Fluctuation and Noise Letters
Vol. 12, No. 0 (2013) 000–000

EMG AMPLITUDE ESTIMATORS BASED ON PROBABILITY DISTRIBUTION FOR MUSCLE-COMPUTER INTERFACE

ANGKOON PHINYOMARK, FRANCK QUAINE, and YANN LAURILLAU
GIPSA Laboratory (CNRS UMR 5216) and LIG Laboratory (CNRS UMR 5217)
University Joseph Fourier (University of Grenoble), Grenoble, France
angkoon.p@hotmail.com, franck.quaine@gipsa-lab.grenoble-inp.fr, yann.laurillau@imag.fr

SIRINEE THONGPANJA, CHUSAK LIMSAKUL, and PORNCHAI PHUKPATTARANONT
Department of Electrical Engineering, Faculty of Engineering,
Prince of Songkla University, Songkhla, Thailand
sirinee.th@gmail.com, chusak.l@psu.ac.th, pornchai.p@psu.ac.th

Received (received date)
Revised (revised date)
Accepted (accepted date)

To develop an advanced muscle–computer interface (MCI) based on surface electromyography (EMG) signal, the amplitude estimations of muscle activities, i.e., root mean square (RMS) and mean absolute value (MAV) are widely used as a convenient and accurate input for a recognition system. Their classification performance is comparable to an advanced and high computational time-scale methods, i.e., the wavelet transform. However, the signal-to-noise-ratio (SNR) performance of RMS and MAV depends on a probability density function (PDF) of EMG signals, i.e., Gaussian or Laplacian. The PDF of upper-limb motions associated with EMG signals is still not clear, especially for dynamic muscle contraction. In this paper, the EMG PDF is investigated based on surface EMG recorded during finger, hand, wrist and forearm motions. The results show that on average the experimental EMG PDF is closer to a Laplacian density, particulary for male subject and flexor muscle. For the amplitude estimation, MAV has a higher SNR, defined as the mean feature divided by its fluctuation, than RMS. Due to a same discrimination of RMS and MAV in feature space, MAV is recommended to be used as a suitable EMG amplitude estimator for EMG-based MCIs.

Keywords: Electromyography (EMG); feature extraction; fluctuating signal; probability density function (PDF); signal-to-noise ratio (SNR).

1. Introduction

Although many advanced time-scale and non-linear algorithms have been developed in the past decade to analyze and identify surface electromyography (EMG) signal [1, 2], features based on the amplitude of surface EMG signals have been still widely used as a control input in muscle-computer interfaces (MCIs) [3–7]. One of the major advantage reasons is about the lower complexity and computational cost of the EMG amplitude estimators compared to the advanced time-scale and non-linear algorithms. They can be implemented in a low-cost-and-performance processor and/or a portable/mobile device [8–10]. Moreover, a combination of an EMG amplitude feature set and a simple classifier, i.e., linear discriminant analysis (LDA), provides classification performance comparable to an advanced combination between time-scale/non-linear features and a more complex classifier, such as artificial neural network or support vector machine [11–13].

Many statistics are applied on EMG amplitudes, e.g., sum, mean and variance, in order to extract the useful information to classify actions associated with surface EMG signals. However, due to a nature of surface EMG signals that has a mean value of about zero, because of its positive and negative deviations, a full-wave rectification is usually applied to make negative EMG values positive. Two convenient and accurate EMG amplitude estimators are root mean square (RMS) and mean absolute value (MAV) [14]. The mathematical definition of RMS and MAV methods is presented in Appendix A. Both features have been used frequently in EMG classification and estimation systems. However, the signal-to-noise-ratio (SNR) performance of RMS and MAV depends on the probability density function (PDF) of EMG signals, i.e., a Gaussian or a Laplacian density [15, 16]. It is important to note that the SNR is used as a standard metric to compare the EMG amplitude estimator performance [15–17].

Theoretically, in the maximum likelihood sense, an optimal EMG amplitude estimator based on the Gaussian model is RMS [16], whereas an optimal EMG amplitude estimator based on the Laplacian model is MAV [15]. However, the main question is about the experimental EMG PDF. Although it is clearly found that the experimental EMG density falls between the Gaussian and the Laplacian densities, conflicting results have been found in the literature about the relationship between the level of muscle contraction and the level of non-Gaussianity of EMG signals [18–20]. In a number of studies, the EMG PDF tends towards the Gaussian density as the muscle contraction level increases [18, 21]. In contrast, Hussain et al. [19] found that the EMG PDF moves towards the Laplacian density when the muscle contraction level increases. In Kaplanis et al. [20], the EMG signal is more Gaussian at mid-level (50%) of maximum muscle contraction while being more Laplacian at low and high levels of muscle contraction.

In addition to the contradicting results, most of studies examine the PDF of surface EMG signals at different isometric/static muscle contraction levels [15, 18, 20, 21]. However, motion recognition methods developed on the basis of static EMG portion only cannot deal well with the real activities of daily living, which combine both static and dynamic contractions (or steady-state and transient EMG signals) [22, 23]. Limiting motion recognition system only on the static EMG portion decreases the usability of MCIs. Furthermore, only the EMG PDF of dynamic lower-limb motions has been examined in the literature [19, 24].

In this paper, the EMG PDF of upper-limb motions including finger, hand, wrist and forearm motions–recorded from two different experiments–is investigated. These motions, which contain both transient and steady-state EMG portions, are widely used and applied in MCI application. After the problem of EMG PDFs is re-examined, a measure of the quality of EMG amplitude estimators, as called SNR, is used to compare the performance of RMS and MAV features. The relationship between the experimental EMG PDF and the SNR performance is discussed. In addition, the classification accuracies computed from several classifiers are used to confirm the performance of both features. The results from relevant EMG-based MCI studies are also reviewed and discussed.

It should be emphasized that to yield a good classification performance, features extracted from the EMG amplitude estimators should have a constant value or less variation around mean value for each motion class. The SNR, in this paper, is defined as the mean of the amplitude estimate, or "signal", divided by its fluctuation, or "noise" [15]. Therefore, the term "noise" does not refer to noise residing in electronic components in the detection and recording equipments including ambient noise and motion artifact [25, 26].

