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A method based on wavelets to analyse overlapped and dependant M-Waves

Lucie William, Mélissa Dali, Christine Azevedo Coste, David Guiraud ^{*†‡}

Abstract

Implanted stimulation restores hand movement in patients with complete spinal cord injuries. However, assessing the response by surface evoked EMG recordings is challenging because the forearm muscles are small and overlapping. Moreover, M-waves are dependent because they are induced by a single stimulation paradigm. We hypothesized that the M-waves of each muscle has a specific time-frequency signature and we have developed a method to reconstruct the recruitment curves using the energy of this specific time-frequency signature. Orthogonal wavelets are used to analyze individual M-waves. As the selection of the wavelet family and the determination of the time-frequency signature were not trivial, the impact of these choices was evaluated. First, we were able to discriminate the 2 relevant M-waves related to the studied muscles thanks to their specific time-frequency representations. Second, the Meyer family, compared to the Daubechies 2 and 4 families, is the most robust choice against the uncertainty of the time-frequency region definition. Finally, the results are consistent with the semi-quantitative evaluation performed with the MRC scoring. The Meyer wavelet transform combined with the definition of a specific area of interest for each individual muscle allows us to quantitatively and objectively evaluate the evoked EMG in a robust manner.

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*All the authors are with INRIA, Montpellier University, Montpellier France

†D. Guiraud is with Neurinnov, Montpellier France

‡lucie.william@inria.fr

¹Key words : EMG; M-wave; Wavelet; Neural stimulation

1 Introduction

Restoring motor functions, for individuals with complete spinal cord injury, through implanted peripheral electrical stimulation may be one of the solutions to restore mobility of the impaired lower [1] or upper limbs [2], [3]. The assessment of the functional outcomes of the obtained movements is usually based on kinematics and dynamics [3], [4]. But at a very early stage i.e. intra-operative, post-operative settings, ElectroMyoGraphy (EMG) is preferred as it reflects almost directly the stimulation activation and thus the muscle response to it without the need to get full functional movements [5], [6]. The recruitment curves obtained using EMGs allow to quantify the activation of each stimulated muscles as well as their selectivity index defined in [7]. Thanks to the recruitment curves, the impact of the multicontact epineural electrode configuration can be quantitatively evaluated. This allows to confirm the efficiency of the selectivity of the multicontact neural stimulation which finally allows to induce different hand gestures with a single epineural electrode but with a different diffusion of the currents [2]. Recording these electrophysiological signals can be achieved through electrodes placed on the surface of the skin in various configurations: monopolar, bipolar, double differential or Laplacian or intramuscular needles inserted in the muscle [8]. In upper limb, recording individual EMGs is a challenge due to the many small muscles in presence (total of about 20 muscles in the forearm [9]) and their overlapping. Even though classical bipolar electrodes are the less selective as regard their ability to record individual muscles signal's sources [10], they remain the most easy to use in particular during a surgery of the forearm. In our study, we used these measurements intraoperatively on individuals with quadriplegia who undergo a surgery of upper limb. For asepsis reasons, only intramuscular or surface bipolar electrodes were available for this use. Bipolar surface electrodes were chosen as they allow for a global muscle response analysis whereas intramuscular electrodes may record only few Motor Unit Action Potentials (MUAP). Further focusing on evoked EMG, the signal analysis can be assimilated to a M-wave analysis if the H-reflex is not elicited. Whatever the electrical stimulation approach is, i.e. surface (neural or muscular), or directly implanted on the nerve [11], several muscle contractions can be elicited. Only intramuscular or epimysial stimulation can evoke individualized responses [5]. In our clinical trial, we carried out implanted multipolar neural stimulation so several M-waves can be elicited during a neural stimulation. Then, the purpose was to extract individual M-waves to compute recruitment

curves. Independent Component Analysis or Principal Component Analysis failed because M-waves are not independent. Indeed, the evoked EMGs are induced by the same cuff electrode [7] even though stimulation parameters may differ, there is a link between the multiple M-waves responses. Template matching is not easy to implement as a pure single M-wave was not always obtained. We hypothesised that the M-wave from different muscles were made of different time-frequency components. The wavelet transform is the indicated method, but with few *a priori* knowledge, the challenge consists in the choice and parametrization of the wavelet family. In literature, wavelet transforms were used for various tasks as **denoising and feature extraction** of surface or needle recorded EMG [12], [13], remove the artefact of stimulation [14], find the local variation of a signal [15], EMG surface classification [16], [17], analyse spectral surface EMG [18], voluntary biomedical signal processing [19] as well as recognition of the direction of a movement [20] or coordinate muscle activity [21]. The Morlet wavelet transform was already used to calculate the Root Mean Square (RMS) value of coefficients to quantify a voluntary movement [22]. The choice of the wavelet family is rarely studied [19] so that we both investigate the wavelet transform as a way to quantify M-wave, and compare 2 families for which properties are complementary: discrete Meyer wavelet transform (orthogonal, with a compact support in frequency domain) and discrete Daubechies wavelet transform (orthogonal, with compact support in time domain) were applied to recover individual M-waves **associated to the thumb and digit flexions**, and the continuous wavelet transform version were used to compute the RMS value to estimate recruitment. In the following, the protocol and the rationale for wavelet selection and parametrization is presented, and the results are discussed demonstrating the relevance of the use of this approach.

