OPTIMIZATION OF EMG-SIGNAL SOURCE CLASSIFICATION BASED ON ADAPTIVE WAVELETS K-MEAN ALGORITHM

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Keywords: EMG decomposition, Spike overlapping, Wavelet coefficient, MUAP's clustering, Firing spikes.

Abstract: In this paper the optimization of EMG signals segmentation and decomposition based on wavelet representation and k-mean clustering technique is presented. It is shown that wavelet decomposition can be usefull in detecting particular spikes in EMG signals and the presented segmentation algorithm may be useful for the detection of active segments in related MUAP's action potentials. The algorithms has been tested on the synthetic model signal and on real signals recorded with intramuscular multi-point electrode. The efficiency of EMG signal decomposition and classification with adaptive wavelet algorithm were presented. Single and multiple fibers MUAP patterns were tested and identified. By applying a Debauchies wavelet transformation and k-mean clustering algorithm to localize the action-potential source in the presence of specific neuromuscular diseases like NMI neuropathy, muscular dystrophy and myasthenia gravis (MG), instead of many decomposition and pattern recognition algorithm, wavelets and k-mean clustering have its flexibility for robustly classify and localize the signal stochastic sources with a linear way, in addition to identify the blind source for EMG bioelectric potential.

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 resolution of a composite EMG signal into its significant, constituent MUAPTs requires the ability to detect the discharges (i.e., MUAPs) of the MUs significantly correlating to the composite signal and to correctly combine each detected MUAP with the MU that generated it. EMG signal decomposition therefore involves the two basic steps of detecting MUAPs and recognizing detected MUAPs. To identify the occurrences of consecutive MUAP's potential signal a parallel electrode should be placed in the path of depolarization waveform, for recording such activities, which considered as a vital point in MUAP's acquisition technique (D. Zazula, 1999). The basic steps of intramuscular EMG signal acquisition was illustrated in fig.1 were the recording electrode detecting spontaneous electrical activity of different myofibers on the basis of three electrical wave propagation zones (1) innervations zone ,(2) depolarization zone and (3) terminal zone. These will accumulatively constructing the different pattern of EMG signals. The definition of MUAP's potential of this scheme, were the spontaneous electrical activity to be recoded can be observed in real time synchronous EMG signal recording technique (Wang et. al, 1997). Adaptive signal decomposition technique have a principal rule in defining elementary methods for EMG signals classification and processing, which can be used for varieties of clinical/biomedical applications, spectral pattern classification of intensity-based development, and modern human computer interaction. The purpose of this paper is to illustrate the various methodologies and algorithms for EMG signal pattern classification based on wavelet signal decomposition to provide efficient and effective ways of understanding the signal and its physiological nature.

2 MATERIALS AND METHODS

EMG signal recorded using Delsys® system for recording surface (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

K. Abbas A., Bassam R. and M. Kasim R. (2009).
OPTIMIZATION OF EMG-SIGNAL SOURCE CLASSIFICATION BASED ON ADAPTIVE WAVELETS K-MEAN ALGORITHM.
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, pages 491-497
DOI: 10.5220/0001542804910497

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 of active motor unit (MUs), the MUAP waveforms, and the innervations time statistics. According to De Luca method (D. Zazula, 1999), the determination of the MUAP waveform and the number of active MUs can be considered as a classification problem, and for further analysis of EMG signals (Wang et. al, 1997; Thompson et. al, 1996).

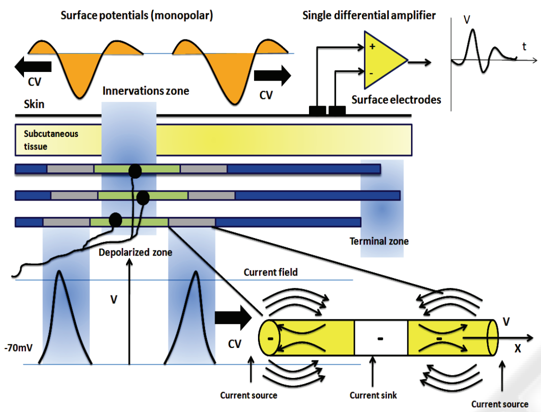

Figure 1: Intramuscular EMG signal acquisition with typical MUAP action potential (Wang et. al, 1997).

