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Zuerst erschienen in:
Proceedings // IECON 2008 . - Piscataway, NJ : IEEE Service Center, ISBN 978-1-424-41766-7. - 2008, S. 2568-2573

Position Control on Nanometer Scale based on an Adaptive Friction Compensation Scheme

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Abstract- **This work concerns a non-model-based friction compensation scheme for dynamic position control on nanometer scale. The main goal of this work is to build up and implement a simple dynamic friction observer which allows an estimation of the friction force in combination with the system inertia against displacement. Experiments in the pre-sliding and sliding friction regimes are conducted on an experimental setup.**

After a short review of friction compensation, the experimental setup is explained in detail. Next, the observer is modeled mathematically and the used control scheme is presented. Finally, the friction observer is utilized as a non-model-based friction estimator combined with a classical feedback controller to compensate the nonlinear friction force and reduce tracking errors significantly. It is shown that the proposed controlling approach is able to realize a fast and ultra precise positioning over long distances.

I. INTRODUCTION

To measure and manipulate structures on nanometer scale, nowadays high resolution positioning stages are used. These stages are able to position a pattern in all three dimensions with a stationary accuracy below 1 nm. To eliminate disturbances introduced by sound waves, ground motion, thermal expansion, etc. the position has to be controlled permanently. States of the art are modified linear PID controllers as described in [9, 10].

To perform well in nano-positioning most of these control laws rely on high stiffness. With increasing operating range of the stages the typically utilized stationary positioning strategy becomes unfeasible due to the proportionally rising measurement time. Therefore a dynamic measurement strategy is desirable. While implementing such an approach, friction introduced by commonly used ball bearing guides is the main challenge. Friction is induced by interaction between two rubbing surfaces and depends on several parameters such as surface materials, surface topography, the lubricant used and so on.

The literature distinguishes between two main regimes, called the pre-sliding and sliding regime. In the pre-sliding domain, the rough surfaces adhere to each other and the system behaves like a nonlinear spring. With increasing tangential force the contacts between the asperities begin to break and the surfaces start to slide against each other. In the sliding regime friction depends mainly on the relative velocity. The transition between sliding and pre-sliding is continuous and it is affected by direction of movement, rate of the applied force, normal load, position and so on. As a result, of these effects friction has a highly nonlinear character. Applying a nearly linear control law leads to tracking errors, limit cycles and stick-slip motion [2]. In order to achieve high-precision dynamic positioning over wide velocity ranges, adaptive compensation of these nonlinear effects is essential. In the last 40 years, dynamic friction modeling and compensation has made a big progress in the control community.

Dahl was the first to develop a dynamic friction model [3]. Through many experiments on servo systems with ball bearings, he found that bearing friction behaves like solid friction. Dahl described the friction dynamics using a modified stress-strain curve of classical solid mechanics. His model is a generalization of the static Coulomb friction model and captures some pre-sliding and hysteresis-related phenomena. The next big step was made by Canudas de Wit *et al.* by developing the well-known "*Lund Grenoble*" (LuGre) model [5]. The LuGre model based on the idea of Haessig and Friedland to characterize the behavior of the rough surfaces with a conglomerate of elastic bristles [7]. If the two interacting surfaces are sliding against one another the bristles deflect and begin to slide when the displacement is sufficient. The deflection of the bristles is expressed by a single state equation. In order to reduce the model dimension, every bristle has the same state and the bristles of one side are assumed as stiff. The LuGre model has only six parameters and is therefore quite simple. It captures almost all friction phenomena except the non-drifting effect and the hysteresis with nonlocal memory. Therefore Dupont *et al.* extended the LuGre model to the so called "*elasto-plastic*" friction model [6]. This extension captures the non-drifting effect as well, but fails to describe the hysteresis with nonlocal memory. Based on the integrated friction model, called the Leuven model Lampaert *et al.* described the friction dynamics with a different approach [12, 14]. The idea is based on the assumption of modelling the behavior of the rubbing surfaces with M elasto-plastic elements in parallel, all having displacement as a common input. Each element consists of a mass connected to a spring. These elements are characterised by a certain spring stiffness, a slipping force limit and a state variable, which reflect the spring deflection. Since it is assumed that the elements have no mass, the relationship between the force and the deflection of the springs is static. With this approach, called the "*Generalized Maxwell Slip*" (GMS) model it is possible to mathematically incorporate the hysteresis with non-local memory as well as all other friction phenomena [13]. Based on the GMS model Rizos *et al.* developed the "*The Dynamic NonLinear Regression with direct application of eXcitation Identification Method*" (DNLRX) approach which models the behavior of a simple mechanical system with two FIR filters [20, 21]. Main advantage of this model is its capacity to describe friction and inertia of the system in one model which is driven by the displacement.

