Ball Nut Preload Diagnosis of the Hollow Ball Screw through Support Vector Machine

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Received 21 July 2017; received in revised form 17 September 2017; accepted 18 November 2017

Abstract

This paper studies the diagnostic results of hollow ball screws with different ball nut preload through the support vector machine (SVM) process. The method is testified by considering the use of ball screw pretension and different ball nut preload. SVM was used to discriminate the hollow ball screw preload status through the vibration signals and servo motor current signals. Maximum dynamic preloads of 2%, 4%, and 6% ball screws were predesigned, manufactured, and conducted experimentally. Signal patterns with different preload features are separated by SVM. The irregularity development of the ball screw driving motion current and rolling balls vibration of the ball screw can be discriminated via SVM based on complexity perception. The experimental results successfully show that the prognostic status of ball nut preload can be envisaged by the proposed methodology. The smart reasoning for the health of the ball screw is available based on classification of SVM. This diagnostic method satisfies the purposes of prognostic effectiveness on knowing the ball nut preload status.

Keywords: ball nut preload, ball screw, support vector machine

1. Introduction

Precision CNC machines are widely used in modern industry for mass production. Recently, many strategies have been proposed to diagnose machine status, providing operators with important information to extending the machine's useful lifespan. Chen and Lee [1] established a prognostic system to acquire and analyze vibration signals corresponding to various ball screw states. Calculated results are saved in a database, and a training model is established using several classification methods. Since ball screws are widely used in linear actuators for various types of machinery and equipment. Preloading is an effective means to eliminate the backlash and increase the stiffness of the ball screw for precision motion, thus maximizing efficiency [2]. Preload loss leads to a lower natural frequency, lower stiffness, oscillatory positioning, and chance of rapid downtime in the manufacturing process. Some methods proposed for tuning preload values are time consuming and incur increased downtime, thus raising the need to predict the ball screw nut preload status during machine operation. Fault diagnosis with most acquired signals requires the assistance of conventional Fourier Transform or Discrete Wavelet Transform in the frequency and time domains [3-4]. However, for many real applications, the signals are multi-components and are often corrupted by noise. As mentioned, loss of ball screw preload not only decreases the bandwidth of the frequency response spectrum but also reduces positioning accuracy. Accordingly, industrial mass production applications would benefit from the lifetime prediction for ball screw preload loss status, but few studies have focused on this topic. The complexity of a ball screw with

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preload in operation is highly nonlinear and non-stationary. Traditional entropy measurements quantify only the regularity (predictability) of a time series on a single scale. No straightforward correlation exists, however, between regularity and complexity. This study applies support vector machine (SVM) [5-8] to classify the complexity of finite length time series. This computational tool has been applied successfully both to physical data sets, and can be used with a variety of measures of different patterns. The feature patterns of preload status are determined and abstracted via the function of SVM. SVM analysis is used to discriminate the prognostic preload status of ball screws in this preliminary study

2. Dynamic Model of the Ball Screw Drive System

To model the feed drive system, this paper sets different ball nut stiffness for different preload between the ball screw shaft and the ball nut. The presetting preload value can be deployed by inserting different ball size for single ball nut design or using disk spring that applied to the ball screw when double ball nut is the preference. Fig. 1 shows the picture of the in-lab single-axis feed drive platform. To analyze the dynamic characteristic of the ball screw system under different preload and varying table mass, the feed drive system is modeled by a lumped parameter system shown in Fig. 2. Fig. 2 is the schematic illustration for the single-axis ball screw feed drive system. In general, mechanical systems have three passive linear components. The spring and the mass are energy-storage elements, while the viscous damper is the dissipated energy. Both of the rotational and translation mechanical system modeled below are actuated by the servo motor torque, indicated as T. The overall stiffness of a ball screw feed drive system can be determined by the stiffness of the ball screw itself, which is comprised of the ball screw shaft, the ball nut, supporting bearings of the ball screw, and the stiffness between the ball screw and the working table [9].