2. Experimental Study One

2.1. *Data Acquisition and Experiment*

The EMG acquisition and experiment for the first EMG data set are described in detail in our previous studies [2, 13]. Briefly, the EMG data were acquired from 18 normally limbed individuals (9 males and 9 females), recording four channels of EMG from bipolar Ag/AgCl electrodes placed on the right forearm during eight hand, wrist and forearm motions. EMG data were collected from 4 muscles: extensor carpi radialis longus (ECRL), extensor digitorum communis (EDC), extensor carpi ulnaris (ECU) and flexor carpi radialis (FCR). A sequence of 15 sets of eight different classes of motion were performed by a day and each subject, resulting in a total of 60 sets for 4 separate days. The exact position of the electrodes was not marked from one day to other days, so the electrode positions may be slightly shifted and fluctuating EMG signals were produced and recorded.

Each data set consisted of 8 randomized action trials without repetition: 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), with an action trial period of 2 s and a rest period of 2 s between trials. The order of motions was independently randomized for each set, so it is possible to have the same order across 60 sets in a subject. Shoulder and elbow positions were fixed at neutral and full extension for all subjects. Measured surface EMG signals were sampled at 1024 Hz and were amplified with a gain of 19.5x using an EMG measurement system (Mobi6-6b, TMS International B.V.). Movement artefact (<20 Hz), power-line interference (50 Hz) and high-frequency noise (>500 Hz) were also removed. In total, 34560 recordings with a length of 2048 samples (2 s) were available for analysis (18 subjects × 4 muscles × 8 motions × 4 days × 15 sets).

2.2. *Methods of Analysis*

Firstly, the absolute area difference (AAD) between a recording histogram (EMG density estimate) and a Gaussian/Laplacian density is used to decide the EMG PDF of upper-limb motions. For each of the 34560 non-overlapping recordings, the 2048 samples (2 s, a whole action trial period) are normalized by adjusting a recording mean to zero and a recording variance to one in order to provide uniformity for EMG PDF estimation [21]. Then, a recording histogram is constructed by using 501 bins, equally spaced over the normalized range of –5 to +5. The AAD results are analyzed by gender (male and female) and by muscle type (extensor and flexor), together with the composite histograms to provide the average density.

Secondly, the SNR is used to decide the quality of the EMG amplitude detectors [15]. The SNR is defined as the ratio of the expected EMG amplitude estimate to the variation about its mean value as mentioned above. A fixed window length of 256 samples (250 ms) is used, so for each recording eight adjacent windows are yielded as a result of the amplitude estimator. In other word, the SNR can be calculated by the square root of the squared mean value of eight adjacent RMS (or MAV) windows divided by its variance.

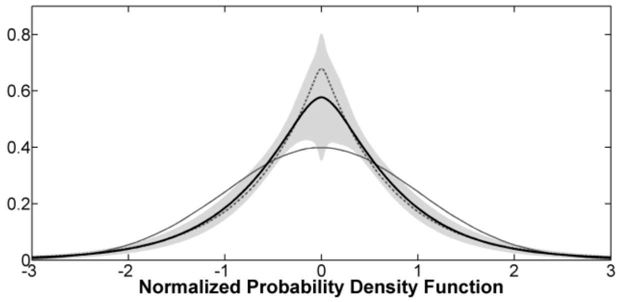
In addition to the SNR, classification accuracies obtained from three classifiers consisting of the LDA, quadratic discriminant analysis (QDA) and *k*-nearest neighbor (*k*NN) with $k = 5$ [4] are used to confirm the optimal EMG ampitude detector for upper-limb EMG-based MCIs. For each subject, a 10-fold cross-validation is used. The original EMG data is randomly partitioned into 10 equal size data. A total of 9 of the 10 subdata are used as the training data and the remaining subdata as the testing data, and then the process is repeated until 10 times, with each of the 10 subdata used once as the testing data. The average accuracy from 10 folds is used as a representative accuracy. The same configuration with SNR performance is used for data segmentation, i.e., an adjacent windowing with a fixed window length of 256 samples. It should be noted that these simple classifiers are used instead of advanced classifiers, i.e., the artificial neural network and the support vector machine, because the advanced classifiers have to be optimized together with feature extraction [11].

2.3. *Results*

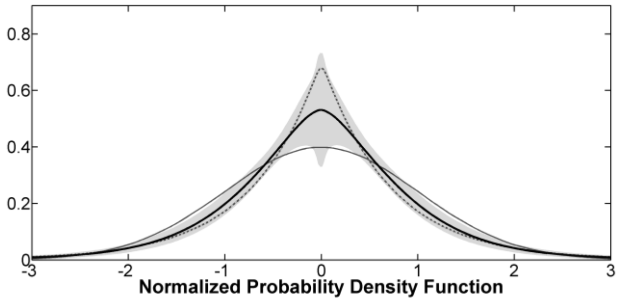
Normalized composite EMG PDFs of all motions and muscles by gender, male and female, are shown respectively in Fig. 1(a) and in Fig. 1(b), and that of all motions and subjects by muscle type, extensor and flexor, are shown respectively in Fig. 1(c) and in Fig. 1(d). For male subjects, the AAD between the composite experimental EMG density and the theoretical Gaussian density is 0.2391, while this difference for the theoretical Laplacian density is 0.0603 (3.96 times smaller). For female subjects, the AAD between the composite experimental EMG density and the theoretical Gaussian density is 0.1902, while this difference for the theoretical Laplacian density is 0.1017 (1.87 times smaller). On the other hand, the AADs between the composite experimental EMG density and the Gaussian density are 0.1915 for extensor muscles and 0.2847 for flexor muscle, while these differences for the Laplacian density are 0.1001 (1.91 times smaller) for extensor muscles and 0.0436 (6.53 times smaller) for flexor muscle. The difference between the two-densities AADs is statistically significant ($p < 0.001$) for all subjects and muscles.

