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The Feedforward Friction Compensation of Linear Motor Using Genetic Learning Algorithm

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Abstract: This paper proposes a feedforward friction compensator based on LuGre friction model. The various parameters in both the friction model and the system plant model would be coarsely estimated by the various experiments, and then the genetic algorithm (GA) finely optimizes the key parameters by a single identification experiment. When compared with the conventional black box learning algorithm, this model-based compensator uses only five parameters to model the nonlinear friction phenomenon and the corresponding convergent rate of parameters is fast in the learning process. Finally, the friction compensated performance of proposed algorithm is evaluated and compared with the traditional uncompensated system. The simulated and experimented results show that the velocity tracking error is drastically improved by the feedforward friction compensator in a linear motor motion system.

1. INTRODUCTION

Friction is one of many forces present and, at most time, induces undesirable phenomena such as stick-slip oscillation, steady state error, and poor tracking performance. The good friction models are required so that we could understand more about the friction phenomena. There are many friction models proposed in different research fields, such as tribology, dynamics, and control. In general, friction model can be grouped into two kinds, i.e., the static friction model and the dynamic friction model. While the static model defines static map between velocity and friction force which has static, coulomb, and viscous friction components, the dynamic friction model predicts the nonlinear behaviours of friction under micro-dynamic scale and the macro-dynamic scale.

The classical static models could not provide any information about presliding displacement (micro-slip) in stiction regime and friction lag. Therefore, Armstrong-Helouvry proposed a seven-parameter integrated friction model to include various observed friction phenomena. This model comprised parameters to account for the presliding displacement, Coulomb, viscous, and Stribeck friction. The behavior of state variable friction models, called dynamic friction models, resembles the behavior of a stiff (nonlinear) spring in pre-sliding region, and also describes the behaviors of slipping region without switch mechanism. Dahl model was the first model in the form of state variable, which could predict friction lag between velocity reversals and leaded to hysteresis loops. Canudas de Wit *et al.* extended the Dahl model by including arbitrary steady state characteristics, such as Stribeck effect, and proposed a modified Dahl model (or the LuGre friction model). This model captured most of the friction behavior that had been observed experimentally. Swevers *et al.* further improved the prediction of presliding behavior by modifying the LuGre model. This new integrated model incorporated a hysteresis function with non-local memory and arbitrary transition curves.

When the requirement in tracking and positioning accuracy is stringent, a good dynamic friction model is necessarily associated with a suitable control scheme**.** There are two classes of compensation techniques, i.e., non-model-based and model-based compensation for friction. The non-model-based compensation techniques include stiff PD control, integral control, EKBF, and learning feed-forward compensation, etc. Basically, the stiff PD control is implemented in a high proportional loop gain with differential controller to tune the damping value. Some researchers modified the simple PD controller by adding another compensators, such as integral controller and nonlinear friction compensators, to improve system performance under friction. Ray *et al.* presented and validated an extended Kalman-Bucy filter (EKBF)-based friction compensation method. This friction estimator was constructed using EKBF by treating friction torque as an unknown state element and estimating the augmented state. Otten *et al.* studied a direct drive linear motor and found that force ripple and friction were the major disturbances to the system. They proposed a learning feed-forward controller structure to eliminate the positional inaccuracy due to force ripple, friction, and any other disturbances.

As motioned above, several friction models have been widely studied for providing a good understanding of friction. Based on different models, the model-based compensation strategies can be employed. Friedland and Park presented an adaptive compensation algorithm for a presumed constant Coulomb friction model. In their approach, a nonlinear reduced-order observer was introduced, which forced the error between the estimated and actual parameter vector to converge asymptotically to zero. Amin *et al.* and Tafazoli *et al.* used this nonlinear observer to estimate dynamic friction. They modified the original nonlinear observer by appending a velocity observer. Leonid *et al.* considered the observer design of LuGre model-based compensation for friction compensation. They proposed some new insights into numerical real time implementation of friction compensators for various LuGre type model. Ro *et al.* designed a robust tracking control with a friction estimate and a direct disturbance observer (DOB). The approximation of friction can be obtained by multilayer neural networks (MNN) or radial basis function networks (RBFN). Horng *et al.* proposed a LuGre model-based neural network friction compensation algorithm for a linear motor stage. For matching the friction phenomena in both the motion-start region and the motion-reverse region, the LuGre dynamic model is employed into the proposed compensation algorithm. Peng *et al.* proceeded to design a servo system for the hard drive using an enhanced composite nonlinear feedback control technique with a simple friction and nonlinearity compensation scheme.

