AUTOMATED EMG-SIGNAL PATTERN CLUSTERING BASED ON ICA DECOMPOSITION

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Keywords: EMG clustering, Motor Unit Action Potentials (MUAPs), Independent Component Analysis (ICA), EMG Entropy, ROC analysis.

Abstract: Adaptive independent component analysis is interactive method for processing and classifying EMG signals pattern through short steps of ICA algorithms. In this work the efficiency and presentation of EMG signal decomposition and classification with adaptive ICA algorithm was investigated and presented. Single and multiple fibers motor unit action potentials (MUAP) patterns were tested and identified. Applying a fixed point modified ICA method, instead of much decomposition and pattern clustering algorithm localization of the action-potential source in the vicinity of specific neuromuscular diseases was achieved. ICA has its flexibility for robustly classify and identify the MUAP's signal stochastic sources with a linear way and localizing the blind source for bioelectric potential. The utilization of adaptive ICA as an embedded clustering algorithm for separating a blind signal source will assist in construction an automated EMG signal diagnosis system with aid of new computerized real time signal processing technique. From the proposed system a stable and robust EMG classifying system based on multiple MUAP's intensity were developed and tested through a standardization of clinical EMG signal acquisition and processing.

1 INTRODUCTION

Electromyography (EMG) signals classification and processing can be used for varieties of clinical/biomedical applications, spectral pattern classification of intensity-based analysis, and modern human computer interaction. EMG signals acquired from muscles require advanced methods for detection, decomposition, processing, and classification. The purpose of this paper is to illustrate the various ICA algorithms for EMG signal pattern classification for identifying the random distribution data clustering, and to provide efficient and stable method of understanding the signal and its physiological nature. A comparison study was given to show performance of various EMG signal analysis methods based on different ICA. This paper provides researchers a good understanding of adaptive ICA EMG signal decomposition and pattern classification (Zazula, 1999).

Adaptive signal processing have a principal rule in defining elementary platform for EMG signals classification and processing. Biomedical signal pattern classification can be used for varieties of clinical/biomedical applications, spectral pattern classification of intensity-based development, and modern human computer interaction. As presented above, the purpose of this work is to illustrate the various methodologies and algorithms for EMG signal pattern classification based on ICA random distribution data clustering to provide efficient and robust ways of understanding the EMG signals and its physiological nature.

2 MATERIALS

EMG signal recorded using Delsys® acquisition system for recording surface EMG (sEMG) and needle EMG with sensitivity between (0.2-10 uV). The suspected area of disorder is identified for EMG recording, for example, the biceps brachii in the upper arm. The EMG is then triggered to record for a predetermined time after which the acquired signal is differentially amplified, band pass filtered, and digitized. The common feature for classifying intramuscular EMG signal is the Euclidean distance between the MUAP waveforms. For clinical interests, the main feature of EMG signal is the number

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of active motor unit (MUs), the MUAP waveforms, and the innervations time statistics. According to Wellig and Moschytz (Zazula, 1999), the determination of the MUAP waveform and the No. of active MUs can be considered as a classification problem (Wang et al., 1997, Thompson et al., 1996).

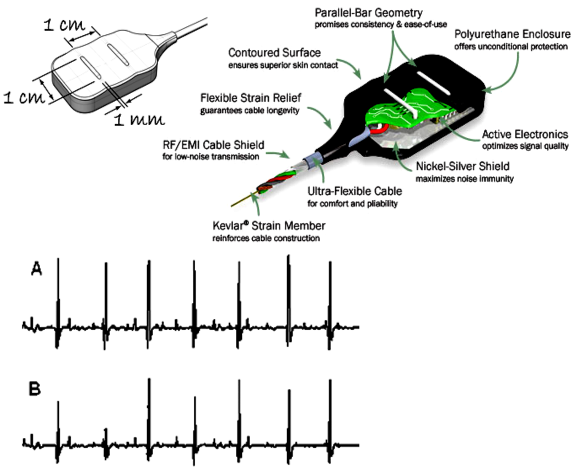

Figure 1: Surface EMG electrode and with typical MUAP action potential unit recorded as single fiber action potential adopted from Delsys® with permission (Wang et al., 1997).

