Realization of shock accelerometer sequence-to-sequence calibration based on deep learning

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Abstract. The sensitivity parameters or mathematical model of sensor are obtained through traditional shock accelerometer under calibration test, and then the measurement signal is restored through compensation and correction. As the shock signal with complex components is used in a harsh environment, it is very difficult to accurately restore the measured signals. In the meantime, the deconvolution process of signal recovery is an inverse problem in mathematical physics, which has ubiquitous ill-posed problems, thereby bringing great challenges to the accuracy and precision of the solution. Thus, we propose a depth calibration network based LSTM, which can be used to learn the mapping relationship between the calibrated sensor signal and the standard signal. The measured signal can be restored through a data-driven sequence-to-sequence calibration network, which is trained and verified through the exclusive open-source data set of shock signals. The test results proved the superior performance of the network in shock signal calibration.

1. INTRODUCTION

The core and most basic function of the sensor is measurement. If the dynamic characteristics of the sensor are not good, it will not be able to quickly and accurately reflect the changes being measured. In order to make the measurement results of the sensor more reliable, the sensor characteristics must be accurately obtained [1]. The sensor characteristics are divided into two categories: static and dynamic. For sensors with harsh application environments and high-reliability requirements such as high-impact acceleration sensors, it is more important to obtain dynamic characteristics than static characteristics [2]. To obtain the static or dynamic characteristics of the sensor, it must be calibrated.
For general sensor calibration, after the sensor model is obtained, the traditional calibration method restores the original measurement signal by constructing the inverse model of the sensor [3-4]. The method of constructing the inverse model belongs to the inverse problem in the sense of mathematics and physics [5]. There are ill-posed problems in the solution process of signal recovery, which brings great difficulties to the recovery of measurement signals. Compared with the vibration signal, the shock signal, especially the high-g shock signal, has a variety of different frequency components, and its signal composition is more complex. The traditional one is based on limited parameters (response time, rise time) and the description of the signal by the linear model method cannot accurately express its essential characteristics [6].

In recent years, deep learning methods have achieved great success in time series forecasting and modeling. Convolutional neural networks, autoencoders, LSTM, Sequence to Sequence, and Attention mechanisms developed on this basis. These methods were first proposed and applied based on text-based time-series data, such as Google’s Bert and Transformer. These data-driven methods enable LSTM to learn the unique characteristics of the time series [7-9].

In this paper, a sequence-to-sequence DNN model from the output signal of the shock accelerometer to the standard shock signal is constructed based on the long and short-term memory neural network, and it is trained and verified on the open-source shock accelerometer calibration data set. The difference from [10] is that the unique structure of LSTM is used in the network designed in this paper to fully consider the time series characteristics of the signal. The main contributions of this paper are:

- For the first time, the neural network of the cyclic neural network is used in the field of shock signal measurement;
• The use of data-driven methods is helpful to solve the ill-posed problem of using deconvolution methods in traditional measurement, and it is more adaptable;
• When the corresponding calibration model is established, the traditional calibration work can be greatly simplified, and higher measurement accuracy can be achieved at the same time.

2. RELATED WORK
Our main work is to design a calibration network for shock accelerometers used to restore the original measurement signal. In this part, we mainly introduce research work in the field of deep learning and sensor calibration.

2.1. Model-based dynamic calibration
Model-based dynamic calibration of accelerometers is the current mainstream research direction. It generates the shock excitation signal through the Hopkinson rod shock calibration device and collects the output signal of the sensor and the output of the standard sensor at the same time. After using frequency domain deconvolution to obtain the sensor transfer function, the model parameters are solved through parameter identification, and a deconvolution filter is constructed according to the model parameters to restore the measured signal [7]. ISO issued an international standard for model-based shock accelerometer calibration in 2012 [11], marking that the model-based calibration method has been standardized for specific industrial applications, but until now, there is no relevant international and international standard for full-process dynamic calibration.

2.2. Dynamic calibration based on deep learning
Up to now, there is still little research on the application of deep learning methods in sensor calibration. [10] is the first time to apply the deep learning method to the calibration of shock and vibration sensors. On the basis of the open-source impact signal data set, a deep learning model of the AE-PPN autoencoder and peak prediction network was constructed to construct the mapping between low-cost sensors and high-precision sensor signals, while considering the overall shape and Peak. Because AE-PPN adopts AE as the baseline model [10], the mapping between signals and signals can only reflect the mapping of a single feature at each moment and does not fully consider the correlation between signals at different moments.

LSTM was proposed by Sepp Hochreiter and Jürgen Schmidhuber in 1997 [7]. It effectively solves the problem of RNN that is difficult to solve and solves the problem of gradient disappearance that RNN is prone to. On this basis, improved models such as GRU and Bi-LSTM have also been developed [12]. LSTM and its improved models have been successfully used in many fields such as machine translation, semantic recognition, trajectory prediction, finance, etc., such as Google's Bert and Transformer [13-14]. In terms of signal processing, LSTM is also used to process vibration signals for fault diagnosis and prediction [15].

