A-mode Ultrasound Driven Sensor Fusion for Hand Gesture Recognition

1st Peter Boyd
School of Computing.
University of Portsmouth
Portsmouth, UK
Peter.Boyd@port.ac.uk

2nd Honghai Liu
School of Computing.
University of Portsmouth
Portsmouth, UK
Honghai.Liu@port.ac.uk

***Abstract*—Traditionally, Surface electromyography (sEMG) has been the predominant method of sensing muscle activity in order to control myoelectric prosthesis. While many prosthesis control schemes used simple direct control, an ever increasing focus has moved to pattern recognition based approaches which promise a greater degree of natural control such as to further improve an amputees quality of life. Although pattern recognition based approaches have shown great promise, they have innate limitations due to changes that may occur during long term use which prevent clinical acceptance. Due to these limitations, researchers have increasingly investigated alternative modalities to provide more robust control schemes. A particular modality that has seen increasing interest is ultrasound based sensing due to its capability to better understand deep tissue activity.**

Within this research, A-mode ultrasound based sensing is proposed not as a replacement for sEMG based sensing but instead to augment and drive sEMG based sensing during activities that may otherwise prove challenging to traditional sEMg based control schemes.

***Index Terms*—A-mode Ultrasound sEMG Hand Motion Recognition Rehabilitation**

I. Introduction

Bio-Signal controlled prosthesis have long been seen as important tools in providing higher quality of life to amputees [1]. Classical approaches use simple direct control schemes that are functional although not fully intuitive, subsequently causing longer periods of rehabilitation and less freedom of use than desirable. In order to overcome this challenge, research has increasingly delved into various sensing modalities that can not only provide an intuitive and natural sense of control to amputees [2] but also one which is robust enough such that daily use can be achieved with minimal training or calibration.

Frequently in both clinical and academic environments, sEMG based sensing has been the chosen modality for these control schemes. The typical approach to detecting sEMG activity is to detect the period of rapid depolarization and repolarization seen within excited muscle fibres, creating an Action Potential (AP) [3]. Typically the relationship between muscle contraction and action potential is exploited in sEMG sensing to detect the collective impulse of the excited muscle fibres within a motor unit can be considered as the Motor unit action potential (MUAP). It can therefore be described that the raw sEMG signal is the output of detecting the recruitment of MUAPs across a muscle and their subsequent firing rates [4]–[6].

Although these MUAPs provide a reasonably high fidelity description of muscle activity provided the proper processing, they also suffer limitations due to the way in which transient changes may occur during long term use when using sEMG based sensing. These transient changes may include electrode shift [7], crosstalk, fatigue [8], changes to skin conductivity, time [9]–[11], and concept drift.

Ultrasound based sensing has long been used as a non-invasive diagnostic device in observing muscoskeletal disorders such as arthritis [12], [13]. Typically this method uses an array of piezoelectric transducers to project a focused wave of ultrasound into the body between a range of 2-20MHz. As these beams interact with varying tissue densities, echos are formed which can be measured in order to infer aspects of the muscles state during contraction [14], [15].

Through this capability to get a reliable stream as to tissue and muscle states within the human body, the application of ultrasound has been found viable in hand motion recognition in roles such as accurately predicting finger location [16], [17].

Within this research, A-mode ultrasound based sensing is proposed not as a replacement for sEMg based sensing but instead to augment and drive sEMG based sensing during activities that may otherwise prove challenging to traditional sEMg based control scehems. A common challenge found in sEMG based sensing is that of large arm movements and in situations where the location of an arm is not in the comfortable position frequently seen within laboratory experiments. As the arm moves into dynamic poses there exists a degree of shift and co-activation of muscle groupings surrounding the targeted muscles which subsequently impact recognition accuracy. The issue is further amplified when considering larger muscle groups in the biceps. Therefore it is proposed that the improved reading of deep muscle activity form ultrasound based sensing can help overcome issues that may otherwise occur during larger arm gestures, as to provide a robust multimodal solution for long term prosthesis control.

