An Investigation of Robustness in Independent Component Analysis EMG

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***Abstract-* We developed a multi-channel electromyogram acquisition system using PSOC microcontroller to acquire multi-channel EMG signals. The two channel surface electrodes were used to measure and record EMG signals on forearm muscles. These two channels of EMG signals were performed a blind signal separation by using an independent component analysis (ICA) technique. The well known ICA algorithm called FASTICA is a useful method to separate two or more linear combination of source signals into statistically independent components. The results show that the ICA applied EMG is more robust than the without ICA applied EMG since the statistic variation is improved.**

I. INTRODUCTION

Electromyography (EMG) is the study of muscle electrical signals. EMG is sometimes referred to a myoelectric activity. Many muscular abnormalities such as muscular dystrophy, inflammation of muscle, peripheral nerve damages could be resulted in an abnormal electromyogram [1-6]. EMG can be recorded by two types of electrodes which are an invasive electrode so-called wire or needle electrodes and a non-invasive electrode so-called surface electrode. Wire or needle electrodes record action potentials of individual muscle fiber which are ideal choices to evaluate the muscle activity [9]. However, fine wire intramuscular electrodes require a needle for insertion into the muscle and may cause a significant pain. The choice of surface electrode is then preferable. However, when EMG is acquired from surface electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscles underlying the skin. Estimating this force in general is a hard problem due to difficulties in activating a single muscle in isolation, isolating the signal generated by a muscle from that of its neighbors, and other associated problems [7-8]. The clinical application of EMG can be classified into two main categories. (i) Standard EMG [8] is recorded from discrete sites on a muscle and then provided only a limited picture of the actual muscular electrical activity in the vicinity of the recording electrode. (ii) Array EMG recorded by an array electrode is facility in the clinical interpretation of electrical activities through mapping of these signals on the muscle surface [9].

In this paper, the application of ICA to the EMG signal was investigated. A PSOC-based two-channel surface electrode array was used as a data acquisition system to acquire EMG data. The ICA was then applied to the acquired EMG to separate into two statistically independent EMG data, namely the ICA EMG. The joint probability density function plotted between the two channels EMG was also provided to test the statistical independent. To verify the robustness of feature extraction, the correlation coefficient between the statistically independent EMG of the repeated measurement of the same contraction was explored. The experiment was also performed to find the coefficients between the statistically independent EMG resulting from the two channels in different contraction.

The paper is organized as follows: Section II is devoted to the design concept of multi-channel electromyogram system. Section III is briefly introduced the independent component analysis. Section IV is the correlation coefficient. The experiment and results are shown in section V. Discussion and Conclusion are provided in section VI.

II. DESIGN AND CONSTRUCTION OF MULTI-CHANNEL EMG

EMG measurement is accomplished by the instrument called electromyograph. The system, in general, consists of instrumentation amplifier, notch filter, offset adjustment, isolator, main amplification, and the CRT display. The instrument amplifier is a front-end, high CMRR differential amplifier which functions to pick-up a low amplitude signal submersed in the high-frequency noise. The notch filter gets rid of the 50Hz noise while keeping the EMG signal intact. The offset adjustment maintains the baseline level especially during the subject's motion. The function of isolator is to separate the front-end section from the rear-end section to protect the possible electrical shock to the patient. The main amplification conditions the EMG prior to be display with CRT. The complexity of the electronic circuit becomes realized with the necessity to monitor the multi-channel of EMG. Such complicate designs, however, are made possible by the creation of entirely reconfiguration and programmable components the so-called Programmable System On Chip Microcontroller (PSOC Microcontroller).