The LuGre model can capture most of the known frictional behaviors, and is suitable for control. In this paper, a feedforward friction compensator based on LuGre friction model is proposed. The key parameters in this model are firstly estimated by various experiments of parameter identification. According to the above identified results, GA finely optimizes the key parameters, using reasonable search space, by a single experiment and the well tuned parameters will be adopted into the feedforward friction compensator. When compared with the conventional black box learning algorithm, this mode-based compensator uses only five parameters to model the nonlinear friction phenomenon and the corresponding convergent rate of parameters is fast in the learning process. Finally, the friction compensated performance of proposed algorithm is evaluated and compared with the traditional uncompensated system. The simulated and experimented results show that the velocity error is drastically improved by the feedforward friction compensator in a linear motor motion system.

2. DYNAMICS OF LINEAR MOTOR STAGE

The linear slide systems are the most common applications of motion control. From the friction study viewpoint, the existing backlash and compliance in a ball-screw-driven system may induce nonlinear phenomena together with multi-source friction effects. This makes it practically impossible to distinguish friction from other nonlinear effects. On the contrary, linear-motor-driven systems are free from the complicated situation because nonlinear backlash and multi-source frictions do not exist in the systems. The observed friction behaviors will be quite different for the same reason. In this paper, a linear-motor-driven motion system is under study.

2.1 Hardware Setup

The experimental motion system setup illustrated in Fig. 1, consists of following components: a linear-motor-driven motion system and a PC with a DAC and encoder interface. The linear motor system is composed of a linear motor (PLSA-A-2-NC) and a servo amplifier (SERVOSTAR CD) operating in torque (current) mode, both of which are made by Kollmorgen Corporation. Some specifications are listed in Table 1. The linear motor is assembled with two linear guide-ways and other mechanical components to form the single-axis motion stage. A linear scale (RENISHAW RGH22Y, resolution 0.4 micrometer) provides position information for the vector control of servo amplifier.

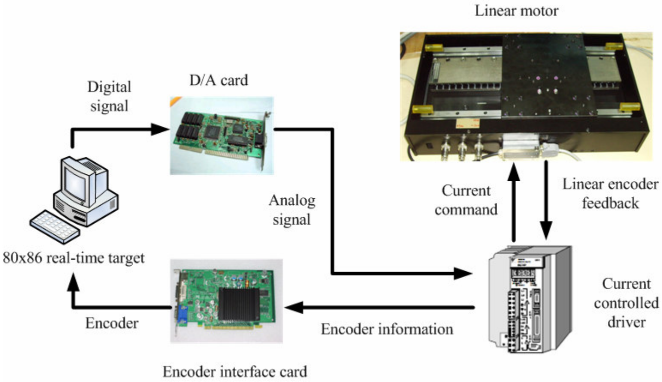


Fig. 1. The experimental linear-motor-driven motion

Table 1
Specifications of linear motor (PLSA-A-2-NC)

Specifications		**Units**
Peak force	205	N
Peak current	9.0	A
Electrical resistance	5.0	Ω
Electrical inductance	2.8	mH
Force constant	23.0	N/A_{rms}

2.2 Modeling of the Linear Motor Stage

In general, the bandwidth of current loop is very fast as compared with mechanical system. If the high frequency modes are ignored, the system equation can be simplified as

$$ma + bv + F_f = u \qquad (1)$$

where m is the inertia (equivalent mass); $bv + F_f$ is the friction force; and u is the input force to the system generated by a current-controlled servo amplifier.

