Abstract—Objective: Sonomyography has been shown to be a promising method for decoding volitional motor intent from analysis of ultrasound images of the forearm musculature. The objectives of this paper are to determine the optimal location for ultrasound transducer placement on the anterior forearm for imaging maximum muscle deformations during different hand motions, and to investigate the effect of using a sparse set of ultrasound scanlines for motion classification for ultrasound-based muscle–computer interfaces (MCIs). Methods: The optimal placement of the ultrasound transducer along the forearm was identified using freehand three-dimensional reconstructions of the muscle thickness during rest and motion completion. Based on the ultrasound images acquired from the optimally placed transducer, classification accuracy with equally spaced scanlines across the cross-sectional field of view was determined. Furthermore, the unique contribution of each scanline to class discrimination using Fisher criterion (FC) and mutual information (MI) with respect to motion discrimination was determined. Results: Experiments with five able-bodied subjects show that the maximum muscle deformation occurred between 40%–50% of the forearm length for multiple degrees-of-freedom. The average classification accuracy was 94% ± 6% with the entire 128-scanline image and 94% ± 5% with four equally spaced scanlines. However, no significant improvement in classification accuracy was observed with optimal scanline selection using FC and MI. Conclusion: For an optimally placed transducer, a small subset of ultrasound scanlines can be used instead of a full imaging array without sacrificing performance in terms of classification accuracy for multiple degrees-of-freedom. Significance: The selection of a small subset of transducer elements can enable the reduction of computation, and simplification of the instrumentation and power consumption of wearable sonomyographic MCIs, particularly for rehabilitative and gesture recognition applications.

I. INTRODUCTION

HUMAN machine interfaces that rely on sensing muscle activity have traditionally been a mainstay in assistive technologies for restoring mobility and function, such as prostheses and exoskeletons [1]–[6]. Recently, muscle computer interfaces (MCIs) have emerged as a new modality for touch-free device-control [7]–[9]. In these scenarios, the aim is the classification of hand gestures or grasps based on noninvasive sensing of muscle activity and interactive control of external devices. In many of these applications, camera-based systems for gesture recognition are not practical. As a result of these advances, there is now renewed interest in developing sophisticated sensing for MCI that can accurately classify gestures or grasps.

Surface electromyography (sEMG) - which measures the electrical activity of motor units, is the most popular noninvasive sensing paradigm for MCIs [7]–[10]. The electrical activity of contracting motor units is measured using surface electrodes and the control achieved by mapping these signals to the function of the interactive devices [11], [12]. Particularly for rehabilitation, this technique has become a predominant approach to drive assistive devices such as modern multi-articulated hands [13], [14] and exoskeletons [3], [4]. Recently, gesture recognition systems using sEMG systems have been commercially introduced targeting applications beyond assistive technologies [7]–[10]. However, the sEMG technique suffers from several fundamental limitations such as low signal to noise ratio (SNR) and lack of specificity which lead to limited and non-intuitive control [15]–[17]. On the other hand, pattern recognition approaches using dense sEMG electrode arrays have shown an improvement in prosthesis control [18]–[20]. Although these strategies enable intuitive control, the limited amplitude resolution of sEMG for fine control, for applications such as multi-articulated prosthetic hands continues to be a hindrance.

Ultrasound imaging has recently emerged as a new paradigm to sense muscle activity, and a number of studies have shown that it could be an attractive alternative to sEMG-based approaches for MCIs [21]–[28]. The main advantage of the ultrasound-based sensing, or sonomyography, over sEMG is the capability to produce robust signals from contiguous functional compartments deep inside the limb with high specificity. In our previous
work, we have demonstrated that ultrasound-based sensing can be used to successfully predict volitional motion intent of both able-bodied and amputee subjects with high accuracy in offline and real-time settings [29]–[31].

Ultrasound imaging systems are increasingly undergoing significant miniaturization and reduction in cost, and portable ultrasound probes that can be connected to and controlled by smartphones are now commercially available [32], [33]. These advancements suggest that ultrasound imaging can be used for developing a wearable sensing system for MCIs. However, traditional ultrasound imaging arrays are bulky and not ideal as a wearable sensor. For a practical ultrasound-based MCI that could be integrated into a compact wearable system, the use of a number of sparsely placed single element ultrasound transducers is more practical than a dense imaging array [28], [34]–[38]. Such systems could have significantly reduced footprint in terms of the transducers, require simpler instrumentation, have reduced computational requirements, as well as reduced power consumption which would be particularly suited for prosthesis control, as well as other gesture recognition applications. However, for these applications there is a need to investigate the effect of scanline (channel) reduction with optimal sensor placement on the motion classification accuracy. To study this effect, this work had two main objectives:

1) To determine the optimal transducer position on the anterior forearm to sense the maximum muscle deformation during volitional motion intent.
2) To explore the effect of spatial information reduction on motion classification performance by systematically limiting the number of ultrasound scanlines.

