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Study on A Novel Strategy for Eliminating Tremor in Vascular Interventional Robot

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Abstract **–With the development of vascular interventional surgical robots, higher and higher requirements for the safety of surgical robots are put forward. For the master-slave surgical robot, the physical tremor of the doctor's hand will affect the safety of the operation, and may even lead to the failure of the operation if not handled properly. In the process of vascular interventional surgery, involuntary hand tremor may occur due to the doctor's long time hand manipulation. For the identification and filtering of physiological tremor, an improved adaptive Kalman filter algorithm and a new zero-phase filter are used to filter out the wrong operation caused by physiological tremor. Among them, the new zero-phase filter identifies the tremor signal, and the improved adaptive Kalman filter obtains the tremor signal at this moment according to the identified tremor signal at the previous moment, and applies the signal with the same phase and opposite amplitude to the control signal, so as to achieve the purpose of filtering physiological tremor. Two combined functions are used to simulate the doctor's hand tremor signal and operation signal, which superimpose the actual operation signal of the doctor's hand. Through simulation comparison, it is found that the improved adaptive Kalman filter can have better filtering effect than traditional low-pass filtering and traditional Kalman filtering, and can better filter out physiological tremor. The proposed method has significantly improved the safety requirements of vascular interventional surgery robots.**

Index Terms –Adaptive Kalman Filtering, New zero-phase filter, physiological tremor, low pass filtering

I. INTRODUCTION

As a minimally invasive surgery, vascular interventional surgery has been widely used in various cardiovascular and cerebrovascular diseases. At present, there are many types of vascular robots, and the general application scenarios are: treatment, surgery, rehabilitation and rehabilitation care. Today's development of robots has had a huge impact on the medical field, and has become a hot field in the medical field today. Therefore, robots in the medical field are constantly increasing and constantly being updated. Since 1990, a series of vascular interventional surgery robots have been developed. overcome the shortcomings mentioned above and promote the promotion of vascular interventional surgery. Catheter Robotics has developed the Amigo Remote Catheter System, a surgical robotic system for remotely pushing catheters. Corindus developed the CorPath 200 system, the earliest clinical trial of a robotic system for vascular intervention using passive catheter technology[1][2].

The robotic vascular interventional surgery system mainly consists of two parts: the main side and the slave side. The doctor performs surgery on the main side outside the operating room, and the computer collects the surgical information of the doctor on the main side and transmits it to the slave side. The computer replaces the doctor to complete the interventional surgery and avoids the doctor receiving radiation[3].

However, in practical applications, the accuracy of surgery is not only dependent on surgical equipment. The final outcome of a surgery is influenced by many factors, the most important of which is the decision of the surgeon and his careful operation. When the surgeon performs an operation for too long, the shaking of the hand can affect the accuracy of the hand movement, which may lead to misoperation. In order to solve the jitter signal problem caused by hand jitter, an algorithm developed at MIT filters the tremor signal based on a low-pass filter. Because the frequency of tremor signal is between 8-12Hz, low-pass filtering can be used to filter the tremor signal, but there is no obvious FAZHI between tremor signal and actual motion signal，Therefore, the use of low-pass filtering may lead to loss of motion signals. Therefore, this method is only suitable for simple signal filtering, and cannot effectively preserve the motion signal while filtering the tremor signal[4].

In addition, the University of Kansas proposed a third-order AR model based on real-time modeling and prediction to filter tremor signals. However, due to the complex modeling and prediction process, this method is only suitable for real-time tremor signals in small systems. However, the disadvantage of this method is that the linear Gaussian random model is used, which simplifies the mathematical expression of the tremor and cannot describe the essential characteristics of the tremor signal[5].

Yang Chenghao proposed a study on the mechanism of minimally invasive surgical robot tremor and its suppression method. The paper compared most of the existing defibrillation algorithms and found that most of the existing tremor filtering algorithms will There are several common problems：

(1) Time lag is inevitably introduced when designing the filter, which reduces the real-time performance of the system.

(2) The filters based on learning algorithms cannot avoid the training period. Although the effect is excellent, the computer with faster calculation speed is required as the host computer, which leads to high cost.

(3) Cannot handle complex signals with uncertainty.

Based on the above problems, a defibrillation strategy is designed, which uses a novel zero-phase filter and adaptive Kalman filter to achieve the purpose of filtering tremor signals[6].