2 Materials and Methods

2.1 participants and Protocol

During scheduled surgeries, a 12-contact electrode cuff (CORTEC GmbH, Freiburg, Germany) was wrapped around the median nerve of four participants (male, 43.6 ± 13 years old) with C5 complete motor cervical injury (AIS A except participant P4 AIS B) to deliver electrical stimulation. The purpose was to investigate the ability to elicit isolated and composed move-

ments of the hand and wrist by spatial (called configurations) and intensity modulation of the currents between contacts (for details, see [2]). The protocol was approved by the ethics committee (CPP Sud Méditerranée, #ID-RCB:2014-A01752-45) and the clinical trial (Reg. Number #NCT03721861) was performed in accordance with the Declaration of Helsinki. All participants gave their informed consent signed by a trusted person. For ethical reasons, the clinical trial was conducted during a scheduled surgery – a tendon transfer to recover active elbow extension – in order to avoid a specific surgery. Moreover, the time slot allowed for the experiment was of 30 min in order to keep the total time under anaesthesia below 2 hours. After exposure of the median nerve about 5 cm above the elbow, one cuff electrode was wrapped around it and then gently sutured to avoid its displacement during the trial. The median nerve innervates predominantly flexor muscles of the forearm and the hand. Digit (except thumb) flexion is ensured by the flexor digitorum superficialis (FDS), the flexor digitorum profundus (FDP, middle and ring fingers) and the lumbricals (L, index and middle fingers). Thumb flexion is ensured by the flexor pollicis longus (FPL) and flexor pollicis brevis (FPB) which is also innervated by the ulnar nerve.

2.2 Stimulating electrodes

A 6-mm diameter, 2-cm length cuff electrode was used (3 x 4 contacts, Cortec GmbH, Freiburg, Germany, Fig. 1). The cuff electrode contacts ($2.79 \times 0.79 \text{ mm}^2$, 5.9-mm spacing between two longitudinal adjacent contacts) were 90/10 Pt/Ir made and embedded with silicone. The electrode integrity was checked before and after the surgery by a continuity test in a saline solution.

2.3 Stimulation protocol

Stimulation was delivered automatically according to a set of predefined electrode configurations (see Fig. 1). The electrode conformation corresponds to the position of the cathode on the row (4 electrode conformations available for each configurations, except for Ring and Bipolar configurations). At the beginning and the end of the stimulation protocol to check stability, the Ring configuration was applied. For each configuration/conformation, a train of stimuli of increasing intensities was delivered (for details, see [2] annex, Table S6, P4 to P8), produc-

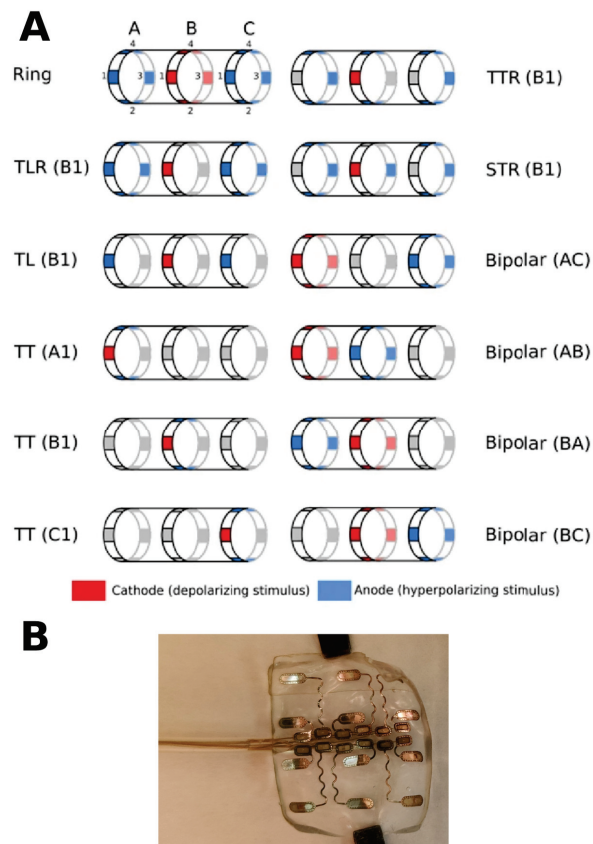


Figure 1: A Electrode configurations from Tigrá *et al.*, B photography of the electrode Cortec, Freiburg, Germany.

ing an increasingly forceful contraction of one or both muscle groups. The contractions were recorded on video tape, and a medical doctor in physical medicine and rehabilitation, later labelled each one as i) an isolated movement, i.e., finger flexion, thumb flexion or opposition, wrist flexion, ii) a compound movement, or iii) functional grasp. In the current paper we focus on the discrimination between fingers and thumb flexion and the associated muscles as the challenge was to discriminate both M-waves in EMG recordings.

2.4 Surface recording electrodes

Surface EMG was recorded intra-operatively with surface sterile patches 2"×2" (TENSproducts, USA) placed over the forearm. The surgeon positioned 2 pairs of EMG electrodes (on pair on each muscle group) after cutting them to adapt their size over the couple FDS and the FDP (ensuring fingers flexion) and the FPL (ensuring thumb flexion). The reference electrode was placed on the lateral epicondyle.