For the first objective, we generated a 3D representation of subject’s forearm muscles in rest and motion states (different hand gestures) using freehand imaging technique and identifying the area with maximum muscle deformation within the length of the forearm. For the second objective, we placed a clinical ultrasound probe at this optimal position and compared the classification accuracy with different subsets of scanlines. Scanlines were extracted at equally-spaced intervals, or, selected utilizing two widely-used, optimal channel selection strategies. The first method is the distance-based optimal channel subset selection using the Fischer criterion as a distance metric [39], [40]. The second method is the correlation-based optimal channel subset selection using mutual information as a similarity metric [41]–[43]. The following sections describe our methods and results in more details.

II. MATERIALS AND METHODS

A. Data Acquisition Protocols

Ultrasound data were acquired from the forearm of five able-bodied subjects as they performed various tasks. The George Mason University Institutional Review Board approved all study procedures. The experimental procedure was explained to the subjects prior to data collection, and informed consent was obtained from all the subjects.

Experiment 1: 3D freehand imaging

For the first experiment, ultrasound imaging data were collected from the forearm of the subjects using a Aixplorer (Super-sonic Imagine, Aix-en-Provence, France) ultrasound imaging system with the SL15-4 linear array transducer. The data were acquired from a depth of 4 cm with a frame rate of 50 Hz. The length of each subject’s dominant anterior forearm in the supine position was measured from elbow to wrist. An electromagnetic position sensor (3D Guidance TrakStar, Ascension Technologies, VT, USA) was attached to the ultrasound probe to track its location and orientation with respect to a fixed transmitter [44]. The ultrasound probe was placed on the anterior portion of the forearm perpendicular to ulna and freely moved along the forearm length from elbow toward wrist. Each subject was asked to perform four different hand gestures (key grip, pinch grip, power grasp and index pointing) one at the time to activate his/her main forearm flexor muscles: flexor digitorum superficialis (FDS), flexor digitorum profundus (FDP), and flexor pollicis longus (FPL) muscles (Figure 1 [45]). To extract the forearm region with maximum muscle deformation, scans were performed at rest (baseline state) and full motion completion for each of the hand gestures. The probe positions, and associated sequential brightness mode images (B-Mode), were streamed into an image analysis software (Stradwin, Cambridge, UK) [44], [46], [47], to reconstruct 3D volumes for further analysis. Figure 2 shows the experimental setup used for freehand ultrasound scans of the forearm.

Experiment 2: Real-time B-mode ultrasound imaging of forearm muscle.

For the second experiment, ultrasound imaging data were collected from the forearm of the five subjects using a SonixRP (Ultrasoundonix Medical Corporation, BC, Canada) with the L14-5 linear array transducer. The data were acquired from a depth of 4 cm with a frame rate of 50 Hz. The research package of the ultrasound system was used to stream the data directly into
MATLAB (The MathWorks Inc., MA, USA), for further processing. The acquired data consisted of 128 beam-formed scanlines of preprocessed RF data. The dynamic range of the envelope of the analytical signal was compressed using the square root function and normalized to reconstruct a B-mode ultrasound image for further analysis. The probe was stabilized on the anterior portion of the subject’s forearm perpendicular to the ulna at a proper location based on our finding from 3D freehand imaging analysis, using a custom designed cuff. Each subject was asked to perform 5 consecutive complex hand gestures (power grasp, pinch grip, index pointing, key grip and wrist pronation) on a beep of metronome. Each motion was performed 5 times in a single session. The collected data were further analyzed to investigate the effect of channel selection on the classification accuracy.