The AADs and the number of times that each recording's estimated density (Gauss/Laplace) best described the EMG data are presented in Tables 1–4 by gender and by muscle type. These tables also present the SNRs and the number of times that each estimator (RMS/MAV) was best. Average SNR performance of all motions and muscles for male subjects is 4.25 using RMS versus 4.47 using MAV and this average value for female subjects is 4.25 using RMS versus 4.42 using MAV. On the other hand, for extensor muscles, average SNR performance of all motions and subjects is 4.47 using RMS versus 4.66 using MAV and this average value for flexor muscle is 3.58 using RMS versus 3.81 using MAV. MAV has a higher SNR than RMS by 4.0%-6.4%, and the difference between the two-estimators SNRs is statistically significant ($p < 0.001$) for all subjects and muscles.

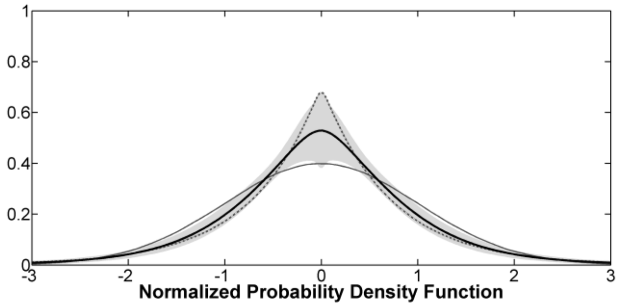
It should be noted that the results of three extensor muscles, i.e., ECU, ECRL and EDC, are similar to each other. So only the results of one extensor muscle, i.e., ECU, are presented in Tables 1–2 as a representative extensor muscle.



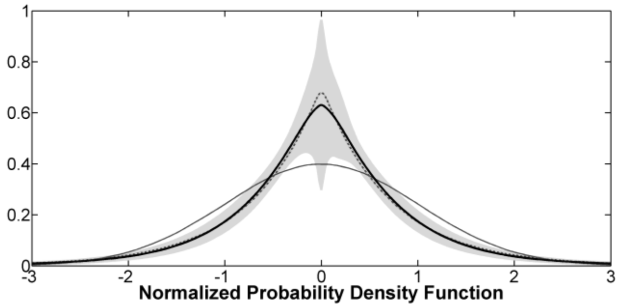
(a)



(b)



(c)



(d)

Fig. 1. Normalized composite PDF estimates for (a) male subjects and (b) female subjects, and for (c) extensor muscles and (d) flexor muscle. Experimental density (solid black line) is the average of (a) 17280, (b) 17280, (c) 25920, and (d) 8640 recordings. Shaded region indicates one standard deviation above and below the average. Solid gray line indicates the Gaussian density and dashed gray line indicates the Laplacian density.

In addition to the SNR performance, the classification accuracies of RMS and MAV obtained from three classifiers are presented in Table 5. On average of three classifiers, the classification accuracies of the MAV are slightly higher than that of the RMS based on various hand, wrist, and forearm motions for both male (84.53%>83.52%) and female (81.49%>80.55%) subjects.

Table 1. AADs, closest PDFs, SNRs and best estimators tabulated by motion (wrist and forearm) from extensor muscle (ECU) and male subjects (M). Each row pools nine-male-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
FP	0.219±0.067	0.139±0.042	133	407	5.53±2.59	5.74±2.52	205	335
FS	0.249±0.083	0.158±0.053	166	374	4.87±2.39	4.93±2.22	217	323
WE	0.152±0.069	0.173±0.053	342	198	5.74±2.19	5.53±2.01	339	201
WF	0.209±0.075	0.160±0.048	203	337	5.56±2.48	5.76±2.52	197	343
WR	0.194±0.060	0.154±0.044	230	310	5.49±2.55	5.71±2.60	216	324
WU	0.168±0.051	0.156±0.035	262	278	4.97±1.86	5.10±1.96	228	312
HO	0.152±0.048	0.170±0.035	338	202	6.99±2.78	6.64±2.71	243	297
HC	0.212±0.092	0.163±0.030	226	314	4.37±1.93	4.64±2.01	153	387
Total	0.194±0.068	0.159±0.045	1900	2420	5.40±2.34	5.51±2.32	1798	2522

Table 2. AADs, closest PDFs, SNRs and best estimators tabulated by motion (wrist and forearm) from extensor muscle (ECU) and female subjects (F). Each row pools nine-female-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
FP	0.158±0.048	0.171±0.033	310	230	5.09±1.91	5.26±1.99	208	332
FS	0.159±0.048	0.170±0.034	312	228	4.88±1.87	4.97±1.90	201	339
WE	0.132±0.036	0.180±0.034	380	160	5.35±1.72	5.22±1.72	339	201
WF	0.166±0.058	0.166±0.036	278	262	5.10±2.10	5.35±2.14	177	363
WR	0.158±0.042	0.159±0.031	274	266	4.72±1.43	4.91±1.62	200	340
WU	0.155±0.055	0.171±0.037	333	207	4.55±1.58	4.63±1.46	212	328
HO	0.153±0.047	0.173±0.035	331	209	5.25±2.00	5.37±2.06	225	315
HC	0.197±0.082	0.170±0.051	215	325	4.09±1.49	4.17±1.56	181	359
Total	0.160±0.052	0.170±0.036	2433	1887	4.88±1.76	4.98±1.81	1743	2577

Table 3. AADs, closest PDFs, SNRs and best estimators tabulated by motion (wrist and forearm) from flexsor muscle (FCR) and male subjects (M). Each row pools nine-male-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
FP	0.347±0.115	0.143±0.078	24	516	3.06±1.41	3.28±1.56	147	393
FS	0.433±0.184	0.233±0.148	13	527	2.86±1.78	3.07±1.86	128	412
WE	0.321±0.176	0.213±0.135	124	416	3.69±1.68	3.81±1.76	178	362
WF	0.293±0.094	0.122±0.063	31	509	3.05±1.22	3.14±1.21	204	336
WR	0.314±0.107	0.126±0.060	31	509	3.72±1.85	3.88±1.89	185	355
WU	0.285±0.108	0.152±0.064	94	446	4.35±2.21	4.84±2.55	130	410
HO	0.325±0.095	0.130±0.058	15	525	3.89±1.88	4.24±2.00	129	411
HC	0.315±0.129	0.159±0.075	60	480	2.99±1.65	3.26±1.84	122	418
Total	0.329±0.126	0.160±0.085	392	3928	3.45±1.71	3.69±1.84	1223	3097