2.3 The Dynamic LuGre Model

The LuGre model, proposed by Canudas de Wit *et al.*, can capture most of the known frictional behaviors, and is suitable for control. In this section, the LuGre model is briefly described first. The interface of two contact rigid bodies can be modeled as a lot of elastic bristles. When a tangential force is applied, the bristles will deflect like springs which give rise to friction force. If the force is sufficiently big, some of the bristles deflect so much that they will slip. The LuGre model is based on the average behavior of the bristles and can be described as follows.

$$\frac{dz}{dt} = v - \frac{|v|}{g(v)}\sigma_0 z \qquad (2)$$

$$F_f = \sigma_0 z + \sigma_1 \frac{dz}{dt} \qquad (3)$$

where z is the average bending displacement of bristles; v is the relative velocity between the two bodies; σ_0 and σ_1 are the stiffness and damping coefficient of average behavior of bristles; F_f is the friction force due to bristles' deflection, and $g(v)$ is a positive function of velocity, and it can be described as

$$g(v) = F_s - (F_s - F_c)(1 - e^{-\left|\frac{v}{v_s}\right|}) \qquad (4)$$

where F_c is the Coulomb (kinetic) friction, F_s is the stick force, and the constant v_s is the Stribeck velocity. A term accounting for the viscous friction could be added to (3), and the whole friction force becomes

$$F = \sigma_0 z + \sigma_1 \frac{dz}{dt} + bv \qquad (5)$$

where b is the viscous friction coefficient.

2.4 Parameter Identification

This previous work by the authors deals with the measurement, identification of friction parameters of dynamic LuGre model in linear motor stage. The identification procedure for the linear motor parameters are: 1) inertia constant, 2) viscous coefficients, Stribect velocity, coulomb and maximum stick force and 3) bristle stiffness and damping coefficients. From the experiments, the identified parameters of this dynamic friction model are list in Table 2.

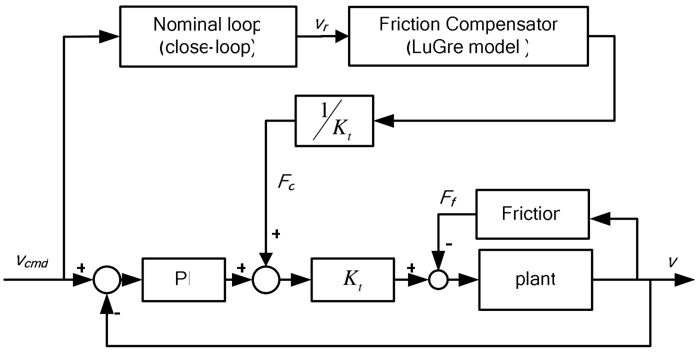
Table 2
Parameters of LuGre Friction model

Symbol	Value	Unit
m	5.557	*kg*
b	6.6135	*Nm/sec*
F_S	8.999	*N*
F_C	5.999	*N*
v_S	0.00055697	*m/sec*
σ_0	3.9162×10^5	*N/m*
σ_1	4.4248×10^3	*Nsec/m*

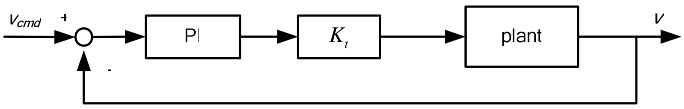
3. PROPOSED FEEDFORWARD FRICTION COMOENSATOR

3.1 The Scheme of Feedforward Friction Compensator

The benefits of feedforward friction compensator versus in feedback are that, 1) feedforward compensation is principally faster than feedback compensation; 2) feedback loop may endanger stability but feedforward loop does not injure the stability. In this paper, a novel feedforward friction compensator is proposed in Fig. 2(a). In this figure, the model of linear motor is depicted with plant and friction, the detail is shown in (1); the nominal loop is a closed velocity loop without the effect of friction; and the friction compensator is the LuGre model, as shown in (2) and (3). When the well tuned parameters of LuGre model are applied in the friction compensator and the corresponding compensated force F_c is fed into the force command, this scheme will be reduced to a nominal velocity loop, as shown in Fig. 2(b). That implies that the friction force F_f is completely compensated by the proposed feedforward friction compensator.



(a)



(b)

Fig. 2. The friction compensation scheme, (a) feedforward friction compensation, (b) nominal velocity loop.

