Optimal EMG Amplitude Detectors for Muscle-Computer Interface

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***Abstract*—To develop an advanced muscle–computer interface (MCI) based on surface electromyography (EMG) signal, a suitable signal processing and classification technique has a key role to play, particularly the selection of EMG features. Two sufficient and well-known methods to extract signal amplitude are root mean square (RMS) and mean absolute value (MAV). Their classification performance is comparable to an advanced and high computational time-scale feature, e.g. discrete wavelet transform. The performance of RMS and MAV, however, depends on a probability density function (PDF) of EMG signals, i.e., Gaussian or Laplacian, and the PDF of motions associated with EMG signals is still not clear yet. In addition, both features provide the same distribution in feature space, thus only one of them should be used to avoid redundancy in a classification scheme. This study investigated the PDFs of eight hand, wrist and forearm motions and then estimated the signal-to-noise ratio (SNR), defined as a mean value divided by its fluctuation, of both amplitude detectors. On average, the experimental EMG density was closer to the Laplacian density, and MAV had slightly higher SNR than RMS for both forearm extensor and flexor muscles and both genders. Lastly, the accuracy of both features in MCI-based EMG classification was reviewed. For MCI applications, MAV is recommended to be used as an optimal EMG amplitude detector.**

***Keywords*—electromyography (EMG) signal; feature extraction; motion recognition; probability distribution function; signal-to-noise ratio (SNR).**

I. Introduction

Many human-computer interaction (HCI) techniques have been proposed over the last few decades, particularly a hand-free interaction technique such as speech or computer vision. However, a major limitation of these interaction techniques is about background/environmental noise, which is hard to avoid. Another advanced hand-free HCI technique is a muscle-computer interface (MCI) [1], [2]. This technique measures electrical potentials generated by a target muscle during human gestures, as called "electromyography (EMG) signal". The MCI has been conventionally used in the controlling prosthetic devices [2]. More research has explored the use of EMG-based MCI for controlling electric-powered wheelchair [3] and computer mouse cursor [4]. In addition, MCI can be used together with other interface such as computer vision and tabletop to provide complementary information and introduce a novel multimodal interaction [5], [6].

In order to enable EMG-based MCI, signal processing and pattern matching algorithms are developed and can be broken down into three algorithmic components: feature extraction, dimensionality reduction and pattern classification [2]. In the extraction of features, continuous EMG time waveforms are divided into an analysis data window which must be kept below 300 ms to response real-time decision control [7]. A set of features is extracted from each window based on EMG amplitude and/or frequency information [8]. Then, a next window is selected and the feature extraction scheme is repeated. In the second step if a proposed feature vector has a high dimension, a dimensionality reduction technique is further used to reduce the dimensions of a feature vector by selecting or projecting original features [9]. In the last step, a pattern classification method is applied to match an input feature set to an output class [10].

The success of the proposed algorithm, however, depends almost entirely on the choice of features used to represent the actions associated with EMG amplitude [11]–[13]. Generally, EMG feature extraction can be broken down into three groups: the amplitude/time-domain (TD) features, spectral/frequency-domain (FD) features, and time-frequency/time-scale (TS) features [2]. TD features can be computed directly from raw EMG signal amplitude [13]. On the other hand, FD and TS methods require an additional transformation, e.g. fast Fourier transform (FFT) or discrete wavelet transform (DWT), before calculating features [9], thus the computation of features in these groups is more complex and higher than that of the TD features. To be easily and possibly computed by any low performance embedded processor, the TD features are widely used in MCI and their performance is comparable to TS features, i.e., DWT [7], [14], in the classification of dynamic motions from both transient and steady-state portions.

Root mean square (RMS) and mean absolute value (MAV) are two well-known and sufficient methods to extract signal amplitude in TD, as known the "EMG amplitude detector" [2]. Both RMS and MAV features provide the same distribution in feature space [11], thus only one of them should be used to avoid redundancy in a classification scheme. The performance of RMS and MAV, however, depends on a probability density function (PDF) of surface EMG signals which can be a Gaussian or a Laplacian density, and the PDF of surface EMG signals is still not clear yet until now [15]–[19]. In this paper, the PDF of upper-limb motions associated with surface EMG signals was investigated.

