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Advanced Control of Micro Electrical Drive Systems

Qian Xin

School of Electrical & Electronic Engineering

**A thesis submitted to the Nanyang Technological University
in fulfilment of the requirement for the degree of
Doctor of Philosophy**

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Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

Oct 12, 2006
Date

Qian Xin

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Summary

The thesis focuses on the development of advanced controller for single and multi-dimensional servomechanisms to enhance their robustness to parameter disturbances, dynamic nonlinearities and load variations.

Servomechanisms are always assumed and identified as linear systems. Friction in the system is often simplified and represented as a constant plus linear damping term in previous work. Nevertheless, highly nonlinear friction is present and it can be vital for the performance of such systems. Friction compensation technique which is usually used as a part of control scheme is firstly introduced in system identification process in the thesis. Moreover, the Kalman filter based radial basis function (RBF) network is designed to fit and compensate the nonlinear friction in servomechanisms. The servomechanism with nonlinear friction compensation approximates a linear system to a great extent. The proposed compensation method is simple to be applied to the servomechanisms. Compared with the math model based friction fitting method, the RBF network realizes a much better fitting error result. Correspondingly, the identified linear system model is very close to the measured frequency response data as well.

Since there is no auxiliary mechanism equipped with the linear motor drive system, payload changes or disturbances will lead to large parameter variations, and therefore, affect the performance of the motor drive system. By using a solution of the Riccati equation, we present a new robust output tracking control scheme for the linear brushless DC motor (LBDCM) drive system. The main feature of this approach is that larger parameter uncertainties are admissible and, as a result, a larger amount of payload can be accommodated. This scheme also guarantees the asymptotic output tracking with an arbitrarily prescribed convergent rate and the resultant controller is

linear optimal for the nominal system. We have applied this scheme to an experimental LBDCM drive system. The strong robustness of the proposed approach has been demonstrated by the experimental results as well.

In some fast and precise motion applications, the speed is another issue which should be taken into consideration as well as the robustness. A robust and fast position controller is proposed for the uncertainty rejection and high-speed tracking problem in the LBDCM system. The friction and load variation are the main uncertainties in the LBDCM drive system. Highly nonlinear friction in the system is measured and compensated by a Kalman filter based RBF network. For solving the problem of load variation, three μ controllers are proposed for different normalized payload conditions. Each of them has its own tolerable load variation range. Moreover, one mass estimator is developed to extend the tolerable load variation to the sum of the three ones. In addition, the mode switching control (MSC) is applied to achieve better time response results. Robust stability and robust performance of the close-loop system are analyzed by μ theory. It is also demonstrated that the proposed controller can suppress the influence of the nonlinear friction and reduce the effect of large load variations.

A new motion system called linear ultrasonic motor (LUM) drive system is also studied in the thesis. LUM is a milestone of new generation linear motor and has attracted many interests as a servo actuator in the field of precise motion due to its totally different operation principle from the one of electromagnetic motors. A reaching law based discrete-time sliding mode controller, which is insensitive to the perturbed state matrix and input matrix and disturbances, is proposed for the LUM drive system. Furthermore, three free parameters in the controller are optimized to achieve better transient performance by real-coded genetic algorithm (GA). A design goal (no overshoot and the integral of square error is less than $1.0\text{E-}4$) is achieved accordingly. A fast and precise swing tracking is realized in the LUM drive system by the proposed controller.

The two-dimensional motion system is investigated as the extension of the research on single axis motion control, which has more industrial applications. The contour path motion is driven by dual LUM motors in the concerned biaxial system. The key point to control such a system is to coordinate the two axis to work together and thus to realize the accurate path tracking. The two inputs and two outputs (TITO) system is not as simple as two additive SISO systems. The interaction coupling is present between the two main loops. To control such a system, the frequency domain models of both two main loops and two interaction loops of the LUM drive biaxial system are firstly obtained by a dynamic signal analyzer (DSA) with nonlinear friction compensation. The reaching law based sliding mode controller is firstly integrated with cross-coupled control concept for the interacted TITO systems. Furthermore, the controller cooperates with a decoupler and a mass estimator to deal with the coupling and robustness problem. The fast and accurate circular and elliptic path tracking is achieved in the LUM biaxial system by the proposed control scheme.

Notations

List of symbols

F	friction force or generated force
F_c	Coulomb friction force
F_N	normal force
v	velocity
F_v	viscous coefficient
F_e	external force
F_s	static friction force
v_s	strobeck velocity
q	approximation function
g	gradient of function
H	Hessian matrix
D	diagonal scaling matrix
s_1	direction of the gradient
s_2	approximate Newton direction or direction of negative curvature
c_i	Radial Basis Function center
w_i	weight
w_0	bias

l	number of centers
w_k, v_k	artificial noise
$\varepsilon(.)$	expectation operator
δ_k	kronexker delta
K_k	Kalman gain
P_k	covariance matrix of the state estimation error
$f(.)$	identity mapping function
y_k	target output of RBF
$\hat{F}_k$	identity matrix
H_k	partial derivative of RBF output to network parameters
V_{abc}	phase voltage vector
i_{abc}	phase current vector
r_s	resistance matrix of winding
λ_{abc}	moving member flux linkage vector
L_{js}	leakage inductance
L_A	The component of self-inductance due to space-fundamental sir-gap flux
L_B	Sinusoidal amplitude of variation of self-inductance
τ	pole pitch
λ_{max}	amplitude of sinusoidal flux linkages
x	displacement of the rotor
h_{dq0}	variable in d-q secondary frame
h_{abc}	variable in abc domain

F_x	propulsion force
K_f	force generation constant
y	carriage position
w_0	bias
M	mass
F_f	disturbance force
u	input voltage
I_q	armature current
R_q	armature resistance
L_q	armature inductance
A,B,C	system matrix in state-space equations
y_r	reference output
V	Lyapunov variable
σ	prescribed degree of stability
J	index function to be optimized
W_s, W_p	frequency dependent weighting function
S	sensitive function or sliding surface
$\sigma(G)$	singular value of G
$\bar{\sigma}(G)$	large singular value of G
μ	Coulomb friction coefficient or structured singular value
f_d	disturbances
T_s	sampling time
G_{11}, G_{22}	transfer function of main loops

G_{12}, G_{21}	transfer function of interaction loops
G_I	decoupler
E	position error vector
E_r	contour error vector
E_r'	estimated contour error vector
V^*	contour error vector
$\bar{V}$	average unit velocity
P^*	position on a desired contour
P	number of poles or actual position vector
L_∞	functions bounded on $\text{Re}(s)=0$ including at ∞
H_∞	the set of L_∞ functions analytic in $\text{Re}(s)>0$
$\ G\ $	spectral norm of G
$\phi(.)$	basis function in neural network
R^n	set of n-dimensional real vectors
$R^{m \times n}$	set of m by n matrices with elements in R
$F_l(G, \Delta)$	lower linear fractional transformation
$F_u(G, \Delta)$	upper linear fractional transformation
$\text{sgn} (.)$	math unit returns the sign of a variable
$\sup \cdot $	the largest limit function of the norm
$\exp(.)$	the exponential for the element
diag	the n by n diagonal matrix with elements $a_1, a_2, \dots, a_n$
$(a_1, a_2, \dots, a_n)$	on the diagonal line

List of abbreviations

DOB	Disturbance Observer
DSA	Dynamic Signal Analyzer
DSM	Discrete-time Sliding Mode
GA	Genetic Algorithm
HDD	Hard Disk Drive
ISE	Integral of Squared Error
LBDCM	Linear Brushless DC Motor
LMI	Linear Matrix Inequalities
LQG	Linear Quadratic Gaussian
LUM	Linear Ultrasonic Motor
MEDS	Micro Electrical Drive System
MSC	Mode Switching Control
NN	Neural Network
PEA	Piezoelectric Actuator
PID	Propotional-Intergral-Derivative
PMSM	Permanent Magnet Synchronous Motor
QSM	Quasi-Sliding Mode
RBF	Radial Basis Function
SMC	Sliding Mode Control
SISO	Single Input and Single output
TITO	Two Inputs and Two Outputs

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CHAPTER 1

Introduction

1.1 Background and Motivation

Electrical drive systems have been the workhorse of industry for many years. In the last decade, Micro Electrical Drive Systems (MEDS) have begun playing a vital role in the more precise and faster application fields, such as the areas of robotics, machine tools, data storage systems, biomedical systems, semiconductor wafer inspection, and so on.

Recently, robust and precise motion control is one of the most interesting research fields in MEDS as the products such as data storage or semi-conducting devices become smaller, faster and subtler.

Motion control is defined [1] by the American Institute of Motion Engineers as:
“The broad application of various technologies to apply a controlled force to achieve useful motion in fluid or solid electromechanical systems.”

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Motion control is one of the technological foundations of industrial automation. Whether in the motion of a product, the path of a cutting tool, the motion of an industrial robot arm conducting seam welding, the motion of a parcel from a storage bin to a loading dock by a shipping cart, or in another application, the control of motion is a fundamental concern. Putting an object in the correct place with the right amount of force and torque at the right time is essential for efficient manufacturing operations. Feedback comparison of the target and actual positions is then a natural step in implementing a motion control system. This comparison generates an error signal that may be used to correct the system, thus yielding repeatable and accurate results. However, feedback signal may cause the poor transient response or even system instability. Therefore, the controller design plays a key role in the motion control system.

1.1.1 Overview of a Motion Control System

The motion controller is part of a complete closed-loop system which includes the power amplifier, motor, and an encoder. Such systems, also known as servo systems, sense the motor position and feed the position signal back to the controller. A typical motion system is shown in Figure 1.1.

Figure 1.1: A block diagram of a servo motion control system

The operation of the various system elements may be described by comparing the servo system with the human body. The combination of the motor and power amplifier is analogous to the muscle that moves the human arm. The motor is the device that generates the motion. The power amplifier generates the current required to drive the

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motor. For example, the amplifier takes a low-current signal and amplifies it to a higher level of current of 10 A. The controller is the intelligent element that commands the motion. As such, it operates as the brain of the system. It generates a signal, referred to as the motion command, which is applied to the power amplifier. The function of the position sensor is analogous to human eyes. It senses the position of the motor and reports the result to the controller, i.e. closes the loop.

A closed-loop system receives its command from an outside source, often a host computer. Continuing our human society analogy, the command source may be seen as the boss, generating commands and often requesting status reports. The commands can also be generated by other sources such as a programmable controller, terminal, or a set of switches.

In summary, a motion control system consists of a number of elements where characteristics must be carefully determined in order to optimize the performance of the complete system. The overall system consists of five elements.

1. The load. The driven element greatly influences the operation of the complete system. It should be noted that a number of parameters, including inertia, external loads, and friction, may vary as a function of time. These need to be fully parameterized at the start of the design process.
2. The transmission system. It takes the motor output and undertakes the required speed changes and, if required, a rotary to linear translation.
3. The encoders and transducers. They are required to provide the feedback of the position of the load and the speed to the controller. Additional encoders may be integral to the motor control loop.
4. The power electronics, local motor controller, and motor. In most cases, these can be considered to be an integral package, the operation and characteristics of the motor being totally dependent on its control package.

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5. The controller. This contains the main control algorithms and provides the point of interface between the whole motion control system and the main control system.

It is well recognized that fundamental issues of motion control systems have been launched for over a hundred years since the first commercially successful version of DC electric machine arose in 1837 and the three-phase induction electric machine was invented in 1887. More research and development activities related to electric drive systems have been carried out accordingly. With the recent developments in power electronics and high speed DSPs, there is a trend to seek superior performance of motion control systems through applying more sophisticated control algorithm derived from modern control theories.

Rotary DC motors have traditionally dominated the domain of motion control systems for over a century and are preferred in the linear motion applications because the wide range of speed and thrust that can be obtained with the help of gearing at an economic cost. Although DC motors have excellent operation properties and control characteristics and have been widely used in electrical drive systems, they are being replaced by AC motors gradually, such as induction motors and permanent magnet synchronous motors (PMSMs), because DC motors are, in general, bulky and expensive compared with AC motors. In addition, the requirement of periodic maintenance for commutators and brushes makes DC motors less reliable and unsuitable to operate at a high speed or in an explosive environment [2].

The history of linear motors goes back to as far as that of rotary motors. Those machines were practically forgotten for nearly half a century, but there has been a genuine revival of interest in them since the 1950s. Recently, the linear motor has become of researchers' major interest as a direct drive type actuator which can realize linear motion without any auxiliary mechanism. A linear DC motor is suitable for a high accuracy servo with small size. Compared to traditional indirect-drives that use rotary motors and lead screw or toothed belts, the direct-drive linear motor exhibits the

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property of contactless transfer of electrical power to mechanical power. The electromagnetic force is applied directly to the payload without the intervention of a mechanical transmission. For linear motion actuation, the linear motor design, therefore, features the following advantages over traditional rotary motors and transmission counterparts [3]:

- Less friction and no backlash, resulting in high accuracy
- No mechanical limitations on acceleration and velocity (the velocity is only limited by the bandwidth of the position measurement system (usually an encoder) or by the power electronics)
- Higher reliability and longer lifetime, due to mechanical simplicity

Two kinds of linear motor drive systems will be investigated throughout the thesis due to their satisfactory characteristics for precise servo motion. One is the linear brushless DC motor (LBDCM) which is basically a permanent-magnet linear synchronous motor with moving member position sensing. The other is linear piezoelectric ultrasonic motor (LUM) which was newly invented in the 1980s. Owing to its large quantity of advantages compared to conventional electromagnetic motors, LUM has been applied in various MEDSs and motion control systems.

1.1.2 LBDCM Drive Motion Control System

LBDCM is attractive because it offers high-power density, reliability, and efficiency. As the phenomena of desynchronization which occur in a linear pulse motor at high-speed operation could be avoided by using the linear DC motor, LBDCM becomes suitable for high-speed operation and many precise positioning control purposes. There has been various research conducted in the application and design analysis and control algorithm of LBDCM in servo motion systems.

In the past decades, the linear motor drive has been applied in various industrial fields. Direct application of linear motor technology for process improvement was performed [4]. In order to enhance machining performance, while increasing speed,

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accuracy and reducing chatter marks on a workpiece surface, a linear DC motor was implemented as a lathe feed drive and the vibration was measured while investigating the dynamic interaction and active damping utilization for machining stability [4]. In evaluating performance, a second order workpiece structure is used to represent the first vibratory mode involving mass, velocity and friction. The research presented a unifying control formulation in which process chatter, disturbance rejection, and servo tracking was taken into consideration [4]. It consists of two major areas: one is the stability factors introduced by the dynamic interactions between machining and linear motor drive, and the other is the design of optimal feed-forward controller to improve tracking performance. The application of linear drives for surface shape control of molten tin was illustrated [5]. The experimental and theoretical design analysis was presented for a single-sided linear motor material handling configuration, which has the potential for improving the gloat process of flat glass production. Strong evidences were provided, theoretically and experimentally, illustrating that the location of the motor is a contributing factor in the formation of molten tin. Linear motor technology is also utilized for the application of precision grinding of high speed bearings [6]. By utilizing high precision linear motors, a precise non-circular inner race of a bearing was machined with an experimental setup to solve roller slippage and surface finish problems in the use of aircraft engines. To overcome roller slippage, a linear motion control scheme was developed for linear drives to replace traditional grinding processes.

Design analysis of linear motors has gained some attention in the servo motion research areas. Dynamic response of electromagnetic force and simulation of modulated and un-modulated current waveforms were achieved [7]. The simulation results were later validated by experiments using an NdFeB equipped linear machine for material handling. The control performance of a slotless linear DC material handling actuator was simulated and investigated in the presence of variants such as winding resistance, moving mass, load, force and friction [8]. Two forces acting on LBDCM moving armature were examined [9]. Unlike the method which was used to

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analyze the direct force from the cross product of the flux density and current density, the force attributed to the leakage flux on the extremities of the armature was analyzed. It was also shown that the specific linear motor design exhibited easier position controllability which may be used extensively in servo motion applications requiring high speed. Moreover, the armature lengthening can provide faster linear travel, however, the linear motor design was shown to be limited by heat-dissipation considerations. A design analysis framework was developed for linear motors in the application of wafer stepper material handling systems for clean room operations [10]. From the research, the design effects of complex magnet arrays, such as the Halbach Array and winding patterns, and verified theoretical results obtained by constructing an experimental magnetic levitator were illustrated.

The LBDCM has been widely used for robots, semiconductor manufacturing systems, and X-Y driving devices, etc. However, it has disadvantages that it is greatly affected by the parameters and load variations in the servo system with the LBDCM because it is not equipped with auxiliary mechanisms. Thus, it is very important to suppress the effects of parameters and load variations of the LBDCM system. On the other hand, the magnitude of the input signal becomes too large if these effects are suppressed too quickly. In this case, the system response deteriorates due to the restricted value of the input variables.

A great deal of effort has been devoted to solving the disturbances suppression problem in controlling linear motors [11-15]. An H_∞ controller was proposed to increase dynamic stiffness for linear motor driven machine tool axes [12]. A disturbance compensation method based on disturbance observer (DOB) and disturbance suppression control was proposed to make the LBDCM robust to model uncertainties [13]. A position control method of a DC linear motor was proposed by using seeking control which is presented to consider the variation of switching lines according to load mass variation [16]. The authors illustrated a control method utilizing a neural network (NN) in which the linear or nonlinear mapping between

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inputs and outputs of a servo motion system, without knowledge of any predetermined model, was feasible. Feed-forward compensation terms, based on an off-line experimentally identified model, were added to a position controller in [11]. A NN based feed-forward controller was proposed to reduce the effect of reproducible disturbance [14]. A tracking controller is provided for a precision positioning table, which was actuated by direct-drive linear motors [17]. The controller employed a disturbance observer and proportional derivative compensation in the feedback path. However, if the parameter or load variations were large or the variations of the dynamics were complicated, the inverse dynamic based disturbance observers cannot achieve robustness for the control system. The first rigorous stability analysis of a nonlinear repetitive controller was proposed in [18]. However, the proposed control law could not handle model uncertainties such as an exogenous disturbance which might not be periodic. Realizing this, the authors added a projection mapping in the learning algorithm in order to guarantee the bound of the repetitive estimate. Although this method was very important and useful from an implementation point of view, it was not well justified theoretically. Recently, a robust learning control scheme by combining the design methods of variable structure control with iterative learning control straightforwardly [19], however, the actual system might have large tracking errors during the initial transient period or had a sluggish response. Three adaptive controllers are proposed for the load disturbance problem in permanent magnet linear synchronous motor motion system [20]. However, the robustness to only the restricted load disturbance is achieved and moreover, it is based on the loss of the fast transient response. An adaptive wavelet neural network based controller is designed to confront approximation errors and disturbance including friction [21]. However, the optimality of the controller is not guaranteed. Besides, the controller is sensitive to the unmodeled dynamics and disturbances.

In a word, although restricted parametric and load variations problem in LBDCM systems were considered in foregoing literatures, it is still an interesting area to design

a controller by which both fast and accurate transient performance and the robustness to large uncertainties and nonlinear dynamics are achieved.

1.1.3 LUM Drive Motion Control System

The other kind of actuator is discussed in the thesis is LUM. It can be called a milestone of a new kind of motor which has a totally different operate principle from the conventional electromagnetic motor. The LUM has a faster response time, higher precision, hard brake with no backlash, high power-to-weight ratio, and smaller packaging envelope which more than compensate for the lack of brute horsepower and speed associated with its electromagnetic motor counterparts. Its greater positioning accuracy, simplicity (fewer parts), lower profile (no iron cores required), and minimal Radio Frequency /ElectroMagnetic Interference noise meet the stringent requirements of today's evolutionary product technology [22]. Piezoelectric motors have been around for years, but acceptance has been slow because they were relatively expensive. However, recent advances have significantly reduced the channel cost of this technology for closed-loop systems that require high positioning accuracy. The list of piezoelectric motor product applications is growing daily. (some of piezoelectric motor applications are shown as follows)

- Micropositioning stages
- Manufacturing process control
- Fiber-optic positioning
- Pick-and-place assembly
- Camera autofocus
- Medical catheter placement
- Semiconductor test equipment
- Computer disk drives

The piezoelectric motor is a type of actuator that uses mechanical vibrations in the ultrasonic range as its drive source. Human ears are capable of detecting sound waves within frequency range of 50Hz to 20kHz, which is called the audible frequency range

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[22]. Ultrasonic waves are sound waves or mechanical vibrations with frequencies above 20kHz. The use of ultrasonic wave is a direct outcome of using piezoelectric ceramics, which expand or contract in accordance with an applied electric field, as the vibration source. In the LUM, a voltage is applied to the piezoelectric ceramic element to generate alternating expansions and contractions, either in the ceramic body itself or in an attached metal piece.

The earliest research into actuators using vibration energy as their drive source was conducted with the piezoelectric motors [22]. In this large family of the motors, they can be in essence classified by their motor functions into two major groups, namely LUM and rotary ultrasonic motor. Only LUMs for position control system are explored in this thesis. Due to the ample advantages that piezoelectric motor offers (The advantages and disadvantages of a piezoelectric motor are listed in Table 1.1 [23].), much research has been done in this area. Different constructions and driving principles of LUMs have been reported [24-28]. As a result, they permit high precision, fast control dynamics and large driving force in small dimensions. For instance, the SP series LUMs of Nanomotion Ltd. Motion accuracy of 1 μm in open-loop operation and 50nm in closed-loop operation have been achieved in [28]. The SP series LUM comprises a thin rectangular piezoelectric ceramic with four electrodes on the front face. These motors are operated using the double-mode vibrations under suitable excitation. To generate a different moving direction, the electrodes were electrified using an AC voltage in the pair of the diagonal electrodes. The dynamic behavior of such motors can be described in a three-dimensional coordinated system. The analytical solution to this problem in the three-dimension space has been obtained only under some particular boundary conditions. Some assumptions were utilized to simplify the problems to one or two-dimensional space. Y. Tomikawa et al. [24] investigated the damping and nonlinear material behavior via the experiment and introduced several design aspects of the motor. Two vibration modes are utilized to construct the LUMs with different motion in the work reported by M. Aoyagi et al. [25]. M. Aoyagi et al. [26] analyzed the characteristics of the effect of the motor that

causes the motor with mode coupling. M. Kummel et al. [27] tried to modify the shape of the piezoelectric ceramic that improves the effect of the motor with mode coupling. However, the control accuracy is much influenced by the existence of uncertainties, which usually comprises parameter variations, external disturbances, and high order dynamics, etc. The investigations for the design of the control system, which will determine the control accuracy and robustness of the controlled plant, are still poor for LUM drive systems.

Table 1.1 Advantages and disadvantages of a piezoelectric motor [23]

Advantages	Disadvantages
Compact, simple structure	Reliability under long operation
Standstill force without excitation	Not suitable for large scale operation
Flexibility in the shape of the motor	Wear-resistant material is required
No danger of electromagnetic interference	Need of high frequency power supply
Large torque in the low speed range	
Silent since no speed reduction gears required	
Precision positioning	

When precision outweighs strength on the desirability scale, a piezoelectric motor might be right choice for the application. As position control requirement becomes more stringent, modern control method is requisite to be applied in the motion system. While the piezoelectric actuator has high potential for applications in ultra-precision motion control system, the highly nonlinear features associated with the dynamics of these elements are challenges to how efficiently these potentials can be realized. Friction and mass variations are the main concern in the piezoelectric motor drive motion system. From the viewpoint of the control system, friction poses an interesting and challenging dilemma to the control problem. On the one hand, it provides the primary transfer mechanism to bring about the motion, and on the other hand, it

opposes the realization of precision motion control. The frictional characteristics associated with servomechanisms are highly nonlinear in nature, and a good friction model is especially important for applications involving high precision motion control of servomechanisms, where the frictional force needs to be adequately compensated in order to improve the transient performance and to reduce steady state tracking errors. Model based approaches are usually proposed for friction compensation. Even in adaptive control of servomechanisms, an initial friction model is also crucial to ensure smooth control signals and rapid parameter convergence. However, friction modeling has always been a difficult and challenging problem [29]. Model of varying complexity have been used to approximate the dynamics of friction. However, under practical conditions, the adequacy of the model for the control system to yield effective friction compensation has always remained questionable. Other efforts have been made toward more advanced control of precision motion systems. In [30], a learning nonlinear PID controller was proposed. The control scheme did not require an accurate system model and it was capable of yielding good motion tracking performance. But the mass variation was not considered in that paper. A recurrent fuzzy neural network controller was developed to control a piezoelectric ceramic linear piezoelectric motor [31]. This method achieved high precision position control with robustness, however, the stability of the control system cannot be guaranteed. A NN controller was designed for an LUM drive system based on adaptive sliding mode technique in [32]. However, one parameter related to the time constant to tracking the sliding surface is decided by experiences, which deteriorates the performance if it is not proper. In recent development of the LUM control, an adaptive supervisory controller is investigated to deal with the uncertainties and nonlinearity in [33]. Although system stability is guaranteed by Lyapunov function and the chattering in control effort is eliminated, the step tracking performance in the practical LUM driving system is not as good as the one in the foregoing literature.

Because the dynamic characteristics of LUM are nonlinear and precise dynamic model is difficult to obtain, moreover, the motor parameters are time varying, robust

control of LUM drive servo motion system becomes an interesting area for potential researchers.

1.1.4 Motion Control Algorithm

Almost every physical system is subjected to certain degrees of model uncertainties. Normally, the model uncertain can be classified into two categories: (i) parametric uncertainties, and (ii) uncertainties nonlinearities. How to handle these uncertainties is, therefore, essential for many applications. In the motion control system, it is inevitable to deal with some parameter variations and uncertainty problem.

Basically, two methods can be used to control uncertain systems: the adaptive control and the robust control. In the adaptive approach, one designs a controller which attempts to “learning” the uncertain parameters of the particular system and, if properly designed, will eventually be the “best” controller for the system in question. In the robust approach, the controller has a fixed-structure which yields “acceptable” performance for a given plant with uncertainty set. In general, the adaptive approach is applicable to a wider range of uncertainties, however robust controllers are simpler to implement and no time is required to “tune” the controller to the plant variations. In the following, we briefly review prior results on adaptive control, robust control, nonlinear friction compensation and coordinated control.

Adaptive Control of Nonlinear Systems

The adaptive control of nonlinear systems has undergone rapid developments in the past decade [34-39]. By using the backstepping design procedure, [37] presented a systematic design of adaptive controllers for a class of nonlinear systems transformable to a parametric strict-feedback canonical form. The overparameterization problem was soon eliminated in [38] by introducing the concept of tuning function. Recently, nonlinear damping was also introduced into the controller by [39 and 41] to improve transient performance. However, all these adaptive controllers deal with the case of parametric uncertainties only. Nonlinearities of the

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system were assumed to be known, and unknown parameters were assumed to appear linearly with respect to these known nonlinear functions. Furthermore, past experience has shown that integral-type adaptation laws may cause instability when even a small disturbance appears [41]. Although some modification techniques, such as σ modification [41 and 42] can be employed to modify the integral-type adaptation law and enhance the system robustness, tracking accuracy can no longer be guaranteed, since the steady state tracking error can only be shown to stay within an unknown ball whose size depends on the disturbances. By using a variant of the σ modification and backstepping design procedure, [43] presented a robust adaptive control design for a class of nonlinear systems in a “semi-strict” feedback form which allows both parametric uncertainties and unknown nonlinear functions. This form extended the class of uncertain systems [39 and 44] to which global adaptive stabilization methods can be applied.

An adaptive controller was proposed for a class of linear systems with parametric uncertainties by using nonlinear methods, such as tuning functions and nonlinear damping [45]. The resulting controller possessed much better transient and steady state performance, as compared to the traditional one. Parameter convergence properties of the controller were also analyzed in [46]. Recently, it was shown that by using fuzzy dynamic models [47 and 48] for the uncertain nonlinear systems, the robustness of this scheme can be improved with respect to both unmodelled dynamics and bounded disturbances.

In addition to parametric uncertainties and uncertain nonlinearities, some systems were further subject to dynamic uncertainties that depend on the unmeasurable states of exogenous dynamic systems [49 and 50]. Practical examples include the nonlinear friction model in [51] and the control of eccentric rotor in [49 and 52]. This class of systems has received a lot of attention in recent years since there are few results available on the general problem of robust control of nonlinear systems with partial state feedback. An adaptive controller was constructed for a class of extended strict

feedback nonlinear systems in which the unmeasurable states enter the systems in a linear affine fashion. As pointed out in [53], it is unclear how the approach can be made robust to modeling errors such as uncertain nonlinearities. The robust adaptive control of nonlinear systems subject to dynamic uncertainties was achieved by using a dynamic signal to dominate dynamic disturbances [53].

Robust Control

A definition of robust control [54] could be stated as:

“Design a controller such that some level of performance of the controlled system is guaranteed irrespective of changes in the plant dynamics within a predefined class.”

Design of the controller with guaranteed closed-loop stability and performance for uncertain plants has been the focus of active research for almost two decades. The robust control defines clear descriptions and bounds for the allowed perturbations and not only guarantees robustness for stability but also for the total performance of the closed-loop system even in the case of multivariable systems.

