Real-Time Performance Assessment of High-Order Tremor Estimators Used in a Wearable Tremor Suppression Device

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Abstract—The side effects and complications of traditional treatments for treating pathological tremor have led to a growing research interest in wearable tremor suppression devices (WTSDs) as an alternative approach. Similar to how the human brain coordinates the function of the human system, a tremor estimator determines how a WTSD functions. Although many tremor estimation algorithms have been developed and validated, whether they can be implemented on a cost-effective embedded system has not been studied; furthermore, their effectiveness on tremor signals with multiple harmonics has not been investigated. Therefore, in this study, four tremor estimators were implemented, evaluated, and compared: Weighted-frequency Fourier Linear Combiner (WFLC), WFLC-based Kalman Filter (WFLC-KF), Band-limited Multiple FLC, and enhanced High-order WFLC-KF (eHWFCL-KF). This study aimed to evaluate the performance of each algorithm on a bench-top tremor suppression system with 18 recorded tremor motion datasets; and compare the performance of each estimator. The experimental evaluation showed that the eHWFCL-KF-based WTSD achieved the best performance when suppressing tremor with an average of 89.3\% reduction in tremor power, and an average error when tracking voluntary motion of 6.6\%/s. Statistical analysis indicated that the eHWFCL-KF-based WTSD is able to reduce the power of tremor better than the WFLC and WFLC-KF, and the BMFLC-based WTSD is better than the WFLC. The performance when tracking voluntary motion is similar among all systems. This study has proven the feasibility of implementing various tremor estimators in a cost-effective embedded system, and provided a real-time performance assessment of four tremor estimators.

Index Terms—Tremor estimator, tremor suppression technique, pathological tremor, wearable tremor suppression device, hand tremor, assistive device.

I. INTRODUCTION

PATHOLOGICAL tremor impairs the ability of an individual to perform daily activities. The most commonly seen pathological tremors include parkinsonian tremor and essential tremor [1]. Approximately two-thirds of the affected individuals’ lives have been significantly affected [2], not only because of functional disability, but also due to social embarrassment that can lead to social isolation.

Surgical intervention [3] and medication [4] are the traditional treatments for pathological tremor. In addition to the traditional treatments, an emerging tremor management approach has been proposed and studied. This approach suppresses tremor by applying external stimulation, such as mechanical loading [5], [6], [7], [8], [9], [10] and electrical stimulation [11], [12], [13], to the target joints and muscles. Although traditional treatments are the mainstay of treatment for managing tremor, the development of a new approach is considered indispensable given the side effects and complications induced by traditional treatments [14]. Furthermore, nearly a quarter of the affected individuals do not respond to traditional treatments [15]. Therefore, the development of a wearable tremor suppression device (WTSD) could become a promising alternative for individuals whose tremor cannot be managed by traditional treatments.

For a WTSD to be used in daily life, an important requirement is that it should be able to separate the tremor motion from the voluntary motion of the user when performing activities of daily living (ADLs). This is typically performed by using tremor estimation algorithms. Since the frequency of tremor is typically higher than the frequency of voluntary motion, classic filters [7], [16], [17] have been widely adopted to prove the feasibility of suppressing tremor using mechatronic devices. This type of estimator works well on signals with a fixed frequency; however, the frequencies of both voluntary motion and tremor motion are not constant. Furthermore, the phase delay and amplitude attenuation present in this type of estimator further limit its use in a WTSD.

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Considering the drawbacks of the aforementioned filters, it is important to include adaptability to the design of a tremor estimator. Riviere et al. [18] proposed a Weighted-frequency Fourier Linear Combiner (WFLC) that is similar to an adaptive notch filter that regulates its notch frequency and notch depth according to the input tremor signal. Although the use of a gradient descent-based algorithm allows the WFLC to track the amplitude and frequency of tremor motion with no phase shift [19], it can only adapt to a single-harmonic signal without degrading its performance [20], [21].

To improve the tremor estimation performance of the WFLC, Veluvolu et al. proposed a Band-limited Multiple Fourier Linear Combiner (BMFLC) [22]. The BMFLC estimates signals with multiple frequencies by incorporating multiple Fourier Linear Combiners (FLCs) [23]. Each FLC tracks a signal with a specific frequency, and the signal of interest can be reconstructed using the combination of the outputs of all FLCs. In spite of its recognized performance in tremor estimation, the drawbacks of the BMFLC include the need for acquiring the frequency of the signal of interest, sensitivity to noise [24], and a high number of weight variables. Upon the realization of the drawbacks of the BMFLC, Veluvolu et al. proposed a double adaptive version [25], Wang et al. proposed an adaptive sliding BMFLC [24], Atashzar et al. proposed an enhanced-BMFLC [26], and Mengiç proposed an adaptive FLC based on modified least mean Kurtosis algorithm [27] to improve the performance of the conventional version. All of these modified BMFLCs possess the advantages of the original one, and incorporate adaptive methods for selecting the frequency band.