In order to evaluate an optimal EMG amplitude detector, a signal-to-noise ratio (SNR), which is defined as the mean value divided by its fluctuation [19], was estimated from surface EMG recorded from eight motions and two forearm muscles for both RMS and MAV. The relationship between the experimental EMG PDF and the SNR of both features was discussed together with their classification accuracies.

II. Methodology

MCI has usually been developed based on upper-limb motions consisting of hand, wrist, and forearm motions recorded from forearm extensor and/or flexor muscles [20]. In this paper, eight motions selected were 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), and two muscles selected were extensor carpi ulnaris (ECU) and flexor carpi radialis (FCR). The EMG PDF and also SNR of the features were calculated and reported as an average value for each possible combination between motion and muscle by gender. EMG data were measured from nine males and nine females.

A. EMG Data Acquisition and Experiments

In experiments, the volunteers performed eight proposed motions by maintaining each motion for 2 s in duration and separating each motion by a rest period of 2 s. Fifteen sessions were performed for each subject per day with a random order of the proposed motions in a session. These 15 sessions per day were employed on 4 separate days to include the effect of fluctuating EMG (60 sessions in total per subject for each motion-muscle combination).

EMG data were collected from two proposed muscles on the right forearm using bipolar Ag/AgCl electrodes (H124SG, Kendal ARBO) with a diameter of 24 mm and an inter-electrode distance of 20 mm. A common ground reference was placed on the wrist using an Ag/AgCl electrode (Red Dot 2223, 3M) with a diameter of 43.1 mm. All electrodes were attached after suitable preparation of the skin with alcohol.

Measured surface EMG signals were sampled at 1024 Hz with a high resolution of 24 bits 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 removed. More details about the experiments and the pre-processing of EMG data can be found in Ref. [21].

B. EMG Amplitude Detectors

Based on theoretically, an optimal EMG amplitude detector based on Gaussian model is RMS [22] ($SNR_{RMS,Gauss} = (2N)^{1/2} > SNR_{MAV,Gauss} = (1.7519N)^{1/2}$), whereas an optimal detector based on Laplacian model is MAV [17] ($SNR_{RMS,Laplace} = (0.8N)^{1/2} < SNR_{MAV,Laplace} = N^{1/2}$). It should be noted that N is the number of statistical degrees of freedom and SNR is a standard metric used to compare the amplitude detectors. More details about the relationship between EMG amplitude detector, EMG probability density model, and SNR performance in theoretical basis can be found in Ref. [17].

The mathematical definition of RMS and MAV methods can be expressed respectively as