In robust control, one highlight of the techniques was named H_∞ control, which has been developed since the beginning of the eighties and was, as a matter of fact, a further application of the classical control design methods, fully applied in the frequency domain. It thus took about forty years to evolve a mathematical context strong enough to tackle this problem. However, the intermediate popularity and evolution of the Linear Quadratic Gaussian (LQG) design in time domain was not in vain, LQG is just one alternative in a very broad set of possible robust controllers each characterized by their own signal and system spaces. Most of the research on robust control has focused on H_∞ like problems. H_∞ optimal control theory is a highly developed theory which yields control laws such that even in the worst case scenario the stability and performance requirements are still met. Of course, the success of finding such a controller depends on the performance specifications. If these are too demanding, no controller can be found. In this case, the objectives have to be adjusted.

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An efficient synthesis method has been developed using state-space algorithms. However, this approach may lead to conservative results, since it neglects possible knowledge of structure in the uncertain model. Moreover, it turns out that many practical problems do not readily fit the standard H_∞ problem setup since the involved model uncertainty is structured rather than unstructured. A way to gain better results is to exploit available information about the structure of the uncertainty. Uncertainties may be present at various components throughout the system. They can be taken into account one by one explicitly, and rearranged to form structured uncertainty at the system level [55]. This uncertainty modeling was done by making extensive use of the theory of linear fractional transformations [54].

The influence of structured uncertainty on system stability and performance can be analyzed explicitly by applying μ analysis. μ analysis is therefore a powerful tool to analyze control systems for uncertain systems in a nonconservative way and during the last decade a lot of research has been reported in this area [56-58]. Unfortunately, no effective synthesis methods have yet been developed to apply μ analysis in the design process of control systems with general uncertainty structure. However, for a restricted class of modeled uncertainties and bounded complex perturbations of the system, a μ synthesis method has been developed. Accordingly, the so called D-K iteration approach [59] yielded good results despite presently unsolved convergence problems. The μ synthesis problem is solved here by alternately combining H_∞ synthesis and μ analysis.

A combination of H_∞ optimal control theory and μ analysis results in μ synthesis which provides a modern approach to design and analyze robust control systems. In many practical applications, μ analysis is more appropriate for system analysis and controller synthesis. μ theory has not been as widely recognized as H_∞ theory probably due to the small amount of literature on μ and the computational difficulties associated with μ .

The other highlight in robust control is sliding mode control (SMC) theory. A high level of scientific and publication activity, an unremitting interest in SMC is enhanced by its effective applications to automation problems. SMC was first proposed and elaborated in the early 1950's in the Soviet Union by Emelyanov and several co-researchers [60]. In their pioneer works, the plant considered was a linear second-order system modeled in phase variable form. Since then, SMC has developed into a general design method being examined for a wide spectrum of system type including nonlinear systems, multi-input/multi-output systems, discrete-time models, large-scale and infinite-dimensional systems, and stochastic systems [60-64]. In addition, the objectives of SMC have been greatly extended from stabilization to other control functions. The most distinguished feature of this control method is its ability to result in very robust control systems, and in many cases, invariant control systems. Loosely speaking, the term "invariant" means that the system is completely insensitive to parametric uncertainty and external disturbances. Today, research and development continue to apply SMC to a wide variety of engineering systems.

Since the controllers nowadays are most likely to be implemented by computers, it is unavoidable to approach a practical SMC design in discrete-time. The SMC theory was originally developed from a continuous-time perspective. It has been realized that directly applying the continuous-time SMC algorithms to discrete-time systems will confront some unconquerable problems, such as the limited sampling frequency, sample/hold effects and discretization errors. Since the switching frequency in sampled-data systems can not exceed the sampling frequency, a discontinuous control does not enable generation of motion in an arbitrary manifold in discrete-time systems. This leads to chattering along the designed sliding surface, or even instability in case of a too large switching gain. In discrete-time systems, the state moves around the sliding surface in a zigzag manner at the sampling frequency.

As digital computers nowadays are widely involved in the implementation of control algorithm, it is apparently necessary to develop or generalize the SMC methodology to discrete-time control systems.

Early contribution on applying the SMC theory in discrete-time systems can be found in [65-68]. These works were based on the concept of quasi-sliding mode (QSM) introduced by [65]. QSM is also termed as “pseudo-sliding mode” by other authors [69]. The concept of QSM was used to express the fact that the conditions for existence of sliding mode in a continuous-time system do not necessarily guarantee the motion of a sampled-data system to bring the state trajectory close to the sliding surface. It is noticed that unlike the case in continuous-time SMC, the switching control in the discrete-time case should be both upper and lower bounded in an open interval, in order to guarantee the convergence of sliding mode [70]. In continuous-time SMC, the control unit is composed of the equivalent control and a switching control like $u = u + \Delta u$. It is observed that if Δu is a relay control with a constant amplitude, the relay must be turned off in some neighborhood of the surface in order to reach the switching surface, otherwise, the trajectory will chatter around the surface with a chatter amplitude at least as large as the amplitude of the relay output [71]. The idea of sliding sector [67] was used to solve this problem, i.e., to specify a region in a neighborhood along the sliding mode, where linear control was used to keep the state inside the region after it has reached the region. The switching control was applied only when the system states were out of range. In this case, derived switching surface and the reaching law was based on a discrete Lyapunov function. It was pointed out that the previous addressed reaching law was incomplete for a satisfactory guarantee of a discrete-time sliding mode (DSM) [72]. A new reaching law was proposed for discrete-time system based on continuous-time reaching law. It was also illustrated that, in steady state, the state trajectory moved within a small band.

Nonlinear Friction Compensation

Problems related to modeling, identification and compensation of friction in mechatronics systems have been very attractive for researchers for decades. Friction compensation is an important part of nonlinear disturbance problems in motion control systems. Most developed friction compensation approaches are model based except a few special techniques such as impulsive control [74 and 74]. Therefore, modeling is often regarded as the first essential component of nonlinear friction compensation. In general, good models are expected to provide good performance in friction compensation.

Both static and dynamic friction models can be found in the literature. Friction models accompanied with different compensation methods were summarized in [75-77]. Static friction models were furnished by a map between force/torque and velocity, and they usually included the static, Coulomb and viscous friction components. Some models also involved the Stribeck effects and other nonlinear phenomena, but the position dependent characteristic was not considered in such kind of models. Dynamic models have also been developed, including the Dahl model [78], the LuGre model [79], the integrated friction model [80] and other models [81 and 82], in order to handle friction effects in vicinity of zero velocity. Among the proposed dynamic models, the LuGre model is the most quoted friction model for dynamic friction compensation. However, in LuGre model, a fictitious variable and additional description equation pose a probable difficulty for the accurate and fast friction compensation.

Model based friction compensation for high precision control has often been reported [83-85]. This method requires accurate identification of friction parameters, hence the selection of a proper identification method is an important issue in control design. Different methods for identifying the parameters of the friction models can also be found in the survey paper [75]. One difficulty of friction identification is the requirement of measuring acceleration for observing the friction force and taking into

account inertia effects at the same time. Unfortunately, acceleration is immeasurable in many practical motion control systems unless additional expensive equipment is used. But there is one alternative which is to use the desired acceleration as an estimate of true acceleration, and then the inertia and friction parameters can be individually identified through a set of experiments, according to e.g. the identification procedure presented in [86]. However, the time-varying friction characteristics, i.e., parameters in friction models which may vary in a wide range during operation, still creates difficulties for accurate friction compensation. It is unlikely that a good compensation can be achieved based on a fixed identified friction model. Therefore, friction compensation often needs to be combined with other robust control methods such as adaptive control [83] or sliding mode control [87 and 88]. Directly adaptive control and observer based adaptive control have been developed to deal with continuously updating friction parameters [89-92]. However, on-line adaptation is in general used for tracing the slowly time-varying parameters such as Coulomb friction, but it can not guarantee good compensation in the low velocity region, in which friction has very fast dynamics. Moreover, the adaptive algorithms become more complicated as the number of parameters that need to be adapted increases. For example, a complex algorithm was proposed when the LuGre friction model was used to compensate dynamic friction at low velocities [90]. In order to simplify the computation algorithm, a strict assumption on structured parameter variation had to be made in the adaptive algorithm. In addition to this possibly quite drastic assumption, the dynamic friction models also require high sampling rates (in the order of 10kHz or more). If the sampling rate is limited, the accuracy of the friction model and the updating speed are highly questionable.

In real-time applications, statistical model estimation techniques, such as the least squares estimator, maximum likelihood estimator, and maximum posteriori estimator, are usually not efficient in terms of the time needed to converge due to the limitation of sequential processing. NN parameter estimators that perform concurrently in real-time will be more advantageous. Recently, many of the applications of neural

networks, particularly in the areas of nonlinear system identification and control, reduce to the problem of approximating unknown functions of one or more variables from discrete measurements [93-99]. A number of authors have established that multilayer feed-forward neural networks, with a variety of activation functions, serve as universal approximators [100-110]. For example, The Stone-Weierstrass theorem is used to prove that a two layer feed-forward network can approximate a continuous real function on a compact subset of R^n arbitrarily closely in the L_∞ norm [100]. More generally, continuous nonlinear functions can be approximated with feed-forward neural networks, and these can be used to directly approximate the outputs of dynamical systems [97 and 98]. The problem of approximating a continuous function of n variables over a compact region can be solved by radial basis function (RBF) network. RBFs implement localized representations of functions and are easier to initialize and train than multilayer perceptions [111-118].

1.2 Objectives

The thesis is devoted to the robust servo motion control of systems subject to parameter variation, varying uncertainties and nonlinear dynamics. Moreover, the robust trajectory control is addressed for the biaxial motion system in the presence of various external disturbances as well as internal cross coupling between the two axes.

1.2.1 General Objective of Robust Motion Control

System Theory

All real systems that have to be dealt within automatic control problems can be classified into one of the following system descriptions. These are, linear systems, nonlinear systems, stochastic systems, discrete-time systems, time delay systems, distributed parameter systems and decentralized systems. To describe the system behavior, measures such as stability, observability, controllability, robustness,

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sensitivity, system structure etc are used. The requisite characteristics of the servo motion systems should be concerned throughout the thesis.

Modeling and Identification

Mathematical models of systems are very important in any automatic control application. If the modeling is completely based on the physics of the particular system, it is called white box modeling. Else, it can be done by conducting experiments, which is called black box modeling. Grey box modeling is another method that uses both the physics and experiments in the process. With the maturity of the system theory, a new sub-field within automatic control called system identification was born. Accurate system modeling and identification is prerequisite to design a controller for a servo motion control system accordingly.

Control Scheme Design

For a given process, it is indispensable to find a suitable controller configuration that can tackle either the servo problem or the regulation problem by following a systematic approach. Parameter variation and nonlinear dynamics remain to be the obstacle and challenge in servo control engineering though many researchers are dedicated to this area and have been applying various modern control theory, such as nonlinear control [119 and 120], optimal control [121 and 122], variable structure control [123-128], adaptive control [129-133], and robust H_∞ control [134] to the related motor drive motion systems to deal with the uncertainties under different operating scenarios.

Learning and Adaptation

The properties of the systems that are being controlled have the tendency to change with varying conditions. The systems that learn about such changes automatically and re-tune the controllers are very handy to have in many applications that need higher

reliability throughout their operating life. Learning and adaptation is the answer for such existing application problems in the motion systems control.

Computing and Simulation

Motion control has been tightly linked to computing throughout its development. Analog computing that was used in the beginning was replaced by digital computing later. Today there are so many mathematical computation tools specially meant for control system analysis and simulation. One example of such tools is Matlab.

Implementation

Implementation again is a very important aspect in control engineering, and it forms the bridge between the theory and real application. The gap between the practice and the theoretical study will have to be overcome at the implementation stage. These implementation aspects are rarely addressed in highly theoretical approaches to problems in automatic control area. However, such research work has a higher possibility of producing novel theoretical contributions to the field. Yet, most of the practical problems associated with the implementation of the methods are not theoretically dealt with in many cases. It is appropriate to quote one description from [135].

"A good implementation requires knowledge of control systems as well as certain aspects of computer science. It is necessary that we have engineers from both fields with enough skills to bridge the gap between the disciplines. Typical issues that have to be understood are windup, real-time kernels, computational and communication delays, and man machine interfaces. Implementation of control systems is far too important to be delegated to a code generator."

This thesis is meant to be a contribution that emphasizes control aspects all the way down to the implementation stage, starting from the basic control theory.

1.2.2 Specific Objectives of Robust Motion Control for Different Systems

Precise System Identification of a Class of Nonlinear Systems

Physical models of most of complex nonlinear plants are hard to be derived, or the structure of the plant is available but accurate parameters of the model remain unknown. It is indispensable to resort to system identification to obtain the precise system model. The purpose of system identification is to extract mathematical model from physical systems. A properly identified model can help us understand the details of a system and estimate its behaviors under specified inputs by means of computer simulation. Nowadays, the increasing need for precision machining and processing of semiconductors, optoelectronic elements, and high-density magnetic memory devices has increased the demand for high-accuracy machining at the level of sub-micrometers. To achieve such precision, accurate system models are mandated. It is common practice to assume linearity of the target system in frequency-domain identification. But most real-world systems are nonlinear in nature, thus the linearity assumption may significantly reduce the accuracy of the identified model. This part of work is addressed to identify a class of linear systems with nonlinear friction exclusive of assumption of linear system.

Advanced Robust Control of Single Axis Motion Systems

Single axis motion systems can be driven by both rotary motors and linear motors. Compared with rotary motors, linear motors possess many advantages in linear motion driving applications, such as direct driving, low fictional log, high position control accuracy, high speed, large structural flexibility. Owing to these merits, the linear motor has gained increasing applications in industry. The parameter variations and uncertainties affect the linear motor drive systems greatly due to no auxiliary mechanisms involved to drive the motor. Friction and load variations are the main uncertainties in the linear motor drive motion systems. Robust controllers, which are

insensitive to the effect of nonlinear friction and load variations, will be proposed for two promising motion systems driven by LBDCM and LUM respectively.

Coordinated Robust Control of Biaxial Motion Systems

The biaxial motion system is not as simple as two additive single axis SISO systems. The coupling exists between the two closed-loop systems. In the conventional control schemes, each axis-of-motion has a separate closed-loop control, so that the control loop of one axis receives no information regarding the other. Any load disturbances error in one of the axes is corrected only by its own loop, while the other loop carries on as before. This causes an error in the resultant path. Since biaxial control systems require both control and coordination of the motion along two axes, it should be possible to improve their accuracy by providing cross-coupling, whereby an error in either axis affects the control loops of both axes. Main task of this work includes setting up both the SISO plant models and decoupling models between the two main loops; achieving robustness to the nonlinear friction and load variation disturbance possible generated from either of the axis; realizing coordinated motion control of the system and tracking the preassigned curve precisely.

1.3 Major Contributions of the Thesis

The thesis focuses on the development of advanced controllers for single axis and biaxial motion systems to enhance their robustness to parameter disturbances, dynamic nonlinearities and load variation. The main contributions are summarized as follow:

- The practical servo motion systems consist of linear part and nonlinear part. Friction is the main component of the nonlinear part. In order to identify and control of the whole systems, Kalman filter based RBF network is designed to fit and compensate the nonlinear friction in the servo motion systems. Friction compensation technique which is usually used as a part of control scheme is firstly

introduced in system identification process. Finally, the accurate frequency-domain system models are obtained from LBDCM, LUM, and dual LUM motion systems.

- A new robust output tracking controller is presented for the LBDCM motion system based on the idea in [136]. The approach can accommodate twice as large as the tolerate system uncertainties in control matrix in [136]. Consequently much larger payload variations of the LBDCM are admissible. It is proven that the proposed scheme also guarantees the asymptotic output tracking with an arbitrarily prescribed convergent rate and the resulting controller is linear optimal for the nominal system.
- A new servo control method is proposed by combining the characteristics of H_∞ and μ synthesis technique to achieve an efficient treatment for the uncertainty rejection problem in the LBDCM drive system. The uncertainties in the LBDCM system are mainly composed of nonlinear friction and payload variations. Practical friction in the LBDCM system is firstly compensated by the Kalman Filter based RBF network during both the system identification and system control process. With the aim of gaining the robustness to large load variation, three μ controllers are designed under different normalized payload conditions and the unknown value of the payload in the system is estimated by the other RBF network. In this controller structure, the estimator behaves as a controller selector to determine which μ synthesis controller is applied at that moment. Robust stability and robust performance analysis of the closed-loop system is also presented by μ analysis theory. Furthermore, mode switching control (MSC) scheme is applied to gain satisfying tracking response with a short settling time, which is much less than the previous related work.
- A reaching law based DSM controller, which is tolerant of perturbed state matrix and input matrix and disturbances, is proposed for LUM drive system. Moreover, three free parameters during the design process are optimized to achieve better position tracking performance by GA. In addition, the on-line mass estimator is adopted to strengthen the robustness of the DSM controller. The proposed

controller is compared with conventional PID controller by the results from simulation.

- A cross-coupled sliding mode controller which is suppressive to both load variation and friction is proposed for the precise contour tracking control of biaxial systems. Both the two main loop transfer function models and the two interaction loop transfer function models are identified by DSA with the Kalman Filter RBF based nonlinear friction compensation. The decoupling of the coupled two inputs and two outputs (TITO) plant model is also achieved. Furthermore, the free parameters of the discrete-time sliding mode controller are tuned by GA. The performance of the proposed control law is compared with that of conventional cross-coupled PID controller.
- The simulation and experiment implementation of all the servo motion systems studies in the thesis are completed to validate the effectiveness of the proposed controller.

1.4 Organization of the Thesis

The thesis consists of eight chapters and is organized as follows:

Chapter 1 is the introduction.

In Chapter 2, Friction measurement procedure is designed for measuring the break-away and steady-state friction in the servo motion systems. Both the conventional model based friction compensation algorithm and the Kalman filter based RBF network based friction compensation algorithm are provided for applications in the practical servo motion systems.

Chapter 3 provides physical model derivation of LBDCM motion system and also presents the physical mathematic model of unit PEA. The frequency-domain system identification procedure is also established in the presence of friction compensation in

CHAPTER 1 INTRODUCTION

the chapter. In the end, a practical and simple system identification algorithm is introduced.

The system identification of the LBDCM drive systems is achieved by DSA with RBF friction compensation in Chapter 4. A new robust controller is proposed for LBDCM system under nonlinear friction and load variation scenarios. The detailed proofs are given to illustrate the internal stability and asymptotic characteristic of the proposed controller. Nonlinear friction in LBDCM system is measured and the data is approximated by both model based algorithm and Kalman filter based RBF fitting algorithm. The outcomes of the friction compensation are shown accordingly. The simulation results as well as the experiment results of tracking control of the LBDCM system under different load conditions are illustrated.

Chapter 5 proposes a robust position control of LBDCM system by combining H_∞ and μ synthesis theory. An RBF network is also established for system identification and mass estimation. A novel structure of three sub- μ controllers is first proposed to achieve more robustness. In the end, SMC is integrated to the proposed controller such that better dynamic performance is achieved accordingly. The performance of proposed control scheme is compared with PID controller by both simulation results and DSP real-time experiment results.

The principle, structure and driver of LUM are introduced firstly in Chapter 6. Kalman filter based RBF friction fitting results are compared with model based fitting results by simulation. Transfer function model of the system is identified. A reaching law based discrete-time sliding mode controller is designed for the LUM motion system. GA is adopted to select the optimal free parameters during the sliding mode controller design process. The tracking results of stepwise and swing reference signal are shown and the mean tracking errors of the proposed controller and PID controller with friction and load variations are both illustrated.

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Chapter 7 deals with the coordinated robust control of LUM drive x-y motion systems. The transfer functions of two main control loops and two interaction loops are identified following the foregoing procedure firstly. A multivariable decoupling controller is presented to compensate the cross coupling between the main control loops. A cross-coupled sliding mode controller is proposed and introduced in detail. The proposed controller realizes both the strong robustness to uncertainties and coordination motion between two single axes. The precise curved path tracking results are achieved in simulation and experiments under different friction, load and reference tracking curve conditions.

Chapter 8 presents conclusions of the thesis and several recommendations for future research.

CHAPTER 2

Nonlinear Friction Compensation in Servo Systems

2.1 Introduction

In various servo mechanisms, friction is regarded as the most significant nonlinear factor. Friction is a natural phenomenon that is quite hard to model, and it is not yet completely understood. The classical model of friction is described by a discontinuous relation between the friction force and relative velocity between the two contacting surfaces. Typical models are the combinations of coulomb friction, viscous friction and Stribeck effect [81]. However, some interesting properties observed in the systems with friction can not be illustrated by classical models. The velocity and position dependent Dahl friction [84] model was proposed by describing the spring-like behavior during stiction. Presliding displacements as well as friction behaviors such as friction lag and varying break-away force were accounted for by the LuGre model [53] which combined the Dahl model with arbitrary steady-state friction characteristics. But the LuGre model has been subjected to several criticisms mainly focused on the linear

relation assumed between the friction force during presliding and the state variable in the model [86]. Model-based friction compensation techniques are based on the knowledge of a suitable friction model that predicts the real friction and commands an opposed control action to compensate it [137-139]. However the model based method requires complex parameter estimation procedure and extra hardware experiment design. More recently, NN has been applied to deal with the problem of friction modeling and compensation due to its strong capability to approximate nonlinear function [140 and 141]. These NN friction models are velocity dependent rather than position dependent, nevertheless, the actual friction in servomechanism is related with both. In this chapter, a Kalman filter based RBF which has the characteristic more close to that of the actual friction is designed to compensate the friction in linear motor drive systems.

2.2 Friction in Servo Systems

The practically measured friction data are considered to be important for accurate friction modeling, analysis of friction related problems, and synthesis of controllers. Various mathematical models have been proposed to approximate a number of these data. Which model is preferred depends on the purpose of it, but the model that accurately describes all the observed phenomena is in general to be preferred. Besides the question of effectiveness, no less important is the question of the model efficiency, e.g., the required computational resources in terms of time, can be of importance when for instance the model will be used in simulation studies. Due to the complexity of the physical mechanisms underlying friction, most models are of an empirical nature. With the computational power available today, it is in many cases possible to deal effectively with friction. This has potential to improve quality, economy, and safety of a system. Friction should be considered early in the system design by reducing it as much as possible through good hardware design. Four classical friction models [77] are shown in Figure 2.1.

The most common representation of dry friction found in engineering is simply referred to as Coulomb friction in Figure 2.1(a). With the standard Coulomb friction model, the friction force is represented in terms of a signum function and expressed as

$$F = F_C \operatorname{sgn}(v) \quad (2.1)$$

where the friction force F_C is proportional to the normal load, i.e. $F_C = \mu F_N$. This description of friction is termed Coulomb friction. Coulomb friction is independent of velocity and is always present. It does not specify the friction force for zero velocity. It may be zero or it can take on any value in the interval between $-F_C$ and F_C , depending on how the sign function is defined.

Figure 2.1: a) Coulomb friction b) Coulomb plus viscous friction, c) Stiction plus Coulomb and viscous friction d) Stribeck friction

In practical conditions, grease and oil, which are both fluid lubricants, enormously extend the working life of machine parts and are thus common in servo controlled mechanisms. Lubricant is drawn into the solid-to-solid interface by the motion of the parts and maintains a film under pressure through its own viscosity. The reduction of wear achieved by fluid lubrication is so great for many applications. When there is full fluid lubrication, which will occur in grease as well as oil lubricated mechanisms, a viscous friction model is appropriate. The result is shown in Figure 2.1(b).

$$F = F_C \operatorname{sgn}(v) + F_v v \quad (2.2)$$

where F_v is the viscous coefficient.

In most situations, the force required to “break-away”, that is to commence motion from rest, is greater than that required to sustain motion, as demonstrated by the model in Figure 2.1(c). It is clear that friction at rest cannot be described as a function of only velocity. It has to be modeled using the external force F_e instead. The friction force for zero velocity is a function of the external force rather than the velocity.

$$F = \begin{cases} F_C \operatorname{sgn}(v) + F_v v & \text{if } v \neq 0 \\ F_e & \text{if } v = 0 \text{ and } |F_e| < F_S \\ F_S \operatorname{sgn}(F_e) & \text{otherwise} \end{cases} \quad (2.3)$$

where F_e is the external force, F_S is the minimum force to move from stiction.

The conventional way of representing friction in block diagrams with velocity as the input and force as the output is therefore not completely correct. If doing so, stiction must be expressed as a multi-valued function that can take on any value between the two extremes $-F_S$ and F_S .

In practical conditions, the velocity dependence is continuous as shown in Figure 2.1(d). The region of the friction drops with increasing velocity is the negative viscous friction. This model is called Stribeck friction which is generally acceptable friction model. A more general description of friction is, therefore,

$$F = \begin{cases} F(v) & \text{if } v \neq 0 \\ F_e & \text{if } v = 0 \text{ and } |F_e| < F_S \\ F_S \operatorname{sgn}(F_e) & \text{otherwise} \end{cases} \quad (2.4)$$

where $F(v)$ is an arbitrary function, which may look as in Figure 2.1(d). Many parameterizations of $F(v)$ have been proposed [9]. A common form of the nonlinearity is:

$$F(v) = F_C + (F_S - F_C)e^{-|v/v_S|^{\delta_s}} + F_v v \quad (2.5)$$

where v_S is called the Stribeck velocity, δ_s usually has a value of 2.

The dynamic friction models are not introduced here because the dynamic model introduces one extra state variable and two dynamic functions describing the state variable, which increase the complexity of the state space function of the servo systems, and correspondingly complicate the control design algorithm.

The Stribeck friction model is widely applied to friction approximation and compensation in industrial servo systems due to its simple structure and high fitting accuracy. It is worth noting here that the Stribeck friction model is only velocity dependent. However, the nonlinear friction in actual servo systems is always velocity dependent as well as position dependent. A method is proposed in this chapter to take full advantage of this friction model. The friction can be measured at different position points along the moving range. One Stribeck friction model can be set up at each point. That is, one set of friction parameters could be proposed at each position points. All these Stribeck friction models are combined together so that a position and velocity dependent friction model is proposed in the end. This improved Stribeck model will definitely perform well in the friction fitting and compensation process.

2.3 Friction Measurement

The first step to identify the friction is to measure experimental friction data from the system. Two different experiments are designed to measure the nonlinear friction in the servo system, the first one is designed to yield the break-away friction force, while the second one to yield the steady state friction. The concerned servo system consists of one carriage on stage base, a linear motor, a motor driver. The linear motor driven carriage can move on the stage base.

2.3.1 Break-away Friction Experiment

In the break-away experiment, the carriage is positioned at one of the two ends of the stage base. The control voltage injected to the motor driver is increased gradually at a small step. When the encoder reads a very small displacement (set at 10 encoder counts), the position and static control current are recorded. After the carriage comes to rest for 20 s, a new experiment is initiated. When the carriage reaches the other end of the moving limit, the direction of the motion is reversed. In this way, the static friction level for the other direction of motion is also measured.

During the break-away experiment, maximum repeatability is the most concerned matters by warm up exercise, fine sampling and suitable force rate. Early in this experiment work, it is observed that after an extended period of inactivity, the friction will start high and diminish quickly to a steady value. A series of empirical trials show that the motion friction comes to its steady value after a minute of moderate velocity activity. Like the motion friction, the static friction is observed to increase with long time inactivity. The rising static friction is perhaps a consequence of the interaction of static friction and dwell time. To improve repeatability, the longer time process is addressed with a vigorous motion at the beginning of each session. The break-away experiment requires considerable time. It is therefore important to maximize the rate of the experiment. As roughly 80% of the experimental time is spent in raising the exerted force, the size of force step rate is a critical experimental issue. The final adopted input voltage step is 0.05v/s for the DC motor servo system after several trails in view of a compromise between repeatability and speed.

2.3.2 Motion Friction Experiment

In the second experiment, the control voltages for various constant carriage velocity motions are measured as a function of carriage position and velocity. For every position point, the friction is measured as a function of velocity. The relationship between friction and velocity has been measured in three ways: open- loop, constant force motions; closed, stiff velocity loop, constant velocity motions; in contact, an

open-loop force ramp against a compliant surface.

Each of these experiments offers an advantage: the open-loop gliding motions provide a test bed for measuring the repeatability of the friction forces in high velocity regime; the closed-loop control provides a means to penetrate the unstable, low velocity regime; the compliant motions provide a way to map the regime of very low velocity. The experiment diagram for friction measurement is shown in Figure 2.2, where u is input voltage, y is the position, v is the velocity, v_r is velocity command. The one in dash frame is open-loop motion process, and the whole diagram is the closed-loop velocity control process.

Figure 2.2: Diagram of experiments on friction measurement

In the open-loop motion process, the constant voltage is exerted to the driver of the motor. The motor is kept in accelerated motion with the decreasing acceleration at the beginning. When the constant external force is equal to the friction at some moment, the motor begins to move in constant velocity. The force is recorded and velocity is measure by tachometers or filtered derivative of position signals under this condition. The motor moves in opposite direction when opposite force involved. The experiment is repeated at every position point. The velocity as well as position dependence friction data is achieved in high velocity regime accordingly.

