

Identification of common synaptic inputs to motor neurons from the rectified electromyogram

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Key points

- Oscillatory drives at the input of a pool of motor neurons are transmitted to the motor neuron output (neural drive to the muscle) in an approximately linear way if these inputs are common to all motor neurons.
- The neural drive to the muscle is transformed in the EMG signal that can be thus used to extract information on the oscillatory inputs to motor neurons.
- The transmission of oscillatory inputs is closer to a linear transmission for the raw or for the rectified EMG depending on the energy of the raw and rectified motor unit action potentials at the input frequency and on the degree of amplitude cancellation.
- Amplitude cancellation negatively influences the effectiveness of EMG rectification in identifying with linear methods oscillatory inputs to motor neurons, so that rectification is preferable over the raw EMG only when the degree of cancellation is low.

Abstract Oscillatory common inputs of cortical or peripheral origin can be identified from the motor neuron output with coherence analysis. Linear transmission is possible despite the motor neuron non-linearity because the same input is sent commonly to several neurons. Because of the linear transmission, common input components to motor neurons can be investigated from the surface EMG, for example by EEG–EMG or EMG–EMG coherence. In these studies, there is an open debate on the utility and appropriateness of EMG rectification. The present study addresses this issue using an analytical, simulation and experimental approach. The main novel theoretical contribution that we report is that the spectra of both the rectified and the raw EMG contain input spectral components to motor neurons. However, they differ by the contribution of amplitude cancellation which influences the rectified EMG spectrum when extracting common oscillatory inputs. Therefore, the degree of amplitude cancellation has an impact on the effectiveness of EMG rectification in extracting input spectral peaks. The theoretical predictions were exactly confirmed by realistic simulations of a pool of motor neurons innervating a muscle in a cylindrical volume conductor of EMG generation and by experiments conducted on the first dorsal interosseous and the abductor pollicis brevis muscles of seven healthy subjects during pinching. It was concluded that when the contraction level is relatively low, EMG rectification may be preferable for identifying common inputs to motor neurons, especially when the energy of the action potentials in the low frequency range is low. Nonetheless, different levels of cancellation across conditions influence the relative estimates of the degree of linear transmission of oscillatory inputs to motor neurons when using the rectified EMG.

(Received 4 October 2012; accepted after revision 18 March 2013; first published online 18 March 2013)

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Abbreviations APB, abductor pollicis brevis muscle; FDI muscle, first dorsal interosseous muscle; PIF neuron, perfect integrate and fire neuron.

Introduction

Oscillatory inputs in various frequency bands, which may have cortical or peripheral origin (Conway *et al.* 1995; Pfurtscheller & Lopes da Silva, 1999; Pohja & Salenius, 2003; Riddle & Baker, 2005), are transmitted to the motor neuron output (neural drive to the muscle) and can be identified with linear analysis methods (Stegeman *et al.* 2010; Negro & Farina, 2011a). The transmission of oscillatory components to the motor neuron output is possible despite the motor neuron non-linearity because the same input is sent to several neurons (Negro & Farina, 2011a, 2012). This distribution of common input linearizes the input–output system made by an array of neurons.

The neural drive to the muscle is transformed into EMG by convolution of the motor neuron spike trains with the motor unit action potentials. Since this transformation is linear, any frequency component present in the neural drive to the muscle is also present in the EMG signal (intramuscular or surface), if it is within the bandwidth of the signal. Because the EMG signal has a relatively large bandwidth, it can in principle reveal oscillatory components at both low and high frequencies. Experimental studies have indeed identified spectral components related to cortical oscillations from the surface EMG in a variety of conditions (Conway *et al.* 1995; Baker *et al.* 1997). Similarly, oscillations that are supposed to have cortical origin have been identified from the coherence analysis of (intramuscular or surface) EMG signals recorded from the same muscle (in different locations) (Halliday *et al.* 2003) or from different muscles (Evans & Baker, 2003; Boonstra *et al.* 2007; Danna-Dos Santos *et al.* 2010; Poston *et al.* 2010; Keenan *et al.* 2012).

The presence of oscillatory input components in the raw EMG can be *satisfactorily* explained by the above reasoning (Negro & Farina, 2011a). However, the empirical observation that the rectified EMG (where the negative phases of the raw signal are transformed into positive values) may also reveal these components is more difficult to justify. This is due to the fact that rectification is a non-linear operator that changes the frequency components of the signal to which it is applied. Even more striking is the fact that often EMG rectification seems to facilitate the detection of oscillatory input components by

enhancing spectral lines associated with these components (Mima & Hallett, 1999; Yao *et al.* 2007). For this reason, rectification is often suggested as a pre-processing step for extracting oscillatory drives (Halliday & Farmer, 2010), despite some researchers strongly disputing this suggestion (Neto & Christou, 2010; Stegeman *et al.* 2010; McClelland *et al.* 2012). The main problem that arises with rectification is that by rectifying a signal, components at frequencies not present in the original raw signal may arise because of non-linearity, as can be exemplified by the rectification of a pure sinusoid (one spectral line) that results in a signal with a series of infinite spectral lines.

Because of its obscure role in transforming the signal frequency spectrum, rectification has been strongly criticized by some researchers who observed that this pre-processing is fundamentally ‘flawed in engineering and digital signal processing’ (McClelland *et al.* 2012). These criticisms are based on the consideration that rectification changes the frequency content of a signal, as observed above, but this is a general statement, not necessarily relevant in this debate. Indeed, the correct question to pose when discussing the appropriateness of rectification of the EMG is whether oscillatory common components *at the input* of motor neurons (which are non-linear) can be better detected in the spectrum of the raw or rectified EMG. In this reasoning, better detection means a transmission of the oscillatory component which is closer to a linear transmission (i.e. with change in amplitude and phase but not in the frequency of oscillation and without introduction of new frequencies of oscillation). In the ideal case of an input component which is ideally linearly transmitted to the output of a general system, the coherence between input and output is maximal. Therefore, we should ask the question, ‘how close to linear transmission is the transmission of oscillatory input components to the raw or rectified EMG?’ To answer the above question, in this study we analytically compute the Fourier transform of the EMG signal, with and without rectification, resulting from the activity of motor neurons that receive a common oscillatory input and we provide a clear and unambiguous explanation for the conditions in which rectification may be useful. Realistic simulations and experimental results support the theoretical derivations.

Methods

Theory

The theory focuses on a pool of motor neurons that receives an oscillatory input. The motor neuron output is transformed into EMG that can be analysed as raw signal or after signal rectification. The theory provides an analytical computation of the Fourier transform of the raw and of the rectified EMG when the pool of motor neurons receives a single oscillatory input. The closer the transmission is to a pure linear transmission, the greater would be the coherence between input and output (better detection of the input component by a linear method). Ideal linear transmission corresponds to the presence at the output of exclusively the input frequency (potentially changed in amplitude and phase). Thus, the larger the amplitude of the input component at the output (raw or rectified EMG) is, with respect to the other components generated at the output by the non-linearity of the motor neurons, the greater would be the coherence between input and output. With the above reasoning, the Fourier analysis of amplitude spectra of the raw and rectified EMG provides all the information for understanding the role of rectification in coherence analysis.

We assume that a common input signal is delivered at the input of N motor neurons. For clarity, we consider this signal as a simple sinusoidal signal (extension to the sum of sinusoids is trivial):

$$I(t) = K \cos(2\pi f_m t + \phi_m) \quad (1)$$

where K is the modulating index (amplitude of the input), f_m is the oscillatory frequency of the input, and ϕ_m its phase.

