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Tremor Suppression in Robot-Assisted Minimally Invasive Surgery by using of Kalman Filter Adapted by Fuzzy System and Reinforcement Learning

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ABSTRACT

Robot-assisted minimally invasive surgery (RA-MIS) has seen growing adoption in recent years due to its advantages in precision, reduced trauma, and shorter recovery times. A critical challenge in RA-MIS, particularly in remote leader-follower robotic configurations, is the suppression of involuntary hand tremors exhibited by surgeons. These physiological tremors, often induced by fatigue, stress, or prolonged procedures, can significantly impair surgical accuracy. To ensure optimal performance, it is essential to attenuate these unwanted vibrations during surgical tasks. One conventional solution is to model the tremor as an external noise source and apply filtering techniques such as the Kalman filter to isolate and remove the noise. However, since the characteristics of hand tremors are inherently time-varying, static filtering approaches may fall short in dynamic surgical environments. To address this, we propose two adaptive methods for enhancing the Kalman filter: one based on a fuzzy inference system, and another using a reinforcement learning technique Q-learning for real-time updating of the filter's error covariance matrix. Simulation results indicate that both approaches significantly improve tremor suppression by dynamically adjusting to variations in the signal. These adaptive filtering techniques provide a promising solution for increasing precision and stability in robotic-assisted surgical systems.

1. INTRODUCTION

In recent years, robot-assisted minimally invasive surgery (RA-MIS) has gained increasing popularity. In comparison to traditional open surgery, this innovative approach offers numerous advantages for patients, including reduced pain, smaller incision area, minimized damage to tissues, lower blood loss, and shorter recovery and hospitalization times [1-3]. Additionally, for surgeons, it enhances the range of motion, field of vision, and facilitates more skillful execution of tasks. The increasing autonomy of surgical robots allows the delegation of complex tasks such as suturing or knot tying entirely to the robot, thereby reducing the surgeon's workload and fatigue, while

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simultaneously decreasing surgical duration [2]. Despite these advantages, challenges exist in this method, with physiological hand tremor being one of the most significant obstacles.

The hand tremor of a surgeon, arising from fatigue, anxiety, or aging, can lead to tremors in the tip of the surgical instrument, potentially compromising the precision required for delicate tissue manipulation, injection, or suturing [2-3]. It is noteworthy that although involuntary hand tremors may be limited, when scaled to the robotic side, they manifest as amplified motion scaling and joint coupling, ultimately reducing the accuracy of the final executor's movements. Hence, extensive efforts have been made in the technical literature to eliminate physiological hand tremors [3-6].

An essential consideration in this context is that hand tremor exhibits time-varying characteristics [3 and 7]. This physiological tremor, referred to as physiological vibration, varies across different ages, body postures, and individual conditions. Unfortunately, this fact has been overlooked in many studies, potentially leading to inaccuracies and instability in filter-based methods applied to minimally invasive surgical systems. In other words, if we employ a filter to eliminate or suppress involuntary tremor signals from the overall hand movement for achieving precise and intentional surgical motions, it is imperative to recognize that the filter operates optimally when its structural parameters remain constant. However, these parameters need to adapt to changes in physiological conditions of the surgeon's hand and consequently, the alteration in the quality of involuntary tremors. In simpler terms, an adaptive filter is necessary, with parameters that need periodic updates [7-9].

In light of this, this article focuses on designing a vibration suppression system in robotic minimally invasive surgery using a Kalman filter. In this design, the error covariance matrix is not considered constant but instead varies over time based on changes in the tremor signal. The reason for choosing the Kalman filter lies in its optimality in estimating the main signal when contaminated with Gaussian noise. Furthermore, to account for the time-varying conditions of physiological tremor signals, we update the error covariance matrix in the Kalman filter using two approaches. In the first method, a fuzzy inference system is employed to adjust the variance of noise corrupted by the signal (tremor) and then update the error covariance matrix. In the second method, not previously applied in surgical robots for tremor suppression, Q-learning (a reinforcement learning approach) is utilized for the same purpose.