All these "physically motivated" models describe the dynamic friction behavior very well, but the amount of model parameters increases proportional to their prediction quality. Due to uncontrollable variations in humidity, temperature, wear or lubricant condition these parameters have to be identified online to ensure a constant performance. For the relatively simple Dahl and LuGre model this has already been achieved [4, 15, 17]. However, estimating simultaneous all model parameters is a challenging task, due to the fact that almost all "physically motivated" dynamic friction models contain parameters that appear nonlinear in the model equations. Thus a fast online estimation of all parameters, especially of the elaborate ones, is not possible to date. The mentioned drawback of the described "Greybox" models makes adaptive non-model-based observers desirable.

The authors of [1] give a very good review of non-model-based friction modeling approaches. The biggest groups of "Blackbox" models are neural networks (NN). Recurrent NN, Generalised shunting NN or classical multilayer percepTrons [19] were already used to predict and compensate nonlinear friction effects. Stochastic models like nonlinear ARX models were utilized, too.

Based on the estimation algorithm proposed by Kalman in the sixties [10] Ray *et al.* modeled the friction force of a DC motor driven inertia by dint of an extended Kalman-Bucy Filter. Compared with LuGre and Dahl model based adaptive observers, the Kalman-Bucy filter performed very well [16]. A closed-loop stability analysis of the proposed method was provided two years later [17].

In this work, we consider a positioning stage with an operating range of 200mm. Based on the approach of Ray *et al.* a modified Kalman Filter is used as disturbance observer to compensate the friction introduced by the ball bearing guides. After explaining the experimental setup, the employed control scheme is presented. Next the architecture of the disturbance observer is described. At the end it is shown by experimental results that the proposed control approach works properly over wide ranges and significantly improves the dynamical behavior of the controlled system.

II. Experimental Set-up

The experimental set-up is a two dimensional fine positioning stage (see Fig. 1). It was constructed by members of the collaborative research centre SFB 622.