2.5 Data acquisition

Data acquisition was synchronized with the stimulator and acquired through a GTec amplifier with LabChart software (ADInstrument, Austria): notch filter 50 Hz, band pass Bessel 2nd order 0.5 Hz - 1 kHz, amplification 1000, sampled at 10 kHz, 16 bits. The aim of the EMG post processing was to quantify the M-wave contribution of the 2 muscles' groups (FDS-FDP, FPL). All data contaminated by movement artefacts (mainly due to strong wrist movements) were discarded. EMG signals were segmented into 40 ms sets (400 points) between 2 stimulation pulses.

2.6 Data processing

Each surface EMG recording captures signals from different muscles; indeed, in the forearm, muscles are close to each other so that these measurements are not selective enough. However, in our case, under median nerve stimulation, a subgroup of forearm muscles may be recorded. We hypothesised that we could discriminate signals from the 2 studied muscles' group using wavelets analysis i.e. their time-frequency contents are supposed to be different. The choice of a wavelet base or wavelet family is not trivial. We thus set some constraints. First, we needed to be able to analyse the EMG signal in the time-frequency domain and then eventually reconstruct the analysed and sorted signals to obtain the individual M-Waves. To do so we limited to orthogonal and bi-orthogonal wavelets: Meyer and Daubechies. Indeed, Meyer wavelets have a compact support (bounded interval outside which the function is strictly 0) in the frequency domain, whereas Daubechies wavelets have a compact support in the time domain. We further decided to use Daubechies 2 (Db2) because it is usually used in EMG processing and Daubechies 4 (Db4) because its similarity with Meyer wavelet (Meyr) in the time domain [19] (see Annex for detailed computations). Then, we used the wavelet transform to find the Area of Interest (AOI) for each muscle's group. First, the continuous form was used to compute the relative energy of each M-wave and the recruitment. The use of the continuous form prevented time shift problem but the orthogonality is lost.

This AOI was determined as time and frequency domain boundaries and corresponded to the area containing signal specific to **an isolated M-wave. The empirical search was based on 3 steps that may be repeated:**

- Find the maximum of the footprint of each M-wave when isolated contraction is available. If not available, find the maxima within the footprint of each M-wave.
- If AOI strongly overlaps, find a compromise so that selected AOI is within M-wave footprint with a sufficient signal to noise ratio and, maximise the distance between AOIs to minimise overlapped information.
- Compute and compare recruitment curves to a clinical MRC (Medical Research Council scale) semi quantitative scaling i.e. If $MRC > 1$, the recruitment should be higher than 0.1 and for a $MRC = 4$, the recruitment should be greater than 0.5

The movement was either an isolated movement (flexion of the fingers, flexion or opposition of the thumb, flexion of the wrist) or a mixed movement composed of simultaneous flexions of the fingers and / or thumb and / or wrist. After applying the continuous wavelet transform, followed by the determination of individual AOIs for each M-wave for each participant, the actual movement is observed and quantified on the modified MRC scale. The MRC was evaluated by a surgeon during the experimentation and a double check was performed off-line with the synchronous audio/video recordings (LabChart software, ADInstrument, Austria) by a second independent neurologist. A MRC equal to 0 correspond to an absence of movement, 1 a contraction without movement, 2 initiated but incomplete movement, 3 initiated but incomplete movement against gravity and 4 complete movement against gravity but without force assessment. Then, the Root Mean Square (RMS) energy within the AOI was computed to extract the recruitment curve. The recruitment curves were normalized to the maximum RMS obtained for each muscle and each patient over the whole session. For each configurations, the resultant recruitment curves were compared with the MRC. If the recruitment curves fit with the MRC, AOI were retained. If not, the AOI was modified until it fits with the MRC (Fig. 2).

To further explore the robustness of the method we explored the sensitivity of the method to: i) the AOI size and compared the obtained recruitment curves (see table 1), ii) the choice of a wavelet family among 3 different ones (Meyr, Db2, Db4). The AOI area variation was defined by $\pm 10\%$ in the time domain and ± 1 level (one octave) in the frequency domain.

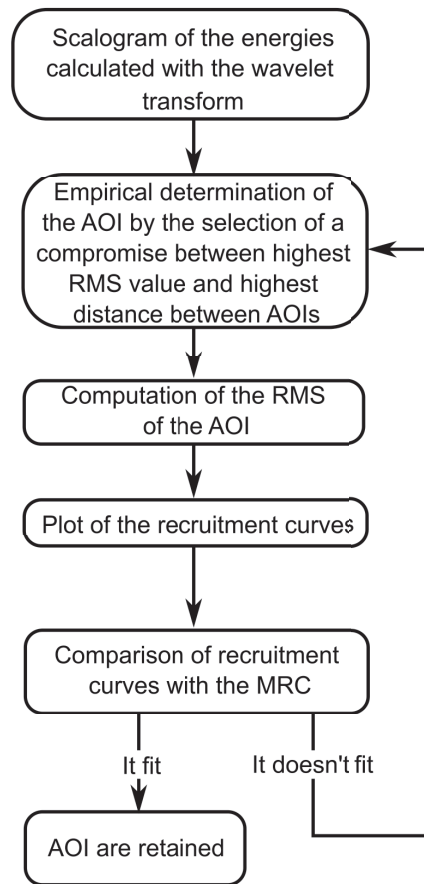


Figure 2: Summary of the steps to determine the Area of Interest (AOI)

2.7 Statistics

In order to find out whether the recruitment curves that can be obtained with the different wavelet transforms and/or with the modulation of AOI are statistically different, and as the data couldn't pass the normality test, signed rank Wilcoxon test was used. The results are presented as rates of RMS differences (called rate of differences). It corresponds to the percentage of configurations that induces statistical differences comparing the wavelet family or the modulation of AOI.