$$M_t \times \ddot{X}_t + B_t \times (\dot{X}_t - 0) = K_n (R\theta_b + X_b - X_t) \tag{1}$$

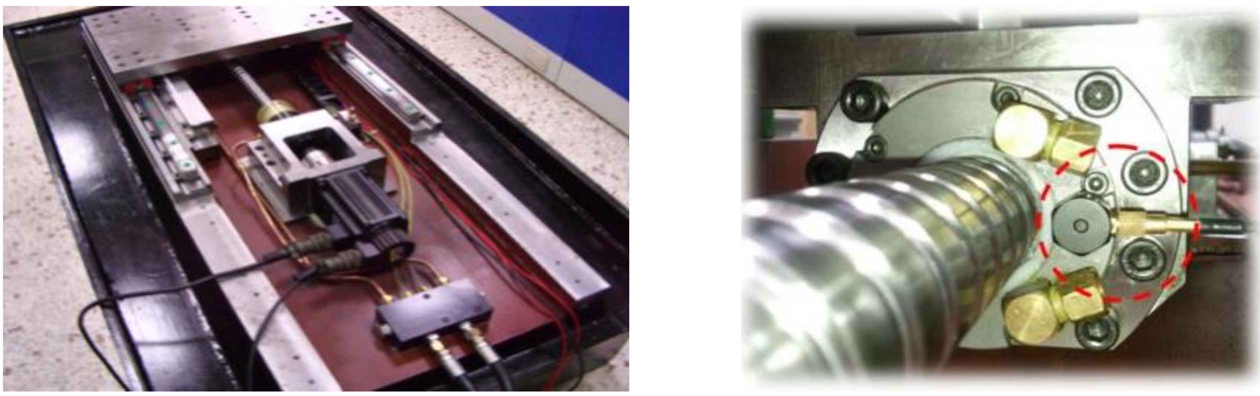
$$M_b \times \ddot{X}_b + B_b \times (\dot{X}_b - 0) + K_e \times (X_b - 0) + K_n \times (R \times \theta_b + X_b - X_t) = 0 \tag{2}$$

$$J_b \times \ddot{\theta}_b + Q_b \times \dot{\theta}_b + R \times [K_n \times (R \times \theta_b + X_b - X_t)] = K_g \times (\theta_m - \theta_b) \tag{3}$$

$$J_m \times \ddot{\theta}_m + Q_m \times \dot{\theta}_m + K_g \times (\theta_m - \theta_b) = T \tag{4}$$

Rearranging Eqs. (1)-(4), we have

$$\begin{bmatrix} M_t & 0 & 0 & 0 \\ 0 & M_b & 0 & 0 \\ 0 & 0 & J_b & 0 \\ 0 & 0 & 0 & J_m \end{bmatrix} \times \begin{bmatrix} \ddot{X}_t \\ \ddot{X}_b \\ \ddot{\theta}_b \\ \ddot{\theta}_m \end{bmatrix} + \begin{bmatrix} B_t & 0 & 0 & 0 \\ 0 & B_b & 0 & 0 \\ 0 & 0 & Q_b & 0 \\ 0 & 0 & 0 & Q_m \end{bmatrix} \times \begin{bmatrix} \dot{X}_t \\ \dot{X}_b \\ \dot{\theta}_b \\ \dot{\theta}_m \end{bmatrix} + \begin{bmatrix} K_n & -K_n & -K_n R & 0 \\ -K_n & K_e + K_n & K_n R & 0 \\ -K_n R & K_n R & K_g + K_n R^2 & -K_g \\ 0 & 0 & -K_g & K_g \end{bmatrix} \times \begin{bmatrix} X_t \\ X_b \\ \theta_b \\ \theta_m \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ T \end{bmatrix} \tag{5}$$



(a) The in-house single axis platform

(b) The picture of the acceleration sensor attached to the ball nut

Fig. 1 Photo of the in-lab single axis servo drive system and the acceleration sensor attached to the ball nut