The designed EMG system is capable of monitoring 16 channels of EMG simultaneously. Each channel consists of 2 main parts; (i) EMG signal processing unit and PSOC microcontroller. Fig. 1 shows the Surface electromyography

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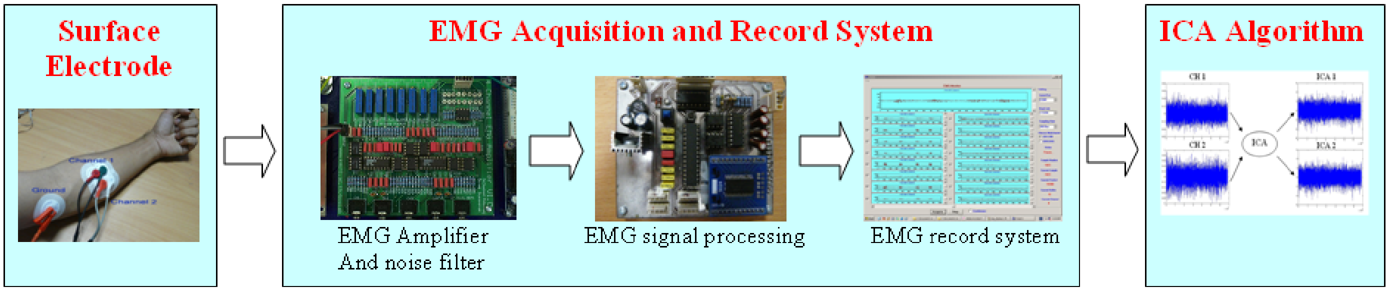


Figure 1. Surface electromyography seperation system.

Seperation system Fig. 2 shows Multi-channel electromyogram acquisition system.

The EMG signal processing units consists of 3 sub-units

(i) Instrumentation Amplifier. This subunit uses the INA2128 BUR-BROWN Integrated Circuit. The IC can achieve a CMRR up to 120 dB and gain up to 1000.

(ii) Noise filter. The function of the filter is to get rid of the 10-20 Hz noise which is classified as a motion artifact.

(iii) Amplifier and Offset Adjustment. The objective of this sub-unit is to Amplifier EMG signal and maintains the appropriate offset voltage prior to interface with the PSOC.

The PSOC microcontroller consists of 4 subunits

(i) PGA (Programmable Gain Amplification) This subunit acts as the buffer and the main amplification of EMG.

(ii) Low pass filter. The function of the filter is to remove of the high frequency noise. The cut-off frequency is at 500 Hz.

(iii) DELTA-SIGMA. This subunit functions as a 8-bit analog to digital converter.

(iv) UART. This subunit functions to perform RS-232 interfacing unit with PC.

Figure 2. Multi-channel electromyogram acquisition system.

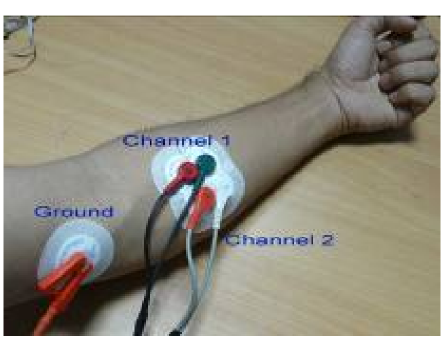


Figure 3. Surface EMG electrode placement.

III. INDEPENDENT COMPONENT ANALYSIS

Goal of independent component analysis (ICA) is to minimize the statistical dependence between the basic vectors. Mathematically, we can write

$$\boldsymbol{WX} = \boldsymbol{U} \tag{1}$$

ICA searches for a linear transformation W that minimizes the statistical dependence between each row of U. There exists a number of iterative algorithm to solve for W [15, 16]. Most of them are optimized for the dependence criteria including Kurtosis, Negentropy, etc[17]. In this paper, we applied the well known ICA algorithm so-called FASTICA purposed by Aapo Hyvarinen [16]. The idea of FASTICA algorithm belong to the family of fix-point algorithms for ICA, is based on the iteration to find the maximum of non-Gaussianity of variables.

Here we focus on the application of ICA for surface EMG signal separation. The basically procedure for using ICA is divided into 2 steps. (i) the preprocessing step and (ii) the FASTICA algorithm step.

The preprocessing step is shown as the following:

(i) The centering step is done by subtract the mean of the observed data x to make its mean zero.

(ii) The whitening step is used to remove the correlation between the observe data. A common method to whitening was done by the eigenvalue decomposition of the covariance matrix of the mixed signal.