For the theoretical derivation, we model each motor neuron as a perfect integrate and fire (PIF) neuron, which is an approximation with respect to the model used for the simulations (see below) but that includes the main non-linear characteristics of the neuron. The Fourier transform of the output of a PIF neuron that receives the input described in eqn (1) is given by the Fourier transform of the expression of the integral pulse frequency modulation process (Bayly, 1968; Nakao *et al.* 1997; Negro & Farina, 2011a):

$$U(f, t_0) = f_0 \delta(f) + \frac{K}{2} f_0 e^{j\phi_m} [\delta(f + f_m) + \delta(f - f_m)] + \sum_{k=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} r(k, n) e^{-j\theta(k, n, t_0)} \delta(f + k f_0 + n f_m), \quad (2)$$

where f_0 is the average discharge rate of the motor neuron, t_0 is the instant of the first discharge of the motor neuron, and the terms $r(k, n)$ and $\theta(k, n, t_0)$ are the module and phase of the frequency components that are generated by the non-linearity of the system. The exact analytical

expressions for $r(k, n)$ and $\theta(k, n, t_0)$ can be found in (Bayly, 1968) but are not relevant for the subsequent discussion.

The motor unit action potential train recorded at the skin surface and generated by the PIF motor neuron considered above is the convolution of the motor unit action potential and its innervation process:

$$x(t) = p(t) * u(t) \quad (3)$$

where $p(t)$ represents the motor unit action potential, $u(t)$ is the inverse Fourier transform of the expression in eqn (2) (output of the motor neuron that drives the muscle), and $*$ is the convolutional operator. In this model, $p(t)$ accounts both for the shape of each action potential and for propagation delays and volume conduction through the tissues to the skin surface. Assuming that the action potential has zero mean (this assumption is not necessary but it is used here to simplify the notations), the Fourier transform of $x(t)$, which represents the frequency content of $x(t)$, is obtained as:

$$X(f) = P(f)U(f) = \frac{K}{2} f_0 e^{j\phi_m} [(P(-f_m)\delta(f + f_m) + P(f_m)\delta(f - f_m))] + \sum_{k=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} r(k, n) e^{j\theta(k, n)} P(-k f_0 - n f_m) \times \delta(f + k f_0 + n f_m) \quad (4)$$

From eqn (4), the frequency component of the input (f_m) is present in the Fourier transform of a single motor unit action potential train. The strength of this input component depends on the amplitude of the input (K) as well as on the average motor neuron discharge rate (f_0) and on the value of the Fourier transform of the motor unit action potential at the input frequency [$(P(f_m))$]. It has to be noted that for an ideal linear and time-invariant system, the expression eqn (4) should contain only the δ function at the input frequency, thus the second term of eqn (4) expresses the non-linearity of the motor neuron. The larger the strength of the first term in eqn (4) with respect to the second, the closer the system approximates a linear transmission of the input. This depends on the term $P(f_m)$, so that frequencies that correspond to the maximum energy of the action potential are transmitted more effectively than others.

We now extend eqn (4) to the case of N motor neurons, all receiving the same input of eqn (1). In this case, the sum of output motor unit spike trains has the following expression:

$$y(t) = \sum_{i=1}^N x_i(t), \quad (5)$$

where $x_i(t)$ is the action potential train for the i -th motor unit and has the Fourier transform as in eqn (4) indexed by i to identify the i -th action potential shape ($p_i(t)$) and the corresponding spike train ($u_i(t)$) (eqn (3)). Equation (5) is valid because of the linearity of the convolution in space and time that determines the action potential. The term $y(t)$ in eqn (5) is the raw EMG signal made of the summation of N motor unit action potential trains. Its Fourier transform is the following:

$$y(f) = \sum_{i=1}^N X_i(f) = \sum_{i=1}^N \frac{K_i}{2} f_0^i e^{j\phi_m} [P_i(-f_m)\delta(f + f_m) + P_i(f_m)\delta(f - f_m)] + \sum_{i=1}^N \sum_{k=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} r_i(k, n) e^{j\theta_i(k, n)} P_i(-k f_0^i - n f_m) \times \delta(f + k f_0^i + n f_m) \quad (6)$$

The input frequency f_m is present in the Fourier transform of the EMG signal and it is multiplied by the amplitude of the input signal, by the sum of the average discharge rates of the N motor units, and by the sum of the values of the Fourier transform of the action potentials associated to the N motor neurons at the input frequency. Therefore, with respect to the case of a single motor neuron transmitting the input, with N motor neurons the input frequency term is amplified significantly whereas the second term does not sum equally, due to the differences in the discharge rates of the motor units. With sufficient motor neurons, the input term becomes the dominant in the expression eqn (6), which is equivalent to an approximately linear transmission. Therefore, the raw EMG contains frequency components corresponding to oscillatory common inputs to the motor neurons. It is underlined again here that these inputs should be common to the motor neurons to be visible at the output.

We conclude the theoretical derivations by showing the relations between the Fourier transform of the raw EMG and that of the rectified EMG. This will explain for the first time the effect of rectification on the spectral component corresponding to the input frequency f_m . We begin by considering an EMG signal made of a single motor unit action potential train $x(t)$, as defined in eqn (3). This is a particularly simple case in which rectifying the signal (i.e. rectifying $x(t)$) results in a signal with the same expression as in eqn (3) but with the action potential rectified:

$$|x(t)| = |p(t)| \times u(t) \quad (7)$$

The relation in eqn (7) *does not* hold in general but only for the specific case in which the action potentials in the train do not overlap in time with each other, which is verified for a single motor unit action potential train. However, this assumption is not correct for the EMG signal

comprising the sum of several trains. The Fourier transform of eqn (7) has the same expression as in eqn (4), with the Fourier transform of the rectified action potential $P'(f)$ instead of the raw action potential $P(f)$:

$$F[|x(t)|] = P'(f)U(f) = f_0 P'(0)\delta(f) + \frac{K}{2} e^{j\phi_m} f_0 [P'(-f_m)\delta(f + f_m) + P'(f_m)\delta(f - f_m)] \lim_{x \rightarrow \infty} + \sum_{k=-\infty}^{+\infty} \sum_{n=-\infty}^{+\infty} r'(k, n) e^{j\theta'(k, n)} P'(-k f_0^i - n f_m) \times \delta(f + k f_0^i + n f_m), \quad (8)$$

where $F[\cdot]$ denotes the Fourier transform. By comparing eqns (4) and (8), it appears that the only difference between the rectified and raw EMG for a single train of action potentials is that the input frequency component is multiplied by the Fourier transform of the rectified or raw action potential shape, respectively. Therefore, for a single train of action potentials, the rectified signal reveals oscillatory input components to motor neurons in a better way than the raw signal (i.e. transmits the input in a more linear way) if the energy of the rectified action potential at the input frequency is greater than that of the raw action potential (relative to the second term in eqns (4) and (8)). The latter condition is almost always verified since the oscillatory drive has frequencies below 30–40 Hz where the energy of the raw action potentials is low and it is increased in the rectified EMG.

Further, we consider the full EMG signal after rectification. Its expression is the following:

$$|y(t)| = \left| \sum_{i=1}^N x_i(t) \right| \quad (9)$$

The property of eqn (7) is *not* valid any more when different action potentials overlap in time. Nevertheless, we can write the following inequality, which is always valid, being a special case of the Cauchy–Schwarz inequality:

$$|y(t)| = \left| \sum_{i=1}^N x_i(t) \right| \leq \sum_{i=1}^N |x_i(t)|. \quad (10)$$

Equation (10) expresses the concept that the absolute value of the sum of signals is never greater than the sum of the absolute values. Interestingly for the successive derivations, the inequality eqn (10) is exactly the definition of the so-called amplitude cancellation in the EMG signal (Day & Hulliger, 2001; Keenan *et al.* 2005), i.e. the rectified sum of the action potential trains (EMG) is less than the sum of the rectified action potential trains (the so-called no-cancellation condition, Keenan *et al.* 2006) and the difference is the amplitude cancelled by the

generation process of the EMG (Day & Hulliger, 2001). Assuming $c(t)$ as the cancelled signal that expresses the difference between the rectified EMG and the sum of the rectified spike trains, by simple algebraic transformation and Fourier transforms, we obtain:

$$\begin{aligned}
 F[|y(t)|] = & \sum_{i=1}^N f_0^i P_i'(0) \delta(f) \\
 & + \sum_{i=1}^N \frac{K_i}{2} f_0^i e^{i\phi_m} |P_i'(-f_m) \delta(f + f_m) \\
 & + P_i'(f_m) \delta(f - f_m)| \\
 & + \sum_{k=1}^N \sum_{n=-\infty}^{+\infty} \sum_{m=-\infty}^{+\infty} r_i'(k, n) e^{i\theta_i'(k, n)} P_i'(-kf_0 - nf_m) \\
 & \times \delta(f + kf_0 + nf_m) - F[c(t)]
 \end{aligned} \tag{11}$$