2. PHYSIOLOGICAL TREMOR

Physiological tremor is a phenomenon observed in both healthy individuals and those with observable pathological changes. Three categories of involuntary tremors are of particular importance: physiological, essential, and parkinsonian. Physiological tremor can be described as involuntary oscillations of limbs with sinusoidal characteristics [7]. Physiological tremors typically have a frequency bandwidth of primarily 8-12 Hz, and their range extends up to 50 micrometers, approximated by a combination of sinusoidal waves [3].

The suppression (reduction of amplitude) or elimination of hand tremors is crucial for maintaining precision and achieving desirable performance in minimally invasive surgical procedures. To model motion contaminated by involuntary tremors, according to references [3 and 7], the tremor signal is represented as a linear combination of several sinusoidal waves with higher frequencies but lower amplitudes than intentional movements, approximating within the frequency bandwidth of the latter. Then, this noisy-shaped signal is added to a baseline signal representing intentional hand movement. In our work, as per the modeling in reference [3] (though noting that the tremor frequency is outside the frequency band):

$$d(t) = 3\cos(\pi t), \qquad n(t) = 0.05\sin(20\pi t) + 0.05\cos(22\pi t) \tag{1}$$

where $d(t)$ represents intentional motion signals and $n(t)$ represents involuntary tremor signals. Then, assuming the x-axis as the observed motion direction, the measured motion in that direction can be expressed as:

$$x_m(t) = d(t) + n(t) \tag{2}$$

3. KALMAN FILTER

Now, let's assume that the motion of the tip of the final manipulator is measured in each one of x, y, and z axes using an accelerometer, and the speed and position of the hypothetical point are calculated through numerical integration at sampling intervals with a time step of *T*. Without reducing the generality of the 3-dimensional problem, for simplicity, we focus on measurements and calculations in one dimension here. Then, the equations related to numerical integration for estimating the position of the hypothetical point in the state-space diagram will be as follows:

$$\begin{aligned} &X(k) = AX(k-1) + w(k) \\ &z(k) = HX(k) + v(k) \\ &H = [0 \quad 0 \quad 1], \end{aligned} \quad , \quad A = \begin{bmatrix} 1 & T & 0.5T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}, \quad \begin{aligned} &\mathrm{E}\big[w(k), w(j)\big] = Q_0 \delta_{k,j} \\ &\mathrm{E}\big[v(k)\ ,\ v(j)\big] = R_0 \delta_{k,j} \\ &\mathrm{E}\big[w(k), v(j)\big] = 0 \end{aligned} \tag{3}$$

In these relations, $w(k)$ and $v(k)$ represent the uncertainties in the model and measurement noise, respectively, added to the state equations and outputs. It is assumed that the random variables are Gaussian with a zero mean and are independent of each other. The state vector, denoted as $X = (x\ \dot{x}\ \ddot{x})^t$ includes the position, velocity, and acceleration of the assumed point, along with $z(k) = \ddot{x}$ measured values of its acceleration. Then, according to the Kalman filter, the estimation of the position of the end effector of the robot, which is intended to be obtained by filtering out the unintended vibrations from the surgeon's hand motion, is calculated in two stages.

In the first stage, called "Prediction," using the state equation, the "prior estimate" of the state variable at the next time step, $\hat{X}(k \mid k-1)$, and the covariance of the prior error, $P(k \mid k-1)$ are calculated. In the second stage, known as "Update," the Kalman gain, $K(k)$ is utilized to compute the "posterior estimate" of the state variable, $\hat{X}(k \mid k)$, and the covariance of the posterior error, $P(k \mid k)$.

Prediction stage:

$$\begin{aligned} &\hat{X}(k \mid k-1) = A\hat{X}(k-1 \mid k-1) \\ &P(k \mid k-1) = AP(k-1 \mid k-1)A^t + Q_0 \end{aligned} \tag{4-a}$$

Update step:

$$\begin{aligned} &K(k) = P(k \mid k-1)H^t S(k)^{-1}, \qquad S(k) = R_0 + HP(k \mid k-1)H^t \\ &\hat{X}(k \mid k) = \hat{X}(k \mid k-1) + K(k)\varepsilon(k), \quad \varepsilon(k) = z(k) - H\hat{X}(k \mid k-1) \\ &P(k \mid k) = \ I - K(k)H \ \ P(k \mid k-1) \end{aligned} \tag{4-b}$$

It is worth mentioning that the posterior estimate is essentially a convex *interpolation* between the prior estimate and the measured value.

