Advancing Quadriceps Muscle Monitoring: Wearable A-mode Ultrasound and Machine Learning Classification for Accurate Estimation of Muscle States

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***Abstract*—Accurately estimating muscle states, including fatigue and contraction, holds significant potential in the fields of rehabilitation and muscle-related disorder identification. However, conventional invasive methods such as intramuscular electromyography (EMG) entail risks and discomfort. This study pioneers the integration of A-mode ultrasound (US) signals from a wearable sparse array with machine learning (ML) classification, advancing quadriceps muscle state estimation. A novel wearable transducer, comprising a 16-element array with a central frequency of 10 MHz, enables the capture of A-mode US signals on curved skin surfaces. Three able-bodied participants engaged in two experimental sets: voluntary knee extension for contraction prediction, and a fatiguing protocol utilizing functional electrical stimulation (FES). Employing US feature extraction, followed by supervised ML classification, resulted in an exceptional average accuracy of 93.66 % in contraction classification and achieved 90.1 % in fatigue classification.**

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

I. Introduction

Skeletal muscle monitoring holds significant potential for evaluating lower-limb function across various applications, including injury rehabilitation, sports medicine [1], and disease management [2]. The accurate estimation of muscle state, encompassing factors like fatigue and degree of contraction, is of utmost importance in various domains such as identifying muscle-related disorders [3]. Moreover, this estimation assumes particular significance in advancing the utilization of functional electrical stimulation (FES) [4] and hybrid exoskeletons with integrated FES [5], especially within clinical rehabilitation settings.

Traditional invasive measurement techniques such as intramuscular electromyography (EMG) carry risks of infections and discomfort. Surface electromyography (sEMG) captures the electrical activity of muscles from the skin's surface [6], serving as a crucial non-invasive technique to portray voluntary motion and movement intention [7], [8]. However, sEMG has inherent limitations, including low signal-to-noise ratio (SNR), inability to monitor deeper muscles reliably, signal degradation due to fatigue, challenges in distinguishing muscle firings among adjacent muscles (muscle crosstalk) [9], and electromechanical delay (EMD) [10]. In contrast, non-invasive methods like B-mode ultrasound (B-mode US) show promise in muscle state estimation due to their non-invasiveness and real-time capabilities [4], [5]. However, these techniques are constrained by complex and cumbersome equipment and the need for sophisticated signal processing such as beamforming, for continuous monitoring applications.

To address the limitations associated with B-mode US, a practical and cost-effective alternative is to acquire raw one-dimensional Amplitude Mode (A-Mode) radio frequency (RF) signals using US transducers. Unlike B-mode, these A-Mode signals don't require intricate processing such as beamforming [11]. A-Mode US presents a more viable choice for affordable and wearable muscle state recognition solutions, as evidenced by its successful utilization in various domains, including classifying muscle states using single elements [11], detecting muscular morphological deformations [12], and recognizing hand gestures [13].

The primary objective of this study was to establish the viability of employing an innovative sparse array-based wearable US device in muscle state detection. To this end, our device combines A-mode imaging, machine learning (ML), and classification with US feature extraction for the estimation of quadriceps muscle states. Our pioneering investigation builds upon previous research, where wearable A-mode US was successfully used to monitor muscle activities in the context of assistive robotics applications [14], [15]. Distinguishing the proposed work from prior literature that has predominantly relied on single elements [11] or rigid multi-transducer setups [12], this study introduces a distinctive approach. Herein, an array of 4 $\times$ 4 PZT-5A transducers is coupled with a substrate crafted from biomedical-grade polydimethylsiloxane (PDMS), affording the system remarkable flexibility and wearability. Notably, the innovation extends to the realm of muscle fatigue detection as well. While extant literature [13] has explored fatigue detection, it is noteworthy that the present work stands out by incorporating FES-induced muscle fatigue as a unique dimension.

