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Embroidered Electrodes for Control of Affordable Myoelectric Prostheses

Samuel Pitou¹, Fan Wu¹, Ali Shafit¹, Brendan Michael¹, Riaan Stopforth² and Matthew Howard¹

Abstract—The low-cost manufacturing and maintenance of prostheses is of vital importance to their successful deployment in developing countries. Low-cost prosthesis actuation is generally achieved by combining pre-programmed control strategies, with surface-electromyographic measurements taken from the residual limb. In a standard setting, these signals are measured with *disposable* gel electrodes. However, this limit on electrode reuse requires that prosthesis users have a stable supply of electrodes. Alternatively, the textile electrodes sewn from conductive thread are studied in the context of hand gesture recognition to consider their future use with low-cost prostheses. In this paper, it is demonstrated that textile electrodes can be applied for gesture recognition. To do so, surface electromyography (sEMG) experiments are run in South Africa on three amputees where they were asked to perform gestures with their phantom limb (*i.e.*, the missing limb segment). A gesture recognition method is implemented, and the classification accuracy with data recorded from textile electrodes is compared to that from gel electrodes. Further analysis examining the relationship between classifier performance and physiological parameters are performed. Results show that textile electrodes can be used to perform accurate gesture recognition, and are comparable to disposable gel electrodes. This demonstrates that low-cost sensory systems are not barrier to myoelectric control in developing countries.

I. INTRODUCTION

In recent years progress in myoelectric control has allowed for the developed of prosthetic devices that can behave like human limbs, to achieve everyday tasks while being compliant with the environment. Many parameters have to be taken into account when designing a new device, such as its weight, size and power supply, as well as its control and actuation systems. Advanced prostheses such as the *i-Limb Ultra Revolution* [1] or the *BeBionic3* [2] prosthetic hands, have complex designs with which to provide a large variety of functionalities to amputees. However their high cost keeps important technological breakthroughs away from the population of the world living in developing countries [3].

As a solution, the *Touch Hand* developed in South Africa [4], implements myoelectric control and uses a modular design that allows the control of up to 7-degrees of freedom (DoF) (1-DoF per finger and 2-DoF for the wrist). In this, user control is achieved by combining embedded electronics for gesture recognition, with sensed electrical activity from gel-based *disposable* electrodes placed on the skin surrounding muscles of interest, in a process known as surface electromyography (sEMG) [5]. However, the disposable nature of these electrodes is a limiting factor in their use in

Fig. 1: (a) The Touch Hand. Surface electromyography acquisition from experimental subjects in South Africa. Electrode placements on the residual limb of (b) S6 (metacarpal amputation) and (c) S7 (trans-humeral amputation).

developing countries because of their cost in long-term use. As an alternative to disposable electrodes, recent studies have shown the possibility of creating electromyography systems using electrodes made out of *conductive textiles* [6], [7], [8], allowing for re-usability, and local manufacturing.

In this paper, the use of embroidered electromyography sensors is investigated with view to assessing their suitability as the myoelectric interface of an affordable prosthesis. The performance of textile electrodes is assessed for decoding discrete patterns of muscle activation corresponding to desired gestures of a myoelectric prosthetic hand. This paper reports an experiment in which $N = 3$ amputees are asked to perform gestures with their phantom limb, while surface electromyography data is recorded in the residual muscles, through (i) textile electrodes and (ii) conventional gel electrodes for comparison. Statistical classification is applied to perform gesture recognition and the decoding accuracy measured. The results indicate that, in this population, there is no significant difference in performance between the different electrode types, suggesting the feasibility of textile sensors as an alternative affordable control interface.

II. BACKGROUND

A. Prostheses for the Developing World

The deployment of prostheses in developing countries remains a challenging issue, due to the high initial manufacturing cost, difficulty in obtaining replacement parts, and reliance on experienced technicians for maintenance [9]. As an example, in South Africa, reports indicate that 86% of

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the total population are not covered by medical insurance due to unemployment [10], which makes access to high-end prosthetic solutions difficult.

To address this, recent research in the area of low-cost mechatronically active prostheses has investigated alternatives that are inexpensive, allow for robust use, and maximise user self-reliance. In contrast to passive prostheses or classical hooks, these allow for increased quality of life and employability [11] by enabling users to perform more task related with daily activities (*e.g.*, grasping, typing). Low-cost solutions such as the *Touch Hand* (see Fig. 1(a)) are made available for approximately £500 in contrast to conventional solutions (up to £27k [12]).