To measure the motion friction at low velocities, a velocity control loop is implemented and a typical speed controller structure is shown in Figure 2.2. At a

constant velocity, the force generated by the motor is used to eliminate the friction and is equal to the friction. The corresponding control voltages injected into the motor driver are recorded. The friction-velocity data values are then obtained by averaging the measured input control voltages at every concerned velocity. The average is necessary due to noise in measured signal and force ripple in the current amplifier.

The data collected by the constant velocity motions which will be illustrated in the following corresponding chapters show clear evidence of an upward turn in the friction curve at low but significant velocities. However, no measurements are made at extremely low velocities, a velocity regime important to force control. Therefore, the extra hardware design is required to collect the extremely low velocity data. The moving item driven by the motor in servo systems is pressed against a hard surface and a spring is inserted between the surface and the moving item. The applied force is ramped up to a value well above static friction and down again. The very low velocity is realized by this kind of motion way. The average friction measurements of a number of trials with different spring stiffness provide a more accurate data of friction as a function of the extremely low velocities [142].

Figure 2.3: Motor driver speed control mode structure

2.4 Friction Compensation

The servo systems consist of a linear part and a nonlinear part as described in last section. However, the plant is always assumed to be linear when applying the frequency domain identification methods based on covariance analysis and Fourier transform. A satisfactory model always cannot be achieved by directly applying frequency domain identification to nonlinear systems. Therefore, the nonlinear friction part is to be identified and compensated in the process of modeling the servo system. As such, with the nonlinear compensation, the servo system is supposed to be a linear system during both the identification and control process. There are two main categories of the friction fitting and compensation method: model based one and non-model based one, which is also called the white-box modeling and black-box modeling in some applications. If detailed prior knowledge about the system is available, the white-box modeling is applicable. But it may result in complex friction descriptions not very suitable for the purpose of control and it is also a time-consuming job to construct these white-box models. On the other hand, black-box models are easier to construct. The black-box model, for instance, NN model can approximate the friction as accurate as possible if only sufficient measured friction data is provided for the fitting purpose.

2.4.1 Model Based Friction Fitting

The friction in the servomechanisms is not only velocity dependant but also position dependant. Thus, the friction model in (2.4) cannot describe the features of friction along all the positions. The friction models with different parameters are set up for different positions of interest so that it can approximate the friction force accurately at whatever position.

For every position point, one set of four parameters need to be estimated. The nonlinear curve-fitting (data-fitting) problem is solved by a subspace trust region method [143] and is based on the interior-reflective Newton method [144]. Many of

the optimization methods are based on trust-regions, a simple yet powerful concept in optimization.

To understand the trust-region approach to optimization, consider the unconstrained minimization problem, minimize $f(x)$, where the function takes vector arguments and returns scalars. Suppose we are at a point x in n -space and we want to improve, i.e., move to a point with a lower function value. The basic idea is to approximate f with a simpler function q which reasonably reflects the behavior of function f in a neighborhood N around the point x . This neighborhood is the *trust region*. A trial step s is computed by minimizing (or approximately minimizing) over N . This is the trust-region sub-problem,

$$\min_s \{q(s) \mid s \in N\} \quad (2.6)$$

The current point is updated to be $x+s$ if $f(x+s) < f(x)$. Otherwise, the current point x remains unchanged and N , the region of trust, is shrunk and the trial step computation is repeated.

The key questions in defining a specific trust-region approach to minimize $f(x)$ are how to choose and compute the approximation q (defined at the current point x), how to choose and modify the trust region N , and how to solve the trust-region sub-problem accurately.

In the standard trust-region method ([145]), the quadratic approximation q is defined by the first two terms of the Taylor approximation to f at x . The neighborhood N is usually spherical or ellipsoidal in shape. Mathematically the trust-region sub-problem is typically stated

$$\min \left\{ \frac{1}{2} s^T H s + s^T g \mid \text{such that } \|Ds\| \leq \Delta \right\} \quad (2.7)$$

where g is the gradient of f at the current point x , H is the Hessian matrix (the symmetric matrix of second derivatives), D is a diagonal scaling matrix, Δ is a positive scalar, and $\| \cdot \|$ is the 2-norm. Good algorithms exist for solving (2.7) (see [145]); such

algorithms typically involve the computation of a full eigensystem and a Newton process applied to the secular equation.

$$\frac{1}{\Delta} - \frac{1}{\|s\|} = 0 \quad (2.8)$$

Such algorithms provide an accurate solution to (2.7). However, they require time proportional to several factorizations of H . Therefore, for large-scale problems a different approach is needed. The approximation approach must restrict the trust-region sub-problem to a two-dimensional subspace S . Once the subspace has been computed, the work to solve (2.7) is trivial even if full eigenvalue/eigenvector information is needed (since in the subspace, the problem is only two-dimensional). The dominant work has now shifted to the determination of the subspace.

The two-dimensional subspace S is determined with the aid of a preconditioned conjugate gradient process described below. The algorithm assigns $S = \langle s_1, s_2 \rangle$, where s_1 is in the direction of the gradient g , and s_2 is either an approximate Newton direction, i.e., a solution to

$$H \cdot s_2 = -g \quad (2.9)$$

or a direction of negative curvature,

$$s_2^T \cdot H \cdot s_2 < 0 \quad (2.10)$$

The philosophy behind this choice of S is to force global convergence (via the steepest descent direction or negative curvature direction) and achieve fast local convergence (via the Newton step, when it exists).

A framework for the optimization approach to unconstrained minimization using trust-region ideas is now easy to describe:

- Formulate the two-dimensional trust-region sub-problem.
- Solve (2.7) to determine the trial step s .

□ If $f(x+s) < f(x)$ then $x = x + s$.

□ Adjust Δ .

These four steps are repeated until convergence.

In order to apply the above algorithm to fit the measured friction data, the observed target data for curve fitting should be obtained from previous experiments firstly. Generally, satisfying performance of fitting is derived from the sufficient measured data, which thoroughly cover the input space of the friction model function. However, a large number of similar experiments should be carried out to achieve the data. This is a time-consuming work and even causes some wear and tear of hardware. A method is addressed to escape from this difficulty. Firstly, some original data are gained through a few experiments. Then, the relationship curve is plotted. Finally, the curve can be sampled by the frequency that is selected based on how many data is sufficient for the recursive parameter estimation. 300 data pairs are generated for the friction compensation in servo systems, among them, 260 samples are used to estimate the parameters and the other 40 to check the fitting validity.

2.4.2 Non-model Based Friction Fitting

NNs have become a very popular choice of black-box structure in recent years because they are capable of approximating highly nonlinear functions without deriving the specific mathematic model. Friction in servo systems is just of highly nonlinear characteristic. NNs are suitable for the friction fitting problem accordingly.

An RBF with decoupled extended Kalman filter training [146] is applied to approximate the friction in servomechanisms. The general schematic of RBF network is shown in Figure 2.3. An RBF network can be described as:

$$F(x) = w_0 + \sum_{i=1}^l w_i \varphi(\|x - c_i\|^2) \quad (2.11)$$

where x is the input vector, w_i is the weight, c_i is known as the RBF center, and l is the number of centers.

Figure 2.4: RBF network architecture

The basis function $\varphi(\cdot)$ has the form as

$$\varphi(x) = [\varphi_0(x)]^{1/(1-p)} \quad (2.12)$$

If $p > 1$, $\varphi_0(x)$ should satisfy the following conditions:

$$\square \varphi_0(x) > 0 \forall x \in (0, \infty) \quad (2.13)$$

$$\square \varphi'_0(x) > 0 \forall x \in (0, \infty) \quad (2.14)$$

$$\square \frac{p}{p-1} [\varphi'_0(x)]^2 - \varphi_0(x) \varphi''_0(x) > 0 \forall x \in (0, \infty) \quad (2.15)$$

If $p < 1$, $\varphi_0(x)$ should satisfy the following conditions:

$$\square \varphi_0(x) > 0 \forall x \in (0, \infty) \quad (2.16)$$

$$\square \varphi'_0(x) < 0 \forall x \in (0, \infty) \quad (2.17)$$

$$\square \frac{p}{p-1} [\varphi'_0(x)]^2 - \varphi_0(x) \varphi''_0(x) < 0 \forall x \in (0, \infty) \quad (2.18)$$

One generator function which guarantees the above condition is the linear function.

$$\varphi_0(x) = ax + b \quad (2.19)$$

where p is the real number, $a > 0$, $b \geq 0$

Consider the RBF in Figure. 2.3 with m inputs, l hidden layer neurons, n outputs. Let y denote the output of RBF network, $h(\hat{\theta}_k)$ denotes the output at the k th iteration of the optimization algorithm.

$$y = [y_{11} \quad \cdots \quad y_{1s} \quad \cdots \quad y_{n1} \quad \cdots \quad y_{ns}]^T \quad (2.20)$$

$$h(\hat{\theta}_k) = [\hat{y}_1 \quad \cdots \quad \hat{y}_{1s} \quad \cdots \quad \hat{y}_{n1} \quad \cdots \quad \hat{y}_{ns}]_k^T \quad (2.21)$$

Note that the y and $\hat{y}$ each consist of ns elements, where n is the dimension of the RBF output and s is the number of training samples.

The elements of weight w_i and those of the RBF centers constitute the state of a nonlinear system. The output of RBF is assumed as the output of the nonlinear system to which the Kalman filter is applied. The state of the system is represented as:

$$\theta = [w_1^T \quad \cdots \quad w_n^T \quad c_1^T \quad \cdots \quad c_l^T] \quad (2.22)$$

The nonlinear system model to which the Kalman filter can be applied is:

$$\theta_{k+1} = \theta_k + \omega_k \quad (2.23)$$

$$y_k = h(\theta_k) + v_k \quad (2.24)$$

where ω_k and v_k are artificially added noise processes.

After applying the Kalman filter algorithm, the desired estimate $\hat{\theta}_k$ is obtained by the recursion.

$$\hat{\theta}_k = f(\hat{\theta}_{k-1}) + K_k[y_k - h(\hat{\theta}_{k-1})] \quad (2.25)$$

$$K_k = P_k H_k (R + H_k^T P_k H_k)^{-1} \quad (2.26)$$

$$P_{k+1} = F_k(P_k - K_k H_k^T P_k) F_k^T + Q \quad (2.27)$$

$$\varepsilon(\omega_k) = 0, \varepsilon(\nu_k) = 0 \quad (2.28)$$

$$\varepsilon(\omega_k w_i^T) = Q \delta_{ki}, \varepsilon(\nu_k c_i^T) = R \delta_{ki} \quad (2.29)$$

where $\varepsilon(\cdot)$ is the expectation operator and δ_{ki} is the Kronexker delta; K_k is known as Kalman gain; P_k is the covariance matrix of the state estimation error; $f(\cdot)$ is the identity mapping function and y_k is the target output of the RBF network; Q and R matrices are running parameters which can be considered as the covariance matrices of the artificial noise ω_k and ν_k ; F_k is the identity matrix; H_k is the partial derivative of the RBF output with respect to the RBF network parameters at the k th iteration of the Kalman recursion.

$$H_k = \begin{bmatrix} H_w \\ H_v \end{bmatrix} \quad (2.30)$$

where H_w and H_v are given by:

$$H_w = \begin{bmatrix} H & 0 & \cdots & 0 \\ 0 & H & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & H \end{bmatrix} \quad (2.31)$$

$$H = [h_1 \quad \cdots \quad h_s] = \begin{bmatrix} h_{01} & \cdots & h_{0s} \\ h_{11} & \cdots & h_{1s} \\ \vdots & \vdots & \vdots \\ h_{l1} & \cdots & h_{ls} \end{bmatrix} \quad (2.32)$$

$$h_{0k} = 1, h_{jk} = \varphi(\|x_k - c_j\|^2) \quad (k = 1, \dots, s), (j = 1, \dots, l) \quad (2.33)$$

$$H_v = \begin{bmatrix} -w_{1l}g'_{1l}2(x_1 - c_l) & \cdots & -w_{1l}g'_{ml}2(x_m - c_l) & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ -w_{1l}g'_{1l}2(x_1 - c_l) & \cdots & -w_{1l}g'_{ml}2(x_m - c_l) & \cdots \\ & & -w_{nl}g'_{1l}2(x_1 - c_l) & \cdots & -w_{nl}g'_{ml}2(x_m - c_l) \\ & & \vdots & \vdots & \vdots \\ & & -w_{nc}g'_{1l}2(x_1 - c_l) & \cdots & -w_{nc}g'_{ml}2(x_m - c_l) \end{bmatrix} \quad (2.34)$$

2.5 Conclusions

In this chapter, the practical method to measure the nonlinear friction in servo systems is proposed. Both model based and non-model based friction fitting and compensation algorithm is presented. The Kalman filter based RBF network is designed as a more promising friction fitting scheme and will be applied to compensate the nonlinear friction in servo systems throughout the research work.

In next chapter, the system identification approach will be developed for the servo systems in the presence of the proposed friction compensation scheme.

CHAPTER 3

System Identification of Servo Systems

3.1 Introduction

Nowadays, many kinds of servomechanisms such as transportation carriages, intelligent robot arms, hard disk drive and optical servo drive, etc., are operating in actual industrial fields. Most of such systems are nonlinear systems due to friction, backlash, saturation which are always ignored in the practical identification process. Control schemes have been derived to realize precise position or velocity performance of the servo systems with the assumption of being linear system [153-155].

Precise model is the basis for high speed and high accuracy in servo control. The largest body of literature on system identification in the last decade has been focused on linear models, with the primary objective of providing a nominal model and an associated uncertainty set suitable for the application of advanced control strategies. Although linear transfer function models are by far the most commonly used system models, it is well known that the real world is unlikely to show linear mechanisms of data generation. Surprisingly often, linear model approximations turn out to provide

good performance. It is still the case that this does not hold in many real world contexts, either because the nonlinear system behavior cannot be neglected or because circumventing nonlinearity through uncertainty over-bounding techniques may be too conservative, preventing the possibility of finding a satisfactory controller. Although identifying the nonlinear system accurately is a big challenge, many researchers have explored this area in two ways: one is to measure the nonlinear plant minimizing the impact of nonlinear components in systems [150 and 151], and the other is to approximate the plant by linear model which is as close as possible to the real plant [152-154]. The latter method is feasible only when the system can be linearized in some specific operation point. The former method will be adopted for the system identification of the studied servo systems. This chapter is organized as follows: physical model of two kinds of servo systems is introduced firstly. Then the design and configuration of the system identification experiment with DSA is proposed. In the end, a practical system identification algorithm in frequency domain is presented in details.

3.2 Physical Model of Servo Systems

Servo systems can use pneumatic, hydraulic, or electromechanical actuation technology. The choice of the actuator type (i.e. the device that provides the energy to move the load) is based on power, speed, precision, and cost requirements. Electromechanical systems are typically used in high precision, low to medium power, and high-speed applications. Motors are the actuators used in such systems and they provide either rotary or linear motion. Servo systems involved in our research are driven by two kinds of motors, LBDCM and LUM.

3.2.1 Model of LBDCM Drive System

A typical linear brushless motor consists essentially of two parts: an armature assembly and a field assembly separated from each other by a small air gap. An armature assembly, in turn, consists of a stack of laminations with a three-phase

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winding positioned in its slots. A field assembly is a soft magnetic plate with the magnets of alternating polarities facing the air gap. The armature can move along the magnets at different speed in servo systems with the inverter switching commutation control being made according to the sensed moving position information. The structure of LBDCM is shown in Figure 3.1. LBDCM is the key component in the LBDCM drive system, thus the dynamic model derivation of it is presented firstly. Several relevant assumptions are made: end-effect is neglected; back-EMFs (Electro-motive force) are sinusoidal; air gap is uniform.

Figure 3.1: Structure of an LBDCM motor

The voltage equations of a P-pole LBDCM can be represented as [155]

$$v_{abc} = r_s i_{abc} + \frac{d}{dt} \lambda_{abc} \quad (3.1)$$

$$\lambda_{abc} = L_s i_{abc} + \lambda_m \quad (3.2)$$

$$L_s = \begin{bmatrix} L_s + L_A - L_B \cos(\frac{P\pi x}{\tau}) & -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{2\pi}{3}) & -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{4\pi}{3}) \\ -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{2\pi}{3}) & L_s + L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{4\pi}{3}) & -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau}) \\ -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{4\pi}{3}) & -\frac{1}{2} L_A - L_B \cos(\frac{P\pi x}{\tau}) & L_s + L_A - L_B \cos(\frac{P\pi x}{\tau} - \frac{2\pi}{3}) \end{bmatrix} \quad (3.3)$$

$$\lambda_m = \lambda_{\max} \left[\sin(\frac{P\pi x}{2\tau}) \quad \sin(\frac{P\pi x}{2\tau} - \frac{2\pi}{3}) \quad \sin(\frac{P\pi x}{2\tau} - \frac{4\pi}{3}) \right]^T \quad (3.4)$$

The parameters in above equations are listed in Table 3.1.

The transformation of variables from abc domain to secondary frame can be written as

$$h_{dqo} = K h_{abc} \quad (3.5)$$

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where

$$K = \frac{1}{2} \begin{bmatrix} \cos(\frac{P\pi x}{2\tau}) & \cos(\frac{P\pi x}{2\tau} - \frac{2\pi}{3}) & \cos(\frac{P\pi x}{2\tau} - \frac{4\pi}{3}) \\ \sin(\frac{P\pi x}{2\tau}) & \sin(\frac{P\pi x}{2\tau} - \frac{2\pi}{3}) & \sin(\frac{P\pi x}{2\tau} - \frac{4\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad (3.6)$$

$$h_{dqo} = [h_q \quad h_d \quad h_o] \text{ and } h_{abc} = [h_a \quad h_b \quad h_c] \quad (3.7)$$

h can be voltage current or flux linkage. By using the assumptions made and through proper arranging, one can derive the following propulsion force expression for P-pole LBDCM:

$$F_x = \frac{3}{2} \frac{P}{2} \frac{\pi}{\tau} \lambda_{\max} i_q = K_t i_q \quad (3.8)$$

where K_t denotes the force generating constant.

Table 3.1 Parameters in voltage equations of an LBDCM

Parameters	Description
$v_{abcs} = [v_{as} \quad v_{bs} \quad v_{cs}]^T$	Phase voltage vector
$i_{abcs} = [i_{as} \quad i_{bs} \quad i_{cs}]^T$	Phase current vector
$r_s = diag[r \quad r \quad r]^T$	Resistance matrix of winding
$\lambda_{abcs} = [\lambda_{as} \quad \lambda_{bs} \quad \lambda_{cs}]^T$	Moving-member flux linkage vector
L_{ls}	The component of self-inductance due to armature leakage inductance
L_A	The component of self-inductance due to space-fundamental air-gap flux
L_B	Sinusoidal amplitude of variation of self-inductance
P	Number of poles
τ	Pole pitch
$\lambda_{\max}$	Amplitude of sinusoidal flux linkages
x	Displacement of rotor

A block diagram of a linear DC motor servo system is shown in Figure 3.2. A

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typical servomechanism consists of a servo controller, amplifier, and motor with a feedback device.

The dash frame in Figure 3.2 (a) represents the plant. In practical servomechanism, the system is composed with both a linear part and a nonlinear part. The nonlinear part denotes the friction existing in the mechanical structure of the servo system, which cannot be ignored due to its significant impact to the servo performance.

(a)

(b)

Figure 3.2 (a) Block diagram of the servo system (b) Block diagram model of the plant

Only the linear part of the servo system is shown in Figure 3.2 (b). The mechanical and electrical dynamics of a DC servo motor can be expressed as follows [156]:

$$M\ddot{y} + F_v\dot{y} + F_t = F_m$$

$$K_e\dot{y} + L_q \frac{dI_q}{dt} + R_q I_q = u \quad (3.9)$$

$$F_m = K_t I_q$$

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where y denotes the motor drive carriage's position; M , F_v , F_m and F_l denote the mechanical parameters: mass, viscosity constant, generated force and disturbance force, respectively; u , I_q , R_q and L_q denote the electrical parameters: input DC voltage, quadrature-axis current, quadrature-axis resistance and quadrature-axis inductance, respectively. K_e is the back EMF constant of the motor.

Since the electrical time constant is typically much smaller than the mechanical one, the delay due to electrical transient response may be ignored, giving the following simplified model of the linear part of the servo system:

$$\ddot{y} = -\frac{K_1}{M}\dot{y} + \frac{K_2}{M}u \quad (3.10)$$

$$\text{where } K_1 = \frac{K_e K_t + R_q F_v}{R_q}, K_2 = \frac{K_t}{R_q} \quad (3.11)$$

In the transfer function form, the dynamics (3.10) can be described by

$$\frac{Y(s)}{U(s)} = \frac{b}{s^2 + as} \quad (3.12)$$

where $a = K_1/M$ and $b = K_2/M$. Obviously, the system parameters a and b will vary with the change of payload, which causes the mass M to change.

3.2.2 Model of Piezo-actuated System

Piezoelectric motor is a totally new kind of motor. Till now, only one Israel company can produce the kind of LUM studied in the thesis. It is smaller, simpler, quieter, easier to control, than conventional DC motors. Therefore, the basic motion principle of the motor is presented prior to modelling the system. The motion takes advantage of a unique physical quality of piezo-ceramic. The quality is that when a voltage is applied to a piezoelectric material, the voltage would change the length of the device. Therefore, different voltages will cause the different lengths of the device. It is the basis of the piezoelectric devices to produce motion. As shown in 3.3, suppose we have a piezoelectric device and insert one side to the solid end with the other side free. If a voltage is applied between the two ends, the end point moves sideways. By changing the applied voltage, the end point can move back and forth.

Figure 3.3: The inverse piezoelectric effect

The basic principle of piezo-actuated mechanism is as simple as the inverse piezoelectric effect. However, many different kinds of linear piezoelectric motors were proposed according to diverse structures and driving principles [24-28]. Linear piezoelectric motor is an innovative invention in 1980. It is difficult to tell which structure of the motor is better or not because there are not many applications and performance experiences to validate it. Therefore, it results in a big challenge to set up models for such kind of motors. The state of the art in this area is limited to model the unit piezoelectric actuator (PEA), which becomes the foundation of modeling complex structure piezoelectric motor.

Figure 3.4: Simplified mechanical model of PEA

Figure 3.4 shows a typical unit of a piezoelectric actuator. Mechanically, a PEA is a mass-spring-damper system. The linearity of the stiffness as well as the simple mass

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property is assumed. The damping of a PEA is well known to be small. Such a unit is modeled so as to find the relationship between the applied voltage u and a PEA generated force F . The relationship is not a linear one but is determined by hysteresis and saturation. However, there are only experimental loops as in Figure 3.5 for demonstrating this relation. When the maximum voltage u_0 in normal working area of a PEA is applied, the corresponding elongation is y_0 . Saturation arises when the elongation goes to more than $2/3$ of the saturation length y_{ps} and hysteresis exists all along the elongations. Generally, a PEA only works in the unsaturated condition. The actuating force has such a relation with elongations:

$$F = ky \quad (3.13)$$

From Figure 3.5, only a graphical representation of the static relation between u and F is demonstrated. The differential equation proposed in [157 and 158] describes the physical quality of piezoelectric materials more closely and therefore is believed to be an accurate mathematical counterpart for the dynamic and static hysteresis phenomenon. It is called the Coleman-Hodgdon (CH) equation:

$$\dot{F} = \alpha |\dot{u}| (f(u) - F) + \dot{u}g(u) \quad (3.14)$$

where

$$\begin{aligned} f(u) &= D_1 \arctan(D_2 u) \\ g(u) &= \frac{D_1 D_2}{1 + (D_2 u)^2} (1 - D_3 e^{-D_4 |u|}) \end{aligned} \quad (3.15)$$

$\alpha, D_1, \dots, D_4$ are constant parameters. The function $f(u)$ is not limited to 'arctan'. It is proved that if the function $f(u)$ has been chosen all parameters can be determined from a given experimental major loop and the start slope.

Figure 3.5: Hysteresis loops of F versus u

As a matter of a fact, the CH equation is not a realistic model for the relation between u and F , because in practical system the applied voltage u is input of the system rather than u and $\dot{u}$. Moreover, $\dot{u}$ as an input is not attractive from a control point of view because the model can not be written in a state-space form. A possible solution to this problem is to make a series connection of a system H , with u as input and u and $\dot{u}$ as output which serves as input of CH equation. The structure is demonstrated as in Figure 3.6.

The $H=[1 \quad s]^T$ transfers u to u and $\dot{u}$. However, the H is not proper. A strictly proper H turns out to be most suitable. Therefore, the initial choice is multiplied by $\frac{1}{k_2 s^2 + k_1 s + 1}$. By an appropriate choice of k_1 and k_2 , H tends to $[1 \quad s]^T$ for low frequencies.

Although the physical model of unit PEA is provided, the accurate LUM model is still an area to be explored due to too many structures and driving principles of such kind of motor.

Figure 3.6: A model from u to F as a series connection of H and Coleman-Hodgdon equation

3.3 System Identification of Servo Systems

Generally, the system identification method can be classified into two major groups, time domain identification and frequency domain identification. The latter will be used to identify the servo system due to following reasons: the data analysis is easier in the frequency domain; the acquisition is much faster than in the time domain; the fundamental excitation is sinusoidal single frequency wave; the frequency domain instrumentation is less expensive than the time domain instrumentation.

As described in last section, the accurate physical models of the two servo systems are hard to obtain. Fortunately, DSA owns the function of identifying the linear systems in frequency domain. Friction compensation technique is firstly introduced into the DSA based system identification process. The block diagram of the experiment to identify the servo systems in the presence of friction by using DSA is shown in Figure 3.7. The friction compensation unit shown in the figure is realized by dSPACE in real-time systems. Input to the dSPACE is the feedback position signal and its output is the voltage which can compensate the friction in the servo system. The rear connector generates the excitation signal. A number of different types of excitation signals are available for the analysis. The swept sine mode is chosen to stimulate the system with a sine wave because it allows for control of the signal level at a single frequency (rather than broadband noise) over the frequency response measurement. The DSA generates swept sine signals with the frequency from 1Hz to

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100Hz to excite the system via the voltage U in Figure 3.7. As a result, the rotor of the motor moves in sine wave. The encoder transfers the feedback position signal to channel 2 in Figure 3.7. As each frequency is tested, the DSA updates a cumulative derived bode plot of the system. DSA can also derive the frequency domain model of linear systems by curve fitting technique. But due to the limitations of the algorithms that are embedded inside, the obtained plant models always have some unexpected unstable zeros or poles. This adds the complexity or even causes trouble for control design. Thus, selecting of a proper system identification algorithm is necessary.

A simple but with high accuracy identification method is proposed for minimum phase process. The LBDCM and LUM driven servo systems normally are considered as minimum phase systems. The transfer function of a minimum-phase is assumed as:

$$G(s) = \frac{\beta_0 + \beta_1 s + \beta_2 s^2 + \dots + \beta_m s^m}{1 + \alpha_1 s + \alpha_2 s^2 + \dots + \alpha_n s^n} = \frac{N(s)}{D(s)} \quad (n > m) \quad (3.16)$$

Figure 3.7: Block diagram of servo system identification experiment

Its corresponding frequency response is then given by

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$$\begin{aligned}
 G(j\omega) &= \frac{\beta_0 + \beta_1 j\omega + \beta_2 (j\omega)^2 + \dots + \beta_m (j\omega)^m}{1 + \alpha_1 j\omega + \alpha_2 (j\omega)^2 + \dots + \alpha_n (j\omega)^n} \\
 &= \frac{(\beta_0 - \beta_2 \omega^2 + \dots) + j(\beta_1 \omega - \beta_3 \omega^3 + \dots)}{(\alpha_0 - \alpha_2 \omega^2 + \dots) + j(\alpha_1 \omega - \alpha_3 \omega^3 + \dots)} \\
 &= \frac{B_1(\omega) + jB_2(\omega)}{A_1(\omega) + jA_2(\omega)} = \frac{N(j\omega)}{D(j\omega)}
 \end{aligned} \tag{3.17}$$

where

$$\begin{cases}
 B_1(\omega_k) = \beta_0 - \beta_2 \omega_k^2 + \beta_4 \omega_k^4 - \dots = \sum_{i=0}^{\lfloor m/2 \rfloor} (-1)^i \beta_{2i} \omega_k^{2i} \\
 B_2(\omega_k) = \beta_1 \omega_k - \beta_3 \omega_k^3 + \beta_5 \omega_k^5 - \dots = \sum_{i=0}^{\lfloor (m-1)/2 \rfloor} (-1)^i \beta_{2i+1} \omega_k^{2i+1} \\
 A_1(\omega_k) = \alpha_0 - \alpha_2 \omega_k^2 + \alpha_4 \omega_k^4 - \dots = \sum_{i=0}^{\lfloor n/2 \rfloor} (-1)^i \alpha_{2i} \omega_k^{2i} (\alpha_0 = 1) \\
 A_2(\omega_k) = \alpha_1 \omega_k - \alpha_3 \omega_k^3 + \alpha_5 \omega_k^5 - \dots = \sum_{i=0}^{\lfloor (n-1)/2 \rfloor} (-1)^i \alpha_{2i+1} \omega_k^{2i+1}
 \end{cases} \tag{3.18}$$

where $k=1,2,\dots,N$. where N is the total number of frequency samples [159] in (3.18) denotes the integer part of variable of interest.

