

Motor Neuron synchronization reduces extraction capacity of common synaptic input

Javier Yanguas

Biomedical Signal Interpretation and
Computational Simulation (BSICoS)
University of Zaragoza
Email: jyanguas@unizar.es

Pablo Laguna

Biomedical Signal Interpretation and
Computational Simulation (BSICoS)
University of Zaragoza
Email: laguna@unizar.es

Jaime Ibanez

Biomedical Signal Interpretation and
Computational Simulation (BSICoS)
University of Zaragoza
Email: jibanez@unizar.es

Abstract—Previously, it has been shown that populations of spinal motor neurons (MN) can act as a linear system transmitting the common inputs they receive in a linear way to the muscles. However, this transmission can be affected by the level of synchronization of sets of MN innervating a muscle. At present, the underlying mechanisms producing MN synchronization and their relation to the transmission of other signals are unclear. Here we propose a computational model to simulate different levels of MN synchronization and study how this synchronization affects the linear transmission of common inputs (information related to cortical processes) to the outputs (MN spike trains) and how this can be compensated using alternative methods to decode common neural inputs to MN pools.

I. INTRODUCTION

In a simplified model of the neural control of muscles, motor neurons (those that connect the nervous system with the muscles) receive common inputs (CI) and independent inputs (II). The CIs represent the sum of all the synaptic inputs that is shared by the pool of motor neurons innervating a muscle [1]. The IIs, on the contrary, represent the part of the net synaptic input that is uncorrelated across the motor neurons in the pool.

Due to the differences in the biophysical properties of the motor neurons innervating a muscle and the differences in the inputs they receive, the way in which motor neurons sample the CIs is partly independent for each neuron. As a consequence of this, the sum of the neural activity generated by a group of motor neurons innervating a muscle is amplified and transmitted linearly to the muscles. This amplification and linearization process has been proposed to be a key property of motor neuron pools allowing robust neural control of movements, by ensuring that low-frequency CIs (<10 Hz) to motor neurons are reliably transmitted to the muscles causing muscle contraction and force generation. Importantly, muscles do not only receive CIs at low frequencies, but they also receive inputs at higher frequencies, such as in the beta and gamma bands (between 13 and 50 Hz) which are likely originated in cortical regions [2] [3]. Similarly to low-frequency contents, high-frequency inputs to motor neuron pools are assumed to be amplified and linearly transmitted by motor neuron pools. This implies that it may be possible to characterize neural oscillations in the central nervous system by characterizing the common neural activity in a motor neuron pool. However, this assumption relies on a critical factor which is the level

of synchronization of motor neurons (that is, the lack of independence in the firing times of different neurons in a pool).

Indeed, the influence that the level of firing synchronization across MN has on the linear transmission of CIs to muscles is insufficiently known. To advance in this area, here we use a computational model of a pool of MN receiving inputs at different frequencies and we study how the simulated CIs can be identified by analyzing the outputs of MNs when different levels of firing synchronization are imposed. In other words, we studied the extraction of common information based on the MN activities in synchronization-dependent contexts.

II. METHODS

A. Computational Model

The model used for the simulations is the one used in [4]. In short, the model simulates a MN pool consisting of 177 slow-type MN. This represents the type of MN active during low-level forces. Each of the 177 MN is represented as a conductance-based two-compartment model (dendritic and somatic compartment), based on previously published work.

B. Inputs Design

We simulated two different CIs. One of the CIs was the synchronization signal (0-10 Hz, like the motor control signal) and the other CI was an input at the beta frequency (26 Hz), which was the input that had to be decoded from the MN activity. The synchronization between MN was induced by increasing the power of the 0-10 Hz signal relative to the power of the IIs. The power of the beta signal was unaltered across conditions to test how synchronization affects the extraction of the beta input. Once adjusted in power, both inputs were combined into one.

Both CIs were simulated by filtering and scaling white Gaussian noise with third-order Butterworth filters. The synchronization signal was low-pass filtered at 10 Hz and the beta signal was band-pass filtered around 26 Hz (3 Hz bandwidth). After filtering, the signals were divided by their root-mean-square and multiplied by the target power.

We tested three different powers of the synchronization signal: 0, 0.5 and 1 μ A. In every case, the power of the beta

signal was 0.08. This is the maximum power of the beta signal so the mean firing rate (FR) of the MN pool is not modified.