Table 4. AADs, closest PDFs, SNRs and best estimators tabulated by motion (wrist and forearm) from flexsor muscle (FCR) and female subjects (F). Each row pools nine-female-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
FP	0.327±0.105	0.168±0.075	68	472	3.27±1.29	3.45±1.43	130	410
FS	0.312±0.157	0.204±0.116	124	416	3.91±2.02	4.15±1.95	155	385
WE	0.241±0.137	0.177±0.094	194	346	3.94±1.92	4.17±1.90	173	367
WF	0.219±0.077	0.144±0.047	165	375	4.06±1.64	4.17±1.68	203	337
WR	0.269±0.088	0.144±0.054	91	449	3.67±1.49	3.95±1.64	142	398
WU	0.262±0.102	0.155±0.064	124	416	3.69±1.46	3.84±1.56	172	368
HO	0.275±0.104	0.151±0.061	95	445	3.72±1.80	4.08±2.00	112	428
HC	0.232±0.088	0.148±0.056	135	405	3.43±1.24	3.69±1.37	116	424
Total	0.267±0.107	0.161±0.071	996	3324	3.71±1.61	3.94±1.69	1203	3117

Table 5. Classification accuracies of eight hand, wrist and forearm motions tabulated by gender from two estimators (RMS and MAV) and three classifiers (LDA, QDA and *k*NN).

Feature	Mean ± SD classification accuracy (%)					
	Male subjects			Female subjects		
	LDA	QDA	*k*NN	LDA	QDA	*k*NN
RMS	78.85±8.63	84.99±8.97	86.71±7.44	77.02±5.93	82.06±6.44	82.56±6.38
MAV	79.78±8.62	86.42±8.75	87.40±7.41	77.94±5.60	83.37±6.35	83.15±6.48

3. Experimental Study Two

3.1. *Data Acquisition, Experiment and Methods of Analysis*

The EMG acquisition and experiment for the second EMG data set are described in detail in Khushaba et al. [27]. Briefly, the EMG data were acquired from 8 normally limbed individuals (6 males and 2 females), recording two channels of EMG from electrodes placed on the right forearm during ten finger and hand motions. EMG data were collected from 2 muscles: extensor and flexor muscles. A sequence of 6 trial sets of ten different classes of motion were performed by each subject from one day. Each trial set consisted of one of the 10 follwing motions: thumb flexion (TF), index flexion (IF), middle flexion (MF), ring flexion (RF), little flexion (LF), thumb-index flexion (TIF), thumb-middle flexion (TMF), thumb-ring flexion (TRF), thumb-little flexion (TLF) and hand close (HC), with an action trial period of 5 s. Shoulder and elbow positions were fixed with an arm support of the chair for all subjects.

Measured surface EMG signals were sampled at 4000 Hz and were amplified with a gain of 1000x using an EMG measurement system (Bagnoli Desktop EMG Systems, Delsys Inc). Movement artefact (<20 Hz), power-line interference (50 Hz) and high-frequency noise (>450 Hz) were also removed. In total, 960 recordings with a length of 20000 samples (5 s) were available for analysis (8 subjects × 2 muscles × 10 motions × 6 sets).

The same analysis methods, as implemented in the first experiment, are applied in this experiment, except the evaluation of gender effect (due to a large difference between the number of male and female subjects). The length of each of the proposed motions is changed from 2048 samples (2 s) to 20000 samples (5 s). In addition, a fixed window length of RMS and MAV is set at the same duration of 250 ms, but due to an increased sampling rate, the window length is changed from 256 samples to 1000 samples. Therefore, twenty adjacent windows are yielded for each recording as a result of the amplitude estimator.

3.2. *Results*

Normalized composite EMG PDFs of all motions and subjects by muscle type, extensor and flexor, are shown respectively in Fig. 2(a) and in Fig. 2(b). For extensor muscle, the AAD between the composite experimental EMG density and the theoretical Gaussian density is 0.2069 (1.49 times smaller), while this difference for the theoretical Laplacian density is 0.1391. For flexor muscle, the AAD between the composite experimental EMG density and the theoretical Gaussian density is 0.2251, while this difference for the theoretical Laplacian density is 0.0903 (2.49 times smaller). The difference between the two-densities AADs is statistically significant ($p < 0.001$) for both muscles.

The AADs and the number of times that each recording's estimated density (Gauss/Laplace) best described the data are presented in Tables 6–7 by muscle. These tables also present the SNRs and the number of times that each estimator (RMS/MAV) was best. Average SNR performance is 5.87 using RMS versus 6.01 using MAV (2.38% larger, a statistically significant difference at $p < 0.01$).

In addition to the SNR performance, the classification accuracies of RMS and MAV obtained from three classifiers are presented in Table 8. On average the classification accuracies of the MAV are slightly higher than that of the RMS based on five individual-finger motions (79.93%>79.35%) and five combined-fingers motions (86.97%>86.22%).