Due to the four conformations for the configurations (excepted Ring and bipolar with only one) corresponding to the four possible cathode positions, the total number of tested configurations/conformations was 34 for each participants. After removing the corrupted data sets, the presented results were obtained on 34 configurations for P1, 34 for P2, 25 for P3, 30 for P4 i.e. a total of 123 configurations/conformations were kept to compute the corresponding recruitment curves.

3 Results

3.1 AOI selection

Table 1: Delimitation of the different areas of interest (AOI) studied in time and frequency. **Top:** fingers flexion - **Bottom:** thumb flexion.

	Fingers flexion	
	Time	Frequency
Initial AOI	5.6 - 24.9 ms	20 - 157 Hz
+10% time	5.0 - 27.4 ms	20 - 157 Hz
-10% time	6.2 - 22.4 ms	20 - 157 Hz
+1 frequency level	5.6 - 24.9 ms	0 - 313 Hz
-1 frequency level	5.6 - 24.9 ms	40 - 79 Hz

	Thumb flexion	
	Time	Frequency
Initial AOI	5.6 - 16.9 ms	157 - 625 Hz
+10% time	5.0 - 18.6 ms	157 - 625 Hz
-10% time	6.2 - 15.2 ms	157 - 625 Hz
+1 frequency level	5.6 - 16.9 ms	79 - 1250 Hz
-1 frequency level	5.6 - 16.9 ms	313 - 625 Hz

The AOI were determined on the scalogram of energy obtained with each wavelet transform. For each participant, when there was a configuration inducing a unique movement, the scalogram was observed and compared with the one of a configuration inducing multiple movements in order to try to identify an area characteristic of the unique movement as described in the Method section. However, AOIs from a same muscle group over patients were close enough to select a unique AOI for each muscle group independent from the patient, even though, pure movements were not observed on all the participants . The scalograms obtained with pure movements were proportional among participants, see Fig.3. The same AOI for a movement was determined for all the participants (see table 1).

3.2 Impact of the wavelet family choice

The statistical comparisons of RMS values obtained using the different wavelet transforms show statistical difference in 14% to 15% of the whole recruitment curves, all movements and participants included (Fig.4 top,). The analysis by movement (all participants included) highlights a higher difference for the fingers (16 - 19%) than the thumb flexion (11%).

All movements and participants together, the modulation in frequency (especially the

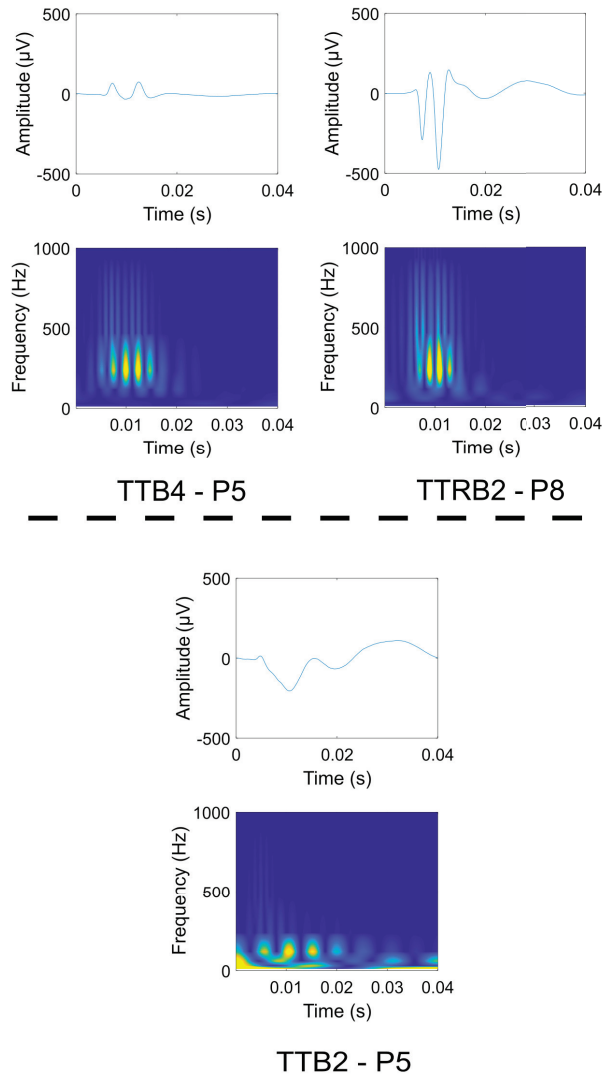


Figure 3: Example of scalograms obtained with the Meyer continuous wavelet transform on two participants **that are pure muscle contractions**. **Top:** two thumb flexions - that look very similar -, **Bottom:** fingers flexion - clearly with a different AOI -. It further shows that the discrimination in the time domain is not possible due to overlapping.

diminution of one level of frequency of the AOI) increases the number of configurations inducing significant recruitment levels differences (11% - 19%) whereas the time modulation is less impacting (14% - 15%).

For all the modulations of AOI, finger flexion produced a higher rate of difference (13% - 23%) than the thumb flexion (8% - 14%).

