Advancing Muscle Monitoring and Intervention: Wearable Ultrasound for Tremor Frequency Measurement and Real-Time Tissue Displacement Analysis

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***Abstract*—Precise monitoring of tremor frequency and tissue displacement (TD) is essential for developing effective non-invasive tremor suppression methods. This study presents a wearable ultrasound (WUS) array designed for continuous, real-time muscle monitoring. The WUS features a 32-element, 1-3 PZT-5H composite array with a center frequency of 7.22 MHz and a -6 dB fractional bandwidth of 52.74 %, optimized for capturing high-resolution ultrasound signals from target muscles like the flexor carpi radialis (FCR). Experiments with Parkinson's disease (PD) patients for tremor frequency detection and TD measurements demonstrated that the WUS system accurately identified tremor frequencies and tracked muscle displacement. These results suggest that WUS can provide a reliable, non-invasive alternative to commercial ultrasound systems, offering continuous muscle monitoring for improved tremor management and intervention strategies.**

***Index Terms*—ultrasound transducers, wearable transducers, muscle activities detection, functional electrical stimulation, tremor management, machine learning**

I. Introduction

Tremors, characterized by involuntary muscle oscillations, particularly in the hands and arms, affect more than 11 million individuals in the United States [1]. These involuntary movements significantly impair daily activities. Current interventions for tremor management include pharmacological treatments, neurosurgical procedures, and external assistive devices. However, each approach has inherent drawbacks: medications often lead to adverse side effects, surgical interventions are invasive and costly, and external devices are frequently limited by their size, weight, and lack of portability. Recent research has demonstrated that both functional electrical stimulation (FES) [2] and afferent stimulation (AS) [3] can be effective alternatives for tremor suppression, without the limitations associated with traditional methods. Unlike FES, which targets muscle activation, AS specifically engages afferent neural pathways using lower stimulation intensities. This reduced intensity makes AS less likely to induce muscle fatigue, presenting it as a more promising and sustainable approach for tremor management. However, the efficacy of AS in tremor suppression remains inconsistent across different studies and clinical applications. A major challenge lies in the absence of a standardized approach to AS strategies, making it difficult to optimize treatment protocols. This variability highlights the need for precise sensing technologies that can accurately capture tremor dynamics and provide real-time feedback for closed-loop control systems [4]. Effective tremor suppression necessitates continuous monitoring of both tremor frequency and target muscle tissue displacement. Tremor frequency is crucial for determining the optimal timing of AS in-

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terventions, while precise measurement of tissue displacement provides valuable insights into muscle movement dynamics, facilitating accurate modeling for AS. This real-time data is essential for informing and adjusting stimulation parameters to achieve optimal therapeutic outcomes.

Commonly employed techniques, such as inertial measurement units (IMUs) and electromyography (EMG), present significant drawbacks. IMUs primarily capture limb displacement, offering limited information on muscle-specific tremor frequency, while EMGs suffer from interference when recording in the presence of active afferent stimulation, necessitating interruptions in AS delivery during data acquisition. Ultrasound (US) imaging has emerged as a promising alternative due to its ability to provide direct, real-time visualization of muscle activity without the interference issues that hamper EMG. However, traditional US probes are rigid and bulky, making them impractical for wearable applications that require continuous, unobtrusive monitoring during movement.

However, conventional US probes are rigid and cumbersome, making them unsuitable for wearable applications that require continuous, unobtrusive monitoring during movement. Thus, there is a critical need to develop wearable, non-invasive sensing technologies, such as wearable ultrasound (WUS) systems, that can provide detailed insights into muscle dynamics and facilitate the design of more effective AS strategies for tremor management. The objective of this study is to assess the feasibility of using a WUS array for tremor monitoring and suppression. Specifically, we aim to validate the WUS array's capability to accurately identify tremor frequency and TD, both of which are essential parameters for closed-loop tremor suppression systems. To our knowledge, this is the first study to investigate the application of WUS technology in this context.

The key contributions of this work are: (1) the development and validation of a novel WUS array; (2) identification of tremor frequency in Parkinson's disease (PD) and essential tremor (ET) using IMU, commercial B-mode US, and A-mode US with WUS, to demonstrate the potential of wearable US for tremor frequency identification; and (3) acquisition of flexor carpi radialis (FCR) muscle TD using the WUS array combined with a machine learning model.