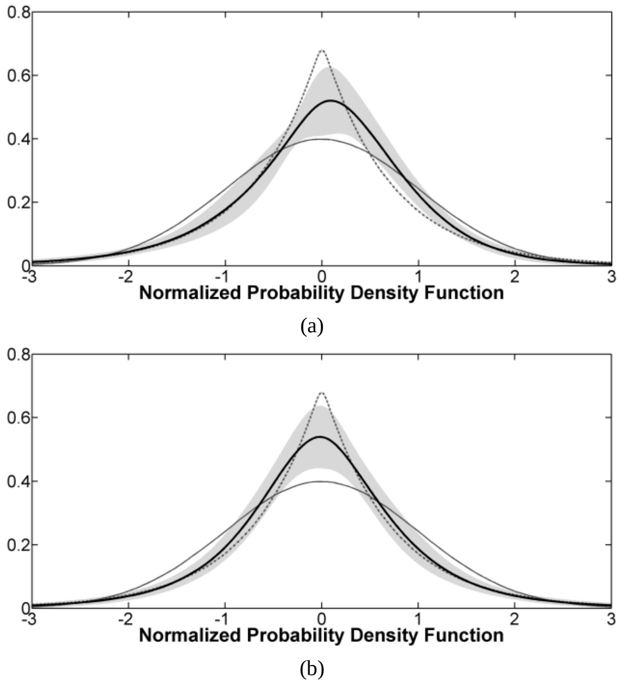


Fig. 2. Normalized composite PDF estimates for (a) extensor muscle and (b) flexor muscle. Experimental density (solid black line) is the average of (a) 480 and (b) 480 recordings. Shaded region indicates one standard deviation above and below the average. Solid gray line indicates the Gaussian density and dashed gray line indicates the Laplacian density.

Table 6. AADs, closest PDFs, SNRs and best estimators tabulated by motion (finger and hand) from extensor muscle. Each row pools eight-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
TF	0.257±0.024	0.233±0.016	25	23	8.14±2.69	8.33±2.53	17	31
IF	0.261±0.028	0.199±0.019	20	28	5.50±2.17	5.60±2.15	23	25
MF	0.246±0.031	0.221±0.018	26	22	6.32±2.69	6.61±2.92	12	36
RF	0.200±0.030	0.190±0.022	29	19	6.08±2.10	5.89±1.81	28	20
LF	0.243±0.026	0.201±0.022	22	26	5.89±1.85	5.93±1.76	22	26
TIF	0.238±0.020	0.219±0.022	25	23	7.42±2.73	7.40±2.65	29	19
TMF	0.250±0.025	0.215±0.019	22	26	5.46±2.25	5.61±2.28	22	26
TRF	0.204±0.026	0.180±0.018	23	25	5.88±1.72	5.76±1.73	29	19
TLF	0.248±0.025	0.207±0.019	20	28	5.88±1.51	5.96±1.65	25	23
HC	0.217±0.074	0.240±0.042	28	20	4.30±2.41	4.53±2.49	9	39
Total	0.237±0.031	0.210±0.022	240	240	6.09±2.21	6.16±2.20	216	264

Table 7. AADs, closest PDFs, SNRs and best estimators tabulated by motion (finger and hand) from flexor muscle. Each row pools eight-subject trials from the indicated motion.

Motion	Mean ± SD AAD Between Experimental PDF and:		No. of Times with PDF Closest in Shape to:		Mean ± SD SNR Using Estimator:		No. of Times in which Estimator with Highest SNR is:	
	Gauss	Laplace	Gauss	Laplace	RMS	MAV	RMS	MAV
TF	0.259±0.028	0.168±0.019	8	40	7.32±3.22	7.36±3.07	17	31
IF	0.259±0.048	0.179±0.029	14	34	5.16±2.34	5.54±2.52	11	37
MF	0.288±0.050	0.184±0.027	0	48	5.01±2.44	5.18±2.52	21	27
RF	0.277±0.040	0.172±0.027	14	34	4.43±1.81	4.54±1.96	17	31
LF	0.304±0.064	0.189±0.041	6	42	5.77±3.13	6.02±3.13	14	34
TIF	0.193±0.038	0.175±0.016	25	23	6.49±3.11	6.96±3.06	12	36
TMF	0.163±0.025	0.196±0.019	36	12	6.88±3.07	7.08±3.01	16	32
TRF	0.263±0.035	0.137±0.021	6	42	6.01±2.47	5.93±2.41	28	20
TLF	0.245±0.046	0.176±0.031	16	32	5.52±1.85	5.72±2.00	19	29
HC	0.236±0.046	0.158±0.019	11	37	4.04±1.95	4.20±2.27	15	33
Total	0.249±0.042	0.173±0.025	136	344	5.66±2.54	5.85±2.60	170	310

Table 8. Classification accuracies of ten finger and hand motions tabulated by gender from two estimators (RMS and MAV) and three classifiers (LDA, QDA and *k*NN).

Feature	Mean ± SD classification accuracy (%)					
	5 individual-finger motions			5 combined-fingers motions		
	LDA	QDA	kNN	LDA	QDA	kNN
RMS	76.00±7.82	80.63±8.94	81.44±9.67	83.88±7.70	87.81±7.36	86.96±8.90
MAV	76.50±8.10	81.38±8.61	81.92±8.79	84.29±7.61	88.17±7.89	88.46±8.65

4. Discussion

4.1. *EMG Density of Upper-Limb Motions*

Although surface EMG has been frequently assumed as a Gaussian density at different isometric/static muscle contraction levels (i.e., constant-muscle-force, constant-joint-angle, and non-fatiguing contractions) of the muscles of the upper and lower limbs, evidence in the literature has clearly shown a mixed PDF between the Gaussian and the Laplacian densities of surface EMG [15, 18, 20, 21]. In addition to the PDF of isometric contractions, the EMG PDF of isotonic/dynamic contraction of the lower-limb muscles during gait cycle can be best adjusted to the Laplacian density [19, 24].

The EMG PDF of dynamic muscle contraction of the upper-limb motions: hand, wrist and forearm motions–in the first experiment–and finger motions–in the second experiment was investigated. Overall the experimental EMG PDF is clearly observed from Figs. 1 and 2 that the PDF falls between the Gaussian and the Laplacian densities. The EMG PDF shifts towards a Laplacian density, particularly for male subject and flexor muscle.

4.1.1. *Influence of subject and gender on EMG PDF*

The PDF of surface EMG has been mentioned in several studies that it largely depends on the subject. For instance, Clancy and Hogan [15] reported that in their first experiment the Laplacian density fits best for 3 of 5 subjects, but in their second experiment the Laplacian density fits best only for 2-3 of 19 subjects (9 males, 10 females) depending on isometric EMG types. Cherniz et al. [24] found that the Laplacian density fits best for all subjects (2 subjects without neurological disorders and 2 subjects with hemiparesia), except only one phase of a gait cycle for 2 normal subjects that the Gaussian density fits best.