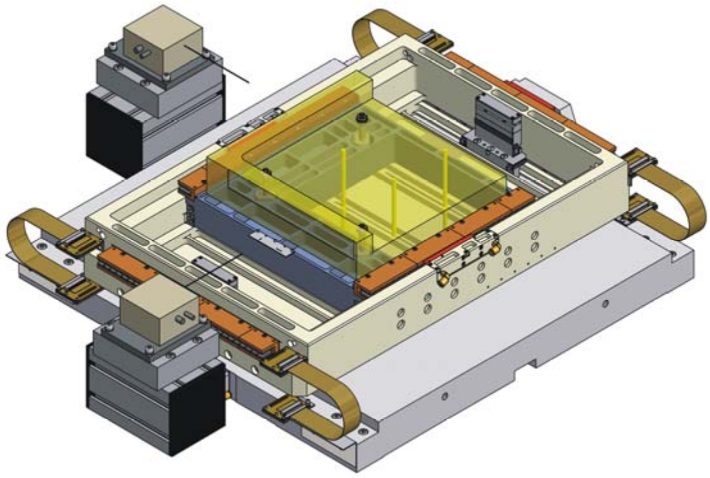

Fig. 1: Two-dimensional fine positioning stage

As can be seen, every axis is driven by two ULIM3-2P-66 linear voice coil actuators of IDAM [8]. The motors are powered by proprietary developed analog amplifiers, which provide the needed current with the required precision. Commutation of the motors is achieved by the controlling system upon magnetic field intensity measurements provided online by Hall sensors. The operating range of this positioning stage is 200x200 mm^2. Each axis is supported by two R6-300-RF-SQ-HA linear guide ways of SCHNEEBERGER [23]. The position is measured by a laser interferometer of the type SP 2000 (manufactured by SIOS Messtechnik GmbH) with a resolution of less than 0.1 nm [24]. For data acquisition and control a modular dSpace® real-time hardware system in combination with Matlab/Simulink® is utilized. The position is provided by the SIOS interferometer unit as a 32-bit digital signal and is sampled by the dSpace® system at a rate of 25 kHz. The control algorithm uses a slower sampling rate of 6.25 kHz and operates on the analog amplifiers with a 16 bit resolution. For the presented study only the outer axis of the demonstrator is used. The inner axis is mechanically jammed at the position shown in Fig. 1.

Neglecting the friction force based on the second Newton's axiom the dynamical behavior of the outer axis can be described as follows:

$$F = m \cdot a(t) \tag{1}$$

F is the applied force, *m* the mass and *a(t)* the resulting acceleration of the slider. Since the motor force has a linear relationship with respect to the applied current, the control algorithm controls the position via the current. The dynamical behavior of the amplifier can be neglected, because its cut-of-frequency is higher than 10 kHz. Hence the force/current relation could be is simply modeled as a gain k_A using the motor parameters provided by IDAM:

$$k_A \cdot i(t) = m \cdot a(t) \tag{2}$$

In state space notation the system can be expressed as:

$$\begin{bmatrix} \dot{x}(t) \\ \ddot{x}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{k_A}{m} \end{bmatrix} \cdot i(t) \qquad (3)$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix} \qquad (4)$$

where *x(t)* is the position and *dx(t)/dt* the velocity of the slider.

III. Control System with Disturbance Observer

A. Control Scheme

To verify the capability of the proposed non-model-based disturbance observer a control scheme as depicted in Fig. 2 is utilized. The advantage of such an approach is its potential to speed up the dynamic behaviour of a controlled system and improve its robustness against external disturbances. It is thus possible for the controlled system to follow highly dynamic set points.

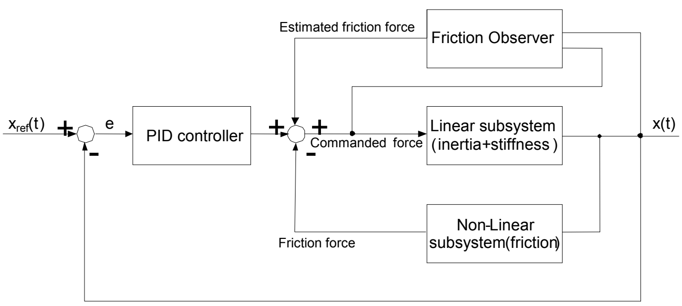

Fig. 2. Block diagram of a position control system with a friction observer

B. Observer design

In order to design a non-model-based friction estimator a Kalman Filter approach is utilized. Considering an estimated friction force term Equ. (1) is extended to:

$$k_A \cdot i(t) = m \cdot \frac{d^2 x(t)}{dt^2} + \hat{F}(t) \qquad (5)$$

with m is the mass of the accelerated system, $k_A \cdot i(t)$ the applied force, *x(t)* the displacement and $\hat{F}(t)$ the (immeasurable) friction force which resists the excited motion. After transforming the system into state space notation, choosing *x(t)*, *dx(t)/dt*, $\hat{F}(t)$ and $\hat{F}(t)/dt$ as states and discretize the system using a zero order hold with the sample time T leads to the internal model of the friction observer:

$$\begin{bmatrix} x_k \\ \dot{x}_k \\ \hat{F}_k \\ \dot{\hat{F}}_k \end{bmatrix} = \begin{bmatrix} 1 & T & -\frac{T^2}{2m} & -\frac{T^3}{6m} \\ 0 & 1 & -\frac{T}{m} & -\frac{T^2}{2m} \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} x_{k-1} \\ \dot{x}_{k-1} \\ \hat{F}_{k-1} \\ \dot{\hat{F}}_{k-1} \end{bmatrix} + \begin{bmatrix} \frac{T^2}{2m} \\ \frac{k_A \cdot T}{m} \\ 0 \\ 0 \end{bmatrix} \cdot i(t) \qquad (6)$$

$$x_k = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_k \\ \dot{x}_k \\ \hat{F}_k \\ \dot{\hat{F}}_k \end{bmatrix} \qquad (7)$$