Let $R(\omega)$ and $I(\omega)$ be the real and imaginary part of the measured frequency response of the system. The frequency response error between the model and the measurement is given by:

$$e(j\omega) = R(j\omega) + jI(j\omega) - \frac{N(j\omega)}{D(j\omega)} \tag{3.19}$$

The parameters of the system can be obtained by minimizing the following index accordingly,

$$J = \sum_{k=1}^N \|e(j\omega_k)\|^2 \tag{3.20}$$

It is a nonlinear optimization problem and difficult to be solved. Following the results of [159], the error norm can be modified as:

$$J = \sum_{k=1}^N \|D(j\omega_k)e(j\omega_k)\|^2 \quad (3.21)$$

The practical meaning of this step is that the original problem now becomes a linear optimization problem. Using (3.17) (3.19) rewriting (3.21) yields

$$J = \sum_{k=1}^N \{ [A_1(\omega_k)R(\omega_k) - \omega_k A_2(\omega_k)I(\omega_k) - B_1(\omega_k)]^2 + [\omega_k A_2(\omega_k)R(\omega_k) - A_1(\omega_k)I(\omega_k) - \omega_k B_2(\omega_k)]^2 \} \quad (3.22)$$

Therefore, J can be minimized by determining $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_m$ and $\hat{\alpha}_0, \hat{\alpha}_1, \dots, \hat{\alpha}_m$ such that,

$$\begin{cases} \frac{\partial J}{\partial \beta_0} \Big|_{\beta_0 = \hat{\beta}_0} = \sum_{k=1}^N \{ 2[A_1(\omega_k)R(\omega_k) - \omega_k A_2(\omega_k)I(\omega_k) - B_1(\omega_k)](-1) \} \Big|_{\beta_0 = \hat{\beta}_0} = 0 \\ \frac{\partial J}{\partial \beta_1} \Big|_{\beta_1 = \hat{\beta}_1} = \sum_{k=1}^N \{ 2[\omega_k A_2(\omega_k)R(\omega_k) - A_1(\omega_k)I(\omega_k) - \omega_k B_2(\omega_k)](-\omega_k) \} \Big|_{\beta_1 = \hat{\beta}_1} = 0 \\ \vdots \\ \vdots \end{cases} \quad (3.23)$$

$$\begin{cases} \frac{\partial J}{\partial \alpha_1} \Big|_{\alpha_1 = \hat{\alpha}_1} = \sum_{k=1}^N \{ 2[A_1(\omega_k)R(\omega_k) - \omega_k A_2(\omega_k)I(\omega_k) - B_1(\omega_k)][-\omega_k I(\omega_k)] + 2[\omega_k A_2(\omega_k)R(\omega_k) + A_1(\omega_k)I(\omega_k) - \omega_k B_2(\omega_k)][\omega_k R(\omega_k)] \} \Big|_{\alpha_1 = \hat{\alpha}_1} = 0 \\ \frac{\partial J}{\partial \alpha_2} \Big|_{\alpha_2 = \hat{\alpha}_2} = \sum_{k=1}^N \{ 2[A_1(\omega_k)R(\omega_k) - \omega_k A_2(\omega_k)I(\omega_k) - B_1(\omega_k)][-\omega_k^2 R(\omega_k)] + 2[\omega_k A_2(\omega_k)R(\omega_k) + A_1(\omega_k)I(\omega_k) - \omega_k B_2(\omega_k)][-\omega_k^2 I(\omega_k)] \} \Big|_{\alpha_2 = \hat{\alpha}_2} = 0 \\ \vdots \\ \vdots \end{cases} \quad (3.24)$$

Rearrange the above two equations,

$$\begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \begin{pmatrix} \beta \\ \alpha \end{pmatrix} = \begin{pmatrix} Q_1 \\ Q_2 \end{pmatrix} \quad (3.25)$$

where $P_{11} \in R^{m \times m}$, $P_{12} \in R^{m \times n}$, $P_{21} \in R^{n \times m}$, $P_{22} \in R^{n \times n}$, and

$$\begin{aligned}
 P_{11} &= \begin{bmatrix} V_0 & 0 & -V_2 & 0 & V_4 & \dots \\ 0 & V_2 & 0 & -V_4 & 0 & \dots \\ V_2 & 0 & -V_4 & 0 & V_6 & \dots \\ 0 & V_4 & 0 & -V_6 & 0 & \dots \\ V_4 & 0 & -V_6 & 0 & V_8 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}, \quad P_{12} = \begin{bmatrix} T_1 & S_2 & -T_3 & -S_4 & T_5 & \dots \\ -S_2 & T_3 & S_4 & -T_5 & -S_6 & \dots \\ T_3 & S_4 & -T_5 & -S_6 & T_7 & \dots \\ -S_4 & T_5 & S_6 & -T_7 & -S_8 & \dots \\ T_5 & S_6 & -T_7 & -S_8 & T_9 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \\
 P_{21} &= \begin{bmatrix} T_1 & -S_2 & -T_3 & S_4 & T_5 & \dots \\ S_2 & T_3 & -S_4 & -T_5 & S_6 & \dots \\ T_3 & -S_4 & -T_5 & S_6 & T_7 & \dots \\ S_4 & T_5 & -S_6 & -T_7 & S_8 & \dots \\ T_5 & -S_6 & -T_7 & S_8 & T_9 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}, \quad P_{22} = \begin{bmatrix} U_2 & 0 & -U_4 & 0 & U_6 & \dots \\ 0 & U_4 & 0 & -U_6 & 0 & \dots \\ U_4 & 0 & -U_6 & 0 & U_8 & \dots \\ 0 & U_6 & 0 & -U_8 & 0 & \dots \\ U_6 & 0 & -U_8 & 0 & U_{10} & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \\
 \beta &= \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \\ \hat{\beta}_4 \\ \vdots \end{bmatrix}, \alpha = \begin{bmatrix} \hat{\alpha}_0 \\ \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \hat{\alpha}_3 \\ \hat{\alpha}_4 \\ \vdots \end{bmatrix}, Q_1 = \begin{bmatrix} S_0 \\ T_1 \\ S_2 \\ T_3 \\ S_4 \\ \vdots \end{bmatrix}, Q_2 = \begin{bmatrix} 0 \\ U_2 \\ 0 \\ U_4 \\ 0 \\ \vdots \end{bmatrix}
 \end{aligned} \tag{3.26}$$

$$\begin{aligned}
 \text{with} \quad V_i &= \sum_{k=1}^N \omega_k^i, \quad S_i = \sum_{k=1}^N \omega_k^i R(\omega_k) \\
 T_i &= \sum_{k=1}^N \omega_k^i I(\omega_k), \quad U_i = \sum_{k=1}^N \omega_k^i [R^2(\omega_k) + I^2(\omega_k)]
 \end{aligned} \tag{3.27}$$

The desired parameters of the LBDCM and LUM drive servo systems both can be obtained by solving (3.25) [159].

3.4 Conclusions

The physical model of LBDCM is analyzed and presented. However, the accurate values of the motor parameters involved in the derived physical model are hard to be achieved. It is worse for physical modeling of LUM servo system. The model of the unit PEA is merely developed. The precise mathematic model of the LUM drive system is still unknown for us and need to be explored.

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As the mathematic model of servo systems cannot be set up for control analysis, DSA becomes to play a key role in the system identification process. It is the first time that the nonlinear friction compensation is applied in the process of DSA based system identification. Furthermore, a suitable frequency domain system identification algorithm is also proposed to derive the linear system model from the measured data.

The following chapters are focused on the robust control of servo systems with the proposed model. Robust position control of two kinds of servo systems will be investigated to realize the precise motion performance as well as depress the uncertainties and parameter variations in the system in Chapter 4 and Chapter 5.

CHAPTER 4

Robust Control of a Transportation Carriage Driven by LBDCM

4.1 Introduction

In the modern manufacturing industry, more and more transportation systems require fast and accurate linear motions. The direct drive design of mechanical applications based on LBDCM plays a key role in meeting the demands of higher accuracy at high speed [160]. Compared with rotary motors, linear motors possess many advantages, such as the transportation carriage connected directly to the mover of the motor, low frictional loss, high position control accuracy, high speed, high acceleration and deceleration capability, large structural flexibility and high reliability [160 and 161]. Incorporating a three-phase brushless design, the LBDCM does not need any iron or slots for the coils to be wound on. Therefore, the motor has zero cogging, light mass and no attractive force between the coil assembly and the magnet path. Owing to these advantages, this type of motor has been widely used in the modern manufacturing

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systems and other factory and office automation equipments. However, the performances, including stability, of the motor drive system are highly dependent on system parameters and load variations, since there is no auxiliary mechanism such as gears or ball screws equipped.

By taking the influence of the parameter variations and load changes as an equivalent disturbance signal, an optimal preview control was proposed for the LBDCM in [162]. While in [163], by employing a disturbance observer and proportional derivative (PD) compensation in the feedback path, a discrete-time tracking controller was developed for a high-speed precision positioning table, which was actuated by direct-drive linear motors. More recently, output tracking control was investigated in [136] for a LBDCM used for transportation. Since an accurate dynamic model of driver with the LBDCM is difficult to obtain analytically, system identification was carried out in [136]. However, parameter uncertainties exist in the identification procedures due to the precision of experimental equipments and some other factors. Furthermore, payload changes may result in large parameter variations in some cases. A robust output tracking control scheme was presented in [136] for the LBDCM. As indicated at the end of [136], if the payload increases, the uncertainties increase accordingly. As long as the condition $1 + 2E \geq 0$ is satisfied, where E is a system uncertainty parameter, the approach of [136] is still applicable. The studies, however, show that the condition $1 + 2E \geq 0$ has imposed a strong constraint on the system uncertainty or the payload increase. Moreover, it is noted that the middle point of payloads, i.e., 1.5kg-case, is chosen as the nominal case for the design of robust controllers in [136]. But this choice is shown to be inappropriate since the system parameters corresponding to the 1.5kg payload lie far from the middle of parameter ranges. If choosing a payload case where the system parameters are near the middle of parameter ranges to represent the nominal case, the design procedure presented in [136] may become inapplicable, due to the constraint, $1 + 2E \geq 0$.

In the mean time, it is noticed that, by using a solution of the Riccati equation, an optimal robust controller design is presented for hard disk drive actuator servo-systems which contain parameter uncertainties [164]. Also using the Riccati equation, interesting results is presented on the robust control of a class of uncertain sampled-data nonlinear systems with the time-varying parameter uncertainty and unknown cone-bounded nonlinearity [165].

In this chapter, firstly, by using a solution of the Riccati equation, a new control scheme for the motor drive system is developed such that robust output tracking is achieved. Since larger system parameter uncertainties are admissible in this procedure, larger amount of payload can be accommodated. This scheme also guarantees the asymptotic output tracking with an arbitrarily prescribed convergent rate. Then, after setting up an experimental LBDCM drive system, the system model is identified by DSA with RBF based friction compensation. Finally, this scheme is applied to the position control of the transportation carriage with this experimental LBDCM drive system. Both computer simulation and experimental implementation are presented.

4.2 Robust Control Scheme for Position Regulation of Carriage

To develop a robust position controller for the LBDCM drive system, the transfer function model (3.12) is firstly converted into the state-space model as follows where

$$\dot{x}(t) = Ax(t) + Bu(t), \quad y(t) = Cx(t) \quad (4.1)$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad A = \begin{bmatrix} 0 & 1 \\ 0 & -a \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ b \end{bmatrix}, \quad C = [1 \quad 0] \quad (4.2)$$

and the state variables x_1 and x_2 are the position and velocity of the carriage, respectively. The control variable u is the voltage input of the driver and the output variable is the position of the carriage.

Choosing the 2kg payload as the nominal case and treating the parameter differences Δa and Δb in other payload cases as parameter uncertainties, we can write the governing equation of a practical LBDCM drive system as

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & -a + \Delta a \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ b + \Delta b \end{bmatrix} u, \quad y = x_1 \quad (4.3)$$

or in a general form

$$\begin{aligned} \dot{x}(t) &= (A + \Delta A)x(t) + (B + \Delta B)u(t) \\ y(t) &= Cx(t) \end{aligned} \quad (4.4)$$

where $x(t) \in R^2$, $u(t) \in R$ and $y(t) \in R$ are the state, control and output vectors, respectively. A , B and C are nominal system matrices of appropriate dimensions with (A, B) being completely controllable. ΔA and ΔB are uncertain parameter matrices with the same dimensions as A and B , respectively. Furthermore, checking the forms of these uncertainties reveals that there exist continuous matrix functions D and E such that [136]

$$\Delta A = BD, \quad \Delta B = BE \quad (4.5)$$

where D is a 1×2 matrix with $\sup \|D\| = \delta$ and E is a real number. This condition is the so-called matching condition [166].

The position regulation of transportation carriages is to drive the carriage from the central position to another prescribed position. In terms of control systems, this implies the output tracking control of system (4.4). To construct a linear output tracking controller, an auxiliary state variable $q(t) \in R$ is first defined as

$$\dot{q}(t) = Cx(t) - y_r \quad (4.6)$$

where $y_r \in R$ is the constant reference output.

Combining (4.4) with (4.6) yields the following augmented system

$$\dot{z}(t) = (A_z + \Delta A_z)z(t) + (B_z + \Delta B_z)u(t) + \zeta \quad (4.7)$$

where

$$z(t) = \begin{bmatrix} x(t) \\ q(t) \end{bmatrix}, \quad A_z = \begin{bmatrix} A & 0 \\ C & 0 \end{bmatrix}, \quad B_z = \begin{bmatrix} B \\ 0 \end{bmatrix},$$

$$\Delta A_z = \begin{bmatrix} \Delta A & 0 \\ 0 & 0 \end{bmatrix}, \quad \Delta B_z = \begin{bmatrix} \Delta B \\ 0 \end{bmatrix}, \quad \zeta = \begin{bmatrix} 0 \\ 0 \\ -y_r \end{bmatrix} \quad (4.8)$$

and the pair (A_z, B_z) is still controllable. It is not difficult to show that this augmented system also satisfies the matching condition, i.e.,

$$\Delta A_z = B_z D_z, \quad \Delta B_z = B_z E_z \quad (4.9)$$

where

$$D_z = \begin{bmatrix} D & 0 \end{bmatrix}, \quad E_z = E \quad (4.10)$$

The optimal index function is chosen as:

$$J = \int_0^\infty \exp(2\sigma t) [\mu z^T(t)z(t) + r u^T(t)u(t)] dt \quad (4.11)$$

which is subject to the augmented system with ζ being neglected, where μ , r and σ are all positive.

By conventional optimal technique, the optimal controller is

$$u(t) = -r^{-1} B_z^T P z(t) = -K z(t) \quad (4.12)$$

where P is the solution of the Riccati equation:

$$(A_z + \sigma I)^T P + P(A_z + \sigma I) - r^{-1} P B_z B_z^T P + \mu I_3 = 0 \quad (4.13)$$

where I_3 is the three dimensional identity matrix.

An adapting factor is added into the controller to suppress more uncertainties [136].

The resulting input is

$$u(t) = -(1 + \beta) K z(t), \quad K = r^{-1} B_z^T P \quad (\beta > 0) \quad (4.14)$$

Theorem 4.1[136]: For system (4.4) with condition (4.5), assume $E > -\frac{1}{2}$ and $\sup\|D\| = \delta$, and choosing β as

$$\beta = \frac{r\delta^2}{\mu} \quad (4.15)$$

The proposed controller realizes an output tracking performance with prescribed convergent rate.

Proof: Under controller (4.14), the augmented system with ζ being neglected becomes

$$\begin{aligned} \dot{z}(t) &= (A_z + \Delta A_z)z(t) + (B_z + \Delta B_z)u(t) \\ &= [A_z + B_z D_z - (1 + \beta)r^{-1}B_z(1 + E_z)B_z^T P]z(t) \end{aligned} \quad (4.16)$$

Lyapunov function is constructed as

$$V(z) = z^T(t)Pz(t) \quad (4.17)$$

Since E is scalar, $E^T = E$, the derivative of V is

$$\begin{aligned} \dot{V}(z) &= \dot{z}^T(t)Pz(t) + z^T(t)P\dot{z}(t) \\ &= z^T(t)[A_z^T P + PA_z + D_z^T B_z^T P + PB_z D_z \\ &\quad - (1 + \beta)r^{-1}PB_z(2 + E_z^T + E_z)B_z^T P]z(t) \\ &= z^T(t)(A_z^T P + PA_z)z(t) + 2z^T(t)D_z^T B_z^T Pz(t) \\ &\quad - (1 + \beta)r^{-1}z^T(t)PB_z(2 + E_z^T + E_z)B_z^T Pz(t) \\ &= z^T(t)(A_z^T P + PA_z)z(t) + 2z^T(t)D_z^T B_z^T Pz(t) \\ &\quad - (1 + \beta)r^{-1}z^T(t)PB_z(2 + 2E)B_z^T Pz(t) \end{aligned} \quad (4.18)$$

Applying the Riccati equation (4.13), then

$$\begin{aligned} \dot{V}(z) &= -2\sigma V(z) - z^T(t)\mu z(t) - \beta r^{-1}z^T(t)PB_z B_z^T Pz(t) \\ &\quad - (1 + \beta)r^{-1}z^T(t)PB_z(1 + 2E)B_z^T Pz(t) + 2z^T(t)D_z^T B_z^T Pz(t) \end{aligned} \quad (4.19)$$

Since $1 + 2E \geq 0$, the term $(1 + \beta)r^{-1}z^T(t)PB_z(1 + 2E)B_z^T Pz(t)$ is positive semidefinite, and yield

$$-\dot{V}(z) \geq 2\sigma V(z) + \mu z^T(t)z(t) + \beta r^{-1}z^T(t)PB_z B_z^T Pz(t) - 2z^T(t)D_z^T B_z^T Pz(t) \quad (4.20)$$

Setting β as in (4.15) and using the facts that

$$\mu z^T(t)z(t) = \mu \|z(t)\|^2 \quad (4.21)$$

$$\mu^{-1} \delta^2 z^T(t) P B_z B_z^T P z(t) = \mu^{-1} \delta^2 \|B_z^T P z(t)\|^2 \quad (4.22)$$

$$2 z^T(t) D_z B_z^T P z(t) \leq 2 \delta \|z(t)\| \|B_z^T P z(t)\| \quad (4.23)$$

Equation (4.19) can be written as

$$\begin{aligned} -\dot{V}(z) &\geq 2\sigma V(z) + \left\{ \mu \|z(t)\|^2 + \mu^{-1} \delta^2 \|B_z^T P z(t)\|^2 - 2\delta \|z(t)\| \|B_z^T P z(t)\| \right\} \\ &= 2\delta V(z) + \left\{ \sqrt{\mu} \|z(t)\| - \left[\sqrt{\mu} \right]^{-1} \delta \|B_z^T P z(t)\| \right\}^2 \\ &\geq 2\sigma V(z) \end{aligned} \quad (4.24)$$

It is thus concluded that this linear uncertain system is exponentially stable with at least a prescribed degree of stability σ . This completes the proof.

Based on the controller proposed in (4.14), a new linear constant output tracking controller is constructed in the same form, but with the different P , and thus different uncertainty parameter E .

In the new controller, $\beta > 0$ is a scalar to be determined and $P > 0$ is the solution of the Riccati equation [167]

$$(A_z + \sigma I)^T P + P(A_z + \sigma I) - r^{-1} P B_z B_z^T P + Q = 0 \quad (4.25)$$

where $\sigma \geq 0$ is a prescribed scalar constant, $Q > 0$ and $r > 0$ are the weighting matrices (r is a scalar in the case considered).

It is noted that equation (4.25) above is a little different from equation (4.13). As is known, the selection of the weighting matrices plays a key role in the Riccati equation-based problems [164-166]. It is noted that the weighting matrix Q in (4.15) does not necessarily take the form of μI_3 as in (4.13).

Now it is in a position to present a robust tracking control scheme for the system described in (4.4).

Theorem 4.2: For system (4.4) with condition (4.5), assume $E > -1$ and $\sup\|D\| = \delta$.

If the weighting matrices in equation (4.25) are chosen such that

$$Q > \delta^2 \text{diag}(1, 1, 0), \quad r = (1 + \beta)\varepsilon - 1 \quad (4.26)$$

where ε is a positive number satisfying $\varepsilon \leq 2(E+1)$, and β is chosen to be sufficiently large such that $r > 0$ is guaranteed, then system (4.4) under control (4.14) will asymptotically approach the constant reference output y_r with a prescribed exponential rate σ .

Proof: the proof is divided into two parts.

(i) *Internal stability*

From (4.8) and (4.26), one can see that (A_z, B_z) is controllable and (Q, A_z) is observable. Therefore, the positive definite solution P of equation (4.25) is guaranteed to exist [167]. Under control (4.14), the augmented system (4.7) with neglecting ζ becomes

$$\begin{aligned} \dot{z}(t) &= (A_z + \Delta A_z)z(t) + (B_z + \Delta B_z)u(t) \\ &= [A_z + B_z D_z - (1 + \beta)r^{-1}B_z(1 + E_z)B_z^T P]z(t) \end{aligned} \quad (4.27)$$

By using the positive definite solution P of equation (4.25), a Lyapunov function candidate is set up as:

$$V(z) = z^T(t)Pz(t) \quad (4.28)$$

The time derivative of $V(z)$ along the solution of equation (4.27) is

$$\begin{aligned} \dot{V}(z) &= \dot{z}^T(t)Pz(t) + z^T(t)P\dot{z}(t) \\ &= z^T(t)[A_z^T P + PA_z + D_z^T B_z^T P + PB_z D_z \\ &\quad - (1 + \beta)r^{-1}PB_z(2 + E_z^T + E_z)B_z^T P]z(t) \end{aligned} \quad (4.29)$$

It is noted that [165, 166 and 168]

$$D_z^T B_z^T P + PB_z D_z \leq D_z^T D_z + PB_z B_z^T P \quad (4.30)$$

Further, in view of (4.5), (4.10) and $\sup\|D\| = \delta$, it is derived that

$$D_z^T D_z = \begin{bmatrix} D^T D & 0 \\ 0 & 0 \end{bmatrix} \leq \delta^2 \text{diag}(1, 1, 0) \quad (4.31)$$

Also, since $E_z = E$ is a scalar and $\varepsilon \leq 2(E+1)$, one can see that

$$\begin{aligned} -(1+\beta)r^{-1}PB_z(2+E_z^T+E_z)B_z^T P &= -(1+\beta)r^{-1}PB_z(2+2E)B_z^T P \\ &\leq -(1+\beta)\varepsilon r^{-1}PB_zB_z^T P \end{aligned} \quad (4.32)$$

By using (4.25) and (4.30)–(4.32), it follows from (4.29) that

$$\begin{aligned} \dot{V}(z) &\leq z^T(t)[-Q-2\sigma P+r^{-1}PB_zB_z^T P+D_z^T D_z \\ &\quad +PB_zB_z^T P-(1+\beta)\varepsilon r^{-1}PB_zB_z^T P]z(t) \\ &\leq z^T(t)\{-Q-2\sigma P+\delta^2 \text{diag}(1, 1, 0) \\ &\quad +r^{-1}PB_z[1+r-(1+\beta)\varepsilon]B_z^T P\}z(t) \end{aligned} \quad (4.33)$$

Applying (4.26) to (4.33), one can show that

$$\dot{V}(z) < z^T(t)(-2\sigma P)z(t) = -2\sigma V(z), \text{ for all nonzero } z \quad (4.34)$$

From (4.28) and (3.34), it is concluded that system (4.27) is exponentially stable with a prescribed rate σ [169]. In other words, the internal stability of the augmented system (4.7) is achieved with a prescribed degree of stability σ .

(ii) *Asymptotic tracking with a prescribed exponential rate*

Similarly to (4.27), the augmented system (4.7) under control (4.14) can be written as

$$\dot{z}(t) = [A_z + B_z D_z - (1+\beta)r^{-1}B_z(1+E_z)B_z^T P]z(t) + \zeta \quad (4.35)$$

Since ζ is a constant vector as shown in (4.8), differentiating both sides of (4.35) with respect to time yields

$$\ddot{z}(t) = [A_z + B_z D_z - (1+\beta)r^{-1}B_z(1+E_z)B_z^T P]\dot{z}(t) \quad (4.36)$$

Defining an auxiliary vector $\rho(t) = \dot{z}(t)$, (4.36) can be rewritten as

$$\dot{\rho}(t) = [A_z + B_z D_z - (1+\beta)r^{-1}B_z(1+E_z)B_z^T P]\rho(t) \quad (4.37)$$

It is obvious that equation (4.37) has the same form as equation (4.27). Therefore, system (4.37) is also exponentially stable with a prescribed rate σ , according to (i). In

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other words, $\rho(t)$ in equation (4.37), or $\dot{z}(t)$, will asymptotically approach zero with an exponential rate σ , no matter what the initial condition is. Furthermore, it follows from (4.1), (4.6) and (4.8) that

$$\dot{z}(t) = \begin{bmatrix} \dot{x}(t) \\ \dot{q}(t) \end{bmatrix} \quad \text{and} \quad \dot{q}(t) = y(t) - y_r \quad (4.38)$$

Therefore, $\dot{q}(t)$ will also asymptotically approach 0 with an exponential rate σ . This implies that the system output $y(t)$ will asymptotically track its reference output y_r with a prescribed exponential rate σ . Obviously, the property of asymptotic tracking with a prescribed exponential rate is attained.

Combining (i) and (ii), the proof is completed.

Remark 4.1: In Theorem 2, it is required that the uncertain parameter $E > -1$ rather than $E > -1/2$ as in Theorem 1. This implies that our scheme can accommodate twice as large system uncertainties in the control matrix as those in previous scheme. Consequently, much larger payload variations of the LBDCM are admissible.

Remark 4.2: The asymptotic tracking with a prescribed exponential rate, or exponential tracking, has been proven. The exponential tracking plays an important role in improving the output tracking performance of the LBDCM drive system. A complete proof can be provided for Theorem 4.2.

Furthermore, it is shown that the robust control (4.14) is linear optimal for the nominal augmented system.

Theorem 4.3: Control (4.14) determined in Theorem 4.2 is linear optimal for the nominal augmented system (4.7) with respect to the index

$$J = \int_0^\infty \exp(2\sigma t) [z^T(t) \bar{Q} z(t) + \bar{r} u^T(t) u(t)] dt \quad (4.39)$$

where $\bar{Q} = Q + \beta r^{-1} P B_1 P > 0$, $\bar{r} = r / (1 + \beta) > 0$ (4.40)

4.3 Experimental LBDCM Drive System and Dynamic Model

4.3.1 System Configuration

Figure 4.1: Experiment setup

As shown in Figure 4.1, the experimental LBDCM drive system includes an LBDCM (model: LMS20-C4-L528-5), a transportation carriage, a motor driver (model: Har-2/200) and dSPACE-based controller (DS1103). The carriage, supported by a number of recirculating ball bearings, is combined with the translator part of the motor. Furthermore, the moving carriage is guided precisely by a linear bearing rail attached to the base plate. Viscous friction is present, as the rail is lubricated with grease. Ironless core armature coils and Hall-effect sensors are installed in the carriage, while the permanent magnets are fixed on the stator side. Moreover, this carriage can move forward or backward on the rail between -15.77cm and $+15.77\text{cm}$. An encoder (model: RGH42) is attached on the stator side to measure the carriage position. The driver, which is used to drive the motor, accepts voltage inputs in the range of $\pm 10\text{V}$ and must be tuned in the current mode before using dSPACE as the controller. The control

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algorithm is implemented on a dSPACE DS1103. A PC serves as the man-machine interface. The experiment process can be divided into two parts: one is the frequency domain identification of the system plant, and the other is validation of the proposed controller.

Correspondent to Figure 4.1, a block diagram of the whole system is illustrated in Figure 4.2. The LBDCM is direct driven by the current from the three phase full bridge inverter. The current-controlled PWM inverter regulates the primary winding currents to closely follow sinusoidal commands. The frequency and magnitude of the controlled current is originally influenced by the designed robust controller. The robust controller part is the core of the servo system. It collects the feedback position signal from the optical encode installed in the linear motor and generates the expected current signals utilizable for PWM unit.

This motor drive system can be applied in laser cutting machines. For the LBDCM in such an application, required specification is the voltage to the driver 10V, continuous current 7A, maximum speed 4.5m/s, acceleration larger than g, pay load weight less than 7kg.

Figure 4.2: Schematic diagram of LBDCM drive systems

4.3.2 System Identification

As to identify the system model, the friction in the systems should be measured firstly. Following the procedure introduced in Chapter 2, the friction data is obtained and shown in Figure 4.3.