The paired comparison of the selection of the wavelet family, for all movement, show a higher rate of differences for Db2 compared to Meyer (13% - 19%) than for Db2 compared to Db4 (11% - 15%) or Db4 compared to Meyer (13% - 15%).

For the thumb flexion recruitment curves, all AOI variations included, Db2/Db4 induces

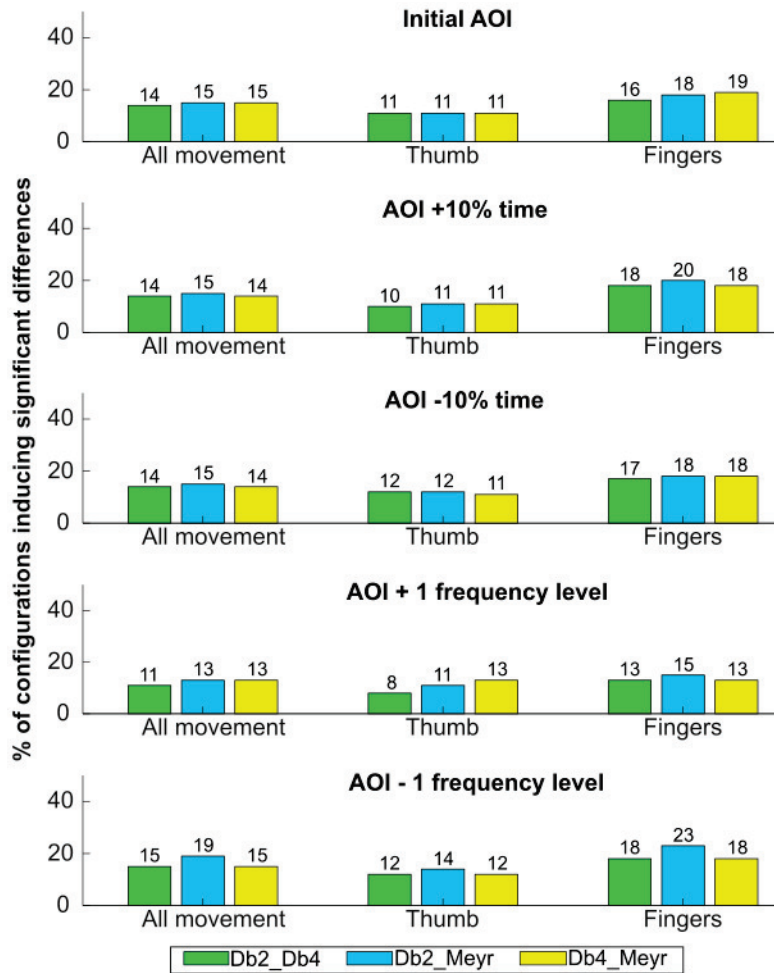


Figure 4: Percentage of configurations inducing RMS differences between the different wavelet transforms. From top to bottom, initial AOI, AOI +10% time, AOI -10% time, AOI +1 frequency level and AOI -1 frequency level. In green the comparison of the RMS between Daubechies 2 and Daubechies 4 wavelet transform, in blue between Daubechies 2 and Meyer wavelet transform and in yellow between Daubechies 4 and Meyer wavelet transform.

8% to 12% of differences whereas Db2/Meyr induces 11% to 14% and Db4/Meyr 11% to 13%. For the fingers flexion recruitment curves, all AOI variations included, Db2/Meyr induces 15% to 23% of differences whereas Db4/Meyr induces 13% to 19% and Db2/Db4 13% to 18%.

The figure 5 is an example of the two opposite cases with statistical differences (Fig.5, A) and without statistical differences (Fig.5, B). Even when there is a statistical difference between the RMS obtain with the different wavelet, curves move together and the difference is quantitative but not qualitative (see Fig.5, A).