II. Interventional Surgical Robotic System

The role of vascular interventional surgery robot is to help doctors stay away from radiation and perform interventional surgery by pushing, pulling, rotating and other actions. Therefore, the master-slave operation of the robot is the most practical way. While operating the robot with force feedback, the doctor can have a more realistic feeling. Therefore, the precision and stability of the control system are highly required for the vascular interventional surgical robot. The control block diagram of the laboratory's control system is shown in Figure 1[7][8].

The main end consists of two parts: a catheter manipulator and a guide wire manipulator. The catheter guidewire can be rotated, advanced and retracted by manipulating the catheter guidewire manipulator at the main end. [9]At the same time, the master end has force feedback. When the catheter at the slave end touches the blood vessel wall, the force returned from the slave end will be amplified and then transmitted to the slave end, so that the doctor's hand can feel the resistance. The actual picture of the master terminal is shown in Figure 2(a).

The slave end is made of a guide rail, and a slider and a motor are installed above the guide tube. The signal input from the master end drives the motor to rotate, thereby driving the slider to move forward and backward on the guide rail to realize the advance and retreat of the guide wire of the guide wire. The physical diagram of the slave terminal is shown in Figure 2(b).

This system is the operating principle of the vascular interventional surgery robot of our laboratory platform. The movement of the slave end is realized by operating the master end, so as to achieve the purpose of operating the robot for surgery. During the operation, the tremor caused by muscle tension threatens the safety of the operation, which may cause misoperation and lead to the failure of the operation[10]. The innovation of this paper is to eliminate the periodic jitter caused by muscle tension, and at the same time ensure the safe operation of the doctor as much as possible. In order to eliminate the periodic jitter of the cycle, thereby improving the safety of the operation, ensuring the smooth operation of the operation and the health of the patient. The most basic requirement is that the surgical robot system has the function of signal recognition and shaking, which can accurately identify the shaking part of the main-side signal operation signal. It predicts the jitter signal in the next second, superimposes the signal with the same phase and opposite value to the filtered signal, and then transmits it to the slave end of the surgical robot to achieve the purpose of filtering the jitter signal[8].

The A new type of zero-phase filter is used to identify the jitter signal. The new type of zero-phase filter consists of a high-pass filter and a low-pass filter. Can accurately identify the 8-12Hz signal. For the identified jitter signal, the adaptive Kalman filter is used to perform the optimal estimation at the next moment, and then the signal of the opposite phase and the same amplitude is superimposed on the control signal to achieve the purpose of filtering the jitter signal. The algorithm block diagram is shown in Figure 3 Show[9].

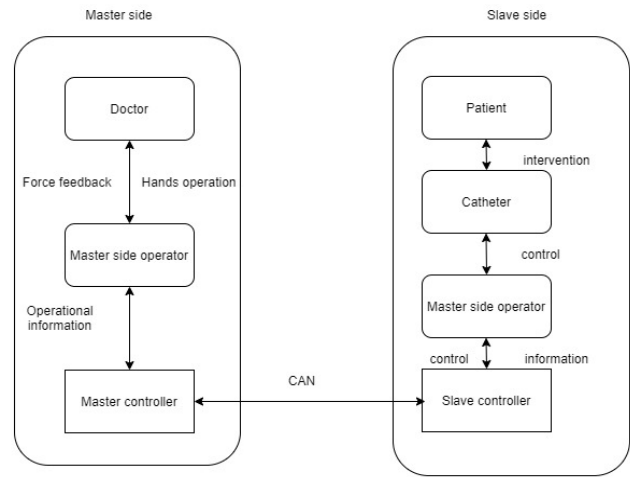
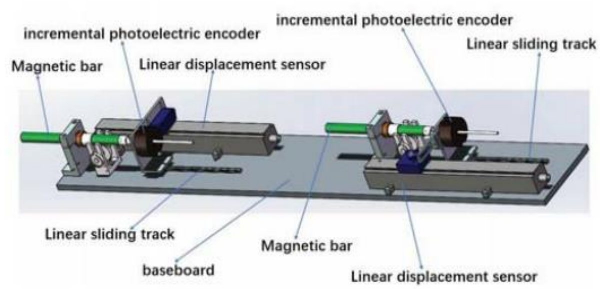
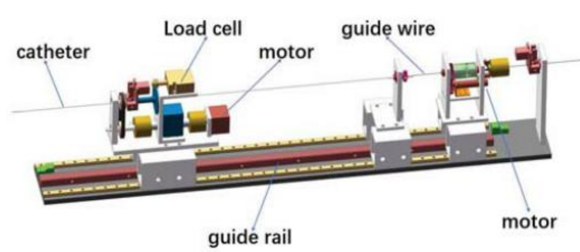


Fig.1 Control System of Vascular Interventional Surgical Robot.