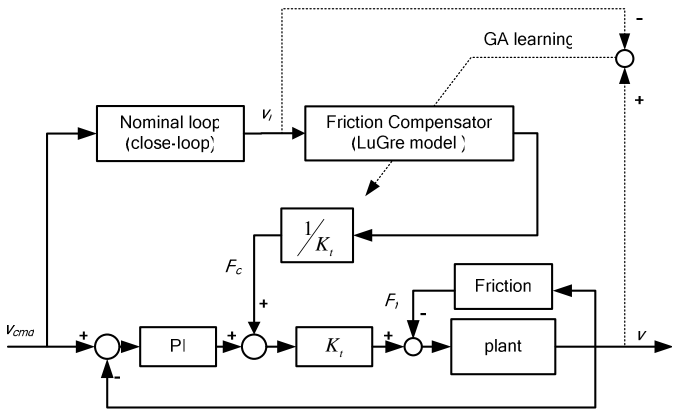


Fig. 3. The GA learning scheme for feedforward friction compensation.

3.2 Feedforward Friction Compensator learning by GA

Genetic algorithms are directed random search techniques which can find the global optimal solution in complex multidimensional search spaces. GA was firstly proposed by Holland and has been applied successfully in many engineering and optimization problems. Friction parameters appear nonlinearly in the LuGre model, which make them difficult to estimate. Using GA, the friction parameters can be estimated by a single identification experiment. In this paper, the five parameters (Stribect velocity, coulomb and maximum stick force, and bristle stiffness and damping coefficients) of LuGre model, coarsely obtained in section 2.4, are optimized by GA. The learning scheme is represented in Fig. 3; where the well tuned parameters of LuGre model are obtained by minimizing the error between velocity response v_r from nominal velocity loop and the actual velocity response v.

The flow chart for the proposed GA learning scheme for feedforward friction compensation is shown in fig. 4. The parameter tuning by GA is carried out using the following steps:

Step 1. Initialization

The parameters identified with various experiments, as mentioned in section 2.4, are given as initial values of the parameters. The corresponding upper and lower limit values of the parameters are specified according to the identified values, as shown in section 2.4. The following fitness function has been selected

$$J = \frac{1}{\sum (v - v_r)^2} \tag{6}$$

Then, the friction parameters are encoded into the real number and the initial generation is generated based on experience.

Step 2. Fitness calculation

The "genetic information" of the real number strings are converted to corresponding friction parameters are known as decoding. Then, the velocity response v_r from the nominal velocity loop and the compensated force F_c, using the new friction parameters, are calculated. A fitness function J defined in (6) is calculated by the summation of square error of velocity response v_r from nominal velocity loop and the actual velocity response v.

Step 3. Evaluation

Evaluation is decided by the evolution number of the set life group or the value of fitness function. The algorithm will stop once the specified number of generations is reached or the value of fitness function is smaller than a predetermined threshold ε. Otherwise, the flow will go to *step 4* to generate the next generation of population.

Step 4. New generation of population

The new generation obtained after genetic operation is treated as the next generation life group. The desired next generation is obtained by the following operations:

1). The selection directs a GA search toward promising regions of the search space, where the elitist strategy is used as the selection method.

2). The crossover operator works on pairs of selected solutions with the adaptive probability of crossover rate, shown as

$$P_c = \begin{cases} k_1 \dfrac{f_{\max} - f'}{f_{\max} - \bar{f}} & , f' \geq \bar{f} \\ k_2 & , f' < \bar{f} \end{cases} \tag{7}$$

where $f_{\max}$ is the maximum fitness value of the current generation; f' is the maximum fitness value of the parents's generation; $\bar{f}$ is the average fitness value of the whole generation; and k_1, k_2 are constants.

3). Mutation is a random alteration with small probability. The operation will prevent GA from being trapped in a local minimum.

4). Both the elitist chromosomes and chromosomes, after crossover and mutation operations, are combined into the next generation, and is return to *step 2*.