Due to the complexity of the impact signal, the use of data-driven methods to build sensor end-to-end calibration shows its superior performance compared to traditional methods. At the same time, time-series data such as sensor output signals and shock signals have certain causal characteristics, which are consistent with the characteristics of LSTM in deep learning. Obviously, it may be more appropriate to calibrate shock accelerometers with LSTM.

3. PROPOSED APPROACH
In the first part of this section, we briefly introduced the relevant situation of the shock signal data set used. The second part describes in detail the network structure we designed, and its training and performance evaluation.

3.1. Dataset
This paper uses the only known open-source dataset of shock signals. The dataset comes from the work in the document [16]. The dataset is given by the calibration of the shock accelerometer comparison
method. The experimental platform uses the collision of a heavy object to generate the shock excitation signal. The signal generated by the calibrated sensor usually has poor anti-interference performance and low manufacturing accuracy due to reasons such as manufacturing. The output signal has more noise and the peak value may have a larger error. The standard sensor has high manufacturing precision and the signal is relatively pure. Although it is not inconsistent with the original collision signal, it is equivalent to the original signal in the comparative calibration due to its high accuracy and reliability [10].

The sampling frequency of the shock signal in the entire data set is 200kHz, the data length is 3000, the sampling time is 15ms, the sampling time before the peak time is 2.5ms, and the sampling time after the peak time is 12.5ms. The data set has a total of 660 sets of samples. From the perspective of shock amplitude, the 660 sets of samples cover shock amplitudes between 1000g and 8000g. We randomly select 500 shock signal pairs from the data set as the training set, and the remaining 160 shock signal pairs as the validation set. Figure 5 shows a set of shock signal pairs composed of the output signal of the calibrated sensor and the standard shock signal in the data set. It can be seen that the output signal of the calibrated sensor contains a lot of noise, which makes the overall shape slightly deformed, and there is a slight deviation in the peak size from the standard signal.

3.2. The network design and training

In this section, we propose a new network architecture based on LSTM to learn the mapping relationship between sensor output signals and standard impact signals. We hope that the network can learn the common characteristics of the same type of sensors. Since the number of samples in the data set is small, the complexity of the designed model should match it, and the model complexity should not be too high.

The shock accelerometer calibration network we designed is mainly composed of two layers of LSTM and one layer of fully connected network. The number of nodes in each layer is 3000 to suit the length of the input signal.

![Figure 3: Depth calibration network structure of shock accelerometer](image)

As shown in Figure 3, the shock accelerometer output signal y and the standard shock signal as the network learning target are first normalized, and then, the data of output signal of the impact accelerometer at each moment is encoded into a feature vector g with a dimension of 32 by a single-layer perceptron, which is used as the input of the two-layer LSTM network by a single-layer perceptron.
\[ g_t = W_6 x_t + b_6 \]

Where \( x_t \) is the calibrated signal in t-th , \( W_6 \) and \( b_6 \) are the parameters of Encoder.

The cycle time step of LSTM is the signal length. For any time step \( t \), The output of each time step of the first layer LSTM is \( h^1_t \).

\[
\begin{align*}
    h^1_t &= O^1_t \ast tanh(C^1_t) \\
    f^1_t &= \sigma(W^1_f \cdot [h^1_{t-1}, x_t] + b^1_f) \\
    i^1_t &= \sigma(W^1_i \cdot [h^1_{t-1}, x_t] + b^1_i) \\
    C^1_t &= \sigma(W^1_c \cdot [h^1_{t-1}, x_t] + b^1_c) \\
    C^1_t &= f^1_t \ast C^1_{t-1} + (1 - f^1_t) \ast \tilde{C}^1_t \\
    O^1_t &= \sigma(W^1_o \cdot [h^1_{t-1}, x_t] + b^1_o) \\
    C^2_t &= f^2_t \ast C^2_{t-1} + (1 - f^2_t) \ast \tilde{C}^2_t \\
    O^2_t &= \sigma(W^2_o \cdot [h^2_{t-1}, h^1_{t-1}] + b^2_o)
\end{align*}
\]

Where \( W^1_f, W^1_i, W^1_c, W^1_o, b^1_f, b^1_i, b^1_c, b^1_o \) are the parameters of first LSTM layer.