II. Materials and Methods

A. Transducer design and fabrication

The wearable transducer utilized in this study has been documented in the previous works [14], [15]. The design and photographs are illustrated in Figure 1 (a). Each element was designed with 10 MHz center frequency for effective muscle movement detection. The active layer, composed of PZT-5A piezo-ceramic (Chengdu Chengyao Technology Co., Ltd. Chengdu, Sichuan, China), was mechanically diced and lapped to attain a thickness of 0.2 mm. Subsequently, the lapped active layer was affixed to an acoustic matching layer employing epoxy (EpoTek 301, Epoxy Tech. Inc., San Jose, CA, USA), which had a thickness of 0.25 mm. This matching layer was composed of aluminum oxide/epoxy with a particle size of 50 nm. On the back side of the active layer, electrically conductive silver epoxy (E-Solder 3022, Von-Roll Inc., Cleveland, OH, USA) formed the initial 0.28 mm thick backing layer. An additional backing layer was then created by applying epoxy blended with tungsten particles over the first backing layer.

The fabrication process involved four distinct steps, as shown in Figure 1 (b). The matching, active, and backing layers were bonded using EpoTek 301 epoxy. The bonded stacks were diced into 1.4 mm elements. Each of these elements was individually wired to coaxial cables, ensuring protection against wire damage during motion. E-Solder 3022 epoxy established ground and positive connections on rear and front active layer electrodes. Parylene-C (SCS Labcoter, PDS 2010, SCS, Indianapolis, IN) provided protective coating. The individual elements were assembled into a 4x4 array using a circular 3D-printed mold. PDMS was poured into the mold to form the flexible substrate, which was cured at 50 °C for six hours.

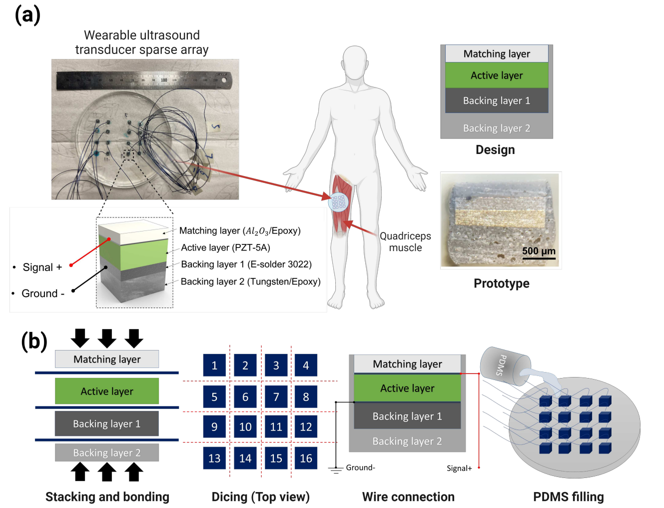

Fig. 1. (a) Schematic demonstration of the wearable US transducer design. (b) The fabrication process for the wearable US transducer

B. Experimental Setup for Quadriceps Muscle States Estimation

1) Subjects: The experimental protocol was approved by the Institutional Review Board (IRB) at North Carolina State University (IRB number: 23630). A total of three able-bodied (AB) subjects, without any neuromuscular conditions, participated in the study. The group consisted of three males with an average age of 32 years. All participants provided informed consent prior to engaging in the experimental procedures.

2) Experimental protocols: Two distinct experimental protocols were executed to acquire A-mode US signals from the quadriceps muscle, encompassing voluntary knee relax/contraction and FES-induced pre/post-muscle fatigue scenarios.

For the initial experiment, participants were seated comfortably on a BIODEX system (Biodex Medical Systems, Inc., Shirley, New York, USA) with their leg secured to the knee extension device. The wearable array was affixed to the quadriceps muscle, and participants were instructed to perform voluntary knee extensions, as illustrated in Fig. 3 (a). In the subsequent experiment, participants were positioned on the same BIODEX system with their legs securely fastened to the knee extension device. Two 2”$\times$2” PALS electrodes (Axelgaard Manufacturing Co., CA, USA) were strategically placed on the proximal and distal ends of the subject’s quadricep to facilitate the stimulation pulse trains (30 mA, 20 Hz, 1.5 s on/0.5 s off) from an FES stimulator (Rehastim1, HASOMED GmbH, Germany). The wearable array was positioned between these electrodes. The experimental arrangement is detailed in Fig. 3 (b). In both experiments, A-mode US signals were acquired using the oscilloscope. Additionally, muscle torque data was collected using the Biodex system during the second experiment.