The WFLC-based algorithms estimate the tremor signal using a truncated Fourier series with prior knowledge of the input signal, i.e., tremor, to estimate the gradient of the mean square error. In contrast, the Kalman filter (KF) computes the optimal solution by minimizing the covariance of the a posteriori estimation error [28] without any a priori assumption. Based on this principle, Zhou et al. [29] have proposed and evaluated an enhanced high-order WFLC-based KF (eHWFLC-KF), in computer simulation, for tremor estimation. The evaluation showed that the eHWFLC-KF achieved better performance than its lower-order counterpart, since parkinsonian tremor consists of multiple frequencies [24], [30]. Furthermore, research on using the KF and its derivative algorithms [21], [31], [32] has shown improved accuracy in tremor estimation compared to gradient descent methods.

The recent explosion of research in artificial intelligence has also facilitated the development of tremor estimation techniques. Several studies have been proposed to estimate tremor signals based on neural networks [33], [34]. Although these estimators have shown promising results, there is not enough evidence to demonstrate that these estimators provide better performance when estimating tremor than the non-neural-network-based estimators, let alone their high requirements for computational power.

The functionality of a WTSD requires it to be compact and light, and its control system to be implemented on a cost-effective embedded system instead of a large-scale computer system that is bulky and power intensive. Although the estimators mentioned above have shown outstanding tremor estimation performance, their suitability for implementation on a cost-effective embedded system has not been studied, since they were only assessed in computer simulation. Therefore, it is important to evaluate these estimators in real time to ensure their functionality and safety prior to testing on humans. Furthermore, most of the existing tremor estimators were evaluated only on single-harmonic tremor signals, their effectiveness for tremor signals with multiple harmonics has not been investigated.

In view of the identified gaps in the literature, this paper presents an evaluation of the real-time tremor suppression performance of a WTSD implementing the eHWFLC-KF, the WFLC, the BMFLC, and the low-order WFLC-KF. To accomplish this goal, 18 recorded tremor datasets that contain multiple tremor harmonics were used to evaluate and compare the performance of these tremor estimators for the WTSD. Testing of the eHWFLC-KF and the other tremor estimators on a cost-effective embedded system provides a realistic evaluation of the use of these estimators on a real-time tremor suppression system and assesses the feasibility and safety of these systems prior to implementation on humans. Furthermore, it yields an important reference for the design of future WTSDs and the choice of an appropriate tremor estimator.

II. TREMOR ESTIMATORS

In this section, the eHWFLC-KF [29] and three commonly used tremor estimator algorithms are briefly introduced. The WFLC [18] was chosen to provide the baseline performance as it has been used widely in the literature. In addition, the BMFLC [22] was chosen as it has been proven to achieve outstanding performance when estimating tremor in a simulation study, with accuracies greater than 96%. Lastly, the WFLC-KF [29] was chosen to be compared with the eHWFLC-KF as a lower-order counterpart. Although the aforementioned BMFLC-based algorithms presented in [24], [25], and [26] have been proposed to solve the drawbacks of the conventional BMFLC, no statistical proof has been found to show a significant improvement in the tremor suppression ratio in these BMFLC-based algorithms (89.1%–93.8%) over the conventional BMFLC (95.9%). Furthermore, their proposed feature of adaptively selecting a tremor frequency band is unnecessary in this application, as the frequency band of pathological tremor is well determined and fairly constant [29], [35]. Therefore, these BMFLC-based algorithms were not used in this study.

A. Weighted-Frequency Fourier Linear Combiner

The WFLC algorithm [18] is an adaptive extension of the FLC with the ability to track different frequencies. Unlike the FLC, which estimates signals with fixed frequency, the WFLC uses the least mean square algorithm to estimate the frequency of a time-varying signal. Practically, the WFLC is frequently used in conjunction with the FLC. In this cascade structure, the WFLC estimates the frequency of the signal of interest, and forwards it to the FLC to construct the estimated...
The discretized algorithm used in this study is given in Eqs. 1–6.

\[ x_r(k) = \begin{cases} 
\sin \left( r \sum_{j=0}^{k} \omega(j) \right), & r \in [1, M] \\
\cos \left( r-M \sum_{j=0}^{k} \omega(j) \right), & r \in [M+1, 2M] 
\end{cases} \]

(1)

\[ \epsilon(k) = s(k) - p(k)^T x(k) \]

(2)

\[ \omega(k+1) = \omega(k) + 2\nu \epsilon(k) \sum_{r=1}^{M} r (p_r(k) x_{M+r}(k) - p_{M+r}(k) x_r(k)) \]

(3)

\[ p(k+1) = p(k) + 2\gamma x(k) \epsilon(k) \]

(4)

\[ \hat{p}(k+1) = \hat{p}(k) + 2\gamma(k) x(k) \epsilon(k) \]

(5)