II. Materials and Methods

A. Transducer design and fabrication

We selected a center frequency of 7.5 MHz to achieve the necessary penetration depth for monitoring arm muscle activity. Each element of the linear ultrasound transducer array is composed of a piezoelectric composite, with PZT-5H as the active pillar material and epoxy serving as the passive filler. To minimize the effects of grating lobes and ensure optimal image quality, the array was designed with a pitch of 0.16 mm, which is less than the wavelength in water. The kerf width was set at 0.03 mm. The array's elevational aperture measures 5.5 mm, while the azimuthal aperture is 10.2 mm. A quarter-wavelength matching layer was implemented to match the acoustic impedance between human tissue and the transducer array. Alumina powder (particle size: 0.05 m) mixed with epoxy was used for the matching layer, and a 0.5 mm-thick backing layer made from E-solder 3022 was applied.

To fabricate the 1-3 piezoelectric composite, a dicing-and-filling method was employed using a dicing machine (DAD322, DISCO, Japan) with a 30 m-thick blade to create kerfs at a 160 m pitch. Once the 1-3 composite was formed, the kerfs were filled with an epoxy solution. After curing, Cr/Au electrodes, with thicknesses of 50 nm and 200 nm, respectively, were deposited on both sides of the composite using an electron beam evaporator (Thermionics, US). The composite was then diced again at a 160 μm pitch to form the individual elements of the linear array, each measuring 130 μm by 5.5 mm. A custom flexible printed circuit (FPC) was bonded to each array element using an epoxy adhesive (EpoTek 301, Epoxy Technology). The FPC was then connected to a PCB converter board for integration with the Verasonics system. The structure and photographs of the WUS are shown in Figure 1.

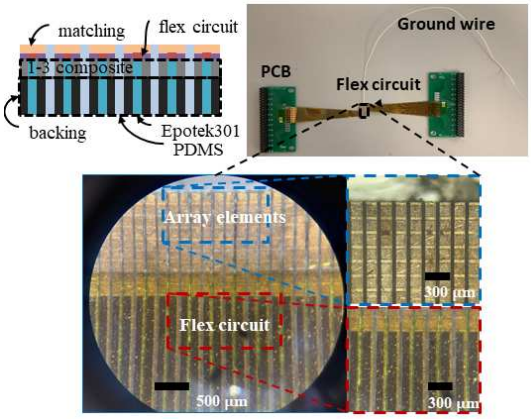

Fig. 1. Structure and Photographs of the WUS Array

B. Transducer characterizations

The performance of the proposed transducer was evaluated using pulse-echo and electrical impedance testing. A pulse-echo test was conducted to assess the bandwidth and center frequency of all 32 elements of the WUS array. Each element was excited using a pulser-receiver unit (5900 PR, Olympus, WA, USA) with a pulse repetition frequency (PRF) of 200 Hz and a pulse energy of 1 μJ. The echo signals were captured through a bandpass filter ranging from 3 to 20 MHz, with a steel bar serving as the reflector. The resulting radio-frequency (RF) signals were recorded using an oscilloscope (DSO7104B, Agilent Technologies, Santa Clara, CA, USA). From the captured pulse-echo signals, the bandwidth and center frequency of the fabricated elements were determined. Additionally, the electrical impedance, capacitance, and loss for each element were measured using an impedance analyzer (4294A, Keysight Technologies, Santa Rosa, CA, USA).

C. Experimental Setup for Tremor frequency and tissue displacement monitoring

1) Subjects: The experimental protocol was reviewed and approved by the Institutional Review Board (IRB) at North Carolina State University. Two subjects, one diagnosed with PD and the other with ET, were recruited for the study. Informed consent was obtained from all participants prior to the commencement of any experimental procedures.

2) Experimental protocols: The subjects were seated comfortably in a chair. A linear US transducer (L7.5SC Prodigy Probe, S-Sharp, Taiwan) connected to a US imaging system (Prodigy, S-Sharp, Taiwan), along with the WUS array linked to the Verasonics US system (Vantage 256, Kirkland, USA), were affixed to the participants' forearm, targeting the FCR muscle. Additionally, IMU sensors (Yost Labs Inc., USA) were attached to their hands. The participants were instructed to perform a cup-holding task for 1 minute. B-mode US from the commercial system, IMU signals, and radiofrequency (RF) US signals from the WUS array were recorded and synchronized using a real-time system (Real-Time Target Machine, Speedgoat, Liebefeld, Switzerland). The experimental setup is illustrated in Figure 2.