The representation of time-triggered and no overlapping MUAPs produce a shimmer. MUAP shimmer is influenced by the time-offset of the sampled waveforms, local fluctuation of the baseline and background noise. Besides background noise and the effects of signal offset, white noise influences the classification. The classification with wavelet coefficient needs the wavelet coefficient (*Ff[m,n]*) of four frequency bands (*m=2, 3, 4, 5*) and not below 150 Hz. Classification performance depends also on distance between the class means, therefore, the best selection of these four frequency bands depends on the Fourier transform of the MUAP waveforms themselves. Boualem (Wang et al., 1997) theorized that the time frequency representation of wavelets decompositions (WVD) provided high-resolution signal characterization in time-frequency space and good noise rejection performance. This theory is useful for EMG signal classification. For purpose of classifying EMG patterns, EMG electrical model is used in combination with fixed point-ICA decomposition by extracted and compared two types of features based on signal processing for the purpose of classifying EMG patterns. The two features were the coefficients of EMG source models and the components of Fourier frequency spectra. The method showed better results while describing the EMG linear envelopes (LE) method (McKeown et al., 2002).

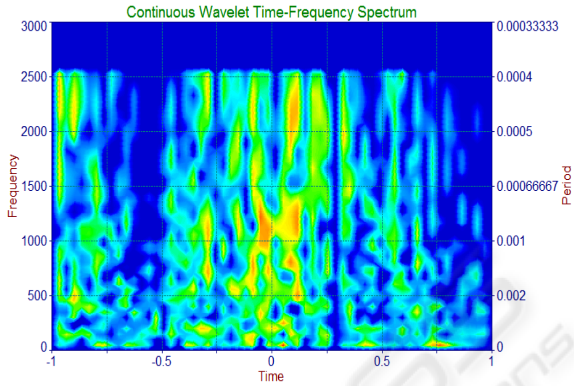

Figure 2: EMG spectra for single MUAP derived with continuous wavelet transform (CWT) (McKeown et al., 2002).

3 EMG PROCESSING METHOD

Surface EMG (sEMG) can be estimated as a mean absolute value (MAV) or as root mean square (RMS) of the time varying standard deviation. In this approach, the signal is first passed through a noise-rejection filter, uncorrelated, demodulated, and smoothed (Thompson et al., 1996). Integrated EMG signal identification can be used in this technique in order to map the bioaction potentials of corresponding fibers during firing intervals of myofibers. The area of MUAP waveform, either the entire waveform or the rectified version of the waveform. The characterization of EMG pattern can be based on the following criteria (Wang et al., 1997, McKeown, et al., 2002),

(a) *Spike Area.* Analogous to compute area under the spikes and calculated only over the spike duration.

(b) *Phases.* No. of baseline crossings that exceeds a certain voltage threshold, e.g., 25 μV.

(c) *Turns.* No. of positive and negative peaks separated by a specified threshold voltage, (e.g. ±25 μV),

(d) *Willison Amplitude (WAMP)* the No. of counts for a change of signal in the EMG amplitude above a predefined threshold (McKeown, 2000, Jung et al., 2001).

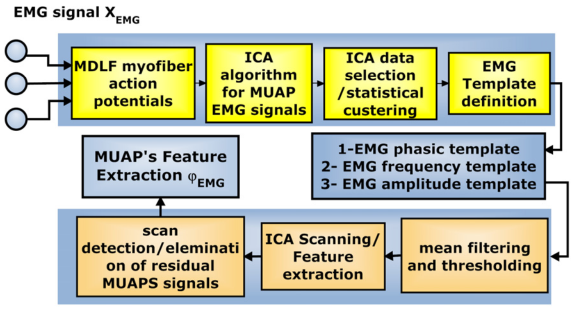

Figure 3: Surface EMG, decomposition and clustering (Garcia et al., 2002) consisting of signal processing, signal decomposition, template matching, and post processing stages (Thompson et al., 1996).

4 INDEPENDENT COMPONENT ANALYSIS (ICA)

ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear or nonlinear mixtures of some unknown latent variables or activation sources, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA (McKeown, 2000, Jung et al., 2001). In the basis of spatiotemporal characteristics of EMG signal, the later behavior can be approximated as band limited white noise (BLWN) with spatial frequency of recorded signal fast ICA algorithms for a hierarchical neural network that extracts the source signals from their mixtures in a sequential fashion. In the hierarchical neural network, the output of the j_{th} extraction processing unit is described as $y_j = w_j^T x_1$, where $w_j = [w_j1, w_j2, \ldots, w_jn]^T$. Contrary to the cascade neural network, the input vector for each processing unit of the hierarchical neural network is the same $x_1 = Q * x$ vector from the prewhitened EMG electrode signals. Let us now consider the cost function and the standard kurtosis for a zero mean signal y (EMG) (Cichocki and Amari, 2003).

$$J(w_1, y_1) = k_4(y(w_1)) = \tfrac{1}{4}\left[E\{y_1^4\} - 3E^2\{y_1^2\}\right] \tag{1}$$