Apart from the term at zero frequency (first term), that we can neglect since it is not of interest for the spectral analysis of the EMG, the spectral content of the rectified EMG (eqn (11)) and that of the raw EMG (eqn (6)) have the same form, with the differences that: (1) the input frequency component is multiplied by the Fourier transform of the raw (for raw EMG) or rectified (rectified EMG) action potentials, evaluated at the input frequency, as for the case of the single action potential train (eqn (8)); and (2) the spectrum of the rectified EMG contains the Fourier transform of the cancellation term ($F[c(t)]$), which is absent from the expression of the spectrum of the raw EMG. It is important to specify here the obvious consideration that the latter statement does not imply that the raw EMG *amplitude* is not affected by cancellation. The Fourier transform of the sum of signals is the sum of the transforms of the signals whereas amplitude, defined as the standard deviation of the signal and estimated by root mean square or other estimators of standard deviation, is influenced by cancellation even for uncorrelated signal components (the standard deviation of the sum is lower than the sum of standard deviations) (Farina *et al.* 2008). Conversely, rectification introduces cancellation in the spectrum of the rectified signal (the Fourier transform of the rectified signal is different from the sum of the transforms of the rectified action potential spike trains). Therefore, rectification does not eliminate amplitude cancellation but actually also introduces it in the amplitude spectrum and not only in the amplitude. This is due to the fact that rectification of the raw EMG signal is obviously different from the rectification of each action potential spike train.

The above derivations relate to the spectrum of the EMG given an input to the pool of motor neurons innervating the corresponding muscle. As discussed at the beginning of Methods, these derivations provide the full information on the factors influencing the transmission of input through

the motor neurons and the results can be extrapolated directly to coherence analysis. For example, if the input signal modelled above is assumed to be a cortical input, the estimated strength of this signal in the EMG is associated to the degree of coherence between a signal containing this input (cortical recording) and the EMG. Given the same relative energy of the input signal in the cortical recording, in this example, the stronger (i.e. closer to pure linear) is the transmission of that signal to the EMG recording, the greater the coherence between the cortical recording and the EMG. The same reasoning can be used if the modelled input signal is part of a second EMG recording (for example, from another muscle). The comparison between eqns (6) and (11) indicates that the choice between rectified and raw EMG depends on which of the two signals maximize the strength of the input component *relative* to the other components (which are created by the non-linearity of the motor neurons). This depends on the factor multiplying the input component, which differs in the two cases since it depends on the Fourier transform of the rectified/raw action potentials at the input frequency, and on the cancellation signal. Rectification of the EMG will be effective when the Fourier transform of the action potentials at the input frequency is greater when rectifying the action potentials than for raw potentials and for low levels of amplitude cancellation. Since the strongest factor influencing amplitude cancellation in the EMG is the actual contraction level (Farina *et al.* 2008), rectification would be effective for low forces up to a maximum force when cancellation becomes an important term in eqn (11). Therefore, amplitude cancellation impairs the effectiveness of rectification in extracting oscillatory input components to motor neurons from the EMG analysis. Without amplitude cancellation, rectification would always tend to increase the relative power of the input frequency component if the energy of the rectified action potential at the input frequency is greater than that of the raw action potential. The latter condition is often verified, especially for intramuscular EMG action potentials for which the signal power at low frequencies is negligible, since rectification increases the energy in the low frequency band where the oscillatory inputs usually occur. Nevertheless, it is worth noting that absence of amplitude cancellation never occurs in practice for biphasic action potentials, thus it is a purely abstract condition.

Simulations

The simulations were based on a model of populations of motor neurons that received common and independent inputs and a model of volume conductor and surface EMG generation. A similar modelling approach has been used in previous studies (e.g. Negro & Farina, 2011*b*) and will be briefly described here.

The motor neuron model was based on that described by Cisi & Kohn (2008). It consists of two compartments, six conductances (with three voltage-dependent conductances, I_{Na} , I_{Kf} and I_{Ks}), and four state variables. The pulse-based simplification used in the original model was removed in the present study and a full formulation, previously proposed (Traub *et al.* 1991), was used instead. The motor neuron parameters were the same as used by Cisi & Kohn (2008; their Table 2) and selected according to an exponential distribution over the pool of motor neurons (Fuglevand *et al.* 1993). The number of motor neurons varied in the simulations up to a maximum of 300.

The input to motor neurons included one sinusoid, as described in eqn (1), at a frequency that varied across simulations, that was assumed common to all motor neurons. A second source of input was independent noise and was simulated as an independent signal for each motor neuron. This input described the membrane noise and was modelled as a band-limited (0–100 Hz), white (in the bandwidth) Gaussian signal (Maltenfort *et al.* 1998). The input to the motor neuron pool was the linear combination of the two input sources with a total variance determined in order to obtain a coefficient of variation for the interspike interval of approximately 15% (Maltenfort *et al.* 1998). Limitations of this model, such as the absence of plateau potentials and of saturation in discharge rate, discussed previously (Negro & Farina, 2011a), do not impact the results of this study.

The EMG model was based on a cylindrical volume conductor, as described by Farina *et al.* (2004c) and applied in several previous studies (e.g. Keenan *et al.* 2007; Farina *et al.* 2008). The parameters of the EMG model were the same as in Keenan *et al.* (2007). Single muscle fibres were independently simulated and the surface-recorded, motor-unit potentials comprised the sum of the action potentials of the muscle fibres belonging to each motor unit. EMG signals were computed at 4096 samples s^{-1} and down-sampled to 1000 Hz. The signals were recorded with electrodes of circular shape (radius 1 mm), arranged in bipolar derivation with 20 mm interelectrode distance.

The full model (motor neuron and surface EMG) was implemented in MATLAB. The system of differential equations for the motor neuron model was solved with the Adams–Bashforth–Moulton PECE solver (Shampine & Gordon, 1975), using optimized time steps within intervals of 1 ms. Each simulation was 10 s long, resulting in 10 segments of 1 s duration.

Experiments

The experiments consisted of the recording of two bipolar surface EMG signals from the first dorsal interosseous (FDI) and the abductor pollicis brevis (APB) muscles during pinching. In these conditions, it has

been previously shown that the coherence level between EMG signals is significant (e.g. Danna-Dos Santos *et al.* 2010, using intramuscular EMG). The main aim of the experiments was to support the analytical and simulation findings with experimental data. For this purpose, it was important to vary the level of EMG amplitude cancellation and to study the effect of rectification on coherence. A way to vary the level of cancellation involves changing the level of muscle activity, as it was done for the simulated conditions. However, by following this method, it would not be possible to separate the changes in coherence due to changes in cancellation from those due to physiological changes in the strength of the common input to the two muscles. Therefore, another approach is proposed here. It is known that the level of amplitude cancellation depends on the duration of the motor unit action potentials (Keenan *et al.* 2005). The duration of the motor unit action potentials can be increased (thus increasing amplitude cancellation) by low-pass filtering the interference EMG signal. Indeed, since such filtering is a linear operation, filtering the interference signal is equivalent to filtering each action potential in the signal. By low-pass filtering the signal, it is thus possible to change the level of amplitude cancellation in the signal without changing any other condition. Therefore, we applied filters with different cutoff frequencies to the raw experimental signals and we analysed the corresponding level of coherence. It was hypothesized, in accordance with the analytical derivations and the simulations, that decreasing the cutoff frequency of the pre-filter would increase the amplitude cancellation level in the signal which would in turn decrease the level of coherence obtained by signal rectification (rectification was obviously applied after the pre-filtering in such a scheme). Conversely, the level of coherence obtained without signal rectification would be maintained unchanged by the low-pass pre-filtering.