Figure 4.3: Original friction data from real time experiment

The Stribeck friction model is employed to approximate the friction. Different sets of friction model parameters are derived at different positions respectively. Part of the parameter sets are listed in Table 4.1. The parameters F_c F_s v_s F_v are consistent with those in (2.5). In addition, δ_s has the value of 2.

Table 4.1 Fitting friction model parameters

Position(m)	F_c (Nm)	F_s (Nm)	v_s (rad/s)	F_v (Nm s/rad)
-0.145	0.4123	1.1096	0.2462	3.4907
-0.1	0.4202	1.1190	0.2471	3.4836
0	0.4499	1.0618	0.2431	3.4138
0.1	0.4581	1.0542	0.2410	3.3274
0.145	0.4678	1.0826	0.2465	3.3852

The math model based friction fitting results along all the velocity and position range all illustrated in Figure 4.4 and Figure 4.5.

Figure 4.4: Friction fitting results by math function

Figure 4.5: Friction fitting error between math function and measured data

The friction in the LBDCM is also approximated by the Kalman filter based RBF. An RBF network is set up for the friction modeling. The RBF network consists of two layers: a hidden radial basis layer and an output linear layer. The RBF network algorithm adopted is identical to what is introduced before. The input-target data for training the neural network are obtained from the previous experiments. With the

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sufficient training data which thoroughly cover the input space of the network, the RBF network can be trained to almost any level of accuracy [108]. Seven neurons in the hidden layer are chosen in the design due to $m=N^{1/3}$, m is the hidden units and N is the size of training sample. Since high accuracy involves an excessively large number of neurons in the hidden layer, care should be taken that there is no overfitting of data in which case the training becomes wasted.

The objective mean error is $10e-4$ and the whole training time is in the order of seconds. The fitting results are shown in Figure 4.6 and Figure 4.7. It is clearly demonstrated that the Kalman filter based RBF fitting result is much better than the model based fitting result. RBF network is more suitable to compensate the nonlinear friction in the servomechanisms.

Figure 4.6: Friction fitting results by RBF network

Figure 4.7: Friction fitting error between RBF model and measured data

Since the friction model is accurately set up by the Kalman filter based RBF network, the friction compensation can be realized simply by applying the output of the fitting model to counteract the real friction force. The linear frequency domain model of an LBDCM system is derived according to the algorithm described in Chapter 3. The measured data and fitting curve under 0kg payload condition are shown in Figure 4.8.

Figure 4.8: Measured and fitted bode plot of the servo system

The final fitting linear models are:

$$\text{For 0kg: } \frac{Y(s)}{U(s)} = \frac{2.5996}{s(s+2.932)} \quad (4.41)$$

$$\text{For 2kg: } \frac{Y(s)}{U(s)} = \frac{1.8052}{s(s+1.743)} \quad (4.42)$$

$$\text{For 8kg: } \frac{Y(s)}{U(s)} = \frac{0.80473}{s(s+0.810)} \quad (4.43)$$

4.3 Simulation and Experiment Results

The experimental LBDCM drive system used in our study is described in previous section. Its payloads range from 0kg to 8kg. The task is to drive the transportation carriage from the central position to the 0.1m position. This implies that a robust tracking controller is required such that the system output (the position of the carriage) approaches the reference output $y_r = 0.1\text{m}$. Moreover, an exponentially convergent rate $\sigma = 3$ is prescribed.

From (3.12), it is obvious that the systems parameters a and b will vary with the change of payload, which cause the mass M to change. But it is noted that the system parameters a and b are not directly proportional to M . therefore, it is not appropriate to choose the middle point of payloads, i.e., 1.5kg case in [136], to represent the nominal case for the design of robust controllers as did in [136] for the LBDCM drive system the original weight of carriage without any payload is around $M_0 = 3.7\text{kg}$. If the payload range from 0kg to 8kg, the load of

$$M = 2\left(\frac{1}{M_0} + \frac{1}{M_0 + 8}\right)^{-1} - M_0 = 1.9921\text{kg} \quad (4.44)$$

According to (4.44), the 2kg payload case is chosen as the nominal case. Based on the identification results (4.41)-(4.43), it is known that

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$$a=1.743, b=1.8052 \quad (4.45)$$

in (4.3) and

$$\Delta a = -1.189, \Delta b = 0.7944 \quad (4.46)$$

for the case of 0kg payload and

$$\Delta a = -0.933, \Delta b = -0.9905 \quad (4.47)$$

for the case of 8kg payload. It follows from (4.5) that

$$D = [0 \quad -0.6587], \|D\| = 0.6587, E = 0.4401 \quad (4.48)$$

for the case of 0kg payload, and

$$D = [0 \quad -0.5168], \|D\| = 0.5168, E = -0.5487 \quad (4.49)$$

for the case of 8kg payload.

It is obvious that the parameters in both (4.48) and (4.49) satisfy the condition $E > -1$ requested by our Theorem 1. Theorem 4.1 can be used to design a tracking controller for this system accordingly.

From (4.48) to (4.49), it is known that

$$\delta = \sup \|D\| = \max(0.6587, 0.5168) = 0.6587, \delta^2 = 0.4338 \quad (4.50)$$

In the light of Theorem 4.2, it is chosen that

$$Q = 0.4338 \times \text{diag}(1, 1, 0) + 0.002 \times \text{diag}(1, 1, 1) \quad (4.51)$$

Also, since $2(1 + E) \geq 2(1 - 0.5487) = 0.9026$, the scalar $\varepsilon = 0.9$ is made, which is less than $2(1 + E)$. Based on (4.26), the parameter $\beta = 0.4$ is chosen such that $r = 0.26 > 0$. Solving equation (4.25) with $\sigma = 3$ yields a positive definite solution. Then the tracking controller is

$$u(t) = [-81.2093 \quad -12.3853 \quad -160.2392]z(t) \quad (4.52)$$

From Theorem 4.1, one can conclude that this uncertain LBDCM system under control (4.52) will asymptotically approach the reference output $y_r = 0.1\text{m}$ with an exponentially convergent rate $\sigma = 3$. In the mean time, it is known from Theorem 4.2

that control (4.52) is an optimal control for the nominal augmented system (4.7) with respect to index (4.39), where

$$\bar{Q} = \begin{bmatrix} 350.3720 & 53.3689 & 690.4811 \\ 53.3689 & 8.5751 & 105.3055 \\ 690.4811 & 105.3055 & 1362.4 \end{bmatrix}, \bar{r} = 0.1857 \quad (4.53)$$

It is noted that the uncertain parameter E in (4.49) does not satisfy the condition $E \geq -1/2$ requested by Theorem 1 in [136]. Therefore, the approach presented in [136] is not applicable to this LBDCM drive system. It is clear that the proposed controller has more robustness to the parameter variations than the robust controller proposed in [136]. The suppressive load variations of the proposed controller have been extended to as large as 8 kg. The resultant simulation and experiment under different payload conditions are carried out to demonstrate the robustness performance of the LBDCM drive control systems.

With the controller (4.52), computer simulation is conducted for the closed-loop LBDCM drive system. The initial conditions of the carriage are set as $x_1(0)=0\text{m}$, $x_2(0)=0\text{m/s}$, and $q(0)=0$. For the cases of three different loads, the simulated dynamic responses of the carriage's position and velocity are given in Figure 4.9 (a) and (b), respectively. It is obvious that good transient and steady performances as well as strong robustness to payload variations have been achieved. The same controller has also been applied into this experimental LBDCM drive system.

(a) Position

(b) Velocity

Figure 4.9: Simulated position and velocity responses (— 0kg--- 2kg--- 8kg)

Figure 4.10 ~ Figure 4.12 give the measured carriage's position and velocity responses in the 0kg, 2kg and 8kg three payload cases. For the 0kg, 2kg and 8kg conditions, the step position response curves seem to be kept unchanged and smooth

during the simulated period. It means that the system performance is not influenced by the change of the load conditions in the system. Thus, clearly, these experimental results also demonstrate good transient and steady performances of the motor drive system.

Figure 4.10: Measured carriage's position and velocity response with 0kg load

Figure 4.11: Measured carriage's position and velocity response with 2kg load

Figure 4.12: Measured carriage's position and velocity response with 8kg load

4.4 Conclusions

Highly nonlinear friction in the LBDCM drive system is measured and compensated by an RBF network. The system model is first obtained by DSA with nonlinear friction compensation. For the position regulation of transportation carriages used in the manufacturing systems, this chapter has presented a new robust output tracking control scheme. Since much larger parameter uncertainties such as E^{-1} instead of previously achieved $E^{-1/2}$ [136] are admissible in the new approach, a larger amount of payload can be accommodated by the developed LBDCM drive system. With the application to an experimental linear motor drive system, good transient and steady performances of the system as well as strong robustness to payload variations have been demonstrated by computer simulations and experimental results.

It is clear from the results illustrated in this chapter that the proposed linear controller owns strong robustness to load variation and system uncertainties, but the

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speed seems not very fast for some fast speed industrial applications like wafer testing and SMT machines. Owing to this condition, one nonlinear robust controller will be proposed in next chapter to achieve faster speed as well as robustness suppressive to both dynamic uncertainties and parameter variations, that is, both the robust performance and transient performance are guaranteed by the proposed controller.

CHAPTER 5

Robust Position Control of an LBDCM Drive System Based on μ Synthesis

5.1 Introduction

High-speed, high-accuracy positioning systems are essential elements in advanced manufacturing systems such as those found in the semiconductor industry. Demands for higher productivity and product quality accelerate the development of high performance positioning devices. The linear motor has been applied as the promising motion device because of its superior performance compared to conventional linear positioning devices such as ball-screw drives. However, as described in last chapter, it loses the advantage of using mechanical transmission gear, which reduces the effect of the model uncertainties. These uncertain nonlinearities are directly transmitted to the load and have significant effects on the motion of the load. In the practical applications, the system uncertainties are generated by imprecise experimental equipment, motor

physics variations, payload variations and friction. This chapter is devoted to develop a high speed as well as strong robust controller for the LBDCM drive systems.

Fortunately, many strategies are available for controlling the systems with uncertainty. The Riccati equation is applied to the linear systems with uncertainty [170]. H_∞ theory is systematized [171] and has become the most popular method in the robust control area. The Linear Matrix Inequalities (LMI) is combined with the H_∞ theory [172]. The concept of structure singular value is employed to analyze the robust stability and performance of systems [173]. In addition, the variable structure control was first proposed by Emelyanov and further investigated [174] and later researchers, and this method makes systems own the ability insensitive to parameter variations and disturbances.

Researchers have applied a variety of control approaches in linear motion system based on the control theory introduced above. One improved proximate time-optimal positioning control approach is proposed for Hard Disk Drive (HDD) [175]. One discrete-time tracking controller employing a disturbance observer and proportional derivative compensation in the feedback path is developed for a high-speed and precise positioning table, which was actuated by direct-drive linear motors [17]. A linear robust controller based on the Riccati equation is presented for the LBDCM drive system [136]. A generalized two-parameter PID controller is presented via genetic algorithm, which guarantees both the frequency domain and time domain specifications [176]. Although these controllers are robust to payload variations, the tolerable load varying is very limited. Moreover, these papers make an assumption that the friction is proportional to the velocity, that is, only the viscous friction is considered. However, experimental results show that the frictions in the linear motor drive system are highly nonlinear. The real friction in the system cannot be fitted by the classical nonlinear friction function well, and let alone the viscous friction.

A robust and fast speed controller is proposed for LBDCM motion system based on combined H_∞ and μ synthesis. The following sections are organized as: the detailed μ synthesis control procedure which consists of uncertainties decomposition, controller design, and selection of weighting function is introduced in Section 5.2. Moreover, the robust stability and robust performance analysis method to the LBDCM system is also presented in the same section. Simulation and experiment results are illustrated in Section 5.3. In the end, conclusions are drawn.

5.2 μ Synthesis Scheme for LBDCM Drive Systems

5.2.1 Uncertainties Decomposition for μ Synthesis Method

Uncertainties should firstly be transferred into Linear Fractional Transformation (LFT) or interconnection of LFTs before employing μ synthesis method [54 and 177]. In the case of linear uncertainties in a state-space model, the uncertainty description can be built up as follow.

Consider a state-space model with uncertainties as:

$$\begin{aligned} \begin{bmatrix} \dot{x}(t) \\ y(t) \end{bmatrix} &= \begin{bmatrix} A_0 + \sum_{i=1}^m \delta_i A_i & B_0 + \sum_{i=1}^m \delta_i B_i \\ C_0 + \sum_{i=1}^m \delta_i C_i & D_0 + \sum_{i=1}^m \delta_i D_i \end{bmatrix} \begin{bmatrix} x(t) \\ u(t) \end{bmatrix} \\ &= \left(\begin{bmatrix} A_0 & B_0 \\ C_0 & D_0 \end{bmatrix} + \sum_i \delta_i \begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix} \right) \begin{bmatrix} x(t) \\ u(t) \end{bmatrix} \end{aligned} \quad (5.1)$$

where, for each $i=1,2,\dots,m$

$$\begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix} \in R^{(n+n_x) \times (n+n_y)}, -1 \leq \delta_i \leq 1, \quad (5.2)$$

Now, define a linear system G_{SS} , with extra inputs and outputs via the state equations as shown in Figure 5.1(a).

Let $r_i := \text{rank} \begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix}$ in (5.3) and factor each matrix as:

$$\begin{bmatrix} A_i & B_i \\ C_i & D_i \end{bmatrix} = \begin{bmatrix} E_i \\ F_i \end{bmatrix} [G_i \quad H_i] \quad (5.3)$$

$$\text{where, } \begin{bmatrix} E_i \\ F_i \end{bmatrix} \in R^{(n+n_i) \times r_i}, [G_i \quad H_i] \in R^{r_i \times (n+n_i)} \quad (5.4)$$

Δ maps $z \rightarrow w$, and has the structure given as

$$\begin{bmatrix} \dot{x} \\ y \\ z_1 \\ \vdots \\ \vdots \\ z_m \end{bmatrix} = G_{ss} * \begin{bmatrix} x \\ u \\ w_1 \\ \vdots \\ \vdots \\ w_m \end{bmatrix} = \begin{bmatrix} A_0 & B_0 & E_1 & \cdot & \cdot & \cdot & E_m \\ C_0 & D_0 & F_1 & \cdot & \cdot & \cdot & F_m \\ G_1 & H_1 & 0 & \cdot & \cdot & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ G_m & H_m & 0 & \cdot & \cdot & \cdot & 0 \end{bmatrix} \begin{bmatrix} x \\ u \\ w_1 \\ \vdots \\ \vdots \\ w_m \end{bmatrix} \quad (5.5)$$

$$\Delta = \{\text{diag}[\delta_1 I_{r_1}, \dots, \delta_m I_{r_m}] : \delta_i \in R\} \quad (5.6)$$

The uncertain system in Figure 5.1(a) is represented as an LFT around G_{ss} , namely

$$y = [G_{11} + G_{12}\Delta(I - G_{22}\Delta)^{-1}G_{21}]u = F_l(G_{ss}, \Delta)u \quad (5.7)$$

5.2.2 μ Synthesis Controller Design

μ synthesis control deals with the problem of remaining system robust stability and robust performance in the presence of exogenous inputs and norm-bounded perturbations.

A block diagram of the general closed-loop system with uncertainty (closed-loop transfer function from $r \rightarrow e_1$ and e_2) is shown in Figure 5.1(a). The shape of the closed-loop frequency response is specified by frequency dependent weighting functions (such as, W_P , W_S). In the study, the transfer function of the plant is like: $\frac{Y(s)}{U(s)} = \frac{b}{s(s+a)}$ and the system uncertainties are included in the parameters a and b .

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The generalized feedback control structure for μ synthesis is shown in Figure 5.1(b). The dash block in the figure is the augmented plant P .

(a)

(b)

Figure 5.1 (a) Closed-loop system with uncertainty (b) General interconnection for uncertain system

The objective of μ synthesis control is to find a stabilizing controller K such that the closed-loop system achieves robust performance, i.e.

$$\sup_{\omega} \mu_{\Delta}(F_L(P, K)(j\omega)) < 1 \quad (5.8)$$

μ synthesis also minimizes the peak value of $\mu_{\Delta}(\cdot)$ of the closed-loop transfer function $F_L(P, K)$ over all stabilizing controllers K . This function is realized by D-K iteration technique.

The D-K iteration procedure starts with an H_{∞} controller and takes a few iterations to obtain the suboptimal solution. If D and K have converged but the performance specifications are not fulfilled, the weights must be changed. The design objectives must be traded off against each other and a new D-K iteration must be done. Moreover, the controller order obtained by μ synthesis is typically very high. This is because the interconnection structure does not only include the actual system, but also the models of the disturbances and the performance weightings, and the order of D scaling which is applied in μ synthesis, generally goes very high. The controller order can be reduced by the model reduction technique [178]. The frequency domain representation of the controller is here approximated by a lower order one. The order reduction is applied in such a way that the robustness properties are still satisfied with the order-reduced controller.

5.2.3 Selection of Weighting Functions

It is very hard to propose a general formula for selecting the weighting functions that will work in every specified case. Following are some guidelines applied to the selection problem in the proposed μ controller.

W_s is the performance weighting function for a closed-loop system. Sensitive function S must be kept small over a range of frequencies, typically low frequencies for the LBDCM system. Suppose the specification of the steady state error is no greater than ε (i.e. $|s(0)| \leq \varepsilon$). Therefore, W_s in the Figure 5.2 is chosen as $|W_s(0)| \geq 1/\varepsilon$ so that $\|W_s S\|_{\infty} \leq 1$ is guaranteed. Thus, one possible W_s can be selected as:

$$W_s = \frac{s / \|S\|_\infty + \omega_0}{s + \omega_0 \varepsilon} \quad (5.9)$$

The relationship between the W_s and S is shown in Figure 5.2: (W_s here is an approximate polygonal line):

Figure 5.2: Selection scheme of the weighting function W_s (upper) and W_p (lower)

The selection of the control weighting function W_p is similar with the preceding one. The low frequency range is limited by allowable cost of control effort and

saturation limit of the motor, while the high frequency gain is essentially limited by the controller bandwidth and the noise frequencies. Ideally, one should be roll off as fast as possible beyond the desired control bandwidth so that the high frequency noises are attenuated as much as possible. One possible W_p can be chosen as:

$$W_p = \frac{s + \omega_1 / |KS|_\infty}{\varepsilon_1 s + \omega_1} \quad (5.10)$$

The relationship between W_p and KS is shown in Figure 5.2, K is the controller function.

5.2.4 Robust Stability and Robust Performance

The robust stability and robust performance are two important criterions to evaluate effectiveness of the designed robust controller. Robust stability is guaranteed if either one of the following conditions is satisfied:

- i. *controller K internally stabilizes every plant belongs to $F_u(P, \Delta)$*
- ii. *$F_u(F_l(P, K), \Delta)$ is stable, $\forall \Delta, \|\Delta\|_\infty \leq 1$ and $F_l(G_{ss}, K)$ is stable.*
- iii. *let $N = F_l(P, K)$, $\mu(N_{11}) < 1$ for $\bar{\sigma}(\Delta) \leq 1 \forall \omega$, and $F_l(P, K)$ is stable.*

where, $\sigma(G) = \sqrt{\lambda(G^T G)}$ is the singular value of G , $\bar{\sigma}(\cdot)$ is the largest singular value.

Robust stability is not the only property of a closed-loop system that must be robust to perturbations. In most cases, long before the onset of instability, the closed-loop performance will degrade to the point of unacceptability. Hence, robust performance is also required to evaluate the controller performance. Robust performance is guaranteed if either one of the following conditions is satisfied:

- i. *performance objectives are guaranteed by K for every plant belongs to $F_u(P, \Delta)$*

- ii. $\|F_u(F_l(P, K), \Delta)\|_\infty < 1, \forall \Delta, \|\Delta\|_\infty \leq 1$ and $F_l(P, K)$ is stable.
- iii. $\mu_{\bar{\Delta}}(F_l(P, K)) < 1 \forall \omega$, and $F_l(P, K)$ is stable.

where $\bar{\Delta} = \begin{bmatrix} \Delta & 0 \\ 0 & \Delta_p \end{bmatrix}$, Δ_p is a full complex perturbation matrix that specifies the performance measurement, and is a fictitious uncertainty block.

The proposed controller is designed to minimize the peak value of the structure singular value of the closed-loop system, and thus achieves robust stability and performance for all possible perturbations. It is convenient to analyze the robust stability and performance by μ in term of item 3 in above descriptions. The robust stability and robust performance will be illustrated in the diagram shown in the numerical and experiment section.

5.2.5 RBF Estimator

For almost all control systems with uncertainty, prior knowledge on the structure of the systems is usually available from analytical derivation. However, some parameters in such systems are unknown, which will influence the system characteristics and become a big challenge for the robustness of the controller. Thus, in these applications, there is often a need for parameter estimation. In the real-time applications, statistical parameter estimation techniques such as the least squares estimator, maximum likelihood estimator and maximum a posteriori estimator are usually not efficient in terms of the converge time due to the limitation of sequential processing. RBF network has such an attractive parallel structure and fast converging characteristic that it is suitable to be used as a parameter estimator. The whole control structure block diagram is shown in Figure 5.3.

The μ controllers 1 2 and 3 are the μ controllers designed in different normalized payload conditions. The input of the estimator in the LBDCM system includes velocity,

acceleration and control signals. Its output works as the controller selector to determine which μ controller is applied in the whole control scheme.

Figure 5.3: RBF based μ controller for the LBDCM drive system

5.3 Validation of the Proposed Controller

An LBDCM used in manufacturing system has been described in last chapter. Payload variation from 0kg to 10kg is considered in the proposed control scheme. And thus, a robust tracking controller is required to allow the output (the position of the stage) to track the constant reference output under different load variations. NN friction compensator and the RBF estimator are both trained before the real-time implementation. The friction compensator generates the negative friction force, which is added to the output of the controller to counteract the effect of the friction, and the RBF

selector receives the feedback signals from velocity, acceleration, and the input of motor drive, and produces the estimated mass value to determine which controller is employed. The μ controllers 1, 2 and 3 are designed for payload range from 0kg to 4kg, 3kg to 7kg, and 6 to 10kg, respectively, that is, the three controllers all have the robustness to a 4 kg payload variation but have different normalized load points. What should be noticed is that 1 kg overlapped area is remained among the three payload ranges. That is because a slight difference probably exists between the real payload value and the estimated value, and in some cases, this error causes the mis-operation of the RBF selector. Thus, the overlapped area increases the reliability of the whole control scheme. For special cases of 3.5kg and 6.5kg, which are the middle points between the two adjacent nominal payload points, the selector is designated to choose the controllers 1 and 2, respectively.

As the corresponding part in last chapter, the curve fitting plant model is identified.

$$\text{For 0kg: } \frac{Y(s)}{U(s)} = \frac{2.5996}{s(s+2.932)} \quad (5.11)$$

In the same manner, the models for the 2kg, 5kg and 8kg are as follow:

$$\frac{Y(s)}{U(s)} = \frac{1.8052}{s(s+1.743)}, \quad \frac{Y(s)}{U(s)} = \frac{1.1827}{s(s+1.142)} \text{ and } \frac{Y(s)}{U(s)} = \frac{0.8147}{s(s+0.810)} \quad (5.12)$$

Conditions with 2kg, 5kg, and 8kg payload are chosen as nominal cases. Therefore, for the controller 1, the parameters $a=1.743$, $b=1.8052$ is applied in (3.12), and during all the load varying conditions, the terms $|\Delta a| \leq |\Delta a|_{\max} = 1.189$, $|\Delta b| \leq |\Delta b|_{\max} = 0.7944$ is satisfied.

In the same manner, for the controller 2, the parameters $a=1.142$, $b=1.1827$, $|\Delta a| \leq |\Delta a|_{\max} = 0.341$, $|\Delta b| \leq |\Delta b|_{\max} = 0.3531$, and for the controller 3, the parameters $a=0.81$, $b=0.8147$, $|\Delta a| \leq |\Delta a|_{\max} = 0.214$, $|\Delta b| \leq |\Delta b|_{\max} = 0.246$.

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As we know, the impedance of motor can be changed a little with the varying of the motor temperature and K_e has almost no change. System model parameters a and b obtained from DSA has the direct relationship with the R_q and L_q by equation (3.9) and (3.11). The parameters a and b are measured by the experiments when the motor is running under different operating conditions. Actually, the impedance is also changing during the experiments under different conditions, that is, the variation of the impedance change is considered during the system model identification process. The variation of the R_q and L_q contributes to the variation of a and b in the system model. Thus, the position controller is also designed to suppress the variation of impedance of the motor. The sensitivity of the controller from parameters variation R_q and L_q can be clearly demonstrated from the performance of the controller under different operation conditions.

In accordance with what is illustrated in previous section, the system matrix P is obtained by LFT and the performance weights for the controllers 1, 2 and 3 are chosen as $W_p = \frac{s+314}{100s+0.314}$, $W_p = \frac{s+471}{100s+0.314}$ and $W_p = \frac{s+565.2}{100s+0.314}$, respectively. The weight is selected to be large at low frequency in order to achieve good regulation performance, in addition, the weight $W_s = \frac{0.1s+314}{s+3.14}$ is selected to prevent the saturation of the controller output due to the $\pm 10V$ limits of DS1103 D/A converter output.

The value of μ is the less the better within its tolerance from theoretical point of view. But when the times of iteration increase, the more memory of the computer will be employed and the more time will be consumed, which do harm to the validity of the control method. Therefore, here the ninth, fifth and fifth iterations are chosen as the final iteration of the calculation for the controllers 1, 2 and 3, respectively.

The resulting controllers obtained by D-K iteration have the orders of 23, 16, and 20, respectively. It is normal that the order of control systems designed by μ synthesis is very high. However, the order of the control system can be reduced by model order

reduction techniques. For this purpose, the Hankel state reduction technique [178] is applied. The reduced order controller is created such that its transfer functions are still about equivalent to those of the original controller.

The final reduced order μ controller 1, 2 and 3 are as follow:

$$K_1 = \frac{1.483 s^5 + 2.609e004 s^4 + 1.068e005 s^3 + 1.047e005 s^2 + 1.266e004 s + 663.1}{1.26 s^5 + 222.4 s^4 + 5185 s^3 + 1.289e004 s^2 + 2347 s + 73.91} \quad (5.13)$$

$$K_2 = \frac{1.335 s^5 + 2.348e004 s^4 + 9.611e004 s^3 + 9.424e004 s^2 + 1.139e004 s + 596.8}{1.26 s^5 + 222.1 s^4 + 5128 s^3 + 1.169e004 s^2 + 2115 s + 66.52} \quad (5.14)$$

$$K_3 = \frac{1.12 s^5 + 1.97e004 s^4 + 6.942e004 s^3 + 4.797e004 s^2 + 5600 s + 284.8}{0.725 s^5 + 127.6 s^4 + 2904 s^3 + 5728 s^2 + 1024 s + 32.12} \quad (5.15)$$

The robust stability and robust performance achieved by the designed controller can be validated by μ analysis [173]. The robust stability and robust performance μ plots for the system subjected to perturbations are shown in Figure 5.4.

Max μ in the robust stability plot is 0.5543, which means that the system is stable for all perturbations Δ with $\|\Delta\|_\infty < \frac{1}{\mu} \approx 1.804$. The robust performance is guaranteed for all perturbations Δ with $\|\Delta\|_\infty < \frac{1}{\mu} \approx 1.307$.

The closed-loop step responses with μ controller are shown in Figure 5.5. As expected, the time domain simulations reinforce the conclusions that are reached in the frequency domain analysis. The step response under 5kg is relatively better than others, and that is because the 5kg is the nominal payload point for the μ controller 2, but the 4 kg and 10kg are the payload range end of the μ controllers 1 and 3. However, the step curve goes to steady state at almost 1s in each of the three plots.

The same controllers are applied in the experimental LBDCM drive system. The system model during simulation process is replaced as the real plant in the experiment.

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Figure 5.6 demonstrates the measured carriage position response for 4kg, 5kg, and 10kg. Notably, the experimental results agree with simulated results very well, which means two points, one is the controller is practical one, the other is that the identified system model from DSA fits the real plant.

It is clearly demonstrated in Figure 5.5 and Figure 5.6 that the settling time is a little bit long and therefore hard to meet the requirement in some fast speed industrial applications.

Figure 5.4: Robust stability (upper) and robust performance (lower) analysis by μ plot

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(a)

(b)

(c)

Figure 5.5: Simulated step responses by the μ controllers with friction compensation (a) 4kg load (b) 5 kg load (c) 10kg load

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(a)

(b)

(c)

Figure 5.6: Experiment step responses by the μ controllers with friction compensation

(a) 4kg load (b) 5kg load (c) 10kg load

From both the simulation and experiment results, it can be observed that the tracking curve increases very fast at the beginning of the process, but it slows down from some moment until it reaches the reference position. It is similar with the condition of track seeking and settling mode in the hard disk control. During the track seeking control, the head is moved to the regulated position as soon as possible usually by some time-optimal control schemes and settling mode is designed for the transition from the fast velocity control to disturbance suppression control. Hence, the mode switching control (MSC) [179], which is widely used in the head positioning systems of hard disk drives (HDD), is firstly applied in the LBDCM system to improve the performance of the proposed controller. The two different servo modes are switched from one to the other in the MSC. The structure of the MSC is shown in Figure 5.7.