II. Related Works

The topic of provision of ultrasound based hand motion recognition has been explored by many researchers. Hodges

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demonstrated that it is possible to observe low level of muscle contractions where the physical muscle architecture changes the most [18] making ultrasound promising when observing smaller muscle activation's. A further aspect is the nature of ultrasound based sensing makes it robust to crosstalk that is often seen in fatigued muscles [19]. Perhaps one of the more promising aspects of ultrasound based sensing is that of the recorded performance in accurately detecting individual finger positions [20]–[22]. Expanding on this work, other researchers have found that ultrasound provides great promise in detecting multiple finger based hand motions [23].

While it has been shown that ultrasound may complement sEMG during wrist extension activities, the space required to mount both an ultrasound probe and sEMG electrodes in the same location was found to be difficult [24]. Within laboratory settings, B-mode ultrasound has been shown to be highly reliable in providing accurate hand motion recognition [25], [26]. As research has progressed, newer ultrasound based devices have been proposed which are increasingly [22], [27]. Further aspects of integrating multiple sensors into these devices has been explored by numerous researchers, largely towards combining sEMG and ultrasound capabilities into a single device [28], [29], especially with A-mode based devices.

Interest in ultrasound based hand motion recognition has increased a wearable ultrasound based devices for hand motion recognition continue to be developed and show great promise in the realm of proportional control and accurate detection in comparison to sEMG based sensing. However, these methods are frequently used as comparisons to sEMG based sensing and are seldom integrated with sEMG based sensing [23], [30], [31].

This paper is structured as follows: Firstly the system and experimental design for this study are described. Secondly a description is given of methods used to perform data data processing and evaluation is given. Finally the results of this study are detailed, a discussion is made as to the implications of these results, and finally a conclusion is given with potential future avenues of research into this topic..

III. Hypothesis

The Hypothesis of this study is therefore that the addition of a-mode ultrasound based sensing to sEMG based sensing can provide a meaningful increase to hand motion recognition during hand motion activation with larger arm movements.

IV. System and Materials

A. Participants

Two able bodied participants aged 26 and 32 were used in this study. Both participants had no history of limb injury and had previous experience with sEMG but not ultrasound. Prior to the study all participants were informed of the contents of the experiments and the series of gestures to be performed. All work done in this study was approved by and done in accordance with the local ethical committee.

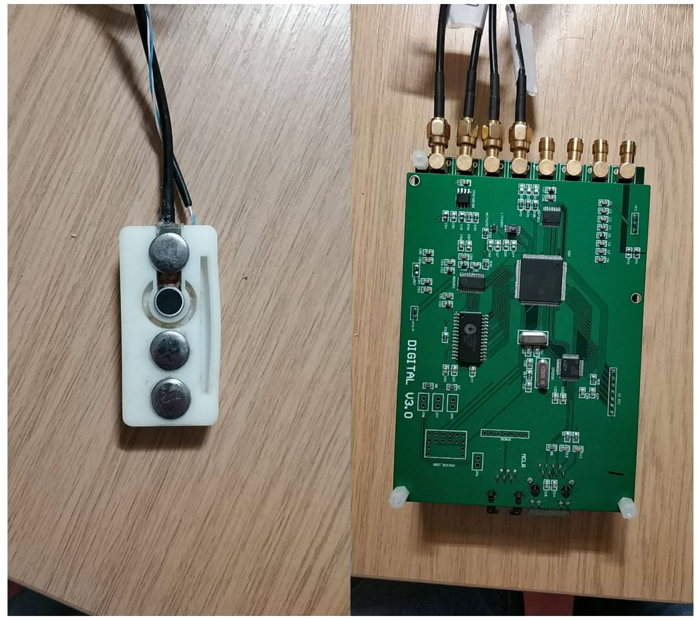

Fig. 1. Ultrasound collection hardware

B. A-Mode Ultrasound Hardware

A-mode Ultrasound manifests itself as a linear set of time points and amplitudes that describe the echo intensity from the Ultrasound diode.