**B. Ultrasound Data Analysis and Algorithms**

1) **Motion Classification Methodology:** For motion classification, an ultrasound frame corresponding to each motion end-state, i.e., the temporal location of maximum muscle engagement during motion performance, was extracted from collected B-mode ultrasound image sequences over each trial. This was accomplished by calculating the Pearson’s correlation coefficient (CC) between each recorded frame and the first frame, assumed to be at ‘rest’ or relaxed state. The temporal location of each motion end-state frame was then determined as the local minima in the calculated CC under the hypothesis that the incoming image is most dissimilar to the assumed rest frame at motion completion. These extracted image frames served as a feature vector of pixel intensities for motion classification. A leave-one-out cross-validation procedure with a Nearest Neighbor classifier was used for classification [30]. In the leave-one-out cross-validation approach, each individual image frame was eliminated from the dataset on which the classifier was trained. Further, we do not tune the classifier based on validation results; therefore, the classifier was validated on data which it had not been previously trained on. Correlation coefficient between motion specific image frames was used as a metric for similarity and classification of each image frame. The average classification accuracy was calculated across all classes (motions) and used as an outcome metric. Figure 4 shows an example of calculated CC value for image sequences of one trial against the rest-state (first frame). The valleys in CC in Figure 4 correspond to the end-state of each performed motion and the peaks in the CC correspond to the rest-state. The variability in the peak value can be attributed to the fact that the subjects were unable to return to the same rest-state consistently.

2) **Scanline Reduction Approaches:** Three approaches were considered for investigating the effect of scanline reduction on motion classification accuracy. Low-dimensional feature maps were computed using an extracted subset of the full 128 scanlines and classification accuracy results were compared against the original data. The first approach, involved selecting different subsets of uniformly distributed scanlines from the full 128-scanline, B-mode images. The other two approaches involved adaptation of two widely used channel selection strategies from brain computer interface and sEMG literature [48]–[54] to systematically select subset of scanlines based on their...
contribution to class discrimination. Implementation details of these approaches are described below.

a) **Uniformly distributed scanline selection (UDSS):** In this method, 4, 8 and 16 subsets of equally spaced scanlines across the ultrasound field of view (FOV) were selected from 128 scanlines under the assumption that all scanlines have similar contribution to class discriminability. A low-dimensional feature map was then computed by stacking the extracted scanlines in a down-sampled 2D representation.

b) **Distance-based scanline selection (DSS) using Fisher Criterion:** In this approach, we use Fisher criterion (FC) as a distance measure to determine the class discrimination impact of each ultrasound scanline. FC maximizes the inter-class separation while minimizing the intra-class variance. Given two feature vectors \( C_1 \) and \( C_2 \) of classes one and two respectively, the FC score for \( j \)th channel (ultrasound scanline) can be calculated as:

\[
R_j(C_1, C_2) = \frac{(\mu_j(C_1) - \mu_j(C_2))^2}{V_j(C_1) + V_j(C_2)}
\]  

Where, \( \mu \) is the mean and \( V \) is the variance of the corresponding example feature vector.

A generalized one-vs-all version of DSS for multiclass analysis is used here, in which each individual class is compared against all the other classes. Using (1), a score is calculated for each scanline in a given class and the corresponding scanlines in the remaining classes, i.e., given \( n \) classes and \( m \) scanlines \( m \times n - 1 \) scores for each class are computed. The computed scores for a given class are then summed together resulting in a single value for each of the \( m \) scanlines. This value represents the contribution of that scanline to the discriminability of a class against all other classes. This calculation is repeated for all trials such that given \( k \) trials each class is represented by \( m \times k \) values. For every class, the computed \( m \times k \) matrix is then averaged across the \( k \) trials and normalized by the maximum FC score of that class. This results in an \( m \times n \) matrix of normalized FC scores for \( n \) classes.

c) **Correlation-based scanline selection (CSS) using mutual information:** In this method, mutual information (MI) is utilized as a measure of similarity to rank and select a subset of scanlines. Since MI computes similarity between two classes, scanlines with low MI values (low similarity across classes) are desirable as they provide higher discriminability. Given two feature vectors \( C_1 \) and \( C_2 \) of classes one and two respectively, the MI score for \( j \)th scanline can be defined as:

\[
I_j(C_1, C_2) = H_j(C_1) + H_j(C_2) - H_j(C_1; C_2)
\]  