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

$$\mathrm{MAV} = \frac{1}{L}\sum_{i=1}^{L} \left| xr_i \right|. \tag{2}$$

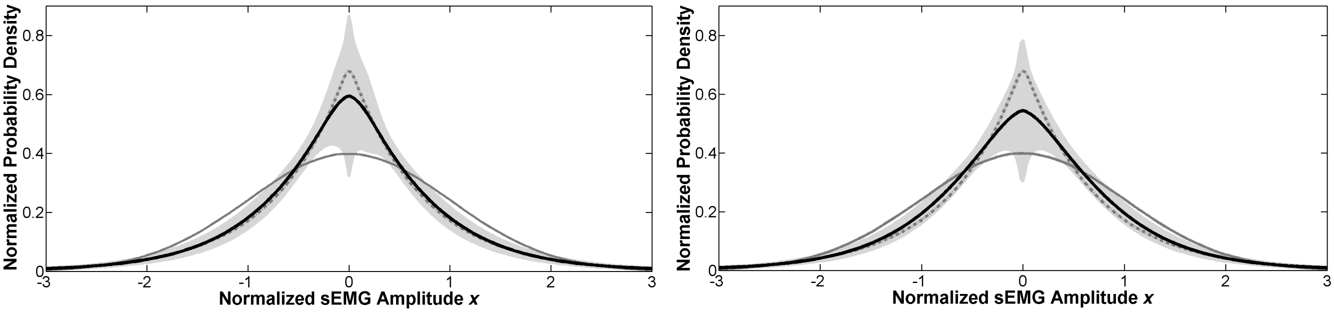
where xr_i represents the ith EMG amplitude sample and L denotes a length of analysis data window. Adjacent disjoint windows with a fixed L of 256 samples (250 ms) were used for both RMS and MAV. Furthermore, RMS feature is similar to standard deviation (SD) value of EMG signal [11], where mean value of EMG signal amplitude is naturally nearly zero. There are many given names for calling MAV feature such as average rectified value, averaged absolute value, integrated absolute value and the first order of v-Order feature [11].

C. Evaluating Functions

Firstly, the absolute area difference (ADD) between a sample histogram via the EMG density estimate (Px) and a Gaussian/Laplacian density (Pt) was used to decide the PDF of the EMG signals. The AAD was computed for each motion in a session (2048 samples, 2 s), and the results were analyzed by gender and by muscle. A sample histogram was computed by using 501 bins (B = 501) equally space (Δs = 0.2) on a normalized EMG (x), in which the sample mean adjusted to zero and the sample variance adjusted to one. The ADD can be defined as

$$\mathrm{ADD} = \Delta \mathrm{s} \cdot \sum_{b=1}^{B} \left| Pt_b - Px_b \right| \cdot \tag{3}$$

Secondly, SNR was used to judge the quality of amplitude detectors [17]. As previously mentioned that SNR was defined as the square root of the squared mean value of RMS (or MAV) divided by its variance, it means that the term "signal" refers to the expected EMG amplitude estimate and the term "noise" refers to the variation about the mean value of the amplitude detector. Therefore, the term "noise" in this paper is distinct from noise residing in the EMG signal measurement, e.g., power-line interference [23].



(a) (b)

Fig. 1 Normalized composite PDF estimates for (a) male subjects and (b) female subjects. Experimental density (solid black line) is the average of 8640 recordings (9 subjects × 2 muscles × 8 motions × 60 sessions). 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 I
DENSITY AREA DIFFERENCES AND CLOSEST DENSITY SHAPE TABULATED BY MOTION FROM EXTENSOR MUSCLE (ECU) AND MALE SUBJECTS. EACH ROW POOLS NINE-MALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Male /ECU	**Mean ± SD Area Difference Between Experimental PDF and:**		**Number of Times with PDF Closest in Shape to:**	
Motion	**Gauss**	**Laplace**	**Gauss**	**Laplace**
FP	0.219±0.067	0.139±0.042	133	407
FS	0.249±0.083	0.158±0.053	166	374
WE	0.152±0.069	0.173±0.053	342	198
WF	0.209±0.075	0.160±0.048	203	337
WR	0.194±0.060	0.154±0.044	230	310
WU	0.168±0.051	0.156±0.035	262	278
HO	0.152±0.048	0.170±0.035	338	202
HC	0.212±0.092	0.163±0.030	226	314
Total	**0.194±0.068**	**0.159±0.045**	**1900**	**2420**

TABLE II
DENSITY AREA DIFFERENCES AND CLOSEST DENSITY SHAPE TABULATED BY MOTION FROM FLEXOR MUSCLE (FCR) AND MALE SUBJECTS. EACH ROW POOLS NINE-MALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Male /FCR	**Mean ± SD Area Difference Between Experimental PDF and:**		**Number of Times with PDF Closest in Shape to:**	
Motion	**Gauss**	**Laplace**	**Gauss**	**Laplace**
FP	0.347±0.115	0.143±0.078	24	516
FS	0.433±0.184	0.233±0.148	13	527
WE	0.321±0.176	0.213±0.135	124	416
WF	0.293±0.094	0.122±0.063	31	509
WR	0.314±0.107	0.126±0.060	31	509
WU	0.285±0.108	0.152±0.064	94	446
HO	0.325±0.095	0.130±0.058	15	525
HC	0.315±0.129	0.159±0.075	60	480
Total	**0.329±0.126**	**0.160±0.085**	**392**	**3928**