The ultrasound data used in this study was collected through a 4 channel A-Mode Ultrasound device that collected 1000 data points (or time dots) at a rate of 10MHZ with an inspection depth of around 39mm. The device was placed on the muscle grouping on the lower forearm, above the wrist of the candidate. To maintain a secure fitting for the US sensors, an elastic skin tape was used to secure the sensors in their correct location along the subjects arm. Hypoallergenic Ultrasound gel was applied prior to each set of data collection as to ensure improve the transmission quality of the ultrasound signals and to reduce interference from air gaps. Data transmission was performed via Ethernet from the ultrasound hardware to a windows 10 based machine.

C. sEMG Hardware

The sEMG based sensing utilized an sEMG data collection device capable of recording 16 channels with 12 bits ADC resolution and 1Khz sampling frequently as is typically used within literature [32]–[34]. Gathered data was within the 10Hz to 500Hz range through a hardware based band pass filter. As power-line noise can degrade the quality of the collected signals, 50Hz power-line noise was removed through a hardware based notch filter and a software based comb filter, the usage of these two filters also aid in removing motion artefacts from the larger arm movements. Data transmission was performed via USB and processed through the same Windows 10 based machine as the ultrasound data. Further information about the hardware device can be found in [35], [36] . The participant was fitted with 6 pairs of bi-polar wet

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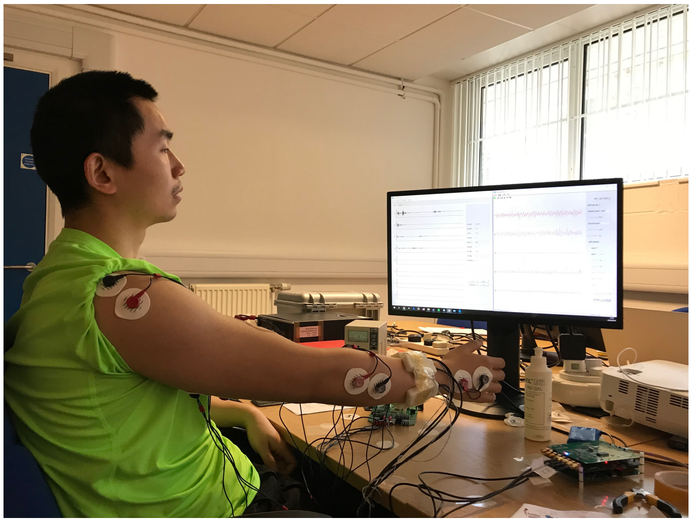

Fig. 2. Multimodal Ultrasound and sEMG experimental setup

electrodes distributed on the major muscle sites of the arm as to provide muscle activation information during larger arm movements. The chosen electrode locations are the lateral deltoid, biceps bracchii shorthead, supinator, and pronator teres and ticeps bacchii. The fitting of the wet electrodes and a-mode ultrasound hardware can be seen in figure 2. Each electrode location was cleaned with an alcohol wipe prior to electrode fitting.

V. Methodology

A. Data Capture

The data capture was divided into 5 trials with ten gestures performed per trial. In order to acquire a dynamic range of motion activity across the whole arm five motion primitives were selected and performed in their open pose and inverse totalling in ten hand and arm motions. The chosen primitives were as follows in order Hand Open (HO), Hand Closed (HC), Forearm Pronation (FP), Forearm Supination (FS), Rotation In (RI), Rotation Out (RO), Humerus Forward (HF), Humerus Backward (HB), Wrist Flexion (WF), Wrist Extension (WE). Each individual motion was performed for five seconds before shifting to its inverse motion and then a rest period of ten seconds between motion primitive. Each trial lasted for a total of 110 seconds including the initial rest period with a total of 50 seconds of motion activity. There was no change of the electrode or ultrasound sensor placement between trials as to introduce a degree of the natural shift that may form with daily use of this combined sensing modality while also removing potential larger shift from donning and doffing.