In our experiments, the Laplacian density best fit the EMG in Experimental Study One from 10 of 18 subjects (for extensor muscles) and from 17 of 18 subjects (for flexor muscle) and in Experimental Study Two from 4 of 8 subjects (for extensor muscle) and from 7 of 8 subjects (for flexor muscle). In Experimental Study One, eight subjects that the Gaussian density fits best are 3 males and 5 females (for extensor muscles).

We can observe that the EMG PDF of female subjects tends to be more Gaussian than the EMG PDF of male subjects. In the both experiments, the subjects were asked to perform and maintain the motions without any target force level. Maybe female subjects performed the higher contraction level of the muscles (% of maximum voluntary contraction, MVC) than male subjects, in the assumption that the EMG PDF tends towards a Gaussian density when the muscle contraction level increases [18]. However, the averaged total power of EMG per recording from the male subjects is higher than that from the female subjects ($1.74\times10^7 > 1.10\times10^7$, in $(\mu V)^2$ unit), based on Experimental Study One.

4.1.2. *Influence of muscle and motion on EMG PDF*

Kaplanis et al. [20] found that the non-Gaussianity level of surface EMG signals depends on the electrode position even on the same muscle, e.g., the biceps brachii. In our experiments, the studied muscles are divided into two groups: extensor and flexor muscles of the forearm. As can be observed in Tables 3–4 in Experimental Study One, the EMG PDFs of flexor muscle from all motions and subjects are close to the Laplacian density.

The EMG PDF of extensor muscle from male subjects is also close to the Laplacian density, as can be seen in Table 1, except wrist extension and hand open which are the extension contraction. In Table 2, although the EMG PDF of extensor muscle, i.e., ECU, from female subjects is close to the Gaussian density (except hand close), the chance that the Gaussian density would best fit the data from three extensor muscles (6580 of 12960 recordings) is $p = 0.9613$, which is not statistically significant. The averaged total power of EMG per recording from extensor muscles is higher than that from flexor muscles for both experiments ($1.58\times10^7 > 0.93\times10^7$ in Experimental Study One and $6.49\times10^3 > 2.83\times10^3$ in Experimental Study Two, in $(\mu V)^2$ units).

In this paper, the PDFs of surface EMG signals are examined at different muscle contraction levels based on finger, hand, wrist, and forearm motions in six forearm muscles.

This finding is consistent with the finding in upper-arm muscles, e.g., the biceps brachii [28] and other forearm muscles, e.g., the abductor pollicis brevis [18]. Moreover, in contrast to most of previous studies [15, 20, 21, 28, 29] in which the EMG signals were recorded at fixed percentages of the MVC, the surface EMG signals in our experiments recorded in a flexible range of muscle contraction levels, as used in a number of recent studies [18, 19].

4.2. *SNR Performance of Upper-Limb Motions*

Theoretically, the SNR performance of RMS and MAV estimators, which are derived from the Gaussian model of EMG, can be expressed as

$$SNR_{RMS,Gauss} \cong \sqrt{2N}\ , \tag{1}$$

$$SNR_{MAV,Gauss} \cong \sqrt{1.7519N}\ , \tag{2}$$

where N is the number of statistical degrees of freedom. On the other hand, the SNR performance of RMS and MAV estimators, which are derived from the Laplacian model of EMG, can be expressed as

$$SNR_{RMS,Laplace} = \sqrt{0.8N}\ , \tag{3}$$

$$SNR_{MAV,Laplace} = \sqrt{N}\ . \tag{4}$$

Hence, an optimal amplitude estimator when an EMG PDF is a Gaussian density is RMS, whereas an optimal amplitude estimator when an EMG PDF is a Laplacian density is MAV. More details about the relationship between EMG amplitude estimator, EMG PDF, and SNR performance in theoretical basis can be found in Refs. [15, 16].

Based on the theoretical and the experimental EMG PDFs, MAV should be an optimal EMG amplitude estimator for MCIs based on flexor muscles in both genders and on extensor muscles for male subject. This finding is confirmed by the SNR performance, as shown in Tables 1, 3, 4 and 7.

In case of the extensor-muscle-and-female-subject that the EMG PDF tends towards a Gaussian density, based on the theoretical, RMS should be an optimal EMG amplitude estimator. However, based on the SNR performance in Table 2, the SNR of MAV feature is higher than the SNR of RMS feature (4.98 > 4.88, 2.05% larger). This conflicting finding can be explained by the simulated experiment in Clancy and Hogan [15]. The relationship is defined in Eq. (5), where $0 \leq w \leq 1$, x_G is a sequence generated by a Gaussian model, and x_L is a sequence generated by a Laplacian model. Both sequences are a unit-variance. It is possible that the EMG density y is closest to a Gaussian density but MAV has a higher SNR than RMS, when the w value is in the range of 0.375 and 0.525.

$$y = w \cdot x_G + \left(1-w\right) \cdot x_L \tag{5}$$

Based on this relationship, MAV can be an optimal EMG amplitude estimator for MCIs based on extensor muscle for female subjects even though their EMG PDFs are closer to the Gaussian density than the Laplacian density.

In contrast to Kreifeldt and Yao [30] in which the SNR of RMS is nearly equal or slightly better than the SNR of MAV, in our experiments the SNR of MAV is slightly better than the SNR of RMS. Our finding is consistent with the finding in a number of studies [15, 17, 31].

4.2.1. *Influence of all experimental factors on EMG PDF*

On average, the SNR performance from male and female subjects shows no statistically significant difference for both RMS (p = 0.89) and MAV (p = 0.06). On the other hand, the SNR performance of RMS and MAV estimators from extensor muscles is better than that from flexor muscles for both the experiments, a statistically significant difference ($p < 0.001$, and $p < 0.01$ in case of MAV SNR in Experimental Study Two).