The FASTICA algorithm step is briefly summarized as follow:

(i) Choose an initial (random) weight vector w.

(ii) Calculate $w^{+} = E\{xg(w^{T}x)\} - E\{g'(w^{T}x)\}w$

(iii) Let $w = w^{T} / |w^{T}|$

(iv) If it is not converged, then repeat step 2

IV. CORRELATION COEFFICIENT

Correlation Coefficient is the statically-based method to measure the similarity between two signals and can be used to measure the repeatability between the two measurements. Given signal *X* and *Y*, the correlation coefficient ρ is defined as follows

$$\hat{\rho}_s(X,Y)=\frac{\hat{C}_s(X,Y)}{\sqrt{\hat{\sigma}_x^2\,\hat{\sigma}_y^2}},-1\le\hat{\rho}_s(X,Y)\le 1 \qquad (2)$$

Where covariance $\hat{C}_s(X,Y)$,variance $\hat{\sigma}_x^2,\hat{\sigma}_y^2$, and means $\overline{X},\overline{Y}$ are defined by

$$\hat{C}_s(X,Y)\equiv\frac{1}{N-1}\sum_{i=1}^{N}\left(X_i-\overline{X}\right)\left(Y_i-\overline{Y}\right) \qquad (3)$$

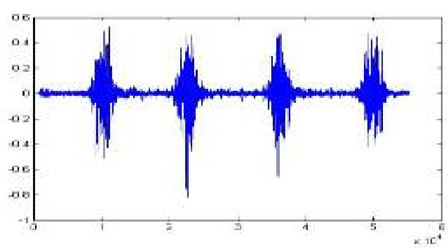
$$\hat{\sigma}_x^2\equiv\frac{1}{N-1}\sum_{i=1}^{N}\left(X_i-\overline{X}\right)^2,\hat{\sigma}_y^2\equiv\frac{1}{N-1}\sum_{i=1}^{N}\left(Y_i-\overline{Y}\right)^2 \qquad (4)$$

$$\overline{X}\equiv\frac{1}{N}\sum_{i=1}^{N}X_i,\overline{Y}\equiv\frac{1}{N}\sum_{i=1}^{N}Y_i \qquad (5)$$

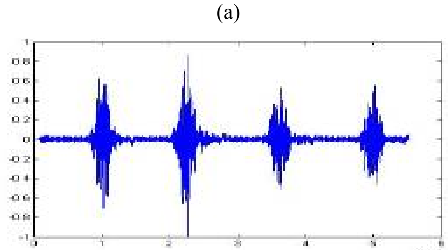
Hence, the correlation coefficient method can be used to measure the repeatability of the EMG signal.

V. EXPERIMENT AND RESULTS

In this paper, we use two channel surface electrodes to measure and record EMG signals of a 28-years-old healthy man. Both two channel surface EMG electrodes of SWAROMED Al/AgCl were placed on forearm muscle. The diameter is 10 mm. The interelectrode distance is fixed at 10 mm. Prior to affix the electrodes, the skin was prepared by shaving off any hair, exfoliated and finally cleaned by 70% alcohol. The first channel is placed on Flexor carpi radialis, whereas the second channel is placed on Flexor carpi ulnaris as shown in fig.3. Fig. 4 and Fig. 6 show the EMG signal from channel 1 and channel 2 during contraction/relaxation and hold contraction, respectively, of wrist flexion movement. Fig. 5 and Fig. 7 show the first and second EMG signals as the results of ICA algorithms.

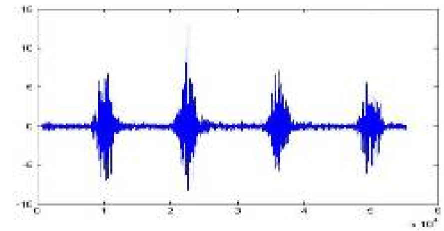


(a)



(b)

Figure 4. (a) The input signal from channel 1.
(b) The input signal from channel 2.