Where, \( H \) represents the joint entropy of the two feature vectors for the \( j \)th scanline. These entropies can be defined as follows:

\[
H_j(C_1) = -\sum_{C_1} p(C_1) \log p(C_1)
\]

\[
H_j(C_2) = -\sum_{C_2} p(C_2) \log p(C_2)
\]

\[
H_j(C_1; C_2) = -\sum_{C_1, C_2} p(C_1, C_2) \log p(C_1, C_2)
\]
III. RESULTS

A. Location of Maximum Muscle Deformation on the Forearm

Figure 6 shows the results from 3D ultrasound analysis to find the location of maximum muscle activity averaged across all subjects when performing complex hand motions. These results demonstrate that the maximum deformation of the main flexor muscles (FDS, FDP, and FPL) occurs approximately in the range of 40% to 50% of the forearm length from the elbow joint and therefore can serve as the optimal zone for ultrasound probe placement. The variability in location of maximum muscle deformation can be attributed to anatomical differences between subjects. For subsequent experiments, the probe was first positioned in this optimal zone and then visually reoriented to ensure that all the flexor muscles are within the ultrasound FOV.

B. Comparison of Scanline Selection Strategies

For each subject, data were then collected for 5 different motions and FC and MI score matrices were computed in order to extract the location of scanlines with highest class discriminability. This is done by summing the scores across classes so that the total discriminability of a given scanline for all classes can be computed. Since higher FC scores result in better discrimination between classes, we identify the positions of the local maxima in the aggregated signal for the DSS approach, and sort them in a descending manner. However, since lower MI values correspond to higher discriminability, we identify the positions of local minima in the aggregated signal and sort them in ascending order. 4, 8 and 16 of the highest discriminability scanline subsets were selected based on the FC and MI scores and the classification performance was evaluated for each case.

Figure 7(A) shows the $m \times n$ ($m = 5$, $n = 128$), FC score matrix for one subject as a function of scanline and motion class normalized to the maximum value of FC score for all classes. Higher pixel intensities correspond to the higher FC score and higher class discriminability. (B) Sum of normalized FC scores for all classes, normalized across all channels. The local maxima/peak locations correspond to the optimal channel offering maximum motion class discriminability.

Figure 7(B) illustrates the sum of the FC scores across all classes normalized across all channels for a particular subject. The identified, local maxima of the normalized sum of FC scores indicate spatial locations with highest inter-class discriminability for a given subject. Similarly, Figure 8(A) shows the $m \times n$, normalized MI score matrix for the same subject. Unlike FC scores (Figure 7(A)) however; brighter intensities in Figure 8(A)
represent lower discriminability. Figure 8B illustrates the aggregation of the MI scores across all classes, normalized across all channels, for the same subject. The identified extrema (local minima) indicate the most discriminative spatial locations for a given subject, as the MI value represents the amount of similarity between classes. The respective locations for the two methods are independently sorted in the order of their discrimination capability.

The inter-trial consistency of FC and MI scores in terms of average standard deviation across all trials for each subject is provided in Table I. The same variability is also shown in Figures 9A and 9B. These results demonstrate that the extracted aggregated scores for each trial have similar patterns and that the discriminative scanline locations appear in the same spatial region. Therefore, it is justified to extract optimal scanlines based on the average FC or MI scores across trials.

The average motion classification accuracy across all classes using nearest neighbor-based leave-one-out cross-validation technique was then computed for all three scanline reduction approaches and are shown in Table II. These results represent the effect of the scanline reduction on the classification accuracy (CA) using three proposed methods averaged over all motions for each subject. For each of the three techniques the CA was calculated for three different subsets (4, 8, and 16 scanlines) and compared to those obtained using feature map from the original 128 scanline data. We performed statistical analyses to test the null hypotheses that, (a) the classification accuracy for sparse sampled scanlines do not differ from the original; and (b) uniform sampling is not different from more sophisticated methods of choosing scanlines (DSS and CSS). Due to the small sample size in the study, we use nonparametric tests for both analyses and Monte-Carlo methods are used to assess the significance level of the nonparametric tests.

To compare the classification accuracy with sparsely sampled scanlines to that of the full resolution case, for each subject and each combination of the three different methods (UDSS, DSS, and CSS) and three sparse sample cases (4, 8, and 16 scanlines), we calculate the differences between the results from the sparse sample methods and the results in the full resolution case. Wilcoxon signed rank test is then used to test whether there is any difference between each of the sparse sampled methods and the full resolution case. The p-values obtained from the permutation approach are 0.781 (UDSS-4), 0.499 (UDSS-8), 0.883 (UDSS-16), 0.685 (DSS-4), 0.589 (DSS-8), 0.883 (DSS-16), 1.0 (CSS-4), 0.351 (CSS-8), and 0.096 (CSS-16), corresponding to the nine sparse sample cases. No significant results were detected at the nominal significance level of 0.05 even without the adjustment of multiple comparisons.