In order to actuate these prostheses, gesture recognition is commonly performed by using sEMG measurements as a simple interface. These are taken by placing electrodes on the skin surrounding the muscle of interest, allowing for a non-invasive monitoring of user muscle activity. Combining this with an embedded gesture recognition system enables user intentions to be decoded that can then be used to provide actuation control signals to a device.

In order to help prosthesis users in the developing world benefit from this technology, it is necessary to seek sEMG systems suitable for incorporation into low cost prostheses, such as the *Touch Hand*. However, to date, few satisfactory solutions have been proposed that provide the right trade off between affordability and functionality.

B. Conventional EMG and Textile-based Alternatives

In the developed world, there are generally two main types of system commonly used for the measurement of sEMG, *gel-electrode systems* that use disposable, adhesive patches, and *dry-electrode systems* that use rigid metal electrodes with sophisticated signal processing techniques to gain a signal.

High-end, commercial dry-electrode systems, such as Delsys Trigno or Biometrics Datalite EMG systems are available and provide highly reliable measurements. They are also reusable, and often come in convenient packages (*e.g.*, combining wireless data transmission with sophisticated data acquisition and signal processing software). However, the cost per sensor is typically around £500-£1k making them unaffordable in the developing world context.

Alternatively, recent EMG systems such as MYO armband [13] and Myoware [14] are commercial affordable solutions for dry-electrode or gel-electrode systems, with a more affordable cost of £141 and £27 respectively. However, while less expensive than the high end systems, the Myoware product remains a gel-electrode system, and suffers from the same requirement for the user to purchase daily disposable electrodes, which can be problematic for users in the developing world. While the MYO armband is a dry-electrode system that allows for collecting EMG data from the muscles around a targeted section of the arm without disposable electrodes, it however has a fixed shape with limited ability to conform, and can result in poor contact when applied to the often irregular shape of residual limbs.

Disposable, adhesive pre-gelled electrodes such as the commercial Ag/AgCl Covidien Kendall Disposable elec-

trodes are very cheap as they cost approximately £0.26 per unit. However, their long term use is hindered by the fact that attachment of multiple electrodes to the residual limb is laborious, and the presence of sweat due to perspiration can interfere with adhesion and conductivity causing poor electrical contact [15]. In addition, this requires that the user have available a stable supply of new *disposable* electrodes, with which to reattach daily to the residual limb. This reliance on external manufacturers is a limiting factor in the deployment of low-cost prostheses to the developing world.

As an alternative, textile electrodes have been previously proposed [7], due to their suitability to the developing world, as they are low-cost, flexible, reusable, washable, and easy to produce. In addition, little raw material, infrastructure, or technical knowledge is required for assembly, providing the potential for local production (and thereby job creation) in low-income communities. With an estimated cost of approximately £0.16 of raw material to manufacture one electrode, this solution presents a price 38.5% lower than gel-based electrodes per unit and 92% lower than gel-based electrodes in the scenario of daily use of prosthesis over a week with a 4 channels EMG system (*i.e.*, 8 textile electrodes or 56 disposable electrodes used over a week). Moreover, these electrodes have been shown to achieve a similar level of sensitivity to muscular force variation as gel-based electrodes [7]. However, their applicability in prosthetics has not previously been researched, and it is uncertain if these textile electrodes will result in similar performance in gesture recognition, compared to standard gel-based electrodes.

III. MATERIALS AND METHODS

This paper reports an investigation into the use of embroidered electrodes for recording surface electromyography data from amputees, and the feasibility of using that data as a discrete control interface for a prosthesis through classification of muscle patterns.¹

A. Experimental Setup

The experimental setup and protocols for collecting data are as follows.

1) *Textile electromyography Acquisition System*: The experiments reported here use textile surface electromyography sensors developed at the the Centre for Robotics Research (CORE) at Kings College London. Four pairs of electrodes created using a Pfaff Creative 3.0 (Pfaff, Kaiser-sleutern Germany) programmable sewing machine are used, employing the design created in [16]. This design is chosen as it has been shown to have an optimal trade-off between the electrical properties of the electrodes and their manufacturability. The CAD design for the electrodes is converted to an embroidery file in the 6D Embroidery Software (provided by the sewing machine manufacturer) and stainless-steel conductive threads (Sparkfun DEV-11791, $3.28 \Omega m^{-1}$) are used to sew out the design in fabric. For convenience, an

¹The data supporting this research are openly available from Kings College London at <http://doi.org/doi:10.18742/RDM01-275>. Further information about the data and conditions of access can be found by emailing research.data@kcl.ac.uk.