（a） The master structure



（b）The Slave structure

Fig.2 The structure of vascular interventional surgery robot

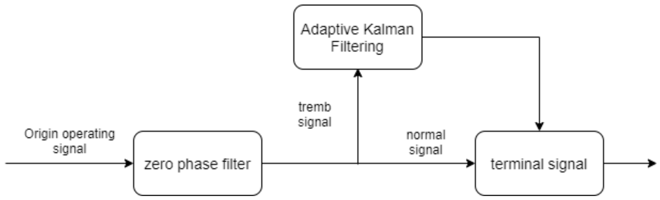


Fig.3 Adaptive Filtering Algorithm Block Diagram

III. Filtering Algorithm

A. Zero phase filter

In the process of proposing the tremor signal, it is only necessary to ensure that there is no phase distortion in the frequency band where the tremor signal is located. According to the foregoing, the zero-phase wave filter only considers the phase change of the signal whose frequency band is distributed in 8-12Hz. The zero-phase filter consists of a traditional high-pass filter and a traditional low-pass filter cascaded. The phase lead caused by the high pass filter can be cancelled by the phase lag caused by the low pass filter. By reasonably designing two filters, the phase distortion in the 8-12Hz frequency band can be controlled to almost zero. The realization principle of the new zero-phase filter is shown in Figure 4[10].

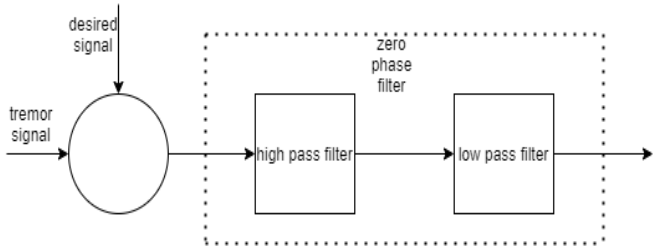


Fig.4 Schematic diagram of the realization of the new zero-phase filter

The high-pass filter filters the lower frequency desired signal and produces a phase lead, and the low-pass filter removes some irrelevant interference and produces a phase lag to cancel the phase lead produced by the high-pass filter. The cascade of the two makes the output tremor signal without phase distortion[14].

B. Kalman filter tremor filtering algorithm

The Kalman filtering process can be divided into a state process and a measurement process:

Status process:

$$X(k) = AX(k-1) = w(k) \tag{1}$$

Measurement process:

$$Z(k) = HX(k) + v(k) \tag{2}$$

In the above formula, X(k) is the state of the tremor signal in the master operator, the state matrix A represents the state change, the vector Z(k) is the signal measurement result, the vector w(k) is the state noise, and the vector v(k) is the measurement noise, in the traditional Kalman filter, we assume that w(k) and v(k) are independent Gaussian white noise with mean zero[11].

That is, w(k) and v(k) satisfy the following conditions:

$$\begin{cases} E[w_k w_i^T] = \begin{cases} Q, i = k \\ 0, i \neq k \end{cases} \\ E[v_k v_i^T] = \begin{cases} R, i = k \\ 0, i \neq k \end{cases} \\ E[w_k v_i^T] = \{0, \forall i.k \end{cases} \tag{3}$$

where Q is the process noise covariance and R is the measurement noise covariance[16].

The filtering process of the Kalman filter is divided into two steps:

Prior estimates:

$$\hat{X}(k|k-1) = A\hat{X}(k-1|k-1) \tag{4}$$

$$P(k|k-1) = AP(k-1|k-1)A^T + Q \tag{5}$$

Measurement update:

$$K(k) = P(k|k-1)H^T[HP(\mathrm{k|k}-1)\mathrm{H^T} + \mathrm{R}]^{-1} \tag{6}$$

$$\hat{X}(k \mid k) = A\hat{X}(k \mid k-1) + K(k)\left(Z(k) + H\hat{X}(k \mid k-1)\right) \tag{7}$$

$$P(k \mid k) = (I - K(k)H)P(k \mid k-1) \tag{8}$$

$\hat{X}(k \mid k-1)$ is the state vector at time k estimated from time k-1, $\hat{X}(k \mid k)$ is the updated state vector at time k based on the estimated state vector, P(k|k-1) is the estimated covariance at time k according to time k-1, P(k|k) is predict the updated time-k covariance from the estimated state vector, K(k) is the Kalman gain at time-k, Q is the process noise covariance, and R is the measurement noise covariance[17].