Seven subjects (3 females, age 24–38 years) participated in the experiments. All subjects were health volunteers, with no known neurological disorders at the time of testing. The subjects provided written informed consent before participation and the local ethical committee (University Medical Center Göttingen, Germany) gave approval to the study, and warranted its accordance with the *Declaration of Helsinki*.

During the experiments, the subject sat comfortably with the dominant hand resting on the table. Two pairs of surface EMG electrodes (Ambu NeuroLine 720, Ballerup, Denmark) were placed over the belly of the FDI and APB muscles. The subject was instructed to pinch his/her thumb and index finger against each other. The EMG signals were acquired by an EMG amplifier (EMG-USB2, OTBioelettronica, Turin, Italy, 2048 Hz sampling rate, and gain 1000). The acquired signals were presented to the subjects as visual feedback by a customized MATLAB (Mathworks Inc., Natick, USA) program, which also saved

the acquired data for offline processing. The subject was instructed to maintain the pinch for 2 min with constant EMG amplitude in the two channels (muscles). The level of EMG amplitude was chosen based on the level that felt comfortable to the subject and that could be maintained for 2 min. This level corresponded to 5–10% of the maximum EMG amplitude, depending on the subject. The precise EMG (or force) level was not relevant for the purpose of these experimental tests since the aim was to investigate the coherence level between the two EMG signals with and without EMG rectification, by varying the level of cancellation with low-pass pre-filtering. The level of EMG crosstalk (Farina *et al.* 2004*a,b*) was tested by selective contractions of the two muscles and recordings from both sites and was negligible in all subjects tested.

The EMG signals were divided into intervals of 1 s and the coherence function (Fourier transform of the cross-correlation function) was computed from these intervals and averaged over the 120 intervals extracted from the 2 min contractions. The coherence in the beta band was quantified by the area under the coherence function between 15 Hz and 25 Hz. The coherence level was calculated from the raw and rectified EMG signals after pre-filtering with a Butterworth low-pass filter (order 4) with cutoff frequency varying between 800, 600, 400, 200, 80, 60 and 40 Hz. The coherence levels were graphically reported normalized by the coherence value obtained from the raw EMGs without pre-filtering. Normalized coherence values were statistically compared between the rectified and raw signal with a two-way ANOVA with factors the pre-filtering cutoff frequency and the presence of rectification (rectified or raw EMG), followed by the *post hoc* Student–Newman–Keuls test. Statistical significance was set at $P < 0.05$ for all comparisons and results are reported as means and SD.

Given the low contraction level, it was expected that the coherence value extracted from the rectified EMG would be greater than from the raw EMG for large cutoff frequencies of the pre-filter. Conversely, the value of coherence would decrease for the rectified EMG for decreasing values of the low-pass cutoff frequency because of the increase in the amplitude cancellation term in eqn (11).

Results

Simulation and experimental results are reported and interpreted with the predictions based on the analytical derivations.

Simulations

Figure 1 shows the raw and rectified EMG signal and their respective amplitude spectra (magnitude of the

Fourier transform) for two simulations in which 30 or 300 motor units were active. In these simulations, the motor neurons received a common input at 20 Hz and independent inputs (power ratio between the common and independent input ~ 0.01). The different number of active motor units determined a different level of amplitude cancellation in the two simulations (37% and 63%) because the level of muscle activation increases the degree of cancellation (Farina *et al.* 2008). In both simulations and for both the rectified and raw signals, a peak at 20 Hz, corresponding to the input, can be identified from the signal spectrum. However, the amplitude of the input signal peak in the spectrum of the raw EMG does not change substantially with the increase in number of active motor units (and thus with the increase in cancellation in the signal). Conversely, the amplitude of the input spectral peak in the spectrum of the rectified EMG relative to the other spectral components is substantially different for the two levels of amplitude cancellation. For a moderate level of cancellation, this spectral peak is enhanced in the rectified EMG with respect to the raw EMG spectrum (Fig. 1A). In the case of a high level of cancellation, however, the input peak is less clearly detected in the rectified than in the raw EMG spectrum (Fig. 1B). This behaviour exactly reflects the analytical predictions. Specifically, the rectified EMG spectrum presents the cancellation component (eqn (11)) that confounds the detection of the input peak and that is not present in the spectrum of the raw EMG (eqn (6)). Figure 1 also indicates that, *although* the peak of the input signal may be enhanced by rectification in some conditions, the same strength of common oscillatory input to the motor neuron pool may result in substantially different spectral peaks in the rectified EMG depending on the cancellation level. In the representative example of Fig. 1 the cancellation level is changed by the number of active motor units whereas in more general conditions this level will also depend on the membrane muscle fibre properties, length of the muscle fibres, volume conductor characteristics, and features of the detection system (Keenan *et al.* 2005). Therefore, the strength of the input frequency peak of the spectrum of the rectified EMG cannot be associated directly with the strength of the oscillatory common input received by the motor neurons. Although this is also true for the raw EMG, because the peak level depends on the spectrum of the motor unit action potentials (eqn (6)), the cancellation level does not influence the peak amplitude in the raw EMG spectrum which is thus less variable with contraction level and muscle anatomical properties (Fig. 1).

Figure 2 shows that without cancellation (a condition never existing experimentally), EMG signal rectification optimally enhances the input frequency component. This figure is generated by similar simulations to those in Fig. 1 (at high cancellation) but with an input frequency of 30 Hz. Moreover, the no-cancellation condition is also

shown. This condition corresponds to rectifying the action potential trains *before* summing them to generate the surface EMG and it is thus a condition that cannot be obtained experimentally. The no-cancellation condition is equivalent to extending eqn (8), which is valid for a single motor unit action potential train, to the full motor neuron pool. In this condition, the signal properties are equivalent to those of an EMG signal made of rectified action potentials, without cancellation.

Figure 3 summarizes the representative results shown in Figs 1 and 2 with data from three simulations where the number of motor neurons was varied. In these simulations, input signals at 10, 20 or 30 Hz were delivered as common inputs to a progressively greater number of motor neurons. The resulting surface EMG signals had various levels of cancellation, depending on the overall muscle electrical activity. The results in Fig. 3 are reported as a function of the number of active motor units (an increase in active units determines an increase

in amplitude cancellation). The reported variable is the ratio between the spectral peak corresponding to the input signal in the spectrum of the raw, rectified, or no-cancellation EMG and the same peak as observed in the cumulative motor unit spike trains (see graphical explanation of this measure in the inset of Fig. 3). The rationale for this performance measure is that the ideal condition would be to detect the peak as it appears in the neural drive to the muscle (cumulative spike train of all active motor units). It has to be noted that this condition could in principle be reached experimentally by a full decomposition of the EMG signal (Farina *et al.* 2010). For the three input frequencies, for a small number of motor units, which correspond to low cancellation levels, the rectified and the no-cancellation EMG performs substantially better than the raw EMG. For a very small number of active units, the rectified and no-cancellation EMG performed similarly, with an increase in performance index with increasing number