Fig. 2: Top (a) and back (b) of one of the embroidered textile electrodes used in this study. The back side, consisting of the conductive stainless-steel bottom thread goes against the skin during electromyography recording.

ordinary haberdasher's snap fastener (Hemline H420.13.G, 13mm, gold brass rust-proof fastener) is sewn to the top side of the electrode to make the connection to a data acquisition device. An example electrode is shown in Fig. 2.

For data acquisition, the *BiTalino (r)evolution Plugged Kit BT* is used to sample data from four channels synchronously at a rate of 1 kHz via Bluetooth. During data acquisition, signals are monitored by the experimenter to verify good contact with the skin (poor contact is indicated by high-amplitude noise) using the OpenSignal software package (v.2017²) to plot the time-dependent signal in real-time. A synthetic kinesiology tape³ is used to affix the electrodes to the subjects' residual limbs at desired skin contact locations.

2) *Participants and Protocol*: The textile electromyography acquisition system is used to record from the residual (stump) muscles of $N = 3$ human subjects with upper limb amputations [17].⁴ Demographic information about the subjects is provided in Table I.

As far as possible, the electrode placement is selected in accordance to the SENIAM recommendations [18]. Four electrodes were placed on the flexor group of the forearm (specifically on the flexor carpi ulnaris) and four other electrodes were placed on the extensor muscle group of the forearm (specifically on the extensor carpi radialis). However, since every amputee has a different shape and length of residual limb, and the physiological condition (remaining muscles and atrophy) of these vary, the electrode locations are selected pragmatically at points where the amplitudes of the signal are the highest [19]. As an example, Fig. 1 shows the residual limbs of subjects S6 and S7, illustrating the different amputation sites and resultant positioning of the electrodes. Here, for example, the electrodes are placed on the upper arm of S7 instead of the forearm, since no residual forearm muscles exist for this subject, see Fig. 1(c). Note that, the signal decoding approach in this paper is based on statistical machine learning of the measurement data, as

²<http://bitalino.com/en/software>

³Note that, tape is used here for purposes experimental convenience. In a long-term usage scenario, positioning of the electrodes is ensured by embedding them either in a garment of clothing or the socket of the prosthesis

⁴All experiments reported here were conducted with the ethical approval of the University of KwaZulu-Natal, South Africa : HSS/0161/011

Fig. 3: The four gestures performed during the experiments: fist contraction (C1), index finger extension (C2), wrist extension (C3) and wrist flexion (C4).

opposed to precise anatomical models of the arm. As such, the precise placement of electrodes is not expected to have a major influence on classification accuracy.

During data recording, participants are asked to visualise performing one of four gestures with their phantom limb (corresponding to the desired movement of a prosthetic hand) while surface electromyography data is collected using the textile-based system. The four classes of gesture are those most commonly used in human hand motion, and are shown in Fig. 3: (i) fist contraction (C1), (ii) index finger extension (C2), (iii) wrist extension (C3), (iv) wrist flexion (C4).

In each trial, a gesture is randomly chosen and demonstrated by the experimenter, then the participant is asked to perform the demonstrated gesture 2-3 times before data acquisition begins to make sure that the participant can visualise the gesture to perform. During a trial, the participant is asked to make the gesture for two seconds, followed by a rest time of two seconds. This is repeated until $P = 20$ examples of each gesture is recorded (a total of $Q = 80$ gestures). For comparison, the whole experiment is also repeated using conventional disposable gel electrodes (Covidien Kendall Arbo H124SG).

B. Data Post-processing and Classification

To evaluate the potential of the textile electromyography system as a prosthesis control interface, the data need to be decoded to recognise the desired gesture. This involves (i) automatic segmentation of the data to extract individual gestures, (ii) computation of segment-wise features, and (iii) classification of the gesture through a pattern recognition

TABLE I: Subject demographic information.

Subject	Type of amputation	Missing hand	Time since Amputation	Type of prosthesis used	Current Job
S4	Transradial	Right	No information	Aesthetic prosthesis	Unemployed
S6	Metacarpal	Right and Left (data recorded on left hand)	Since birth	None	Student
S7	Transradial	Left	32 years	None	Consultant

algorithm. The following describes these post-processing steps in detail.