4. ADAPTIVE KALMAN FILTER

As mentioned in the introduction, physiological tremor is a time-varying quantity, and thus, fixing its variance, denoted as R_0, in the update stage can lead to inaccurate estimates. Although these variations do not adhere to a specific deterministic dynamics, an adjustment must be made in some way: $R(k) = R_0 + \Delta R$, which ΔR, represents the uncertainty in the variance of the expected error from the measurement of intentional hand movement. In other words, the value of R_0 in the Kalman filter process should be considered a time-varying variable, and its changes should be adaptively calculated. If, in the update equations (4-b), we denote $\varepsilon(k)$ and $S(k)$ as the innovations (the error between the new measurement and the prior output estimate) and the innovation covariance, respectively, then, at each step, an approximation for ΔR can be expressed as follows:

$$\Delta R(k) \simeq D_R(k) = S(k) - \hat{\mathrm{C}}\mathrm{ov}(\varepsilon(k)) = R_0 + HP^{-}(k)H^t - \frac{1}{M}\sum_{k-M+1}^{k} \varepsilon(k)^t \varepsilon(k) \tag{5}$$

Wherein, $\hat{\mathrm{C}}\mathrm{ov}(\varepsilon(k))$ here is essentially an estimation of the innovation covariance calculated over a time window with a length of M. Thus, the following adaptive law for updating the on-line estimate of the variance of measurement noise (equivalent to non-intentional tremor) is presented:

$$R(k) = R(k-1) + \Delta R(k) \tag{6}$$

Note that in equation (5), we have found an approximation for ΔR, which we refer to as the deviation, D_R. In other words, there is not necessarily an equivalence between ΔR and D_R, and for further accuracy improvement, one can employ a static mapper such as a fuzzy inference system or a reinforcement learning algorithm like Q-learning to better determine the relationship between these two quantities.

4.1. Fuzzy Inference System

A fuzzy system consists of fuzzyfier, inference engine, rule base, and defuzzifier. Our intention with this system is to map input D_R to output ΔR. Both input and output are linguistically quantified with three fuzzy variables: negative N, zero Z, and positive P, using triangular membership functions, as depicted in Figure 1. The rule base is constructed with three "if-then" rules, as given in (7), and Mamdani inference is employed for reasoning. Finally, the center-of-area method is utilized for defuzzification. According to [10], such a system, leveraging the *interpolation* property, can find the relationship between input and output with a minimal number of fuzzy rules.

$$\begin{aligned} &(1)\text{: if } x \text{ is } N \text{ then } y \text{ is } P,\\ &(2)\text{: if } x \text{ is } Z \text{ then } y \text{ is } Z,\\ &(3)\text{: if } x \text{ is } P \text{ then } y \text{ is } N. \end{aligned} \tag{7}$$

Based on the designed fuzzy system, the removal of the tremor signal from the given time function in equation (2) has been well-executed, and the result is depicted in Figures 2 and 3. The crucial point here is that the design of this fuzzy inference system, including determining input and output membership functions as well as establishing rules, directly relies on the expert knowledge about the system under consideration. Therefore, in the absence of such initial knowledge, alternative methods like reinforcement learning can be employed for a more accurate computation of uncertain quantities.

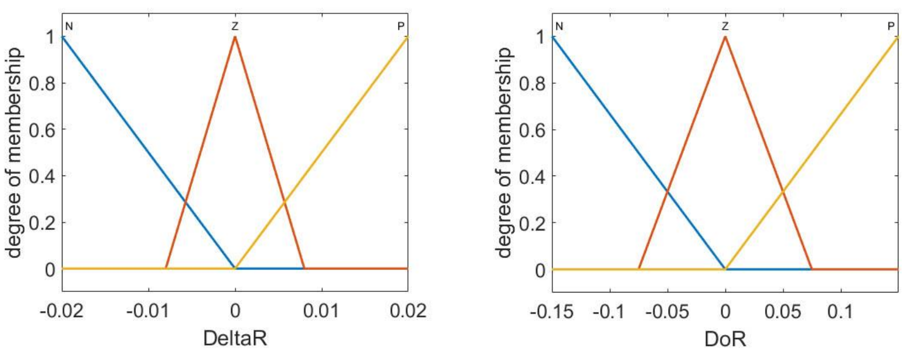

Fig. 1. Fuzzy Adaptive Kalman Filter membership functions.