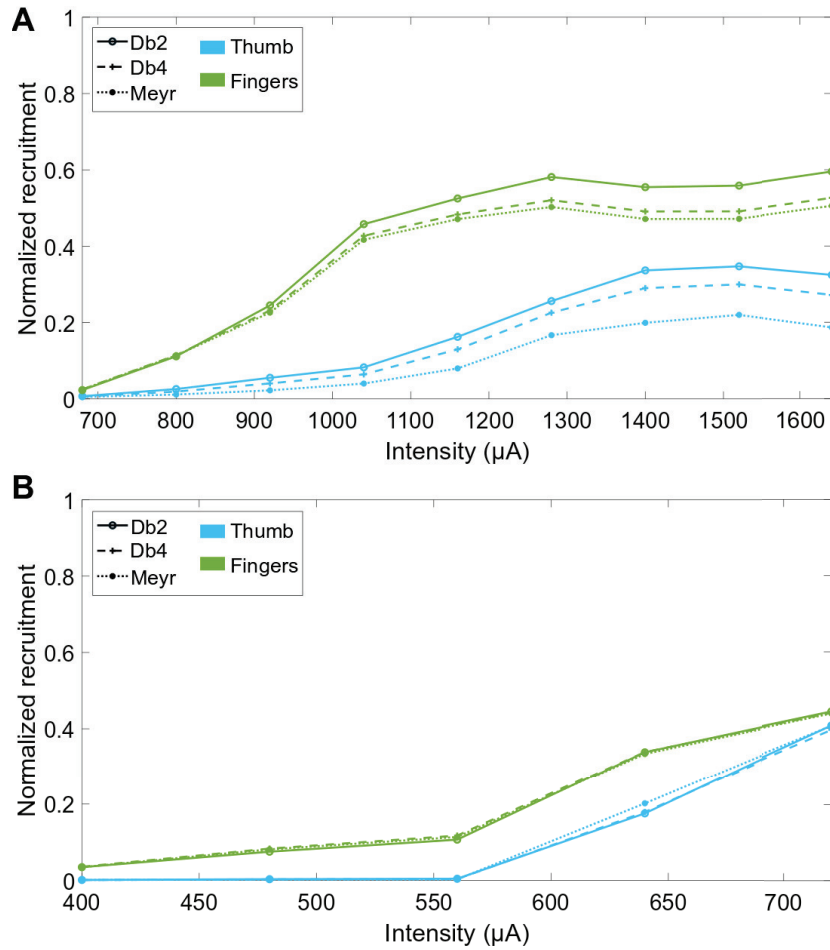


Figure 5: Recruitment obtained with the different wavelet transforms studied for two different configurations and participants. A) example for one configuration with significant differences and B) with no significant differences.

3.3 Sensibility analysis of the size of the AOI

In order to know if the modulation of the AOI in time and frequency induces significant differences of the recruitment curves, we compared the one obtained with initial AOI to the ones obtained with modified AOI (Fig.6).

Increasing the AOI by 10% in the time domain induces exactly the same rate of significant differences for all the wavelet transforms, higher for the thumb flexion than for the fingers flexion (15% for the thumb and 10% for the fingers flexion). In contrast, decreasing the AOI by 10% induces different results for the finger flexion where Db4 induces higher rate of differences than the others (14% for Db4, 9% for Db2 and 10% for Meyr).

Modulating the AOI by one level of frequency increases, for all the wavelet transforms, the rate of differences for the finger flexion compared to the modulation in the time domain (the

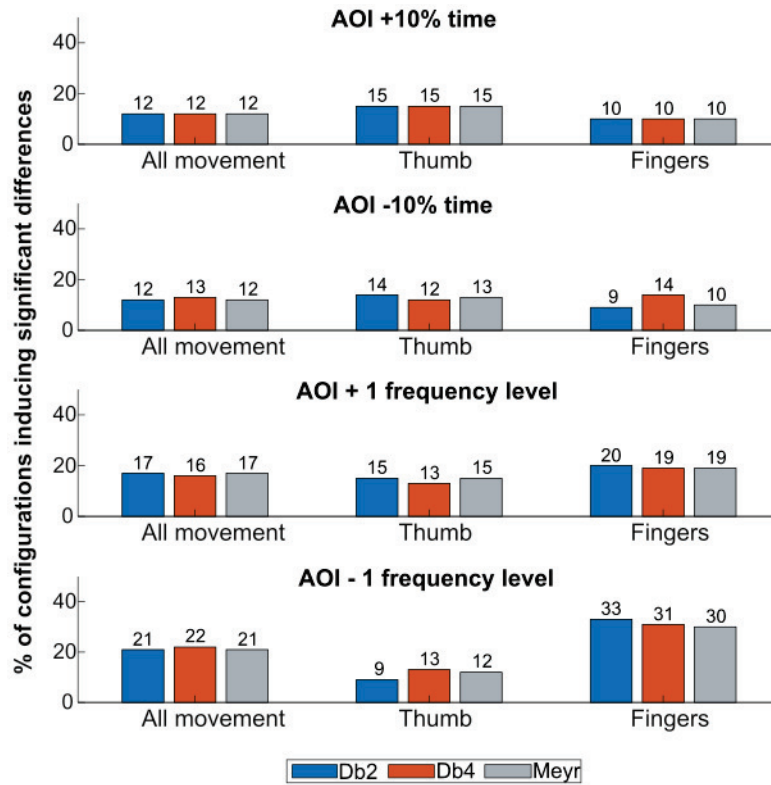


Figure 6: Percentage of configurations inducing statistical differences between the RMS values (recruitment curves) obtained with initial AOI and the one obtained with a modulation of the AOI in time or frequency. In blue the wavelet transform use is Daubechies 2, in orange Daubechies 4 and in grey Meyer.

rate of differences almost double when the AOI is increased by one level, and triple when the AOI is decreased by one level, example Fig7). For the thumb flexion, decreasing the AOI by one level of frequency induces rate of differences lower than increasing it by one level (9% to 13% against 13% to 15% respectively).

4 Discussion

The paper shows a method to extract the isolated contribution of two M-waves from a composite evoked EMG signal and thus give a method to assess quantitatively each contribution. As the M-waves are elicited by a single multi-contact cuff electrode, even though configurations may change the ratio of contribution, the 2 M-wave are not independent in a statistical sense and thus explained why we failed with either ICA or PCA methods. Template matching also failed because it relies on the capacity of extracting pure M-waves that was not the case for all movements and all patients.

