An Approach to Decomposition of Muscle and Nerve Signals

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Abstract: This paper considers the decomposition of surface electromyograms (SEMG) using higher-order statistics (HOS). Modelling surface EMG by a MIMO system whose inputs in the form of innervation pulse trains are considered independent identically distributed (i.i.d.) random white noise, the system identification methods based on higher-order statistics may be introduced. We disclose how a two-phase procedure lead to SEMG decomposition using HOS, firstly, obtaining a coarse estimation of the EMG building blocks, i.e., the motor-unit action potentials (MUAPs) via a simpler and less complex cumulant-based identification, and, secondly, refining the outcomes of the first phase by a more demanding optimisation method. In our experiments on synthetic SEMG signals, we used multivariate C(q,k) in the first phase, and non-linear LMS optimisation of third-order cumulants in the second phase. The simulation results in rather noisy case with 10 *dB* additive white Gaussian noise prove the robustness and efficiency of the proposed approach.

Key-Words: Third-Order Cumulants, Surface EMG Decomposition, Non-Linear LMS Optimisation, Motor-Unit Action Potentials

1 Introduction

Modern way of living causes people to neglect the necessity of everyday physical activity on the one hand, on the other hand a better medical care and treatment have made people live much longer today. Too less motion and age bring high risk of nerve and muscle diseases. So, the whole society puts a lot of efforts in providing services and ways to detect and cure these problems of the elderly, and younger as well, successfully [1].

The nerve system is responsible for the activation of muscles. The mechanism is based on electrical triggering, i.e., electrical pulses the nerves conduct from the brain to the muscles. Every muscle is composed of many tiny muscle fibres which, when electrically excited, contract and, at the same time, produce a measurable electrical potential, called action potential (AP). Action potentials emerge at the neuro-muscular junction about the middle of the muscle body, in the so called innervation zone, and propagate along the fibres to both directions towards muscle tendons. Several fibres are innervated by the same nerve, i.e. axon. Those triggered by one axon form a so called motor unit (MU)–see Fig. 1.

Electrical activity of muscles, the so called electromyograms (EMG), can be measured by several types of electrodes, ranging from a very precise wire electrodes that detect even single fibre action potentials, to another invasive type called needle electrodes that may detect a few MU potentials, and to surface electrodes that are placed on the skin to pick up a large amount of the muscle electrical activity [2]. It is important for a successful diagnosing, prognosis, or treatment to recognize the patterns of as well the innervation pulse trains as the MU activities, i.e. MU action potentials (MUAPs). Both can be decomposed from the measured EMG, while the complexity of the problem increases with the number of active MUs. This number is rather high in surface EMG–however, it is exactly the surface measuring that is preferred because of its non-invasiveness [2, 3, 4].

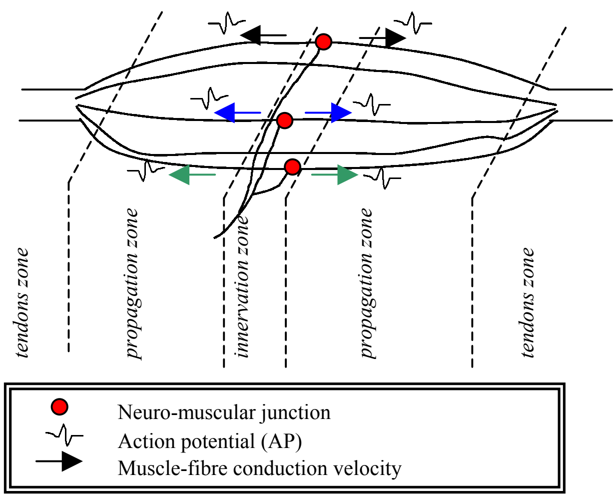


Fig. 1: Muscle with the innervating axon, the innervation zone, and the propagating action potentials

In this paper we are going to discuss an approach to surface EMG decomposition based on higher-order statistics (HOS). Section 2 reveals the decomposition model and the necessary conditions for HOS approaches to be efficient. Section 3 analyses the character of surface EMG signals and shows it is appropriate for a HOS application. A decomposition approach supported by a short example with synthetic EMG signals is depicted in Section 4, while Section 5 concludes the paper.

2 MIMO modelling and higher-order statistics

Higher-order statistics can play an important role in system identification. It has been shown that a system's impulse response can be deconvolved when the system's input is excited by independent identically distributed (i.i.d.), zero-mean, random white noise [5, 6]. Already the second order statistical methods solve the problem, but only the amplitude response is obtained, while the phase remains undetected unless cross-statistics are applied (as, for example, in blind source separation [14]). However, higher-order statistics do recover the signal phase.