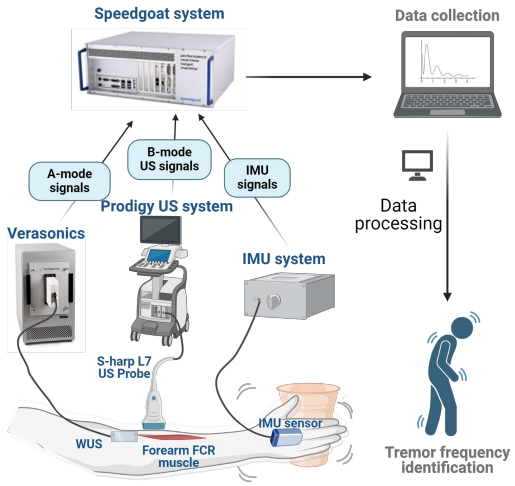

Fig. 2. Experimental setup for tremor monitoring with WUS array, commercial US, and IMU sensors.

3) Tremor Frequency identification from B-mode US, IMU, and WUS Data: RF US signals were collected at 100 Hz using the Verasonics system. To identify the tremor frequency from the RF data acquired by the WUS, the data were first converted into M-mode images. These images were then analyzed across all 32 channels. For each channel, a Fast Fourier Transform (FFT) was performed to generate the frequency spectrum of the tissue movement. The magnitude spectrum was examined to identify the dominant frequency within the tremor range of 4 to 12 Hz, based on existing studies [5]. The maximum magnitude within this range, along with its corresponding frequency, was recorded for each channel. By averaging the results across all 32 channels, the tremor frequency was determined by focusing on the channel with the highest magnitude, providing an accurate method for quantifying tremor frequency from the WUS RF data.

B-mode US images were captured at 1 kHz using the Prodigy US system, equipped with an NVIDIA Titan V GPU. A GPU-based speckle tracking algorithm [6] was applied to these images to measure tissue motion associated with tremor activity. Similar to the RF data, an FFT was performed on the tissue motion data to extract the frequency spectrum of the tremor behavior. In addition, IMU signals were collected at 1 kHz, specifically targeting the FCR muscle. Given the muscle's involvement, the yaw angular velocity data from the IMU was selected for frequency analysis. A similar FFT-based approach was used to analyze the IMU data and determine the tremor frequency.

4) Tissue Displacement Estimation via Machine Learning Using WUS and B-mode US: In the previous section, we estimated the FCR muscle TD using a speckle tracking algorithm applied to B-mode images obtained from the commercial US system. Following this, we applied US feature extraction to the RF data acquired from the WUS array. The feature extraction process adhered to methodologies established in studies [7], [8]. A brief summary of this procedure is provided, as the full details are available in the referenced works and will not be repeated here. For the machine learning model, the extracted US features from the WUS served as inputs, while the tissue displacement values obtained from the B-mode commercial US system were used as the output.

The dataset was divided, with 70 % utilized for model training and the remaining 30 % split evenly between testing and validation. A neural network consisting of 10 layers was trained using a Bayesian regularization approach [9], implemented via MATLAB's Neural Network Fitting Toolbox (R2023b, MathWorks, MA, USA). The process of analyzing and processing the RF US data, along with the machine learning model framework, is illustrated in Figure 3.