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 decomposition (WVD) provided high-resolution signal characterization in time-frequency space and good noise rejection performance as fig.2 illustrated the continuous wavelet transformation for the EMG signals using a Db-WT. This theory is useful for EMG signal classification. For purpose of classifying EMG patterns, EMG electrical model is used in combination with wavelet 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 signal the components of Fourier frequency spectra. The method showed better results while describing the EMG linear envelopes (LE) method (McKeown et. al, 2002).

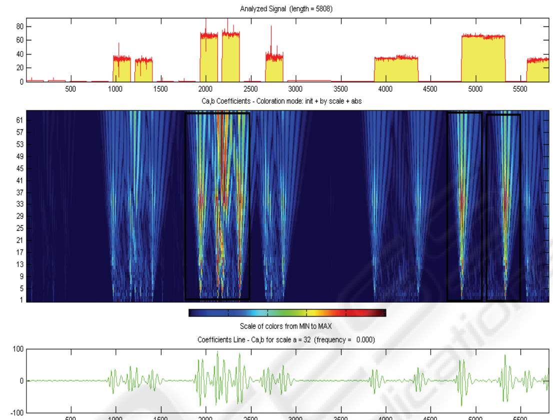

Figure 2: EMG wavelets transformation for single MUAP using Db WT (McKeown et. al, 2002).

3 EMG PROCESSING METHOD

The complexity of a detected EMG signal and the ease with which it can be decomposed depend on the type of electrode, electrode positioning, profile of muscle contraction, and muscle selected. The electrode should be positioned so that it is close to active muscle fibers and detects MUAPs of maximum amplitude and sharpness in order to maximize the relative differences in the distances between the fibers of different MUs and the electrode surface. MUAPs distinct from the background noise can be detected in this way. The suggested procedure is to initially position the electrode in a minimally contracting muscle to detect MUAPs of maximum amplitude and sharpness, and then to increase muscle contraction as isometrically as possible and initiate data acquisition once the contraction is at the desired level. If the decomposition system can process signals acquired during force-changing contractions, data acquisition should start immediately after needle positioning (McKeown et. al, 2002; M. J. McKeown, 2002).

4 MUAPS VOLTAGE DETECTION AND RESOLUTION

Complete EMG signal decomposition requires the detection of all MUAPs generated by MUs active during signal acquisition. In practice, however, there are many MUAPs produced by MUs with no fibers close to the detection surface. These MUAPs are generally small, primarily of low-frequency content, and similarly shaped. Therefore, it is difficult to consistently assigning such MUAPs to their correct MUAP and it is easy to miss the small MUAPs when they occur in close temporal proximity to larger MUAPs. Consequently, it is more useful to only detect MUAPs that can be consistently correctly assigned. MUAP detection usually involves calculating, for each sample of the composite signal acquired, a statistic and comparing its value to a preset threshold. Some of the signal statistics used include the raw or band pass-filtered signal amplitude (M. J. McKeown, 2002; Fang et. al, 1999) or variance (Thompson et. al, 1996; McKeown et. al, 2002), or a combination of both raw signal slope and amplitude (Thompson et. al, 1996; Jung et. al, 2001). When the threshold value is exceeded, a candidate MUAP can be defined as a fixed length section of a neighboring signal or a variable-length signal section, assumed to possibly contain several significant MUAP contributions (Wang et. al, 1997; Thompson et. al, 1996). Any selected signal section may be an isolated MUAP, a superposition of MUAPs from two or more MUs, only a portion of a single MUAP, or a spurious noise spike. Therefore, before further processing, it is required that the composition of a detected section be determined, and properly aligned and represented.

