A Feasibility Study on the Use of Anthropometric Variables to Make Muscle-Computer Interface More Practical

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Abstract

High classification accuracy has been achieved for muscle-computer interfaces (MCIs) based on surface electromyography (EMG) recognition in many recent works with an increasing number of discriminated movements. However, there are many limitations to use these interfaces in the real-world contexts. One of the major problems is compatibility. Designing and training the classification EMG system for a particular individual user is needed in order to reach high accuracy. If the system can calibrate itself automatically/semi-automatically, the development of standard interfaces that are compatible with almost any user could be possible. Twelve anthropometric variables, a measurement of body dimensions, have been proposed and used to calibrate the system in two different ways: a weighting factor for a classifier and a normalizing value for EMG features. The experimental results showed that a number of relationships between anthropometric variables and EMG time-domain features from upper-limb muscles and movements are statistically strong (average r = 0.71-0.80) and significant ($p < 0.05$). In this paper, the feasibility to use anthropometric variables to calibrate the EMG classification system is shown obviously and the proposed calibration technique is suggested to further improve the robustness and practical use of MCIs based on EMG pattern recognition.

Keywords

Circumference; Electromyography (EMG); Feature extraction; Gesture recognition; Hand motion; Muscle size.

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1. Introduction

Muscle-computer interfaces (MCIs) based on surface electromyography (EMG) recognition have been rapidly developed for various applications, i.e. prosthesis and electric-power wheelchair, in the last few years (Ahsan et al., 2010; Oskoei and Hu, 2007; Peerdeman et al., 2011; Phinyomark et al., 2011a). Nearly all previous works on EMG-based MCIs focus on classification accuracy improvement and the number of discriminated movements (Hariharan et al., 2012; Ju et al., 2011; Oskoei and Hu, 2007; Phinyomark et al., 2011a; Wojtczak et al., 2009). The success rate of these interfaces is usually higher than 80-90% based on recognizing several common tasks such as the movements of flexion/extension and abduction/adduction (Peerdeman et al., 2011). In laboratories, the number of discriminated tasks, i.e. grasping and wrist motions, has increased to cover most activities of daily living (ADLs) and to control a multiple DOF prosthesis (Cipriani et al., 2008).

While this interface holds so much potential, a few works have given attention to the context of real-world requirements such as long-term use or EMG's uncertainties, i.e. EMG electrode location shift (Tkach et al., 2010) and variation in muscle contraction between days (Phinyomark et al., 2012a), compatibility, i.e. minimal or no need for calibration and training between subjects (Saponas et al., 2010), and robustness, i.e. noise (Phinyomark et al, 2009). Among these requirements, the development of calibration and training issues is still far from being a practical one (Cannan and Hu, 2011; Saponas et al., 2010). In this study, we aimed to address these challenges with special emphasis on EMG and anthropometric techniques that can automatically or semi-automatically calibrate a system.

Due to different body compositions between users, EMG-based MCIs has never really reached the general population (Cannan and Hu, 2011). Every user has different types of muscles with varying sizes and other characteristics, so currently the systems still require new calibration and training (between users and also between days) to compensate for discrepancies. Moreover, this limitation prevents the development of standard interfaces that are compatible with almost any user.

In order to reduce the need for new training and calibration, some useful information should be added as automatic training input parameters. For a simple system that uses thresholding techniques, maximum voluntary contraction (MVC) alone is used and may be enough to adapt a system from one user to another. Based on the finding in several related works about a relationship between features of EMG and force, estimating the users MVC can be used to normalize the EMG signals or adjust the threshold values (Bolgla and Uhl, 2007; Vera-Garcia et al., 2010).

However, this relationship is strong only in an isometric or static contraction (Kamavuako et al., 2009), which can be linear or non-linear. When the muscle is free to change length and the joint is free to move as a dynamic muscle contraction, the relationship of EMG features and forces is more complicated (Oatis, 2008). Although force, or MVC, certainly plays a role, it is not significant enough to be used alone in adapting advanced EMG systems, and other additional useful information is necessary.

We know that muscle size, consisting of cross-sectional area (CSA) and length, can be employed together with EMG signal in order to determine muscle force (Hof et al., 1987). This relationship can be explained by the equation of Marras and Sommerich (1991) as shown in Appendix A. It means that there are correlations between muscle size, muscle force, and EMG signal (Raez et al., 2006; Ray and Guha, 1983). Hence, anthropometric variables, a measurable characteristic of the body, are considered. These variables can roughly estimate some muscle-size characteristics such as estimating thigh muscle cross-sectional area by segment circumference (Housh et al., 1995). On the other hand, measuring anthropometric variables is easier and some variables can be measured directly together with EMG signal via armband (Cannan and Hu, 2011; Saponas et al., 2009).

One of the related anthropometric variables is forearm circumference, which can be measured automatically via a wearable device. Cannan and Hu (2011) used forearm circumference for estimating MVC in order to calibrate the EMG thresholding technique based on the linear relationship between grip strength and forearm circumference as presented in Anakwe et al. (2007). However, the relationship between EMG during MVC and forearm circumference is not strong as found with grip force, and further anthropometric variables are recommended to be incorporated to make a reliable adaptive system (Cannan and Hu, 2011).