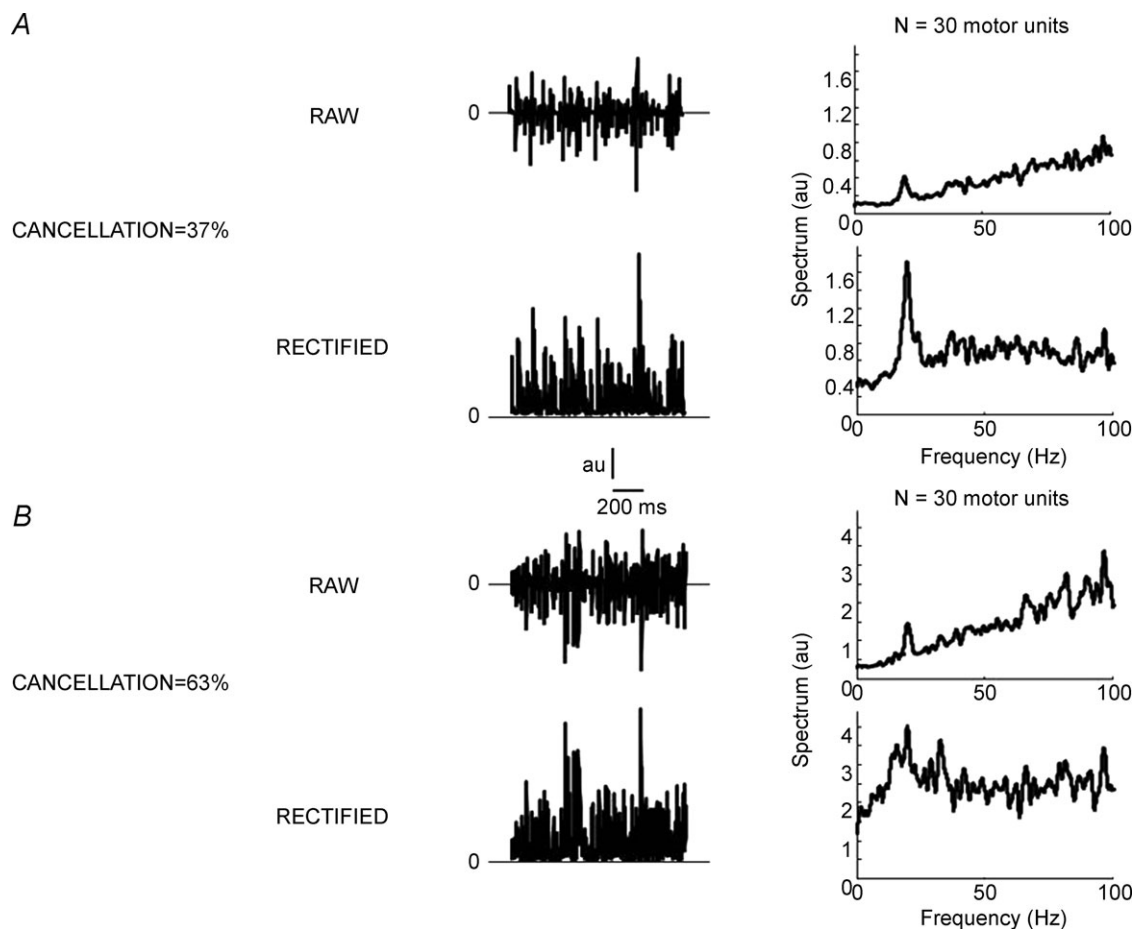


Figure 1. Effect of cancellation on spectral peaks of raw and rectified EMG

Two simulations are presented in which an input at 20 Hz is sent to 30 (A) and 300 (B) motor neurons. The surface EMG signal is simulated and the level of cancellation corresponds to 37% (A) and 63% (B). The common oscillatory input at 20 Hz is summed with noise (see Methods for the properties and power of the independent noise components). The raw and rectified EMG and their respective amplitude spectra are shown. au: arbitrary units.

of active units. This behaviour is expected since the first term in eqn (11) is becoming progressively larger relative to the second term with increasing number of active units. This same effect is also visible in the case of the raw EMG and is explained in the same way (first *vs.* second term in eqn (6). After reaching a peak value, the performance index decreases due to two terms for the rectified EMG: the second and third (cancellation) term in eqn (11). Conversely, the decrease for the no-cancellation condition is only due to the second term in eqn (11) (since cancellation is artificially not present). Consequently, the rate of decrease in the spectral input peak with respect to the cumulative spike train input peak is much faster for the rectified than for the no-cancellation EMG. For the same reason, such rate of decrease is also much faster in the rectified EMG with respect to the raw EMG. Due to the different rate of decrease in peak amplitude with respect to number of active units, for input frequencies of

20 and 30 Hz there is point (approximately 60 active units for 20 Hz and 30 units for 30 Hz, in these simulations) after which the peak amplitude for the rectified EMG becomes smaller than that obtained from the raw EMG. Conversely, the peak amplitude is always greater in the case of the no-cancellation condition, as predicted by the analytical derivations. Therefore, for a small number of active units the rectification may be beneficial whereas it would not be useful for a greater number of active units. Note that in these simulations, the input at 10 Hz is always transmitted better in the rectified than in the raw EMG (Fig. 3A). This is due to the progressively lower power of the surface action potentials at lower frequencies. Obviously the exact number of active units (or EMG level) after which rectification is not useful any more depends on a variety of parameters that influence amplitude cancellation (Keenan *et al.* 2005; Farina *et al.* 2008) with respect to the other terms in eqn (11). Therefore, it

