Machine tool operating vibration prediction based on multi-sensor fusion and LSTM neural network

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This study proposes a machine tool vibration prediction method based on multi-sensor fusion and a long short-term memory (LSTM) network. Machine tool vibration significantly impacts machining quality, surface roughness, dimensional accuracy, and tool wear. By combining deep learning with industrial applications, this method achieves high-precision vibration prediction through multi-sensor data fusion. Data is input into the LSTM model to predict the next moment's vibration. Experimental results demonstrate strong prediction capability for periodic vibrations and machining-specific vibration errors, effectively enhancing machining accuracy.

Introduction: The vibrations generated by machine tools during operation can adversely affect machining quality, increase surface roughness, and reduce dimensional accuracy [1–3]. Traditional methods typically rely on single-sensor measurements, which are prone to poor accuracy, noise, and data drift issues [3–5]. And, existing vibration prediction techniques often involve data fitting, which lacks precision. This study employs multi-sensor fusion and deep learning to improve vibration data collection and prediction [3, 6–8]. The predicted vibration values are then used to adjust the tool's motion coordinates, thereby reducing machine tool vibrations and enhancing workpiece machining accuracy [6, 9, 10].

The main contributions of this paper are as follows:

1. A vibration data set based on common machining actions in machine tool machining was established, providing data support for this study and subsequent related studies.
2. A multi-sensor fusion algorithm based on machine tool vibration measurement was studied to improve the accuracy of machine tool vibration measurement.
3. Based on actual machine tool vibration data, a long short-term memory (LSTM)-based neural network model was trained, and the vibration of the machine tool was predicted with high accuracy.

Related works: Many researchers have studied machine tool vibration prediction in recent years. Kuo's study introduces an effective pre-processing method for chatter data, enhancing neural network learning even from sparse data through the use of a modified convolutional neural network and a generative adversarial net, which minimizes variability and enables robust data generation [11]. Karimova et al. [12] explored the use of artificial neural networks (ANN) to predict the wear level of cutting tools, utilizing a large data set from real manufacturing scenarios. Their configured neural network demonstrated strong performance during testing. Romanssini et al. [13] reviewed vibration monitoring techniques for predictive maintenance of rotating machinery and discussed examples of vibration monitoring systems that use Internet of Things technology for continuous monitoring. Song and Tan [14] proposed a method for predicting CNC spindle rotation errors based on short-time Fourier transform and an improved weighted residual network, which adaptively weights data from different channels to highlight important information while suppressing redundant information. Chan et al. [9] applied the finite element method to analyse the modal and spatial accuracy of machine tools, implemented compensation values to improve accuracy, and evaluated machine tool status, and vibration errors through spindle vibration signal prediction. But few of these research efforts have used multi-sensor fusion and neural network models in combination.

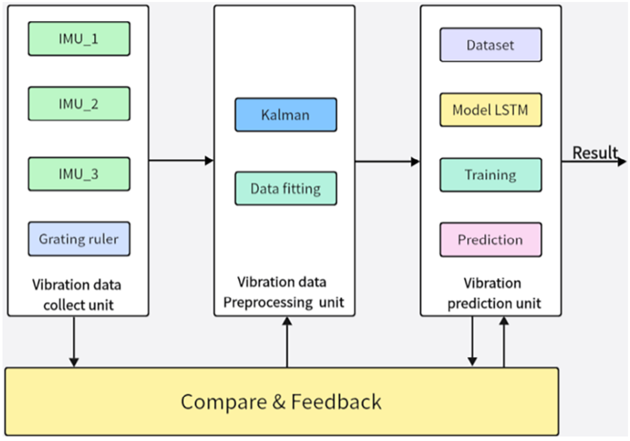

Fig. 1 *Composition and design block diagram of machine tool vibration prediction system*

System design: The machine tool working vibration based on Kalman and LSTM is mainly divided into four parts: vibration data acquisition unit, vibration data pre-processing unit, vibration prediction unit, and compare and feedback unit. The vibration data acquisition system unit mainly consists of inertial measurement unit (IMU) and scale, vibration data pre-processing unit will fit the data from IMUs to the vibration displacement in a certain direction, and the vibration prediction unit is based on LSTM model, which is put into practical use after training through historical data. During the system operation, the compare and feedback unit will receive the pre-processed vibration data in real time, compare the difference between the predicted data and the actual data, and utilize the data to train the LSTM model periodically, so as to enhance the adaptability of the neural network model to the current machine tool. The system composition and design block diagram are shown in Figure 1.