In this paper, the relationship between common-used EMG time-domain features and related anthropometric variables is investigated. As mentioned, features of the EMG signal were used to find the correlation instead of EMG associated with 100% MVC because we would like to move from calibrating the simple thresholding techniques to machine learning and pattern recognition. It should be noted that feature extraction is used as an input vector for classifier to make a decision output (Phinyomark et al., 2012b). So actions associated with EMG signal, e.g. forearm pronation/supination and hand open/close (dynamic contraction), are also used instead of EMG isometric (static) contraction.

Every strong and significant association between EMG feature and anthropometric variable, found in this study, could benefit a further design of EMG systems. It could automatically adapt the setting to a wider population. Moreover, due to a rapid increased number of wearable devices, anthropometric variables would become more practical and important in the near future.

2. Material and methods

The EMG data, which were used to investigate the relationship between anthropometric variables and EMG features in this study, were recorded from eight movements, five positions and twenty subjects during four days.

Eight movements consisting of forearm pronation (FP), forearm supination (FS), wrist extension (WE), wrist flexion (WF), wrist radial deviation (WR), wrist ulnar deviation (WU), hand open (HO), and hand close (HC) were chosen based on the frequently used in MCIs studies (Oskoei and Hu, 2007; Peerdeman et al., 2011; Phinyomark et al., 2011a), as shown in Fig. 1. These are movements of hand, wrist and arm. In addition, the shoulder was positioned at 0 degree (neutral) with elbow in full extension.

EMG recordings from five muscles were selected from both upper-arm and forearm and from both flexor and extensor muscles. The amplitude shape of EMG signals acquired from all muscles was significantly different according to the direction of eight movements as shown in Fig. 2 (Phinyomark et al., 2011b). There were: extensor carpi radialis longus

(ECRL), extensor carpi ulnaris (ECU), extensor digitorum communis (EDC), flexor carpi radialis (FCR) and biceps brachii (BB), as shown in Fig. 3.

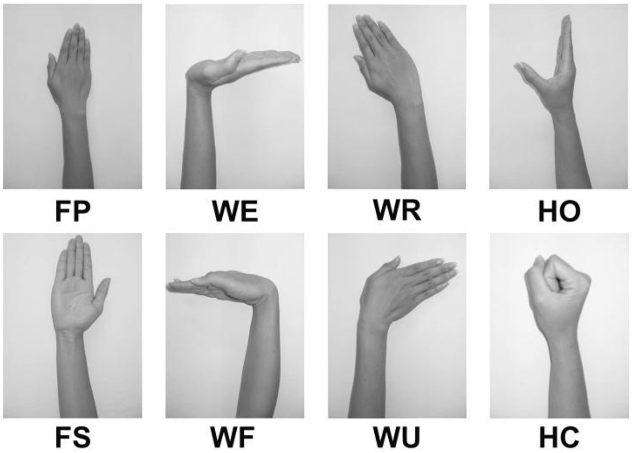


Fig. 1. Eight upper-limb movements.

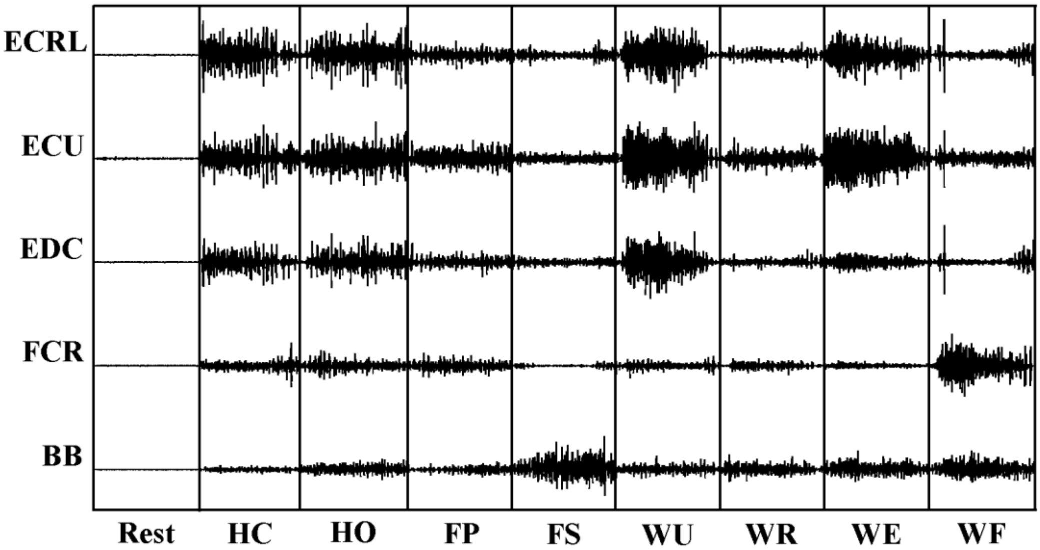


Fig. 2. The example amplitude shape of EMG signals acquired from 5 muscles and 8 movements with rest state.