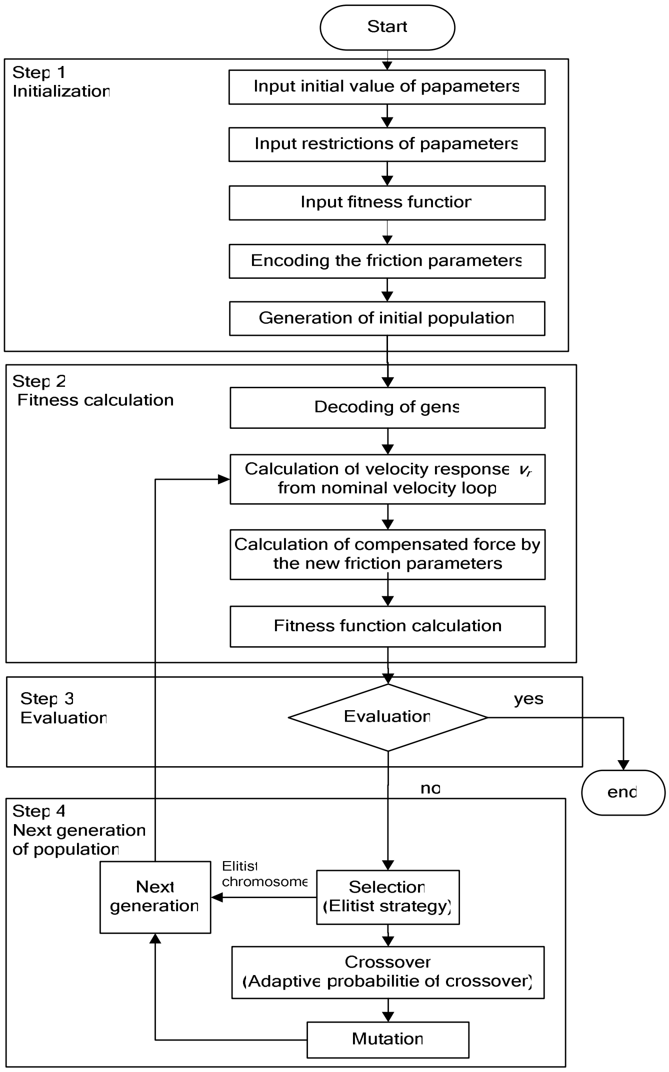


Fig. 4. The flow chart of parameter tuning using GA.

4. EXPERIMENT

4.1 Experimental Setup

A linear motor feed drive servomechanism, which is shown in Fig. 1, is used to test the friction compensated performance of our proposed compensator. The LuGre friction dynamic model is learned to match both the friction phenomena in the motion-start region and the motion-reverse region because the phenomena between these two regions are different. As mentioned in section 2.4, the various parameters in both the friction model and the system plant model would be estimated by the various experiments. From the results, the identified parameters of this LuGre model and other parameters are list in Table 2. Search space for each parameter must be specified before using the GA to estimate the parameters of LuGre model. Generally, the larger search spaces more generation are needed for the GA to converge to the optimal solution. In this paper, the corresponding upper and lower limit values of the parameters are specified as 100 times and 0.1 times of the identified values. And the parameters of genetic learning algorithm are shown in Table3. Then, the following experiments are based on this set of parameters.

Table 3
Parameters of genetic learning algorithm

parameter	Setting value
Resolution	0.0001
Number of chromosome	10
Number of gene	10
crossover rate	adaptive probability of crossover rate
mutation rate	0.15
Elitist rate	0.2
generations	100

4.2 Experimental Results

In the training phase, a velocity command is designed to enhance the friction phenomena of motion-start and motion-reverse regions so as to learn the friction model in these regions. The sinusoid signal, with frequency form 0.1 *Hz* to 5 *Hz* and amplitude form 30 *mm/sec* to 40 *mm/sec* , will be the excellent velocity command because they can fully capture the start and reverse motions. The cost function converges with stepped profile, shown in Fig. 5, and the corresponding steps implies it stay at local minimum values. Finally, it converges to the value of 1.7×10^{-3} after 100 generations.