C. Adaptive Kalman Filtering

The traditional Kalman filter assumes that both the process noise and the measurement noise of the system obey a Gaussian distribution with a mean of 0, that is, Q and R are fixed values. For linear systems, such an assumption is reasonable, but for nonlinear systems, process noise and measurement noise are not strictly Gaussian with mean zero. At this time, if Q and R are regarded as fixed values, the ideal filtering effect cannot be achieved[12].

The simplified Sage-Husa adaptive filtering algorithm is as follows:

$$\hat{\boldsymbol{X}}_{k,k-1} = \boldsymbol{\phi}_{k,k-1}\hat{\boldsymbol{X}}_{k-1} \tag{9}$$

$$\hat{X}_k = \hat{X}_{k,k} = \hat{X}_{k,k-1} + K_k\left(Z_k - H_k\hat{X}_{k,k-1}\right) \tag{10}$$

$$\boldsymbol{P}_{k,k-1} = \boldsymbol{\phi}_{k,k-1}\boldsymbol{P}_{k-1}\boldsymbol{\phi}_{k,k-1}^{\tau} + \boldsymbol{Q}_{k-1} \tag{11}$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{k,k-1}\boldsymbol{H}_k^{\tau}\left[\boldsymbol{H}_k\boldsymbol{P}_{k,k-1}\boldsymbol{H}_k^{\tau} + \hat{\boldsymbol{R}}_k\right]^{-1} \tag{12}$$

$$\begin{aligned} \hat{\boldsymbol{R}}_k = (1-d_k)\hat{\boldsymbol{R}}_{k-1} + d_k\big[(\boldsymbol{I} - \boldsymbol{H}_k\boldsymbol{K}_k)\boldsymbol{\varepsilon}_k\boldsymbol{\varepsilon}_k^{\mathrm{T}} \times \\ (\boldsymbol{I} - \boldsymbol{H}_k\boldsymbol{K}_k)^{\mathrm{T}} + \boldsymbol{H}_k\boldsymbol{P}_k\boldsymbol{H}_k^{\mathrm{T}}\big] \end{aligned} \tag{13}$$

$$\begin{aligned} \boldsymbol{P}_k = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)\boldsymbol{P}_{k,k-1}(\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H}_k)^{\mathrm{T}} + \\ \boldsymbol{K}_k\hat{\boldsymbol{R}}_{k-1}\boldsymbol{K}^{\mathrm{T}}(k) \end{aligned} \tag{14}$$

In the formula, d_k is the forgetting factor, d_k= (1 - b) / (1 - b^{k+1}),0<b<1, P_k is the filter error variance matrix.

Kk in the formula needs to know $\hat{\boldsymbol{R}}_k$, to get $\hat{\boldsymbol{R}}_k$ to know Pk, to get Pk to know Kk.

Therefore, the simplified Sage-Husa filtering algorithm actually has an infinite loop, which increases the calculation amount of the system, and in general, the interference of the system has a certain stability[19]. From the perspective of preventing filter divergence, new observation data should be strengthened. role in the current filter. The motion state of the slider at adjacent moments does not change much, and the outside world does not change much, so it can be considered that the probability distribution of the observed noise at adjacent moments is the same. Therefore, Rk-1 can be used instead of R_k, which can be simplified as the gain matrix Kk in the algorithm becomes:

$$\boldsymbol{K}_k = \boldsymbol{P}_{k,k-1}\boldsymbol{H}_k^{\tau}\left[\boldsymbol{H}_k\boldsymbol{P}_{k,k-1}\boldsymbol{H}_k^{\tau} + \widehat{\boldsymbol{R}}_{k-1}\right]^{-1} \tag{15}$$

After the gain matrix is obtained, the estimation error square matrix and the observation noise can be calculated, so that the problem of infinite loop will not occur. It can be seen from the improved algorithm that $\widehat{\boldsymbol{R}}_{k-1}$ is required to calculate Kk, Pk-1 is required to calculate $\widehat{\boldsymbol{R}}_{k-1}$, and Kk-1 is required to calculate Pk -1. When the initial conditions are known, the algorithm will can be well implemented. The improved Sage-Husa filtering algorithm solves the infinite loop problem in the simplified Sage-Husa filtering algorithm, and the new observation data obtained at each moment is well valued in the filtering at the corresponding moment, Therefore, part of the interference in the system can be effectively eliminated, resulting in more filtering results. Therefore, the adaptive Kalman can effectively solve the problem of filter divergence, thereby making the filtering accuracy more accurate[20].