The output of each time step of the first layer LSTM is \( h^2_t \).

\[
\begin{align*}
    h^2_t &= O^2_t \ast tanh(C^2_t) \\
    f^2_t &= \sigma(W^2_f \cdot [h^2_{t-1}, h^1_{t-1}] + b^2_f) \\
    i^2_t &= \sigma(W^2_i \cdot [h^2_{t-1}, h^1_{t-1}] + b^2_i) \\
    C^2_t &= \sigma(W^2_c \cdot [h^2_{t-1}, h^1_{t-1}] + b^2_c) \\
    C^2_t &= f^2_t \ast C^2_{t-1} + (1 - f^2_t) \ast \tilde{C}^2_t \\
    O^2_t &= \sigma(W^2_o \cdot [h^2_{t-1}, h^1_{t-1}] + b^2_o)
\end{align*}
\]

Where \( W^2_f, W^2_i, W^2_c, W^2_o, b^2_f, b^2_i, b^2_c, b^2_o \) are the parameters of second LSTM layer.

The impact signal after two layers of LSTM is re-encoded into a feature vector with a dimension of 64: \( h^2_{t, t} = 1, 2, \cdots, 3000 \). And then, the feature vector \( h^2_t \) is decoded into a feature vector \( H \) of dimension 1, which is used as the input of the full connection layer.

\[ H_t = W_d h^2_t + b_d \]

Where \( W_d \) and \( b_d \) are the parameters of Decoder.

The other part of the network is a fully connected layer, which is composed of an input layer, an output layer, and a single hidden layer, and the activation function uses sigmoid. The network output is \( \hat{y}_t \).

\[ y_t = S(W^3_h H_t + b_h) \]

Where \( W_h \) and \( b_h \) are the parameters of the full connected layer.

The entire network loss is composed of the normalized MSE between each pair of impact signals:

\[
Loss = \frac{1}{N} \sum_{i=1}^{M} \sum_{t=1}^{N} (y^i_t - \hat{y}^i_t)^2
\]

Where \( M \) and \( N \) are signal length (3000 in this case), \( \hat{y}^i_t \) is the output of calibration network in the i-th training signal \( y^i \) at t-th time step.

The network uses the normalized signal for learning, and uses MSE as the overall loss. The depth calibration network we designed is built using the Pytorch framework. The model uses the Adam optimizer. The entire model is trained on the NVIDIA GeForce GTX1650GPU platform. Considering the memory limitation, the network training Batch size is set to 4.

4. RESULTS AND DISCUSSION

In [10], the specific error of using low-pass filter LPF, linear regression LR, autoencoder, and AE-PPN method to calibrate the impact signal under this data set is given. We use the same index to evaluate the performance of the designed calibration network to reflect its good performance in calibration.
\[\epsilon_p = \frac{1}{N} \sum_{i=1}^{N} \frac{\max(\hat{y}_i^t) - \max(y_i^t)}{\max(y_i^t)}\]

\[\epsilon_s = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{M} \frac{|y_i^t - \hat{y}_i^t|}{\max(y_i^t)}\]

Where \(\hat{y}_i^t\) is the output of the calibration network in the \(i\)-th testing signal \(y_i^t\) at \(t\)-th timestep. As a matter of fact, \(\epsilon_p\) is the relative prediction error of peak value, \(\epsilon_s\) is the relative overall error in the peak value.

Figure 4 shows the learning performance of the network proposed in this paper on the overall shape and amplitude of the signal. Figure 5 shows the mapping relationship near the peak from the details. It can be seen from these pictures that not only the depth calibration network we proposed maintains the overall shape of the standard shock signal as a whole, but also the network output perfectly fits the standard shock signal and maintains the consistency of input and output at the peak. Comparing the input of the network—the output of the calibrated shock accelerometer, our deep calibration network significantly reduces the noise of the output signal of the calibrated sensor, and extracts the process of shock excitation to gradual attenuation from the signal submerged by noise.

|     | LPF  | LR   | AE   | AE-PPN | Ours  |
|-----|------|------|------|--------|-------|
| \(\epsilon_p\) | 48.8% | 7.9% | 6.9% | 5.7%   | 4.8%  |
| \(\epsilon_s\) | 138.6| 44.8 | 37.9 | 35.2   | 27.83 |
It can be seen from Table 1 that in each evaluation index, peak error and shape error of the network we designed is lower than other methods. From these performance evaluation indicators, it can be seen that the calibration network we proposed has learned the important characteristics of the shock signal sequence. Using this network for dynamic calibration can restore the measured shock signal with high precision.

5. CONCLUSION

For the first time, we used the long and short-term memory networks in the calibration of shock accelerometers. Using LSTM, we designed a deep learning network that can fully extract the time characteristics of the signal before and after, and the network has shown in various performance evaluation indicators. The network can be used for calibration and to restore the measured signal. However, due to the inherent defects of LSTM, the network cannot be parallelized during training and prediction, making the training and prediction time longer than other methods. We hope that the research carried out in this article can contribute to the practical application of sensor dynamic calibration.

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