TABLE III
DENSITY AREA DIFFERENCES AND CLOSEST DENSITY SHAPE TABULATED BY MOTION FROM EXTENSOR MUSCLE (ECU) AND FEMALE SUBJECTS. EACH ROW POOLS NINE-FEMALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Female /ECU	**Mean ± SD Area Difference Between Experimental PDF and:**		**Number of Times with PDF Closest in Shape to:**	
Motion	**Gauss**	**Laplace**	**Gauss**	**Laplace**
FP	0.158±0.048	0.171±0.033	310	230
FS	0.159±0.048	0.170±0.034	312	228
WE	0.132±0.036	0.180±0.034	380	160
WF	0.166±0.058	0.166±0.036	278	262
WR	0.158±0.042	0.159±0.031	274	266
WU	0.155±0.055	0.171±0.037	333	207
HO	0.153±0.047	0.173±0.035	331	209
HC	0.197±0.082	0.170±0.051	215	325
Total	**0.160±0.052**	**0.170±0.036**	**2433**	**1887**

TABLE IV
DENSITY AREA DIFFERENCES AND CLOSEST DENSITY SHAPE TABULATED BY MOTION FROM FLEXOR MUSCLE (FCR) AND FEMALE SUBJECTS. EACH ROW POOLS NINE-FEMALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Female /FCR	**Mean ± SD Area Difference Between Experimental PDF and:**		**Number of Times with PDF Closest in Shape to:**	
Motion	**Gauss**	**Laplace**	**Gauss**	**Laplace**
FP	0.327±0.105	0.168±0.075	68	472
FS	0.312±0.157	0.204±0.116	124	416
WE	0.241±0.137	0.177±0.094	194	346
WF	0.219±0.077	0.144±0.047	165	375
WR	0.269±0.088	0.144±0.054	91	449
WU	0.262±0.102	0.155±0.064	124	416
HO	0.275±0.104	0.151±0.061	95	445
HC	0.232±0.088	0.148±0.056	135	405
Total	**0.267±0.107**	**0.161±0.071**	**996**	**3324**

III. RESULTS AND DISCUSSION

In the literature, the experimental EMG PDFs at different isometric muscle contraction levels tend to have a shape between the Gaussian and Laplacian densities [15]–[17]. In addition to the EMG PDF of isometric contraction, it has been experimentally found that the EMG PDFs of isotonic muscle contraction levels during gait cycle or lower-limb motions can be best adjusted to the Laplacian distribution [18], [19]. However, the EMG PDFs of upper-limb motions, i.e., hand, wrist and forearm motions, have not been investigated yet. EMG recorded from the subjects during upper-limb motions, which combined short transient portions at the beginning and the end and a steady-state portion at the middle of motion, are widely used in most of MCI application.

Normalized composite EMG PDFs of eight motions and two muscles by gender, male and female, are shown in Fig. 1(a) and 1(b), respectively. For male subjects, the absolute area difference between the composite experimental density and the theoretical Gaussian density was 0.2478, while this difference for the theoretical Laplacian density was 0.0466. For female subjects, the absolute area difference between the composite experimental density and the theoretical Gaussian density was 0.2007, while this difference for the theoretical Laplacian density was 0.0909. The absolute area differences and the number of times each recording's estimated density best described the data were presented by gender and by muscle in Tables I-IV.