B. Data Processing

All data processing was completed using Matlab r2017b. The first step of pre-processing for both the ultrasound and sEMG data was to remove 0.5 second of motion data from the beginning and end of each 5 second gesture performance as to remove transition data. The resulting data set provided

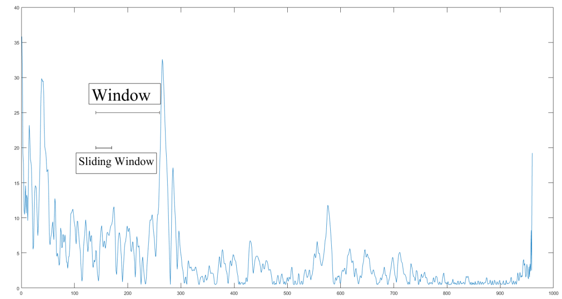

Fig. 3. Windowing of Ultrasound Signal

4 seconds of stable motion data from each 4 second gesture performed with 5 trials in total per participant of all gestures providing a total of 20 seconds of gesture data across all trials.

The A-mode ultrasound data consists of a single frame every 100ms containing 1000 time points, these time points indicating the muscle activity at a given depth from the US Diode. The starting and ending 20 time points of each frame of ultrasound data were removed as the information carried here was not considered meaningful with the initial 20 time points holding largely skin boundary data and final 20 time points being unlikely to properly represent any usable muscle boundaries that it comes into contact with, resulting in each frame holding 960 time points. Presently, there exists little comparative US feature selection strategies or comparisons. Therefore, traditional feature extraction methods for EMG data were to be modified to better exploit the generalizable traits of the data. The approach to feature extraction was to operate directly on the time points within each frame, as opposed to across multiple frames, using a 120ms window and a 30ms sliding window. It was shown in [37] that the Waveform Length feature provides a robust performance in A-mode ultrasound based hand motion recognition and is resilient to diode shift.

Waveform length can be considered to be the measure of complexity of the sEMG signal over a specific time segment [38]

$$\mathrm{WL} = \sum_{i=1}^{n-1} |x_{i+1} - x_i| \tag{1}$$

As stated above, transient changes in the signal were removed as to assure that only stable signal is used for training and testing. The feature extraction for sEMG signal was performed using a 250ms window with a 50ms sliding window, this time was selected as it provided the maximum degree of time for activity detection while also being below the quantity of time that can create a perceivable delay to a person [39].

the Root mean square (RMS) feature was selected to represent the sEMG signal in this study. The RMS feature can be considered as the square root of the mean values for a set of squared raw sEMG values over a period of time. This method

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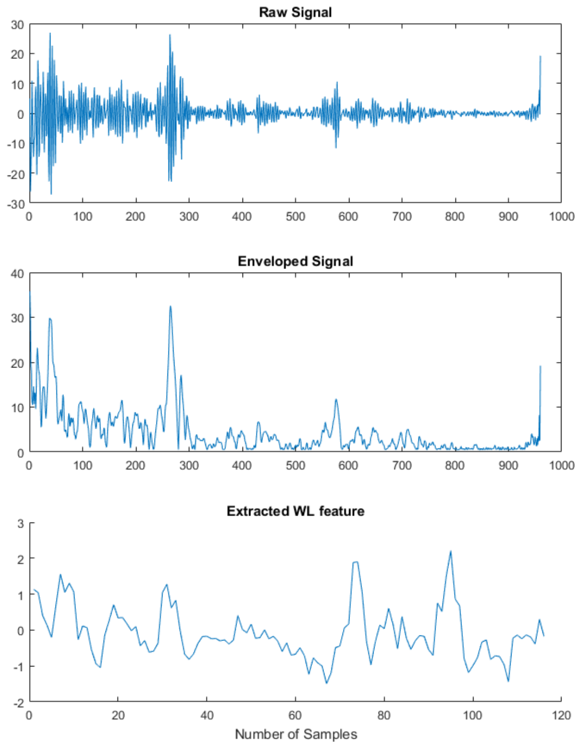

Fig. 4. Process of ultrasound signal processing and feature Extraction

is frequently used as a relatively stable measure in domain both hand motion classification and analysis of stroke patients [40]–[42].

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i-1}^{N} x_i^2} \tag{2}$$

C. Evaluation

Within this study, the three conditions were evaluated as unimodal sEMG, unimodal Ultrasound, then finally multimodal Ultrasound driven sEMG. Synchronisation of the sEMG signal and Ultrasound signal was performed through manual recognition of the first muscle activation of each gesture set in sequence during the multimodal condition.