Figure 5.7: Block diagram of the mode switching control

The function of the MSC in the system is to switch to connect the PD controller instead of μ controller when the position signal arrives at 90 percent of the target value. The PD controller is designed based on the information from RBF mass estimator. The process is similar as RBF based μ controller design, and three PD controllers are designed for the three payload ranges. Thus, the PD controller in the system owns some robustness in a way. This method is simple and easy to be implemented in practical experiment. The simulated step responses of the controllers with MSC and PID controller are illustrated in Figure 5.8 and Figure 5.9 respectively.

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Figure 5.8: Simulated step responses by the controllers with MSC (a) 4kg load (b) 5 kg load (c) 10kg load

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Figure 5.9: Simulated step responses by PID controller (a) 4kg load (b) 5kg load (c) 10kg load

It is demonstrated that the basic performance specification, i.e., the settling time less than 0.15s and no overshoot is realized by the controllers with MSC, that is, the μ controller with MSC. Moreover, the controllers with MSC perform well in the presence of a large load variation from 0kg to 10kg. Compared with the controllers with MSC, step responses from PID controller are slow and when the load exceeds some specific range, the performance of the PID controller is deteriorated.

The performance from μ controller without MSC are shown by Figure 5.5-Figure 5.6 and the performance from the controllers with MSC is clearly illustrated from results Figure 5.8-Figure 5.9. It can be noticed that the step response curves with MSC are smoother and the settling time is less than those by only μ controller.

The comparison is demonstrated more clearly by the mean squared error plot in Figure 5.10. The corresponding experiment results are shown in Figure 5.11. The experimental results are consistent with those obtained from numerical simulations. The figures demonstrate effectiveness of the controllers with MSC for the robust position tracking control of LBDCM.

Figure 5.10: Mean squared error of step responses with the controllers with MSC (dark) and PID controller (light) under payload variations

(a)

(b)

Figure 5.11: Experiment step responses by the controllers with MSC. (a) 4kg load (b) 5kg load (c) 10kg load

5.4 Conclusions

The combined H_∞ and μ synthesis method has been presented for the linear motion system driven by LBDCM. The structure of combined mass estimator and three sub- μ controllers extends tolerable load variation of the controller considerably. The allowable payload range of the robust controller is as large as 0~10kg in the study and both the robust stability and robust performance are guaranteed under the perturbations. Moreover, the mode switching control which is widely used in hard disk drive systems is first applied in the LBDCM system and better time response results are achieved. The settling time is reduced to about 0.15s, which is much less than that in previous work. The simulated and experimental results demonstrate that the controllers with MSC ensure the satisfactory tracking position performance as well as suppress the effect of large parameter variations of the plant.

From the next chapter on, the other new servo motion system which is driven by the newly invented motor called LUM is investigated. The delicate robust control and nonlinear friction compensation will also be designed to achieve the satisfying regulation and tracking performance in next chapter.

CHAPTER 6

GA Based DSM Control of an LUM Drive System

6.1 Introduction

Electromagnetic motors have actually existed for more than a hundred years. While these motors still dominate the industry, further improvement of the current designs is limited. In recent years, a variety of novel types of piezoelectric motors have attracted special interest as new operating principle-based servo actuators in the field of precision motion control applications due to its faster response times, higher precision, lowest electromagnetic interference, high power-to-weight ratio, and smaller packaging envelope. The piezoelectric motor can be called a milestone of new generation motor, which has a totally different operating principle from the electromagnetic motor counterpart. The first applied LUM appeared in the 1970s [180]. Different construction and driving principles of LUM have been reported [24-28]. While highly nonlinear features of the piezoelectric actuator are challenges to precise

control, the precise motion control of the LUM drive system requires detailed system model prior to the controller design. However, the mathematical modeling is relatively complex [181] and the motor parameters are influenced by the uncertainties and disturbances generated by payload variations, friction, imprecise experimental equipment and motor physics variations. Friction and mass variations are the main concern in LUM drive systems. Several friction models and parameter measurement methods have been presented for adequate friction compensation [51, 77 and 90]. However, the parameter measurement always requires special hardware design or extra hardware requirement. Another method for modeling friction is NN approximation. Nonlinear functional mapping properties of NN qualify it for identification and control of dynamic systems [182]. RBF network has the best performance in this particular area [183]. Load variations problem in the system can be solved by two ways: one is to resort to the robust controller which can realize satisfying performance for all the load changing ranges, and the other is to resort to the load estimator, which can estimate the load variation and the information is transferred to the controller for tuning the parameters in the control law.

During the last two decades, VSC has gained significant interest and is gradually applied in the industrial applications. The VSC theory is originally developed from a continuous time perspective. It has been realized that directly applying the continuous time SMC algorithms to discrete-time systems will confront some unconquerable problems, such as the limited sampling frequency, sample hold effects and discretization errors. To solve the problem, the DSM control has been introduced. A new concept of “sliding mode” is proposed for an arbitrary finite-dimensional discrete-time system [184]. A reaching law based approach for designing the DSM control law is proposed [67 and 72]. However, many works on DSM control only deal with exogenous disturbances and matching conditions, where friction is lumped into system uncertainties and the nonlinear dynamic characteristic of friction cannot be compensated effectively. In addition, some free parameters in the DSM controller

design procedure are generally selected by the experience of engineers in practical application, which will influence resulting performance of the controller. GA is a global optimization algorithm [185]. In GA, the search process is executed at multiple points concurrently and statistically, and the process progresses with the fitness value of the current searching point, which represents the degree of attainment of the control objective. These features make GA a powerful algorithm for control system parameter optimization.

A robust position controller is proposed for LUM drive systems by combining GA and sliding mode control technique. Firstly, in Section 6.2, the structure and driver of LUM are introduced briefly, followed by the system identification of the system with nonlinear friction compensation in Section 6.3. In Section 6.4, one DSM controller in cooperation with GA based parameter optimization is proposed for LUM drive systems. Simulation and experiment results under a wide range of operation conditions are demonstrated to validate the effectiveness of the proposed controller in Section 6.5.

6.2 Model of LUM

6.2.1 Principle and Structure of LUM

The inverse piezoelectric effect in piezoceramics converts electrical field to mechanical strain. Under special electrical excitation drive and ceramic geometry of piezoelectric motors, longitudinal extension and transverse bending oscillation modes are excited at close frequency proximity. The simultaneous excitation of the longitudinal extension mode and the transverse bending mode creates a small elliptical trajectory of the ceramic edge, thus achieving the dual mode standing wave motor. By coupling the ceramic edge to a precision stage, a resultant driving force is exerted on the stage, causing stage movement.

Based on the principle introduced above, numerous piezoelectric motors have been designed to provide a micromotor with higher speed, greater driving force and smaller minimum step size than micromotors of the prior art in the past two decades [25-27]. The motor in this study is commercialized by Nanomotion Ltd.. The series of motors take advantage of the most frequently researched operating principle. It is based on the excitation of a longitudinal and a superposed bending mode of a rectangular piezoelectric plate to achieve the elliptic motion of the driving tip. Figure 6.1 shows that the motor comprises a thin rectangular piezoelectric ceramic with at least one electrode on one of the large faces thereof and a plurality of electrodes on the other large face [28].

Figure 6.1: Structure of the linear piezoelectric motor from Nanomotion

Figure 6.2: Two-phase high-frequency resonant inverter for driving piezoelectric motor

6.2.2 Driver of LUM

A power conversion circuit in Figure 6.2 was proposed for driving the piezoelectric motor [186]. The power conversion processing system is composed of a high frequency boost-chopper-type dc-dc converter circuit and two-phase high-frequency half-bridge series load resonant inverter circuits using parasitic LC parameters of the electrostrictive ceramics.

6.2.3 Control Model of LUM

The LUM is driven by a high-frequency (39.6kHz) sine wave voltage, which is generated by an inverter operating over the resonance frequency [187]. A command voltage of $\pm 10\text{V}$ is applied to the driver. The driver then generates a 39.6kHz sine wave whose amplitude is proportional to the command voltage. The sine wave drives the linear piezoelectric motor. Thus, the motor features a linear voltage response. The motor and drive can be modeled as a DC motor with friction driven by a voltage amplifier.

The motion system is modeled as follow:

$$\begin{aligned} m\ddot{y} &= F(u) - F_v\dot{y} - f_{fric}(y, \dot{y}) - f_d(t) \\ F(u) &= K_t i(t) \\ u &= f(\dot{y}, i) \end{aligned} \tag{6.1}$$

where u is the V_{in} , command voltage to the driver; $i(t)$ is current to the motor; $F(u)$ is the applied force; F_v is the viscosity constant; K_t is the electromechanical energy conversion constant; $f_{fric}(y, \dot{y})$ is the highly nonlinear friction in the system; $f_d(t)$ represents the overall force effect from disturbances and noises present in the motor.

6.3 System Identification of an LUM Drive System

6.3.1 System Configuration

The experimental components are DC power source, LUM (it is such a small one but it can drive a big stage as shown in Figure 6.3), motor driver, position encoder, dSPACE DS1103 card and DSA. The experiment platform is shown in Figure 6.4. The specification of the elements is given in Table 6.1.

The whole experiment platform is similar to the BLDCM drive system described in Chapter 5. Power supply generates DC voltage sources for the motor and the motor driver. DS1103ADC receives the position signal and transfers it to the DSP card, which is installed in the computer. The DS1103 PPC Controller Board is interfacing with the host pc and acts as the center of the whole control system. It receives feedback information from the position encoder (resolution is $0.1\mu\text{m}$) in the motor and realizes the control algorithm. The optical encoder is installed very close to the motor. The -10V to 10V voltage is generated by the controller. After the calculation of the DSP card memory, the controller generates the satisfying input, which flows into the corresponding port of the driver and the high-frequency sine wave voltage suitable for driving the motor is generated. If the controller is designed well, the motor should move accurately according to the command.

The LUM drive system can be applied in inspection machines. The required specification is voltage to motor 270V rms , maximum current 600mA rms , speed 0.25m/s , maximum pay load 7kg , static holding force 28N .

The real-time experiment also consists of two parts: one is the system identification of the plant with nonlinear friction compensation, and the other is the regulation and tracking experiments for validation of the proposed controller.

Figure 6.3: The overall experimental system setup

Table 6.1: Specification of the experimental elements

Name	Brand	Model
Linear motor	Nanomotion	HR8-1-S-3
Motor driver	Nanomotion	AB1A driver box
Encoder	MicroE Systems	M2000-SS200c
DSP	dSPACE	DS1103
DSA	HP	HP35670A

6.3.2 Frequency Domain Identification of an LUM Drive System with RBF Friction Compensation

The plant is divided into a linear part and a nonlinear part due to the friction. DSA can only identify the linear system model. Hence, the first thing should be completed is to

compensate the nonlinear friction of system during the identification. The friction in the system should be measured prior to designing the friction compensator. Following the procedure applied in previous chapters, the experiment friction data points are obtained and shown in Figure 6.4.

The Stribeck friction model is also employed to approximate the friction. Different sets of friction model parameters are identified at different positions. Part of the parameter sets are listed in Table 6.2. The parameters F_c F_s v_s F_v are consistent with those in (2.5). In addition, δ_f has the value of 2.

Figure 6.4: Original friction data from real time experiment

Table 6.2: Fitting friction model parameters

Position(m)	F_c (Nm)	F_s (Nm)	v_s (rad/s)	F_v (Nm s/rad)
-0.145	0.6132	0.4798	71.6654	21.2402
-0.1	0.6182	0.4848	71.6766	21.2402
0	0.6732	0.5399	71.6429	21.2402
0.1	0.6641	0.5307	71.7002	21.2568
0.145	0.6792	0.5459	71.6296	21.2395

The math model based friction fitting curve and fitting error curve are shown in Figure 6.5 and Figure 6.6.

Figure 6.5: Friction fitting results by math function for LUM system

Figure 6.6: Friction fitting error results by math function for LUM system

The Kalman filter based RBF network is applied to fit the friction in the LUM drive system. The sample data skills and the same network structure designed for the LBDCM drive system are adopted in the system. The objective mean error ($10e-5$) of

the fitting result is achieved and the whole training time is in the order of seconds. The fitting result is shown in Figure 6.7 and Figure 6.8.

Figure 6.7: Friction fitting results by RBF for LUM system

Figure 6.8: Friction fitting error by RBF for LUM system

This NN friction model can be applied as the nonlinear friction compensator directly, which receives the feedback velocity signal and generates the expected compensation force to eliminate the effect of the friction.

The bode diagram of the plant with 0kg payload is shown in Figure 6.9. The curve fitting can be fulfilled by the algorithm described in Chapter 3.

The curve fitting model of the linear part of the plant for 0kg payload is:

$$\frac{Y(s)}{U(s)} = \frac{10.25}{s(s+30.025)} \quad (6.2)$$

In the same manner, the models for the 3.5kg and 7kg payloads are as follow:

$$\frac{Y(s)}{U(s)} = \frac{5.27}{s(s+15.43)} \quad \text{and} \quad \frac{Y(s)}{U(s)} = \frac{3.54}{s(s+10.382)} \quad (6.3)$$

Figure 6.9: Bode plot of the system model data for 0kg from DSA

6.4 Robust Controller Design

In a motion control system, many control schemes are suitable for the system control if the system only has the fixed parameters and little uncertainty. However, real conditions are not as above and always comprise the changing parameters. If the values of actual motion system parameters deviate from those assumed in the controller, the performance of the system will deteriorate. The SMC is adopted to control LUM drive systems because it can achieve an accurate servo-tracking response, and it is moderately

robust to plant parameter variations and external disturbances. Although sliding mode control is insensitive to the plant parameter variations, its performance can be affected greatly by large parameter variations. Therefore, this method does not work well under a wide range of the parameter variations. To solve the problem, the sliding mode control is combined with the on-line mass estimator to make the unknown parameters known to the controller. Moreover, GA is applied to optimize the design parameters to improve the transient response performance. The main structure of the motion system is shown in Figure 6.10.

Figure 6.10: The structure block diagram of the motion system

6.4.1 DSM Control

Sliding mode control has received much attention from researchers in the area of motion control due to its desirable features such as fast response, insensitivity to system parameter variations and simplicity of design and implementation [62].

The motion system is modeled as

$$m\ddot{y} = K_1 u - K_2 \dot{y} - f(\dot{y}, y) \quad (6.4)$$

that is,

$$\ddot{y} = \frac{1}{m} (K_1 u - K_2 \dot{y} - f(\dot{y}, y)) \quad (6.5)$$

where $f(\dot{y}, y)$ represents the total force from f_{fric} and f_d in (6.1).

The equation (6.5) can be represented in the standard state-space form:

$$\begin{aligned}\dot{y} &= v \\ \dot{v} &= -k_2 v / m + k_1 u / m - f(\dot{y}, y) / m\end{aligned}\quad (6.6)$$

The system will be digitalized in the practical application by computer-aim method.

Thus, denote

$$\begin{aligned}y_k &= y(kT_s), v_k = v(kT_s), \dot{v} = (v_{k+1} - v_k) / T_s \\ \text{and } f &= T_s f(kT_s) / m\end{aligned}\quad (6.7)$$

where T_s is the sampling time. The system is discretized by the forward Euler method.

$$\begin{aligned}x_{k+1} &= \Phi x_k + \Gamma u_k + f \\ y_k &= C x_k\end{aligned}\quad (6.8)$$

where

$$\begin{aligned}x_k &= \begin{bmatrix} y_k \\ v_k \end{bmatrix}, \Phi = \begin{bmatrix} 1 & T_s \\ 0 & 1 - T_s k_{fv} / m \end{bmatrix}, \\ \text{and } \Gamma &= \begin{bmatrix} 0 \\ T_s k_f / m \end{bmatrix}, C = [1 \quad 0]\end{aligned}\quad (6.9)$$

The friction function and the mass are time varying and uncertain parameters of the system. However the extent of the parameter is bounded by known. The control problem is to get the state x_k to track a specific time varying state x_d under the time varying friction and mass.

Let us define a sliding surface S by the scalar equation $s_k = 0$ as

$$S = \left\{ s_k \left| \begin{aligned} s_k &= \Lambda(x_k - x_k^d) = 0, \\ k &= 0, 1, \dots, s(kT_s) = s_k \end{aligned} \right. \right\} \quad (6.10)$$

where, $\Lambda = [\lambda \quad 1]$, λ is a positive real number and $x_k^d = [y_k^d \quad v_k^d]^T$ is the reference input.

Given the initial condition $x(0) = x_d(0)$, the problem of tracking $x \equiv x_d$ is equivalent to that of remaining on the surface S for all $k > 0$. Thus, the problem of tracking the x_d can be reduced to that of keeping the scalar quantity s_k at zero.

Adopting the reaching law [187]:

$$s_{k+1} - s_k = -QT_s s_k - \eta T_s \operatorname{sgn}(s_k), QT_s < 1 \quad (6.11)$$

$$\begin{aligned} s_{k+1} - s_k &= \Lambda(x_{k+1} - x_{k+1}^d) - \Lambda(x_k - x_k^d) \\ &= \Lambda(\Phi x_k) + \Lambda(\Gamma u_k) + \Lambda f \\ &\quad - \Lambda x_k - \Lambda(x_{k+1}^d - x_k^d) \end{aligned} \quad (6.12)$$

Solving u from the (6.11) and (6.12), we get

$$\begin{aligned} u_k &= -(\Lambda\Gamma)^{-1}[\Lambda(\Phi x_k) + \Lambda f - \Lambda x_k + QT_s s_k \\ &\quad + \eta T_s \operatorname{sgn}(s_k)] + \Gamma^{-1}(x_{k+1}^d - x_k^d) \end{aligned} \quad (6.13)$$

Moreover,

$$\operatorname{sgn}(1 - QT_s s_k) = \operatorname{sgn}(s_k) \quad (6.14)$$

Then, the sign of s_{k+1} must be opposite to that of s_k according to the definition of quasi-sliding mode (QSM) [187]. In the region, every state x satisfies:

$$\left\{ x \mid |s(x)| < \frac{\eta T_s}{1 - QT_s} \right\} \quad (6.15)$$

And the width of the DSM bound is:

$$\Delta = \frac{\eta T_s}{1 - QT_s} \quad (6.16)$$

Consider the system (6.8) under the unknown mass and friction condition.

$$\begin{aligned} x_{k+1} &= \tilde{\Phi} x_k + \Delta \Phi x_k + \tilde{\Gamma} u_k + \Delta \Gamma u_k + f \\ y_k &= C x_k \end{aligned} \quad (6.17)$$

For the current system, the following matching conditions are satisfied:

$$\begin{aligned} \Delta \Phi &= \tilde{\Gamma} \tilde{\Phi} \\ \Delta \Gamma &= \tilde{\Gamma} \tilde{\Gamma} \\ f &= \tilde{\Gamma} \tilde{f} \end{aligned} \quad (6.18)$$

Consider the system (6.17), the (6.13) becomes

$$\begin{aligned} u_k &= -(\Lambda \tilde{\Gamma})^{-1}[\Lambda(\tilde{\Phi} x_k) - \Lambda x_k + QT_s s_k \\ &\quad + \eta T_s \operatorname{sgn}(s_k)] - \tilde{\Gamma} u_k - \tilde{\Phi} x_k - \tilde{f} \\ &\quad + \tilde{\Gamma}^{-1}(x_{k+1}^d - x_k^d) \end{aligned} \quad (6.19)$$

The $\tilde{\Phi}, \tilde{\Gamma}, \tilde{f}$ in (6.19) are unknown elements, thus, (6.19) cannot be used to design the controller. Assume $\tilde{\Phi}, \tilde{\Gamma}, \tilde{f}$ can be replaced by the elements Φ_c, Γ_c, f_c , which will be specified by the following procedure.

After the substitution, (6.19) becomes:

$$\begin{aligned} u_k = & -(\Lambda\tilde{\Gamma})^{-1}[\Lambda(\tilde{\Phi}x_k) - \Lambda x_k + QT_s s_k \\ & + \eta T_s \text{sgn}(s_k)] - \Gamma_c u_k - \Phi_c x_k - f_c \\ & + \tilde{\Gamma}^{-1}(x_{k+1}^d - x_k^d) \end{aligned} \quad (6.20)$$

From the (6.12) (6.17) and (6.20), the incremental change in s_k is expressed:

$$\begin{aligned} s_{k+1} - s_k = & -QT_s s_k - \eta T_s \text{sgn}(s_k) \\ & + (\Lambda\tilde{\Gamma})[\tilde{\Gamma}u_k - \Gamma_c u_k + \tilde{\Phi}x_k - \Phi_c x_k \\ & + \tilde{f} - f_c] \end{aligned} \quad (6.21)$$

For simplification, let

$$\begin{aligned} \hat{T} &= \Lambda\tilde{\Gamma}(\tilde{\Gamma}u_k), T_c = \Lambda\tilde{\Gamma}(\Gamma_c u_k) \\ \hat{S} &= \Lambda\tilde{\Gamma}(\tilde{\Phi}x_k), S_c = \Lambda\tilde{\Gamma}(\Phi_c x_k) \\ \hat{F} &= \Lambda\tilde{\Gamma}\tilde{f}, F_c = \Lambda\tilde{\Gamma}f_c \end{aligned} \quad (6.22)$$

Then (6.21) can be expressed as:

$$\begin{aligned} s_{k+1} - s_k = & -QT_s s_k - \eta T_s \text{sgn}(s_k) \\ & + (\hat{T} - T_c) + (\hat{S} - S_c) + (\hat{F} - F_c) \end{aligned} \quad (6.23)$$

For the LUM drive system, $\hat{T}$, $\hat{S}$ and $\hat{F}$ have some corresponding relationship with mass and friction in the system. They have the upper bound and lower bounds as the mass and friction in the system is not unlimited.

$$T_{\min} \leq \hat{T} \leq T_{\max}, S_{\min} \leq \hat{S} \leq S_{\max}, F_{\min} \leq \hat{F} \leq F_{\max} \quad (6.24)$$

Since the value of T_c , S_c and F_c are needed to be specified to guarantee the sign of $s_{k+1} - s_k$ is opposite to the sign of s_k , the simple solution is:

$$\begin{cases} T_c = T_{\max}, S_c = S_{\max}, F_c = F_{\max} & \text{sgn}(s_k) = 1 \\ T_c = T_{\min}, S_c = S_{\min}, F_c = F_{\min} & \text{sgn}(s_k) = -1 \end{cases} \quad (6.25)$$

To formulate (6.21) as follow:

$$\begin{cases} T_c = \left(\frac{T_{\max} + T_{\min}}{2}\right) + \left(\frac{T_{\max} - T_{\min}}{2}\right) \text{sgn}(s_k) \\ S_c = \left(\frac{S_{\max} + S_{\min}}{2}\right) + \left(\frac{S_{\max} - S_{\min}}{2}\right) \text{sgn}(s_k) \\ F_c = \left(\frac{F_{\max} + F_{\min}}{2}\right) + \left(\frac{F_{\max} - F_{\min}}{2}\right) \text{sgn}(s_k) \end{cases} \quad (6.26)$$

The final control law is referred from (6.18) (6.20) and (6.26):

$$\begin{aligned} u_k = & -(\Lambda \bar{\Gamma})^{-1} \{ \Lambda(\bar{\Phi} x_k) - (1 - QT_s) s_k \\ & + \eta T_s \text{sgn}(s_k) - \Lambda(x_{k+1}^d - x_k^d) \\ & + \left(\frac{T_{\max} + T_{\min}}{2}\right) + \left(\frac{S_{\max} + S_{\min}}{2}\right) + \left(\frac{F_{\max} + F_{\min}}{2}\right) \\ & + \left[\left(\frac{T_{\max} - T_{\min}}{2}\right) + \left(\frac{S_{\max} - S_{\min}}{2}\right) + \left(\frac{F_{\max} - F_{\min}}{2}\right)\right] \\ & * \text{sgn}(s_k) \} \end{aligned} \quad (6.27)$$

6.4.2 On-line Parameter Estimator

Although the sliding mode control method has strong robustness for the uncertainties, it is not unlimited. When the parameter is changing in a large range, the method itself cannot tackle the condition. When there are large uncertainty variations in a dynamic system, one way to reduce it is to use parameter estimation, i.e. inferring the value of the parameters from the measurement of input and output signals of the system. Parameter estimation can be done either on-line or off-line. Off-line estimation may be preferable if the parameters are constant and there is sufficient time for estimation. However when the parameter is unknown and cannot be identified until the operation begins. On-line parameter estimation is necessary to keep track of the parameter values.

The recursive least square with forgetting factor is adopted as the parameter estimation algorithm. The aim of applying the method is to on-line estimate the value of the unknown mass of the motion system. The system input and output at time t are generally denoted as $u(t)$ and $y(t)$ respectively. Perhaps the most basic relationship between the input and output is a linear difference equation:

$$y(t) + a_1 y(t-1) + \dots + a_n y(t-n) = b_1 u(t-1) + \dots + b_m u(t-m) \quad (6.28)$$

A pragmatic and useful way to see (6.28) is to view it as the way of determining the next output value with previous observations:

$$y(t) = -a_1 y(t-1) - \dots - a_n y(t-n) + b_1 u(t-1) + \dots + b_m u(t-m) \quad (6.29)$$

Let $\theta = [a_1 \dots a_n, b_1 \dots b_m]^T$, $\varphi(t) = [-y(t-1) \dots -y(t-n), u(t-1) \dots u(t-m)]^T$. With these, (6.29) can be rewritten as:

$$\hat{y}(t|\theta) = \varphi^T(t)\theta \quad (6.30)$$

which means that $y(t)$ can be calculated from the past data depending on the parameters in θ , and vice versa, θ can be identified by the simulation data. The estimation algorithm of the recursive least square with forgetting factor is as follow [188]:

$$\begin{aligned} \hat{\theta}(t) &= \hat{\theta}(t-1) + L(t)[y(t) - \varphi^T(t)\hat{\theta}(t-1)] \\ L(t) &= \frac{P(t-1)\varphi(t)}{\lambda(t) + \varphi^T(t)P(t-1)\varphi(t)} \\ P(t) &= \frac{1}{\lambda(t)} \left[P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{\lambda(t) + \varphi^T(t)P(t-1)\varphi(t)} \right] \end{aligned} \quad (6.31)$$

6.4.3 GA Based Optimization in Sliding Mode Control

GA is a powerful search algorithm based on the mechanisms of natural selection and natural genetics that operate without knowledge of the task domain and utilize only the fitness of evaluated individuals.

Three free parameters λ , Q and η are present in the SMC design process. They have been chosen by experience in most of previous work. Thus, it is not the optimal one. GA can realize the optimal design with a suitable fitness function.

To formulate the problem as chromosomes by a coding procedure is the first step in utilizing GA. The binary representation traditionally used in GA has some drawbacks when applied to multidimensional, high – precision numerical problems. The use of real-coded genes could solve these problems [189]. In this design, the real number parameters are directly applied in population sets without coding. The initial population is a potential solution set P , the first set of population is usually generated randomly

$$P = \{P_1, P_2, \dots, P_{pop_size}\} \quad (6.32)$$

$$P_i = [P_{i1}, P_{i2}, \dots, P_{ij}, \dots, P_{no_var}] \quad (6.33)$$

$$i = 1, 2, \dots, pop_size; \quad (6.34)$$

$$j = 1, 2, \dots, no_var; \quad (6.35)$$

$$P_{min}^j \leq P_{ij} \leq P_{max}^j \quad (6.36)$$

where pop_size denotes the population size; no_var denotes the number of variables to be tuned; P_{ij} are the parameters to be tuned; and P_{min}^j P_{max}^j are the minimum and maximum values of the parameter P_{ij} , respectively for all.

The upper and lower limits of the parameters are specified by experience. For instance, when λ is 50, the system step response is overdamped, but when λ is 100, the system step response is underdamped. The [50 100] can be one candidate of the bounds of λ . Searching process in a large space is a time-consuming work, thus, efficiency is an important issue which should be concerned. The bound of the variables in GA searching process is the smaller the better if only it does not influence the optimization performance.

A fitting function should be set up in order to evaluate the performance of every new generation of the parameters. The position response result is fed into the fitness function, which calculates the fitness of the individual character. The fitness function should be suitably designed to incorporate the restrictions. In this study, the integral of squared error (ISE) of position response is adopted as one part of the fitness function. Moreover, since the overshoot of the time response is also crucial for the system transient performance, the integral of the overshoot acts as the other part of the fitness function.

$$g = g_{ise} + g_{overshoot} \quad (6.37)$$

$$g_{ise} = \int_0^T (y(t) - r)^2 dt \quad (6.38)$$

$$g_{overshoot} = \int_0^T f(y(t)-r)^2 dt, f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (6.39)$$

The fitness evaluation has a close relationship with the system performance, and it guarantees the specified tracking error, settling time, less overshoot, etc. If the ISE and integral of overshoot is a minimum, the settling time will be a minimum correspondingly. Thus, it is not necessary to include one settling time component in the fitness function due to the simplicity and high efficiency.