HOS approaches are applicable to multi-channel systems too. Modelling such systems, it means we deal with a multiple-input multiple-output (MIMO) model. In Fig. 2, K inputs $w_i(n)$ are convolved by the channel impulse responses $h_{ij}(n)$, which results in M outputs $y_j(n)$:

$$y_j(n) = \sum_{i=1}^{K}\left(h_{ij}(n) * w_i(n)\right), j = 1..M \tag{1}$$

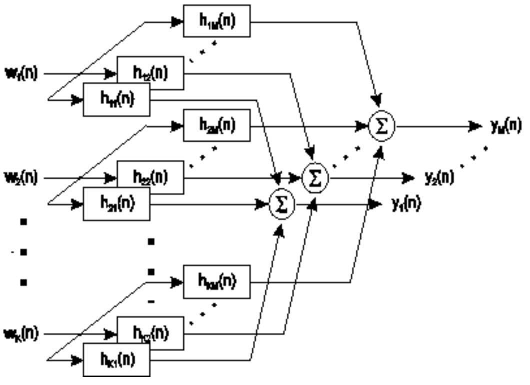


Fig. 2: A MIMO model with inputs $w_i(n)$, channel impulse responses $h_{ij}(n)$, and outputs $y_j(n)$.

Every output contains superimposed contributions of all the inputs.

There are some quite efficient MIMO identification methods based on HOS [7], but only a few fulfill the expectations for a flexible and reliable signal decomposition. One would prefer solutions with as few knowledge about the system channels and inputs necessary to be known in advance as possible. Two HOS approaches can be mentioned which are independent of the model type (MA, AR, or ARMA) and of the channel orders: polycepstral decomposition [6, 9, 10] and w-slice method [8]. If the input excitation $w_i(n)$ corresponds to i.i.d,, zero-mean, random white noise, then only taking the system's outputs $y_j(n)$ into account the channel impulse responses are identified. Proceeding afterwards from the known outputs and responses, also the system's input excitation is obtainable.

3 Surface EMG modelling and HOS decomposition

Recalling Fig. 1and Eq. (1), it is obvious that surface EMG may be modelled the same way. The innervation pulse trains resemble Bernoulli noise sequences, although they are not entirely i.i.d., which will be studied in the sequel. MUs respond as the system's channels, and the outputs correspond to multiple EMG measurements.

Make sure first of the innervation pulse train characteristics that would allow considering them a proper random white noise excitation and, thus, suitable for further processing using HOS. Eq. (2) describes the innervation pulse train behaviour:

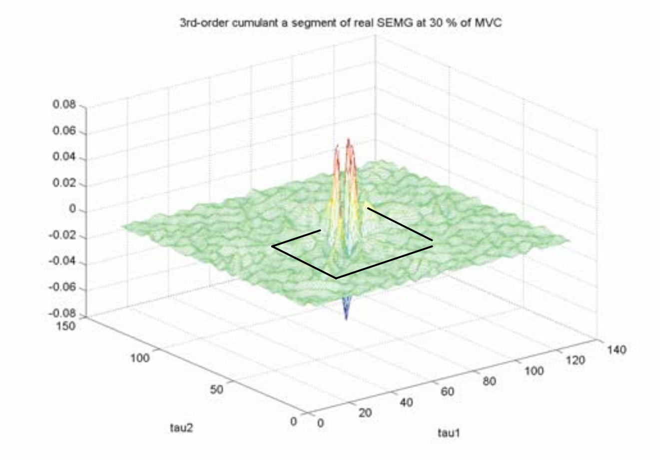
$$w_i(n) = \sum_{k=-\infty}^{\infty} \delta(n - kT + \Phi_k) \tag{2}$$

where T stands for the mean inter-pulse interval and Φ_k for the k^{th} realisation of a Gaussian distributed random variable. We have shown in [15] that the third-order statistics (cumulants) of such sequences exhibit only negligible disturbances inside the space bounded by the length of the mean inter-pulse interval T. This means an EMG may be processed by HOS approaches in spite of the fact that the innervation pulse trains do not behave thoroughly as i.i.d, random white noises (see Eq. (2)). Fig. 3 shows the third-order cumulant of a part of real EMG recording. The central encircled area is not degraded considerably because of the fact that the innervation pulse trains do not behave thoroughly as random white noise. This is where the cumulant values are to be taken for decomposition purposes.

