A Review of Methods to Characterize Motor Unit Firing Properties and Underlying Determinants

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1 OBJECTIVES

This paper reviews traditional and novel techniques for the characterization of motor unit firing properties and the determination of their underlying determinants.

These methods are becoming increasinly important because of advances on techniques to accurately identifiy the spike trains of several motor units non-invasively (Holobar and Zazula, 2007, Holobar et al., 2009), which enables the assessment of the neural drive to muscle in an unprecedented accurate fashion. It is further motivated by the fact that traditional analysis using the surface electromyogram (EMG) is largely influenced by a number of intrinsic factors that limit the accuracy that may be attained (Farina et al., 2004). Being the most relevant among them the effect of the spatial filter effect due to volume conduction of motor unit action potentials through soft tissues to the skin (where they are recorded, Merletti et al., 2008), the influence of cross-talk among neighboring muscles (Farina et al., 2004), and the effect of cancellation of motor unit actions potentials (Keenan et al., 2004).

Throughout this review we employ the terms motor unit or motor neuron according to common usage in literature.

2 SIGNAL PROCESSING METHODS

2.1 Motor Unit Firing Statistics

Statistical properties of the interval between motor unit discharges provide the first relevant piece of information when investigating the neural drive to muscle. The histogram representing the distribution of the time period between consecutive motor unit discharges, termed inter-spike interval (ISI) histogram has been widely used in the field. For example, it has been shown that, in patients suffering from some neurological diseases (e.g., Parkinson's disease, Christakos et al., 2009), these histograms exhibit abnormal patterns. Second and third order distributions, which reflect the interval between two and three consecutive discharges, have also proved to be useful in some contexts.

2.2 Motor Unit Synchronization

The development of techniques to accurately estimate motor unit synchronization has received considerable attention (see the reviews in Nordstrom et al., 1992, and Negro and Farina, 2012) because of the observed relation between common-stem synaptic inputs and the increased possibility of motoneurons firing simultaneously (Kirkwood and Sears, 1978).

Most existing techniques are based on the calculation of the cross-correlogram between pairs of motor neurons, and the calculation of metrics based on its characteristics. Relevant examples of this are the Common Input Synchronization index (CIS) proposed in (Nordstrom et al., 1992), which is defined as the count of discharges in excess of chance, and calculated as the area of the peak in the cross-correlogram divided by its duration. Other relevant synchronization metrics based on the cross-correlogram are De Luca's common drive index (CDI, De Luca et al., 1982), and the synchronous impulse probability (SIP, Datta et al., 1990).

Interestingly, it has also been shown that the cumulative sum of the cross-correlogram permits identifying the significant peak in the cross-correlogram (Ellaway, 1978), and it is useful to assess whether such peak is statistically significant (Davey et al., 1986).

L. Dideriksen J., Gallego J., Negro F., Holobar A. and Farina D..
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The influence of the frequency of the synaptic input has been a traditional concern as to the usage of metrics to assess motor unit synchronization using the cross-correlograms (Nordstrom et al., 1992). A recent study by Negro and Farina demonstrated that such influence significantly distorts the results in healthy subjects, based on simulation and experimental data (Negro and Farina, 2012). The authors of that paper showed that a method based on the activities of several motor units provides a better, unbiased indicator of the properties of common synaptic input to motor neurons (Negro and Farina, 2012), as explained below.

2.3 Common Synaptic Inputs to Motor Neurons

As previously mentioned, animal studies proved that the presence of an input common to a population of motor neurons increases the possibility of such units firing synchronously (Kirkwood and Sears, 1978). However, the estimation of this input is largely influenced by the statistics of input current and the discharge rate of the motor neurons (Negro and Farina, 2012). Indeed, higher discharges rates imply a better sampling of the input current, and thus allow a better reconstruction.

Under the assumption that groups of motor unit spike trains (referred to as composite spike trains) increases the average sampling rate of the common input to motor neurons (Negro and Farina, 2011, 2011b), Negro and Farina showed that the coherence between such composite spike trains provides the best estimate of the strength and frequency of common synaptic inputs to motor neurons. Notice that coherence is the normalized Fourier transform of the cross-correlation function, and that it is independent of filter functions.

Interestingly, traditional methods for the estimation of motor unit synchronization (see Section 2.2), and thus of common input properties, consisted in applying certain filters to the cross-correlogram (e.g., De Luca et al., 1982, Nordstrom et al., 1992), which corresponds, in the frequency domain, to considering a certain frequency band of the coherence spectrum (Negro and Farina, 2012). This clearly shows that such estimators are intrinsically influenced by the input frequency.

2.4 Corticospinal Coupling

The projection of supraspinal, typically cortical, oscillations to the muscle has been commonly investigated by computing the coherence between the supraspinal signal and the surface EMG. This technique has allowed demonstrating the existence of cortical involvement during different type of muscle contractions in healthy subjects (Conway et al., 1995, Raethjen et al., 2008), and also in the case of tremor (Volkmann et al., 1996).

Remarkably, since coherence is a linear technique, the existence of significant coherence between the supraspinal signal and the EMG implies that the transmission is partly linear, despite the non-linearity of the motor neuron transfer function (Gerstner and Kistler, 2002, Negro and Farina, 2011). However, due to the intrinsic limitations of the surface EMG, it is not possible to gather further insight on how such projection actually occurs.

A recent study showed that linearity of the transmission can only be achieved if the supraspinal inputs mediating voluntary contraction are a common synaptic input to the motor neuron pool (Negro and Farina, 2011). This was demonstrated based on two facts. The first was that sampling a few motor neurons already provided significant coherence, which implies that a few motor neurons are able of transmitting the cortical input. The second observation was that the accuracy of such estimation (magnitude of the coherence) did not further increase after a few motor neurons were sampled, which indicates to a saturation in sampling, only possible in the case of common inputs.

The demonstration of the linearity of the transmission also has physiological implications, because due to the non-linear properties of interneurons (Gerstner and Kistler, 2002), linear transmission implies that direct pathways mediate voluntary contractions. Thus, such finding further supports the relevant role of the corticospinal tract in voluntary movement control (Lemon, 2008).

3 CONCLUSIONS

In this paper we have reviewed traditional and novel methods to assess motor unit properties and their underlying determinants. These methods are becoming increasingly important since they permit to assess motor unit activities with an unprecedented accuracy, thereby enabling advances in basic neuroscience, muscle physiology and motor control, thanks to a more accurate characterization of the neural drive to muscle

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