Here, \( x(k) = [x_1(k), \ldots, x_{2M}(k)]^T \) is the state vector of the WFLC. \( p(k) = [p_1(k), \ldots, p_{2M}(k)]^T \) is the amplitude weight vector of the WFLC. \( r \) is the index of each vector. \( \omega(k) \) is the estimated time varying frequency of the estimated signal. \( \epsilon(k) \) is the error between the output of the WFLC, i.e., the estimated signal, and the input signal \( s(k) \). \( M, \nu, \gamma \) and \( \gamma \) are the order of the Fourier series, the frequency adaptation gain, and the amplitude adaptation gain of the WFLC. \( \hat{p}(k) = [\hat{p}_1(k), \ldots, \hat{p}_{2M}(k)]^T \) is the amplitude weight vector of the FLC. \( \hat{\epsilon}(k) \) is the error between the estimated tremor signal \( \hat{p}(k)^T x(k) \) and the input signal. Lastly, \( \gamma \) is the amplitude adaptation gain of the FLC.

### B. Band-Limited Multiple-Fourier Linear Combiner

The BMFLC [22] is a nonadaptive derivative of the FLC. In practice, it is often configured to have a large number of FLCs with a fixed frequency interval. The discretized algorithm used in this study is given in Eqs. 7–9.

\[ x^a_q(k) = \begin{cases} 
\sin \left( 2\pi f_0 + \frac{2\pi q}{G(k)} \right), & q \in [1, N] \\
\cos \left( 2\pi f_0 + \frac{2\pi q-N}{G(k)} \right), & q \in [N+1, 2N] 
\end{cases} \]

(7)

\[ \epsilon^a(k) = s(k) - p^a(k)^T x^a(k) \]

(8)

\[ p^a(k+1) = p^a(k) + 2\gamma x^a(k) \epsilon^a(k). \]

(9)

Here, \( x^a(k) = [x^a_1(k), \ldots, x^a_{2N}(k)]^T \), \( p^a(k) = [p^a_1(k), \ldots, p^a_{2N}(k)]^T \), \( q \) is the index of each vector. \( f_0 \) represents the initial frequency of the frequency band of interest, \( 1/G \) represents the frequency interval, \( N \) represents the length of the frequency band, and \( \epsilon^a(k) \) is the error between the estimated tremor signal \( p^a(k)^T x^a(k) \) and the input signal \( s(k) \). Note that the superscript “a” is used to distinguish the BMFLC parameters from the ones introduced for the WFLC and the eHWFLC.

### C. eHWFLC-Based KF and the WFLC-Based KF

The eHWFLC-KF [29] consists of an eHWFLC that independently extracts the frequency of each tremor harmonic, and a KF that constructs the estimated tremor using the estimated frequencies of the tremor harmonics and the input signal. The discretized eHWFLC is given in Eqs. 10–13.

\[ x^b_u(k) = \begin{cases} 
\sin \left( \sum_{j=0}^{k} \omega^b_u(j) \right), & u \in [1, L] \\
\cos \left( \sum_{j=0}^{k} \omega^b_{u-L}(j) \right), & u \in [L+1, 2L] 
\end{cases} \]

(10)

\[ \epsilon^b(k) = s(k) - p^b(k)^T x^b(k) \]

(11)

\[ \omega^b_u(k+1) = \omega^b_u(k) + 2\nu (u) e^b(k) \left[ p^b_u(k) x^b_{L+u}(k) - p^b_{L+u}(k) x^b_u(k) \right], \quad u \in [1, L] \]

(12)

\[ p^b(k+1) = p^b(k) + 2\gamma x^b(k) e^b(k). \]

(13)

Here, \( x^b(k) = [x^b_1(k), \ldots, x^b_{2L}(k)]^T \), \( p^b(k) = [p^b_1(k), \ldots, p^b_{2L}(k)]^T \), \( v = [v_1, \ldots, v_L]^T \) is a vector of the frequency adaptation gain, \( \Sigma = \text{diag} \{ \gamma_1, \ldots, \gamma_L, \gamma_1, \ldots, \gamma_L \} \) is a diagonal matrix of the amplitude adaptation gain, \( e^b(k) \) is the error between the estimated tremor signal \( p^b(k)^T x^b(k) \) and the input signal \( s(k) \), \( \omega^b_u(k) \) is the estimated time varying frequency of the estimated signal, \( L \) is the number of the tremor harmonics, and \( u \) is the index of each vector. Note that the superscript “b” is used to distinguish the eHWFLC-KF parameters from the ones introduced for the WFLC and the BMFLC.

Assuming that the tremor signal can be approximated by a 3rd order Fourier series, the state transition matrix \( (U(k)) \) can be given as follows:

\[ U(k) = \begin{bmatrix} U_1(i) & 0 & 0 \\
0 & \cdots & 0 \\
0 & 0 & U_L(k) \end{bmatrix} \]

\[ U_u(k) = \begin{bmatrix} \cos(S(k)) & \sin(S(k)) / S(k) \\
-\sin(S(k)) & \cos(S(k)) \end{bmatrix}, \quad u \in [1, L], \]

\[ S(k) = 2\pi f_u(k) T_s \]

(14)

where \( f_u(k) = \sum_{j=0}^{k} \omega^b_u(j) / (kT_s) \) is the estimated frequency of a tremor’s \( u^{th} \) harmonic from the eHWFLC and \( T_s \) is the sampling time. Since the eHWFLC-KF is an enhanced higher order version of the WFLC-KF, the eHWFLC-KF can be used as a conventional WFLC-KF when the estimator order \( L \) is set to 1.