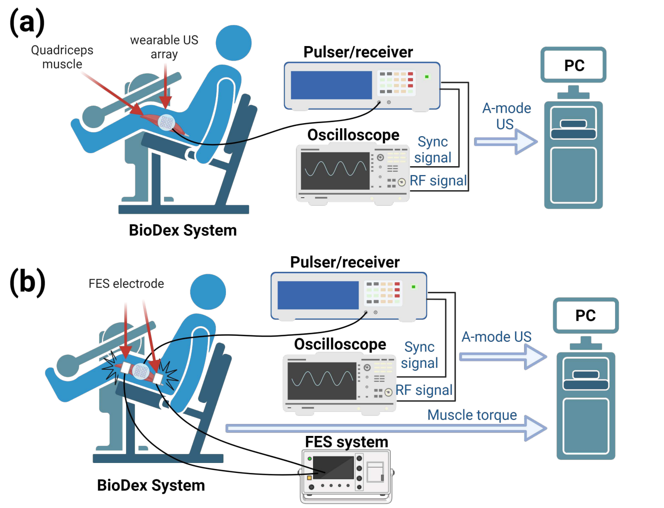

Fig. 2. Schematics of the experimental setups for test protocols: (a) Knee relax/contraction tests; (b) FES induced pre/post-muscle fatigue tests

3) Data Collection: In the voluntary knee relaxation/contraction experiment, three sets of A-mode US data were acquired for both contracted and relaxed positions, using each of the four transducer elements. Following a 3-minute rest period for each participant, the FES-induced pre/post-muscle fatigue experiment was initiated. A 2-minute FES pulse train was applied to the subject's quadriceps, during which A-mode data was manually collected using a single transducer element for every alternate contraction cycle. Muscle torque data was concurrently collected using the Biodex system throughout the duration of the experiment. This process constituted a single trial, with a 15-minute resting interval between consecutive trials. A total of three trials was conducted. The representation of the data collection process is illustrated in Fig. 3.

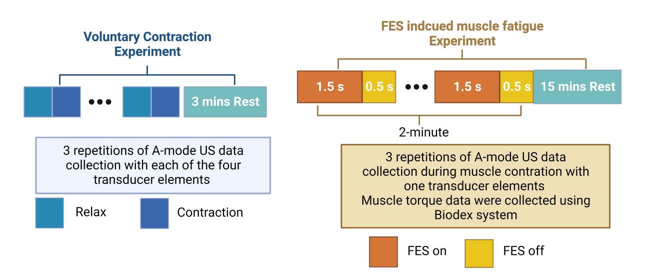

Fig. 3. Experimental Data Collection Process for Voluntary Contraction and FES-Induced Muscle Fatigue Trials

4) A-mode US signals analysis and processing: In the voluntary knee relaxation/contraction experiment, A-mode data was systematically categorized and labeled as "relax" and "contraction," corresponding to the leg position during the data acquisition. For the FES-induced pre/post-muscle fatigue experiment, the fatigue state was identified when contraction torques dropped below 80 % of the maximum contraction torque (averaged from three peak contraction torques). This criterion was used to assign labels of "pre-fatigue" and "post-fatigue". Since each participant's muscle shape is distinct, data for each subject was kept separate.

Prior to the application of machine learning algorithms for muscle state classification, a series of US feature extraction steps were undertaken. This extraction process followed the procedure established in previous works such as [13], [16], [17]. A concise overview of the procedure is provided herein. The raw A-mode US data underwent essential processing steps including time gain compensation (TGC), Hilbert transformation, and log compression, aimed at noise reduction and enhancement of meaningful information. Within each A-mode US data frame, a total of 1000 sample points were recorded. The initial 20 and final 20 data points were excluded as they did not contribute relevant information [17]. Subsequently, the remaining 960 data points were divided into 48 segments, and the mean and standard deviation were computed for each segment, collectively forming the mean and standard deviation (MSD) feature [16]. The MSD features from the four transducer elements were averaged for subsequent analysis.