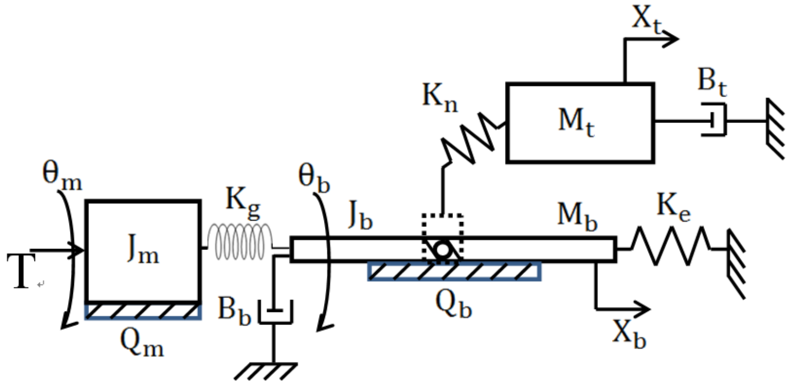


Fig. 2 Illustration for the schematic diagram of the single-axis lumped parameters ball screw drive system

3. Support Vector Machine

Conventionally, there are many possible linear classifiers that can be divided into two different featured data. SVM provides a method that can maximize the margin in between two separated data. One of linear or nonlinear classifiers is termed the optimal separating hyperplane, as shown in Fig. 3. Intuitively, one would expect margin boundary to generalize well as opposed to the other possible boundaries.

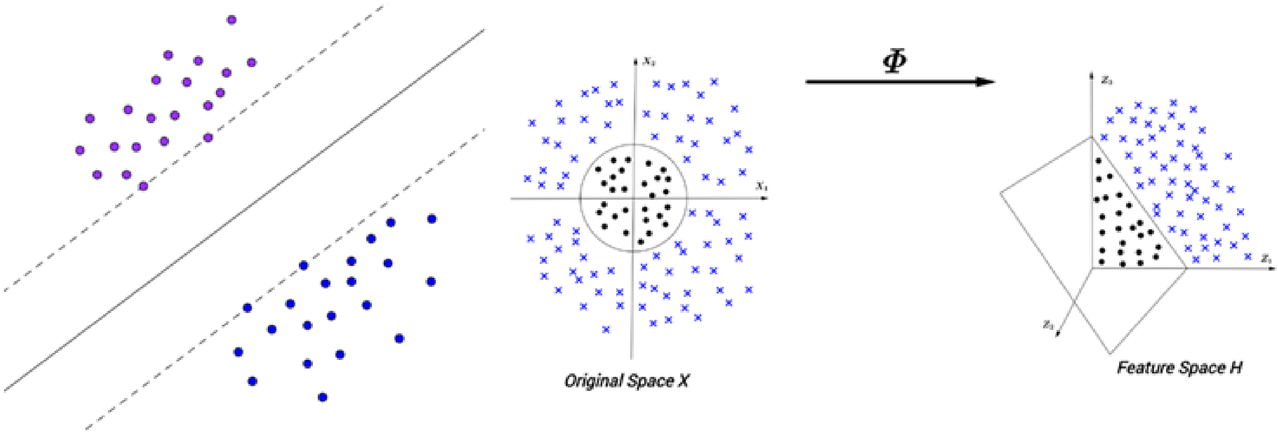


Fig. 3 Illustration for the seperating hyperplane for linear (left) and nonlinear (right) SVM