1) *Signal segmentation*: The first post-processing step is to segment the raw signal into parts corresponding to the individual gestures performed by the subjects. For this, the following procedure is applied.

Denoting $\mathbf{e}_t \in \mathbb{R}^4$ as a column vector whose elements consist of the raw electromyography values for each channel at time step t , the moving average of the rectified, instantaneous sum of the samples is computed, *i.e.*,

$$\bar{e}_s = \frac{1}{S} \sum_{t=s}^{s+S} \bar{e}_t \quad (1)$$

where $S = 200$ is the window size (*i.e.*, 200 ms) and $\bar{e}_t = |\sum_{i=1}^4 (\mathbf{e}_t)_i|$ (where $(\mathbf{e}_t)_i$ denotes the i th element of $\mathbf{e}_t$). A threshold τ is then applied to the signal to create a mask that eliminates parts of the signal for which the amplitude is lower than a fixed value, resulting in a set of R discrete envelopes. The masking threshold τ is then tuned until $R = P$ (*i.e.*, the correct number of segments is found), and the mask is applied channel-wise to the raw data $\mathbf{e}_t$, $t \in [1, T]$. The whole process is summarised in Fig. 4.

2) *Feature Selection and Classification*: Once segmentation is complete, individual gestures are decoded through a statistical pattern recognition approach based on features computed segment-wise from the data. Specifically, in this paper, a one-versus-one multi-class [20] Support Vector Machine (SVM) [21] with a Gaussian kernel [22] is used for classification. The latter is selected because it has shown good performance in previous work, outperforming comparable one-versus-all methods in general [23], [24].

Classification speed and performance generally depends on selecting appropriate data features as inputs to the classifier. In [25], it is shown that recognition accuracy above 80% for the recognition of nine gestures can be reached by simply using the root mean square of the data coming from each electromyography channel. In [26], good classification accuracy is achieved with the mean square and the standard deviation of the signal. For simplicity, in this paper, the mean of each segment is used $\phi_i = \sum_{s=1}^S (\mathbf{e}_s)_i / S$. This simple feature is chosen as it is fast to compute, making it suitable for implementation in the real time control of a prosthesis.

To train the SVM, first, a 10-fold cross-validation is performed to find the optimal hyper-parameters (*box-constraint* and *kernel scale*) with respect to the accuracy

$$E = \frac{(|T_+| + |T_-|)}{|T_+| + |T_-| + |F_+| + |F_-|} \quad (2)$$

where $|T_+|$ (respectively, $|T_-|$) is the number of true positives (negatives) and $|F_+|$ (respectively, $|F_-|$) is the number of false positives (negatives).

Fig. 4: Diagram showing the steps of the segmentation presented in this study: (a) Input signals from each channel (b) Computation of the sum of channel 1, 2, 3 and 4, (c) Computation of the absolute value and thresholding of peaks, (d) Computation of a mask indicating the beginning and the end of a segment.

After the hyperparameters are set, the classifier is trained on a random 70% of the gestures, with the remainder held back for testing. This procedure is repeated ten times for each data set (*i.e.*, for each electrode type and for each subject) and the gesture recognition accuracy is computed each time according to (2).

IV. RESULTS

A. Gesture Recognition with Embroidered Electrodes

The classification results for the embroidered and gel-based electrodes are summarised in Table II. It can be seen that, the overall classification of the four gestures using the textile electrodes reaches a maximum accuracy of 97.91%, and is greater than 90% for each of the subjects. In comparison to the textile electrodes, conventional gel electrodes achieve a slightly higher accuracy (Table II, right column), with the difference being most noticeable in S4 and S7. With both types of electrodes, the gesture recognition accuracy of S6 is better than the other participants, even though the

skin where electrodes are placed is damaged (due to the cause of amputation), which could have changed the signal recorded due to the damages on the dermis and epidermis [27]. However, this *increase* in accuracy is due to the fact that this participant has a wrist segment remaining, which allowed him to make the gestures C3 and C4 physically instead of having to visualise them like S4 and S7 who have lost their hand, wrist and a part of the forearm.

While these results show that the textile electrodes perform with a slightly lower accuracy than the gel-based electrodes, robust gesture recognition can still be performed. Overall, these results suggest that classification performance does not significantly degrade when moving to a system that uses reusable textile-based electrodes.