In the presented approach the friction force is treated as an unknown state element. By measuring motion along with the applied force, one can estimate the external friction force using the algorithm proposed by Kalman [10]. This method of friction cancellation has already been proven in other applications, e.g. by Ray *et al.* [15, 17].

The Kalman filter has two tuning parameters, the variance of the measured signal, in this case the measured position, and the variance of the state vector. These parameters influence directly the quality of the estimated friction force and are tuned to minimize the *Normalized Root Mean Square Error (NRSME)* over a wide spectrum of reference trajectories. The *NRSME* is defined as:

$$NRSME = \sqrt{\frac{1}{\Theta_x^2} \cdot \frac{\sum_{k=1}^{N} \left(x_{ref_k} - x_k \right)^2}{N}} \times 100\% \qquad (8)$$

with Θ_x is the variance of the reference position, N the number of samples, x_{ref} the reference position and x the measured position.

IV. Experimental Study

The control scheme described in section III is used to control one axis of the positioning stage to test the performance of the presented friction cancellation method on nanometer scale. A well tuned nonlinear PID controller works in the feedback loop [10].

For experimental study two significant reference trajectories are chosen. First a sinusoidal reference input is utilized with a desired position, $x_{ref}(t) = a \cdot \sin(2\pi f t)$. Three different frequencies are employed with f = 0.5 Hz, 1 Hz and 1.5 Hz. Also the amplitude of the sine was varied with a = 1000 nm, 2000 nm, 5000 nm and 10000 nm.

Second a linear motion (with return fare) of 10,000,000 nm distance is carried out. It should be mentioned that this trajectory is generated by a trajectory generation algorithm, which accounts for kinematic constraints in velocity, acceleration and jerk.

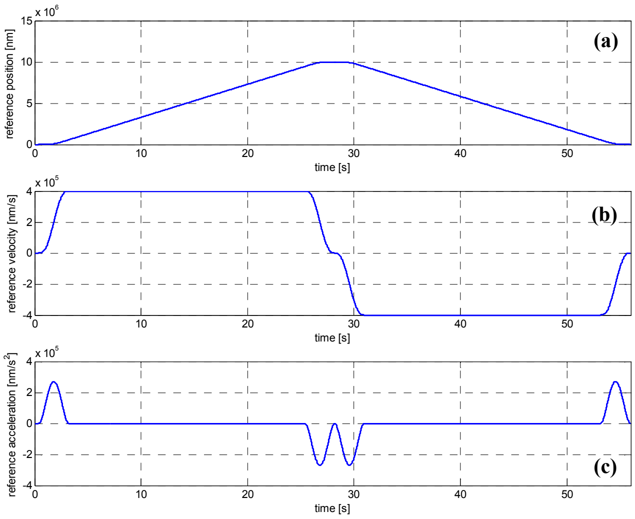

Fig. 3: (a) Reference position, (b) reference velocity, (c) reference acceleration

The used constraints are v_{max} = 400,000 nm/s, a_{max} = 2,000,000 nm/s^2 and j_{max} = 300,000 nm/s^3. For more detailed information about the trajectory generation algorithm the reader is referred to [22]. The used trajectories in position (a), velocity (b) and acceleration (c) are shown in figure 3.