4. Experiment Results

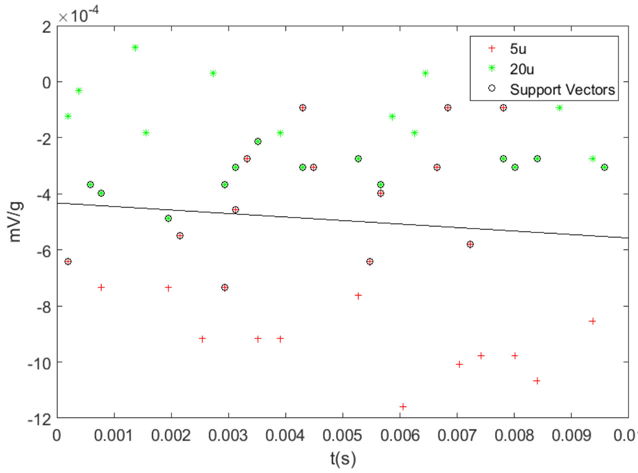


Fig. 4 Linear SVM kernel function for vibration signals by 5 minutes running with 2% preload ball nut by pretension of 5μ and 20μ of the ball screw

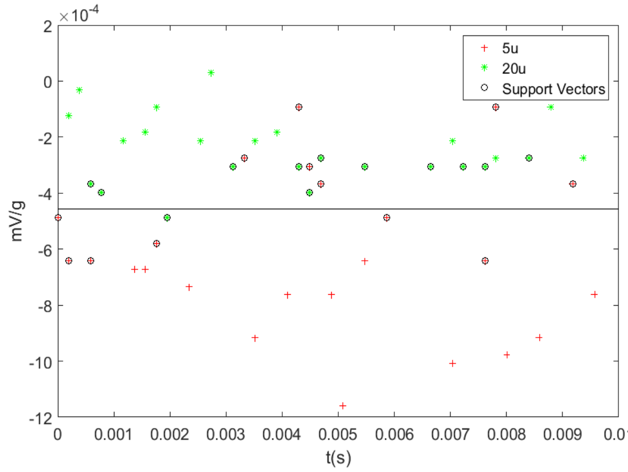


Fig. 5 Linear SVM kernel function for vibration signals by 30 minutes running with 2 % preload ball nut by pretension of 5μ and 20μ of the ball screw

Figs. 4-5 show the hyperplane divides pretension of 5μ (with + mark in red color) and 20μ(with * mark in green color) into two half-spaces when the table with 2 % ball nut preload was operated by 5 and 30 minutes, respectively. Though using one sensor signals, the classification rate is not very high. Nevertheless, it can be used as the initial decision boundary of a binary classifier when the CNC table does the repetitive backward and forward motion consecutively under 30 minutes. Fig. 6 shows that deploying such linear decision boundary can't classify the two pretensions by 60 minutes using SVM's linear kernel function. The average classification rate was only 79 %, 69 % and 48 % by running CNC table with 5, 30 and 60 minutes, respectively. Since 2 % preload ball screw was treated as the preload loss condition while 4 % one was in the standard condition. After consecutive 30 minutes operation, the increasing temperature distribution of the ball screw causes the pretension effect loss and less mechanical complexities sensed by vibration sensor naturally. From Figs. 4-6, the experimental results illustrate the thermo expansion around the ball nut and ball screw renders the diagnosis effect on the classification of the ball pretension vanished.

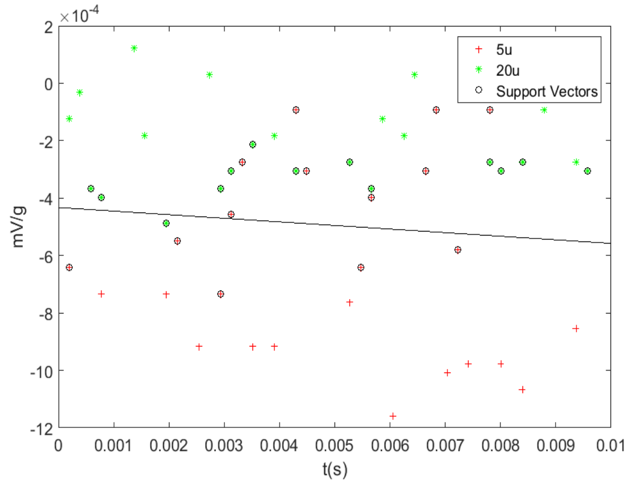


Fig. 6 Linear SVM kernel function for vibration signals by 5 minutes running with 2 % preload ball nut by pretension of 5μ and 20μ of the ball screw