All classification was performed using LDA with naive bayes. The decision to select LDA is due to the classifiers robustness to changes in the transient changes in the signal when compared to other traditional classifiers, such as SVM, as demonstrated in literature [43]–[46]. Classifier training was performed using a single trial that was evaluated against other 4 trials for each participant.

VI. Results

To verify the performance of the ultrasound led method, each set of 5 trials were evaluated on the basis of sEMG alone,

TABLE I
CLASSIFICATION ACCURACY

Modality	Accuracy (%)	Standard Deviation (%)
sEMG	71.77	6.83
A-Mode Ultrasound	77.43	8.32
Ultrasound driven sEMG	80.21	8.44

a-mode ultrasound alone, and finally the a-mode ultrasound led approach.

As seen in fig.5, the sEMG unimodal approach demonstrated the poorest performance overall, achieving an accuracy of 71.77% across both participants and all trials. The A-mode ultrasound unimodal approach demonstrated some improvement over unimodal sEMG with an accuracy of 77.43%. The strongest modality for performance was the ultrasound led multimodal approach with an accuracy of 80.21%.

It can be inferred from this result that sEMG unimodal sensing is more susceptible to reduced classification accuracy during larger arm motions where crosstalk and interference from cabling may be more apparent. Furthermore, while the sEMG sensor locations and electrodes used should ensure decent coverage and signal collections, it is quite possible that the activating muscle groupings in larger gestures may become less separable than lower arm gestures alone. An interesting result is that of the performance from the unimodal ultrasound approach, which although only focused on the forearm area had managed to achieve reasonable accuracy during larger arm motions. The cause of this performance increase may likely come from smaller muscle changes that occur due to physiological changes of the arm as opposed to active MU activity, something which would explain the poorer results from unimodal sEMG. The results of Ultrasound led multimodal approach are quite promising in displaying that the ultrasound can provide a high degree of accuracy in the hand motions while further improving sEMG based sensing. The potential for ultrasound to better recognize subtle changes in muscle boundaries is promising for future usage of a-mode ultrasound.

VII. Discussion

As demonstrated in the results section, the proposed multimodal a-mode ultrasound led control scheme showed promising performance over unimodal implementations of sEMG and ultrasound based sensing. The implications that can be inferred from this is that while sEMG based solutions are capable of providing high fidelity information into muscle group activity, when undesirable arm positions are obtained then robustness may not always be guaranteed. Much like other researchers who have seen improved performance in monitoring muscle grouping activity for smaller adjustments within the hand and arm [16], [17], [20]–[22]. Furthermore this promising result reaffirms findings of other researchers towards augmenting sEMG based sensing through ultrasound [23]. Although this study differs by using sEMG to bolster ultrasound in providing

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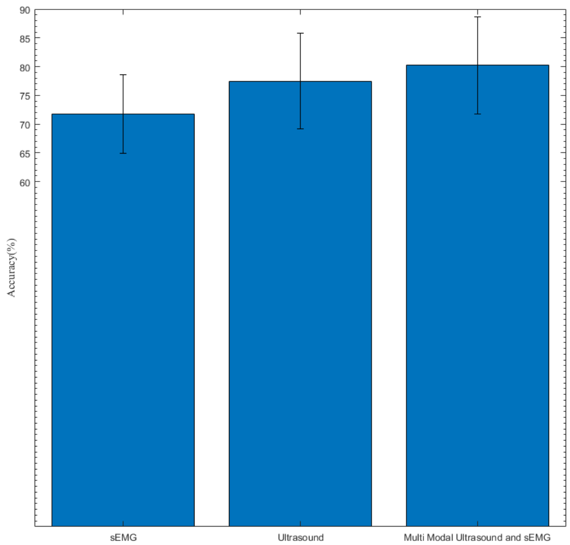

Fig. 5. Multimodal hand motion recognition results

extra context as to larger arm movements while the ultrasound signal focuses on the hands activity.