TABLE II: Percentage recognition accuracy in classifying gestures from electromyography data from the experimental subjects. Results are mean $\pm$ s.d. over 10 trials.

Subject	Textile Electrodes	Gel Electrodes
S4	90.83 $\pm$ 4.30	95.83 $\pm$ 3.92
S6	97.91 $\pm$ 2.94	98.33 $\pm$ 0.40
S7	92.53 $\pm$ 3.28	97.50 $\pm$ 3.51
Average	93.74 $\pm$ 3.50	97.22 $\pm$ 2.61

TABLE III: Percentage recognition accuracy in classifying gestures from electromyography data from the experimental subjects after removing features from a channel. Results are mean $\pm$ s.d. over 10 trials.

S4	Textile Electrodes	Gel Electrodes
<i>Channel1 – Out</i>	90.41 $\pm$ 6.81	94.58 $\pm$ 3.43
<i>Channel2 – Out</i>	87.50 $\pm$ 5.55	96.25 $\pm$ 3.07
<i>Channel3 – Out</i>	93.75 $\pm$ 6.58	96.66 $\pm$ 3.83
<i>Channel4 – Out</i>	92.91 $\pm$ 6.53	87.50 $\pm$ 3.93
S6		
<i>Channel1 – Out</i>	100.00 $\pm$ 0.00	92.91 $\pm$ 5.21
<i>Channel2 – Out</i>	95.83 $\pm$ 4.39	93.75 $\pm$ 2.19
<i>Channel3 – Out</i>	97.50 $\pm$ 2.15	87.91 $\pm$ 4.98
<i>Channel4 – Out</i>	93.75 $\pm$ 3.54	96.66 $\pm$ 3.28
S7		
<i>Channel1 – Out</i>	72.50 $\pm$ 9.25	96.66 $\pm$ 4.30
<i>Channel2 – Out</i>	86.25 $\pm$ 6.22	95.00 $\pm$ 3.82
<i>Channel3 – Out</i>	91.25 $\pm$ 6.39	97.08 $\pm$ 3.95
<i>Channel4 – Out</i>	92.08 $\pm$ 6.93	96.25 $\pm$ 4.14

B. Classifier Evaluation

To investigate why the overall classifier performance is lower for S4 and S7, further insight can be gained by examining (i) the within-gesture accuracy (*i.e.*, the performance of the classifier in distinguishing *between* specific gestures) and (ii) the gesture recognition accuracy when using less channels (*i.e.*, forming the feature vector from only three segmented channels).

1) *Within-Gesture*: To investigate the within-gesture accuracy, Fig. 5 displays a *confusion matrix* for the classifier trained on data from S4 and S7 using textile electrodes.⁵

⁵The diagonal of the *confusion matrix* indicates the positive predictive rates (*i.e.*, $r_+ = |T_+|/(|T_+| + |F_+|)$), meaning that it represents the proportion of feature vectors that are classified correctly. The other cells of the matrix indicate false discovery rates (*i.e.*, $r_- = |F_+|/(|T_+| + |F_+|)$) representing the rate of feature vectors that are misclassified as another of the gestures.

There, it can be seen that, for S4, 80% of C1 data is predicted as C1 but 20% of C1 data is predicted as C2. This shows that the classifier computed for S4 presents difficulties in differentiating the gestures C1 and C2. This is also seen in S7, where the classifier has difficulties in differentiating between C2 and C3, and C1 and C3. The lower gesture recognition accuracy for S4 and S7 overall can be explained by the presence of noise in the signal induced by the motion of the electrodes or by the presence of hair that reduced fixation the contact of the electrodes to the skin. Also, the presence of hair could also have reduced the fixation property of the kinesiology tape which was use to maintain the contact between the electrodes and the skin.

2) *Channel-Removal*: In these experiments, classifier training and prediction is performed after removing a channel. This is to investigate if a particular muscle group played a greater contributory role to gesture recognition. These results are displayed in Table III. In this, it is seen that in particular, the removal of *Channel4* induces a decrease in the recognition accuracy when using gel electrodes, for all subjects. In contrast, removing *Channel4* when measuring with textile electrodes leads to similar or higher recognition accuracy. This implies that important information is being measured from gel electrodes at *Channel4*, and that this information is not conveyed by the textile electrodes at the same position. This can be explained by the fact that the muscular activity recorded at this position on the arm is of lower signal strength, due to the condition of the forearm of the subjects (*i.e.*, atrophy). As such, the gel-electrodes, which are more sensitive to minute changes in electrical muscular activity [7] are able to detect activation, while textile electrodes cannot. However, the inability of the textile electrodes to record muscular activity in these atrophied muscular, does not significantly affect gesture recognition performance.