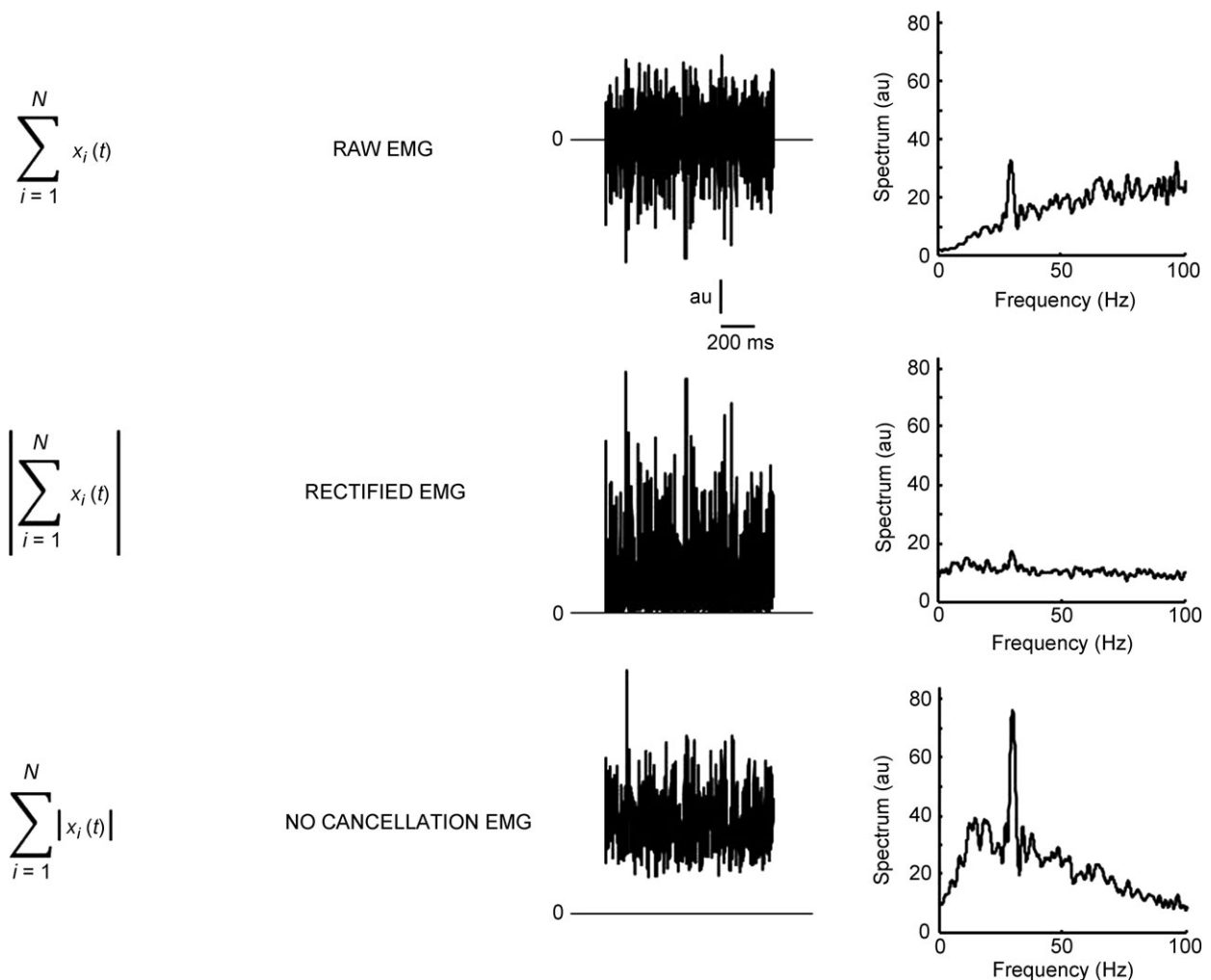
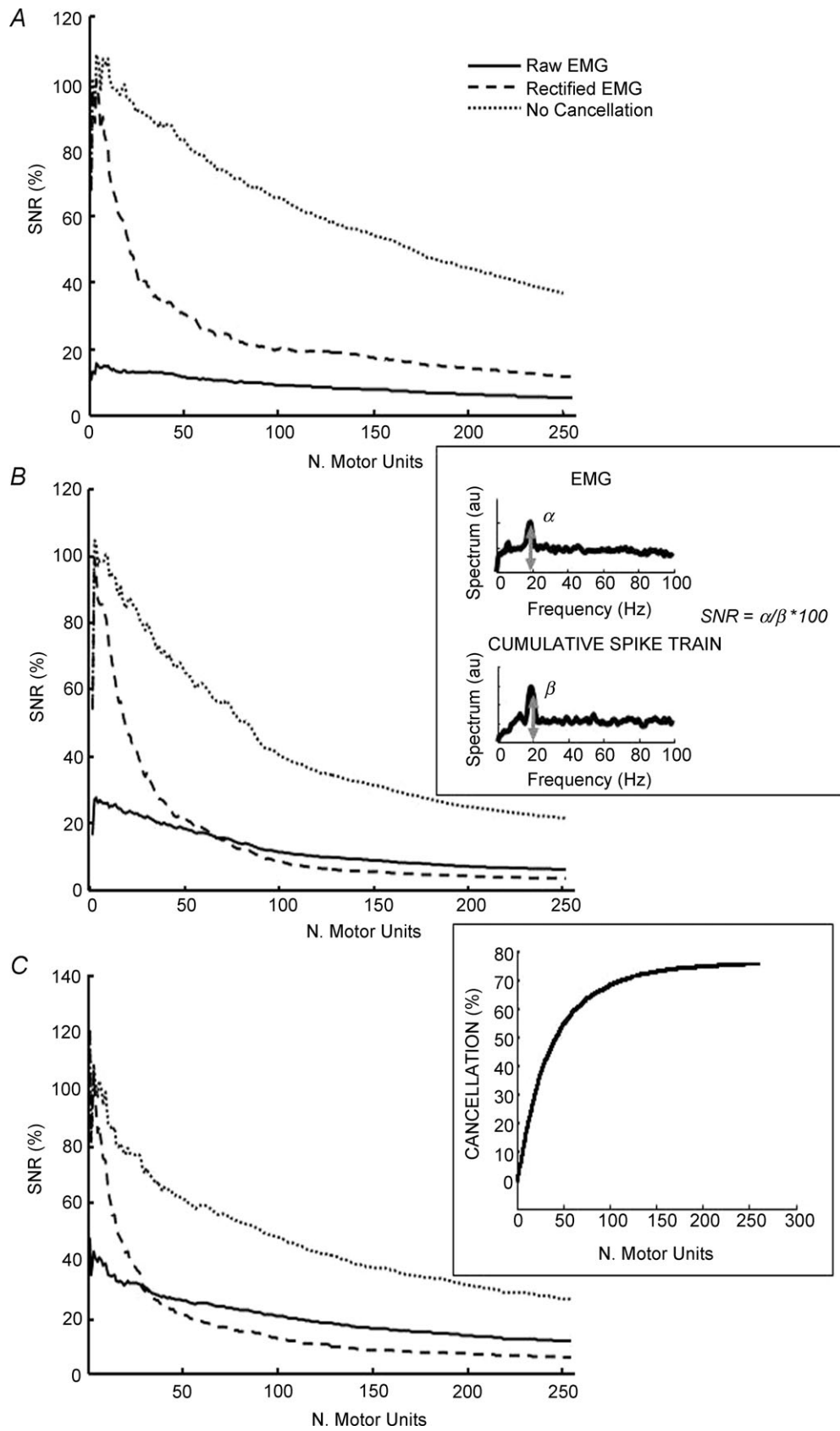


Figure 2. The no-cancellation condition corresponds to ideal transmission
 Raw, rectified and no-cancellation EMG (see text for the definition of the no-cancellation EMG) signals when activating 300 motor neurons with a common oscillatory input at 30 Hz and additive noise as in Fig. 1. The signals and corresponding spectra are shown. au: arbitrary units.



is not possible to determine it exactly or to provide an exact suggestion for deciding on the best choice. It is only possible to provide the general consideration for which rectification may be effective in extracting spectral input peaks mainly for low contraction forces. In addition, as also underlined when discussing Fig. 1, it has to be noted that the amplitude peak varies much more over the range of active motor units investigated for the rectified than for the raw (and no-cancellation) conditions (consider that the strength of the input signal is always the same in Fig. 3). This implies that the spectral peak in the rectified signal is more influenced by the level of muscle activity than the raw EMG (see also Fig. 1).

Figure 4 reports the comparison between the different signal modalities with a different performance index with respect to Fig. 3. In this case, the coherence peak value at the input frequency is computed between the EMG signals (raw, rectified, and no-cancellation) and the peak in the neural drive to the muscle (Fig. 4A) or the actual simulated input (Fig. 4B). These coherence values are alternative indices to indicate the capability of the different signal modalities to extract the input frequency. These indices are closer to the practical applications of EMG for extracting oscillatory components with EMG–EMG coherence or EMG–EEG coherence methods. The results are reported as a function of the number of motor units, as for Fig. 3, and for an input at 20 Hz (similar observations can be done for other input frequencies). The coherence peak with respect to the spike trains (Fig. 4A) is approximately constant over the number of active units for both the raw and the no-cancellation conditions whereas it decreases for the rectified EMG condition. This result is fully explained by the analytical analysis since the rectified EMG condition is the only one in which the cancellation term has an effect (third term in eqn (11)). This term decreases the coherence with the spike train which does not contain cancellation. The coherence with the actual input signal (Fig. 4B) increases with the number of active units for all modalities due to the relative increase in the linear part of transmission with increasing number of active motor neurons (eqn (6)) and eventually it saturates (Negro & Farina, 2011a). The coherence value is greater for the rectified than the raw EMG for a low number of units whereas it is lower for a large number of units, in accordance with the theoretical predictions.

Experiments

Figure 5A presents the coherence function between the EMG signals detected from the FDI and APB muscles of a representative subject. The coherence is computed for different pre-filtering low-pass cutoff frequencies. In this subject, a large cutoff frequency (800 Hz), which does not substantially influence the signal, corresponds to a coherence peak greater for the rectified than the raw EMG. However, while the coherence peak when using the raw EMG does not change with cutoff frequency, the peak obtained by prior rectification progressively decreases. Note that in Fig. 5A the cutoff frequencies shown are always greater than the range of frequencies shown in the x -axis for the coherence functions. Therefore, the filtering does not have any effect on the 20 Hz coherence peak from the raw signals. Conversely, there is an effect after rectification due to the non-linear nature of rectification.

Figure 5B summarizes the group results. The coherence levels are normalized with respect to the coherence level obtained from the raw EMG without pre-filtering. The level of coherence estimated from raw EMG signals does not change with the pre-filtering cutoff frequency (note also that the standard deviation is negligible) whereas the coherence level estimated from the rectified EMG decreases with decreasing cutoff frequency. A two-way ANOVA with factors the cutoff frequency of the pre-filter and the modality of EMG analysis (raw or rectified) showed a significant interaction between the two factors ($P < 0.01$), with the coherence peak greater for the rectified than for the raw EMG for frequencies larger than 200 Hz ($P < 0.05$) and smaller for frequencies lower than 200 Hz ($P < 0.05$) (Fig. 5B). These results are fully in agreement with the analytical derivations and with the simulations and are explained by the varying levels of amplitude cancellation depending on the pre-filtering cutoff frequency.