Where $y_j = w_1^T . x_1$ is the output of EMG signal processing unit.
In order to find the optimal value of vector w, we apply the following iteration rule:

$$w_1\left(l+1 = \frac{\nabla_{w1} k_4(w_1(l))}{\left\|\nabla_{w1} k_4(w_1(l))\right\|}\right), \tag{2}$$

Where $\nabla_{w1} k_4(w_1) = \partial k_4(w_1)/\partial w_1$. equivalently applying the following training formula:

$$w_1^+(l+1) = \nabla_{w1} k_4(w_1(l)); \tag{3}$$

$$w_1(l+1) = \frac{w_1^+(l+1)}{\left\|w_1^+(l+1)\right\|}, \tag{4}$$

Figure 4 illustrate anatomy of adaptive fixed-point ICA algorithm used for EMG signal processing and classification, as illustrated the main module of algorithm consist of weighting coefficient of independent signal decomposition in which the output pattern indicated the assigned source of EMG potentials (Cichocki and Amari, 2003).

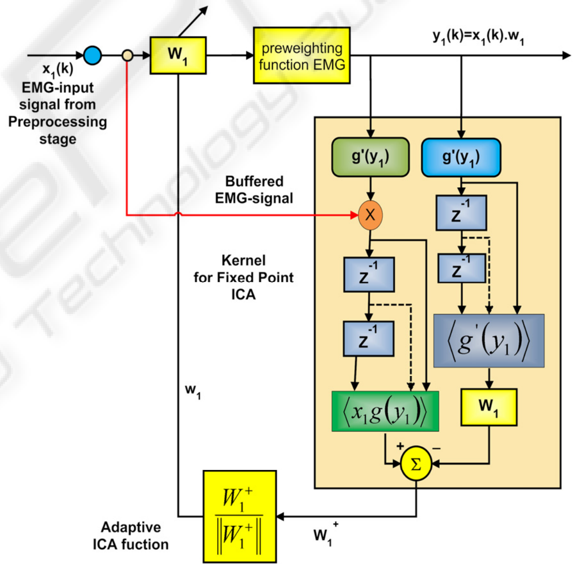

Figure 4: Adaptive fixed Point-ICA algorithm for EMG signal clustering and processing corresponds of stable function.

The vector *w (l+1) j* has unit length in each iteration step through enforcing minimizing cost function (J). The gradient of the cost function of EMG ICA Algorithm can be evaluated as:

$$\nabla_{w_1} k_4(wl) = \frac{\partial k_4(wl)}{\partial wl} = E\{y_1^3 x_1\} - 3E\{y_1^2\}E\{y_1 x_1\} \tag{5}$$

Thus the fixed-point algorithm in its standard form can be written as:

$$w_1^+(l+1) = \left\langle y_1^3 x_1 \right\rangle - 3w_1(l), \;\; y_1 = w_1^T(l)x_1$$
$$w_1(l+1) = \frac{w_1^+(l+1)}{\left\| w_1^+(l+1) \right\|} \tag{6}$$

To find a stable solution for EMG classification criteria, an embedded in ICA –learning kernel were placed in the path of general clinical module. Prototyping of an adaptive EMG pattern clustering is one of the task were achieved, based on a biopotential acquisition module.
Figure 5 that illustrated the overall EMG acquisition procedure from site recording to the final output clustered data in the final clinical decision module. The capability to improve clinical data transfer protocols, the physiologist and physicians can use a wireless transmission module form the main clinical workstation via a standard protocol of IEEE 802.14a wireless communication system to visualize and interact with acquired EMG physiological data. The automated clinical diagnosis system can be also integrated as graphical user interface in PDA platform or other mobile communication devices (Bell and Sejnowski, 1995, Micera et al., 2001).

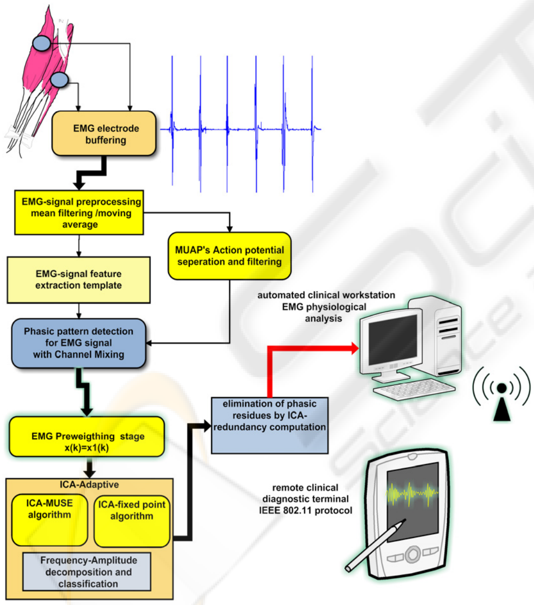

Figure 5: Block diagram of EMG-ICA decomposition and pattern clustering with adaptive fixed point-MUSE ICA algorithm.