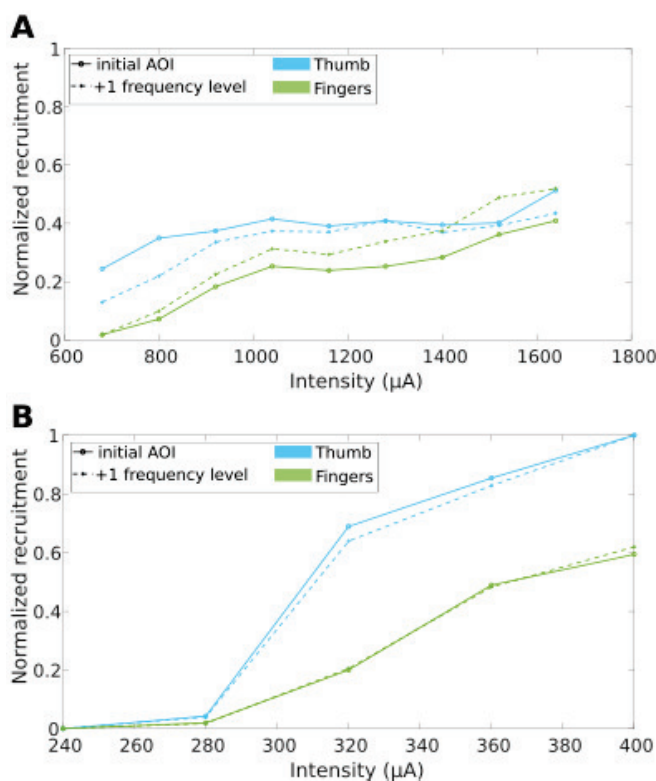


Figure 7: Recruitment obtained with the initial AOI and AOI with +1 frequency level using Db2 wavelet transform. A) example for one configuration with significant differences and B) with no significant differences.

The hypothesis we demonstrated is that a time-frequency analysis leads to separate M-waves through their span in both dimensions. Further hypotheses were that these **time-frequency footprint** may overlap but at least have clearly distinguishable areas so-called AOI. First, the good matching of the recruitment curves with the MRC / movement assessments (see annex) shows that we need not the entire time-frequency domain that represents each M-wave, part of it is **sufficient**. It is due to the fact that we consider relative recruitment curves from 0 to 100% so the absolute RMS value is not meaningful. Part of the area is supposed to be proportional to the whole area as the **wavelet** transformation is linear.

Second, we saw that AOIs were almost the same across patients for a given muscles' group. It is not surprising as it is related to the shape of the M-wave as regards the frequency content, and the travel time of the Action Potential then the EMG from the cuff electrode to the muscle. Indeed, muscles are almost of the same structure, innervation profile and location from patient to patient, so that these features are similar enough to be selected as a unique AOI per muscle. It is a strong property that further improves the robustness of the method.

Third, wavelet family selection is always a challenge and there is no method to make this

choice *a priori*. We thus check the influence of this choice through typical wavelet families with dual properties (in the time frequency domain), it shows that the impact on the outcome is less than 20% of the whole recruitment curves. Even when a significant difference occurs, as illustrated in Fig. 5, this difference is about a scale factor so does not change the qualitative trend of the recruitment curves, and relative values between both muscles, but does change the exact recruitment level. **It means that comparing selectivity will not be deeply impacted as it relies on relative recruitment curves.** As we do not have the accurate ground truth we should take these recruitment curves with some care but overall they are not so sensitive to the choice of the wavelet family.

Finally, the **setting of the boundaries of** the AOI is more sensitive to the frequency settings than the time settings. It is all the more true that the components are low frequency ones i.e. fingers flexor M-wave in our case. It is inherent to the wavelet analysis that is known to be less accurate concerning time location at low frequency so the spanning over bands maybe more needed. On the contrary, high frequency components are better localised in the time domain. However, for both M-waves the frequency settings are obviously more important as they induce the largest modification of the performances. All the 3 wavelets families have the same kind of sensitivity to these parameters even though Meyer seems to be slightly the less sensitive. When looking at the data it seems that the frequency overlap of the thumb M-wave over the finger M-wave maybe the source of the variation. The use of a continuous wavelet in the frequency domain (so with a **higher frequency resolution**) should be used instead to further enhance the discrimination.

5 Conclusion

This paper propose and discuss the efficient use of wavelet transforms to quantitatively assess evoked EMG when several M-waves are superimposed but dependent from each other. The method is quite robust versus the wavelet family choice and the time-frequency area settings for RMS computation. However, further enhanced wavelet algorithms with increased frequency resolution may help to increase the robustness and the accuracy of the method, but needs for more complex computations and settings.

Acknowledgement

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Annex

The general definition of a wavelet transform is derived from a mother wavelet defined by:

$$\psi_{s,\tau} = \frac{1}{\sqrt{s}} \Psi \left(\frac{t - \tau}{s} \right) \quad (1)$$

s being the scale factor, τ the time delay and Ψ the mother wavelet. Then, the wavelet coefficients are computed through a scalar product with the function (signal) to analyse and each wavelet basic vector $\psi_{s,\tau}$. In our paper we choose 3 different mother wavelets: Daubechies 2 and 4 and one type of Meyer wavelets for which the auxiliary function is defined as follows (for $0 \leq x \leq 1$):

$$y = x^4 (35 - 84x + 70x^2 - 20x^3) \quad (2)$$

The discretization of the scale corresponds to a frequency band parsing (with an approximate correspondence between scales and frequencies band not detailed in this paper) while within a defined scale, discretization of the delay leads to time localization screening. To obtain an orthogonal, thus discrete basis, the scale should be chosen in a dyadic scale and then the delay is also scanned with a dyadic evolution such as at a level m we have $s_m = s_0 2^m$, $\tau_m(k) = k \tau_0 2^m$. In a discrete space, it means that the number of levels is limited by the length of the data record, i.e. for a 256 long data set from level 1 (highest frequency band with highest time resolution of 2 samples) to level 8 (lowest frequency with only one wavelet coefficient) and the mean value. Each frequency band from a level to another is thus an octave based splitting. What we call 'continuous wavelet' in our paper is that τ is evenly distributed at a single sample delay disregarding the level. It means that the information is overlapped and the transform no more orthogonal but with the highest time resolution. Still the frequency follows a dyadic distribution. Continuous scaling is possible but with more complex algorithms not used in this paper.