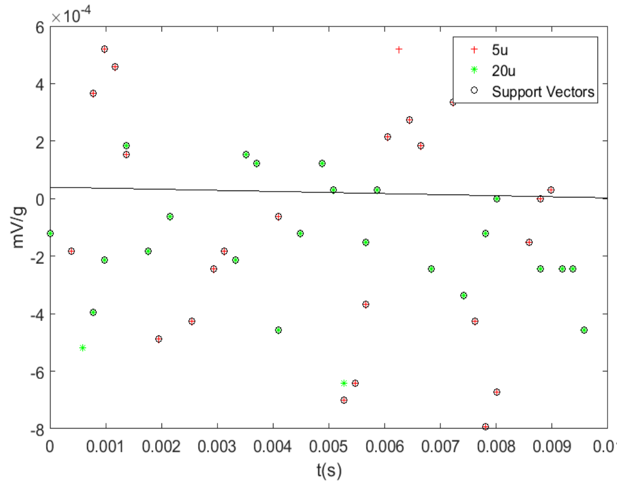


Fig. 7 Linear SVM kernel function from vibration signals by 5 minutes running with 4 % preload ball nut by pretension of 5μ and 20μ of the ball screw

Research study here is aim to produce a classifier that can work well on different ball nut preload situations when they are applied by different ball screw pretensions. Figs. 7-8 show the hyperplane divides pretension of 5μ (with + mark in red color) and 20μ(with * mark in green color) into two half-spaces when the table with 4 % ball nut preload was operated by 5 and 30 minutes, respectively. The linear classifier is termed the optimal separating hyperplane when the machine was operated by 30 minutes. The maximum margin (maximizes the distance between the 5μand 20μ) is in Fig. 8 with 100 % average precision classification. Experimental results show based on standard preload, the conventional warm-up procedure in industry can do the machine diagnosis with two different pretension on the ball screws by vibration signals. Since different pretension creates different ball screw stiffness in axial direction, the SVM can generate very good classification by standard operations. Nevertheless, in Fig. 9, after 60 minutes, the separating hyperplane generated by linear kernel function of SVM can't determine the pretension features by classification. The average precision classification was only 48 % and 54 % by running CNC table with 5 and 60 minutes, respectively. The reason was that due to the initial 5 minutes, the 4 % ball nut preload dominated the total stiffness of the ball screw. After 60 minutes operation, the increasing temperature of the ball screw renders the ball screw pretension effect diminished and the stiffness of the ball nut and the blurred vibration signals were loss thereof. Fig. 10 shows using linear SVM kernel function can't separate the 2 % and 6 % ball nut preload features when the CNC table was running after 30 minutes for each ball screw pretension fixed at 5μ and 20μ. Nevertheless, using nonlinear radial basis function (RBF) SVM kernel function, the features patterns in Fig. 11 can be separated. Such promising results were based on the nonlinear kernel function. Heuristically, one or more sensors can facilitate the SVM classification and toward successfully.

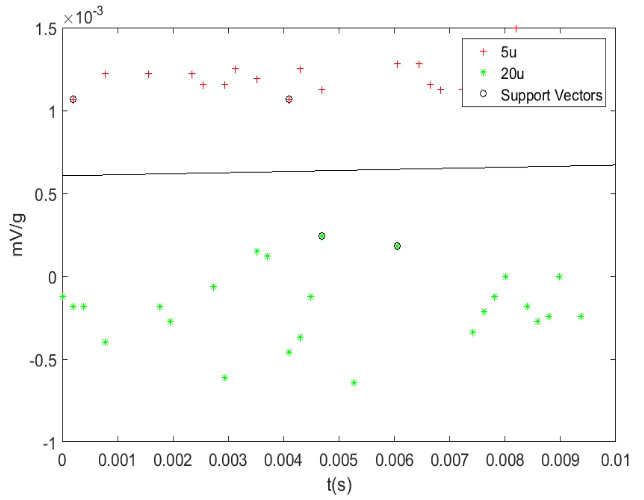


Fig. 8 Linear SVM kernel function from vibration signals by 30 minutes running with 4% preload ball nut by pretension of 5μ and 20μ of the ball screw

