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(General article)

Comparative Study of Different EMG Signal decomposition Techniques

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Abstract

EMG signals are electromyogram signals generated by firing of MUs (motor units) in muscle fibers. The decomposition of EMG signal of a muscle provides useful information for the diagnosis of neuro-muscular diseases by physician and neurologist. In decomposition of EMG signal different MUAPs (Motor Unit Action Potentials) are classified into different categories. This paper gives a review of different techniques used for decomposition of EMG signal. The techniques discussed are the decomposition of surface EMG signal based on blind source separation of convolved mixtures[11] , An artificial neural network (ANN) technique based on unsupervised learning, using the self-organizing feature maps (SOFM) algorithm and learning vector quantization (LVQ)[1] and high precision EMG signal decomposition using communication techniques[5].

Key words: *EMG:-Electromyography, MVC:-Maximum Voluntary Contraction, MUAP:-Motor Unit Action Potential ANN:-Artificial Neural Network, AcS:-Active Segments*

1. Introduction

EMG signal is analyzed and processed using different techniques of digital signal processing. The EMG signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuromuscular activities. The nervous system always controls the muscle activity (contraction/relaxation). Hence, the EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. EMG signal acquires noise while traveling through different tissues. Moreover, the EMG detector, particularly if it is at the surface of the skin, collects signals from different motor units at a time which may generate interaction of different signals [2]. There are different methods proposed for decomposition of EMG signal LeFever and DeLuca [7] used a special three channel recording electrode, template matching and firing statistics for classification. Their decomposition method required operator intervention. Haas and Meyer [3] in their system called ARTMUP used potential features like duration, area, amplitude and number of turns as input to a hierarchical Clustering technique for classification, followed by two stage decomposition. McGill et al. [8] developed the ADEMG system that used template matching and a specific alignment algorithm for classification. In the present work the object is to review EMG signal decomposition techniques in context of accuracy.

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2. Methods

(A) Decomposition of EMG signal using BSS of convolved mixtures*.

The first technique which uses blind source separation considers generation of SEMG as convolved mixing model. The input from *n* fingers of EMG instrument is

$S(t)=[S1(t),\ldots\ldots.Sn(t)]^T$ ………………………….....…(1)

Where 't' is a time index,

By filtering and mixing through a transmission medium the observational signal

$$x_i(t)=\sum_{j=1}^{n}\sum_{k=0}^{P-1}a_{ijk}s_j(t-k), i=1,\ldots,m \qquad (2)$$

Where a_{ij} is FIR filter coefficient between the j_{th} source signal and the i_{th} electrode, a_{ijk} is the k_{th} coefficient of the FIR filter, P is the filter length [10]. The whole process can be described by

$x(t)=\underline{A}s(t)$……………………………….…………..………(3)

Where A is an unknown FIR matrix which is composed of FIR filters instead of scalars, the multiplication between two such FIR matrix elements is defined as their convolution [10] and A is the mixing matrix.
For this method two assumptions are made:
(a) the no. of electrodes is not less than the no. of sources
(b) The source signals are statistically independent with each other.
The unmixing matrix W is found to reverse the process and estimate the recorded signals. The reverse process can be described by the equation below

$\dot{s}(t) = \underline{W}x(t)$……………….......… ………………….(4)

Where $\dot{s}(t)$ is estimate of the source vector and W is FIR unmixing matrix.

(B)ANN technique based on SOFM and LVQ

The second method is an artificial neural network (ANN) technique based on unsupervised learning, using the self-organizing feature maps (SOFM) algorithm and learning vector quantization (LVQ)[1].

The steps followed for this method are as follows:-

1. Segmentation
Segmentation is process of extraction useful signal portion from a raw recorded signal and segmented signal contains signal of interest.

2. Classification
Classification is composed of three steps, first two steps include learning phases of ANN and the third step carries out classification based on the training of ANN.
First training phase uses SOFM (self organizing feature map) and second phase uses LVQ (Least Vector Quantizer) learning. For the final step of classification winner take all NN is used.

(C)Decomposition of EMG signal using communication techniques.