It was clearly seen that the experimental EMG PDFs of flexor muscle from all motions and both genders were close to the Laplacian density (Tables II and IV). The experimental EMG PDFs of extensor muscle from male subjects were also close to the Laplacian density (Table I). However, the EMG PDFs of extensor muscle from female subjects were close to the Gaussian density (Table III).

TABLE V

SNR'S TABULATED BY MOTION AND MUSCLE FROM MALE SUBJECTS. EACH ROW POOLS NINE-MALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Male	Mean ± SD SNR of ECU Using Processor:		Mean ± SD SNR of FCR Using Processor:	
Motion	**RMS**	**MAV**	**RMS**	**MAV**
FP	5.53±2.59	5.74±2.52	3.06±1.41	3.28±1.56
FS	4.87±2.39	4.93±2.22	2.86±1.78	3.07±1.86
WE	5.74±2.19	5.53±2.01	3.69±1.68	3.81±1.76
WF	5.56±2.48	5.76±2.52	3.05±1.22	3.14±1.21
WR	5.49±2.55	5.71±2.60	3.72±1.85	3.88±1.89
WU	4.97±1.86	5.10±1.96	4.35±2.21	4.84±2.55
HO	6.99±2.78	6.64±2.71	3.89±1.88	4.24±2.00
HC	4.37±1.93	4.64±2.01	2.99±1.65	3.26±1.84
Total	**5.40±2.34**	**5.51±2.32**	**3.45±1.71**	**3.69±1.84**

TABLE VI

SNR'S TABULATED BY MOTION AND MUSCLE FROM FEMALE SUBJECTS. EACH ROW POOLS NINE-FEMALE-SUBJECT TRIALS FROM THE INDICATED MOTION.

Female	Mean ± SD SNR of ECU Using Processor:		Mean ± SD SNR of FCR Using Processor:	
Motion	**RMS**	**MAV**	**RMS**	**MAV**
FP	5.09±1.91	5.26±1.99	3.27±1.29	3.45±1.43
FS	4.88±1.87	4.97±1.90	3.91±2.02	4.15±1.95
WE	5.35±1.72	5.22±1.72	3.94±1.92	4.17±1.90
WF	5.10±2.10	5.35±2.14	4.06±1.64	4.17±1.68
WR	4.72±1.43	4.91±1.62	3.67±1.49	3.95±1.64
WU	4.55±1.58	4.63±1.46	3.69±1.46	3.84±1.56
HO	5.25±2.00	5.37±2.06	3.72±1.80	4.08±2.00
HC	4.09±1.49	4.17±1.56	3.43±1.24	3.69±1.37
Total	**4.88±1.76**	**4.98±1.81**	**3.71±1.61**	**3.94±1.69**

Based on the experimental EMG PDFs, MAV is an optimal EMG amplitude detector for MCIs based on flexor muscle for male and female subjects and on extensor muscle for male subjects. This finding is confirmed by SNR performance, as presented in Tables V and VI. Average SNR performance for flexor muscle of male subjects was 3.69 using MAV versus 3.45 using RMS and that of female subjects was 3.94 using MAV versus 3.71 using RMS. For extensor muscle of male subjects, average SNR performance using MAV was also higher than that using RMS (5.51 > 5.40).

Although the experimental EMG PDFs of flexor muscle from female subjects were close to the Gaussian density, the average SNR performance for extensor muscle of female subjects using MAV was higher than that using RMS (4.98 > 4.88). Based on the experiments of Clancy and Hogan [17] on a simulated EMG sequence y, it means that a weight parameter w in Eq. 4 is in the region $0.375 \leq w \leq 0.525$. In this region, the EMG PDF (the density of y) is closer to Gaussian but MAV has a higher SNR.

$$y = w \cdot x_G + (1 - w) \cdot x_L , \tag{4}$$

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 unit-variance. Hence, MAV is an optimal EMG amplitude detector for MCIs based on extensor muscle for female subjects. On average, the MAV is an optimal EMG amplitude detector for the upper-limb motions and the forearm muscles although the EMG PDF of some motions from the extensor muscle of female subjects is close to the Gaussian density.