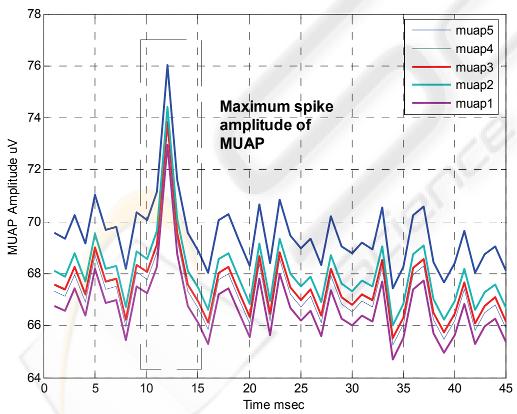

Figure 3: Localization of MUAP's intensity profile within repeated recording of single needle EMG electrode (Fang et. al, 1999).

5 WAVELETS TRANSFORMATION

The wavelet transform (WT) of signal S(t) corresponds to its decomposition with respect to a family of function obtained by dilations and translations of an analyzing wavelet denoted ψ(t). The coefficients WS (a,b) deduced from this decomposition are expressed by:

$$WS(a,b) = \langle s, \psi_{a,b} \rangle = \int_{-\infty}^{\infty} \psi^{*}_{a,b}(t) s(t) dt \qquad (1)$$

where the superscript * denotes the complex conjugate. The parameter *a* and *b* are the scale factor and shift factor respectively. This transformation acts on the signal as a filter bank whose frequency characteristics are linked to *ψ(t)* and to the parameter ***υ***. In multiresolution signal analysis (Thompson et. al, 1996), WT may be used to decompose a signal at various resolutions. The details of a signal at different resolutions generally characterize different physical structures. From wavelet representation, the exact reconstruction of the signal can be carried out. This makes it feasible to compute and manipulate data in compressed parameters via WT.
These parameters characterize the behaviour of the signal and can be served as features. In our paper, we select wavelet coefficient with the maximum absolute value at each scale to be the features of EMG signals. These values represent in some way the correlation between the raw signals and the base vectors of the corresponding detail subspaces.

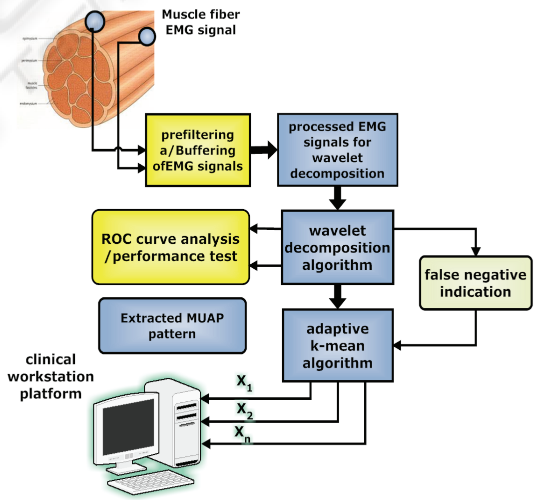

Figure 4: EMG- decomposition and pattern clustering with adaptive wavelet / k-mean algorithm.

6 ADAPTIVE WAVELET DECOMPOSITION

The EMG is decomposed in a number of levels (different resolutions) of an appropriate wavelet basis.

The Daubechies wavelet db5 from Daubechies (Thompson et. al, 1996; McKeown et. al, 2002) has been used with 5 decomposition levels. The wavelet coefficients are roughly classified into two different classes: a burst zone where artefacts and myoelectric signals coexist and an inter-burst zone where only artefact contribution is present. By using hard thresholding the high-frequency components are set to zero. In cases where there is no artefact superimposed to the myoelectric signal and associated MUAP's potentials, the coefficients are supposedly lower so they will be set to zero with higher probability. The noisy components of the wavelet decomposition are truncated and the signal is reconstructed from the remaining components, additionally the MUAP's mapping feature with adaptive wavelets reflects an accurate definition of pre and post-firing interval identification with related movement of the subjects (McKeown et. al, 2002; Fang et. al, 1999).