Table I presents the parameters values that were used for each algorithm considered in this study. The parameters of the WFLC were chosen according to the value ranges reported in [18] and [23] with fine adjustments to achieve the simulated tremor suppression performance reported in these studies as closely as possible. The parameters of the BMFLC were chosen according to the values reported in [22], and the bandwidth of the BMFLC was selected according to the tremor frequency reported in [29]. Last but not least, the values of the WFLC-KF and the eHWFLC-KF were chosen according
to the values reported in [29] with fine adjustments to achieve the simulated tremor suppression performance as close as possible to the results reported in that study. Note that the measurement noise covariance was obtained by estimating the average covariance of the noise characteristics of the sensor. In addition, a white-noise acceleration model was used to determine the process noise covariance [28], [36]. This model assumes that tremor motion has a constant acceleration change between each two consecutive samples.

### III. EXPERIMENTAL PLATFORM AND PROTOCOL

In this section, the development of a bench-top mechatronic tremor simulator and a tremor suppression system are presented, together with the experimental protocol, data processing, and statistical analysis methods.

#### A. Experimental Setup and Patient Motion Data

To assess the performance of the aforementioned four algorithms when used in a WTSD, a wearable tremor suppression glove (WTSG) that was developed in our previous study [37] (Fig. 1) was used as the test object in the experiment. In addition, the experimental setup (Fig. 2) consists of a bench-top mechatronic tremor simulator that reproduces recorded motion datasets from individuals with parkinsonian tremor. The mechatronic simulator was constructed in the shape of the human hand, such that the WTSG could be attached. The experimental setup was constructed such that the performance of the WTSG when following the voluntary motion and when attenuating the tremor motion could be assessed. These motions are reproduced by the simulator using different algorithms.

A total of 18 motion datasets recorded from 18 individuals with parkinsonian tremor [29] were used in this experiment. These motion data were collected using inertial measurement units (IMU) in the format of angular velocity. The total MDS-UPDRS rating value of their tremor, *i.e.*, Items 3.15–3.18, was 8.72 ± 2.47. Each motion dataset consists of three subsets, as follows:

- **Resting tremor (Subset A):** data were collected when the participant was instructed to maintain the arm in the rest position on a table.
- **Postural tremor (Subset B):** data were collected when the participant was instructed to keep the hand outstretched at approximately 45° above the table level.
- **Kinetic tremor and voluntary motion (Subset C):** data were collected when the participant was instructed to pinch a lightweight object with the thumb and the index finger, then move it from the hand outstretched position to the rest position.

The recorded signals from the metacarpophalangeal (MCP) joint of the participants’ index fingers were reproduced on a bench-top mechatronic tremor simulator (Fig. 2, #7, #8, and #10). The simulator consists of a 3D printed hand...
model (#10), a brushless DC motor (#8, MaxonMotor®, EC-max 16, Sachseln, Switzerland) with a planetary gearbox (29:1) and an incremental encoder (256 pulses per turn), and a motor controller (#7, MaxonMotor®, EPOS2 24/2, Sachseln, Switzerland). The shaft of the BLDC motor is connected directly to the finger joint of the hand model to generate motion in the joint. A velocity PID controller was constructed and tuned to reproduce the recorded motion with the motor using LabVIEW software (Version 2019, NI) on a PC (HP® laptop Probook 440G3, Core i7, CPU @ 2.5 GHz Windows 10) [38]. The measured average control error of the simulator was 4.7% with a maximum error of 7.2%.

Fig. 2 presents the key components of the WTSD that were used for suppressing tremor in the index finger MCP joint. They consist of a 3D printed glove frame (#1 in Fig. 1 and 2), a brushless DC motor (#2, MaxonMotor®, EC-max 16, Sachseln, Switzerland) with a planetary gearbox (29:1) and an incremental encoder (256 pulses per turn), a motor controller (#3, MaxonMotor®, EPOS2 24/2, Sachseln, Switzerland), a motion controller (#4, EC-max 16, Sachseln, Switzerland), a communication converter (#5), a microcontroller (#6, LPC1768, NXP Semiconductors®, Eindhoven, Netherlands), an inertial measurement unit (#9, LSM9DS1, ±2000°/s angular rate scale, 16-bit resolution, STMicroelectronics®, Geneva, Switzerland). The tremor simulator was securely fixed onto an optical table (SmartTable®, Sachseln, Switzerland), a communication converter (#5), a microcontroller (#6, LPC1768, NXP Semiconductors®, Eindhoven, Netherlands), and an inertial measurement unit (#9, LSM9DS1, ±2000°/s angular rate scale, 16-bit resolution, STMicroelectronics®, Geneva, Switzerland). The tremor simulator was securely fixed onto an optical table (SmartTable®, Sachseln, Switzerland), a communication converter (#5), a microcontroller (#6, LPC1768, NXP Semiconductors®, Eindhoven, Netherlands), and an inertial measurement unit (#9, LSM9DS1, ±2000°/s angular rate scale, 16-bit resolution, STMicroelectronics®, Geneva, Switzerland). The tremor suppression system was attached to the tremor simulator. In this study, the data collected from the pitch axis of the gyroscope of the IMU was used as the input to the microcontroller (#6).