Discussion

Rectification of the EMG to detect common oscillatory input components to the motor neurons is considered either an important step of pre-processing that should be adopted (e.g. Halliday & Farmer, 2010) or as an unnecessary and inappropriate method (e.g. McClelland *et al.* 2012). These opposite views currently co-exist

Figure 3. Transmission of spectral peaks from the neural drive to the muscle to the EMG signal

A signal-to-noise ratio (SNR) measure is defined here as the ratio between the spectral peak corresponding to the oscillatory common input to motor neurons in the raw, rectified and no-cancellation EMG and the same peak in the cumulative motor unit spike train (expressed as %) (see inset). The simulations are as in Fig. 1 but varying the number of active motor units (x -axis). The input frequency is 10 (A), 20 (B) and 30 Hz (C). The second inset represents the relation between the number of active motor units and the level of amplitude cancellation.

without strong arguments for one or the other. The present study has clarified this issue by providing an analytical approach to the problem. The main theoretical contribution is that the spectra of the rectified and raw EMG have similar components but differ by the contribution of amplitude cancellation. Therefore, the degree of amplitude cancellation is the key factor of influence on the effectiveness of EMG rectification in extracting spectral peaks due to common oscillatory inputs to motor neurons.

A first important aspect to discuss when debating on EMG rectification is the nature of the information to be extracted by spectral/coherence analysis of the rectified/raw EMG. This information is the spectral component relative to an oscillatory input common to a population of motor neurons. This may be investigated in relation to cortical oscillations by EEG–EMG coherence

(Mima & Hallett, 1999) or to common oscillations to different muscles with EMG–EMG coherence (Evans & Baker, 2003; Boonstra *et al.* 2007; Keenan *et al.* 2012) or to cortical oscillations to one muscle with EMG–EMG coherence over a single muscle (Halliday *et al.* 2003). These oscillations are not related to the average motor unit discharge rate (f_0 in the theoretical expressions in this paper). In debates on EMG rectification, the work by Myers *et al.* (2003) is often cited and their results on the usefulness of rectification for extracting the average discharge rate of motor units are often discussed in relation to the more advanced simulations presented by Farina *et al.* (2004a). However, these works addressed the problem of estimating the average motor unit discharge rate and not common oscillatory inputs to motor neurons.

The theory we proposed indicates that it is possible to identify the frequency of oscillation of inputs to motor

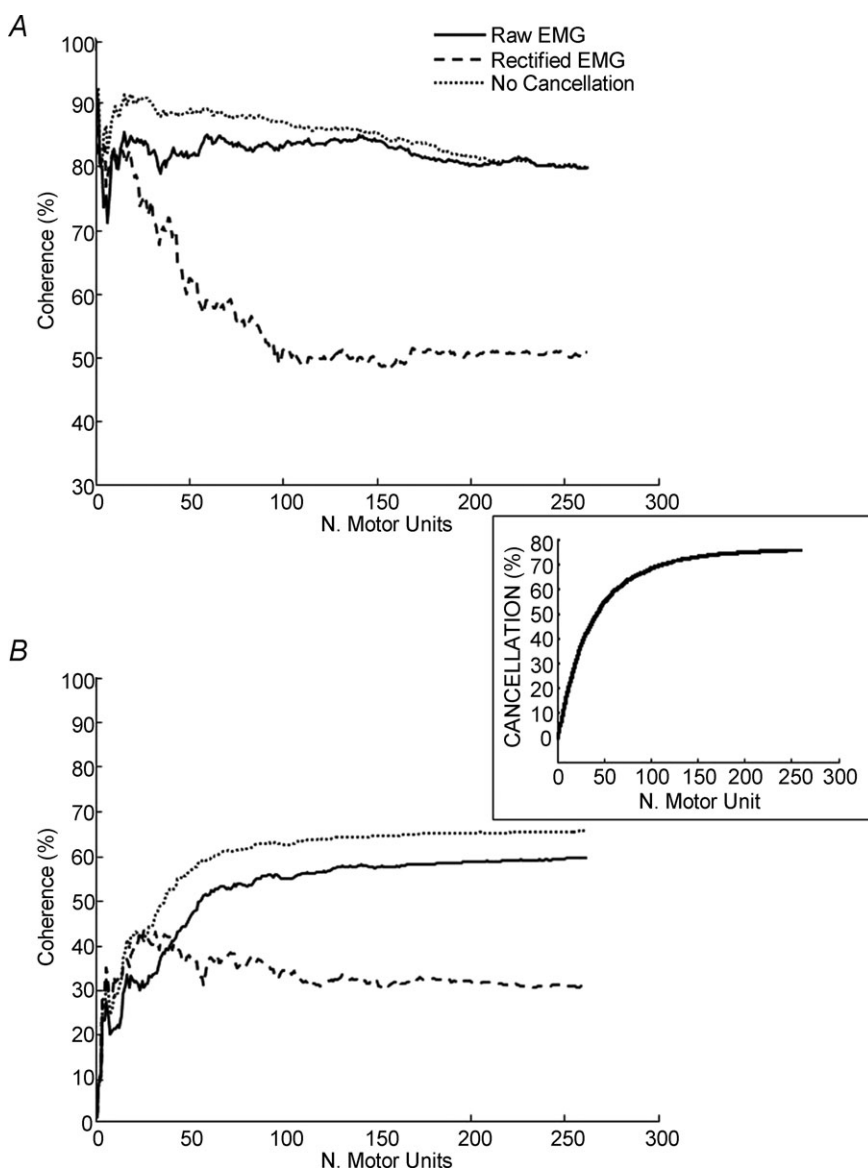


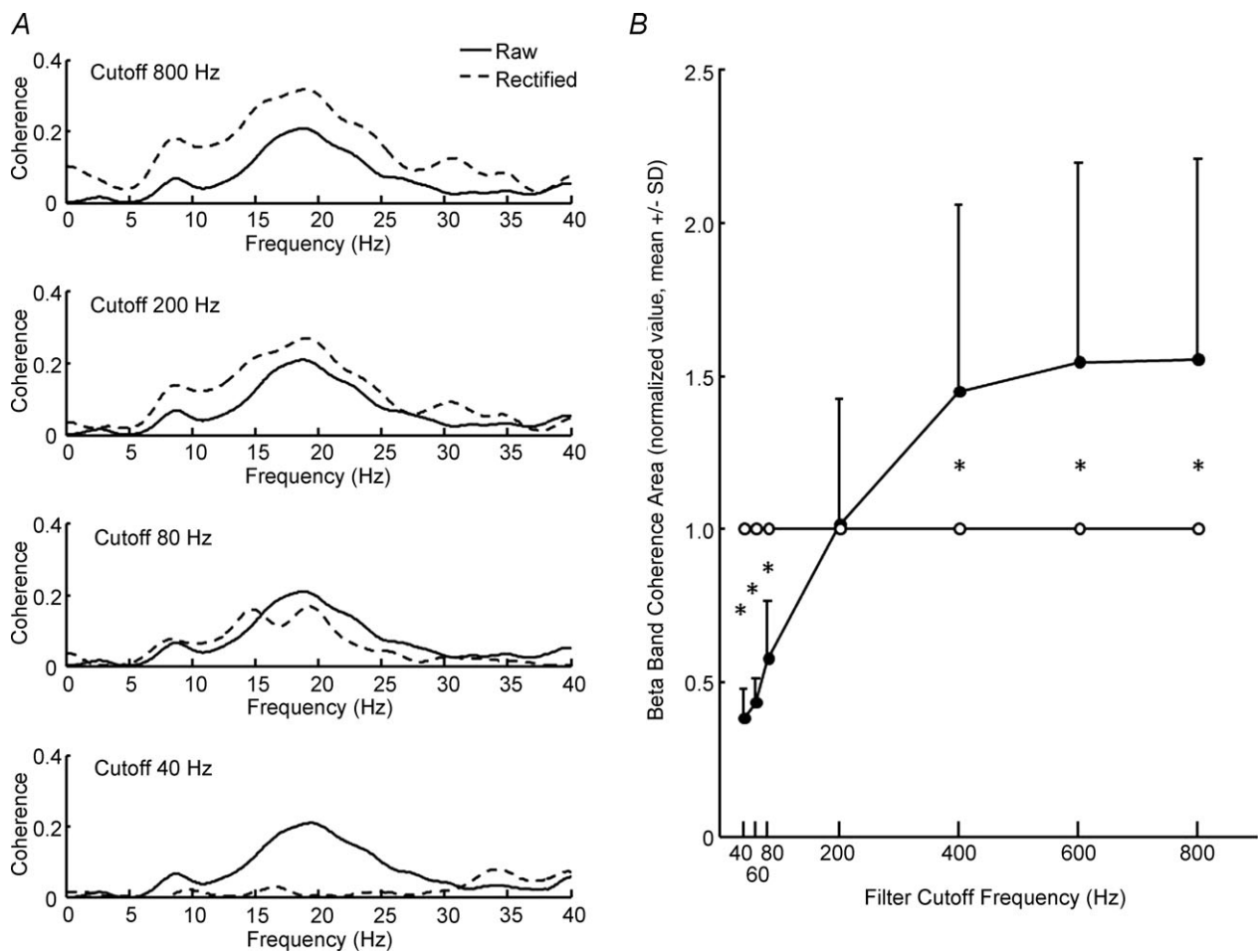
Figure 4. Coherence between input and EMG