7 ROC PERFORMANCE ANALYSIS

As EMG signal inherited a vast number of noise interference, this will affect result of clustering and then need to characterize EMG sensor itself for calibration and buffering purpose. Receiver operating characteristics (ROC) curve, is analysis of sensor signals clustering were it is calculated through repeatable EMG recording which tend to be classified in a specific classification algorithm (Jung et. al, 2001). The robustness of wavelet/k-mean algorithm was tested in contrast to the amplifier gain of interface (Andrzej Cichocki and Shun-ichi Amari, 2003). Intramuscular EMG electrode which is used in clinical experiment is reusable and composed of lined conductive area used for increasing measurement stability and reduction of parasitic noise associated with physiological measurement session. 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.

As table 1. illustrated that the average efficiency of classified MUAP's potential in related EMG signal , the obvious maximum asymptotic properties $\Omega_{EMG}(t)$ of 0.97716 and of minimum one of 0.011208 and this reflects high contrast between the recorded EMG potential ,in which can be considered as differentiated parameters in classifying associated MUAP's signal. For further investigation of this effect, additional analysis was applied to the classified EMG signals using the non-negative matrix decomposition after a k-mean clustering stage, in which a relevant result of the EMG classification shows the approximated results in relation to the MUAP's intensity. A performance test was applied to the 9 clustered patterns, by which illustrate that, the same maximum and minimum asymptotic probabilities for the verified EMG patterns, which in corresponding 25-test pattern that presented only a 3 EMG-MUAP's pattern with relevant high voltage intensity (A. J. Bell and T. J. Sejnowski, 1995), (Kadefors et. al, 1999).

As observed from the performance index of adaptive wavelet decomposition could be noticed a well discriminated EMG pattern such as low firing contraction, mid –firing contraction , and high firing contraction and other elated MUAP's biopotential action signals associated with muscular fibers firing schemes (Andrzej Cichocki and Shun-ichi Amari, 2003), (Micera et. al, 2001).

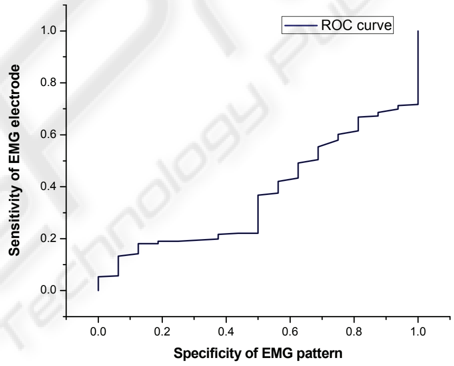

Figure 5: ROC curves analysis of 24 EMG pattern using k-mean clustering algorithm after wavelet decomposition of MUAP intensity patterns.

Table 1: ROC curve analysis of EMG signal patterns based on wavelet k-mean clustering technique*.

EMG pattern*	Area Under curve	Std. Error SE	Asymptotic Prob Ω(EMG)	95.% LCL	95.% UCL
EMG1	0.23013	0.1632	0.1083	-0.08975	0.55
EMG2	0.09751	0.29079	0.16498	-0.47243	0.66745
EMG3	0.3714	0.08492	0.08572	0.20496	0.53785
EMG4	0.5083	0.49786	0.97716	-0.46749	1.48409
EMG5	0.60189	0.19039	0.48479	0.22873	0.97505
EMG6	0.49024	0.23233	0.95367	0.03489	0.94559
EMG7	0.12033	0.32535	0.19027	-0.51734	0.758
EMG8	0.53122	0.19993	0.81122	0.13937	0.92307
EMG9	0.33194	0.20502	0.31729	-0.0699	0.73377
EMG10	0.59129	0.4909	0.75282	-0.37085	1.55342
EMG11	0.51452	0.49979	0.96004	-0.46505	1.49409
EMG12	0.09066	0.1331	0.01486	-0.17021	0.35152
EMG13	0.2125	0.24776	0.16159	-0.2731	0.6981
EMG14	0.57797	0.09307	0.42753	0.39556	0.76038
EMG15	0.73418	0.10483	0.07323	0.52872	0.93964
EMG16	0.28801	0.15334	0.20715	-0.01253	0.58854
EMG17	0.48729	0.05748	0.91535	0.37463	0.59995
EMG18	0.03942	0.19281	0.11208	-0.33849	0.41732

*18 subject were tested in the vicinity of ROC curve analysis.