5 ADAPTIVE ICA ALGORITHM

As modified ICA, adaptive algorithm was implemented in the path of the main independent component estimation method, were the training data and the main entropy of ICA minimized in order to obtain residual differences in EMG intensity (Cichocki and Amari, 2003, Merletti and Parker, 2004).

6 ROC ANALYSIS AND EMG SENSOR ENTROPY

For testing the overall performance of the EMG data classifier performance, a statistical test for the robustness and optimality of the data classifier was applied, to illustrate the results of clustering and then need to characterize EMG sensor itself for calibration and buffering purpose. Receiver operating characteristics (ROC) is analysis of sensor inference were it is calculated through repeatable EMG recording. Therefore the identification of sensitivity vs. specificity should consider in this analysis. The robustness of ICA algorithm was tested in contrast to the amplifier gain of interface (Bell and Sejnowski, 1995). Surface EMG electrodes which are used in clinical experiment are disposable and composed of lined conductive area used for increasing measurement stability and reduction of parasitic noise associated with physiological measurement session. Therefore sensor characteristics should be taken into account for further classification steps to improve accuracy of overall clinical assessment. The definition of sensitivity and selectivity with ROC analysis, have the following criteria for recursive data clustering and pattern classification of biomedical and clinical data (Cichocki and Amari, 2003).

Table1: Stability and performance index for ICA-methods.

EMG signal ICA- algorithms performance comparison			
ICA methods	EMG-intensity classified pattern	Entropy (ψ)*	Correlation index (ξ)**
ICA-MUSE	E_1,E_2,M_1,M_2,M_3	0.1342	2.23
ICA-JADE	E_1,E_2,M_2,M_3	0.1275	2.41
ICA-SOBA	E_1,E_2,M_1,M_3	0.1448	2.83
ICA-Adaptive	$E_1,E_2,M_1,,M_3$	0.2030	2.51
ICA-REA	E_1,E_2,M_1	0.1942	30
ICE-MJADE	E_1,M_1,M_2,M_3	0.1820	29
ICA-Standard	E_1,M_1,M_2	0.1872	32
ICA-NLE	E_1,M_1,M_3	0.1922	36
ICA-Wavelet	E_2,M_1,M_2,M_3	0.2051	35

* Entropy index for ICA-decomposition not for EMG classifier.
**Correlation index for EMG derived spectral information.

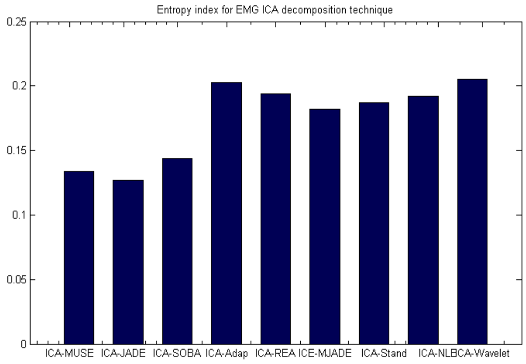

Figure 6: Entropy index of EMG-ICA decomposition algorithm.

As noticed from the performance index of adaptive ICA observer a good EMG M_1, M_2 classes corresponding to good potential preweighting and separation, as well as the low indexing criteria for the E_1,E_2 classes, indicate a non-stabilized bioaction potential pattern that exist in clustered EMG signals (Micera et al., 2001, Karhunen and Oja, 1997).

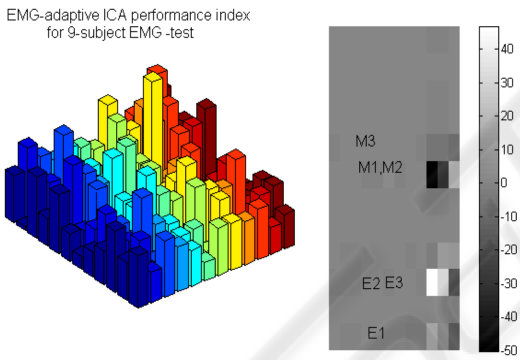

Figure 7: 3D Performance index of decomposed EMG signal based on Adaptive ICA algorithm indicate main components of E_1, E_2, E3, M_1, M2, M3 spatial scheme of EMG.