The figure S.1 represents the recruitment curves obtained with the three different wavelet transforms for the configurations of each participant with an MRC= 4 ([2], Table 3). These recruitments show a high correlation between the semi quantitative scale (MRC scale) and the recruitment rate of the corresponding muscle which is always the highest. The recruitment is indeed most of the time even equal to 1 except around 0.7 for P3 configuration TLB3 for the thumb flexion and around 0.6 for P1 configuration TTB4 for the thumb flexion.

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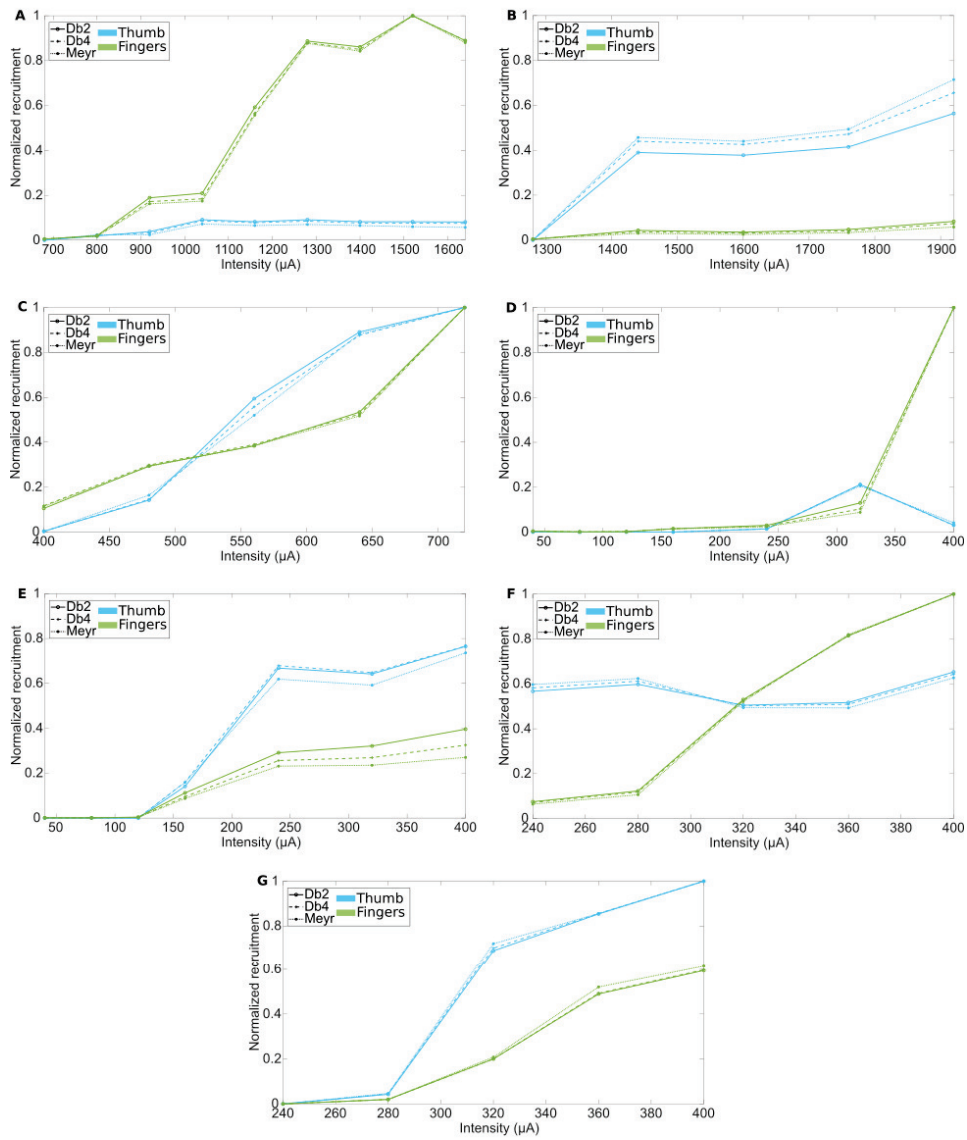


Fig. S 1: Recruitment curves obtained with the three wavelet transforms of the configurations for the four participants with an MRC= 4 for the thumb flexion (in blue) and fingers flexion (in green). In A, participant 1 configuration bipolar AC, MRC= 4 for the finger, B participant 1 configuration TTB4, MRC= 4 for the thumb, C participant 2 configuration TLB1 MRC= 4 for the finger and the thumb, D participant 3 configuration TLB1, MRC= 4 for the finger, E participant 3 configuration TLB3, MRC= 4 for the thumb, F participant 4 configuration TLRB2, MRC= 4 for the finger and G participant 4 configuration STRB2, MRC= 4 for the Thumb.

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