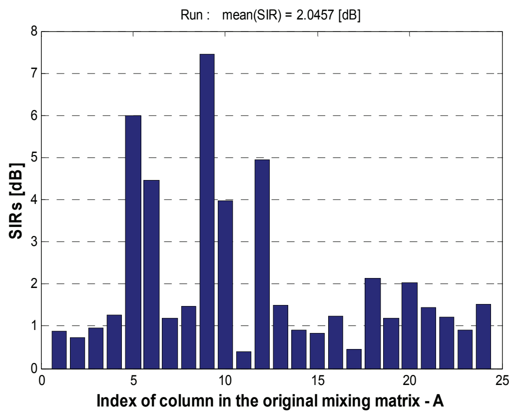

Figure 6: Entropy index of EMG-wavelet k-mean decomposition algorithm for 24 EMG pattern.

8 EVALUATION OF EMG SIGNAL DECOMPOSITION PERFORMANCE

Verification of the accuracy of an intramuscular EMG signal decomposition requires the availability of signals for which the decomposition result is known and the definition of quantitative indexes that allow comparison of performance. Moreover, for completeness and to assess robustness, the performance of a specific algorithm should be evaluated based on a number of signals of different complexity. The reference results were obtained by manual decomposition of a number of experimental signals by expert operators. However, different patterns may result when the same or different operators attempt to decompose the same signal twice, especially if the MU firing rates are irregular, the MUAPs are similar, superposition of MUAPs are frequent, and some MUs may be intermittently recruited (Farina et. al, 2001; Kadefors et. al, 1999).

In addition different wavelet algorithms may weigh different information, such as waveform similarity or firing regularity; differently and therefore produce different results. Furthermore specific algorithms may be more appropriate in certain cases and others in other cases. To assess accuracy, DeLuca (Andrzej Cichocki and Shun-ichi Amari, 2003) proposed to detect signals (using multiple electrode surfaces) from the same MU at different locations and to compare the results of the decomposition of the two signals obtained. This way the probability of incorrectly decomposing the different signals and yet having the same firing pattern for an investigated MU is low. When the decomposition results agree for all the channels, the decomposition is considered correct. The variability degree of different wavelet algorithm was calibrated with each EMG–sensor channel with reference ROC curve as illustrated in Fig.5. The reference decomposition result can also be obtained from synthetic signals generated by a model. In this case the crucial issue is to describe all the relevant characteristics of the experimental signals. A model is the only way to test the algorithms with signals having selected characteristics in order to evaluate the sensitivity of the decomposition algorithms to different EMG signal parameters. Whatever the approach for the generation of reference decomposition results, it is necessary to introduce indexes of performance computed from the comparison of the results obtained by the application of the algorithm under test and the reference. Fig.8 that and Fig.9 which illustrated the k-mean separation hyperplan for 24 MUAP's signal recorded as synchronized EMG recording system.

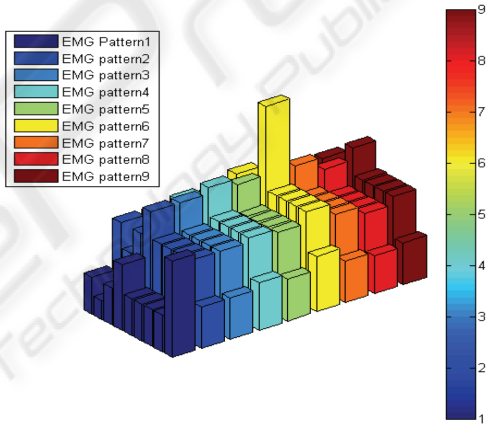

Figure 7: 3D Performance index of decomposed EMG signal based on wavelet algorithm indicate main components of 9 EMG extracted pattern from the 24 overall EMG patterns.