D. simulation verification

In order to verify the effectiveness of the improved adaptive Kalman filter, Matlab simulation is used for verification. First, we construct a mixed signal to be filtered, which is superimposed and combined by the ideal control signal and the tremor signal. First, we use the following signal to simulate the ideal control signal in the hands of the main operator[21]:

$$y(t) = 20\cos(\pi t) + 10\sin(2\pi t) \tag{16}$$

At the same time, the following signals are used to simulate the tremor signal in the hands of the main operator:

$$n(t) = \cos(22\pi t) + 2\sin(18\pi t) \tag{17}$$

Then, the mixed signal acting on the main operator is the superposition signal of the above two:

$$s(t) = y(t) + n(t) \tag{18}$$

The time domain characteristics of the above three signals are shown in Figure 5, Figure 6 and Figure 7. Meantimes the frequency spectrum of the tremor signal is shown in Figure 8.

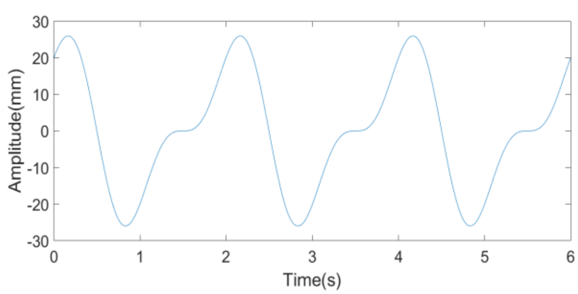


Fig.5 The ideal signal for simulation

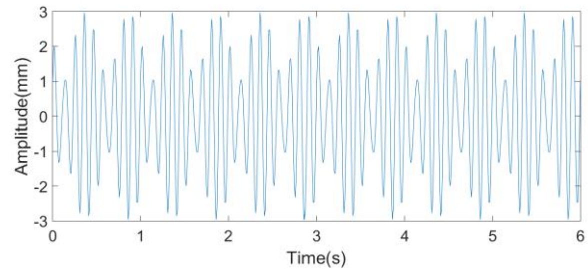


Fig.6 Simulated tremor signal

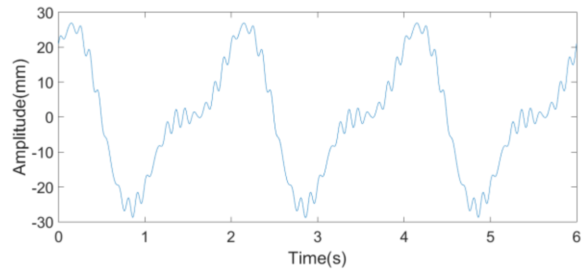


Fig.7 Simulated mixed signal

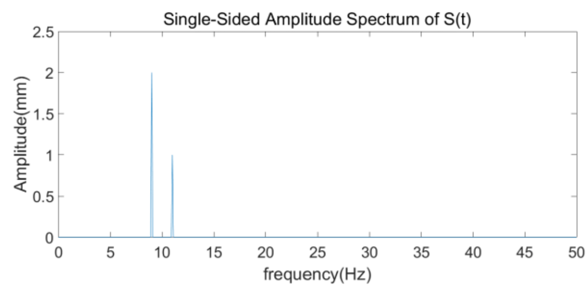


Fig.8 Tremor Signal Spectrogram

It can be seen that the frequency of the simulated tremor signal is between 8-12 Hz, which is in line with the research results of the researchers on the physiological tremor signal of the human hand.

The main advantage of the adaptive Kalman filter algorithm compared with the ordinary low-pass filter algorithm is to solve the problem of obvious time delay and information loss in the ordinary low-pass filter. First, we use a fourth-order Butterworth low-pass filter to filter the mixed signal, and the filtering effect is shown in Figure 9[14]:

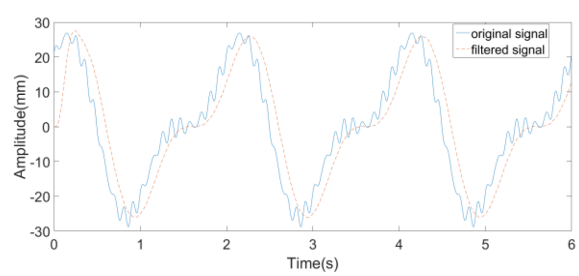


Fig.9 Butterworth low-pass filter before and after comparison

From Figure 9, we can see that the chatter component in the mixed control signal can be effectively filtered out by the Butterworth low-pass filter, but the filtered signal produces loss and obvious time loss compared with the unfiltered signal. Delay. We use the traditional Kalman filter to filter the same signal again, and the comparison chart of the signal before and after filtering is shown in Figure 10.

