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Improved forecasting compensatory control through Kalman filtering

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Abstract

The deformation of large thin-walled parts during the cutting processing will decrease the part accuracy, and on-line error forecasting and compensation control is usually used. The forecasting compensatory control (FCC) depending on modelling technique is usually helpful for some regular deformation. Random deformation of weak rigid thin-walled parts in the cutting process cannot be compensated easily. This paper develops an improved forecasting compensatory control method based on Kalman filtering algorithm to improve the prediction accuracy. The Kalman filtering algorithm produces the estimation of the real deformation based on the measured deformation data, and the statistical noise in measuring and cutting process modeling can be reduced. The effectiveness of the proposed method is validated with simulation examples.

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Keywords: Large thin-walled part processing, Forecasting compensatory control (FCC), Kalman filtering, Prediction accuracy.

1. Introduction

Large thin-walled parts play a key role in the aerospace industry, such as aircraft and rocket. They are usually used in extreme conditions such as high pressure and low temperature. The mechanical performance and surface accuracy of the machined parts are important. Take the huge fuel tank cylinder as an example. In the inner wall, thousands of triangular or quadrilateral grids should be machined to reduce the weight and improve the transport capacity. The wall thickness of the triangle grid is critical to compromise the weight reduction and strength, and the tolerance of wall thickness should be controlled in the machining process.

However, random deformation, caused by the weak rigidity of the part, severely affects the accuracy of the wall thickness during the processing. As shown in Fig.1, the deformation of the huge fuel tank during the milling process is quite stochastic, and it is difficult to predict by off-line modelling method.

The technique of on-line error forecasting and compensation control is useful to improve the accuracy of the surface profile of the large thin-walled parts. Forecasting compensatory control(FCC), first proposed by Wu[1], is employed to solve the time-lag problem, and considered as one of the most effective methods to improve the manufacturing accuracy in various machining operations. It is successfully applied to precise motion control in micromanufacturing[2], machine tool error compensation[3], precision control in grinder[4], roundness improvement in taper turning[5, 6] and etc. Most researchers focus on process modelling, like Autoregressive moving average (ARMA) modelling[6, 7] and grey model[4, 8], to improve the prediction accuracy of the FCC scheme. The accuracy of these methods mainly rely on the modelling technique. Kalman filtering algorithm[9], which has been proved that it can reduce the accuracy requirement of the model because of its correctable power[10],is introduced to improve the prediction accuracy of the FCC.

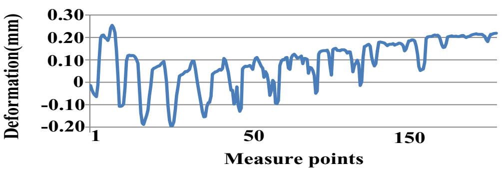

Figure 1 The deformation of huge fuel tank in the milling process

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Nomenclature

$\mathbf{Q}$	the process noise covariance
$\mathbf{R}$	the measurement noise covariance
$\mathbf{u_k}$	control signal
$\mathbf{w_k}$	the process noise
$\mathbf{v_k}$	the measurement noise
$\hat{\mathbf{x}}_k^-$	a priori state estimate at step k
$\hat{\mathbf{x}}_k$	a posteriori state estimate at step k
$\mathbf{P}_k^-$	priori estimate errors covariance at step k
$\mathbf{P_k}$	posteriori estimate errors covariance at step k

2. Improved forecasting compensatory control algorithm

Compared with the conventional FCC, the improved algorithm based on Kalman filtering can achieve better performance. The reasons for employing Kalman filtering method are listed as follows. First, according to the Bayes principle, the error between the predicted value and the actual value at the next step will grow smaller and smaller[10]. Kalman filtering method can not only predict data but also correct the established model to approach the actual value. Second, the filter parameters, like the process noise covariance Q and the measurement noise covariance R, can be adjusted to improve the accuracy of the estimation. Third, Kalman filtering method is compatible with the common modelling methods.