The diagram of the control flow of the entire system is presented in Fig. 3. Considering that the MCP joint and the BLDC motors produce angular motion, in this study the angular velocity was chosen as the control variable instead of linear acceleration, in order to avoid an additional conversion from angular motion data to linear motion data. The angular velocity reproduced on the 3D hand model is sampled by the main controller through the IMU. The sampled signal is first sent to the tremor estimator to generate the estimated tremor signal. This estimated tremor signal is then subtracted from the sampled signal to produce the estimated signal of the voluntary motion. Lastly, the estimated signal of the voluntary motion is used as the direct input to Motor Controller 2, which controls the actuation system of the WTSD to follow the voluntary motion of the 3D hand model while suppressing the tremor motion.

B. Post-Trial Data Processing and Data Analysis

The angular velocity measured from the IMU was transferred to the PC through serial communication using a custom-built software interface. The interface was developed to obtain, transfer, and store data from the IMU to the PC at a frequency of 50 Hz. Herein, the 18 motion datasets recorded from individuals with parkinsonian tremor are defined as the original datasets, the motion datasets recorded from the current experimental setup are defined as the measured datasets.

Both post-trial processing and analysis of the experimental data were performed in MATLAB (R2019a, The Mathworks, Inc.). Before calculating quantitative metrics, a 2nd order zero-phase Butterworth bandpass filter (filtfilt function) with passband frequencies of 3 Hz to 18 Hz was used on both the original dataset and the measured dataset to extract the tremor signals, and a 2nd order zero-phase Butterworth bandpass filter with passband frequencies of 0.1 Hz to 2 Hz was used to extract the voluntary motion signals.

The following quantitative metrics were calculated to evaluate the tremor suppression performance of the WTSD, while following the voluntary motion, using the different tremor estimators:

- The tremor power suppression ratio (TPSR) [6] is defined as the percentage difference between the power of the tremor motion of the 3D hand model and the power of the original tremor motion. The tremor power is calculated by adding the power of the signal between 3 Hz and 18 Hz [29].
- The error when tracking voluntary motion (ETVM) is calculated as the root mean square error (RMSE) between the angular velocity of the original voluntary motion and the measured angular velocity of the 3D hand model.
- The correlation coefficient is calculated using the filtered voluntary motion from both the measured dataset and the original dataset.
- The time delay is calculated as the time shift between the measured signal and the original signal.
- The computational complexity is the amount of time and space required to execute the algorithm based on the input size. The time complexity is measured by considering the elementary operations in each iterative step, and the space complexity is measured by calculating the memory space required for the algorithm. Herein, the big O notation [39] is used to describe both the time and space complexities.

C. Statistical Analysis

The performance of the four tested estimators was compared using statistical analysis methods. The processed data were first analyzed for normality using the Shapiro-Wilk test. It was found that the correlation coefficient and the time delay are not normally distributed. For the normally distributed data, between-group comparisons were performed using multivariate analysis of variance (MANOVA) with a Bonferroni correction. For the nonnormally distributed data, a Kruskal-Wallis test with a Bonferroni correction for multiple comparisons was used. The α was set to 0.05 and an 80% power was used. The IBM Statistical Package for the Social
Fig. 4. Time series and frequency distribution of one original resting tremor motion collected from one individual with parkinsonian tremor (red) and the suppressed motion outputs of the WTSD (blue) using different algorithms. “a”, “b”, “c”, and “d” represent the motion collected from the WTSD using the WFLC, the BMFLC, the WFLC-KF, and the eHWFLC-KF, respectively.

Sciences (SPSS Statistic v24) statistics software was used to perform all statistical analyses.

IV. RESULTS AND DISCUSSION

This paper describes an experimental evaluation of a WTSD using four different tremor estimators on a bench-top mechatronic tremor simulator. The performance of each system was compared with the other systems. The intention was to evaluate the real-time performance of tremor suppression using these tremor estimators on a WTSD to ensure their functionality and safety prior to the testing on individuals with tremor. The implementation and online evaluation of the eHWFLC-KF and the other tremor estimators on a cost-effective embedded system is an important advancement towards the safe implementation of a WTSD for humans; in addition, this study is novel insofar as most of the existing studies implemented and evaluated the performance of these estimators in offline software simulation, on large-scale computer systems. The use of tremor signals with multiple harmonics has proven the effectiveness of using these estimators on signals with multiple frequencies. The results obtained from this study provide direct evidence to support the use of these estimators on humans and provide a realistic reference for the design of future WTSDs and the selection of an appropriate tremor estimator.