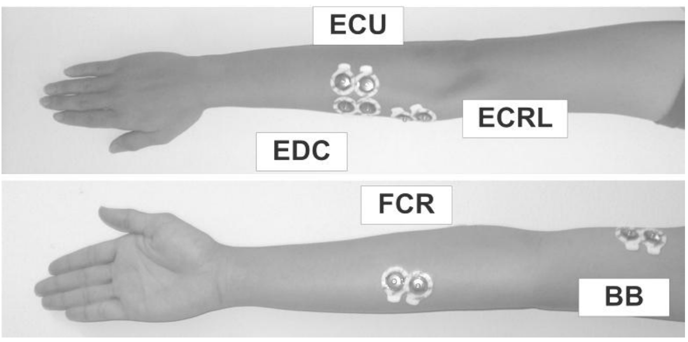


Fig. 3. Five electrode positions.

Twenty healthy subjects participated in the experiment consisting of 10 males (M1-M10) and 10 females (F1-F10). The age of the male subjects was 21.5±0.97 years and of the female subjects was 21.2±0.79 years. All subjects were dexterous with their right hands. They signed an informed consent in accordance to the University guideline. The EMG data were recorded on 4 separate days. Each day the subjects were asked to perform 15 sessions, which every movement was maintained for 2 s and the order of movements was randomized in each session. Based on a large fluctuating EMG data that was measured in this study, the effect of fluctuating EMG signals during different days was also considered.

In the experiment, the EMG data were collected from the positions on the right arm using bipolar Ag/AgCl electrodes (H124SG, Kendal ARBO) with 24 mm diameter and 20 mm inter-electrode distance. All EMG signals were amplified with a gain of 19.5x and sampled at 1024 Hz with a 24-bit resolution by a commercial wireless EMG measurement system (Mobi6-6b, TMS International B.V.). The EMG data were also passed through a band-pass filter with a cutoff frequency of 20 and 500 Hz to remove noise and unwanted signals.

2.1 Extraction of EMG features

As mentioned in the experiment above, 60 data sets with 2-s in duration in total were collected for each movement for each subject. In order to contain all EMG information, a window size of the extraction was set as a whole length of action (2-s) (Hudgins et al., 1993; Wojtczak et al., 2009). Five common used features based on Hudgins' time-domain approach (Hudgins et al., 1993) were used as the representative features in this paper: mean absolute value (MAV), mean absolute value slope (MAVS), waveform length (WL), zero crossing (ZC), and slope sign change (SSC). A set of Hudgins' time-domain features has usually been employed as a baseline feature set for comparing with a newly developed feature set, and the success of this feature set has been established in many recent studies, e.g. Li et al. (2011, 2010).

(1) MAV is commonly used as an EMG amplitude detector. It is defined as an average of the absolute value of the EMG signal amplitude in a window size L, which can be expressed as

$$MAV = \frac{1}{L}\sum_{i=1}^{L}|x_i|, \tag{1}$$

where x_i is an EMG signal amplitude at the i^{th} sample and L is the length of the window, which is set at 2048 samples (2-s) for all features.

(2) MAVS is defined as a difference between two mean absolute values of the signal in adjacent segments, k and k+1, where the window size L is divided into sub-windows or segments for k = 1, …, K-1. The definition is given by

$$MAVS_k = MAV_{k+1} - MAV_k \,. \tag{2}$$

It should be noted that MAV, WL, ZC and SSC provide only one feature value per window, whereas MAVS provides K-1 feature values per window. To provide a fair comparison between methods, the number of feature values for each window/movement trial was set at one for all methods. Hence, the value of K was set at 2 in this study. In other words, only MAVS_1 value was yielded and so, in the rest of this paper, MAVS refers to MAVS_1.

(3) WL is a simple complexity measure of the EMG signal. It is defined as a cumulative length of the waveform over the time window, which can be expressed as

$$WL = \sum_{i=1}^{L-1} \left| x_{i+1} - x_i \right|. \tag{3}$$

(4) ZC is a simple frequency measure of the EMG signal. It can be obtained by counting a number of times that the EMG waveform crosses zero amplitude level. To reduce the effect of background noise, a predefined threshold *thr* was set at 10 for ZC, and also SSC. Mathematically, it is calculated as

$$ZC = \sum_{i=1}^{L-1} \left[\operatorname{sgn}\left(x_i \times x_{i+1}\right) \cap \left| x_i - x_{i+1} \right| \geq thr \right]; \quad \operatorname{sgn}(y) = \begin{cases} 1, & \text{if } y < 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

(5) SSC is another measure of frequency content of the EMG signal. It is a number of times that the slope of the EMG waveform changes sign. The number of changes between the positive and negative slopes among three sequential samples is performed with the predefined threshold *thr* as used in ZC. SSC can be mathematically expressed as

$$SSC = \sum_{i=2}^{L-1} \left[f\left[\left(x_i - x_{i-1}\right) \times \left(x_i - x_{i+1}\right) \right] \right]; \quad f(y) = \begin{cases} 1, & \text{if } y \geq thr \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

As described in Phinyomark et al. (2012b), these five features in Hudgins' group share the distribution in space, and using two or three features out of them in the classification could achieve the same performance as using all features. MAV and WL have a little difference in discriminating patterns where MAV contains energy information and WL contains complexity information. MAVS is an extension version of the MAV features. ZC and SSC, two features based on frequency information, have a similar distribution in space. Hence, it is not necessary to use all features in the final feature vector. The relationship with the anthropometric variables should be discussed for each individual feature. To be flexible in the future design of EMG-based MCIs, the correlation was also summarized for each muscle position.