The vibration data collection unit uses the MPU6050 as the vibration data collection sensor, and at the same time uses the scale to collect motion data in a certain direction, we can establish a conversion function between the IMU data and the machine tool motion axes data, then the subsequent data collection unit can run without the use of scales, to realize a low-cost and high-precision data collection solution. The vibration data pre-processing unit processes the IMU data through Kalman to obtain data closer to the actual vibration of the machine.

To train the LSTM neural network model and enhance the adaptation of the neural network model to the current machine tool, a data set is constructed using the machine tool for daily machining work, especially focusing on machining actions such as cutting, turning, milling, and drilling, by collecting the three-axis acceleration data from the three IMUs, fused computed data, and the time of collection of the original data. The LSTM neural network model is trained using the constructed data set, and ultimately the LSTM neural network model is used to predict the future vibration of the machine tool, and the vibration error of the predicted output is compensated on the next mechanical movement. So, it can improve the machining accuracy of the machine tool.

(1) Vibration data collection and pre-processing programmer

The vibration of a machine tool can be conceptualized as displacement motion, characterized by the acceleration along each axis of motion. Here, the IMUs are mounted on the machine fixture, allowing the vibration of the fixture to be taken as representative of the vibration of the workpiece during the machine tool operation. To achieve a more precise measurement of the workpiece vibration during machining, three MPU6050 sensors are mounted on the machine tool fixture, with simultaneous measurements being conducted to enhance the accuracy of the original data. The installation setup is depicted in Figure 2. Specifically, the MPU6050 sensors are bolted to the side of the machine fixture, with a dust cover affixed to their surfaces to ensure protection.

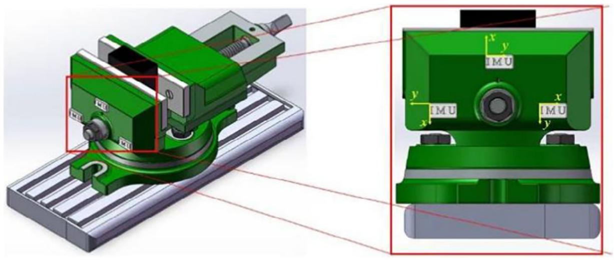

Fig. 2 *Inertial measurement units (IMUs) (the module marked with white 'IMU' in the figure) installation diagram on X5032B machine tool*

Changes in acceleration indicate machine tool vibrations, but MPU6050 data is often affected by measurement and environmental noise. Using a Kalman filter to fuse data from the three MPU6050 sensors can effectively suppress noise through weighted averaging, thereby enhancing data accuracy and stability. This approach provides more accurate vibration data for subsequent calculations and addresses issues such as data drift, maintaining the precision of vibration measurements.

Take the X axis direction of the machine tool as an example, we set the three MPU6050s measured acceleration values are a_1, a_2, and a_3, respectively, and the fused acceleration value is a_{fusion}, set the Kalman filter to get the initial state estimation value as a_{fusion}, the initial state covariance matrix as P, state transfer matrix is F, process noise covariance matrix is Q, and Kalman gain is K.

First, the Kalman filter is initialized, that is, the initial state estimate

$$\hat{a}_{\text{fusion}} = a_1 \tag{1}$$

Then, predict the state estimate for the next moment:

$$\hat{a}_{\text{fusion}} = F * \hat{a}_{\text{fusion}} \tag{2}$$

And, predict the state covariance matrix at the next moment:

$$P = F \times P \times F^T + Q \tag{3}$$

After the prediction is completed, the prediction values and parameter matrices are updated, calculate the measurement error:

$$y = a_2 - \hat{a}_{\text{fusion}} \tag{4}$$

Update the state estimate:

$$\hat{a}_{\text{fusion}} = \hat{a}_{\text{fusion}} + K * y \tag{5}$$

The fusion of a_1 and a_2 is achieved by the above steps, and repeat the steps to fusion $\hat{a}_3$ and $\hat{a}_{\text{fusion}}$, set the final fusion value as $\hat{a}_{\text{f}}$.

It is necessary to establish the relationship between acceleration and displacement as a function of the X, Y, and Z axes in the preliminary works. Define the change in displacement measured at the current sampling moment of the scale from the previous sampling moment as ΔL.