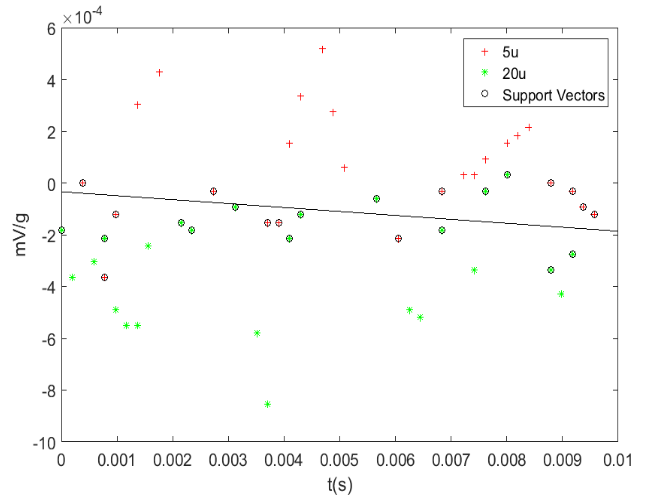
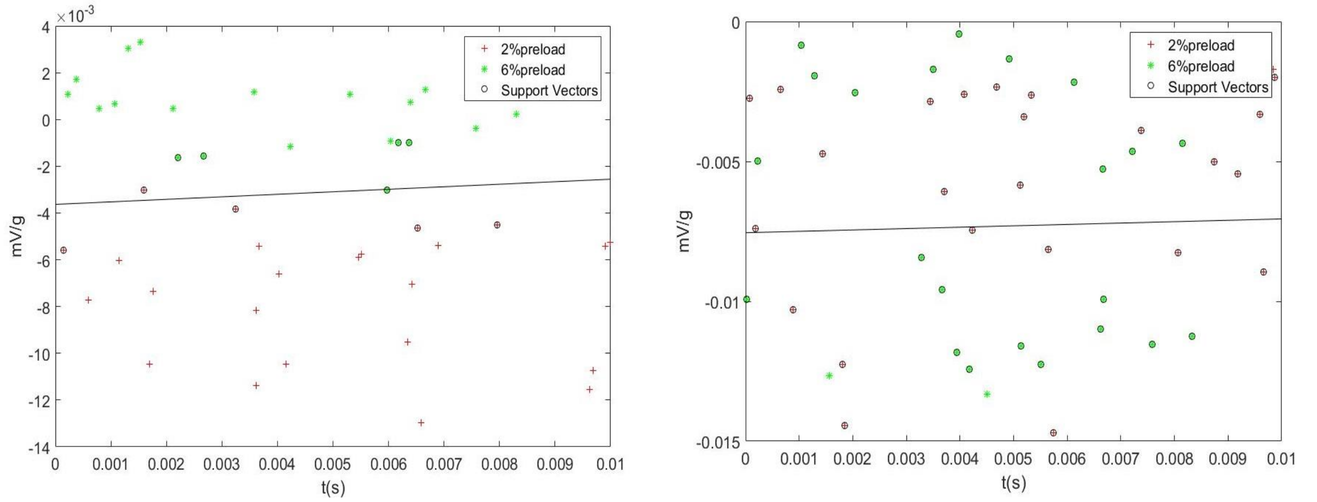