Finally, to compare the uniform sampling method with the two more sophisticated methods of choosing scanlines, i.e., DSS (FC) and CSS (MI), for each sparse sample case, we calculate the differences between the uniform sampling method and the more sophisticated method. The three resulting outcome variables, corresponding to the three sparse sample cases (4, 8, and 16 scanlines), are then used for comparison. To account for the potential correlations among these three variables, we apply the multivariate nonparametric (distribution free) test using the spatial signed ranks [55]. This nonparametric test allows for arbitrary dependence structures among the multivariate outcome variables. No significant difference was detected either between the uniform sampling method and the DSS (FC) methods (p-value = 0.313) or between the uniform sampling method and the CSS (MI) method (p-value = 0.293). Hence, the use of 4 uniformly distributed scanlines provides comparable classification accuracy results to those calculated using the adopted optimal channel selection approaches (DSS, CSS) and a full set of 128 scanlines.

### Table I

| Subject | 1   | 2   | 3   | 4   | 5   |
|---------|-----|-----|-----|-----|-----|
| DSS     | 0.06| 0.06| 0.1 | 0.05| 0.06|
| CSS     | 0.02| 0.02| 0.02| 0.03| 0.02|

IV. Discussion

In this paper we investigated the feasibility of using a sparse set of ultrasound scanlines for classification of hand motions using sonomyography. We first investigated optimal sensor placement on the anterior forearm and then investigated the effect of scanline reduction on classification accuracy.

Our results have shown that the largest deformation (change in muscle thickness) of the forearm flexors appears between 40 to 50% of the forearm length from the elbow during the performance of a range of complex hand motions. This observation corroborates well with known functional anatomy of the three primary forearm flexors, FDS, FDP and FPL [56]. The highest muscle deformation is likely to occur within the first half of the forearm, where the muscle belly of the three primary flexors is located (Figure 1). Ultrasound imaging allows us to reproducibly identify the appropriate region of interest in able-bodied subjects with a relatively low inter-subject variability. Ultrasound imaging can potentially enable a determination of the functional anatomy for personalized sensor placement for reliable performance in ultrasound-based MCIs. We anticipate that this ultrasound imaging method can also be used for optimal placement of sEMG electrodes; however, this needs to be investigated in the future.

We then explored the effect of limiting the number of ultrasound scanlines on classification performance within this optimal zone on the forearm. The main motivation for scanline selection is to investigate whether it is possible to utilize a small number of single-element ultrasound transducers rather than imaging arrays while maintaining reliable performance. We compared a simple equidistant scanline distribution approach to adapted versions of a distance-based (DSS) and a correlation-based (CSS) feature/channel subset selection strategies commonly used by the brain-computer interface and sEMG community [48]–[54]. DSS evaluates the class discrimination impact of each scanline using a distance measure such as Fisher’s criterion (FC). On the other hand, CSS uses mutual information (MI) between the respective scanlines across classes.

Our results show that equidistant scanline distribution yields classification performance that is comparable to discriminative...
scanline selection with FC or MI. For all three scanline reduction methodologies, our cross-validation accuracy results demonstrate that the number of scanlines can be reduced from 128 to 4 without significant effect on the performance. Given all 128 scanlines, the average CA across five motion classes and five subjects, was $94 \pm 6\%$. With 4 selected scanlines, the average CAs across subjects were $94 \pm 5\%$, $94 \pm 8\%$ and $94 \pm 6\%$ for equidistant scanline distribution, FC and MI respectively. As shown in Figure 9, the FC and MI signatures were consistent over trials. It is important to note however, that the computed signature is subject-specific, as is expected due to the slight differences in anatomical structure and probe placement.

Our results also show that using four scanlines was sufficient for maintaining the classification performance, however, including more data scanlines resulted in a slight improvement in CA. The average CA for FC was $94 \pm 10\%$ and $95 \pm 4\%$ for 8 and 16 scanlines respectively. Likewise, the CA for MI was $95 \pm 3\%$ and $97 \pm 3\%$ for 8 and 16 scanlines respectively. These results show that ultrasound data being rich in spatial information content, a sparse, equally-spaced transducer configuration that...
images all the principal forearm muscle groups is sufficient for complex hand motion classification applications.