The displacement changes ΔL and the fused acceleration value $\hat{a}_{\text{f}}$ are collected synchronously in real time at the same moment, and the relationship between the acceleration value and the displacement change value can be obtained by curve fitting these two values using spline interpolation:

$$\Delta L = f_{la}(\hat{a}_{\text{f}}) \tag{6}$$

Once this conversion relationship has been derived, the displacement change can be obtained on the condition that the acceleration value is measured, without the need to install a scale.

(2) Construction of the data set, model training and deploy

The machine model used for the study is X5032B vertical lift table milling machine from Wannan Machine Tool Factory. We set the sampling frequency is set to 100Hz, and the values of three IMUs and the scale are recorded synchronously at each sampling moment, and the three IMUs correspond to the relative displacement values measured by the scale at the same moment after Kalman processing. The above raw data and pre-processed data form a data set. The data set contains the machine tool spindle rotation and static vibration data and common cutting, turning, milling, and drilling vibration data in mechanical processing.

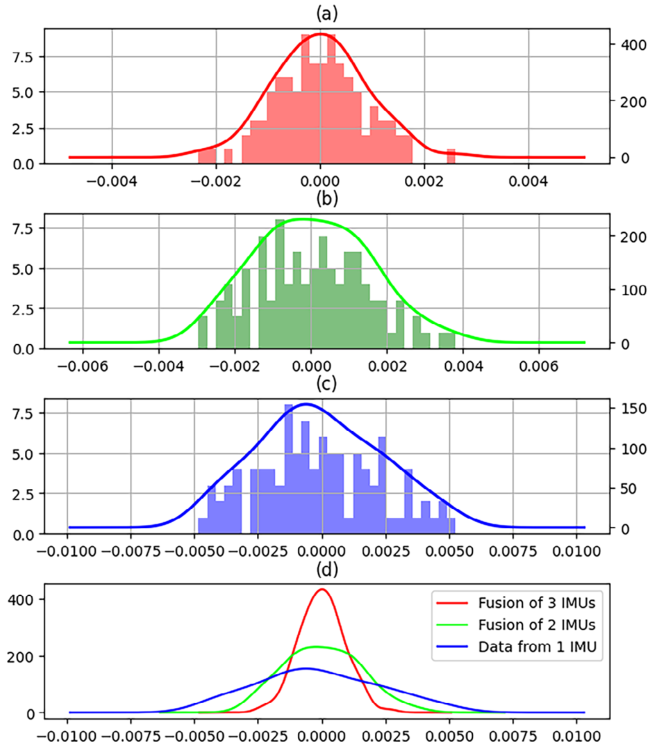

Fig. 3 *Results of multi-sensor fusion ablation experiment: (a) Data distribution after fusion of three inertial measurement units (IMUs). (b) Data distribution after fusion of two IMUs. (c) Data distribution of a single IMU. (d) Comparison of normal distributions with different numbers of IMUs*

The LSTM we used are from the Keras, an open-source ANN library was chosen as the model. Set the inputs and outputs at each moment to take the past vibration data as inputs and the vibration at the next moment as the target, observe the change in the loss value of the validation set. The predictive ability of the model is judged manually using the test set, and the training is stopped when the trend and the predicted values reach the desired target.

After the model is trained, the model is deployed and the Kalman fused values are compared with the scale values in real time to determine the sensor fusion accuracy. The fused values are passed to the neural network model and the fused values and the output values of the neural network model are recorded at each moment for comparison and judgement.

Experiments and analysis: Here, we carried out verification of multi-sensor fusion performance and verification of prediction performance of LSTM model.

Ablation experiment for multi-sensor fusion performance: Ablation experiments are used to evaluate the importance and impact of different components or modules within a model. Typically, certain modules are removed or altered to observe the resultant performance changes. We conducted ablation experiments to assess the performance of the multi-sensor fusion algorithm by reducing sensor data inputs and observing the effects on the output data. In the experiments, raw data from three IMUs were collected simultaneously. The raw data from all three IMUs, as well as the raw data from only two IMUs, were input into the multi-sensor fusion unit for calculation. The experimental results were recorded separately. Additionally, the raw data from a randomly selected single IMU were used as the baseline experimental result. These three sets of result data were analysed and compared, as illustrated in Figure 3.