4 A HOS-based surface EMG decomposition

Applying HOS-based methods to the EMG signals, it is not only the innervation pulse trains that may hinder an efficient decomposition owing to their non-i.i.d. character, but also a bad influence of variance in finite

Fig. 3: Third-order cumulant of a part of real EMG



recording: the marked rectangular area depicts where the fact that the innervation pulse trains do not behave thoroughly as random white noise is negligible.

cases, the inaccuracies of the cumulant estimations, and various sources of errors (computational, methods inherent, etc.). So, to make such a decomposition feasible it is important that the most robust and reliable HOS-based procedure is constructed. It is known that the best identification results appear with HOS-based optimisations [6]. Moreover, to count on an optimisation success, one has to start the optimisation procedure with a fairly good approximation of the final results. This is why we propose the following HOS-based surface EMG decomposition algorithm in 5 steps:

1. Take surface EMG recordings of steady and stationary signals of a duration of at least a minute or more (a few thousand repetitions of MUAPs are needed);
2. Compute higher-order cumulants of these measurements only up to the lag which corresponds approximately to the MUAP duration (a few 10 ms);
3. Obtain the first coarse decomposed estimates of MUAPs using one of blind multi-channel identification methods (polycepstral, w-slices, or similar);
4. Use the coarse estimates as starting points in the optimisation procedure run on the cumulants combining a certain set of lags, as will be shown later;
5. Optimise until the best possible estimates are reached.

4.1 Analytical background of applied HOS methods

If there are K different MUAPs, $h_{ij}(n)$, and M measurements of EMG, $y_j(n)$, then according to Eq. (1) and Fig. 1 it follows:

$$\mathbf{y}(n)=\sum_{i=0}^{\infty}\mathbf{H}^T(i)\mathbf{w}(n-i), \qquad (3)$$

where $\mathbf{H}^T(n)$ stands for

$$\mathbf{H}(n)=\begin{bmatrix} h_{11}(n) & h_{12}(n) & \cdots & h_{1M}(n) \\ h_{21}(n) & h_{22}(n) & \cdots & h_{2M}(n) \\ \vdots & & & \vdots \\ h_{K1}(n) & h_{K2}(n) & \cdots & h_{KM}(n) \end{bmatrix}.$$

Let us now calculate the m^{th} third-order cumulant, m corresponding to an observed channel ($1 \le m \le M$):

$$\mathbf{C}_m(\tau_1,\tau_2)=cum\left[\mathbf{y}(n+\tau_1)\mathbf{y}^T(n)y_m(n+\tau_2)\right];\ m=1\ldots M \qquad (4)$$

Eq. (4) represents a basis for the so called multivariate C(q,k) identification. Although we suggest a cumulant-based identification via one of blind approaches in step 3 of the proposed procedure, we adopted multivariate C(q,k) in our experiments because of its ease and the characteristics of the analysed synthetic signals known *a priori*. So, the MUAP shapes, i.e. the system channel responses, can be determined as

$$\mathbf{H}(k)=\mathbf{L}^{(i)T}(q,k)\mathbf{L}^{(i)}(q,0)\left[\mathbf{L}^{(i)T}(q,0)\mathbf{L}^{(i)}(q,0)\right]^{-1}, \qquad (5)$$

where

$$\mathbf{L}^{(i)}(q,k)=\left[\mathbf{c}_1^{(i)}(q,k),\ldots,\mathbf{c}_M^{(i)}(q,k)\right]$$

and $\mathbf{c}_m^{(i)}(q,k)$ represents the i^{th} column of matrix $\mathbf{C}_m(q,k)$.

We considered the results of multivariate C(q,k) decomposition as the first coarse estimates of MUAPs. They were used to initialise a subsequent optimisation (step 4 in the proposed procedure). Synthetic EMG recordings were included into a least-mean square (LMS) cumulant-based optimisation [6]. The basis for such decomposition is a system of non-linear equations of the following form:

$$f_j(\tau_1,\tau_2)= \sum_{i=1}^{K} h_{ij}(n)h_{ij}(n+\tau_1)h_{ij}(n+\tau_2)-\hat{C}_{3,y_j}(\tau_1,\tau_2) \qquad (6)$$

where $h_{ij}(n)$ stand for the model MUAP shapes as detected in a certain step (iteration) of decomposition, and the hat (^) denotes the cumulant estimation based on the measured output $y_j(n)$.