For the muscle contraction effect, theoretically the SNR is not influenced by muscle contraction level, but experimentally the SNR decreases with increasing muscle contraction level: 10%-75% MVC in [15] and 5%-25% MVC in [17]. In our experiments, the exact levels of MVC are unknown. Based on the power of EMG signals, we did not observe any consistent trend in the EMG power relative to the muscle contraction level. For instance, the EMG power of male subjects is higher than female subjects while the SNR from both genders are the same. On the other hand, the EMG power and SNR from extensor muscles are higher than the EMG power and SNR from flexor muscles. So it has a direct relationship.

4.3. *Accuracy of RMS and MAV in Classification of Upper-Limb Motions*

In order to confirm an optimal EMG amplitude detector in classifying upper-limb motions using forearm muscles for MCIs, classification accuracies of MAV and RMS using three classifiers, i.e., LDA, QDA and *k*NN, are presented in Table 5 (Experimental Study One) and Table 8 (Experimental Study Two). The classification accuracies of the MAV estimator are slightly higher than the RMS estimator based on various finger (flexion of the single and multiple fingers), hand (close and open), wrist (flexion, extension, radial and ulnar deviation) and forearm (pronation and supination) motions for all classifiers.

The results are consistent with Oskoei and Hu [32] in which six motions: hand open and close, wrist flexion and extension, and arm flexion and extension were classified using LDA and artificial neural network based on six upper-arm and forearm muscles.

In contrast to our experiments, if only the directions of wrist motion (i.e. forward, backward, left and right) during hand close are considered and the most of surface EMG channels are measured from extensor muscles, the classification accuracies of the RMS estimator are slightly higher than the MAV estimator and the results are also dependent on the classifier type [4, 33].

However, if the MCI is developed under the different motions of upper-limb including finger, hand, wrist and arm, on average the MAV estimator would provide comparable or slightly higher classification accuracy compared to the RMS estimator. Furthermore, the RMS and MAV estimators provide the same discrimination in feature space [34], thus only one of them should be used to avoid redundancy in a classification scheme. Due to a lower computational cost of the MAV estimator compared with the RMS estimator (see Appendix A), MAV is recommended to be used as a suitable EMG amplitude estimator for the upper-limb motions and the forearm muscles.

Combined, SNR and accuracy results also suggest that EMG amplitude estimators based on the modification of MAV processing would provide better classification performance than those based on the modification of RMS processing. For instance, classification accuracies of QDA, LDA, kNN, and maximum likelihood estimation (MLE) used difference absolute mean value (DAMV) are higher than the difference absolute standard deviation value (DASDV), as presented in Kim et al. [4] and Yu et al. [33].

5. Summary

The PDF of surface EMG recorded from forearm muscles associated with finger, hand, wrist, and forearm motions, was examined experimentally. It was clearly seen from the figures that the observed densities fell in between the Gaussian and Laplacian densities, but based on the the absolute area difference, the experimental EMG PDF can be best adjusted with less error to the Laplacian density on average. Based on the EMG PDF and SNR performance, MAV is recommended to be an optimal EMG amplitude detector for EMG-based MCIs. The results are evaluated based on two experiments, twenty-six subjects, six forearm muscles, and eightteen different motions. This finding is confirmed by the classification results obtained from three state-of-the-art classifiers, i.e., LDA, QDA and *k*NN.

Acknowledgements

The authors gratefully acknowledge the support of Dr.Rami Khushaba for providing EMG dataset (Experimental Study Two). This work is supported in part by the FI MSTIC University Joseph Fourier Grenoble 1 (TIGRE project) and by Prince of Songkla Graduate Studies Grant.

Appendix A. EMG amplitude estimators

RMS and MAV are two popular EMG amplitude estimators [14]. There are several ways for calling RMS and MAV features, for instance, RMS is similar to a standard deviation of surface EMG signal, where mean value of EMG is naturally nearly zero. There are many given names for calling MAV, e.g., average rectified value, averaged absolute value, integrated absolute value, and the first order of *v*-Order feature [34]. Mathematical definition of both methods can be expressed respectively as

$$\mathrm{RMS} = \sqrt{\frac{1}{L}\sum_{i=1}^{L} x_i^2}\,, \tag{A.1}$$

$$\mathrm{MAV} = \frac{1}{L}\sum_{i=1}^{L} |x_i|\,, \tag{A.2}$$

where x_i represents the i^{th} EMG amplitude sample and L denotes a length of analysis data window. Adjacent disjoint windows with a fixed L of 250 ms (256 samples for Experimental Study One and 1000 samples for Experimental Study Two) were used for both estimators.

References

[1] M. Hariharan, C. Y. Fook, R. Sindhu, B. Ilias and S. Yaacob, *A comparative study of wavelet families for classification of wrist motions*, *Comput. Electr. Eng.* **38** (2012) 1798–1807.

[2] A. Phinyomark, P. Phukpattaranont, C. Limsakul and M. Phothisonothai, *Electromyography (EMG) signal classification based on detrended fluctuation analysis*, *Fluctuation Noise Lett*. **10** (2011) 281–301.

[3] I. M. Rezazadeh, S. M. Firoozabadi, H. Hu, and S. M. R. H. Golpayegani, *A novel human-machine interface based on recognition of multi-channel facial bioelectric signals*, *Australas. Phys. Eng. Sci. Med*. **34** (2011) 497–513.

[4] K. S. Kim, H. H. Choi, C. S. Moon and C. W. Mun, *Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions*, *Curr. Appl. Phys.* **11** (2011) 740–745.

[5] D. Tkach, H. Huang and T. A. Kuiken, *Study of stability of time-domain features for electromyographic pattern recognition*, *J. Neuroeng. Rehabil.* **7** (2010) 21.

[6] M. A. Oskoei and H. Hu, *Support vector machine-based classification scheme for myoelectric control applied to upper limb*, *IEEE Trans. Biomed. Eng*. **55** (2008) 1956–1965.

[7] T. S. Saponas, D. S. Tan, D. Morris and R. Balakrishnan, *Demonstrating the feasibility of using forearm electromyography for muscle-computer interfaces*, *Proc. SIGCHI Conference on Human Factors in Computing Systems*, Florence (Apr. 2008) 515–524.