Third method is based on the communication techniques used in communication system. The new approach is based on a communication technical interpretation of the EMG signal. The source is modeled as a signaling system with intersymbol interference, which encodes a well-defined sparse information sequence. This point of view allows a maximum-likelihood (ML) as well as a maximum a posteriori (MAP) estimation of the underlying firing pattern to be made. In this method segmentation is based on Active segment (AcS). For the segmentation, a sliding time window is used. If the mean slope within this window exceeds a certain threshold, the beginning of an AcS is postulated. The end of a segment is reached when the total variation of the EMG within the window falls below another threshold. Fast single algorithm [6] is used for clustering of AcS.

It consists of the following steps.

• The minimal Euclidean distance d_{ij} between two time aligned AcSs is used as a measure for the distance or dissimilarity between AcSs.
• By means of a single linkage cluster analysis, a hierarchy of partitions is built. The hierarchy starts with a partition in which every active segment forms a cluster by itself. A stepwise fusion of the nearest neighboring clusters ends with a single cluster containing all segments.
• The optimum partition is determined by choosing that partition for which the loss of homogeneity with respect to the next partition is maximal. The time aligned, filtered, and unfiltered members of each cluster are used to build the corresponding reference action potentials by averaging.

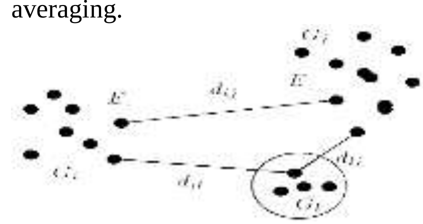

Fig 1 :- Fast Single Linkage Algorithm[5]

3. Results And Discussion
In the first technique two parameters are used to quantify the method. One is C_S i.e. correlation coefficient between the output vectors of different inputs, as the value of C_S is lower, the better is the performance. The other one is C_F i.e fidelity between the output vector and the source vector, as the value of C_F is higher, the performance of decomposition is better. Following is the table of results obtained by this method.

Table 1 Statistic result of decomposition using BSS method

SNR (dB)	Mix C_S	BSS of convolved mixtures C_S	C_F1	C_F2
0	0.99	0.1321	0.8979	0.9407
5	1.00	0.1118	0.9000	0.9440
10	0.97	0.0975	0.9050	0.9482
15	0.99	0.0963	0.9116	0.9510
20	0.99	0.0881	0.9053	0.9539
25	0.97	0.0797	0.9057	0.9504
30	0.99	0.0647	0.9092	0.9514

Here C_F1 and C_F2 are output vectors of two channels. If we convert correlation into percentage, the best result found by this method at a nominal SNR is 95.10 %.

In second method, ANN technique using SOFM and LVQ, 24 subjects were observed out of which 8 normal, 8 with motor neuron disease and 8 were suffering from myopathy. For comparison purpose we have considered only normal subjects. Basically this technique is a pattern recognition algorithm. With normal subjects this technique gives 95% results [1].

Table 2: Classification success rate of ANN technique using SOFM and LVQ [1]

Subjects	**Results**
NOR	95%
MND	94%
MYO	98%
TOTAL	96%

NOR-Normal subject
MND-Subject with motor neuron diseases
MYO-Subject suffering from myopathy

In the third Method implementing communication techniques to eliminate the uncertainty of the manual decompositions, a corresponding set of ten artificially generated EMG signals was produced. The artificial EMG signals were based on the manual decomposition. Two different cases were studied: the decomposition of a noiseless set of EMG signals and the decomposition of EMG signals with the same noise floor as the original signals. The obtained mean result was 94.2% correctly detected MAP sequences [5]:

Table 3

EMG signal	MAP estimation (%)
1	94.4
2	91.9
3	95.0
4	91.0
5	95.4
6	95.7
7	91.6
8	95.2
9	93.4
10	98.6
Mean	94.2

(3) Achieved decomposition accuracy with measured EMG signals [5]

The comparison table for the results attained by these three methods is shown hereunder.
Table 4 Comparative analysis of three discussed techniques

S. No.	**Method**	**Percentage Result**
1.	Blind source separation of convolved mixture	95.10
2.	Artificial neural network (ANN) technique based on unsupervised Learning, using the self-organizing feature maps (SOFM) algorithm and learning vector quantization (LVQ)	95
3.	High precision EMG signal decomposition using communication techniques	94.2

Blind source separation is the best observed method but it gives nominal performance with low MVC (upto 10%).

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