While the number of electrode positions should be reduced to the minimum, the number of discriminated movements should be increased as much as possible. Four movements have been used like a standard minimal number of control commands in EMG-based MCIs (Peerdeman et al., 2011; Phinyomark et al., 2011a). Hence, only the combinations between anthropometric variable, EMG feature and EMG position that have the strong and significant correlations in at least four movements will be presented in this paper.

2.2 Anthropometric variables

Anthropometry is a measurement of the dimensions of the different parts of the body and other physical characteristics. There are two types of measurement: static and dynamic dimensions. In this paper, only static dimensions were considered. Twelve related anthropometric variables were chosen: 1. Body mass (kg), 2. Standing height (cm), 3. Body mass index or BMI (kg/m^2), 4. Biceps circumference (cm), 5. Forearm circumference (cm), 6. Hand breadth (cm), 7. Hand length (cm), 8. Elbow-hand grip length (cm), 9. Elbow-fingertip length (cm), 10. Shoulder-elbow length (cm), 11. Bi-deltoid breadth (cm), and 12. Forward grip reach (cm). All variables were measured from all the subjects in the same day and from the right arm.

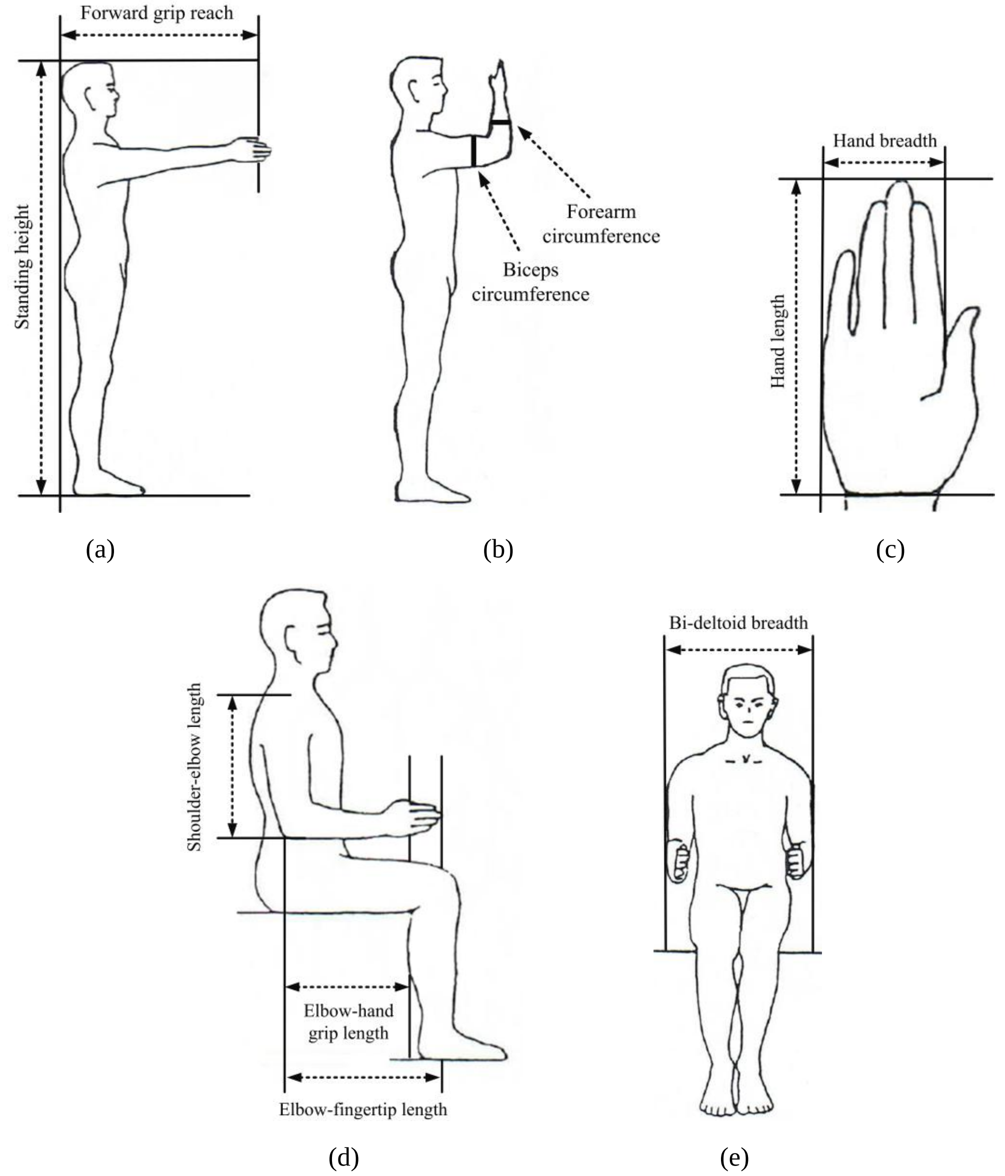


Fig. 4. Anthropometric (body) measurements (a) standing height and forward grip reach, (b) biceps circumference and forearm circumference, (c) hand breadth and hand length, (d)