After comprehensive tests the two tuning parameters of the Kalman filter are defined as follows:

1. Variance of the states in the internal model (Equ. (6)):

$$Q = \begin{bmatrix} 100 & 0 & 0 & 0 \\ 0 & 10^{20} & 0 & 0 \\ 0 & 0 & 10^{35} & 0 \\ 0 & 0 & 0 & 10^{20} \end{bmatrix}$$

2. Variance of the measurement noise:

$$R = 10^{27}$$

A. Sinusoidal motion

Figure 4 shows an experimental data-set composed of the reference, actual position trajectory (a) and the related position error (b). In the example depicted, the reference trajectory has a frequency of 0.5 Hz and an amplitude of 2000 nm. The position is controlled without a friction cancellation and it can be clearly seen, that the feedback controller is not able to follow the reference trajectory satisfyingly. The *NRMSE* is 8.42 % and a significant phase shift is observable.
For comparison figure 5 shows the behavior of the controlled system under operation of the proposed friction compensation. If the Kalman filter is utilised the system is able to follow the trajectory (see figure 5b) satisfactorily. Since the disturbance observer predicts the force which will be needed to reach the next set-point, the task of the feedback controller is only to compensate the estimation error and

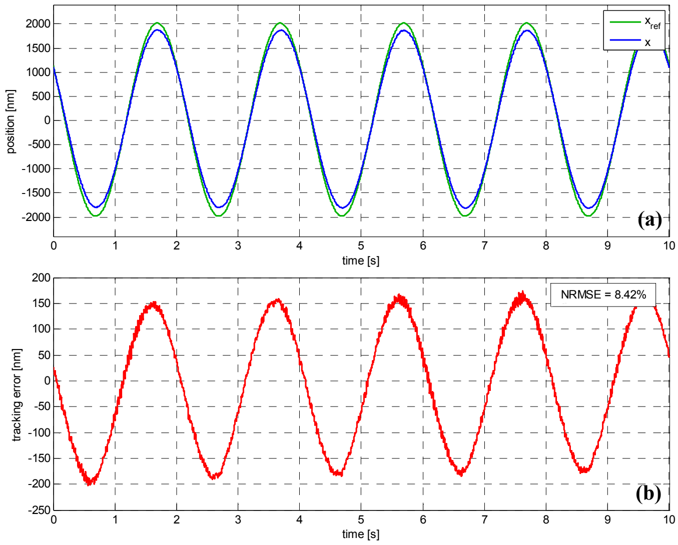

Fig. 4: Position reference vs. actual position and (b) tracking error without friction compensation

external disturbances. As easily can be seen, the disturbance observer is able to reduce the amplitude of the tracking error nearly by factor 10. The *NRSME* is alsominimized to 0.56%. This is a remarkable improvement compared to the performance shown in figure 4.

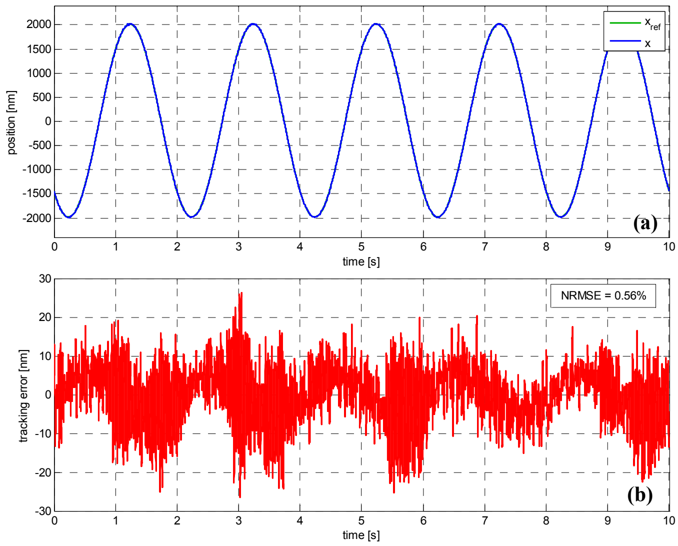

Fig. 5: Position reference vs. actual position and (b) tracking error with friction compensation

Regarding the other experiments conducted with sinusoidal reference trajectories, the results are almost similar to figure 4 and figure 5. Figure 6 shows the *NRMSE* without a friction observer and figure 7 presents the *NRMSE* with friction observer in the control system.