A. Tremor Suppression Performance

The tremor suppression performance was evaluated on three types of tremor: resting tremor, postural tremor, and kinetic tremor.

Fig. 4 presents the original tremor (red curve) and the suppressed tremor (blue curve) of a sample resting tremor dataset in both the time and the frequency domains. In each figure, rows “a”, “b”, “c”, and “d” present the results of the WFLC, BMFLC, WFLC-KF, and eHWFLC-KF, respectively. Both the original tremor and the suppressed tremor are shown in the form of angular velocity in the time domain (left column).

It can be seen in the left columns of Fig. 4 that tremor motion (red curves) is present throughout the recording and it is evident that the profiles of the suppressed tremor (blue curves) are narrower than the profile of the original tremor for all four algorithms. Furthermore, the comparison of the power spectrum density between two tremor signals (right column) indicates a clear reduction in the power of the suppressed tremor signal. The suppressed tremor motion is lower in amplitude in the systems that had employed BMFLC (b) and eHWFLC-KF (d) than the others. Similar results can be found in the power spectrum density analysis.

The distribution of the TPSR of the resting tremor, the postural tremor, and the kinetic tremor are given in Fig. 5. The average value and the standard deviation (SD) are given in Table II. The MANOVA test was performed between each pair of algorithms. In Fig. 5, a statistically significant difference ($p < .05$) is labeled by a “*”, and a statistically highly significant difference ($p < .001$) is labeled by a “***”. The statistical analysis showed that the eHWFLC-KF has higher TPSRs than the WFLC and the WFLC-KF for all three types of tremor. Although the TPSR of the eHWFLC-KF for suppressing resting tremor is higher than the BMFLC, the differences of the postural tremor and kinetic tremor are not significant. In addition, the BMFLC has higher TPSRs than the WFLC for all three types of tremor, and it has higher
TSR than the WFLC-KF only for the resting tremor. Lastly, the WFLC-KF has higher TSRs than the WFLC for all three types of tremor.

The comparison between the eHWFLC-KF-based system and the other systems when suppressing resting tremor reveals that the eHWFLC-KF-based system suppresses more tremor than the other three systems as indicated by Fig. 5. Although both the WFLC-KF and the eHWFLC-KF share the same estimation principle, the eHWFLC-KF achieved significantly better tremor suppression performance. This is likely because most of the parkinsonian resting tremor (17 out of 18 datasets) contains multiple harmonics [29], and the eHWFLC-KF covers more tremor harmonics than the WFLC-KF. Similarly, since the BMFLC has a wider tremor frequency bandwidth than the WFLC and the WFLC-KF, the BMFLC-based system also achieved better suppression of resting tremor than the WFLC and the WFLC-KF ($p < .05$).

As for the performance when suppressing postural tremor, both the eHWFLC-KF and the BMFLC achieved higher TSRs than the WFLC, and only the eHWFLC-KF achieved higher TSR than the WFLC-KF. Interestingly, no significant difference was found between the TSRs of the eHWFLC-KF and the BMFLC. This is likely because only 11 out of 18 postural tremor datasets present multiple harmonics [29]. The absence of the higher tremor harmonics reduces the significance of the higher-order components in both algorithms, hence the difference between the performance of each algorithm is reduced. Similar results were also obtained when comparing kinetic tremor suppression. There was no significant difference found between the TSRs of the eHWFLC-KF and the BMFLC.

To show the performance of each algorithm when suppressing tremor with different intensity levels, Fig. 6 illustrates the relationship between the TSR and the power of the original tremor signal. The $x$ axis shows the common logarithm of the power of the original tremor from all three data subsets (A, B, and C). The $y$ axis shows the TSR. For each algorithm, the data from all 18 datasets are indicated in the figure with markers along with a first-order polynomial fit of the acquired data.

To identify any differences in the performance of each algorithm when suppressing tremor with different levels of power, the entire TSR dataset that was acquired from each algorithm was separated into two groups by the median value of the power of the original tremor. The common logarithm of the power of the original tremor ranges from 1.91 to 5.78, with a median value of 4.12, and a mean value of 4.18. The data within the range of 1.91 to 4.12 were categorized into the “Low Tremor Power” group, and the data within the range of 4.13 and 5.78 were categorized into the “High Tremor Power” group. Subsequently, the MANOVA test was performed to compare the two groups for each algorithm.

Fig. 7 presents the estimated marginal means of each set of comparisons. A significantly higher value was obtained from the High Tremor Power group for the eHWFLC-KF algorithm, which is indicated by a “***” in Fig. 7. No significant difference was obtained from the comparison of the other algorithms.