elbow-hand grip length, elbow-fingertip length and shoulder-elbow length, (e) bi-deltoid breadth.

These twelve measurement techniques, as shown in Fig. 4, can be measured using different kinds of instruments (Centurion Kit, Rosscraft): (1) Balance type scales for body mass, (2) Anthropometer for standing height, (3) Tape for biceps and forearm circumferences, (4) Small bone caliper for hand breadth and hand length, (5) Wide sliding torso caliper for elbow-hand grip length, elbow-fingertip length, shoulder-elbow length and bi-deltoid breadth, and (6) Measuring block with tape measure for forward grip reach.

It should be noticed that the circumferences were measured with elbow flexed 90 degrees (the arms are abducted). For other variables, the specific locations were defined as:

(1) Hand breadth is measured between metacarpalphalangeal joint II and V.

(2) Hand length is measured from the wrist landmarks to dactylion.

(3) Elbow-hand grip length is measured from the posterior tip of the olecranon process to the center of grip during holding a pencil.

(4) Elbow-fingertip length is measured from the posterior tip of the olecranon process to dactylion.

(5) Shoulder-elbow length is measured from the right acromion landmark to the inferior tip of the olecranon process of the right elbow.

(6) Bi-deltoid breadth is measured across the body at the level of the deltoid landmarks.

(7) Forward grip reach is measured from the back wall to the tip of the thumb.

In addition, BMI, which is a roughly estimation of human body fat, is calculated as

$$BMI = \frac{body\ mass}{(standing\ height)^2}. \quad (6)$$

2.3 Evaluating functions

Correlation analysis measures a relationship or association and gives a statistic known as the correlation coefficient or r coefficient. This value shows the degree or strength of linear association between two measured variables. The interpretation of correlation coefficients can be defined as presented in Table 1. The r value contains both a magnitude and a direction (positive and negative) of the relationship. However, in this paper we reported the absolute value of average r or only the magnitude of correlation.

Table 1. The strength category of correlation coefficients r (Taylor, 1990).

Ranges of r in absolute value	Interpretation
$r \leq 0.35$	low or weak correlations
$0.35 < r \leq 0.67$	modest or moderate correlations
$0.67 < r \leq 1$	strong or high correlations

As we mentioned that only the combinations that have the strong correlations will be presented, it means that the value of r must be higher than 0.67. Moreover, the correlation coefficient has to be statistically significant too. In this study, the significant level was set at p

< 0.05. Due to a small samples ($n \leq 20$), t-test was employed to test the significance of a correlation coefficient, as can be defined by

$$t = r\sqrt{\frac{n-2}{1-r^2}} \,. \qquad (7)$$

Note that the degrees of freedom for entering the t-distribution is n-2.

3. Results

The different results of the relationship of muscle size/force and anthropometric variable between male and female subjects are found in several studies (e.g. Anakwe et al., 2007; Holzbaur et al., 2007). Therefore, the relationships of anthropometric variables have usually been investigated and discussed for each gender: male and female. All anthropometric variables of male and female subjects, which were measured in the experiment, are reported respectively in Table 2 and Table 3.

Table 2. Anthropometric variables of ten male subjects (M1-M10) with the mean and the standard deviation (SD) of each variable.

Variables \ Subjects	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	Mean	SD
Body mass	49.0	62.0	65.0	74.0	73.0	58.0	57.0	55.0	63.0	54.0	61.0	8.1
Standing height	166.5	170.0	173.0	177.0	172.0	170.0	170.0	167.5	167.0	164.0	169.7	3.7
Body mass index	17.7	21.5	21.7	23.6	24.7	20.1	19.7	19.6	22.6	20.1	21.1	2.1
Biceps circumference	23.1	26.2	27.5	32.6	32.4	30.7	26.1	23.6	26.7	25.6	27.5	3.4
Forearm circumference	22.5	22.4	25.2	29.1	28.2	26.8	23.4	23.1	24.3	22.7	24.8	2.5
Hand breadth	7.4	7.2	8.4	9.1	8.9	12.6	11.7	7.5	7.8	7.6	8.8	1.9
Hand length	17.2	17.8	15.5	18.2	18.9	19.1	19.3	17.4	18.3	17.1	17.9	1.1
Elbow-hand grip length	34.4	35.1	37.6	39.3	39.7	33.9	33.8	36.0	38.5	38.4	36.7	2.3
Elbow-fingertip length	46.8	49.7	52.2	52.2	52.6	46.2	46.2	47.2	50.0	49.7	49.3	2.5
Shoulder-elbow length	37.7	33.6	36.9	37.8	38.2	35.7	38.4	35.4	38.3	36.6	36.9	1.6
Bi-deltoid breadth	39.3	46.4	44.6	54.7	47.3	37.4	30.4	42.1	45.9	47.4	43.6	6.7
Forward grip reach	75.6	74.5	80.7	89	80.4	74.3	75.7	72.6	83.5	78.1	78.4	5.0

Table 3. Anthropometric variables of ten female subjects (F1-F10) with the mean and the standard deviation (SD) of each variable.