4.2. Q-Learning Algorithm

Reinforcement learning is a semi-supervised method that, based on the cumulated reward over a sequence of interactions between an "agent" and the "environment," eventually learns the "optimal policy" for selecting the "optimal action" in each "state" taken by the agent. Depending on whether the states and actions of the assumed system are considered discrete or continuous, reinforcement learning methods can be categorized. Q-learning is a method proposed for "discrete state and action spaces," where a table called the "Q-table" is learned. If we assign the rows of this table to states and its columns to executable actions, each cell of this table represents the value of the adopted "state-action pair," corresponding to the row and column of that cell. Additionally, the "value" of a state-action pair is the expected value of the cumulative reward that the agent can obtain after selecting that action in that state at the end of the "episode."

Specifically, in a given time step, if the agent is in state s, takes action a, and after its application, as a result of interaction with the environment, transitions to the subsequent state s', earning an immediate reward of r during this interaction, then the quadruple (s,a,s',r) represents this transition in that time step. The cumulated reward obtained during the course of N time steps until the end of the episode will be discounted by a factor of γ (considered to ensure convergence of the given numerical series within the range $0<\gamma<1$) and is expressed as follows [11]:

$$G_k = r_{k+1} + \gamma r_{k+2} + \gamma^2 r_{k+3} + \dots = \sum_{t=0}^{\infty} \gamma^t r_{k+t+1} \tag{8}$$

Then, the "optimal" value function for the state-action pair is defined as follows:

$$Q^*(s,a) = \max_{\pi} \mathrm{E}\left[\gamma^k r_k \middle| s,a\right] = \mathrm{E}\left[r + \gamma \max_{a'} Q^*(s',a') \middle| s,a\right] \tag{9}$$

where the first equality represents the fundamental definition, and the second equality is a recursive relationship for its computation, known as the "Bellman Optimality Equation." It is evident that we are initially unaware of the values for the state-action pairs, and during the learning process, through multiple iterations and exploration in the environment, we evaluate them. Therefore, with each new experience, the previous estimate of the value function is updated as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \tag{10}$$

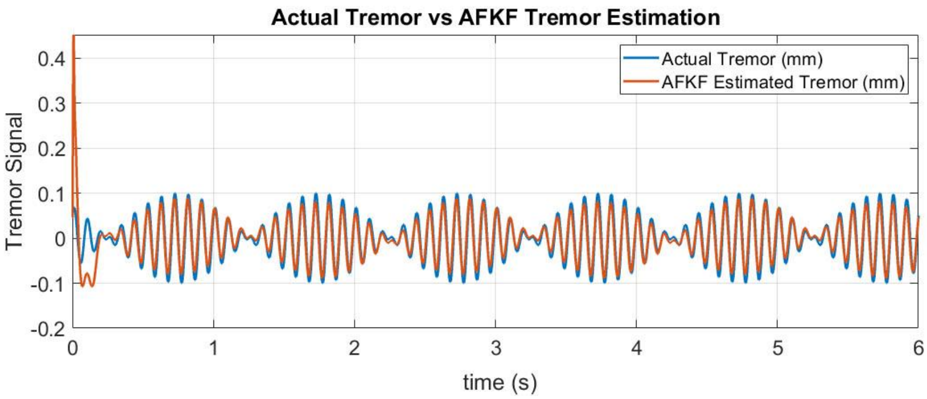

Fig. 2. Performance of the Fuzzy Adaptive Kalman Filter in tremmor signal estimation.