To be able to solve the system of equations from (6), the number of equations must be at least $K \cdot N$ if the length of K source signals (MUAPs) equals N. To decompose the generated synthetic SEMGs, we applied the MATLAB function called *lsqnonlin*, which minimises the least square norm of the system using the large-scale, trust-region reflective Newton algorithm [12]. The cumulant estimates used in these equations are taken from 1/6 of the cumulant matrix in such a manner that $\tau_1=0,\ldots,\sqrt{\quad}$, $\tau_2 \le \tau_1$.

4.2 Experimental results with synthetic surface EMGs

To verify the appropriateness of the suggested approach, we simulated surface EMGs with known parameters, i.e. known shapes of MUAPs and innervation pulse trains. The generation of MUAPs and recorded signals was done using the EMG simulator of the LISIN laboratory of Torino, Italy [11]. As a matter of fact, their MATLAB routines *Model_final.m* and *genera_sig.m* are based on physiological considerations and create surface EMG signals with certain parameters. We simulated two MUAPs with rather different shapes (Fig. 4) and three pick-ups for the EMG measurements (Fig. 5) [13].

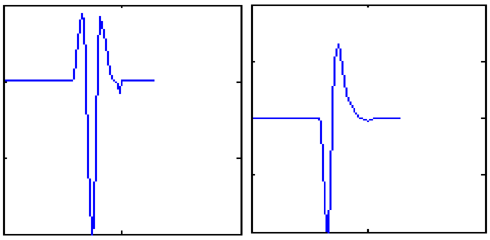


Fig. 4: Two MUAPs generated for simulations

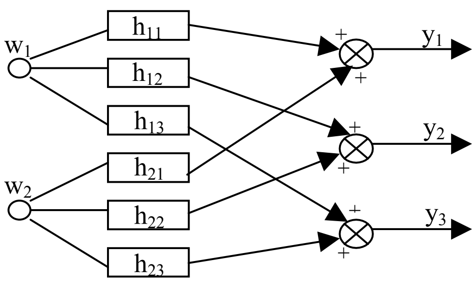


Fig. 5: MIMO(2,3) model for the synthetic EMG signal generation

The main model parameters applied were the following:

- ARMA(2,3) model was chosen, so 2 MUAPs were generated and measured by 3 surface pick-ups;
- one MU was assumed 3 *mm*, the other 6 *mm* deep, the former with 5 and the latter with 20 fibres;
- fibres of the first MU were aligned with the electrode placement, while the second one had fiberes inclined by 10 degrees and shifted 10 *mm* in the *x* direction from the electrode array;
- spread of the innervation zone was taken 0 *mm* for the first, and 10 *mm* for the second MU;
- conduction velocity was taken 4 *m/s* for all fibres;
- measurements were supposed double differential;
- rectangular electrodes 5 by 1 *mm* were simulated;
- the interelectrode distance was taken 10 *mm*;
- the electrode array was assumed placed between the innervation zone and tendons of fibres of length of 70 *mm;*
- sampling frequency of 1024 *Hz* was used for the generated EMG signal;
- three synthetic SEMG signals were generated in duration of 100 *s*.

Fig. 6 depicts 1 *s* of the generated first channel synthetic surface EMG. All three, also the second and the third channel output measurements, consist of highly superimposed replicas of the two MUAPs from Fig. 4.

After applying the proposed decomposition procedure, we obtained the following results:

Step 1: We generated 100 s of 3-channel synthetic surface EMG.

Step 2: Third-order cumulants of dimension 64×64 were calculated out of each channel output measurement.

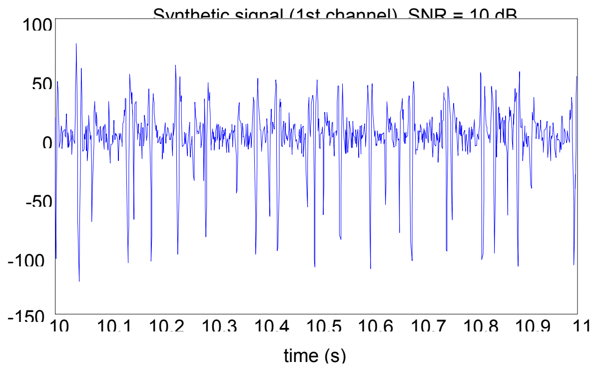


Fig. 6: A part of the first channel synthetic EMG with 10 *dB* additive white Gaussian noise

Step 3: The *C(q,k)* method was applied to obtain the rough estimates of MUAP. It turns out that the decomposition outcomes depend on the choice of the cumulant matrix column denoted by superscript *i* in Eq. (5). Fig. 7 shows the MUAPs as decomposed with three different cumulant-matrix columns. None of the estimated MUAPs matches the original, although some resemblance may de observed.