In the case of a normal PID controller it could be noticed that the *NRMSE* decreases with an increasing amplitude and behaves relatively independent from the used frequency of the reference signal. The reason for this observation is the relation between sliding and pre-sliding phases. The pure PID is tuned for the sliding regime and therefore the controller works well in this domain. In contrast to the sliding domain as expected, the PID controller fails in pre-sliding regime.

Using the friction observer in the control system, the system performed much better. Regarding the dependency of the control performance to the amplitude of the reference signal, the same relation as using the pure PID controller could be observed. The tracking error of the controlled system decreases with rising amplitudes. But one difference attracts attention in figure 7. With a rising frequency of the reference trajectory the performance degrades slightly. Cause of this deterioration of performance is probably the limited band width of the friction observer.

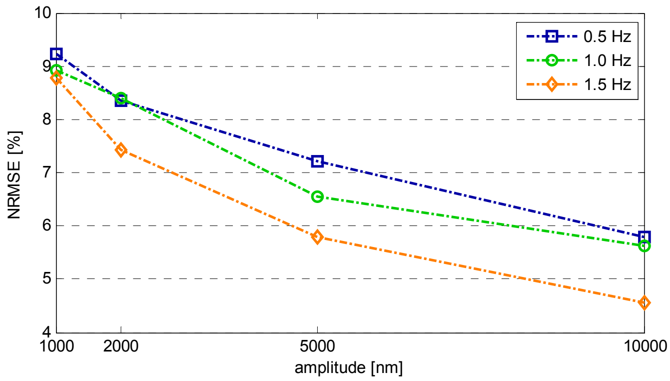

Fig. 6: NRMSE without friction cancellation

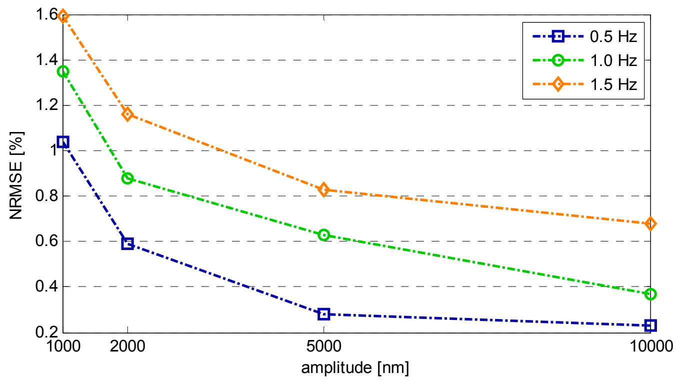

Fig. 7: NRMSE with friction cancellation

B. *Linear motion*

The major task of measuring machines is following a straight line. Therefore a trajectory shown in figure 3 was executed several times. Using only a pure PID controller the tracking error is quite big – almost 2000 nm at peak. Figure 8 shows the tracking error over time. Most significant are the peaks in the tracking error at motion reversal. This clearly shows the weakness of the PID controller in pre-sliding domain.

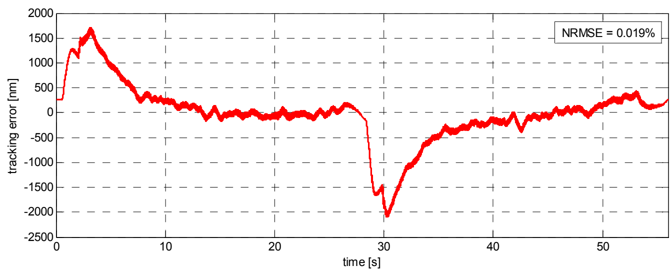

Fig. 8: Tracking error while following a straight line without friction compensation

In the next step the friction observer is utilized in the position control loop. Carrying out this experiment a problem occurred. As shown in figure 9 the system started to oscillate around 6000 nm when nearly constant velocities were reached.