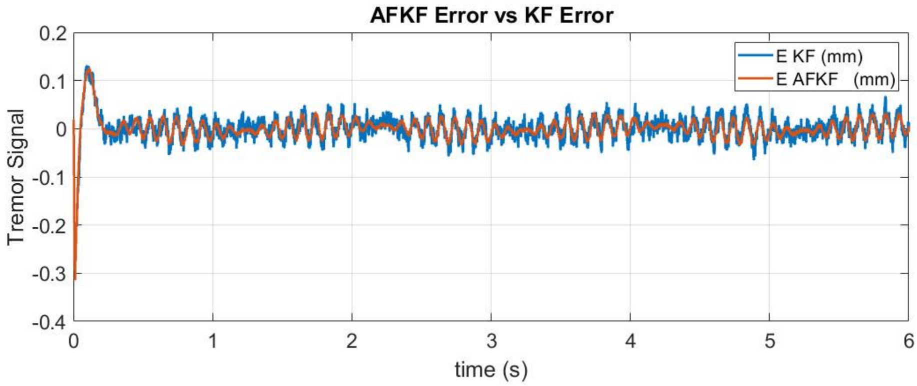

Fig. 3. Comparison between the Kalman filter and Fuzzy Adaptive Kalman Filter in tremmor signal estimation.

With a closer look, we realize that this update law essentially utilizes *interpolation* between the previous estimate and the reward obtained in the new experience. After completing the learning process and converging the Q-table to its optimal values, when adopting the "greedy policy," we have:

$$\pi^*(s) = \operatorname{argmax} Q^*(s,a) \tag{11}$$

Now it is sufficient to define the reward function for the current problem, which is finding the actual value of the vibration variance during surgery. In this problem, according to the reference [9], we consider the "state" as the variance of vibration, $R(k)$, with its possible values discretized within a specified range. The agent, by exploring this discretized space, aims to find the best one for implementing the Kalman filter. In this context, our actions enable "state transitions." Therefore, if they generate discrete state values, the action space consists of 3 movements: staying still a_0, moving one cell to the left a_1, and moving one cell to the right a_2. In other words, these 3 actions correspond to staying unchanged, decreasing by one unit, and increasing by one unit the value of $R(k)$, respectively. Now, the reward received from taking an action is defined as the difference between the calculated predictions in the Kalman filter update stage for the variance values corresponding to the previous and subsequent states during a state transition:

$$r_k = r(s_k, a_k, s_{k+1}) = \varepsilon(R_k) - \varepsilon(R_{k+1}) \tag{12}$$

This means that if the update of the estimate in the Kalman filter for the new state, $s_k = R_{k+1}$, has improved, leading to a reduction in the calculated prediction error, $\varepsilon(R_{k+1})$, then the result of the above difference, or the reward earned in step k, is positive. The results obtained from implementing this reinforcement learning algorithm are shown in Figure 4 and 5.

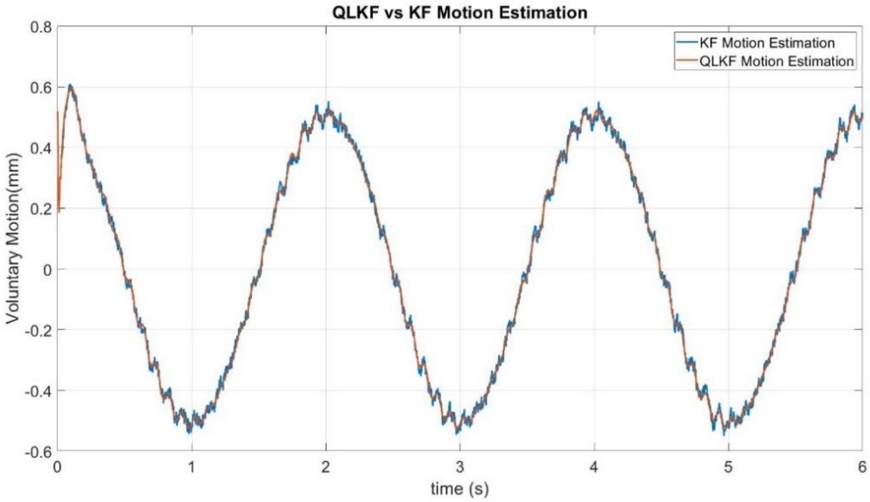

Fig. 4. Performance of the Q-learning Kalman Filter in tremmor signal estimation.