V. DISCUSSION

In this paper, the application of embroidered textile electrodes in gesture recognition has been presented, with view to future use in prosthesis control to avoid the issue of user reliance on disposable gel-based electrodes.

To do so, textile electrodes are used for muscular activity monitoring, allowing for inexpensive, locally made sensors to be used as an alternative. Evaluation of the proposed approach is performed in a gesture recognition and prosthesis control task in collaboration with amputees in South Africa. Experiments in learning user gestures show that textile electrodes perform similarly to gel-based disposable electrodes, with the additional benefits of reusability and local manufacturing. While, the classification accuracy is slightly lower for textile electrodes, the performance remains high, demonstrating that sensor affordability is not a barrier to myoelectric control.

In future studies, the robustness of the textile electrodes during daily use will be investigated, to evaluate the performance of the electrodes under conditions such as changes in temperature, humidity (and associated perspiration), electrode displacement due to movement (*e.g.*, when using sockets to attach the device to the residual limb [28]),

C1	80.00	20.00	0.00	0.00
C2	10.00	90.00	0.00	0.00
C3	1.67	5.00	93.33	0.00
C4	0.00	0.00	0.00	100.00
(a)	Pred1	Pred2	Pred3	Pred4

C1	90.00	0.00	10.00	0.00
C2	0.00	91.67	8.33	0.00
C3	11.67	0.00	88.33	0.00
C4	0.00	0.00	0.00	100.00
(b)	Pred1	Pred2	Pred3	Pred4

Fig. 5: Within-gesture recognition rate of four gestures for (a) S4 and (b) S7 using textile electrodes. Results are mean over 10 trials.

mechanical noise, and change in limb volume. This will be explored in conjunction with the low-cost myoelectric control implemented in the Touch Hand [29].

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REFERENCES

- [1] Touch Bionics, "i-limb Ultra Revolution Clinician Manual," Tech. Rep., 2014. [Online]. Available: <http://www.touchbionics.com/sites/default/files/files/i-limb%20ultra%20revolution%20clinician%20manual%2012%2023%2014.0.pdf>
- [2] R. Steeper, "Technical information," *Building Research & Information*, vol. 22, no. 3, pp. 141–142, 1994. [Online]. Available: http://bebionic.com/distributor/documents/bebionic3_technical_information_-_Lo_Res.pdf
- [3] C. S. Harkins, A. McGarry, and A. Buis, "Provision of prosthetic and orthotic services in low-income countries: A review of the literature," *Prosthetics & Orthotics Int.*, vol. 37, no. 5, pp. 353–361, 2013.
- [4] D. van der Riet, R. Stopforth, G. Bright, and O. Diegel, "The low cost design of a 3D printed multi-fingered myoelectric prosthetic hand," *Mechatronics: Principles, Tech. & Apps.*, pp. 85–117, 2015.
- [5] M. A. Oskoei and H. Hu, "Myoelectric control systems – A survey," *Biomed. Sig. Processing & Control*, vol. 2, no. 4, pp. 275–294, 2007.