Since the GA algorithm is to make the fitness function a maximum, the minimization of the evaluation function g is transformed into a maximization search fitness function F by

$$F = \frac{\alpha}{g} \quad (\alpha \text{ is a constant}) \quad (6.40)$$

When the population is very convergent, the average fitness will be close to the best. This fact leads to a strong competition between many individuals displaying very similar fitness, thus generating a somewhat erratic behavior of the algorithm. Therefore, it is necessary to normalize the fitness function in order to keep the competition more or less the same in generation after generation. This situation can be controlled by the normalization number.

$$N = \frac{F_{max}}{F_{aver}} \quad (6.41)$$

where F_{max} is the maximum fitness, F_{aver} is the averages fitness. These values should be taken between 1.2 and 2 for small population [190]. Here, N has been taken for all generations.

The main objective behind the float point representation is to move the genetic algorithm closer to the problem space. Such a move forces the operators to be more problem specific by utilizing some specific characteristics of real space. For instance,

the representation has the property that two points close to each other in the representation space must also be close in the problem space and vice versa. Thus, a float point representation is adopted as it is conceptually closest to the problem space and also allows for an easy and efficient implementation of closed and dynamic operators. For float point implementation, the crossover operator is quite analogous to that of the binary ones. However, it is different for the mutation operator. In the chapter, non-uniform mutation is applied for improving single-element tuning and reducing the disadvantage of random mutation in the float point implementation. Let a_i and b_i be the lower and upper bound, respectively, for each variable i , x_i is an element in the chromosome and x_i' is the next generation of x_i .

$$x_i' = \begin{cases} x_i + (b_i - x_i)f(G) & \text{if } r_1 < 0.5 \\ x_i - (x_i - a_i)f(G) & \text{if } r_1 \geq 0.5 \end{cases} \quad (6.42)$$

where

$$f(G) = \left(r_2 \left(1 - \frac{G}{G_{\max}}\right)\right)^b \quad (6.43)$$

r_1, r_2 : a uniform random number between (0,1)

G : the current generation

$G_{\max}$: the maximum number of generations

b : a shape parameter

The GA moves from generation to generation selecting and reproducing parents until a termination criterion is met. The most frequently used stopping criterions are shown here:

- *a design goal (no overshoot and ISE is less than 10E-4) is reached.*
- *no improvement in the best chromosome is noted for a set number of generations.*
- *a fixed number of generations (200) has passed.*

However, sometimes the process stopped but the specified performance is not fulfilled. In the practical point of view, the following strategies are optional by experience.

- *increasing the mutation probability, which can reinforce the random search ability in the begin phase of the evolution.*
- *adjusting the selection probability, which can be realized by optimizing the probability value as the function, for instant, the meta GA method.*
- *selection of suitable normalization number.*
- *keeping diversity of the individuals in chromosome, for instance, increase the population and distance of crossover individuals, and localization, which is realized by splitting the chromosome into some sub-chromosome, and the sub-chromosomes are selected independently.*

6.5 Demonstration of Position Tracking Results

6.5.1 Numerical Validation of the Proposed Controller

The proposed sliding mode control and conventional PID controller are both simulated and the results are compared to validate the robustness and accuracy of the proposed control method.

The model used is corresponding to (6.1):

$$3.7\ddot{y} = 37.925u - 111.1\dot{y} - f(\dot{y}) \quad (6.44)$$

Φ and Γ in (6.7) are derived as:

$$\tilde{\Phi} = \begin{bmatrix} 1 & 1.0e-3 \\ 0 & 1 - \frac{0.1111}{m} \end{bmatrix}, \tilde{\Gamma} = \begin{bmatrix} 0 \\ \frac{0.0379}{m} \end{bmatrix} \quad (6.45)$$

The mass of the system is estimated by the mass estimator and the difference between the real mass and the estimated one definitely exists. In the control scheme, this must be considered. The error between them is bounded as $0.2m_0$, m_0 is the estimated mass. This action obviously reinforces the robustness of the controller. Moreover, the

friction characteristic is fitted and compensated by RBF, and the ISE between fitting curve and real friction curve is less than $1.0\text{E-}4$.

The unknown parameters in (6.19) can be further determined:

$$\begin{aligned} -0.167 &\leq \bar{\Gamma} \leq 0.25 \\ [0 \ -0.733] &\leq \bar{\Phi} \leq [0 \ 0.488] \\ -0.04 &\leq \hat{f} \leq 0.04 \end{aligned} \quad (6.46)$$

The simulation is presented under the condition of friction and mass variations. The friction is simulated and compensated by an RBF network. The payload changes from 0 to 7kg. The nominal friction value in the system is assumed to be f_0 . Then, $f_0 \leq f(\dot{y}) \leq 2f_0$ is supposed. Noises in the system are also considered in the simulation process.

The reference signals in this case are a stepwise change position signal and a swing signal $g(t)=\sin(t)*\sin(10t)$, which are shown in Figure 6.11.

The sliding mode controller designed from (6.27) includes three free parameters, λ , Q and η . The three parameters have different function during the controller design process. For a second order system, λ is the slope of the sliding surface. Starting from any initial condition, the state trajectory approaches the surface in a finite time, the slides along the surface towards reference point with a time constant equal to $1/\lambda$. The distance to the sliding surface decreases along all system trajectories. The values of Q and η determine the speed of this kind of movement. In a word, these parameters have a close relationship with the transient performance and robust stability of the system.

The three parameters are chosen to achieve the optimality with respect to the fitness function (6.37) based on GA. Specifications of the GA process are the population size of 100, the normalized geometric ranking selection, the one-point crossover with its probability of 0.6, and the non-uniform mutation with its probability of 0.05,

respectively. The genetic process is iterated until 200 generations are achieved. In the genetic process, it is indispensable to predetermine an appropriate solution space to be searched for higher convergence. After the GA based optimization procedure, the resulting values of them are 30.1, 0.3, and 0.02, respectively. The GA based sliding mode controller from (6.27) is derived:

$$u_k = -\frac{\bar{m}}{0.0379} \{ [30.1 \ 1] \tilde{\Phi} x_k - 0.9997 s_k - [30.1 \ 1] (x_{k+1}^d - x_k^d) + 2e - 5 \operatorname{sgn}(s_k) \} \\ + \frac{0.095}{\bar{m}} \operatorname{sgn}(s_k) + \frac{0.0379}{\bar{m}} [0 \ 0.6105] x_k \operatorname{sgn}(s_k) + \frac{1.516e-3}{\bar{m}} \operatorname{sgn}(s_k) \} \quad (6.47)$$

Figure 6.11: The reference position signals in the simulation

When the system is far away from sliding surface, the required magnitude of this control may become arbitrarily large. Taking into account a saturation value of u_k , the control law [191] is as follow:

$$u_k = \begin{cases} u_k & \text{if } |u_k| \leq u_m \\ u_m \frac{u_k}{|u_k|} & \text{if } |u_k| > u_m \end{cases} \quad (6.48)$$

Figure 6.12 shows the results of position control based on the two methods under the condition of $f(\dot{y})=1.2f_0$ and payload $m=0\text{kg}$. It can be noticed that the response curve in the lower picture is with some tremble signals, which do harm to the system response and even cause the unstable of the whole motion system. Figure 6.13 shows the case under the condition of $f(\dot{y})=1.2f_0$ and payload $m=7\text{kg}$. An obvious overshoot is illustrated in the lower picture. Moreover, the setting time of the lower curve is a little longer than the upper one. The proposed controller provides the satisfying step response under the conditions of without payload as well as with a payload of 7kg. The PID controller performs relatively poor and even worse when a large payload occurs.

Figure 6.14 and Figure 6.15 show the position response curve tracking the second reference signal under different friction and mass conditions. It can be easily found that the order of the magnitude of the position tracking error in upper pictures in the figures is $1.0\text{e-}5$ or $1.0\text{e-}6$. However that in lower ones in the figures is $1.0\text{e-}4$. Therefore, it is clear to illustrate that the proposed controller performs better than the conventional one in the position tracking process.

To evaluate the robustness of the proposed control method, the control results are obtained under lots of different frictions and masses. The friction ranges from f_0 to $2f_0$ and the payload range from 0kg to 7kg. Under every different condition, the mean tracking error during the whole simulation time is calculated. Figure 6.16 shows all the average absolute tracking errors to step reference signal at every condition point clearly. The tracking error in the upper picture varies from $1.9\text{E-}5$ to $1.5\text{E-}4$. The one in the lower picture ranges from $2.2\text{E-}4$ to $5.2\text{E-}4$.

Figure 6.12: Tracking performance of proposed method (upper) and PID controller (lower) under the condition of $f=1.2 f_0$ and payload $m=0\text{kg}$

Figure 6.13: Tracking performance of proposed method (upper) and PID controller (lower) under the condition of $f=1.2 f_0$ and payload $m=7\text{kg}$

Figure 6.14: Tracking performance of proposed method (upper) and PID controller (lower) under the condition of $f=1.2 f_0$ and $m=3.5\text{kg}$

Figure 6.15: Tracking performance of proposed method (upper) and PID controller (lower) under the condition of $f=1.2 f_0$ and payload $m=7\text{kg}$

Figure 6.16: Mean position tracking error of the proposed method (upper) and PID (lower) with the variations of friction and payload.

Moreover, the increasing speed of the tracking error along with friction and mass variations is comparatively smaller in the proposed control method. Hence, the simulation results demonstrate that the proposed controller scheme highly improves the control performance compared with the conventional PID controller in the varying payload and friction conditions.

6.5.2 Real-time Experiment

The same controllers are applied in the experimental LUM drive system. The real plant replaces the simulated system model in the experiment. Figure 6.17 and Figure 6.18 demonstrate the measured carriage stepwise position response under 0kg and 7kg payload and $1.2f_0$ friction condition. Figure 6.19 and Figure 6.20 demonstrate the swing position response under 3.5kg and 7kg payload and $1.2f_0$ friction condition, respectively. Notably, the experimental results agree with simulated results very well and the proposed controller designed by numerical method also provides the same performance in the real-time experiment, which means two points, one is the controller is practical one, the other is that the identified system model from DSA fits the real plant.

Figure 6.17: Experiment stepwise response under payload of 0kg and $1.2f_0$ condition

Figure 6.18: Experiment stepwise response under payload of 7kg and $1.2f_0$ condition

Figure 6.19: Experiment swing response under payload of 3.5kg and $1.2f_0$ condition Figure 6.20: Experiment swing response under payload of 7kg and $1.2f_0$ condition

6.6 Conclusions

In this chapter, a DSA is first used to identify the LUM drive system and the transfer function of motor together with the driver is obtained. Highly nonlinear friction in the system is measured and compensated by an RBF network. A DSM controller is designed for the system with perturbed state matrix and input matrix and nonlinear external disturbance based on reaching law approach. In addition, the free parameters in the design process are chosen via GA and the least ISE and overshoot of position response are achieved. The large tolerable payload 7kg of the LUM drive system is realized by

combined the sliding mode controller and an on-line mass estimator. The simulation results of the proposed controller and PID controller demonstrate that the proposed controller is insensitive to the mass and friction variations and noise and holds less mean position tracking error and better transient response than PID controller. The experiments are also achieved to validate the effectiveness of the proposed scheme.

In foregoing chapters, the precise and robust control of single axis motion systems has been studied and both linear and nonlinear robust algorithms are proposed for achieving the satisfactory tracking performance. The research work will be extended to multi-dimensional motion systems in next chapter. The coordinated controller will be proposed due to the new cross-coupling and contour tracking problems in the multi-axes motion systems. The proposed control scheme will also be applied in real LUM drive biaxial system, which is nowadays the most promising in many applications, such as wafer inspection, biomedical depositing system.

CHAPTER 7

Cross-coupled DSM Control of an LUM Drive Biaxial System

7.1 Introduction

Precise and robust contouring control is attracting more attention for many industrial applications, for instance, lower power laser cutting, wafer detection, nuclear magnetic resonance cancer detector, etc. In some applications, not only the single axis motion is inevitable, but two dimensional or even multi-dimensional motion is desired to be realized. The dual LUM drive biaxial systems are further studied after the robust precise control of LUM driven single axis motion systems are achieved in last chapter.

The biaxial system is not as simple as two additive SISO systems. The coupling between two SISO loops consists of not only the disturbance coupling but error information coupling. That means, if the disturbance occurs in one loop, it must have an effect on the other loop through coupling between loops. Similarly, if the tracking

error in one loop met a jump or fall, it should have an effect on the control effort for the other loop at the moment. Many scholars have investigated the coordinated control scheme to solve such a coupling problem.

It was proposed that the accurate contour control is guaranteed only if the matched dynamics of the loop is fulfilled [192]. One approach was developed to design a tracking controller when the reference relationship between axes is linear [193]. Tracking performance of each axis was improved by taking into account the dynamics of trajectory for each axis [194]. One novel method was presented to generate the tracking trajectory for each axis [195]. The approaches discussed above assume the biaxial system is a decoupled system, and the decoupled controller is only designed for each single axis to track the respective reference trajectory. Thus, the coupling effect may degrade the performance of the overall contour control.

The cross-coupled concept was proposed in [196] and many researchers have addressed control structures based on this concept. A time varying cross-coupled controller was designed to improve the contouring response of biaxial systems [197]. A cross-coupled adaptive controller was provided to increase the feedrates without degrading the contouring accuracy [198]. A coupled adaptive feedforward controller was introduced to solve the synchronization error problem in the biaxial motion system [199]. A time-varying coordinate frame was formulated to design the contouring controller and the stability analysis was also provided [200 and 201]. However, the schemes cited above all are not involved to take into account the model uncertainty and friction, which exist in every industrial motion system.

In this chapter, a cross-coupled sliding mode controller which is suppressive to both load variation and friction is proposed for the precise contour tracking control of biaxial systems. The chapter is organized as follows. The system model is identified by DSA under the RBF nonlinear friction compensation in Section 7.2. And the decoupling of the coupled two inputs and two outputs (TITO) plant model is also

achieved in this section. In Section 7.3, the cross-coupled DSM control is proposed for the two dimensional motion problem. Furthermore, the simulation and experiment results of the contour tracking control for biaxial system are both presented to demonstrate the robustness of the proposed control scheme in Section 7.4. Finally, conclusions are drawn.

7.2 System Identification and Decoupling of an LUM Biaxial System

7.2.1 System Configuration

As shown in Figure 7.1, a PLS4 X-Y table (from Motiotechn), driven by two LUMs from Nanomotion Ltd., is controlled by a DS1103 card (from dSPACE) which is mounted in a host computer. To measure the displacement of the X-Y table, two linear optical encoders M3500 (from MicroE) with a high resolution of 5nm are installed in each axis. The position signals are measured and sent to the DS1103 ADC ports. After calculation of the controller, control signal is generated and transferred from DS1103 DAC port to the corresponding port of the motor driver. If the controller is designed well, the tables can move along any expected path. The difference between this platform and the platform described in last chapter is that two motor drivers and two motors are involved in the biaxial system. The DS1103 works as two coordinated controllers to provide suitable control voltage signals to two corresponding motor drivers. As a result, the two motors move simultaneously to achieve two dimensional position tracking objective.

Figure 7.1: Hardware platform of biaxial motion system

7.2.2 Model Identification with Nonlinear Friction Compensation

The LUM drive biaxial motion system is a typical TITO system. The block diagram of the dual axial system is shown in Figure 7.2. The 2×2 system consists of two interaction loops G_{12} and G_{21} , the loop gains of which are far less than the other two loops G_{11} and G_{22} . Thus, the inputs and outputs can be paired as 11 and 22 without determining relative gain array.

Figure 7.2: Biaxial system structure

Since the physical parameter values of the system are difficult to obtain, we resort to system identification. Fortunately, DSA can identify the linear system model from some real time experiments.

A Kalman Filter based RBF network is set up for the friction modeling of both the upper stage and lower stage by following the algorithm described in Chapter 2. The measured friction data are shown in Figure 7.3. The math model based friction fitting curve and fitting error are shown in Figure 7.4 and Figure 7.5. The NN fitting results are shown in Figure 7.6 and Figure 7.7.

Figure 7.3: Measured friction data for upper axis (left) and lower axis (right)

Figure 7.4: Friction fitting results (left) and fitting error results (right) by math function for LUM upper axis

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

Figure 7.5: Friction fitting results (left) and fitting error results (right) by math function for LUM lower axis

Figure 7.6: Friction fitting results (left) and fitting error results (right) by NN for LUM upper axis

Figure 7.7: Friction fitting results (left) and fitting error results (right) by NN for LUM lower axis

The four transfer functions in Figure 7.2 can be obtained with the NN nonlinear friction compensation by DSA. When the various-frequency swept sine signals are added to input 1 with input 2 unchanged in Figure 7.2, the output of the two loops are recorded for identifying G_{11} and G_{12} . Similarly, when the signal is added to input 2 with input 1 unchanged, the output of the two loops are recorded for identifying G_{21} and G_{22} . The bode diagrams of two main loops and two interaction loops are shown in Figure 7.8 and Figure 7.9.

Figure 7.8: TITO system identification results of two main loops

Figure 7.9: TITO system identification results of two interaction loops

The fitting frequency domain system models are:

$$G_{11} = \frac{4.96}{s(s + 73.845)} \quad G_{22} = \frac{1.2}{s(s + 51.029)} \quad (7.1)$$

$$G_{12} = \frac{0.0015}{s(s + 2.4)} \quad G_{21} = \frac{0.0007}{s(s + 1.1)} \quad (7.2)$$

7.2.3 Decoupling of the Plant

Cross coupling exists in the biaxial system, however most control schemes are designed for the SISO system. Thus, it is desirable to design a decoupler to

compensate the loop interaction. It is therefore clear that any technique which can eliminate the effect of the undesired cross coupling improves control performance. Note that the purpose is not to eliminate the cross coupling, that is impossible, since to do this requires altering the physical nature of the system. The main objective of decoupling is to compensate the effect of the interactions brought about by cross coupling. As depicted in Figure 7.10, decoupling is achieved by introducing an additional transfer function “block” (the interaction compensator) between the single loop controllers and plant. This interaction compensator, together with the single loop controllers, constitutes the multivariable decoupling controller. In the ideal case, the decoupler makes the control loops totally independent of one another, thereby reducing the controller tuning tasks to that of tuning several SISO controllers.

Figure 7.10: Control structure of biaxial system with decoupler

The decoupler design is as simple as introduced below. For the plant demonstrated in Figure 7.2, the transfer function of the system is:

$$\begin{aligned}
 Y &= GU \\
 Y &= [y_1 \ y_2]^T, U = [u_1 \ u_2]^T \\
 G &= \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix}
 \end{aligned} \tag{7.3}$$

Inputs of the decoupler which is also the outputs of the controller are denoted as V , G_I is the decoupling transfer function.

$$U = G_I V \quad (7.4)$$

$$G_I = \begin{bmatrix} G_{I11} & G_{I12} \\ G_{I21} & G_{I22} \end{bmatrix} \quad (7.5)$$

The objective of decoupling is to make GG_I a diagonal matrix. G_I can be given by:

$$G_I = G^{-1} \text{diag}[G] \quad (7.6)$$

Thus,
$$Y = \text{diag}[G]V \quad (7.7)$$

As a result, the relationship between Y and V becomes totally non-coupled. The whole structure of the system is shown in Figure 7.10.

7.3 Control Scheme

One new problem in multi-axis system is that the motion of multiple axes must be coordinated to achieve contour tracking target. The most important factor in the biaxial control system is the contour error. The detail explanation of contour error is to be addressed in following section. In order to suppress the disturbances and parameter uncertainties in the system, two DSM controllers are proposed for the biaxial system. Moreover, one online mass estimator is involved to extend the robustness of the controller.

7.3.1 Contour Error

Contour error is a different concept from tracking error. Contour error is defined as the shortest distance between the actual position and the desired position [202]. Tracking error is the difference between the desired position and the actual position at a given instant. Satisfying tracking performance can not be guaranteed when only the tracking

error rather than contour error is taken into consideration during the controller design. In the LUM biaxial system, a small tracking error does not imply a large contour error, and vice versa. The situation is demonstrated clearly in Figure 7.11.

Figure 7.11: Tracking error (solid arrow) and contour error (dash arrow)

7.3.2 Computing of Contour Error

One arbitrary curved trajectory is shown in Figure 7.12 to illustrate the process of deriving the contour error estimation. Let P^* represent a position vector on a desired curved contour. Let P represent the corresponding actual position vector. Also, let P_I^* be the position vector on the desired contour which is closest to P .

Figure 7.12: Contour error calculation

The position error vector E is defined as:

$$E = \begin{bmatrix} E_x \\ E_y \end{bmatrix} = P^* - P = \begin{bmatrix} P_x^* \\ P_y^* \end{bmatrix} - \begin{bmatrix} P_x \\ P_y \end{bmatrix} \quad (7.8)$$

The contour error vector E_r is defined as:

$$E_r = \begin{bmatrix} E_{rx} \\ E_{ry} \end{bmatrix} = P_1^* - P = \begin{bmatrix} P_{1x}^* \\ P_{1y}^* \end{bmatrix} - \begin{bmatrix} P_x \\ P_y \end{bmatrix} \quad (7.9)$$

Let V^* and V be the unit velocity vectors associated P^* and P , respectively.

$$V^* = \frac{\dot{P}^*}{\|\dot{P}^*\|}; V = \frac{\dot{P}}{\|\dot{P}\|} \quad (7.10)$$

And average unit velocity vector is defined as:

$$\bar{V} = \begin{bmatrix} \bar{V}_x \\ \bar{V}_y \end{bmatrix} = \frac{\dot{P}^* + \dot{P}}{\|\dot{P}^* + \dot{P}\|} \quad (7.11)$$

Let Δt is the transition time from P_1^* to P^* , v is the average velocity from P_1^* to P^* .

$$v = \frac{P^* - P_1^*}{\Delta t} \quad (7.12)$$

$$E_r = E - (P^* - P_1^*) = E - v\Delta t \quad (7.13)$$

$$E_r = \begin{bmatrix} E_{rx} \\ E_{ry} \end{bmatrix} = \begin{bmatrix} E_x - |v| \bar{V}_x \Delta t \\ E_y - |v| \bar{V}_y \Delta t \end{bmatrix} \quad (7.14)$$

The Δt can be assumed as a variable.

From $\frac{\partial \|E_r\|}{\partial \Delta t} = 0$, it is obtained that:

$$\Delta t = \frac{(E_x \bar{V}_x + E_y \bar{V}_y)}{\|v\|} \quad (7.15)$$

Finally, E_r can be calculated as

$$E_r = \begin{bmatrix} E_{rx} \\ E_{ry} \end{bmatrix} = \begin{bmatrix} \bar{V}_y (E_x \bar{V}_y - E_y \bar{V}_x) \\ -\bar{V}_x (E_x \bar{V}_y - E_y \bar{V}_x) \end{bmatrix} \quad (7.16)$$

Thus,

$$\|E_r\| = E_x \bar{V}_y - E_y \bar{V}_x \quad (7.17)$$

The n dimensional case can be derived in a similar way. The same notations are followed as in the two dimensional one. The contour error vector is:

$$E_r = -\frac{1}{2}[(E \times V^*) \times V^* + (E \times V) \times V] \quad (7.18)$$

where, ' $\times$ ' is vector cross product. Since the difference between V^* and V is small, the above equation can be approximated as:

$$E_r = -(E \times \bar{V}) \times \bar{V} = E - (E \bar{V}) \bar{V} \quad (7.19)$$

where, ' $\bar{\cdot}$ ' is vector inner product. When $n=2$, it is the same as (7.16) [202].

7.3.3 Conventional Cross-coupled Control

In existing biaxial control systems for machine tools, each axis of motion has a separate closed-loop control so that the control loop of one axis receives no information regarding the other. Any load disturbances error in one of the axes is corrected only by its own loop, while the other loop carries on as before. This causes an error in the resultant path. Since biaxial control systems require both control and coordination of the motion along two axes, it should be possible to improve their accuracy by taking advantage of cross-coupling, whereby an error in either axis affects the control loops of both axes. The cross-coupled control method was developed in [196] and was widely used in the biaxial motion control systems. The basic structure of the cross-coupled control is shown in Figure 7.13.

The contour error is calculated by cross coupler T , which connects the information of one axis position and that of the other. The two controllers will work in a coordinated way through T between the main loops. The controllers in such kind of structure are capable of tracking the 2-D trajectory more accurately.

Figure 7.13: Cross-coupling control scheme

7.3.4 Cross-coupled DSM Control

The discrete-time model of biaxial systems which is similar to the system axis system is shown as:

$$\begin{aligned} x_{k+1} &= \Phi x_k + \Gamma u_k + f \\ y_k &= C x_k \end{aligned} \quad (7.20)$$

where

$$\begin{aligned} x_k &= \begin{bmatrix} y_k \\ v_k \end{bmatrix}, \Phi = \begin{bmatrix} 1 & T_s \\ 0 & 1 - T_s k_{fv} / m \end{bmatrix}, \\ \text{and } \Gamma &= \begin{bmatrix} 0 \\ T_s k_f / m \end{bmatrix}, C = [1 \quad 0] \end{aligned} \quad (7.21)$$

For single axis motion system, a sliding surface is built by an easy scalar equation.

$$S = \left\{ s_k \left| \begin{aligned} s_k &= \Lambda(x_k - x_k^d) = 0, \\ k &= 0, 1, \dots, s(kT_s) = s_k \end{aligned} \right. \right\} \quad (7.22)$$

where $\Lambda = [\lambda \quad 1]$, λ is a positive real number and $x_k^d = [y_k^d \quad v_k^d]^T$ is the reference input.

Not only the single axis position error but the contour error in biaxial system should be considered in the controller design. Thus, a new sliding surface which is

different from the conventional one is proposed here to meet the requirement of convergence of the contour error. Let us define the sliding surface as:

$$S = \left\{ s_k \left| \begin{array}{l} s_k = \Lambda(x_k - x_k^d) + |E_r| \operatorname{sgn}(y_k) = 0, \\ k = 0, 1, \dots, s(kT_s) = s_k \end{array} \right. \right\} \quad (7.23)$$

Adopting the reaching law [187]:

$$s_{k+1} - s_k = -QT_s s_k - \eta T_s \operatorname{sgn}(s_k), QT_s < 1 \quad (7.24)$$

$$\begin{aligned} s_{k+1} - s_k &= \Lambda x_{k+1} - \Lambda x_k + |E_{r(k+1)}| \operatorname{sgn}(y_{k+1}) - |E_{r(k)}| \operatorname{sgn}(y_k) \\ &= \Lambda(\Phi x_k) + \Lambda(\Gamma u_k) + \Lambda f \\ &\quad - \Lambda x_k - \Lambda(x_{k+1}^d - x_k^d) + |E_{r(k+1)}| \operatorname{sgn}(y_{k+1}) - |E_{r(k)}| \operatorname{sgn}(y_k) \end{aligned} \quad (7.25)$$

Firstly, if the effect of E_r is ignored, solving u from (7.24) and (7.25)

$$\begin{aligned} u_k &= -(\Lambda\Gamma)^{-1} [\Lambda(\Phi x_k) + \Lambda f - \Lambda x_k + QT_s s_k \\ &\quad + \eta T_s \operatorname{sgn}(s_k)] + \Gamma^{-1}(x_{k+1}^d - x_k^d) \end{aligned} \quad (7.26)$$

Moreover, the item to suppress the effect of the contour error between two loops of biaxial system is named u_x . Then, the controller turns out to be:

$$\begin{aligned} u_k &= -(\Lambda\Gamma)^{-1} [\Lambda(\Phi x_k) + \Lambda f - \Lambda x_k + QT_s s_k \\ &\quad + \eta T_s \operatorname{sgn}(s_k)] + \Gamma^{-1}(x_{k+1}^d - x_k^d) + u_x \end{aligned} \quad (7.27)$$

Consider the system (7.20) under the unknown mass and friction condition.

$$\begin{aligned} x_{k+1} &= \tilde{\Phi} x_k + \Delta \Phi x_k + \tilde{\Gamma} u_k + \Delta \Gamma u_k + f \\ y_k &= C x_k \end{aligned} \quad (7.28)$$

For the current system, the following matching conditions are satisfied:

$$\begin{aligned} \Delta \Phi &= \tilde{\Gamma} \hat{\Phi} \\ \Delta \Gamma &= \tilde{\Gamma} \hat{\Gamma} \\ f &= \tilde{\Gamma} \hat{f} \end{aligned} \quad (7.29)$$

Consider the system (7.28), the (7.27) becomes

$$\begin{aligned} u_k &= -(\Lambda\tilde{\Gamma})^{-1} [\Lambda(\tilde{\Phi} x_k) - \Lambda x_k + QT_s s_k \\ &\quad + \eta T_s \operatorname{sgn}(s_k)] - \tilde{\Gamma} u_k - \tilde{\Phi} x_k - \hat{f} \\ &\quad + \tilde{\Gamma}^{-1}(x_{k+1}^d - x_k^d) + u_x \end{aligned} \quad (7.30)$$

Since the $\tilde{\Phi}, \tilde{\Gamma}, \tilde{f}$ in (7.30) are unknown elements, (7.30) cannot be used to design the controller. Assume $\hat{\Phi}, \hat{\Gamma}, \hat{f}$ can be replaced by the elements Φ_c, Γ_c, f_c , which will be specified by the following procedure.