One interesting result is about the difference of EMG PDFs from the extensor muscle between genders. Based on the same motions, the EMG PDFs of female subjects tend to be more Gaussian density than that of male subjects (Tables I and III). As mentioned in the literature that when muscle contraction level increases the EMG PDF tends to a Gaussian distribution (using kurtosis and negentropy analysis) [15], [24]. It may be because female subjects have to use more muscle contraction level than male subjects to perform and maintain the same upper-limb motions (Fig. 1). Furthermore, Kaplanis et al. [16] found that the Gaussianity results depend on the electrode positions too, thus in future works the EMG PDFs of other useful forearm muscles should be examined.

In order to confirm an optimal EMG amplitude detector in classifying upper-limb motions using forearm muscles for MCIs, the classification accuracies of MAV and RMS using different EMG data sets were presented in Table VII. On average the classification accuracies of the MAV feature are slightly higher than that of the RMS feature based on various hand, wrist, and forearm motions [11], [25]. The classification accuracies are obtained from state-of-the-art classifiers, i.e., the linear discriminant analysis (LDA) and the artificial neural networks (ANN).

However, if only directions of wrist motions, e.g., forward, backward, left and right, are considered and the EMG are measured from extensor muscles more than flexor muscles, the classification accuracies of RMS are slightly higher than that of the MAV, as found in Yu et al. [26] and Kim et al. [27] by using the maximum likelihood estimation (MLE) and the LDA classifiers, respectively. This finding can be explained by the EMG PDFs of wrist motions from extensor muscle, as can be observed in Tables I and III that tend to a Gaussian distribution more than hand and forearm motions and also flexor muscle.

TABLE VII
A SURVEY OF CLASSIFICATION ACCURACIES OF MAV AND RMS IN THE CLASSIFICATION OF UPPER-LIMB MOTIONS. NOTE THAT EDC IS EXTENSOR DIGITORUM COMMUNIS MUSCLE, ECRL IS EXTENSOR CARPI RADIALIS LONGUS MUSCLE, BB IS BICEPS BRACHII, ECR IS EXTENSOR CARPI RADIALIS, FCU IS FLEXOR CARPI ULNARIS, BCR IS BRACHIORADIALIS, AE IS ARM EXTENSION, AF IS ARM FLEXION, AND 4WD IS FOUR DIRECTIONS OF WRIST MOTION INCLUDING FORWARD, BACKWARD, LEFT AND RIGHT.

Ref.	**Muscle**	**Motion**	**Classi-fier**	**Accuracy, %**	
				RMS	**MAV**
[11]	ECU,FCR,EDC, ECRL,BB	WE,WF,HO,HC, FP,FS,WR,WU	LDA	86.21	86.49
[25]	ECU,FCR,ECR, FCU,BCR,BB	WE,WF,HO,HC, AE,AF	LDA	88.12	88.55
[25]	ECU,FCR,ECR, FCU,BCR,BB	WE,WF,HO,HC, AE,AF	ANN	85.43	88.84
[26]	ECU(both arms), FCR,ECRL	4WD	MLE	96.40	95.98

IV. CONCLUDING REMARKS

The PDF of surface EMG recorded from forearm muscles associated with hand, wrist, and forearm motions was examined experimentally. It was found that the observed densities fell in between the Gaussian and the Laplacian densities, but the experimental EMG PDF can be adjusted with less error (the absolute area difference) to the Laplacian density on average. Based on the EMG PDF and the SNR performance, MAV is suggested to be an optimal EMG amplitude detector for EMG-based MCIs, in which EMG data are measured from forearm muscles during various upper-limb motions. This finding is confirmed by the classification results obtained from several state-of-the-art classifiers, i.e., LDA and ANN.

ACKNOWLEDGMENT

This work is funded in part by the FI MSTIC University Joseph Fourier Grenoble 1 (TIGRE project) and by Prince of Songkla Graduate Studies Grant.

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