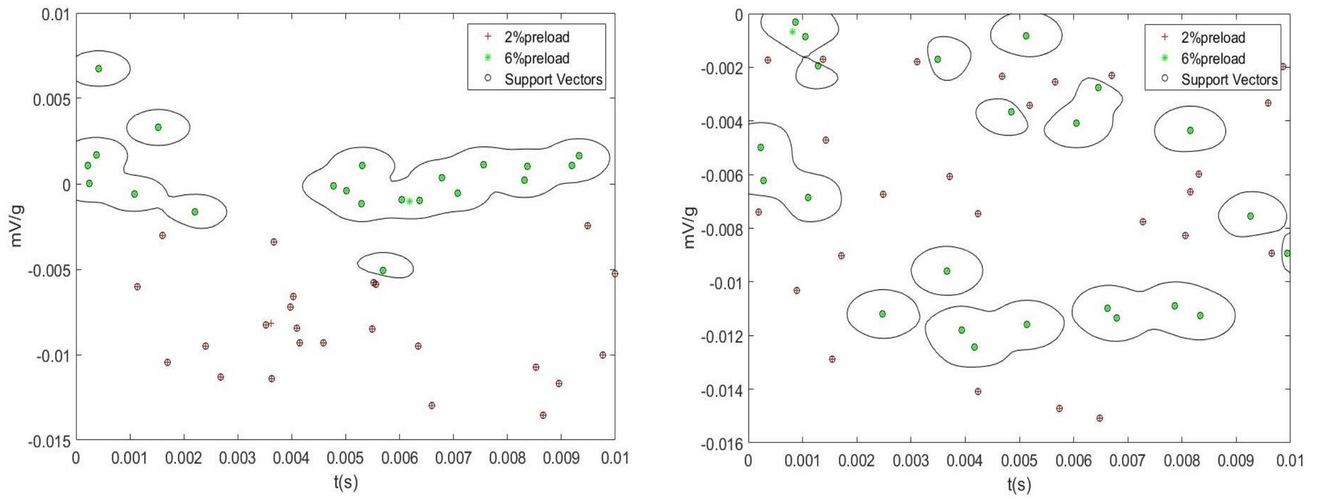
Fig. 9 Linear SVM kernel function from vibration signals by 60 minutes running with 4% preload ball nut by pretension of 5μ and 20μ of the ball screw



(a) For separating 2 % and 6 % preload ball nut with pretension of 5μ of the ball screw

(b) For separating 2 % and 6 % preload ball nut with pretension of 20μof the ball screw

Fig. 10 Linear SVM kernel function from vibration signals by 30 minutes running



(a) For separating 2 % and 6 % preload ball nut with pretension of 5μ of the ball screw

(b) For separating 2 % and 6 % preload ball nut with pretension of 20μ of the ball screw

Fig. 11 Nonlinear RBF SVM kernel function from vibration signals by 30 minutes running

5. Concluding Remarks

This research uses the signal analysis techniques by SVM to detect the preload status of hollow ball screw nuts. Different ball screw pretensions and ball nut preload in a one axis machine tool feed drive table were studied. Both the highly nonlinear processing SVM methods and linear hyper plane were used to diagnose the machinery health status. Vibration measure was used to dynamically quantify the hollow ball screw's complexity and identify the irregular development of the ball nut preload. Experimental results show the sensed vibration signals of the preload features were extracted clearly with standard 4 % preload when the CNC table was operated by 30 minutes. Compensated positioning technique by ball screw pretension with 5μ and 20μ was not significantly contaminated by CNC 30 minutes operation time by linear SVM prognostic diagnosis when the ball nut preload was 4 %. Nonlinear RBF SVM was able to separate the 2 %ball nut preload 6 % ball nut preload when the CNC table was operated by 30 minutes. Heuristically, with more sensors, the SVM can facilitate the bettering classification and toward high precision classification. Future work will combine the vibration signals and motor current signals as new training data through the support vector machine process.

Acknowledgement

This work was supported by MOST Grant 106-2218-E-018-001 for which the authors are very much grateful.

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