Variables \ Subjects	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Mean	SD
Body mass	47.0	45.0	53.0	46.0	54.0	45.0	43.0	56.0	50.0	49.0	48.8	4.4
Standing height	150.0	160.0	156.0	155.0	160.0	146.0	159.0	163.0	167.0	162.0	157.8	6.3
Body mass index	20.9	17.6	21.8	19.1	21.1	21.1	17.0	21.1	17.9	18.7	19.6	1.8
Biceps circumference	24.4	19.8	27.6	24.2	24.8	25.5	22.6	24.9	22.3	21.5	23.8	2.2
Forearm circumference	21.6	19.1	22.9	21.5	22.2	21.9	19.7	22.7	20.6	20.9	21.3	1.2
Hand breadth	7.4	6.4	7.3	7.5	6.9	6.6	6.9	8.1	7.4	7.2	7.2	0.5
Hand length	15.6	16.7	16.8	16.6	16.4	14.7	16.1	15.2	17.1	17.2	16.2	0.8
Elbow-hand grip length	32.8	35.0	34.8	34.6	34.4	32.6	34.3	35.2	38.4	36.2	34.8	1.6
Elbow-fingertip length	43.3	46.8	46.4	46.4	46.2	39.1	46.2	47.1	49.0	47.7	45.8	2.8
Shoulder-elbow length	34.9	35.3	36.1	35.8	33.1	34.2	33.0	37.1	37.8	36.0	35.3	1.6
Bi-deltoid breadth	41.9	36.8	43.4	41.2	41	37.8	36.9	37.0	37.2	38.7	39.2	2.5
Forward grip reach	65.1	72.0	60.8	68.1	75.7	65.2	70.2	63.3	74.4	70.6	68.5	4.9

The differences between parameters of male and female subjects were highly significant at $p < 0.01$ for 8 parameters and significant at $p < 0.10$ for the remainders: BMI, elbow-hand grip length, shoulder-elbow length, and bi-deltoid breadth. However, the difference between ages of male and female subjects was not significant ($p = 0.458$) in this study (subjects of the same age).

The strong and significant correlations between EMG features and anthropometric variables for each muscle are presented in Table 4 for male subjects and Table 5 for female subjects. From Table 4, two features (MAV and WL) from different two muscles (ECU and BB) showed a strong relationship with bi-deltoid breadth for 4-5 movements. On the other hand, from Table 5, four features (MAVS, WL, ZC, and SSC) from two muscles (FCR and BB) have high correlations with a number of anthropometric variables i.e. hand length, biceps circumference, and bi-deltoid breadth. The correlation coefficients *r* ranged between 0.69 and 0.87. It should be emphasized that all features were computed from the EMG data recorded from 4 separate days, thus the effect of fluctuating EMG signals between days was also included in the finding results. In other words, the correlated anthropometric variables with EMG features could be used to calibrate the system even though the EMG feature values have been changed from one day to another day. Additionally, the correlations from each single day are similar to that from all days. The interesting result is in the case of the third day and the fourth day. The correlations between features and anthropometric variables improved a litter bit. It may be due to an increasing experience of the subjects to perform the stable movements. The performance of EMG pattern classification has been found that it improves when the data used for training a classifier are recorded from the third day and the fourth day (Phinyomark et al., 2012a; Zhang et al., 2008).

Table 4. Correlation coefficients *r* between anthropometric variables and EMG features in cases of strong and significant relationships, at least 4 movements for a muscle, based on 10 male subjects.

Feature	Anthropometric variable	Position	Movements	Average $\|r\|$ (min-max)
MAV	Bi-deltoid breadth	ECU	FP, WE, WF, WU, HC	0.77 (0.73-0.82)
WL	Bi-deltoid breadth	BB	WE, WR, WU, HC	0.71 (0.69-0.73)

Table 5. Correlation coefficients *r* between anthropometric variables and EMG features in cases of strong and significant relationships, at least 4 movements for a muscle, based on 10 female subjects.