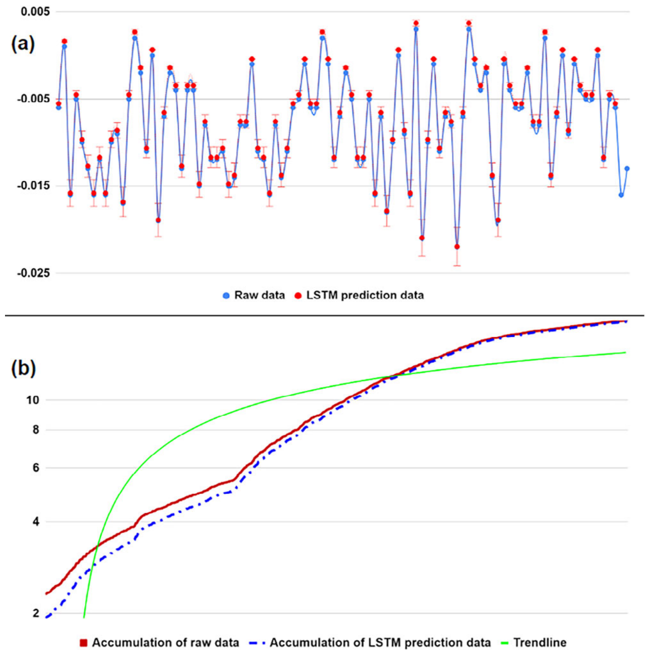

Fig. 4 *(a) Comparison chart of machine tool's own vibration data and predicted data. The blue solid line is the raw data, and the red dotted line is the predicted data. (b) Changes between the predicted and actual values of the tool stable motion machining workpiece. The curve in the figure represents the cumulative error*

From Figure 3, it can be observed that the results of multi-sensor fusion become more convergent, that is, more accurate, as the amount of sensor data increases. This is because the increase in the number of sensors provides more information and redundancy for the multi-sensor fusion algorithm. At the same time, sensor data can complement each other, compensating for the inaccuracies caused by the limitations of individual sensors and addressing issues such as sensor drift and noise. The presence of multiple sensors also mitigates the impact of interference affecting a single sensor, thereby ensuring more accurate output results.

Conversely, as the number of sensors decreases, the amount of information available to the fusion algorithm is reduced, leading to decreased robustness in the measurement results. In Figure 3, the noise level increases significantly and the error margin widens as the number of sensors decreases. This is because the fusion algorithm can effectively reduce the random noise of individual sensors, and the noise reduction effect diminishes when the number of sensors decreases.

Validation of LSTM model prediction performance: Using the test set data mentioned earlier, the trained LSTM model was subjected to testing and validation. The model performance was observed from two perspectives: time-domain prediction and cumulative vibration values. Figure 4 illustrates the comparison between the LSTM model's time-domain predictions and the measured vibration values when the machine tool is not performing any machining operations. From Figure 4, it can be observed that the predicted vibration values and the measured vibration values have consistent trends in the time domain. While there are discrepancies between the predicted and measured values at the same moments, the overall prediction trend is consistent and shows high expected accuracy. If the predicted values are incorporated into the system for compensation, it can significantly reduce errors caused by system vibrations.

To evaluate the model's predictive capability during the machining process, cumulative vibration values were used to assess the machining effect on the workpiece. During the machining process, the actual vibration values were accumulated, and the predicted vibration values by the model were also accumulated. These two sets of values were then compared, with the comparison results illustrated in Figure 4. The figure depicts the comparison between the actual cumulative vibration values and the predicted cumulative vibration values during the machining of a U-shaped groove. When the tool first contacts the workpiece, the working state of the machine tool changes.

Consequently, both the predicted cumulative vibration values and the actual cumulative vibration values initially show significant differences. As the machining action stabilizes, the predicted cumulative vibration values and the actual cumulative vibration values gradually become consistent. Over the entire workpiece machining cycle, the vibration prediction accuracy is relatively high.

Conclusion: This study integrates acceleration data from three MPU6050 sensors positioned in the x, y, and z directions on the machine tool fixture. Subsequently, the fused data is used to train an LSTM model to generate a neural network model capable of adapting to the current machine tool. This model is designed to predict the vibration at the next moment.

Experimental results demonstrate that the data fusion of three MPU6050 sensors using the Kalman filter yields a closer approximation to the actual machine tool motion vibration error. Furthermore, the LSTM-based vibration prediction model for machine tool operations exhibits superior performance in prediction accuracy. Future research will explore how to identify the specific machining actions being performed by the machine tool, thereby enabling enhanced functionality.

Author contributions: **Zhonglou Shi**: Conceptualization; methodology; validation. **Jinjie Duan**: Data curation; formal analysis; software. **Faquan Li**: Resources; validation; writing—original draft.

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Data availability statement: After the paper is published, the data that support the findings of this study will be available on request from the corresponding author.

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