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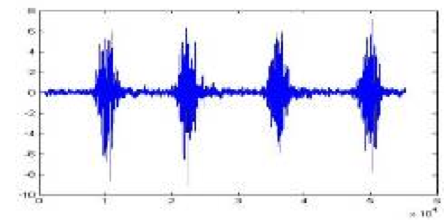
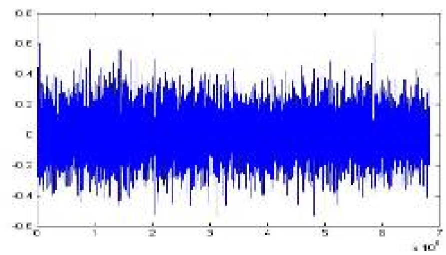


(b)

Figure 5. (a) The first result of the ICA.
(b) The second result of the ICA.



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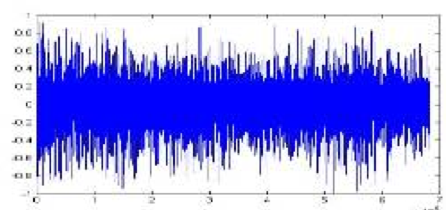
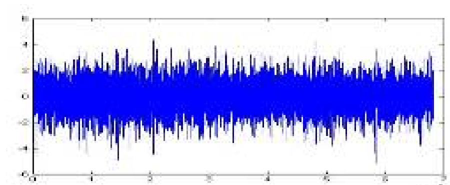
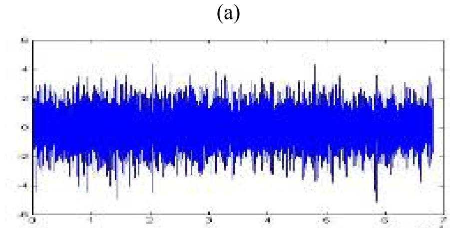


(b)

Figure 6. (a) The input signal from channel 1.
(b) The input signal from channel 2.



(a)



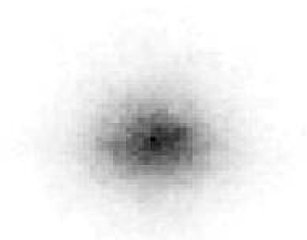
(b)

Figure 7. (a) The first result of ICA.
(b) The second result of ICA.

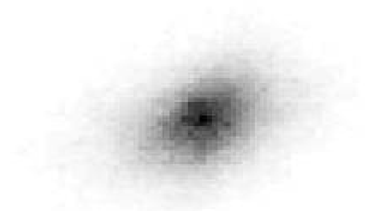
To explore the statistically independent between two-channeled EMG, the joint distribution of the two input signals before and after ICA application were plotted. The result is shown in fig. 8. Evidently, the statistically independent between two-channeled EMG with ICA is more prominent than without-ICA; i.e. the shape gets closed to the ideal linear distribution resulting from the ICA algorithm. Hence, the ICA EMG is more suitable for further feature extraction. To provide quantitative measurement of robustness of ICA application, the correlation coefficient between two EMG signals acquired at difference time instance, i.e., the repeatability measurements, was provided. Table 1 shows the results of this robustness measurement. To test the robustness of ICA to EMG feature extraction, the feature defined in [18-19] was also provided to compare the feature of ICA-applied EMG and without ICA-applied EMG. The result is also provided in Table 1.

TABLE I
QUANTITATIVE MEASUREMENT OF ROBUSTNESS OF ICA APPLICATION

	Correlation Coefficient between two measurements of EMG.	Feature extraction of the same contraction
ICA-Applied EMG	1.0733e-14	274
With out ICA-Applied EMG	0.4710	42



(a)



(b)

Figure 8. (a) The joint distribution of input signal.
(b) The joint distribution of ICA signal results.

VI. DISCUSSION AND CONCLUSION

Independent component analysis is the well known algorithm to separate the linear combination of the signals into the signals with statistically independent. The application of ICA to EMG is studied in this paper. The investigation demonstrated that the ICA-applied EMG is more robust. The statistic variation is less than without ICA-applied EMG and hence makes it more suitable for feature extraction which is used in EMG contraction classification.

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