Subsequently, through the usage of a-mode ultrasound led sEMG based sensing there was a clear improvement in robust sensing in larger arm movements beyond that of the constituent modalities. placed in context of the investigation into ultrasound diode shift [37], [47] and present research into sEMG sensor shift [48], there exists an argument that the ultrasound based approach provides robustness to larger arm movements, whereas sEMG based sensing may improve the robustness to sensor shift during daily use.

VIII. Conclusion

In this study, a multi modal a-mode ultrasound led sensing platform was implemented and demonstrated to be feasible during larger arm motions particularly in comparison to unimodal sEMG and furthermore was shown to contribute to improving the quality of sEMG based sensing in this area.

It is suggested that future directions in Ultrasound hand motion recognition is to investigate whether the inclusion of more channels when considering sensor shift may further improve the classification accuracy alongside the impact of larger arm motions. Furthermore, it is suggested to further investigate the relative comparison of Ultrasound based hand Motion Recognition, in comparison and in complement to sEMG when considering Long Term Use. Finally, it is suggested to explore the capability of ultrasound led hand and arm motion recognition during more dynamic tasks as a multi modal approach with sEMG sensing.

References

[1] E. a. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: a survey of the last 25 years." *Prosthetics and orthotics international*, vol. 31, no. 3, pp. 236–257, 2007.

[2] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 643–660, 2011. [Online]. Available: http://www.rehab.research.va.gov/jour/11/486/pdf/scheme486.pdf

[3] P. J. Kerry, "The ABC of EMC," 2005.

[4] K. Kanosue, M. Yoshida, K. Akazawa, and K. Fujii, "The Number of Active Motor Units and Their Firing Rates in Voluntary Contraction of Human Brachialis Muscle," *Japanese Journal of Physiology*, 1979.

[5] R. H. Chowdhury, M. B. Reaz, M. A. Bin Mohd Ali, A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," pp. 12 431–12 466, sep 2013.

[6] S. H. Nawab, S. S. Chang, and C. J. De Luca, "High-yield decomposition of surface EMG signals," *Clinical Neurophysiology*, vol. 121, no. 10, pp. 1602–1615, oct 2010.

[7] A. J. Young, L. J. Hargrove, and T. a. Kuiken, "The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2537–2544, 2011.

[8] T. D. Lalitharatne, Y. Hayashi, K. Teramoto, and K. Kiguchi, "Compensation of the effects of muscle fatigue on EMG-based control using fuzzy rules based scheme," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2013, pp. 6949–6952.

[9] S. Amsuss, L. P. Paredes, N. Rudigkeit, B. Graimann, M. J. Herrmann, and D. Farina, "Long term stability of surface EMG pattern classification for prosthetic control," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2013, pp. 3622–3625.

[10] P. Kaufmann, K. Englehart, and M. Platzner, "Fluctuating EMG signals: Investigating long-term effects of pattern matching algorithms," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010.

[11] P. Boyd, Y. Fang, and H. Liu, "Preliminary results of emg-based hand gestures for long term use," in *Intelligent Robotics and Applications*, Y. Huang, H. Wu, H. Liu, and Z. Yin, Eds. Cham: Springer International Publishing, 2017, pp. 98–108.

[12] R. S. C. Cobbold, "Foundations of Biomedical Ultrasound," *Oxford University Press*, 2007.

[13] P. C. Ramos, "Ultrasound imaging in juvenile idiopathic arthritis for the rheumatologist," *Clinical and Experimental Rheumatology*, 2014.

[14] R. D. Herbert and S. C. Gandevia, "Changes in pennation with joint angle and muscle torque: in vivo measurements in human brachialis muscle." *The Journal of Physiology*, vol. 484, no. Pt 2, p. 523, 1995.

[15] D. Critchley, "Instructing pelvic floor contraction facilitates transversus abdominis thickness increase during low-abdominal hollowing." *Physiotherapy research international : the journal for researchers and clinicians in physical therapy*, 2002.

[16] C. Castellini and G. Passig, "Ultrasound image features of the wrist are linearly related to finger positions," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, sep 2011, pp. 2108–2114. [Online]. Available: http://ieeexplore.ieee.org/document/6094831/

[17] C. Castellini, G. Passig, and E. Zarka, "Using ultrasound images of the forearm to predict finger positions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 6, pp. 788–797, 2012.