Feature	Anthropometric variable	Position	Movements	Average $\|r\|$ (min-max)
MAVS	Hand length	FCR	FS, WE, WF, WR, HC	0.77 (0.70-0.86)
MAVS	Hand length	BB	FS, WE, WF, WU	0.80 (0.75-0.87)
WL	Bi-deltoid breadth	BB	FP, FS, WF, WR, HC	0.75 (0.72-0.83)
ZC	Biceps circumference	BB	FP, FS, WF, HO	0.76 (0.69-0.85)
ZC	Bi-deltoid breadth	BB	FP, FS, WF, WU, HC	0.77 (0.70-0.84)
SSC	Bi-deltoid breadth	BB	FP, FS, WF, WU, HC	0.80 (0.70-0.86)

To observe the results, for instance, the average MAV feature extracted from ECU muscle and WF movement of each male subject was plotted in space with the bi-deltoid breadth value of that subject, and the linear line of best fit representing the association was also shown in Fig. 5. It showed that both measured variables have an inverse relationship (one variable increased when another one decreased) and the variable points closed to a straight line (r = 0.82 at p < 0.05).

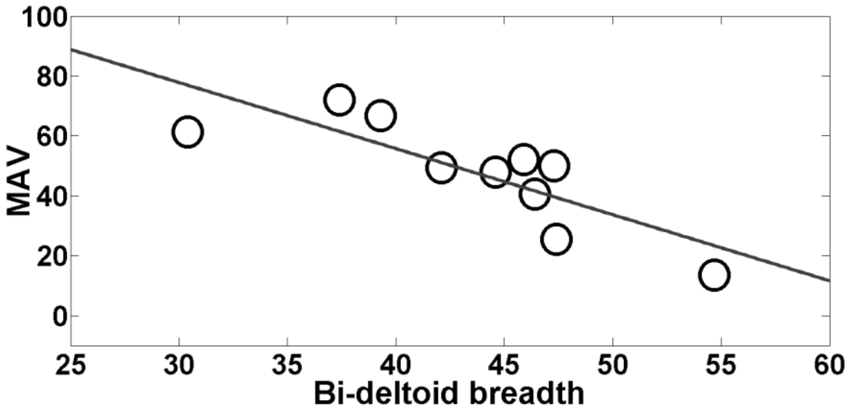
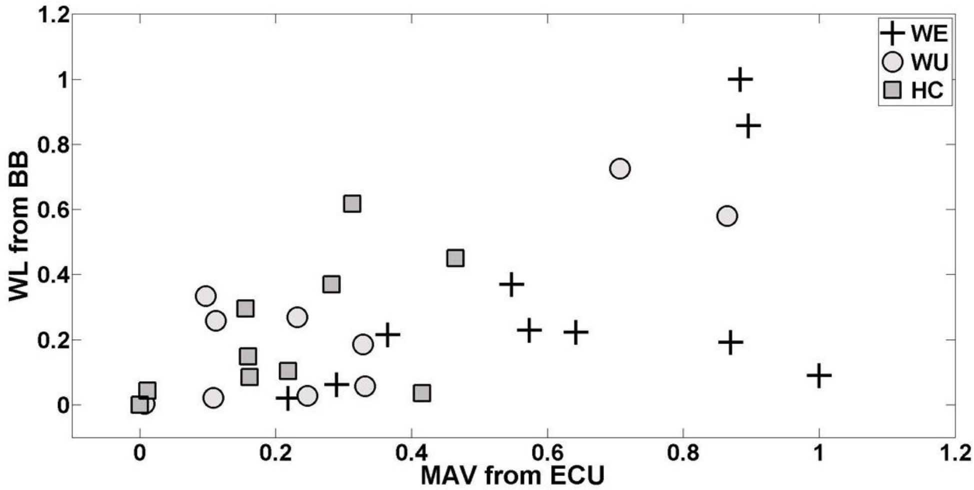
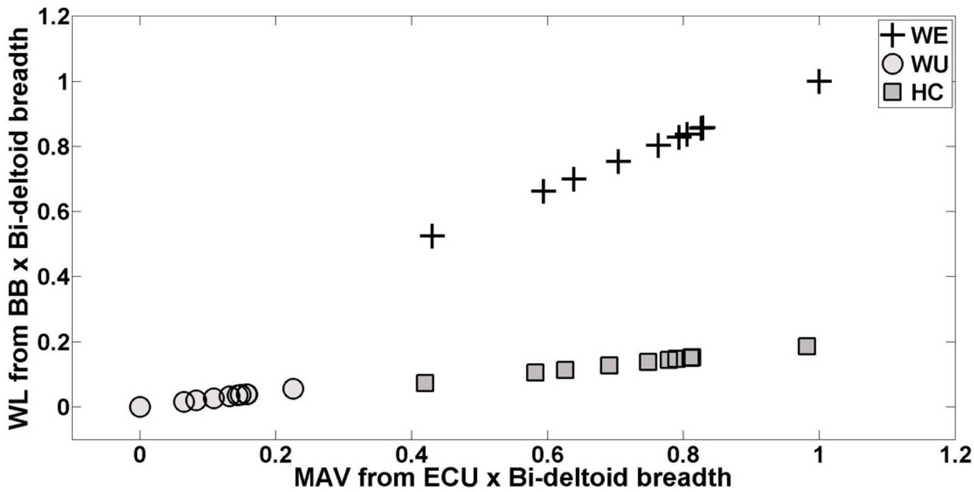


Fig. 5. The relationship between average MAV features extracted from ECU muscle and bi-deltoid breadth values for 10 male subjects with a line of best fit applied for WF movement.