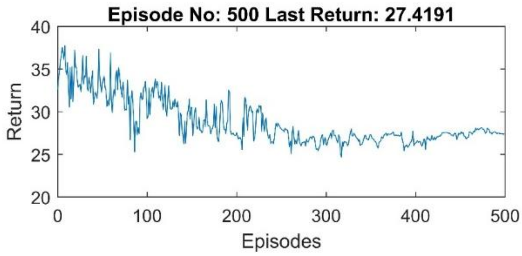

Fig. 5. Temporal Evolution of Cumulative Reward over 500 Iterations.

5. CONCOLUSION

In this paper, we investigated methods for eliminating physiological hand tremors in minimally invasive robotic surgery technology. The Kalman filter was capable of optimally removing this involuntary tremor as noise from intentional hand movements, assuming its variance remained constant and predetermined. However, in physiological tremors, the variance of the tremor is time-varying and cannot be determined at a fixed value during the estimation update phase. Therefore, we introduced an adaptive Kalman filter in which the measurement variance was adaptively adjusted. We employed two methods for this purpose. First, we designed a fuzzy inference system, and due to the availability of prior knowledge, achieved a satisfactory solution for tremor elimination. The second method involved Q-learning, where the agent, through exploration in the state-action space, autonomously reached an optimal policy for estimating tremor variance.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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REFERENCE

[1] Du, Z., Liang, Y., Yan, Z., Sun, L., & Chen, W. (2021). Human-robot interaction control of a haptic master manipulator used in laparoscopic minimally invasive surgical robot system. Mechanism and Machine Theory, 156, 104132. https://doi.org/10.1016/j.mechmachtheory.2020.104132

[2] Su, H., Mariani, A., Ovur, S. E., Menciassi, A., Ferrigno, G., & De Momi, E. (2021). Toward teaching by demonstration for robot-assisted minimally invasive surgery. IEEE Transactions on Automation Science and Engineering, 18(2), 484–494. https://doi.org/10.1109/TASE.2020.3045655

[3] Sang, H., Yang, C., Liu, F., Yun, J., Jin, G., & Chen, F. (2016). 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, 12(4), 658–669. https://doi.org/10.1002/rcs.1741

[4] Zheng, L., & Guo, S. (2021). A magnetorheological fluid-based tremor reduction method for robot-assisted catheter operating system. International Journal of Mechatronics and Automation, 8(2), 72–79. https://doi.org/10.1504/IJMA.2021.115234

[5] Pan, M., Yang, Q., Su, T., Geng, K., & Liang, K. (2022). An effective tremor-filtering model in teleoperation: Three-domain Wavelet Least Square Support Vector Machine. Applied Soft Computing, 130, 109702. https://doi.org/10.1016/j.asoc.2022.109702

[6] Korayem, M. H., & Vahidifar, V. (2022). Detecting hand's tremor using leap motion controller in guiding surgical robot arms and laparoscopic scissors. Measurement, 204, 112133. https://doi.org/10.1016/j.measurement.2022.112133

[7] Liu, Z., Mao, C., Luo, J., Zhang, Y., & Chen, C. P. (2014). A three-domain fuzzy wavelet network filter using fuzzy PSO for robotic assisted minimally invasive surgery. Knowledge-Based Systems, 66, 13–27. https://doi.org/10.1016/j.knosys.2014.03.025

[8] Du, Z., Wang, W., Yan, Z., Dong, W., & Wang, W. (2017). Variable admittance control based on fuzzy reinforcement learning for minimally invasive surgery manipulator. Sensors, 17(4), 844. https://doi.org/10.3390/s17040844

[9] Xiong, K., Wei, C., & Zhang, H. (2021). Q-learning for noise covariance adaptation in extended Kalman filter. Asian Journal of Control, 23(4), 1803–1816. https://doi.org/10.1002/asjc.2336

[10] Nguyen, H. T., Prasad, N. R., Walker, C. L., & Walker, E. A. (2002). A first course in fuzzy and neural control. CRC Press. https://doi.org/10.1201/9781420035520

[11] Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction. MIT Press.