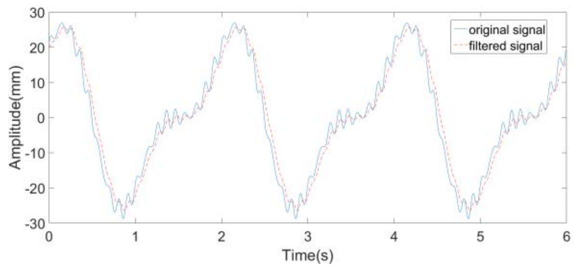


Fig.10 Comparison before and after traditional Kalman filter

As can be seen from Figure 10, the traditional Kalman filter can not only effectively filter out the tremor components in the mixed control signal, but also has a significantly improved time delay compared with the Butterworth low-pass filter. However, in actual surgery, different operators and different surgical environments may correspond to different R constants, so it is unreasonable to set R as a constant in this filter. Next, we use the adaptive Kalman tremor filtering algorithm to filter the same signal above, and the filtering effect is shown in Figure 11.

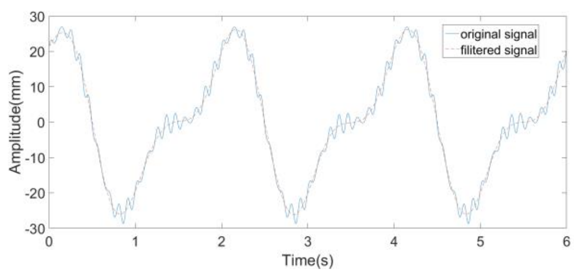


Fig.11 Adaptive Kalman Filter before and after comparison

In order to verify the effect of filtering, the filtered curve and the ideal signal are fitted and compared, as shown in Figure 12:

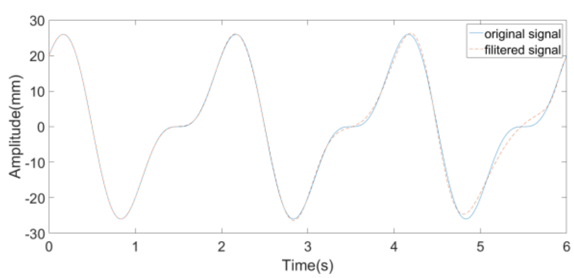


Fig.12 Comparison of Adaptive Kalman Filtering and Ideal Signal Fitting

It can be seen from Figure 12 that the curve after adaptive Kalman filtering is compared with the ideal control signal, and it is found that the fitting degree is very high. It has a good filtering effect and can meet the requirements of surgery. Through the comparison of the above figure, we can find that the filtering effect of the low-pass filter is not very good, which will cause the loss of information and the delay is relatively high. Use the root mean square error between the two signals. To describe the amplitude error between them, the root mean square error of the two signals is 3.81, and the Kalman filter can find that the delay is very low at about 0.035s, which has met the requirements of surgery.

IV. Experiments And Results

A. Experimental set up

To verify the effectiveness of defibrillation, physical experiments were carried out. The experimental equipment is shown in Figure 13. Figure 14 Physical picture of primary operator. During the experiment, we push the main manipulator to make the sensor output signals. Get the signal from the end to move. NDI is used to collect the master and slave displacement. Then the waveform is compared with the acquired displacement.