Although, FC and MI utilize different metrics to measure the contribution of each scanline to overall class discrimination, our results indicate that there is some consistency between the two techniques in predicting the overall region of scanlines with higher discriminability. Additional studies are needed to investigate the anatomical dependence of optimal channel selection by determining whether the consistency in the locations identified through DSS and CSS extend to other more complex channel selection paradigms, such as common spatial patterns [57].

The ability to classify motions with high accuracy using small number of transducers is critical in prosthetics control and other applications because it enables optimal, subject-specific system design ensuring that the operation of the given device is appropriately tuned to user behavior. Such design permits more intuitive control of device functionality and thus is likely to reduce user’s cognitive load. Furthermore, the ability to reduce the number of required transducers and associated instrumentation without sacrificing the classification accuracy, increases the practicality of a gesture recognition system by reducing both the hardware complexity and the power consumption requirements, which are desirable traits for a practical MCI.

### V. Conclusion

In conclusion, this paper describes a systematic procedure to quantify the number and appropriate placement of ultrasound transducers required for control of MCIs. Our results show that only a small subset of scanlines can be used instead of a full imaging array without significant degradation of classification accuracy. In future, we hope to utilize the techniques detailed in this paper to design practical wearable systems and quantify their performance in order to further validate our hypothesis that a small number of ultrasound transducers can be used to achieve high gesture recognition accuracy.

### REFERENCES

[1] M. Zecca et al., “Control of multifunctional prosthetic hands by processing the electromyographic signal,” Crit. Rev. Biomed. Eng., vol. 30, nos. 4–6, pp. 459–485, 2002.

[2] C. Cipriani et al., “On the shared control of an EMG-controlled prosthetic hand: Analysis of user–prosthesis interaction,” IEEE Trans. Robot., vol. 24, no. 1, pp. 170–184, Feb. 2008.

[3] K. Kiguchi and Y. Hayashi, “An EMG-based control for an upper-limb power-assist exoskeleton robot,” IEEE Trans. Syst. Man, Cybern. Part B, vol. 42, no. 4, pp. 1064–1071, Aug. 2012.

[4] T. Leniz et al., “Intention-based EMG control for powered exoskeletons,” IEEE Trans. Biomed. Eng., vol. 59, no. 8, pp. 2180–2190, Aug. 2012.

[5] P. Heethanajali, “Myoelectric control of prosthetic hands: state-of-the-art review,” Med. Devices, vol. 9, pp. 247–255, 2016.

[6] A. Fouger et al., “Control of upper limb prostheses: Terminology and proportional myoelectric control—A review,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 5, pp. 663–677, Sep. 2012.

[7] H. Benko et al., “Enhancing input on and above the interactive surface with muscle sensing,” in Proc. ACM Int. Conf. Interact. Tabletop Surf., 2009, pp. 93–100.

[8] T. S. Saponas et al., “Making muscle-computer interfaces more practical,” in Proc. SIGCHI Conf. Human Factors Comput. Syst., 2010, pp. 851–854.

[9] T. S. Saponas et al., “Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces,” in Proc. SIGCHI Conf. Human Factors Comput. Syst., 2008, pp. 515–524.

[10] T. S. Saponas et al., “Enabling always-available input with muscle-computer interfaces,” in Proc. 22nd Annu. ACM Symp. User Interface Softw. Technol., 2009, pp. 167–176.

[11] R. Song et al., “Assistive control system using continuous myoelectric signal in robot-aided arm training for patients after stroke,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 16, no. 4, pp. 371–379, Aug. 2008.

[12] S. A. Dalley, H. A. Varol, and M. Goldfarb, “A method for the control of multigrasp myoelectric prosthetic hands,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 1, pp. 58–67, Jan. 2012.

[13] C. Castellini and P. Van Der Smagt, “Surface EMG in advanced hand prosthetics,” Biomed. Cybern., vol. 100, no. 1, pp. 35–47, 2009.

[14] A. H. Al-Timemy et al., “Classification of finger movements for the dexterous hand prosthesis control with surface electromyography,” IEEE J. Biomed. Health Inform., vol. 17, no. 3, pp. 608–618, May 2013.

[15] H. S. Raitt, A. S. Arora, and R. Agarwal, “Study of issues in the development of surface EMG controlled human hand,” J. Mater. Sci., Mater. Med., vol. 20, suppl. 1, pp. 107–114, 2009.

[16] R. Vinjanur et al., “Limitations of surface EMG signals of extrinsic muscles in predicting postures of human hand,” in Proc. Int. Conf. IEEE Eng. Med. Biol. Soc., 2006, vol. 1, pp. 5491–5494.