Coherence values between the raw, rectified and no-cancellation EMG and the composite spike train (A) or the input signal (B), varying the number of active motor units (and thus cancellation level; see inset). The common oscillatory input is in this case set to 20 Hz. The inset represents the relation between the number of active motor units and the level of amplitude cancellation.

neurons from the EMG because this input is common. The spreading of common input to populations of neurons linearizes the input–output relation (Negro & Farina, 2011a). This explains how non-linear transmission in individual neurons can be identified with linear analysis methods (coherence). The second important aspect of the theory is that the oscillatory input components are also present in the rectified EMG (eqn (11)), even if this is a non-linear transformation of the raw EMG. Actually these components may even be strengthened by rectification. Claims that rectification is not appropriate for EMG analysis based on signals that do not share the same structure of the EMG (McClelland *et al.* 2012) are clearly not valid. Similarly, simulations of the EMG that do not consider this structure (Neto & Christou, 2010) are not

appropriate for discussing the issue at hand, as correctly indicated by Halliday & Farmer (2010).

The input oscillatory component is multiplied in the EMG spectrum by the Fourier transform of the action potentials (rectified or raw depending on the pre-processing step) at the input frequency. If the rectified action potential has more energy than the raw potential at the input frequency, then the gain factor is greater for the rectified EMG. Usually, this is indeed the case since oscillatory inputs are generally below 30 Hz, a region where the raw action potential may have negligible energy (this is more marked for intramuscular EMG than for surface EMG which explains the need to rectify the intramuscular EMG to detect coherence peaks in EMG–EMG coherence studies; Danna-Dos Santos *et al.* 2010). For



very low contraction levels when the number of active motor neurons is relatively small and for low input frequencies, coherence with the raw EMG may not even allow the detection of any peak in correspondence to the input frequency whereas the use of the rectified EMG may magnify this component because of the greater energy of the rectified action potential at that frequency. Therefore, rectification may be *necessary* in *some* conditions. Conversely, when the contraction level increases, the gain due to the number of active motor neurons increases and the raw signal spectrum may show the input peaks. At the same time, the amplitude cancellation term increases and the rectified signal spectrum may display a less marked peak at the oscillatory input frequency because of the cancellation term (Figs 2, 3 and 5). Similarly, in conditions in which amplitude cancellation is particularly high (for example, with long action potentials; Keenan *et al.* 2005), rectification may be less appropriate than using the raw signal. In general, it is worth noting that the strength of oscillatory input components as assessed by the rectified EMG depends on the level of amplitude cancellation, which changes with contraction level, fatigue, or across subjects and muscles. Comparisons among these conditions are thus complicated by the unknown effect of cancellation on the expression of oscillatory input peaks in the rectified EMG spectrum. Conversely, the raw EMG spectrum is not influenced by cancellation and is thus less influenced by these factors. The generality of the conclusions drawn from this study derive from the association between an effect that has been quantified and investigated extensively in the past (amplitude cancellation) with the effectiveness of rectification in enhancing the oscillatory input components in the EMG signal. Since the conditions that influence amplitude cancellation have been well established (e.g. Farina *et al.* 2008), it is possible to infer the conditions in which rectification is critical for identifying oscillatory drives to motor neurons.

Being a general theory, the proposed framework explains a number of previous observations that were based on specific simulations and were thus limited to some conditions. For example, Boonstra & Breakspear (2012) noted that the uniformity in shapes of the action potentials across motor units had an influence on the effectiveness of EMG rectification in identifying common frequency components at the input of two populations of motor neurons. It is well known that amplitude cancellation in the EMG is maximum when all action potential shapes are the same and in general it decreases the more heterogeneous are such shapes (Farina *et al.* 2008). Therefore, the observation by Boonstra & Breakspear (2012) based on simulations is now explained by the influence of uniformity in shapes among action potentials on the degree of cancellation and thus on the spectrum of the rectified EMG. Similarly, pre-filtering the surface

EMG has an impact on the shapes of action potentials that in turn influence cancellation (Keenan *et al.* 2005). Thus, it is not surprising that pre-filtering may change the effectiveness of EMG rectification with respect to the raw signal (Boonstra & Breakspear, 2012). This property, that was theoretically predicted in this study, has been actually used for supporting this prediction with experimental evidence (Fig. 5).

Finally, it is worth noting that the linearization of the input/output characteristics of a pool of motor neurons may be a strategy also adopted in other parts of the nervous system. For example, the decoding of the activity of a population of retinal ganglion cells shows a rapid saturation of the information transferred when using just a few neurons, indicating common projections (Warland *et al.* 1997). Similar results have been observed in the auditory system (Machens *et al.* 2001) and Baker *et al.* (2003) showed this concept in the central nervous system of primates, with the observation that a small population of pyramidal track neurons could transmit the cortical oscillations recorded by local field potentials correctly. Therefore, apart from the specific methodological focus of the present contribution, the conclusions on linear transmission by common projections may have a more general validity.

In conclusion, EMG rectification is not necessarily an inappropriate way to pre-process the EMG signal to identify oscillatory common inputs to motor neurons. Rather, in some cases it may be a necessary pre-processing step to identify these components. Oscillatory common components at the input to motor neurons are present both in the raw and in the rectified EMG and may be stronger in one or the other signal depending on the level of amplitude cancellation. The degree of cancellation indeed influences the effectiveness of rectified EMG in transmitting input signal components. As a note of caution, each time rectification is used, the transmission of oscillatory inputs to motor neuron outputs cannot be compared using coherence methods across conditions in which cancellation may vary (e.g. different subjects, levels of fatigue, etc.; Keenan *et al.* 2005). Finally, common projections of the same input to arrays of neural cells, as shown for motor neurons in this study, may be a strategy to linearize the input/output characteristics of a pool of neurons also adopted in other parts of the nervous system, such as in the auditory system. In these conditions, the common input characteristics can be extracted from the cumulative output of the cell pool.

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Author contributions

The experiments were conducted at the Department of Neurorehabilitation Engineering, University Medical Center Göttingen, Germany. All authors contributed to the conception and design of the experiments, and to the collection, analysis and interpretation of the data. D.F. drafted the manuscript and all authors contributed in revising it and approved the final version of the manuscript.

Acknowledgements

We acknowledge financial support by the German Ministry for Education and Research (BMBF) via the Bernstein Focus Neurotechnology (BFNT) Göttingen (grant no. 1GQ0810) (D.F.).