[8] A. S. Kundu, O. Mazumder and S. Bhaumik, *Design of weable, low power, single supply surface EMG extractor unit for wireless monitoring*, *Proc. 2nd International Conference on Nanotechnology and Biosensors*, Dubai (Dec. 2011) 69–74.

[9] Y. C. Du, C. H. Lin, L. Y. Shyu and T. Chen, *Portable hand motion classifier for multi-channel surface electromyography recognition using grey relational analysis*, *Expert Syst. Appl*. **37** (2010) 4283–4291.

[10]E. Costanza, S. A. Inverso, R. Allen and P. Maes, *Intimate interfaces in action: Assessing the usability and subtlety of EMG-based motionless gestures*, *Proc. SIGCHI Conference on Human Factors in Computing Systems*, San Jose, California (Apr.–May 2007) 819–828.

[11]T. Lorrain, N. Jiang and D. Farina, *Influence of the training set on the accuracy of surface EMG classification in dynamic contractions for the control of multifunction prostheses*, *J. Neuroeng. Rehabil.* **8** (2011) 25.

[12]K. Englehart and B. Hudgins, *A robust, real-time control scheme for multifunction myoelectric control*, *IEEE Trans. Biomed. Eng.* **50** (2003) 848–854.

[13]A. Phinyomark, P. Phukpattaranont and C. Limsakul, *Investigating long-term effects of feature extraction methods for continuous EMG pattern classification*, *Fluctuation Noise Lett*. **11** (2012) 1250028.

[14]M. A. Oskoei and H. Hu, *Myoelectric control systems–A survey*, *Biomed. Signal Process. Control* **2** (2007) 275–294.

[15]E. A. Clancy and N. Hogan, *Probability density of the surface electromyogram and its relation to amplitude detectors*, *IEEE Trans. Biomed. Eng.* **46** (1999) 730–739.

[16]N. Hogan and R. W. Mann, *Myoelectric signal processing: Optimal estimation applied to electromyography–Part I: Deviation of the optimal myoprocessor*, *IEEE Trans. Biomed. Eng*. **BME-27** (1980) 382–395.

[17]N. Hogan and R. W. Mann, *Myoelectric signal processing: Optimal estimation applied to electromyography–Part II: Experimental Demonstration of Optimal Myoprocessor Performance*, *IEEE Trans. Biomed. Eng*. **BME-27** (1980) 396–410.

[18]K. Nazarpour, A. H. Al-Timemy, G. Bugmann and A. Jackson, *A note on the probability distribution function of the surface electromyogram signal*, *Brain Res. Bull.* **90** (2013) 88–91.

[19]M. S. Hussain, M. Reaz, F. Yasin and M. Ibrahimy, *Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction*, *Expert Syst.* **26** (2009) 35–48.

[20]P. A. Kaplanis, C. S. Pattichis, L. J. Hadjileontiadis and S. M. Panas, *Bispectral analysis of surface EMG*, *Proc. 10th Mediterranean Electrotechnical Conference*, Lemesos (May 2000) 2, 770–773.

[21]G. R. Naik, D. K. Kumar and S. P. Arjunan, *Kurtosis and negentropy investigation of myo electric signals during different MVCs*, *Proc. ISSNIP Biosignals and Biorobtics Conference*, Vitoria (Jan. 2011) 1–4.

[22]D. Yang, J. Zhao, L. Jiang and H. Liu, *Dynamic hand motion recognition based on transient and steady-state EMG signals*, *Int. J. Humanoid Rob.* **9** (2012) 1250007.

[23]Z. Ju, X. Zhu and H. Liu, *Empirical copula-based templates to recognize surface EMG signals of hand motions*, *Int. J. Humanoid Rob.* **8** (2011) 725–741.

[24]A. S. Cherniz, C. E. Bonell and C. B. Tabernig, *Study of the SEMG probability distribution of the paretic tibialis anterior muscle*, *J. Phys.: Conf. Ser*. **90** (2007) 012054.

[25]A. Phinyomark, P. Phukpattaranont and C. Limsakul, *Wavelet-based denoising algorithm for robust EMG pattern recognition*, *Fluctuation Noise Lett*. **10** (2011) 157–167.

[26]A. Phinyomark, C. Limsakul and P. Phukpattaranont, *EMG feature extraction for tolerance of 50 Hz interference*, *Proc. 4th PSU-UNS International Conference on Engineering Technologies*, Novi Sad (Apr. 2009) 289–293.

[27]R. N. Khushaba, M. Takruri, S. Kodagoda and G. Dissanayake, *Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals*, *Expert Syst. Appl*. **39** (2012) 10731–10738.

[28]K. Nazarpour, A. Sharafat and S. Firoozabadi, *Application to higher order statistics to surface electromyogram signal classification*, *IEEE Trans. Biomed. Eng*. **54** (2007) 1762–1769.

[29]D. F. Yuan, Y. T. Zhang and W. Herzog, *The probability density function of vibromyographic and electromyographic signals for different levels of contraction of human quadriceps muscles*, *Proc. 16th Annual International Conference of IEEE Engineering in Medicine and Biology Society*, Baltimore, MD (Nov. 1994) 1, 351–352.

[30]J. G. Kreifeldt and S. Yao, *A signal-to-noise investigation of nonlinear electromyographic processors, IEEE Trans. Biomed. Eng*. **BME-21** (1974) 298–308.

[31]Y. St-Amant, D. Rancourt and E. A. Clancy, *Influence of smoothing window length on electromyogram amplitude estimates, IEEE Trans. Biomed. Eng*. **45** (1998) 795–799.

[32]M. A. Oskoei and H. Hu, *GA-based feature subset selection for myoelectric classification*, *Proc. IEEE International Conference on Robotics and Biomimetics*, (Dec. 2006) 1465–1470.

[33]S. Yu, E. Jeong, K. Hong and S. Lee, *Classification of nine directions using the maximum likelihood estimation based on electromyogram of both forearms*, *Biomed. Eng. Lett*. **2** (2012) 129–137.

[34]A. Phinyomark, P. Phukpattaranont and C. Limsakul, *Feature reduction and selection for EMG signal classification*, *Expert Syst. Appl*. **39** (2012) 7420–7431.