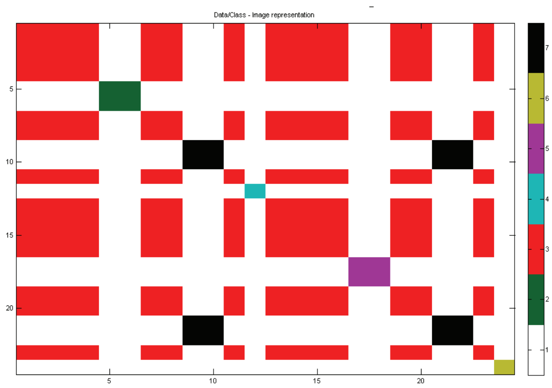

Figure 8: k-mean clustering result for 24 MUAP's recorded in needle EMG electrode, illustration of white cross and red block pattern in the EMG signal for corresponding MUAP's clusters.

9 RESULTS AND DISCUSSION

Adaptive Wavelet-decomposition for EMG signal illustrates optimality in clustering efficiency of about (p=0.0128) for spontaneous EMG vector classification. Some deviation was reported with the linearity of MUAP classes due to different standard deviation (SD), of each recorded EMG signal. The signal deviation can be compensated by increasing the correlation index, or selecting the same order number of (Finite impulse response) FIR filtering module to attenuate the parasitic noise in the EMG transmission pathway.

Testing additional wavelet/ k-mean algorithms to evaluate clustering efficiency presents with robust hyperplane classification based on other criteria such as EMG signal turns, spike area, integrated area, and phases. The tested classes that have been presented in fig.9 also shows maximum intensity differntiality performed in adaptive wavelet 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.

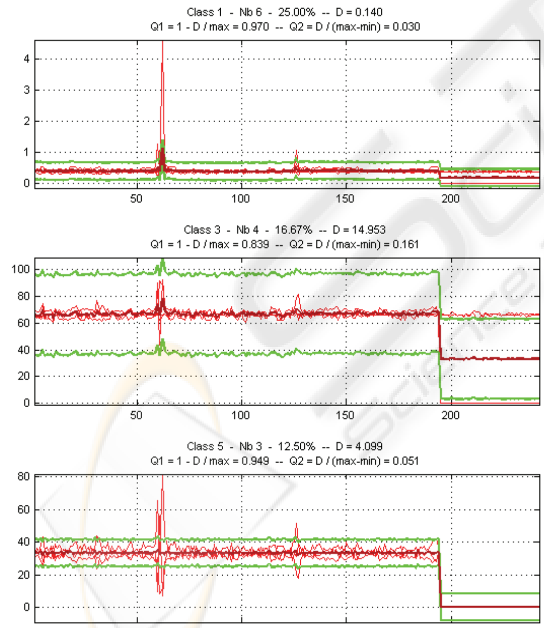

Figure 9: Selective MUAP's classed that corresponding to maximum spike activity pattern in recorded EMG signals.

As fig.10 illustrated the clustered coefficients of the MUAP's potential signal cab be differentiated in accordance to the maximum intensity which in this case considered as discriminative characteristics for clinical classification system. Odd clusters as it shown in fig.6 that have been selected for comparative purposes to localize the pre and post-firing myofibers relative to subject movement. Prospective clustering data for MUAP's based on k-mean clustering technique that can be demonstrated in fig.7 where

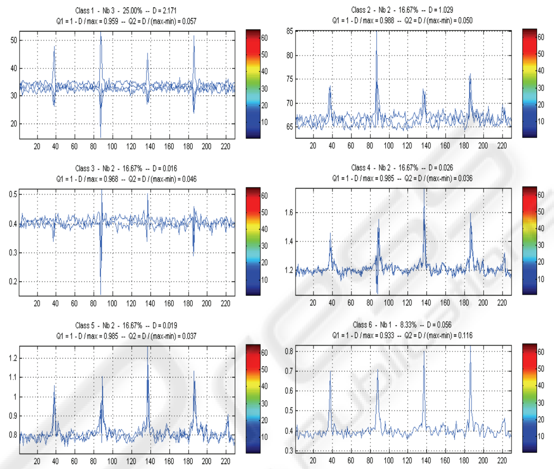

Figure 10: Clustered coefficients of MUAP's signal using wavelet decomposition and K-mean clustering using 18 EMG samples.