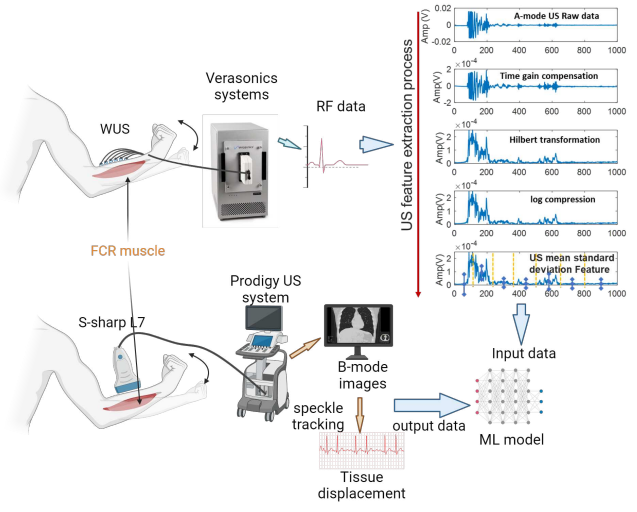

Fig. 3. Workflow of RF data processing and machine learning model for tissue displacement estimation

III. Results

A. Transducer characterizations

The transducer characterization was performed using pulse-echo and electrical impedance tests. In this section, we present the experimental results to validate the completeness and accuracy of the developed system. The WUS exhibited an average center frequency of 7.22 MHz, a -6 dB fractional bandwidth of 52.74 %, and a peak-to-peak voltage of 12.38 mV. Moreover, the electrical impedance test yields an average capacitance of 50.44 pF, an average loss of 12.85 mU at 1 kHz, and an average impedance of 391.59 Ω at 7.5 MHz. The system, including the cable and printed circuit board, weighs 16.5 g, making it lightweight and suitable for wearable applications.

B. Tremor frequency and tissue displacement sensing

For tremor frequency identification, the dominant frequencies obtained from the IMU, B-mode US, and WUS for both PD and ET patients were consistent, as illustrated in Figure. 4. Notably, the WUS results aligned well with both the IMU and B-mode US measurements, demonstrating the WUS system's ability to overcome limitations such as the non-muscle specificity of IMU and the complex beamforming required for B-mode US.

For TD estimation, we collected 6,000 samples of RF data from the PD patient, with the corresponding TD values derived from the commercial B-mode US system. As shown in Figure 5, the neural network fitting results demonstrated strong performance, with an R value of 0.903 on the training set, indicating a high correlation between predicted and actual TD values. The model also showed reasonable performance on the validation and test sets, achieving R values of 0.749 and 0.769, respectively. The overall R value of 0.860 indicates good generalization across the entire dataset, confirming the effectiveness of the model in estimating real-time tissue displacement.

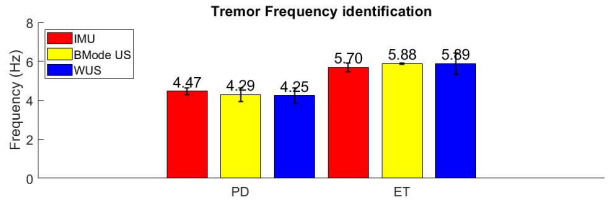

Fig. 4. Comparison of dominant tremor frequencies identified from IMU, B-mode US, and WUS for PD and ET patients

IV. Conclusion

This study demonstrated the feasibility of using a WUS System for tremor frequency identification and TD estimation. The WUS array was validated against IMU and commercial B-mode US systems, showing consistent results for tremor frequency in both PD and ET patients. Additionally, a machine learning model trained with RF data from the WUS

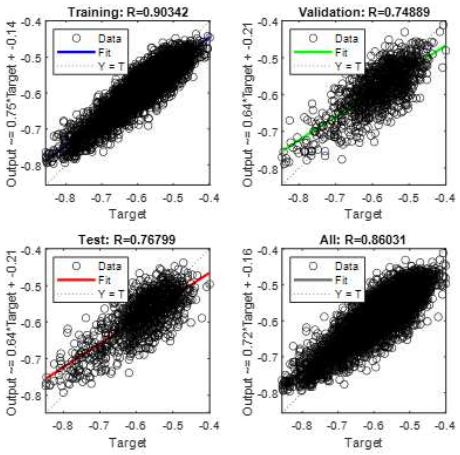

Fig. 5. Comparison of dominant tremor frequencies identified from IMU, B-mode US, and WUS for PD and ET patients

successfully estimated TD, achieving high correlation with B-mode US-derived measurements. Future work will focus on investigating additional parameters and expanding the subject pool to improve the model's accuracy and generalizability. Further exploration of integrating the WUS with closed-loop control systems will be conducted to enable real-time tremor suppression, paving the way for more effective and personalized therapeutic interventions.

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