In this work a robust technique for extracting and classifying MUAPs for EMG signal was developed. This technique is based on single-channel and short periods real-time recordings from normal subjects and artificially generated recordings. This EMG signal decomposition technique has several distinctive characteristics compared with the former decomposition methods:
(A) Band pass filtering the EMG signal through wavelet filter and utilizes threshold estimation calculated in wavelet transform for noise reduction in EMG signals, and to detect MUAPs before amplitude single threshold filtering;
(B) Removing the power interference component from EMG recordings by combining both, (ICA) and wavelet filtering method as adaptive ICA.
(C) Similarity measure for MUAP clustering is based on the entropy (ψ_{EMG}) value normalized with the sum of median values for EMG signal;
(D) Lastly uses ICA method to subtract all accurately classified MUAP spikes from original EMG signals. The technique of our EMG signal decomposition is fast and robust, which has been evaluated through synthetic EMG signals and real one, where the synthetic (artificial) EMG data generated using an approximated band-limited white noise model with varying seeding noise developed by Farina (Merletti and Parker, 2004, Farina and Merletti, 2001).

Table 2: EMG Classification performance index.

EMG-data subject	*p*-value	Uncorrected pattern	Corrected pattern	Percentage
1	0.0023	4	32	88.90%
2	0.0027	3	34	91.90%
3	0.0031	4	34	89.4%
4	0.0032	2	33	94.28%
5	0.00362	3	30	90.09%
6	0.00317	2	29	93.54%
7	0.0047	3	32	91.42%
8	0.00528	4	36	90.0%
9	0.00571	3	35	92.10%

7 RESULTS AND DISCUSSION

Adaptive ICA-decomposition for EMG signal illustrates optimality in clustering (approx. 0.0187) for spontaneous EMG vector classification, but with a deviation in linearity of MUAP classes due to different standard deviation (SD), of each signal, which can be compensated by increasing the correlation index or selecting the same order number of finite impulse response (FIR) filtering module. Testing additional ICA algorithms to evaluate clustering efficiency presents with robust hyperplane classification based on other criteria such as EMG signal turns, spike area, integrated area, phases performed in an adaptive ICA algorithm as concise effective methods to increase stability of overall clustering schemes. Euclidean distance have been computed in background algorithm as state vector mapping (SVM) matrices for each EMG signal within individual channel in contrary this will overload computation time for reiterative clustering. As we can observed form the Fig.7 where the presentation of 3D performance matrix seen, there are a convergent efficiency in ICA clustering method were the positive value of EMG signal intensity clearly visible instead of relatively negative value, which mean an inhibited EMG intensity due to the transition effect of depolarization wave through the muscle fibers, in which this obviously considered as a good marked triggering for online EMG acquisition and diagnosis.

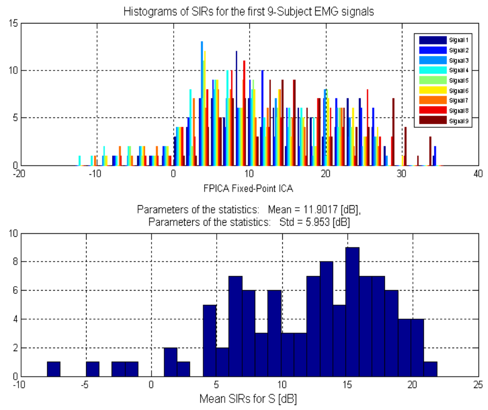

Figure 8: Histogram of ICA decomposed EMG signals based on fixed-point adapted ICA algorithm.

8 CONCLUSIONS

Pattern clustering and decomposition based on adaptive ICA will improve diagnostic performance of different neuromuscular pathology patterns. EMG consisted of activity for six different principal patterns which are identified and extracted. The clustered EMG activities notated as (E1,E2, E3,M1,M2,M3) , E-related to eccentric myoelectric activity which dominated in near-surface electrode and M pattern which related to myofibers compartment, each of which have been classified for a 9 subject group. Source localization and identification are robustly computer through ICA template algorithm, although some pattern in EMG signal the algorithm were not detected or classified, this due to the some leakage in optimization cycle of EMG signals inside ICA algorithm. The overall behavior of adaptive ICA classifier predicted a considerable percentage of poor to moderated classified intensity modulated EMG signals and this due to invalid classified or decomposed respective EMG coefficient, which indeed needs improvement for advanced research and work on EMG pattern classification optimization. Future perspective of EMG pattern clustering was introduced, which may use for developing a cutting edge electrophysiology module. ICA technique will assist in developing a robust portable clinical system, by which acquisition, processing, and diagnosis for several myopathic and neuropathic EMG pattern could be achieved.

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