[18] P. W. Hodges, L. H. M. Pengel, R. D. Herbert, and S. C. Gandevia, "Measurement of muscle contraction with ultrasound imaging," *Muscle and Nerve*, 2003.

[19] J. Shi, Y. P. Zheng, X. Chen, and Q. H. Huang, "Assessment of muscle fatigue using sonomyography: Muscle thickness change detected from ultrasound images," *Medical Engineering and Physics*, vol. 29, no. 4, pp. 472–479, may 2007.

[20] J. Shi, S. X. Hu, Z. Liu, J. Y. Guo, Y. J. Zhou, and Y. P. Zheng, "Recognition of finger flexion from ultrasound image with optical flow: A preliminary study," in *2010 International Conference on Biomedical Engineering and Computer Science, ICBECS 2010*, 2010.

[21] J. Shi, J. Y. Guo, S. X. Hu, and Y. P. Zheng, "Recognition of Finger Flexion Motion from Ultrasound Image: A Feasibility Study," *Ultrasound in Medicine and Biology*, vol. 38, no. 10, pp. 1695–1704, oct 2012.

[22] S. Sikdar, H. Rangwala, E. B. Eastlake, I. A. Hunt, A. J. Nelson, J. Devanathan, A. Shin, and J. J. Pancrazio, "Novel method for predicting

dexterous individual finger movements by imaging muscle activity using a wearable ultrasonic system," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 1, pp. 69–76, jan 2014.

[23] Y. Huang, X. Yang, Y. Li, D. Zhou, K. He, and H. Liu, "Ultrasound-Based Sensing Models for Finger Motion Classification," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 5, pp. 1395–1405, sep 2018.

[24] J.-Y. Guo, Y.-P. Zheng, Q.-H. Huang, and X. Chen, "Dynamic monitoring of forearm muscles using one-dimensional sonomyography system." *Journal of rehabilitation research and development*, vol. 45, no. 1, pp. 187–95, 2008. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/18566937

[25] X. Chen, Y. P. Zheng, J. Guo, Z. Zhu, S. C. Chan, and Z. Zhang, "A novel approach for detection of muscle boundary in ultrasound images," in *Proceedings - 2011 4th International Conference on Biomedical Engineering and Informatics, BMEI 2011*, vol. 1, 2011, pp. 56–59.

[26] J. Li, Y. Zhou, X. Chen, G. Dan, and Y. P. Zheng, "Characterization of individual muscle activities during isometric contraction using ultrasound imaging," in *International Conference on Digital Signal Processing, DSP*, vol. 2014-January. Institute of Electrical and Electronics Engineers Inc., 2014, pp. 162–166.

[27] N. Hettiarachchi, Z. Ju, and H. Liu, "A New Wearable Ultrasound Muscle Activity Sensing System for Dexterous Prosthetic Control," in *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*. Institute of Electrical and Electronics Engineers Inc., jan 2016, pp. 1415–1420.

[28] A. Botter, T. M. M. Vieira, I. D. Loram, R. Merletti, and E. F. Hodson-Tole, "A novel system of electrodes transparent to ultrasound for simultaneous detection of myoelectric activity and B-mode ultrasound images of skeletal muscles," *Journal of Applied Physiology*, vol. 115, no. 8, pp. 1203–1214, oct 2013.

[29] W. Xia, Y. Zhou, X. Yang, K. He, and H. Liu, "Toward portable hybrid surface electromyography/a-mode ultrasound sensing for human-machine interface," *IEEE Sensors Journal*, vol. 19, no. 13, pp. 5219–5228, jul 2019.

[30] H. Huang, T. Li, C. Antfolk, C. Enz, J. Justiz, and V. M. Koch, "Experiment and investigation of two types of vibrotactile devices," in *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, vol. 2016-July. IEEE Computer Society, jul 2016, pp. 1266–1271.

[31] X. Yang, J. Yan, Z. Chen, H. Ding, and H. Liu, "A proportional pattern recognition control scheme for wearable a-mode ultrasound sensing," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 1, pp. 800–808, jan 2020.