Steps 4 and 5: The MUAPs obtained using the first cumulant-matrix column (step 3), *i=1,* introduced initial values to the non-linear LMS optimisation. The number of linear equation we respected in the optimisation from Eq. (6) was 36, meaning that for each of the two expected source MUAPs 18 samples were estimated. Noisy case was simulated by superimposing 10 *dB* of additive white Gaussian noise to the EMGs prior to the cumulant calculation. The decomposition outcomes obtained after the optimisation process are depicted in Fig. 8.

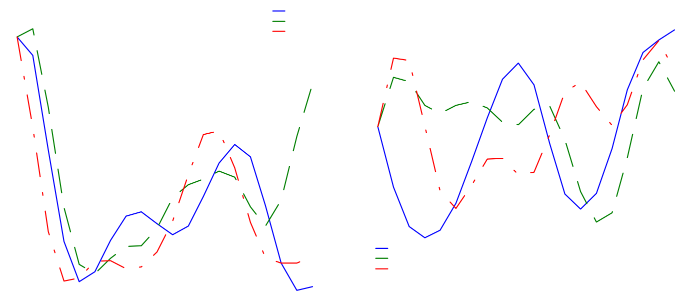


Fig. 7: Identification of the system responses h_{11} (left) and h_{23} (right). Influence of the selected column of the cumulant matrix, *i* in Eq. (5) and depicted as *col* in the images, is obvious: columns *i=1, 2,* and *3* generated the outcomes depicted by solid, dashed, and dotted lines, respectively.

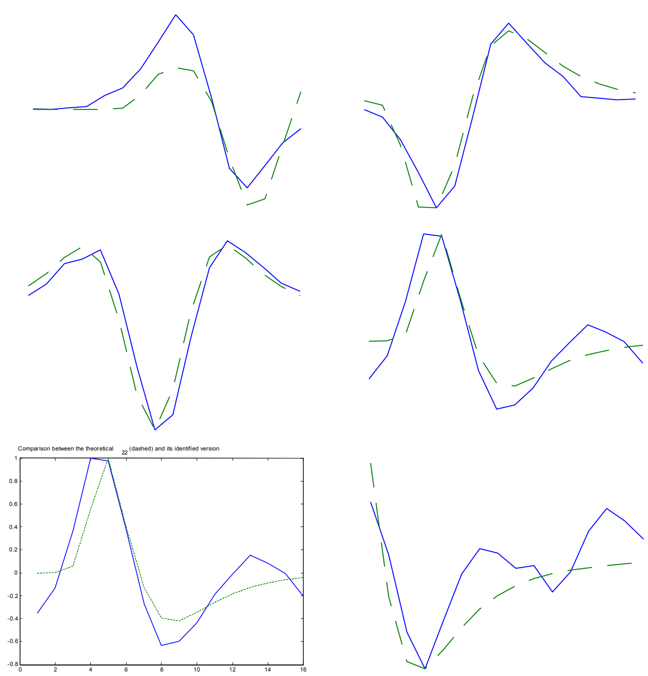


Fig. 8: Results of the cumulant-based non-linear LMS optimisation: the original MUAP shapes dashed, decomposed MUAPs in solid lines.

As we can see from Fig. 8, the results has been significantly improved comparing to the initial stage after the C(q,k) decomposition. The original MUAP shapes are dashed, while the decomposition results are depicted with solid lines.

5 Conclusion

Higher-order statistical approaches can be successful in all the cases where a random but also repetitive nature of appearance of signal building blocks is present. Bioelectric signals, such as EMGs, exhibit exactly such kind of behaviour. The reason why there have not been many trials of decomposing the bioelectric signals by HOS-based methods probably lie in the drawbacks that hinder wider implementation of such processing. The main two are a need for long steady, stationary signals and a very high computational complexity. Looking from the SEMG decomposition view point, the need of long, stationary recordings of up to a few minutes duration cannot always be fulfilled.

In spite of this, HOS-based methods have many nice properties, probably the most attractive be a capability of considerable suppression of Gaussian additive noise. We have shown in this paper the way of how an SEMG decomposition can be supported by HOS. It is important that several MUAPs can be decomposed from fewer parallel SEMG recordings, e.g. from only one-channel measurement. The MUAP superimpositions do not hinder a thorough decomposition. The MUAP shapes can be obtained directly, the innervation trains, however, must be recognised by some other means, e.g. using the time-scale phase representations as shown in [16].

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