[17] C. Desselhorst-Klug, T. Schmitz-Rode, and G. Rau, “Surface electromyography and muscle force: Limits in eEMG-force relationship and new approaches for applications,” Clin. Biomech., vol. 24, no. 3, pp. 225–235, Mar. 2009.

[18] A. B. Aijiboye and R. F. F. Weir, “A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthetic control,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 13, no. 3, pp. 280–291, Sep. 2005.

[19] J. U. Chu, I. Moon, and M. S. Mun, “A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand,” IEEE Trans. Biomed. Eng., vol. 53, no. 11, pp. 2232–2239, Nov. 2006.

[20] G. Li, A. E. Schultz, and T. A. Kuiken, “Quantifying pattern recognition-based myoelectric control of multifunctional transradial prostheses,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 18, no. 2, pp. 185–192, Apr. 2010.

[21] X. Chen et al., “Sonomyography (smg) control for powered prosthetic hand: A Study with normal subjects,” Ultrasound Med. Biol., vol. 36, no. 7, pp. 1076–1088, Jul. 2010.

[22] Y. P. Zheng et al., “Sonomyography: Monitoring morphological changes of forearm muscles in actions with the feasibility for the control of powered prostheses,” Med. Eng. Phys., vol. 28, no. 5, pp. 405–415, Jun. 2006.

[23] J. Shi et al., “Recognition of finger flexion motion from ultrasound image: a feasibility study,” Ultrasound Med. Biol., vol. 38, no. 10, pp. 1695–1704, Oct. 2012.

[24] J. Shi et al., “Recognition of finger flexion from ultrasound image with optical flow: A preliminary study,” in Proc. Int. Conf. Biomed. Eng. Comput. Sci., 2010, pp. 1–4.

[25] J. Shi, Q. Chang, and Y.-P. Zheng, “Feasibility of controlling prosthetic hand using sonomyography signal in real time: Preliminary study,” J. Rehabil. Res. Develop., vol. 47, no. 2, pp. 87–98, 2010.

[26] C. Castellini et al., “A virtual piano-playing environment for rehabilitation based upon ultrasound imaging,” in Proc. 5th IEEE RAVEMS Int. Conf. Biomed. Robot. Biomechatronics, 2014, pp. 548–554.

[27] C. Castellini, G. Passig, and E. Zarka, “Using ultrasound images of the forearm to predict finger positions,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 20, no. 6, pp. 788–797, Nov. 2012.

[28] J. McIntosh et al., “EchoFlex,” in Proc. CHI Conf. Human Factors Computing Syst., 2017, pp. 1923–1934.

[29] S. Sikdar et al., “Novel method for determining dexterous individual finger movements by imaging muscle activity using a wearable ultrasonic system,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 22, no. 1, pp. 69–76, Jan. 2014.

[30] N. Akhlaghi et al., “Real-time classification of hand motions using ultrasound imaging of forearm muscles,” IEEE Trans. Biomed. Eng., vol. 63, no. 8, pp. 1687–1698, Aug. 2016.

[31] C. A. Baker et al., “Real-time, ultrasound-based control of a virtual hand by a trans-radial amputee,” in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Aug. 2016, pp. 3219–3222.

[32] W. D. Richard, D. M. Zar, and R. Solek, “A low-cost B-mode USB ultrasound probe,” Ultrasound Imag., vol. 30, no. 1, pp. 21–28, Jan. 2008.

[33] Philips, Amsterdam, The Netherlands, “Philips Lumify, portable ultrason.” 2016, [Online]. Available: https://www.lumify.philips.com/web?origin=%2Crnck%2Cdcid=240894965887%2Cplid%2C Accessed: Jan. 24, 2018.
[34] Y. Li et al., “Human-machine interface based on multi-channel single-element ultrasound transducers: A preliminary study,” in Proc. IEEE 18th Int. Conf. e-Health Netw., Appl. Serv., 2016, pp. 1–6.

[35] N. Hettiarachchi, Z. Ju, and H. Liu, “A new wearable ultrasound muscle activity sensing system for dexterous prosthetic control,” in Proc. IEEE Int. Conf. Syst., Man, Cybern., 2016, pp. 1415–1420.

[36] R. F. M. Recognition et al., “Towards wearable a-mode ultrasound sensing for real-time finger motion recognition,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 26, no. 6, pp. 1199–1208, Jun. 2018.