10 CONCLUSIONS

The decomposition of the intramuscular EMG signal is a complex task that involves advanced signal processing and pattern recognition techniques. Their application covers the fields of basic physiology, neurology, motor control, ergonomics, and many others. Current available techniques and the presented wavelet- k mean allow reliable decomposition at low /medium force contraction levels during short and long contractions in static and dynamic conditions. The availability of such methods for automatic intramuscular EMG signal analysis allows the completion of experimental studies that were unthinkable some years ago, such as the investigation of MU activity during very long contractions (up to hours). Intramuscular EMG signal decomposition is, however, still carried out mainly in research environments while it finds limited clinical application. This is mainly due to the limitations that EMG signal decomposition still has, such as the amount of time required to obtain clinically useful information (especially if high reliability on a number of conditions is required), the necessity in most cases of an interaction with an expert operator, the applicability to only low-to-medium contraction levels, and the need of specially trained persons for the proper positioning of the needle electrode to obtain the high-quality signals required for reliable decomposition. These limitations are being addressed by current research efforts. The obtained result of this work and other related work could be contribute to optimize the efficiency and reliability of intramuscular EMG signal

ACKNOWLEDGEMENTS

We acknowledge Aachen University of Applied Sciences, RWTH-Aachen University and DAAD (Deutsche Akademische Ausländische Dienst) for providing accessibility with financial and scientific support to put this work on the track of success.

REFERENCES

Zazula, D. (1999). Higher-order statistics used for decomposition of sEMGs. *Proceedings of the 12th IEEE Symposium on Computer Based Medical System*, 72–77.

Wang, R., C. Huang, and B. Li (1997). A neural network-based surface electromyography motion pattern classifier for the control of prostheses. Proceedings of the 19th Annual International Conference of the IEEE-EMBS 1277.

Thompson, B., P. Picton, and N. Jones (1996). A comparison of neural network and traditional signal processing techniques in the classification of EMG signals. IEEE Colloquium on Artificial Intelligence Methods for Biomedical Data Processing, Vol 2:1996 , Pp 321-327.

McKeown, M. J., Torpey, D.C., Gehm W. C.: Non-Invasive Monitoring of Functionally Distinct Muscle Activations during Swallowing. Clinical Neurophysiology (2002). 109, 112

McKeown, M. J.: Cortical activation related to arm movement combinations. Muscle Nerve. 9:19-25 (2000). 110, 112

Fang, J., G. C. Agarwal, and B. T. Shahani, "Decomposition of multiunit electromyographic signals," *IEEE TransBME* 46 , 685–697 (1999).

Jung T.P., Makeig S., McKeown M. J., Bell A. J., Lee T.W., Sejnowski T. J.: Imaging brain dynamics using independent component analysis. Proc. IEEE. 89(7): 1107-22, (2001). 112

Andrzej Cichocki, Shun-ichi AMARI, " Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications", Wiley Press ,2003.

Bell A. J., Sejnowski T. J.: An information-maximization approach to blind separation and blind deconvolution, Neural Computation, 7:1129-1159, (1995). 112

Micera S.,Vannozzi G., Sabatini A.M., Dario P.: Improving Detection of Muscle Activation intervals, IEEE Engineering in Medicine and Biology, vol. 20 n.6:38-46 (2001). 112, 113

Karhunen J., Oja E.: A Class of Neural Networks for Independent Component Analysis, IEEE Transactions on Neural Network, vol. 8 n. 3:486-504, (1997). 112.

Farina, D., R. Colombo, R. Merletti, and H. Baare Olsen, "Evaluation of intra-muscular EMG decomposition algorithms," *J Electromyogr Kinesiol* 11**,** 175–187 (2001).

Kadefors, R., M. Forsman, B. Zoega, and P. Herberts, "Recruitment of low threshold motor-units in the trapezius muscle during different static arm positions," *Ergonomics* 42, 359–375 (1999).

Olsen, H. B., H. Christensen, and K. Søgaard, "An analysis of motor unit firing pattern during sustained low force contraction in fatigued muscle," *Acta Physiology Pharmacology Bulg* 26, 73–78 (2001).