To simulate the IIs we used white Gaussian noise with mean equal to variance. The mean of the II was preliminary adjusted to make the simulated motor neuron pool achieve a mean FR of approximately 11 Hz without common signals. As we adjusted the IIs to achieve a mean FR of 11 Hz, the beta frequency of the CI was set to 26 Hz to avoid misinterpretations due to interference effects of the first harmonic of the FR (around 21-22 Hz). For each condition tested (power of the low-frequency CI equal to 0, 0.5 and 1), 3 simulations of 20 seconds each were performed.

C. Correlation and synchronization

To assess the effectiveness of the transmission of the 26 Hz CI at different synchronization levels, the Pearson correlation coefficient was computed between the instantaneous amplitude of the filtered cumulative spike train and the filtered CI. The composite spike train was obtained by summing the spike trains of individual motor neurons. The amplitude correlation was computed as a function of the number of MN (randomly selected) used to construct the cumulative spike train. Results were averaged across 50 iterations. To compute the amplitude correlation, the beta input and the cumulative spike trains were band-pass filtered at 26 Hz and Hilbert transformed. The synchronization was measured using the cross-correlation histogram between pairs of motor neuron spike trains. 50 iterations were calculated in each condition. The population power spectrum was computed by calculating the power spectrum of the cumulative spike train.

III. RESULTS

Figure 1 shows the effect of increasing the power of the low-frequency (0-10 Hz) common signal. As the power of this CI increases, MN start firing synchronously, which is reflected by the increased power at the frequency matching the average FR in the population power spectrum (around 11 Hz, Fig.1 left). The consequence of increased levels of synchronization is a lower capacity of adequately transmitting other frequencies by the motor neuron pool, as revealed by a lower correlation between the filtered composite spike train and the CI at 26 Hz (Fig.1 right). These results show that synchronization explicitly worsens the extraction of the beta signal, and suggest that independence in MN firing may be a necessary condition for CI extraction.

Interestingly, when using higher frequencies to define the synchronization signal (filtering white noise from 30 to 40 Hz instead of 0 to 10 Hz, for example), this increased power in the FR in the population power spectrum is not observed and the correlation of the beta frequency is not reduced (results not shown), suggesting that the low-frequency motor control signal is indeed responsible of the motor neuron synchronization. This phenomenon can be explained as a non-linearity in the MN system. When using the first condition (null power of the synchronization signal), the sum of the power spectra of the individual spike trains is not equal to the power spectrum of

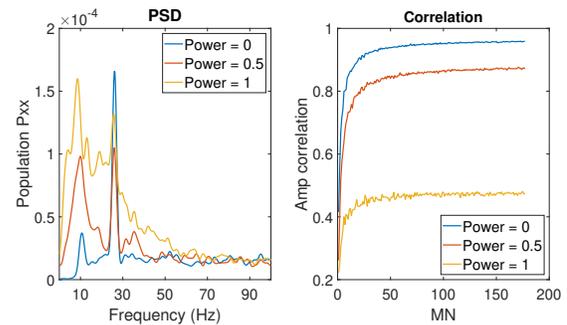


Fig. 1: **Left:** PSD of simulated population (sum of 30 MN) at powers (0 [blue], 0.5 [red] and 1 [yellow]) of the 0-10 Hz oscillation. **Right:** Amplitude correlations between cst and CI at 26 Hz as a function of the number of MN included in the cst.

the sum of the individual spike trains, with the first having its maximum power at the FR frequency and the latter having its maximum at the frequency of transmission (26 Hz). However, when increasing the power of the synchronization signal, then the sum of the individual power spectra of each spike train and the power spectrum of the sum of spike trains become more similar (especially when increasing the number of MN involved), as the synchronization produces an increase in the FR frequency power and a decrease in the beta frequency power.

IV. CONCLUSION

In this work, we studied how synchronization affects the extraction of beta signals, where synchronization was modeled by increasing the power of the low-frequency CIs. The main conclusion of this study is that MN synchronization reduces the capacity of the MN pool to linearly transmit common inputs in high frequency inputs such as in the beta band. As these results complement our understanding of MN sampling process, new methods driven by this information could be developed to estimate neuronal sources better.

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