[37] W. Xia et al., “Towards portable hybrid surface electromyography/a-mode ultrasound sensing for human-machine interface,” IEEE Sens. J., vol. 19, no. 13, pp. 5219–5228, Jul. 2019.

[38] X. Yang et al., “A proportional pattern recognition control scheme for wearable a-mode ultrasound sensing,” IEEE Trans. Ind. Electron., vol. 67, no. 1, pp. 800–808, Jan. 2020.

[39] R. N. Khushaba and A. Al-Jumaily, “Channel and feature selection in multifunction myoelectric control,” in Proc. Conf. Proc., Annu. Int. Conf. IEEE Eng. Medicine Biol.—Proc., 2007, pp. 2171–2174.

[40] H. M. Al-Angari et al., “Feature and channel selection using correlation based method for hand posture classification in multiple arm positions,” in Replace, Repair, Restore, Relieve—Bridging Clinical and Engineering Solutions in Neurorehabilitation. Cham, Switzerland: Springer, 2014, pp. 227–236.

[41] H. M. Al-Ángari et al., “Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements,” Biomed. Signal Process. Control, vol. 27, pp. 24–31, May 2016.

[42] M. Arvaneh et al., “EEG channel selection using decision tree in brain-computer interface,” in Proc. 2nd APSIPA Ann. Summit Conf., 2010, pp. 225–230.

[43] H. Tang et al., “On the relevance of linear discriminative features,” Inf. Sci., vol. 180, no. 18, pp. 3422–3433, Sep. 2010.

[44] G. M. Treece et al., “High-definition freehand 3-D ultrasound,” Ultrasound Med. Biol., vol. 29, no. 4, pp. 529–546, Apr. 2003.

[45] F. H. Netter, Atlas of Human Anatomy. Amsterdam, The Netherlands: Elsevier, 2006.

[46] A. Gee et al., “Processing and visualizing three-dimensional ultrasound data,” Brit. J. Radiol., vol. 77, no. suppl_2, pp. S186–S193, Dec. 2004.

[47] G. Treece et al., “3D ultrasound measurement of large organ volume,” Med. Image Anal., vol. 5, no. 1, pp. 41–54, Mar. 2001.

[48] A. Al-Ani and A. Al-Sukker, “Effect of feature and channel selection on EEG classification,” in Proc. Annu. Int. Conf. IEEE Eng. Medicine Biol.—Proc., 2006, pp. 2171–2174.

[49] T. Shibano et al., “A quasi-optimal channel selection method for bioelectric signal classification using a partial Kullback-Leibler information measure,” IEEE Trans. Biomed. Eng., vol. 60, no. 3, pp. 853–861, Mar. 2013.

[50] Y. Geng et al., “A novel channel selection method for multiple motion classification using high-density electromyography,” Biomed. Eng. Online, vol. 13, no. 1, Jul. 2014, Art. no. 102.

[51] H. J. Hwang, J. M. Hahne, and K. R. Müller, “Channel selection for simultaneous myoelectric prosthesis control,” in Proc. Int. Winter Workshop Brain-Comput. Interface, 2014, pp. 1–4.

[52] J. P. W. Pluim, J. B. A. A. Maintz, and M. A. Viergever, “Mutual-information-based registration of medical images: A survey,” IEEE Trans. Med. Imag., vol. 22, no. 8, pp. 986–1004, Aug. 2003.

[53] F. Lotte and C. Guan, “Regularizing common spatial patterns to improve BCI designs: Unified theory and new algorithms,” IEEE Trans. Biomed. Eng., vol. 58, no. 2, pp. 355–362, Feb. 2011.

[54] K. P. Thomas et al., “A new discriminative common spatial pattern method for motor imagery brain—computer interfaces,” IEEE Trans. Biomed. Eng., vol. 56, no. 11, pp. 2730–2733, Nov. 2009.

[55] H. Oja and R. H. Randles, “Multivariate nonparametric tests,” Statist. Sci., vol. 19, no. 4, pp. 598–605, 2005.

[56] J. A. Gosling, Atlas of Human Anatomy With Integrated Text. Philadelphia, PA, USA: J. B. Lippincott Co., 1985.

[57] T. Aotaiby et al., “A review of channel selection algorithms for EEG signal processing,” EURASIP J. Adv. Signal Process., vol. 2015, no. 1, Dec. 2015, Art. no. 66.