Fig. 6 clearly presents a hierarchical structure with the eHWFLC-KF-based system having the highest overall TSR, and followed by the BMFLC, the WFLC-KF, and the WFLC. Interestingly, the linear fit of the data obtained from the eHWFLC-KF-based system shows a noticeable increasing trend with the tremor power, while the WFLC-based system shows a decreasing trend; however, the statistical analysis only showed a significant difference between the groups with different tremor power for the eHWFLC-KF-based system. These findings may indicate that the eHWFLC-KF-based system is more effective in suppressing severe tremor than mild tremor. This is likely because most of the tremor datasets with high power contain multiple harmonics, which would lead to a better performance for the eHWFLC-KF-based system when suppressing tremor with high power. As for the other algorithms, the WFLC does not cover a wide frequency range. Although the BMFLC covers a wide frequency range, this algorithm does not guarantee a minimized covariance of the $a$ posteriori estimation error as a KF does. Furthermore, its performance is highly dependent on the number of FLCs ($N$ in Eq. (7)) and the frequency interval (1/$G$ in Eq. (7)). In contrast, the WFLC-KF computes the optimal solution using a KF, however, it does not cover a wide frequency range. Therefore, the pros and cons of these algorithms did not result in outstanding differences in the tremor suppression...
B. Performance When Tracking Voluntary Motion

The time series of the ETVM collected from one sample dataset tested with different algorithms. “a”, “b”, “c”, and “d” represent the motion collected from the WTSD using the WFLC, the BMFLC, the WFLC-KF, and the eHWFLC-KF, respectively.

![Fig. 8. Time series of the ETVM collected from one sample dataset tested with different algorithms.](image)

Performance with different levels of severity. To achieve better tremor suppression, the eHWFLC-KF should be considered as the first candidate for use in a WTSD.

Although this study has presented several interesting findings, an inherent limitation is the use of recorded tremor motion on a single-axis bench-top simulator. This simulation results in higher experimental repeatability compared to that expected from human trials; however, it may not fully resemble the actual tremor, which often contains multiple degrees of freedom. [1A5-3] Furthermore, while BLDC motors have high efficiency and are relatively easy to control, the lack of mass–spring components in the simulator mechanism means that it cannot accurately simulate human joint impedance, which is an essential feature in human joint dynamics.

C. Computation Comparison

![Fig. 9. Distribution of the ETVM of different algorithms. No significant difference was found between each pair of algorithms.](image)

To quantify the performance of each algorithm when following voluntary motion, Fig. 9 presents the quantitative distribution of the ETVM. The MANOVA test was performed to compare each algorithm. There is no significant difference found in the ETVM between the eHWFLC-KF and any other algorithms. In addition, the mean ETVM of each estimator is under $10^2/\text{s}$, which may be acceptable as a safe tracking error when these systems are used on humans if additional safety precautions are also implemented to prevent hyperextension of the joints. Although all four systems have similar mean values in ETVM, the BMFLC and the eHWFLC-KF-based systems have lower variability compared to the other two. The mean and SD values are given in Table II.

Fig. 10 shows the distribution of the correlation coefficient between the filtered voluntary motions from the original dataset and the measured dataset. Every algorithm resulted in a mean correlation coefficient greater than 0.9. The Kruskal-Wallis test shows that both the WFLC and the WFLC-KF have higher correlation coefficients than the BMFLC, and that there is no significant difference between the eHWFLC-KF and any other algorithm. The mean and SD values are given in Table II.

If the performance of tremor suppression was not considered as the highest priority design requirement, compared to the performance when tracking voluntary motion, either the BMFLC or the eHWFLC-KF can be considered as a promising candidate for use in a WTSD; however, the correlation coefficient (Fig. 10) obtained from the BMFLC-based system is significantly lower than the WFLC and the WFLC-KF, while no difference was found between the eHWFLC-KF-based system and any of the other systems. Therefore, the eHWFLC-KF-based system may achieve better performance when following voluntary motion than the BMFLC. Note that both systems have high correlation coefficients (greater than 0.9). Whether the difference in the correlation coefficient between each pair of systems is clinically important should be further investigated during human trials.

Lastly, the parameter values used for each algorithm were chosen according to the literature. Although the reported tremor suppression performance supports the selection of these parameters, the values were not optimized to minimize tremor in the current experimental setup. As such, parameter optimization should be considered for the future development of WTSs.

D. Computation Comparison

Algorithm analysis is an important tool to compare the efficiency of algorithms [40]. It can also be used to develop more efficient algorithms by studying and identifying the costly steps of an algorithm. The running time is often an essential resource for a system [40], especially for a WTSD that requires the run time of its tremor estimator to be significantly shorter than the tremor cycle. Therefore, it is important for a WTSD to minimize the time delay of its algorithm in order to suppress tremor in real time. In addition to the time complexity, the space complexity is another essential factor to be considered.
when designing a tremor estimator for a WTSD; however, this factor is less essential than the time complexity as a more powerful controller can be selected and/or additional memory can be incorporated into the system.