[32] K. Englehart and B. Hudgins, "A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, 2003.

[33] J. Robertson, "Effects of Confidence-Based Rejection on Usability and Error in Pattern Recognition-Based Myoelectric Control Confidence-Based Rejection Threshold and User Error View project Myoelectric Control View project," *Article in IEEE Journal of Biomedical and Health Informatics*, 2018. [Online]. Available: https://www.researchgate.net/publication/328597123

[34] D. Farina, R. Merletti, R. M. Enoka, M. Amann, G. M. Blain, L. T. Proctor, J. J. Sebranek, D. F. Pegelow, and J. A. Dempsey, "The extraction of neural strategies from the surface EMG Neural Control of Movement The extraction of neural strategies from the surface EMG," pp. 1486–1495, 2012.

[35] Y. Fang, X. Zhu, and H. Liu, *Development of a Surface EMG Acquisition System with Novel Electrodes Configuration and Signal Representation*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 405–414.

[36] Y. Fang, H. Liu, G. Li, and X. Zhu, "A multichannel surface emg system for hand motion recognition," *International Journal of Humanoid Robotics*, vol. 12, no. 02, p. 1550011, 2015. [Online]. Available: http://www.worldscientific.com/doi/abs/10.1142/S0219843615500115

[37] P. Boyd, Y. Fang, and H. Liu, "Ultrasound Feature Evaluation for Robustness to Sensor Shift in Ultrasound Sensor Based Hand Motion Recognition," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11649 LNAI. Springer Verlag, 2019, pp. 115–125.

[38] B. Hudgins, P. Parker, and R. N. Scott, "A New Strategy for Multifunction Myoelectric Control," *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 1, pp. 82–94, 1993.

[39] M. Asghari Oskoei and H. Hu, "Myoelectric control systems-A survey," 2007.

[40] J. Vinstrup, J. Calatayud, M. D. Jakobsen, E. Sundstrup, J. R. Jørgensen, J. Casaña, and L. L. Andersen, "Hand strengthening exercises in chronic stroke patients: Dose-response evaluation using electromyography," *Journal of Hand Therapy*, vol. 31, no. 1, pp. 111–121, jan 2018.

[41] L. Wei, H. Hu, and K. Yuan, "Use of forehead bio-signals for controlling an intelligent wheelchair," in *2008 IEEE International Conference on Robotics and Biomimetics, ROBIO 2008*, 2008, pp. 108–113.

[42] C. J. De, "THE USE OF SURFACE ELECTROMYOGRAPHY IN BIOMECHANICS," Tech. Rep., 1993.

[43] M. A. Oskoei and H. Hu, "Support vector machine-based classification scheme for myoelectric control applied to upper limb," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 8, pp. 1956–1965, aug 2008.

[44] Q. Ding, X. Zhao, Z. Li, and J. Han, "An incremental EMG classification model to detect and recognize randomly-occurred outlier motion," in *2017 IEEE International Conference on Robotics and Biomimetics, ROBIO 2017*, vol. 2018-January. Institute of Electrical and Electronics Engineers Inc., mar 2018, pp. 1–6.

[45] T. Matsubara and J. Morimoto, "Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 8, pp. 2205–2213, 2013.

[46] Z. Li, X. Zhao, J. Han, and G. Liu, "Comparisons on different sEMG-features with dimension-reduction methods in hand motion recognition," in *ICARM 2016 - 2016 International Conference on Advanced Robotics and Mechatronics*. Institute of Electrical and Electronics Engineers Inc., oct 2016, pp. 631–634.

[47] Y. Huang, X. Yang, Y. Li, D. Zhou, K. He, and H. Liu, "Ultrasound-based Sensing Models for Finger Motion Classification," pp. 1–11, 2017.

[48] L. Pan, D. Zhang, N. Jiang, X. Sheng, and X. Zhu, "Improving robustness against electrode shift of high density EMG for myoelectric control through common spatial patterns," *Journal of NeuroEngineering and Rehabilitation*, vol. 12, no. 1, dec 2015.

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