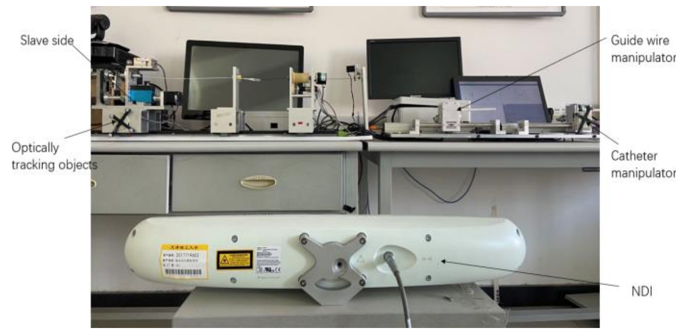


Fig.13 Master slave displacement experiment

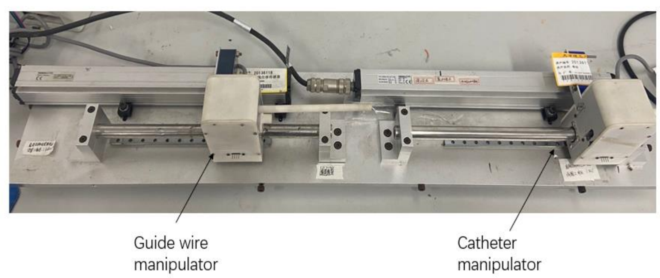


Fig.14 Master manipulator

B. Experimental results

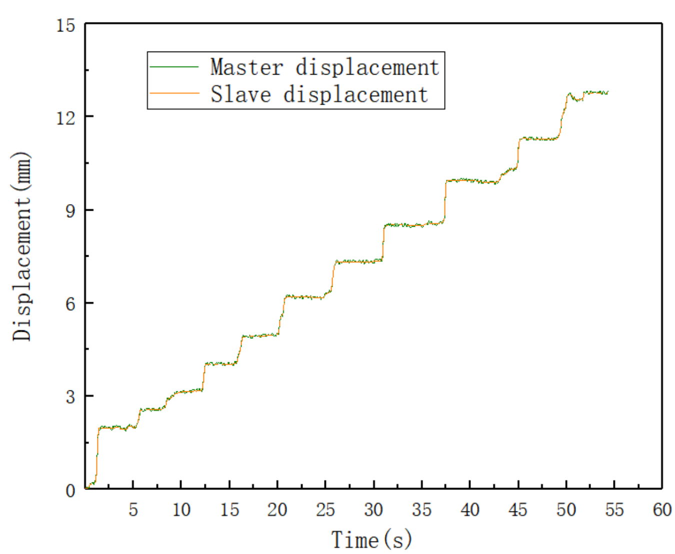


Fig.15 Comparison between master displacement and slave displacement

Figure 15 shows a comparison of the primary end displacement and the secondary end displacement. As can be seen from the figure, the operator will naturally produce a certain physiological tremor in the process of operating the main end operator, which is difficult to avoid. After the adaptive Kalman filter, the tremor signal of the hand is well filtered, and the displacement curve of the slave end operator becomes smoother.

V. CONCLUSION

This paper mainly designed a tremor filtering method, which uses a zero-phase filter to extract the tremor signal, and then uses an adaptive Kalman filter to estimate the tremor signal, so that the tremor signal can be superimposed with opposite amplitudes and the same phase. next moment. Through simulation verification, it is found that this method can effectively filter the tremor signal, and can effectively prevent doctors from misoperation. This is of great significance to the development of vascular interventional surgery. Although it can be seen from the simulation results and experiments that the adaptive Kalman filter can effectively filter the tremor signal, there are still many shortcomings in the current research, and further improvement is needed. At present, only one person has been found to conduct the experiment, and multiple people need to be found for further verification in the future.

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REFERENCE

[1] Yan Zhao, Shuxiang Guo, Yuxin Wang, Jinxin Cui, Youchun Ma, Yuwen Zeng, Xinke Liu, Yuhua Jiang, Youxiang Li, Liwei Shi, Nan Xiao, "A CNNs-based Prototype Method of Unstructured Surgical State Perception and Navigation for an Endovascular Surgery Robot", Medical & Biological Engineering & Computing, pp. 1-4,2019.

[2] Wei Zhou, Shuxiang Guo,, Jin Guo, Fanxu Meng, Zhengyang Chen and Chuqiao Lyu, "A Surgeon`s Habits-Based Novel Master Manipulator for the Vascular Interventional Surgical Master-Slave Robotic System", IEEE Sensors Journal, Print ISSN: 1530-437X Online ISSN: 1558-1748; Vol.22, No.10， pp.9922-9931, DOI: 10.1109/JSEN.2022.3166674, 2022.

[3] S. Guo, C. Yang, X. Bao, and N. Xiao, "A Novel Design of Grasper for the Interventional Surgical Robot," In proceedings of the 2017 IEEE International Conference on Mechatronics and Automation, Vol.402, No.8, pp.22-24,2011.

[4] Cheng Yang, Shuxiang Guo, Xianqiang Bao "An Isomorphic Interactive Device for the Interventional Surgical Robot after In Vivo Study", Micromachines 2022, Vol.13, No.1, DOI: 10.3390/mi13010111, 2022.

[5] Shuxiang Guo, et al, "Design and CharacteristicEvaluation of a Novel Amphibious Spherical Robot", Microsystem Technologies, Vol.23, No.6, pp.1-14,2017.

[6] X. Bao, S. Guo, N. Xiao, Y. Li, and L. Shi, "Compensatory force measurement and multimodal force feedback for remote-controlled vascular interventional robot," Biomedical Microdevices, Vol. 20, No. 3, pp.3-8,2018.