After the substitution, (7.30) becomes:

$$\begin{aligned} u_k = & -(\Lambda\tilde{\Gamma})^{-1}[\Lambda(\tilde{\Phi}x_k) - \Lambda x_k + QT_s s_k \\ & + \eta T_s \text{sgn}(s_k)] - \Gamma_c u_k - \Phi_c x_k - f_c \\ & + \tilde{\Gamma}^{-1}(x_{k+1}^d - x_k^d) + u_x \end{aligned} \quad (7.31)$$

From the (7.25) (7.28) and (7.31), the incremental change in s_k is expressed:

$$\begin{aligned} s_{k+1} - s_k = & -QT_s s_k - \eta T_s \text{sgn}(s_k) + (\Lambda\tilde{\Gamma})[\tilde{\Gamma}u_k - \Gamma_c u_k + \tilde{\Phi}x_k - \Phi_c x_k \\ & + \tilde{f} - f_c] + \Lambda\tilde{\Gamma}u_x + |E_{r(k+1)}| \text{sgn}(y_{k+1}) - |E_{r(k)}| \text{sgn}(y_k) \end{aligned} \quad (7.32)$$

The equation (7.32) can be considered as two parts, in the right side, the first part is the items before term $\Lambda\tilde{\Gamma}u_x$ and the rest is the second part.

In the first part, for simplification, let

$$\begin{aligned} \tilde{T} &= \Lambda\tilde{\Gamma}(\tilde{\Gamma}u_k), T_c = \Lambda\tilde{\Gamma}(\Gamma_c u_k) \\ \tilde{S} &= \Lambda\tilde{\Gamma}(\tilde{\Phi}x_k), S_c = \Lambda\tilde{\Gamma}(\Phi_c x_k) \\ \tilde{F} &= \Lambda\tilde{\Gamma}\tilde{f}, F_c = \Lambda\tilde{\Gamma}f_c \end{aligned} \quad (7.33)$$

Then (7.32) can be expressed as:

$$\begin{aligned} s_{k+1} - s_k = & -QT_s s_k - \eta T_s \text{sgn}(s_k) \\ & + (\tilde{T} - T_c) + (\tilde{S} - S_c) + (\tilde{F} - F_c) \\ & + \Lambda\tilde{\Gamma}u_x + |E_{r(k+1)}| \text{sgn}(y_{k+1}) - |E_{r(k)}| \text{sgn}(y_k) \end{aligned} \quad (7.34)$$

For the LUM drive system, $\tilde{T}$, $\tilde{S}$ and $\tilde{F}$ have some corresponding relationships with mass and friction of the system. They have the upper bounds and lower bounds as the mass and friction in the system is not unlimited.

$$T_{\min} \leq \tilde{T} \leq T_{\max}, S_{\min} \leq \tilde{S} \leq S_{\max}, F_{\min} \leq \tilde{F} \leq F_{\max} \quad (7.35)$$

The value of T_c , S_c and F_c are needed to be specified to guarantee the sign of $s_{k+1} - s_k$ opposite to the sign of s_k , the simple solution is:

$$\begin{cases} T_c = T_{\max}, S_c = S_{\max}, F_c = F_{\max} & \text{sgn}(s_k) = 1 \\ T_c = T_{\min}, S_c = S_{\min}, F_c = F_{\min} & \text{sgn}(s_k) = -1 \end{cases} \quad (7.36)$$

To formulate (7.36) as follow:

$$\begin{cases} T_c = \left(\frac{T_{\max}+T_{\min}}{2}\right) + \left(\frac{T_{\max}-T_{\min}}{2}\right) \text{sgn}(s_k) \\ S_c = \left(\frac{S_{\max}+S_{\min}}{2}\right) + \left(\frac{S_{\max}-S_{\min}}{2}\right) \text{sgn}(s_k) \\ F_c = \left(\frac{F_{\max}+F_{\min}}{2}\right) + \left(\frac{F_{\max}-F_{\min}}{2}\right) \text{sgn}(s_k) \end{cases} \quad (7.37)$$

The control law is referred from (7.29) (7.31) and (7.37):

$$\begin{aligned} u_k = & -(\Lambda\tilde{\Gamma})^{-1} \{ \Lambda(\tilde{\Phi}x_k) - (1-QT_s)s_k \\ & + \eta T_s \text{sgn}(s_k) - \Lambda x_{k+1}^d \\ & + \left(\frac{T_{\max}+T_{\min}}{2}\right) + \left(\frac{S_{\max}+S_{\min}}{2}\right) + \left(\frac{F_{\max}+F_{\min}}{2}\right) \\ & + \left[\left(\frac{T_{\max}-T_{\min}}{2}\right) + \left(\frac{S_{\max}-S_{\min}}{2}\right) + \left(\frac{F_{\max}-F_{\min}}{2}\right)\right] \\ & * \text{sgn}(s_k) \} + u_x \end{aligned} \quad (7.38)$$

For the second part of (7.38), chatting issue is taken into account in the design by replacing $\text{sgn}()$ with $\text{sat}()$ function. For cross-coupled control, the term

$|E_{r(k+1)}| \text{sgn}(y_{k+1}) - |E_{r(k)}| \text{sgn}(y_k)$ is bounded as

$$\left| |E_{r(k+1)}| \text{sgn}(y_{k+1}) - |E_{r(k)}| \text{sgn}(y_k) \right| < E \quad (7.39)$$

u_x can be thereby chosen as:

$$u_x = -(\Lambda\tilde{\Gamma})^{-1} E \text{sat}(s) \quad (7.40)$$

The final controller is designed as:

$$\begin{aligned} u_k = & -(\Lambda\tilde{\Gamma})^{-1} \{ \Lambda(\tilde{\Phi}x_k) - (1-QT_s)s_k \\ & + \eta T_s \text{sgn}(s_k) - \Lambda(x_{k+1}^d - x_k^d) \\ & + \left(\frac{T_{\max}+T_{\min}}{2}\right) + \left(\frac{S_{\max}+S_{\min}}{2}\right) + \left(\frac{F_{\max}+F_{\min}}{2}\right) \\ & + \left[\left(\frac{T_{\max}-T_{\min}}{2}\right) + \left(\frac{S_{\max}-S_{\min}}{2}\right) + \left(\frac{F_{\max}-F_{\min}}{2}\right)\right] \\ & * \text{sgn}(s_k) \} - (\Lambda\tilde{\Gamma})^{-1} E \text{sat}(s) \end{aligned} \quad (7.41)$$

In the same way, the controller for the other axis can be derived easily.

7.3.5 Mass Estimator

The LUM drive biaxial system is a highly nonlinear, time varying and uncertain system. As described in foregoing chapters, the mass estimator is indispensable for extending the robustness of the controller itself.

The recursive least square with forgetting factor scheme described in Chapter 4 is also adopted as the parameter estimation algorithm. The aim of applying the method is to online estimate the value of the unknown mass of the motion system and provide the load information to the controller in order to be suppressive to the large load variations.

7.4 Circular and Elliptic Tracking Results

7.4.1 Numerical Demonstration

The simulation result under the proposed cross-coupled sliding mode controller and conventional cross-coupled controller are both illustrated to validate the effectiveness of the proposed control scheme.

The main loops and interaction loops frequency domain models are listed in (7.1) and (7.2). Firstly, decoupling should be achieved by a decoupler structure as in Figure 7.10. The decoupling is realized by the following four transfer functions:

$$\begin{aligned} G_{I11} &= G_{I22} = \frac{(s+2.4)(s+1.1)}{s^2 + 3.5s + 2.6393} \\ G_{I12} &= \frac{-0.0018(s+73.845)(s+1.1)}{5.952s^2 + 20.832s + 15.709} \\ G_{I21} &= \frac{-0.003472(s+1.1)(s+51.029)}{5.952s^2 + 20.832s + 15.709} \end{aligned} \quad (7.42)$$

After decoupling, the TITO acts as two single loop systems without influencing each other.

In the experiment, moving top plate is weighted 550g and top plate plus one LUM and stage base is weighted 1.9kg.

The mass of the system is estimated by the mass estimator and the difference between the real mass and the estimated one definitely exists. In the control scheme, this must be considered. The error between them is bounded as $0.1m_0$, m_0 is the estimated mass. This action is the same as the one applied in last chapter. Moreover, the friction characteristic is fitted and compensated by RBF, and the ISE between fitting curve and real friction curve is less than $1.0E-4$.

For the upper axis, the physical equation is:

$$0.55\ddot{y} = 2.728u - 40.61475\dot{y} - f(\dot{y}) \quad (7.43)$$

Φ and Γ in (7.21) are:

$$\Phi = \begin{bmatrix} 1 & 0.001 \\ 0 & 0.926 \end{bmatrix}, \Gamma = \begin{bmatrix} 0 \\ 0.00496 \end{bmatrix} \quad (7.44)$$

The unknown parameters in (7.35) can be further determined as:

$$[0 \ -1.6542] \leq \hat{\Phi} \leq [0 \ 1.3535], -0.091 \leq \hat{\Gamma} \leq 0.111, -0.03 \leq \hat{f} \leq 0.03 \quad (7.45)$$

For lower axis, the physical equation is:

$$1.9\ddot{y} = 2.28u - 96.9551\dot{y} - f(\dot{y}) \quad (7.46)$$

Φ and Γ in (7.21) are:

$$\Phi = \begin{bmatrix} 1 & 0.001 \\ 0 & 0.949 \end{bmatrix}, \Gamma = \begin{bmatrix} 0 \\ 0.0012 \end{bmatrix} \quad (7.47)$$

In the same way, the unknown parameters in (42) can be further determined as:

$$[0 \ -4.7249] \leq \hat{\Phi} \leq [0 \ 3.8658], -0.091 \leq \hat{\Gamma} \leq 0.111, -0.04 \leq \hat{f} \leq 0.04 \quad (7.48)$$

The sliding mode controller designed from (7.41) includes three free parameters, λ , Q and η . GA is also applied to optimize the six parameters involved in the upper axis and the lower axis controllers. The resultant sliding mode controller for the upper axis is:

$$u_k = -\frac{\bar{m}}{0.00273} \{ [40.1 \ 1] \ddot{\Phi} x_k - 0.955 s_k + [40.1 \ 1] (x_{k+1}^d - x_k^d) + 0.0001 \operatorname{sgn}(s_k) \} \\ + \frac{3.028e-3}{\bar{m}} \operatorname{sgn}(s_k) + \frac{0.00273}{\bar{m}} [0 \ 1.50385] x_k \operatorname{sgn}(s_k) + \frac{8.184e-5}{\bar{m}} \operatorname{sgn}(s_k) - 0.202 \operatorname{sat}(s_k) \} \quad (7.49)$$

The sliding mode controller for the lower axis is:

$$u_k = -\frac{\bar{m}}{0.00228} \{ [54.1 \ 1] \ddot{\Phi} x_k - 0.991 s_k + [54.1 \ 1] (x_{k+1}^d - x_k^d) + 0.00015 \operatorname{sgn}(s_k) \} \\ + \frac{2.5308e-3}{\bar{m}} \operatorname{sgn}(s_k) + \frac{0.00228}{\bar{m}} [0 \ 4.29535] x_k \operatorname{sgn}(s_k) + \frac{9.12e-5}{\bar{m}} \operatorname{sgn}(s_k) - 0.833 \operatorname{sat}(s_k) \} \quad (7.50)$$

The controllers cooperate with mass estimators and RBF friction compensators so as to achieve the motion objective of the whole biaxial system. The control structure of the proposed scheme is shown in Figure 7.14.

Figure 7.14: Structure block diagram of the biaxial system

To achieve some specific path tracking motion, the reference signal should be generated firstly. To generate the arc section of the reference trajectory, the center of the arc should be as (x_0, y_0) specified firstly. The direction of the arc is decided by d , $d=1$ for counterclockwise, and $d=-1$ for clockwise direction. The radius of the arc is R , finally the start angle is ϕ_s . Generally, the parameterized circle has the form:

$$x(t) = x_0 + R \cos(2d\pi ft + \phi_s) \quad (7.51)$$

$$y(t) = y_0 + R \sin(2d\pi ft + \phi_s) \quad (7.52)$$

Following [192], circular and elliptical trajectories are used in this study to examine the performance to the proposed control scheme. One advantage of these reference trajectories is that the effectiveness of the control method to disturbances can be inspected by its ability to reduce quadrant glitches (caused by stiction and friction when one of the feed drive axes' velocity changes sign). Another advantage is that the contouring error can be exactly computed by (7.16). The two reference trajectories applied are circle and ellipse as shown in Figure 7.15.

Both the traditional cross-coupled PID and proposed cross-coupled sliding mode controller are applied in the biaxial system and the tracking performance is shown in the following figures. Different friction and load conditions are considered to demonstrate the robustness of the proposed controller. The parameters in PID controller and proposed controller are tuned in normal condition, i.e., friction f_0 and payload 0kg. All the parameter is fixed whatever friction and payload occur. Figure 7.16 and Figure 7.17 show the circular tracking responses with PID controller and proposed controller under the 0kg and $1.2f_0$ condition. Figure 7.18 and Figure 7.19 illustrate the circular tracking responses of the two controllers under the 3kg and $1.2f_0$ condition. Figure 7.20~Figure 7.23 demonstrate the corresponding elliptic path tracking responses under various load and friction conditions. In both the circular and elliptic tracking process under various payload and friction conditions, the tracking

errors with PID controller are in the order of 10^{-5} m, on the other hand, those with proposed controller are in order of 10^{-6} m. Moreover, from the figures, it is clearly demonstrated that the proposed controller is capable of suppressing the effect of friction and load variations, while the PID controller degrades the performance with such variations.

Figure 7.15: Reference motion trajectory (circle and ellipse)

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.16: Circular path tracking with 0kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.17: Circular path tracking with 0kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.18: Circular path tracking with 3kg load and 1.2f₀ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.19: Circular path tracking with 3kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

Figure 7.20: Elliptic path tracking with 0kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.21: Elliptic path tracking with 0kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.22: Elliptic path tracking with 3kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.23: Elliptic path tracking with 3kg load and $1.2f_0$ friction condition with proposed controller

7.4.2 Experiment Results

The hardware platform is shown in Figure 7.1. The same controllers in simulation are applied in the experimental LUM drive system. The real plant replaces the simulated plant model in the experiment. Corresponding operation conditions during simulations are all implemented in the experiment. Figure 7.24 and Figure 7.25 illustrate the real-time implementation of the circular tracking responses of the two controllers under 0kg and $1.2f_0$ condition. Figure 7.25 and Figure 7.26 show the circular tracking experiment results under the 3kg and $1.2f_0$ condition. Figure 7.27~Figure 7.31 demonstrate the elliptic tracking responses under the corresponding operation conditions in Figure 7.24~Figure 7.27 respectively.

Every real-time implementation figure consists of three plots: X axis tracking represents the real-time motion locus of the upper stage; Y axis tracking denotes the real-time motion locus of the lower stage; XY axis tracking represents real locus of the item put on the stage. Two curves are included in each of the X axis tracking plots and Y axis tracking plots. The upper curve demonstrates the tracking locus and lower one represents the tracking error to the reference path. Whether in the circular tracking responses or elliptic tracking responses, the tracking error with proposed controller is much smaller than the one with PID controller. It is proven that the proposed cross-coupled DSM controller performs better than the conventional PID controller in the two dimension tracking control system. From the comparison of the real-time implementation results in this section and simulated results shown in last section, it is demonstrated that the experiment results agree with simulated results very well, which proves two things, the identified frequency domain system model is close to the real plant, and the proposed controller by numerical method also provides good performance in real-time applications.

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.24: Circular path tracking with 0kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.25: Circular path tracking with 0kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.26: Circular path tracking with 3kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.27: Circular path tracking with 3kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAxIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.28: Elliptic path tracking with 0kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.29: Elliptic path tracking with 0kg load and $1.2f_0$ friction condition with proposed controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.30: Elliptic path tracking with 3kg load and $1.2f_0$ friction condition with PID controller

CHAPTER 7 CROSS-COUPLED DSM CONTROL OF AN LUM DRIVE BIAXIAL SYSTEM

(a) X axis tracking

(b) Y axis tracking

(c) XY axis tracking

Figure 7.31: Elliptic path tracking with 3kg load and $1.2f_0$ friction condition with proposed controller

7.5 Conclusions

This chapter has presented a cross-coupled DSM controller for the LUM drive biaxial motion system. A TITO frequency domain model of the plant has been firstly set up by DSA with RBF friction compensator. The reaching law based sliding mode controller has been designed for the system due to its robustness to parameter variations and external disturbances, and the controller parameters are tuned to optimal by GA. Furthermore, the cross-coupled control scheme is also integrated to make the two sliding mode controllers coordinate with each other. The accurate contour following performance as well as the robustness to large parameter variations of the proposed controller have been verified by both simulated and experiment results.

CHAPTER 8

Conclusions and Recommendations

This chapter concludes with a summary of research work done so far and recommended tasks for the future.

8.1 Conclusions

The thesis is devoted to advanced robust control of nonlinear system with dynamic uncertainties, parameter variations and nonlinear disturbances. The precise and robust servo motion control is achieved in single axis motion system driven by LBDCM and LUM as well as biaxial systems driven by two coordinate LUMs.

The servo motion systems are high nonlinear systems. Moreover, parameter variations, load varying condition and nonlinear friction have resulted in numerous troublesome control constraints for the application of advanced control algorithms. All these increase the complexity to achieve the precise and robust control of such systems.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

Nonlinearity in the systems can be dealt with in two ways. One is input-output feedback linearization technique, the other is nonlinearity compensation. Input-output feedback linearization is not very effective in the servo motion systems because parameter variation and load uncertainties become an obstacle to the exact cancellation of the nonlinearity during the process. Thus, it is advisable to apply the nonlinearity compensation technique to the control of the servo motion systems. Nonlinear friction is the main nonlinear component in the servo systems. Three experiments called break-away and steady-state and super low velocity friction measurement are designed and implemented to catch sufficient friction data for friction approximation and compensation, whereafter nonlinear friction is compensated by both the model based and non-model based method, which are also called the white-box modeling based and black-box modeling in some applications. An RBF with decoupled extended Kalman filter training is applied for nonlinear friction fitting due to its superior approximating ability to nonlinear functions. The Kalman filter RBF fitting achieves better results and then it is applied as the nonlinear friction compensation algorithm throughout the thesis.

Accurate system modeling is the first step towards any precision control problem. The physical model of LBDCM servo motion system is analyzed and presented firstly. However, some parameters involved in the motor and drive model derivation can not be measured accurately and therefore the exact values of the parameters are not available. On the other hand, the physical model of LUM is still an unknown area and only the model of a unit of PEA is derived. Considering these conditions, DSA is used to obtain the frequency domain model of the servo systems. It is the first time that the nonlinear friction compensation is used to cooperate with the DSA to identify such a class of concerned nonlinear servo systems. Furthermore, a practical frequency domain system identification algorithm is proposed to derive the linear system model from the measured data from DSA. The resulting identified models fit the original frequency data very closely.

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

A new ARE based scheme is proposed for robust position control of LBDCM systems in Chapter 4. It is proved that the control constraints addressed in [136] is too strong for large uncertainties conditions. Furthermore, it is not effective to choose the middle point of the load as the nominal condition for the design of robust controller since the system parameters corresponding to the normal load lie far from the middle of parameter ranges. More effective nominal load points are selected and looser control constraints is achieved in the new robust control approach. Consequently, the larger admissible uncertainties of the approach are as twice as much the one presented in [136], as a result, a larger amount of payload can be accommodated. This scheme also guarantees the asymptotic output tracking with an arbitrarily prescribed convergent rate. Due to its simplicity, the controller can be designed easily and implemented effectively. Computer simulation and experiment have demonstrated the good transient and steady performance of the system as well as the strong robustness to the load variations.

Speed is also concerned as well as robustness in some applications of LBDCM servo motion systems. The combined H_∞ and μ synthesis method is proposed for robust and fast position control of LBDCM systems. With the purpose of larger tolerable load variations, three μ controllers are designed in different nominal load conditions but with same load variation range and work together to obtain global stronger robustness. An RBF mass estimator is designed to function as a controller selector which decides which one of the three μ controllers is on duty at the moment. The nonlinear friction in the systems is also compensated according to the foregoing algorithm. The robust stability and the robust performance of the proposed controller are proved by μ analysis theory. Moreover, the MSC which is widely used in HDD drive control systems is applied and satisfying tracking response with short settling time is realized accordingly. Settling time is reduced to about 0.15s for 0.1m tracking, which is much less than that in previous work. The mean squared errors of step response with proposed controller and PID controller under load variations are simulated and calculated. It is illustrated that the proposed controller performs better

than the PID controller at almost all range of load variation especially for the conditions far from the nominal load point. The simulated and experiment results demonstrate that the proposed controller ensures satisfactory position servo performance as well as suppresses the effect of the large parameter variation of the LBDCM systems.

From Chapter 6 on, another linear motor called LUM drive motion systems are investigated. This kind of motor can be called a milestone of new kinds of motor. It has the totally different operation principle from the conventional electromagnetic motors. It takes advantage of mechanical vibration force and moves without the existence of magnetic field. Firstly, system model of LUM motion system is identified with nonlinear friction accordingly to the foregoing algorithm. Then, a reaching law based DSM controller is proposed mainly for dealing with the large load variations problem. Although the SMC is insensitive to the plant parameter variations, its performance can be affected greatly by large parameter variations. Therefore, this method does not perform well under a wide range of the parameter variations. With the aim of solving such a problem, the SMC cooperates with an online parameter estimator which makes the load information almost known to the controller. Moreover, real-coded genes based GA is applied to optimize the design parameters to achieve the least ISE and overshoot of position response through the design of the suitable fitness function related to the transient performance objective of the controller. The resulting controller can suppress as large as 7kg load variation and provides smooth and fast response as expected. The simulations of tracking performance are obtained under lots of different friction and masses. The friction ranges from f_0 to $2f_0$ and the load varies from 0kg to 7kg. The mean tracking errors under every different condition are calculated during the total simulation time. Apparently, the tracking error of proposed controller is comparatively smaller than that of conventional one. The experiment results also demonstrate that the proposed controller is very effective for the position servo control of LUM system under large load variations and nonlinear disturbances.

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After robust control of single axis motion system is discussed in previous chapters, the two LUMs drive biaxial motion system is investigated in Chapter 7. The biaxial system is not as simple as two additive SISO systems. The coupling between two SISO loops consists of not only disturbance coupling but also error information coupling. That means, if the disturbance occurs in one loop, it must have an effect on the other loop through interaction loops. Similarly, if the tracking error in one loop met a jump or fall, it should have an influence on the control effort for the other loop at the moment. Firstly, system identification is carried out in two main SISO loops as well as the two interaction loops. Four transfer functions are obtained by DSA with the nonlinear friction compensation. And then a decoupler is developed to counteract the interaction between the two main control loops. The cross-coupled concept is introduced to make the two SMCs coordinate with each other to realize the precise multi-dimension motion. The conventional cross-coupled controller and proposed controller are both applied in the biaxial system. The performances of tracking circular and elliptical trajectories are illustrated correspondingly. The experiment results also verify the accurate contour following performance as well as the robustness to large parameter variations of the proposed controller.

8.2 Recommendations in Future Work

The thesis has focused on the position control of single axis and biaxial systems, and satisfactory experimental results have been achieved. However, there are still some issues need to be looked into to enhance the performance of servo motion systems. Following is the area of interests can be further done.

8.2.1 Position Control of N-dimension Motion Systems

It is desirable of three or even N-dimension motion in applications such as satellite, unmanned autonomous vehicle, and robotics. The proposed cross-coupled sliding mode controller can be easily extended to the three or N-dimension motion systems by

calculating the E_r in multi-dimension space. Correspondingly, the cross-coupled unit and decoupler are to be designed according to the structure and dimension of the new systems. The control structure is similar as what is proposed for the biaxial system in the thesis.

8.2.2 Ultra-precise Nano-motion Control

Nanotechnology is a group of generic technologies that are becoming significantly important to many industrial applications and it is poised to revolutionize new trends in technological advancement. Nano-motion maybe deemed as a natural next step to precision engineering as ultra-precision manufacturing progresses through micrometer accuracy capability to enter the nanometer scale regime. Several important challenges remain to the ultra-precision motion control systems.

First, the measurement system must be capable of yielding a very fine resolution in position measurements. Today, laser interferometers can readily yield a measurement resolution of down to one nanometer. Interpolation factors up to 4096 time have been reported. This will effectively yield a resolution in the nanometer regime, specified fine scales manufacturing tolerance currently achievable.

Secondly, the control electronics must have a sufficient bandwidth to cope with the high encoder count frequency associated with high speed motion and a sufficiently high sampling frequency to circumvent anti aliasing pits when motion is at a very low speed.

Thirdly, the geometrical imperfections of the mechanical system should be adequately accounted for in the control system, if absolute positioning accuracy is crucial to the application concerned. A three dimension motion machine, for instance, has 21 possible sources of geometrical errors (linear, angular, straightness, orthogonality errors from the 3 axes combined)

8.2.3 Vibration Monitoring and Control

Mechanical vibration more or less exists in all the electromechanical systems. The vibration in machines and equipment can occur due to many factors, such as unbalanced inertia, bearing failures on turbines, motors, generators, pumps, drives, etc., poor kinematic design resulting in a non-rigid support structure, component failure and operations outside prescribed load ratings. The machine vibration signal can be typically characterize as a narrow-band interference signal anywhere in the range from 1Hz to 500kHz. To prevent equipment damage from the severe shaking that occurs when machines malfunction or vibrate at resonant frequencies, a real-time monitoring or control device will be very useful. When the machine is used to perform highly precise positioning functions, undue vibrations can lead to poor repeatability properties, impeding any systematic error compensation effort. This results directly in a loss of precision and accuracy achievable.

Two approaches can be used to deal with mechanical vibrations. The first one utilized an adaptive notch filter to identify the resonant frequencies and to subsequently terminate any signal transmission at these frequencies via a narrow-bandstop filter. The adaptive notch filter can be directly incorporated into the control system. The second one used a real-time analyser to detect excessive vibration. This solution can be implemented independently of the control system, and as such, can be applied to existing equipment without modification.

8.2.4 Sensorless Control

Since accurate rotor position information is essential for the closed loop control of motor drive systems, these drives usually employ a shaft-mounted encoder or a resolver to measure the rotor flux position. In most applications the presence of an encoder or resolver causes several disadvantages due to additional cabling cost, higher number of connections between motor and controller, noise interference and reduced robustness. These are the reasons that motivate the need to develop sensorless control

CHAPTER 8 CONCLUSIONS AND RECOMMENDATIONS

schemes for motor drive systems. Elimination of the direct rotor position and speed measurement means that one obviously has to use as much information as possible contained in supply voltages and currents of the motor in order to extract the rotor position information. This can be done by having suitable sensors fixed closer to the control and power electronics (inverter). Thus, the number of cable connections between the control hardware and the motor is reduced to a minimum of 3 (three supply lines). In fact, this can be used as a definition for sensorless operation of motor drive systems. It can be given as follows.

"If complete variable speed operation of a motor drive is achieved, while keeping the three power conductors as the only galvanic connection between the motor and the control electronics, that operation can be called as sensorless operation of the particular drive."

Different sensorless control strategies for all types of motor drives have been suggested in many publications. However, less computationally heavy, parameter insensitive and more robust sensorless control algorithms are still in demand.

8.2.5 Time Delay Compensation

Control of time delay systems is of practical importance because time delays are very common in actual application such as process control, electromechanical systems, and micro electrical drive systems.

Time delays in dynamic systems are usually caused by sensor measurement delays, control computation delays, actuator reaction delays, and etc. in general, time delay systems have an infinite number of poles, which makes it difficult to apply conventional control methods to assign the eigenvalues to specified area in the left half part of a complex plane, in order to achieve desired system properties such as stability. However, it is well known that the cardinality of poles of time delay systems in any

right half plane is finite. Numerous researches have been done to control nominal time delay systems, for instance, predictive control [202], ring model [205], H_∞ sensitivity minimization [204], state transformation [205]. And also a variety of robust control of uncertain time delay system has been of great interest in the past decade [206-209]. Lyapunov approach was used in most of these papers to obtain some sufficient conditions for the existence of linear feedback controller.

8.2.6 Saturation

In many practical dynamic systems, physical input saturation on hardware dictates that the magnitude of the control signal is always constrained. Saturation is a potential problem for actuators of control systems. The saturation of the controller output is only considered by using `sat()` in stead of `sgn()` in the thesis. Nowadays, more subtle disposal can be achieved for saturation problems by some advanced algorithm. For linear systems with saturation, a few schemes for adaptive control law design have been proposed in [210-212]. Intelligent compensation of actuator nonlinearities for a class of nonlinear systems was considered in [213 and 214] by using NN. Transient performance can be further enhanced by introducing the effective saturation compensation.

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