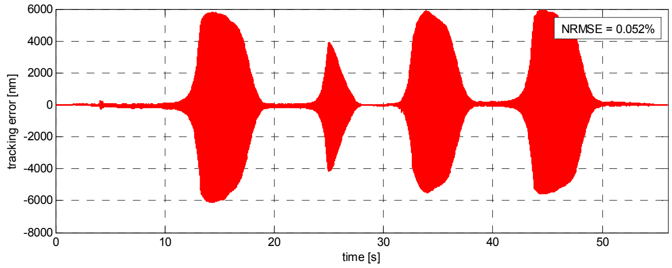

Fig. 9: Tracking error while following a straight line with friction compensation

These oscillations are caused by the interaction between the PID controller and the Kalman filter. As a result of nonlinear effects like e.g. stick-slip, the system starts to vibrate around the reference trajectory. A rising measurement noise is caused by this increasing vibration. The Kalman filter starts to accommodate this growing measurement noise due to the fact that the beforehand tuned parameter R was not valid any more. Result of this accommodation is an oscillation in the estimated friction force and this leads to further rising vibrations of the overall system and so on. The system behavior can be compared to an oscillating circuit at resonance frequency. Thus the system becomes unstable while performing high velocities.

To solve this problem an adaptive variance R is implemented. With rising velocity, the variance R is scaled up in a certain ratio. Due to this modification the adaption rate of the Kalman filter is very high at low velocities to compensate minimal deviations. With increasing velocity the adaption capability is degrading in order to increase the damping within the Kalman filter. These finding guarantee a stable system behavior over the hole traveling range shown in figure 10.

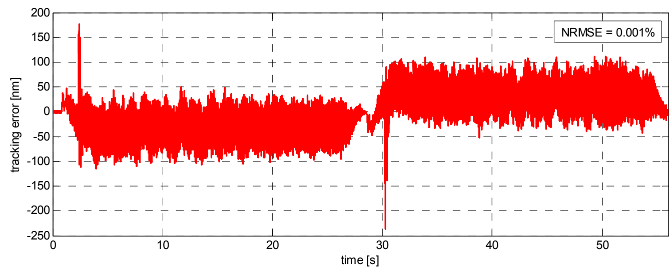

Fig. 10: Tracking error while following a straight line with a modified friction compensation

Compared to figure 8 the tracking error is uniform and significantly smaller. The friction observer reduces the *NRSME* nearly by factor 20. These results show clearly the capability of the proposed non-model-based friction compensation scheme to enhance the performance of a position control system on nanometer scale. Also the Kalman filter is able to adapt to new conditions, shown by the experiments conducted with sinusoidal reference trajectories. It has to be mentioned, that while scaling up/down the amplitudes of the reference sine the system behaved stable and followed the varying amplitudes very quickly. The experiments also indicate that the Kalman filter is quite robust against disturbances, e.g. variations in temperature and so on.

V. CONCLUSION

A non-model-based friction compensation scheme on nanometer range is addressed. Basis of the proposed friction observer is the well known adaptive estimation algorithm developed by Kalman. The implemented observer is used as part of a highly dynamic controlling system, which is able to control the position on nanometer scale.

The friction observer is utilised to estimate nonlinear effects introduced by friction of a one-dimensional ball bearing guide on nanometer scale. The reason for selecting this non-model-based approach is its capability to capture nearly all nonlinear phenomena and perform well without deeper knowledge about the friction dynamics. Furthermore the Kalman filter is adaptive and accommodates to changing reference trajectories and new external conditions. After modeling the system behavior in state space, the original algorithm proposed by Kalman was implemented. For constant variances R and Q the controlling system performs well in the case of sinusoidal reference trajectories. Trying to carry out a long straight motion planed by a trajectory generator, the observer fails. After deeper analysis the Kalman algorithm was modified to assure a stable system behavior. Using this modification, the friction observer is able to precisely predict the system characteristics on the nanometer scale and reduce the tracking error by a factor of nearly 20 while performing sinusoidal as well as linearly motions.

ACKNOWLEDGMENT

The work was done within the framework of the Collaborative Research Centre 'Nanopositioning and Nanomeasuring Machines' at the Technische Universität of Ilmenau, which is supported by the German Research Foundation (DFG) and the Thuringian Ministry of Science. The authors would also like to thank all colleagues who offered help to the work presented.

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