[7] S. Guo, C. Yang, X. Bao, N. Xiao, and R. Shen, "Characteristic Evaluation of a Master-Slave Interventional Surgical Robot Control system," In Proceedings of the 2018 IEEE International Conference on Robotics and Biomimetics, pp.421-425, 2018.

[8] Y. Song, S. Guo, X. Yin, L. Zhang and Y. Wang, "Design and performance evaluation of a haptic interface based on MR fluids for endovascular tele-surgery," Microsystem Technologies, DOI: 10.1007/s00542-017-3404-y, pp. 1-10, 2017.

[9] Yan Zhao, Shuxiang Guo, Nan Xiao, Yuxin Wang, Youxiang Li, Yuhua Jiang, "Operating Force Information On-line Acquisition of a Novel Slave Manipulator for Vascular Interventional Surgery", Biomedical Microdevices, Vol.20, No.2, pp. 10-24,,2018 .

[10] Wang, LM ; Sun, LM ; Luo, WP " Robust constrained iterative learning predictive fault-tolerant control of uncertain batch processes" science china-information sciences, pp. 10-20,2019.

[11] L. Zhang, S. Guo and H. Yu, "Performance evaluation of a strain-gauge force sensor for a haptic robot-assisted catheter operating system," Microsystem Technologies, DOI: 10.1007/s00542-017-3380-2, pp. 1-10, 2017.

[12] Linshuai Zhang, Shuoxin Gu, Shuxiang Guo, Takashi Tamiya, "A Magnetorheological Fluids-based Robot-assisted Catheter/guidewire Surgery System for Endovascular Catheterization", Micromachines, Vol.12, No.6, DOI:10.3390/mi12060640,.2021

[13] Yan Zhao, Huiming Xing, Shuxiang Guo, Yuxin Wang, Jinxin Cui, Youchun Ma, Yu Liu, Xinke Liu, Junqiang Feng, Youxiang Li, "A novel noncontact detection method of surgeon's operation for a master-slave endovascular surgery robot", Medical & Biological Engineering & Computing, Vol.58, No.4, pp.871-885, DOI: 10.1007/s11517-020-02143-7, 2020.

[14] Shuxiang Guo, Yuxin Wang, Yan Zhao, Jinxin Cui, Youchun Ma, Gengsheng Mao, Shunming Hong, "A Surgeon's Operating Skills-based Non-interference Operation Detection Method for Novel Vascular Interventional Surgery Robot Systems," IEEE Sensors Journal, Vol.20, No.7, pp.3879-3891, DOI: 10.1109/JSEN.2019.2960926, 2019.

[15] Modenese L, Ceseracciu E, Reggiani M and David G. Estimation of musculotendon parameters for scaled and subject specific musculoskeletal models using an optimization technique. Journal of Biomechanics, 2015, 49(2):141-148.

[16] Zhou C, Xie L, Shen X. Cardiovascular-interventional-surgery virtual training platform and its preliminary evaluation. The International Journal of Medical Robotics and Computer Assisted Surgery, 2015, 11(3):375-387.

[17] E. Rocon, et al. "Multimodal BCI-Mediated FES Suppression of Pathological Tremor," Annual International Conference of the Ieee Engineering in Medicine and Biology Society, pp.3337-3340, 2014.

[18] Khan E M, Frumkin W, Ng G A, et al. "First experience with a novel robotic remote catheter system: Amigo™ mapping trial," *The Journal of Interventional Cardiac Electrophysiology*, vol.37, no.2, pp.121-129, 2013

[19] Chris J., Paul S., Ma X. "The effect of supporting a surgeon's wrist on their hand tremor," The Journal of Microsurgery, vol.30, no. 7, pp.565-568, 2010.

[20] A. Ghorbanian, M. Zareinejad, S. M. Rezaei, H. Sheikhzadeh, K. Baghestan, "A novel control architecture for physiological tremor compensation in teleoperated systems," The International Journal of Medical Robotics and Computer Assisted Surgery, vol. 9, pp. 280-297, DOI: 10.1002/rcs.1436, 2013.

[21] H. Sang, C. Yang, F. Liu, J. Yun, G. Jin, F. Chen, "A zero phase adaptive fuzzy Kalman filter for physiological tremor suppression in robotically assisted minimally invasive surgery," The International Journal of Medical Robotics and Computer Assisted Surgery, vol. 12, pp. 658-669, 2016.

[22] S. Chandra, M. Hayashibe, A. Thondiyath, "Empirical mode decomposition-based filtering for fatigue induced hand tremor in laparoscopic manipulation," *Biomedical Signal Processing and Control*, vol. 31, pp. 339-349, 2017.