For classification utilizing machine learning algorithms, 90 % of the dataset was employed for training, while the remaining 10 % was allocated for testing and validation purposes. The muscle state classification involved logistic regression, support vector machines (SVM), neural networks (NN), and K-Nearest Neighbors (KNN) algorithms. MATLAB's Classification Learner (R2022b, MathWorks, MA, USA) was employed for training and validating estimation accuracy. The process of A-mode US data analysis, its processing, and the machine learning model is visually outlined in Fig. 4.

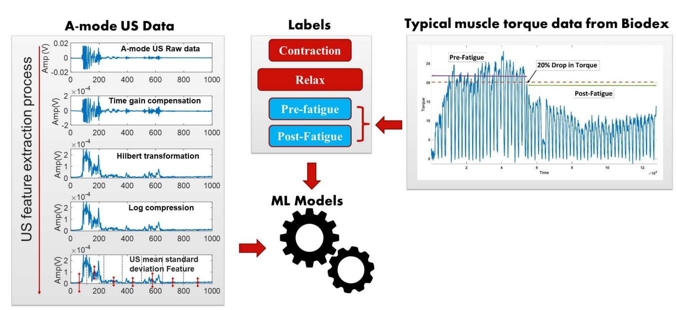

Fig. 4. Visualization of A-mode US Data Analysis, Processing, and Machine Learning Model

III. Results

A. Transducer characterizations

The transducer's characterization involved conducting pulse-echo and electrical impedance tests. Details of the experimental setup for these tests can be found in previous works [14], [15]. In this section, we present the experimental results to establish the completeness and accuracy of the work. The central frequency's average value is 10.78 MHz, accompanied by a -6 dB fractional bandwidth of 61 %. The loop sensitivity demonstrates an average of -40 dB. Moreover, the electrical impedance test yields an average capacitance of 289.04 pF, an

TABLE I
AVERAGE CROSS-VALIDATION ACCURACY OF EACH MACHINE LEARNING MODEL ACROSS ALL DATA

Voluntary Contraction Experiment Cross-Validation Accuracy(%)				
ML models	Subject 1	Subject 2	Subject 3	Average
SVM	98.48	89.47	84.21	90.72
NN	97.22	83.55	84.21	88.33
KNN	98.73	92.11	90.13	**93.66**
Logistic Regression	78.23	68.42	65.13	70.59
FES induced muscle fatigue Experiment Cross-Validation Accuracy(%)				
ML models	Subject 1	Subject 2	Subject 3	Average
SVM	89.7	92.9	87.4	90
NN	88.5	92.9	87.4	89.6
KNN	89.7	96.4	84.2	**90.1**
Logistic Regression	77	89.3	73.7	80

average loss of 12.86 mU at 1 kHz, and an average impedance of 63.85 Ω at 10 MHz.

B. In-vivo results

We obtained 192 labeled data points for both contracted/relaxed states and 96 data points for pre-fatigue/post-fatigue states from each participant. The results of cross-validation for each employed algorithm are elaborated in Table I. Notably, the KNN model exhibited outstanding performance, achieving an average accuracy of 93.66 % for contraction classification and 90.1 % for fatigue classification. These accuracies surpass those reported in recent literature, which documented 84 % accuracy for fatigue classification and 85 % for contraction classification using A-mode US signals from a single element. It is noteworthy that the proposed machine learning models required notably shorter training times, with each model completing training in less than one minute, in contrast to the 20 minutes reported in previous studies.

IV. CONCLUSION

In conclusion, this study introduces a novel approach that integrates wearable A-mode US with machine learning (ML) classification to accurately estimate quadriceps muscle states. This research pioneers the design of a wearable 16-element sparse array with a central frequency of 10 MHz, enabling A-mode signal capture even on curved skin surfaces. Experimental trials encompassed voluntary knee relax/contraction scenarios and FES-induced fatigue protocols. Results demonstrate the effectiveness of the proposed approach, achieving remarkable accuracy through ML models. The KNN model exhibited outstanding performance, achieving an average accuracy of 93.66 % for contraction classification and 90.1 % for fatigue classification. These outperformances of recent literature benchmarks underscore the potential of this integrated technology for continuous and non-invasive muscle state monitoring. In the future, we plan to focus on leveraging advanced ML techniques and larger datasets to further enhance accuracy and applicability in clinical and research domains.

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