(a)



(b)

Fig. 6. Scatter plots of MAV features extracted from ECU muscle and WL features extracted from BB muscle with 3 movements (WE, WU, and HC) from 10 male subjects (a) original features (b) normalized feature. Note that all features were normalized to be [0, 1].

In practice, we can use the correlated anthropometric variables to calibrate the EMG classification system in two different ways: a weighting factor for classifier and a normalizing value for EMG features. This topic is out of scope for this paper because the approach depends on the types of the classifier. However, in order to show the feasibility to use this anthropometric variable, two original features of 3 movements (WE, WU and HC) of 10 male subjects from Table 4 were plotted in space as shown in Fig. 6(a) and the normalized EMG features (original EMG feature multiply by bi-deltoid breadth value of the same subject) were also plotted as shown in Fig. 6(b). By comparing Figs. 6(a) and 6(b), it is clear that the distribution in space of each movement of the original features is very poor. It is difficult to classify the movements because of the large variation of each feature between the subjects. If we train the classification system using EMG features extracted from one of the subjects and test the system with features from the remaining subjects, we would get a low classification accuracy. On the other hand, the discrimination between three movements of the normalized features, in Fig. 6(b), is very good. It could be possible to achieve a high classification accuracy by training the EMG system using features extracted from one of the subjects and testing with features calculated from the remaining subjects.

4. Discussion and future works

Based on the results of both tables, Table 4 and Table 5, we can observe that bi-deltoid breadth and BB muscle usually have a strong correlation and should be paid more an interest in further study. However, the bi-deltoid breadth cannot automatically and/or directly be measured from the EMG wearable device like the forearm or biceps circumference. On the other hand, biceps circumference had a strong correlation only with ZC features extracted from BB muscle. It is not enough for achieving very high classification accuracy for many gestures. However, a strong correlation between anthropometric variables and EMG features was obviously present, and further studies should be done in two different ways.

First, for an automatically calibrated system using measures directly obtained from the EMG armband, the relationship between biceps/forearm circumference and other EMG features should be investigated and used together with ZC to make a useful feature vector. Based on the results in this paper, only one out of five features has a strong relationship and the proposed time-domain features share mathematical definition and information with most of time-domain features (Phinyomark et al., 2012b). Hence, maybe only a few features will have a strong correlation with circumference variable, as found with the EMG MVC in Cannan and Hu (2011). However, the relationship with other types of EMG features like frequency-domain or time-scale features have not been evaluated yet; such feature types may have a high association.

Second, for a semi-automatically calibrating system, bi-deltoid breadth parameter showed a strong association with 4 out of 5 features and the remaining feature MAVS has low classification performance and was not used in several previous EMG systems e.g. Li et al.

(2011). Thus the bi-deltoid breadth could be useful in future works to be used as a weighting factor for classifier or a normalizing parameter for EMG features.

However, more attention should be paid to two limitations in the future: (1) the number of discriminated movements and (2) gender. In the experiments, eight movements were performed but only 4-5 movements had strong relationships. Other kinds of upper-limb movements may be needed in order to increase the ability of the system such as grasping and finger movements. In addition, strong correlations between anthropometry and EMG features were not found across the gender (both male and female subjects) in this study. The maximum r coefficient across the gender was 0.64, which was calculated between ZC and bi-deltoid breadth from BB muscle based on 8 movements.

In future works, the evaluation of the relationship between useful anthropometric variables and other types of features, movements and also muscle locations should be done. An EMG classification system that can automatically or semi-automatically calibrate should be implemented and its classification accuracy measured to evaluate the performance of the calibration. The system should be trained using EMG features extracted from one or a few subjects and tested with EMG features of the remaining (many subjects) like a 10-fold cross-validation between the subjects.

5. Conclusion

This paper presented the feasibility study on the use of anthropometric variables to make EMG-based MCIs easy to use in general population. The relationship of twelve anthropometric variables with five popular well used time-domain features have been evaluated based on five muscle positions and eight movements of upper-limb. Some strong associations between anthropometric variables and EMG features have been found and can be used to calibrate the EMG classification system automatically or semi-automatically.

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Appendix A

Equation A.1 (Marras and Sommerich, 1991) is used to determine a muscle force level at each sampling point in time. It sums up all of the modifications made to the EMG signal and can convert the empirical EMG signal into muscle force.

$$Muscle\ \ force = gain \times \frac{EMG}{EMG_{\max}} \times area \times LS\ \ factor \times V\ ratio, \tag{A.1}$$

where $Muscle\ \ force$ = muscle tension associated with EMG;

$gain$ = factor that includes maximum muscle force per unit of area;

EMG = measured EMG value at a particular time;

$EMG_{\max}$ = maximum EMG value for specific muscle at specific angle of operation;

$area$ = muscle cross-sectional area;

$LS\ \ factor$ = length-strength modulation factor;

$V\ ratio$ = velocity modulation factor.