2.1. Kalman filtering theory

Kalman filtering, a generalization of the least-square method, is a set of mathematical equations that provides an efficient computational means to estimate the state of a process, and minimizes the mean of the squared error[11]. In addition, Kalman filtering can estimate the future states without precise nature of the modeled system. Consider a linear discrete system and the state observer as presented in Eq. (1):

$$\begin{cases} \mathbf{x_{k+1}} = \mathbf{Ax_k} + \mathbf{Bu_k} + \mathbf{w_k} \\ \mathbf{z_k} = \mathbf{Hx_k} + \mathbf{v_k} \end{cases} \quad (1)$$

where the state $\mathbf{x} \in \mathbf{R}^n$ belongs to a discrete-time controlled process that is governed by the linear stochastic difference equation, $\mathbf{z} \in \mathbf{R}^n$ is a measurement, and the variable $\mathbf{u_k}$ is a control signal. The random variables $\mathbf{w_k}$ and $\mathbf{v_k}$ represent the process and measurement noise, respectively. The matrix $\mathbf{A}$ is the state matrix which relates the state at the previous time step to the state at the current step, and the matrix $\mathbf{B}$ is the input matrix which relates the optional control input $\mathbf{u}$ to the state $\mathbf{x}$, and the matrix $\mathbf{H}$ is the output matrix which relates the state to the measurement $\mathbf{z}$. $\mathbf{w_k}$ and $\mathbf{v_k}$ are assumed to be independent of each other and obey a Gaussian distribution, as presented in Eq. (2):

$$\begin{aligned} \mathbf{p(w)} &= \mathbf{N(0,Q)} \\ \mathbf{p(v)} &= \mathbf{N(0,R)} \end{aligned} \quad (2)$$

where $\mathbf{p(w)}$ is the state distribution of $\mathbf{w}$, $\mathbf{Q}$ is the process noise covariance and $\mathbf{R}$ is the measurement noise covariance.

In practice, $\mathbf{Q}$ and $\mathbf{R}$ might change with each time step, but they are assumed to be constant in this paper. The measurement noise covariance $\mathbf{R}$ can be measured practically by taking some off-line sample measurements. The process noise covariance $\mathbf{Q}$ is difficult to be determined because we are not able to observe the process we are estimating. In general, tuning the filter parameters $\mathbf{Q}$ and $\mathbf{R}$ can acquire statistically superior filter performance. The tuning is usually performed off line with the help of system identification. In addition, $\mathbf{A}$ 、 $\mathbf{B}$ and $\mathbf{H}$ also might change with each time step or measurement, but here we assume they are constant.

2.2. Improved forecasting compensatory control algorithm

The block diagram of the improved forecasting compensatory control algorithm is shown in Fig.2. Four key elements are included in this algorithm: a. On-line measurement and signal processing; b. prediction model establishment; c. Kalman filtering; d. compensation control.

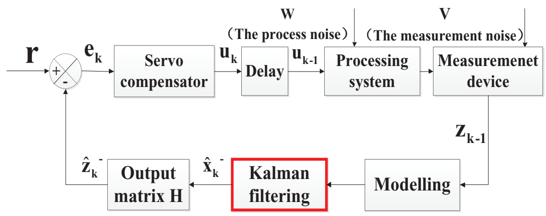

Figure 2 Design flow of improved forecasting compensatory control algorithm

A On-line measurement and signal processing

Unlike the off-line measuring methods, the on-line one can be more close to the actual processing situation and monitor the process variables continuously. The on-line measurement accuracy is the core issue of the on-line measurement technology and severely affected by the harsh processing environment. To improve the on-line measurement accuracy, high reliability measuring equipment and the on-line signal processing are needed.

B Prediction model establishment

To estimate the state of a process through Kalman filtering, it is necessary to set up a model based on the measured data. In digital signal processing, many mathematical modelling methods, like Autoregressive moving average (ARMA) modelling [6, 7] and Grey model[4, 8], have been used. Autoregressive integrated moving average model (ARIMA)[11] has been widely used because of good prediction of random factor of system. ARIMA(5,0,0), extended to 5 previous observations, is taken as an example in this article: