

Prediction of Physiological Tremor Based on Deep Learning for Vascular Interventional Surgery Robot

Liuqing Zhang¹, Shuxiang Guo^{1,2*}, Cheng Yang¹

¹Key Laboratory of Convergence Medical Engineering System and Healthcare Technology,
The Ministry of Industry and Information Technology, School of Life Science, Beijing Institute of Technology,
No.5, Zhongguancun South Street, Haidian District, Beijing 100081, China,

²Faculty of Engineering, Kagawa University, 2217-20 Hayashi-cho, Takamatsu, Kagawa 760-8521, Japan,
E-mails: guoshuxiang@bit.edu.cn, zhangliuqing@bit.edu.cn

* Corresponding author

Abstract - Physiological tremor seriously affects the operation accuracy of the master-slave vascular interventional surgery robot (VISR), which is very necessary to be eliminated. However, there are some issues in the existing methods. For instant, some methods require the prior knowledge of the prediction horizon for accurate estimation tremor signal. Furthermore, these methods assume the process to be nonstationary in the given prediction horizon. Besides, the phase delay of the system has a great influence on the performance of the surgical operating system. Therefore, the effective tremor signal compensation that can be used to generate the reverse motion signal in real time is needed. The paper proposes a multi-step signal prediction method based on LSTM. Combined with the existing method, the deep learning method improves the accuracy of tremor prediction compared with the other prediction method.

Index Terms – Physiological Tremor, multistep prediction, Long-Short Term Memory (LSTM), vascular interventional surgery robot (VISR).

I. INTRODUCTION

Nowadays, cardiovascular disease has become one of the most common diseases, and vascular interventional surgery has become the mainstream treatment. Professor Guo of Beijing Institute of Technology has done a lot of related research on vascular interventional surgery robots. The team developed a master-slave vascular surgery robot, which allows the doctor to operate the master device controlling the slave device [1]-[4]. And for the clear experience of surgery, a surgical robot force feedback system was designed [5]-[9]. In addition, a lot of researches have been done on images processing such as catheter and guidewire navigation [10]-[14]. When a master-slave vascular interventional surgery robot is used for surgical treatment, the master hand of the robot is held by the doctor. Therefore, the doctor could control the slave hand entering in the patient's body to complete the operation [15]-[17]. The size of human tissue structure is at the level of 0.1mm, and physiological tremor will cause intolerable misoperation in surgery. In minimally invasive surgery, the diameter of the incision on the body surface is only 8mm~10mm. The feature of the vascular interventional surgery determines that the instrument will be rotated around the fixed point of the incision, which may amplify the movement range. When the doctor performs the corresponding operation, the amplitude of the hand tremor will affect the accuracy of the operation. And the

enlargement of the surgical instrument will further affect the accuracy of the operation. This shows that tremor disrupts voluntary movement and causes unnecessary interference. At present, the understanding of tremor characteristics is not comprehensive, and it cannot be fully described from the perspective of mathematics. There are only some researches on physiological tremor in the medical field. Tremor is an unconscious spontaneous hand movement. Simple function combinations cannot be used to express the law of motion. The tremor signal exists in a frequency band with a certain bandwidth. Physiological tremor is an indispensable part of the process of controlling and adjusting the body. Because of the physiological tremor of the limbs, the whole limbs of the person are in a state of constant vibration, so that people can realize the fine adjustment of the movement of the limbs. An indispensable physical behavior at the beginning and end of a movement.

For eliminating tremor signal, many research institutions and universities have done a lot of research work. The research team in MIT put up with a method to eliminate the tremor signal using a lowpass filtering algorithm for the operator's hand tremor problem in its surgical robot system [18]. The lowpass filtering method can effectively suppress tremor motion signals, but the use conditions are extremely limited. Because the premise of the effectiveness for this method is that there is a clear threshold between the tremor signal and the normal motion signal. Once this premise is not true, the tremor signal cannot be filtered out, so that the doctor's correct surgical operation signal will still be distorted with method. The method is simple and it is easy to implement. And it can be applied to scenes that do not require high precision. Relevant research teams from Carnegie Mellon University in the United States, Johns Hopkins University in the United States and Nanyang Technological University in Singapore have jointly developed a smart handheld microsurgery instrument for eye surgery [19]-[21]. The microsurgery instrument is composed of three functional modules: the function of the sensor module is to collect the operator's hand movement information in real time, and to accurately quantify the movement of the instrument user's hand to obtain its three-dimensional space position information and posture information. The basic function of the filter module is to use the weighted linear Fourier equalizer (WFLC) method to mathematically model the operator's hand tremor signal from frequency, amplitude and phase, and

calculate the theoretical and dithering signals, etc. In order to improve the efficiency of the WFLC algorithm, Veluvolu of Nanyang Technological University and others put forward a new band-limited multiple linear Fourier linear combiner (BMFLC) algorithm after lucubrate the problem about physiological tremor [22][23]. Unlike the WFLC algorithm, this algorithm no longer performs fitting based on the fundamental frequency, but directly performs fitting based on the passband, which greatly improves the fitting efficiency of the algorithm in the passband. Although BMFLC has a good fitting effect, it also has obvious defects: it does not make full use of the known frequency distribution information of the tremor signal, and the step length is selected too large in the frequency band where the tremor signal is not concentrated.

Tatinat compared the performance of some tremor prediction algorithms, and the results showed that the two algorithms, band-limited multiple Fourier linear combiner (BMFLC) combined with Kalman filter (KF) (BMFLC-KF), autoregressive model (AR) combined with KF (AR-KF), are better than other algorithms [24]. Although these methods provide good prediction accuracy, due to the phase delay problem of the algorithm, the performance of the algorithm will be adversely affected. Tatinat and Veluvolu [25] recorded the influence of phase delay on tremor compensation in surgical robot applications. As a solution to overcome the phase delay, KF-AF and KF-KF are proposed. Both methods assume that the process is non-stationary within a given forecast range. Since the tremor characteristics change with time in the 6-14 Hz frequency band (depending on the surgeon), it cannot estimate the tremor signal in real time. Because after bandpass filtering, the signal will have a certain time delay. The existence of these time delays caused a sharp decline in KF's prediction performance.

In the previous work, our research team designed a tremor recognition and suppression algorithm based on the characteristics of the motion signal in the time domain and frequency domain through the classification and recognition of the doctor's hand tremor. The algorithm uses the SVM algorithm to identify and classify offline through the spectrum range of the tremor motion signal, while designs a high-pass filter for isometric tremor, and uses Phantom products to design an active vibration isolation tremor suppression algorithm model for physiological tremor. Offline simulation experiments and volunteer operation experiments have verified the reliability and accuracy of the method.

Conclusions can be drawn from the above literature research. Most of the current tremor eliminate methods use low-pass filters or band-pass filters. These methods have clear ideas and are easy to implement, but also have unavoidable defects: they cannot specifically filter the tremor signal, cause excessive filtering of effective exercise information. This type of filtering method filters out all the motion signals within the frequency threshold. Thus, the filtering process is bound to modify the signals that should not be processed, resulting in distortion of the operating signals transmitted between the master and slave

systems. Real-time identification and elimination of tremor signals cannot be achieved. The low-pass filtering algorithm will affect the real-time performance of signal transmission and cause delay. This delay will cause unpredictable consequences when the entire operation is not timely, which will affect the efficiency and quality of the operation. Because the hand tremor signal has certain randomness or other complicated characteristics during the operation, it is very difficult to establish the tremor signal model. At present, the filtering method adopted by most researchers is to weaken the hand tremor signal, and then perform linear identification or nonlinear identification to obtain the essential characteristics of the signal. These algorithms fail to consider the coupling relationship between the tremor signal and the working principle of the vascular interventional surgical robot, resulting in a great limitation in the suppression and elimination of the hand tremor signal during the operation. At present, how to design efficient, real-time and intelligent hand tremor recognition and suppression algorithms to improve the quality and accuracy of surgery performed by surgical and vascular interventional surgical robots, and how to improve the robustness of surgical robot systems in the tremor elimination state, has become a medical issue. Industrial fusion faces one of the difficulties to be solved in the field of robot-assisted surgery.

Based on the above research, the research proposes a moving windows multi-step LSTM algorithm to predict the tremor signal for physiological tremor. Then uses the predicted signal as a compensation signal to eliminate the physiological tremor.

The structure of this article is as follows. In Section I, we introduce of the tremor research on surgery robot. Then in Section II we give the method LSTM and the use of it in our paper. Later, in Section III, we introduce how to get the tremor data. Finally, concludes are provided in Section IV.

II. METHODS

In this section, we first introduce the basic principles of standard LSTM. Then, the proposed online training method of LSTM based on moving window and the problem of tremor prediction using this method are discussed.

A. RNN

Recurrent Neural Network (RNN) [26] (Fig. 1) is a neural network structure, which can handle sequence problems well. It can process previous information, so the model is suitable for time series forecasting problems.

Given the function:

$$f: h', y = f(h, x) \quad (1)$$

where, x is the input of data in the current state, and h represents the input of the previous node received. y is the output in the current node state, and h' is the output passed to the next node. It can be seen from the above formula that the output h' is related to the values of x and h . And y often uses h' to invest in a linear layer (mainly for dimensional mapping) and then uses *softmax* for classification to obtain the required data. How to calculate y here through h' often depends on the usage

of the specific model.

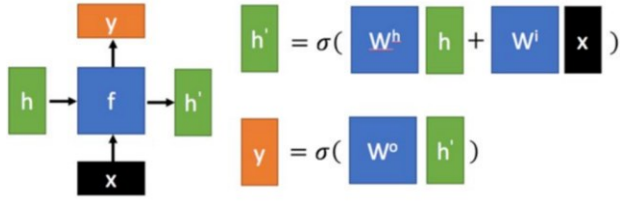


Fig. 1 RNN Cell

B. LSTM

Long short-term memory (LSTM) [27] as shown in Fig. 2 is a special kind of RNN. It mainly solves the problems of gradient disappearance and gradient explosion that may exist in long time series training. Compared to ordinary RNN, LSTM have a better performance in longer time series sequences. The main input and output differences between the LSTM structure (pictured right) and ordinary RNN are as follows:

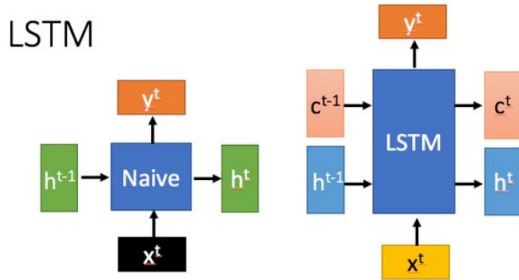


Fig. 2 Structure of LSTM

There are two states in LSTM, c^t (cell state) and h^t (hidden state), but there is only one transmission state h^t in RNN. Among them, the passed c^t changes very slowly, and the usually output c^t is the c^{t-1} passed from the previous state plus some values. And h^t tends to be very different under different nodes.

The following specifically analyses the internal structure of the LSTM as shown in Fig. 3.

$$c^t = z^f c^{t-1} + z^i z \quad (2)$$

$$h^t = z^o \tanh(c^t) \quad (3)$$

$$y^t = \sigma(w^h h^t) \quad (4)$$

Main stages inside LSTM:

1) Forgetting stage. This stage is mainly to selectively forget the input from the previous output. z^f (f stands for forget) is used as a forget gate to control which c^{t-1} in the previous state needs to be kept and which needs to be forgotten.

2) Select the memory stage. This stage selectively "memorizes" the input of this stage. It is mainly to select and memorize the input x^t . The selected gating signal is controlled by z^i (i stands for information). Add the results obtained in the above two steps to get the c^t transmitted to the next state. That is the first formula in the figure above.

3) The output stages. This stage will determine which will be regarded as the output of the current state. It is controlled by

z^o . And also scaled the c^t obtained in the previous stage (change by a \tanh activation function). Similar to ordinary RNN, the output y^t is often finally obtained through h^t change.

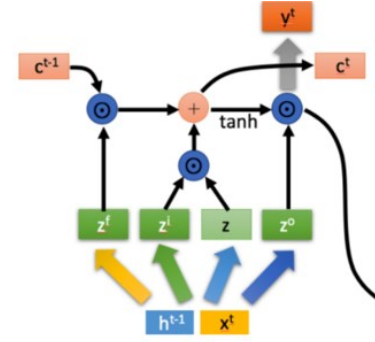


Fig. 3 The internal structure of the LSTM

LSTM algorithm has quite good effect in processing time series signals. The tremor signal is a non-stationary random time series signal, so the LSTM algorithm can better predict it.

In the online training of LSTM, as long as some new data comes, the LSTM training data will update the training set by adding new dates in the training dates, and then discard the oldest sample in the training set, as shown in Figure 1. In order to reduce the computational complexity, an incremental algorithm is used to increase the training set, and a decreasing algorithm is used to remove the oldest samples. This multi-step training method based on moving windows enables LSTM to track tremor signals more effectively. The increment and decrement algorithms used by MWLSTM are shown as Fig. 4.

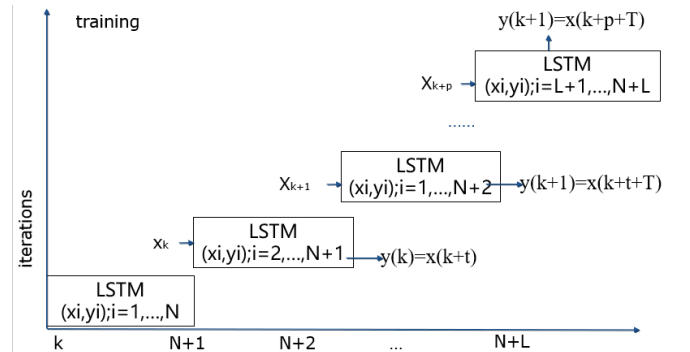


Fig. 4 Block diagram representation for tremor prediction with MWLSTM

The training process of LSTM is shown in the following flowchart. First, the data is smoothed by difference. Then the data is converted into a supervised data set, and the NAN value generated after shifting is filled with 0. After that, the data is normalized, a scaler is created, the data in the data set is scaled to the value range of $[-1, 1]$, and the scaler is used to scale the training data and test data. After processing the data, put it into the LSTM neural network for training and prediction. After the prediction result obtained, it is subjected to inverse scaling and inverse difference processing, and finally output the prediction result. In Algorithm 1, we give the LSTM real-time update of the training signal to predict the algorithm flow of the tremor

signal.

Algorithm 1: MW Multistep LSTM for Tremor Prediction

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1. Input training data(data)
2.   difference (data, interval=k)
3.   timeseries to supervised (data, lag=j)
4.   scale(data)
5.   Loop (epoch)
6.     Lstm model =fit lstm (data, batch size, epochs,
        unit number)
7.     Forecast lstm (lstm model, step length, data)
8.     Invert scale
9.     Inverse difference ( )
10.    Predict
11.    if loop time==epoch
12.  end loop

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III. EXPERIMENT AND RESULT

We first give the collection method of physiological tremor in the section. Then, we analysis the multi-step tremor prediction performance based on moving window LSTM is discussed.

In paper, we choose 5 subjects to do experiment and get the date. Then according to the date to analysis the performance. We employ the root mean square(RMS) defined as

$RMS(S) = \sqrt{\sum_{k=1}^{k=m} (s_k)^2 / m}$, where m is the number of tremor signal and s_k is the input physiological tremor signal at time k . Based on RMS, %Accuracy is defined as:

$$\%Accuracy = \frac{RMS(s) - RMS(e)}{RMS(s)} \times 100 \quad (5)$$

Where, e represents prediction error between the true signal and the predicted signal.

In order to collect and record hand tremor signals, we used Geomagic TouchX, a three-dimensional force feedback device produced by SenseAble Technologies. The operator holds the pen-shaped handle of Geomagic TouchX for control. Geomagic TouchX is a 6-DOF joint coordinate tactile feedback robotic arm. As shown in the Fig. 5, its mechanical mechanism contains 3 joints, and each joint is equipped with a photoelectric code disk, which can detect and record the angle of each joint in real time. The sampling period is 1000 Hz, which can accurately collect joint information in real time. The angle change can be calculated to obtain the three-dimensional space position information of the tip of the pen-shaped handle through the posture calculation of its internal algorithm. In this study, five volunteers used Geomagic TouchX and held a pen-like handle to perform a uniform linear advancement operation to imitate the advancement of a guidewire catheter during cardio-cerebral vascular interventional procedures, and perform stable and uniform reciprocating movements many times. This experimental system collects the movement signal and electromyography signal of hand tremor, relying on the

laboratory platform and the electromyography sensor and gyroscope acceleration sensor blessed on the hand. The distribution of sensors placed on the volunteers' arms is shown in Figure 4.6, and the EMG sensor product used is BTS FREE EMG 300 (the signal transmission and processing flow is shown in Fig. 5). The detection of hand tremor signals is mainly realized by the gyroscope in the Geomagic TouchX device and the external EMG signal acquisition device.

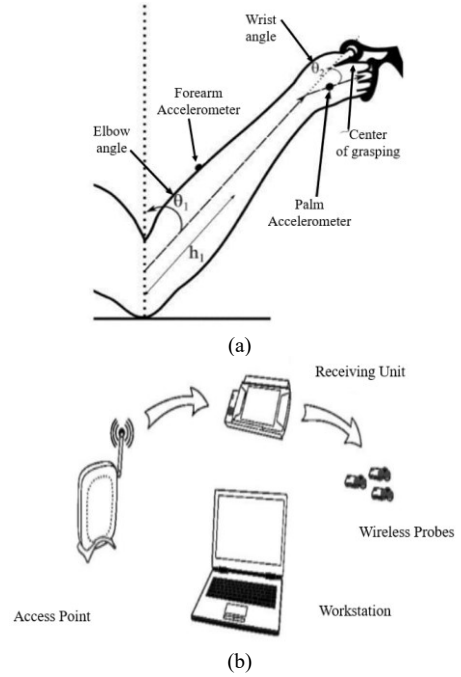


Fig. 5 (a) Collecting signal of hand tremor (b)The signal transmission and processing flow.

Simulation:

In the processing of experimental data, the data is filtered first, and the tremor signal is obtained by using the 5th-order Butterworth filter. In the training network of LSTM, 70% of the data is selected as the training data 10% for validation data and the rest 20% as the verification data. In the experiment, choose the moving window size $N=9$, the built network model depth $deep=4$, the chosen loss function is the mse root mean square function, and the optimizer chooses Adam. Enter neurons=50 in the first layer, input (batch size, input timesteps, input dim), the second- and third-layers neurons=100, and in the dense layer neurons=1, select linear as the activation function. At the same time, in order to prevent overfitting, dropout=0.2 is selected to reduce it.

Comparing performance with some existing methods, the parameters are given in TABLE I. The step in the simulation we chose is step=3. Results (Fig. 6 to Fig. 8) show that MWLSTM provides a better prediction accuracy. It can be seen from following figures, AR and ARIMA provide the worse prediction accuracy, the result is shown as TABLE II. According to the result, the LSTM method improve nearly 23% accuracy in predict the tremor signal. Then use the method to the experiment.

TABLE I
METHODS AND PARAMETERS

Method	Model parameters
AR	$p=1$
ARIMA	$p=5, q=1, d=0$
LSTM	Epoch=1000, deep length=4, seq=8, input= (16,1,8)

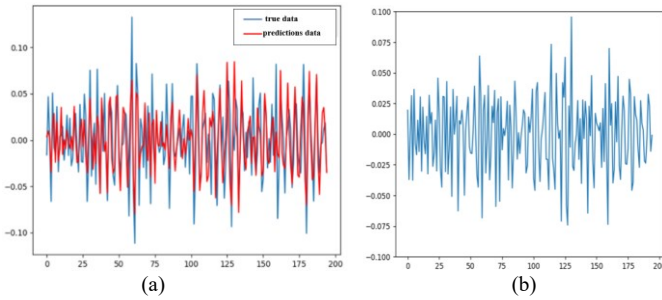


Fig. 6 (a)The true tremor signal data and the prediction tremor data, (b)The prediction error of tremor data with AR.

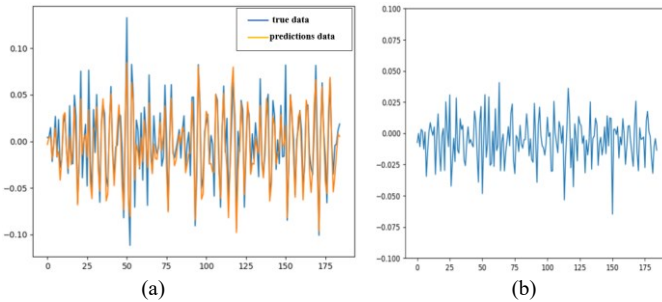


Fig. 7 (a)The true tremor signal data and the prediction tremor data, (b) The prediction error of tremor data with ARIMA.

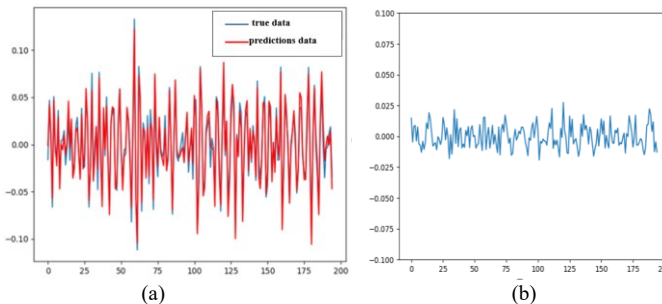


Fig. 8 (a)The true tremor signal data and the prediction tremor data, (b) The prediction error of tremor data with LSTM.

TABLE II
COMPARISON WITH OTHER METHODS

method	% Accuracy
AR	43.32
ARIMA	48.15
LSTM	71.84

Experiment:

Simulation experiments show that the algorithm can predict tremor signals well. The prediction signal is input into the control signal as a compensation signal to achieve the purpose of eliminating tremor. Next, use the VISR system (Fig. 8) to verify the experiment.

Since the operation of vascular interventional surgery is

basically divided into rotational movement (choose the blood vessel at the bifurcation, as shown in the figure) and linear movement (pushing or withdrawing the catheter/guide wire), the actual operation scenarios of these two are simplified to linear movement operation and the fixed-point drawing circle operation. This paper studies the linear motion. The operator holds the joystick, quickly moves in a straight line, records the route taken by the operator's handle and performs data analysis (the device of the joystick is shown in the figure). At the same time, it is required to perform the above-mentioned linear movement before and after 3 minutes of drawing along a specific trajectory with a hand-held fine needle, and volunteers operate to obtain linear data.



Fig. 9 Device of the VISR.

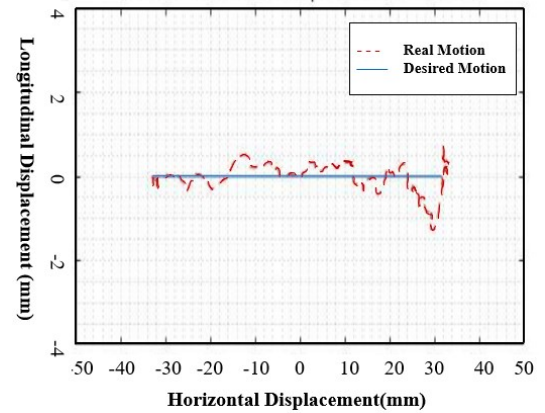


Fig. 10 The linear motion of the VISR.

The red line is the actual motion signal, and the blue line is the signal obtained after adding the suppression algorithm. From the above experimental results, the tremor suppression algorithm in this study has a relatively obvious inhibitory effect in the operator's hand pushing motion.

IV. CONCLUSIONS

In the paper, a multi-step LSTM tremor prediction method based on a moving window is used to improve the accuracy of tremor prediction. Collecting tremor data, and then analyse it through simulation experiments. Then compared with other mainstream algorithms, the results show that the method in this

paper has a better performance. Afterwards, the method was used for vascular intervention for experimental verification. The experimental results show that the proposed method can effectively eliminate the tremor signal.

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