A complexity comparison between algorithms is provided in Table III by comparing the time and space complexities of the algorithms. The computational comparison shows that the WFLC and the BMFLC have the lowest time and space complexities, which are $O(m^2)$ and $O(m)$, respectively, while the time and space complexities of the WFLC-KF and the eHWFLC-KF are one magnitude higher than the others. The higher computational complexities in the KF-based algorithms are mainly caused by the use of matrix multiplication operations [39]. This issue will likely become more problematic, especially for the time complexity, when multiple eHWFLC-KFs are used in a WTSD to suppress tremor in multiple joints. Therefore, to reduce the time complexity of the KF-based algorithms, a Coppersmith–Winograd algorithm [41] can be used to optimize the matrix operation. With the use of the Coppersmith–Winograd algorithm, the time complexity of both the KF-based algorithms can be reduced from $O(m^3)$ to $O(m^{2.375})$.

Although both the WFLC-KF and the eHWFLC-KF have the same complexity, in practice their performance may differ when they are implemented on an embedded system and run in real time. Specifically, the higher dimensions of the vectors and matrices used in the eHWFLC-KF may result in a larger time delay between the time when a tremor motion is measured and when the actuator responds. This delay includes the time that the microcontroller takes to compute the command value, the communication time between the microcontroller and the motor controller, the electromechanical delay of the motor, and the data collection time from the IMU to the microcontroller. The distribution of the time shift (time delay) between the measured voluntary motion and the original voluntary motion from Subset C is shown in Fig. 11. The mean and SD values are given in Table II. The Kruskal-Wallis test on the time delay did not show a significant difference between any of the systems (Fig. 11); however, if the comparison had greater statistical power, the WFLC-based system is expected to have less time delay than the WFLC-KF and the eHWFLC-KF since the computational complexity of the WFLC is one order of magnitude lower than these two algorithms.

Unlike the other metrics, the time delay is an inherent drawback of any tremor estimator as it does not predict motion ahead of time; therefore, a WTSD that uses a tremor estimator will likely produce some level of unwanted force on the user’s joint(s). Although this impact can be mitigated by increasing the sampling frequency, such an approach likely requires more computational resources and may increase the cost of the system. To find a solution to this issue, an artificial intelligence-based tremor predictor could be considered. Lastly, considering the limitations of WTSDs for human use, a producer of these devices needs to identify and balance the tradeoff between algorithm performance and computational resources. Although the current study investigated the computational complexity of the algorithms, the relationship between algorithm performance and computational power was not studied.

### V. Conclusion

This paper presented the implementation of four tremor estimators on a WTSD, the real-time evaluation of these tremor estimators on a bench-top mechatronic tremor simulator with 18 reproduced parkinsonian tremor datasets, and the comparison of their performance with each other. The novelty of the presented study is the implementation of the eHWFLC-KF and three other tremor estimators on a cost-effective embedded system, while most of the existing studies implemented and evaluated the performance of these estimators in offline simulation, on large-scale computer systems. This study also proved the effectiveness of using these estimators on signals with multiple frequencies by testing these estimators with tremor signals with multiple harmonics. The results obtained serve to better inform the design of future WTSDs.

The experimental evaluation showed that the eHWFLC-KF-based WTSD achieved the highest average TPSRs for the resting tremor (91.1%), postural tremor (91%), and kinetic tremor (85.7%). Statistical analysis showed that its performance when suppressing tremor is significantly better than the WFLC and WFLC-KF, while more data are required in order to find a significant difference with the BMFLC. The BMFLC-based WTSD is better than the WFLC. It was also found that the eHWFLC-KF-based WTSD suppresses severe tremor better than mild tremor. In addition, no significant difference was found in the ETVM or in the correlation coefficient between the eHWFLC-KF-based WTSD and the others. Note that the correlation coefficient of the BMFLC-based system is significantly lower than the WFLC and the WFLC-KF.

The computational complexity of a tremor estimator determines the feasibility of it being implemented in a fully portable WTSD. The calculation of the time and space complexities showed that the eHWFLC-KF and the WFLC-KF is one order of magnitude higher than the other two algorithms. It was identified that the use of a Coppersmith–Winograd algorithm can largely reduce the time complexity of the KF-based algorithm to a similar level as the BMFLC.

In summary, the implementation of the eHWFLC-KF in a WTSD, and its evaluation on a real-time bench-top
experiment, has shown its promising performance for suppressing pathological tremor; however, its performance when tracking voluntary motion does not exceed that of the other algorithms. Furthermore, the computational complexity of the eHWFLC-KF is higher than the other algorithms. These quantitative assessments on a bench-top setup have highlighted the pros and cons of implementing the eHWFLC-KF on a WTSD in real time; however, a decision on whether the overall performance of this algorithm exceeds the others when used on human subjects may require a quantitative assessment of the end-users performing functional tests when wearing the WTSD, such as the Action Research Arm Test, along with their qualitative feedback.

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