Then, the trapezoid velocity command, shown in Fig. 6(a), will be fed to the servo loop to verify the compensation performance based on the above GA learning scheme. The performance comparisons between the proposed method and without friction compensation are presented by the maximum tracking error and root mean square tracking error at these two regions. They are defined as

$$E_{\max} = \max_{N_i} |v_{cmd} - v| \tag{8a}$$

$$E_{rms} = \sqrt{\frac{1}{N_i}\sum_{N_i}(v_{cmd} - v)} \tag{8b}$$

where N_i are the data numbers corresponding to motion-start and motion-reverse regions. And the error reduction ratio is defined as

$$E_r = \frac{E_{\max, rms(without\ compensation)} - E_{max, rms\,(with\ compensation)}}{E_{max, rms(without\ compensation)}} \tag{9}$$

Fig. 6(b) and (c) show the experiment results of velocity and velocity error during the motion-start and motion-reverse regions. In motion start region, the maximum tracking error reduction ratio with friction compensation is 22% and the mean square error reduction ratio is 44%. In motion-reverse region, the maximum tracking error reduction ratio with friction compensation is 59% and the mean square error reduction ratio is 73%. The maximum tracking error and root mean square tracking error for this experiment are shown in Table 4.

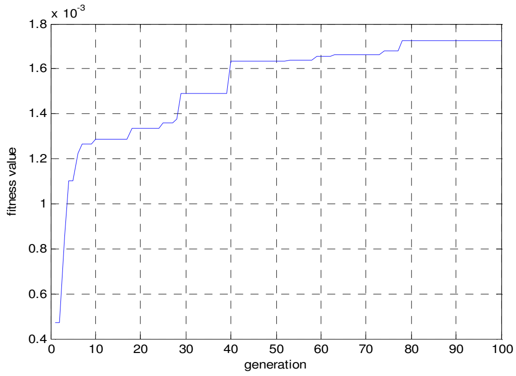
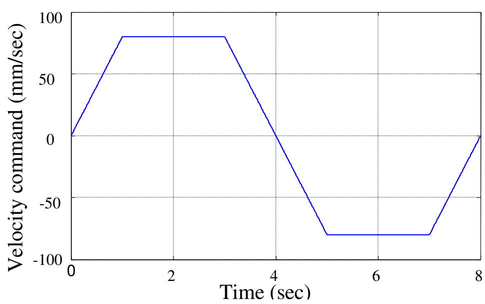


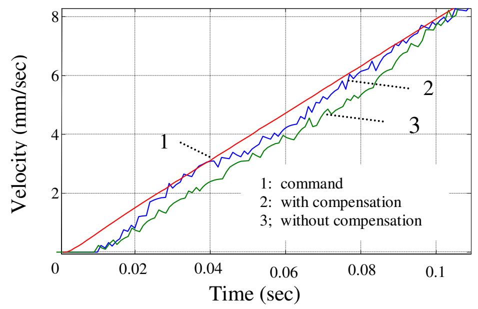
Fig.5 Fitness function.

5. CONCLUSIONS

This paper proposes a feedforward friction compensator based on LuGre friction model. The various parameters in both the friction model and the system plant model would be coarsely estimated by the various experiments, and then the GA optimize the key parameters by a single identification experiment. The friction can be estimated so as to compensate the friction in a linear motor stage. When compared with the conventional black box learning algorithm, this model-based compensator uses only five parameters to model the nonlinear friction phenomenon and the corresponding convergent rate of parameters is fast in the learning process. Finally, the proposed compensator is evaluated and compared experimentally with a traditional uncompensated system on a microcomputer controlled linear motor positioning system. The experimental results show that the maximum tracking and the mean square error reduction ratio are 22% and 44%, respectively for motion start region, and are 59% and 73%, respectively for motion reverse region.



(a)



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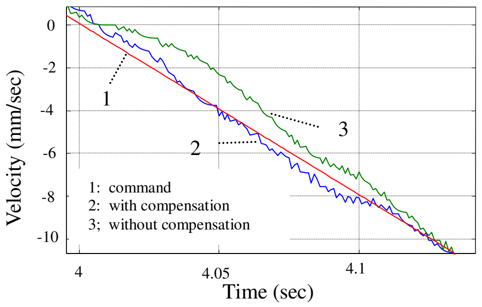

(c)

Fig. 6 The experimental results of friction compensation, (a) input velocity command, (b) start-motion region, (c) reverse-motion region.

Table 4
Friction compensation at motion-start and motion-reverse regions

	Motion-start region		Motion-reverse region	
	E_{max}	E_{rms}	E_{max}	E_{rms}
without compensation	0.98	0.86	1.76	1.62
with compensation	0.76	0.48	0.72	0.44

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