < 1 \tag{16}$$

If α closes to 1, temperature drops slowly. α is set as 0.95.
(3) The principle of the algorithm ending
The algorithm ends when temperature is less than the threshold and the cost function don't change.

3.2.4 The Characteristics of SAA

SAA has the advantages such as the simple calculation process, universal, strong robustness, suitable for parallel processing and can be used to solve complex nonlinear optimization problems.

4. Result of Experiment

4.1 Data Acquisition and Preprocessing

In the experiment, three positions of the projectile marked white bright streaks are selected as the projectile displacement signal sign in figure 1. The parameters of the experiment are defined as follow: sampling frequency is 1kHz and the total recording time is 0.272 seconds.

Considering system response by collision is more abundant than that by friction and pushing force in high frequency. The error is produced by the difference of the displacement signal. By using Butterworth low pass filter to process the difference, velocity signal is got and shown in Figure 3. The projectile acceleration signal is obtained and shown in Figure 4.

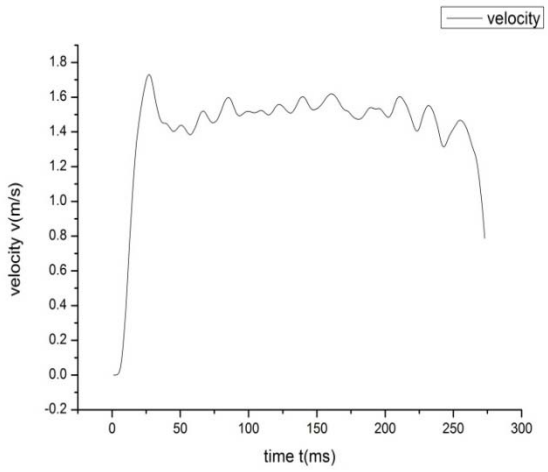


Figure 3. Velocity Signal

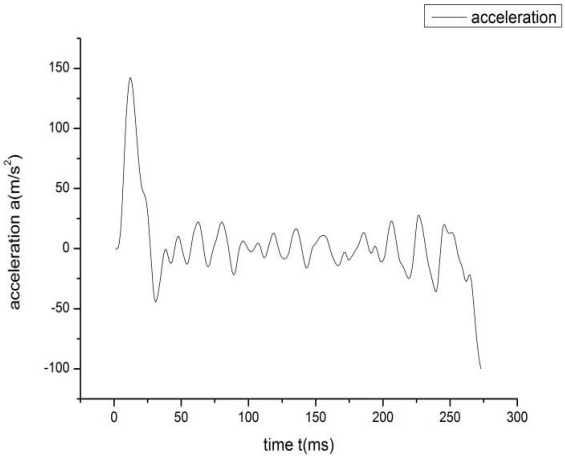


Figure 4. Acceleration Signal

4.2 Identification Results and Analysis

The results of identification for the methods of RDSA, CSAA and DSAA are shown in Table1~4 and Figure 5.

Table 1. Results of parameters identification

Parameters	RDSA	CSAA	DSAA
F_0	444.2	432.7	430
F_c	35.71	30.00	30
F_v	3763.9	3749.9	3750
F_s	186.16	189.99	190
V_s	0.119	0.121	0.125

Table 2. Results of parameters identification

Parameters	RDSA	CSAA	DSAA
F_{p1}	678.1	667.5	664.3
F_{p2}	996.5	998.1	996.2
F_{p3}	1113	1118.9	1114.9
F_{p4}	876.3	879.9	880
F_{p5}	546.1	559.9	560
F_{p6}	44.80	49.99	50
F_{p7}	268.5	279.9	280
F_{p8}	133.5	139.9	140
F_{p9}	411.0	413.0	414.9
F_{p10}	9.39	9.99	10.00

Table 3. Results of parameters identification

Parameters	RDSA	CSAA	DSAA
φ_1	0.74	0.71	0.69
φ_2	0.98	0.96	0.95
φ_3	1.26	1.24	1.23
φ_4	1.51	1.49	1.48
φ_5	1.57	1.57	1.55
φ_6	0.454	0.499	0.500
φ_7	0.001	0.001	0.001
φ_8	0.005	0.001	0.001
φ_9	0.002	0.001	0.001
φ_{10}	1.19	1.00	1.00

Table 4. Error mean square (EMS)

Method	RDSA	CSAA	DSAA
EMS	59209	58322	58335

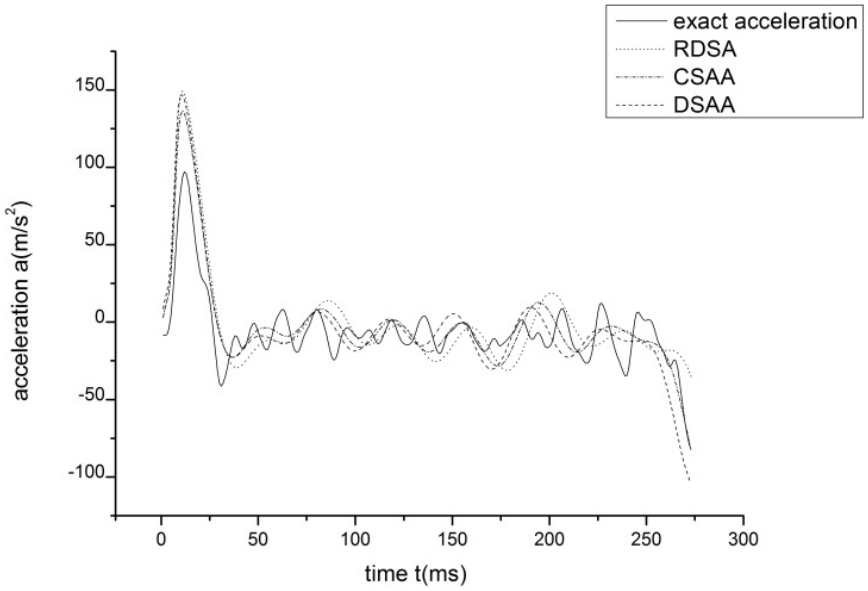


Figure 5. Actual Acceleration and Theory Acceleration Comparison

5. Conclusion

In this paper, identification methods of CSAA and DSAA are applied to identify friction parameters. As a traditional optimization method, RDSA can't solve optimization problem effectively which may have local optimal solution. SAA is an extension of local searching algorithm. Three different results are obtained by RDSA, CSAA and DSAA. Some recommendations based on these results are:

(1) In comparison to RDSA, the identification error of CSAA and DSAA are reduced effectively.
(2) The identification parameters based on CSAA and DSAA converge to almost the same value and have more stability in comparison to RDSA.

(3) If the time of searching is sufficient, the identification parameters of CSAA have a better accuracy than DSAA because DSAA produces errors during the coding procedure.

If parameters of SAA cannot be controlled effectively, SAA will degenerate to local search algorithm. SAA has the disadvantage of lower convergence speed, long execution time and the performance of the algorithm sensitive with initial values and parameters. Future work of this study would do more research on the annealing control of CSAA and DSAA to improve algorithm efficiency.

Acknowledgements

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