- [6] A. Mangezi, A. Rosendo, M. Howard, and R. Stopforth, "Embroidered archimedean spiral electrodes for contactless prosthetic control," in *IEEE Int. Conf. on Rehab. Robotics*, 2017, pp. 1343–1348.
- [7] A. Shafti, R. R. Manero, A. Borg, K. Althoefer, and M. Howard, "Embroidered electromyography: A systematic design guide," *IEEE Trans. on Neural Sys. & Rehab. Eng.*, vol. 25, pp. 1472–1480, 2016.
- [8] H. Zhang, L. Tian, L. Zhang, and G. Li, "Using textile electrode emg for prosthetic movement identification in transradial amputees," in *IEEE Int. Conf. Body Sensor Networks*, 2013, pp. 1–5.
- [9] G. K. Jones, A. Rosendo, and R. Stopforth, "Prosthetic Design Directives : Low-cost hands within reach," *IEEE Int. Conf. on Rehab. Robotics*, pp. 1524–1530, 2017.
- [10] C. Friderichs, "South africa mobile health market opportunity analysis," Groupe Spéciale Mobile Association (GMSA), Tech. Rep., 2011.
- [11] S. Millstein, H. Heger, and G. Hunter, "Prosthetic use in adult upper limb amputees: a comparison of the body powered and electrically powered prostheses," *Prosthetics and Orthotics international*, vol. 10, no. 1, pp. 27–34, 1986.
- [12] D. Van Der Riet, R. Stopforth, G. Bright, and O. Diegel, "An overview and comparison of upper limb prosthetics," *IEEE AFRICON Conf.*, 2013.
- [13] M. G. C. A. Thalmic Labs, "MYO Armband Technical Specification," 2014. [Online]. Available: <https://www.myo.com/techspecs>
- [14] M. M. S. Advancer Technologies, "3-lead Muscle / Electromyography Sensor for Microcontroller Applications," 2015. [Online]. Available: https://github.com/AdvancerTechnologies/MyoWare_MuscleSensor/blob/master/Documents/AT-04-001.pdf
- [15] C. Pylatiuk, M. Muller-Riederer, A. Kargov, S. Schulz, O. Schill, M. Reischl, and G. Bretthauer, "Comparison of Surface Monitoring Electrodes for Long Term Use in Rehabilitation Device Control," *IEEE Int. Conf. on Rehab. Robotics*, pp. 300–304, 2009.
- [16] A. Shafti, R. B. R. Manero, A. M. Borg, K. Althoefer, and M. J. Howard, "Designing embroidered electrodes for wearable surface electromyography," *IEEE Int. Conf. Robotics & Automation*, pp. 172–177, 2016.
- [17] T. R. Farrell and R. F. Weir, "A Comparison of the Effects of Electrode Implantation and Targeting on Pattern Classification Accuracy for Prosthesis Control," *IEEE Trans. on Biomed. Eng.*, vol. 55, pp. 2198–2211, 2008.
- [18] H. J. Hermens, B. Freriks, R. Merletti, D. Stegeman, J. Blok, G. Rau, C. Disselhorst-Klug, and G. Hägg, "European Recommendations for Surface ElectroMyoGraphy," *Roessingh Research & Development*, pp. 8–11, 1999.
- [19] X. Zhang, X. Chen, Z.-Y. Zhao, Y.-Q. Tu, J.-H. Yang, V. Lantz, and K.-Q. Wang, "Research on gesture definition and electrode placement in pattern recognition of hand gesture action SEMG," *Int. Conf. on Med. Biometrics*, vol. 4901 LNCS, pp. 33–40, 2008.
- [20] M. Galar, A. Fernández, E. Barrenechea, H. Bustince, and F. Herrera, "An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes," *Pattern Recognition*, vol. 44, no. 8, pp. 1761–1776, 2011.
- [21] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.
- [22] S. S. Keerthi and C.-J. Lin, "Asymptotic behaviors of support vector machines with gaussian kernel," *Neural Computation*, vol. 15, no. 7, pp. 1667–1689, 2003.
- [23] C. Hsu and C. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, 2002.
- [24] E. L. Allwein, R. Schapire, and Y. Singer, "Reducing multiclass to binary: A unifying approach for margin classifiers," *J. of Machine Learning Res.*, vol. 1, pp. 113–141, 2000.
- [25] D. Farina, I. Vujaklija, M. Sartori, T. Kapelner, F. Negro, N. Jiang, K. Bergmeister, A. Andalib, J. Principe, and O. Aszmann, "Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation," *Nature Biomedical Engineering*, vol. 1, p. 0025, 2017.
- [26] C. Castellini and P. Van Der Smagt, "Surface EMG in advanced hand prosthetics," *Biological cybernetics*, vol. 100, no. 1, pp. 35–47, 2009.
- [27] L. DeSanti, "Pathophysiology and current management of burn injury," *Advances in Skin & Wound Care*, vol. 18, no. 6, pp. 323–332, 2005.
- [28] G. Jones and R. Stopforth, "Mechanical design and development of the touch hand ii prosthetic hand," *RD J. South African Inst. Mech. Eng.*, vol. 32, pp. 23–34.
- [29] G. K. Jones and R. Stopforth, "Improvements on a prosthetic hand," in *PRASA/RobMech and AfLaT International Joint Symposium*, 2014.