CHARACTERIZATION OF NEURON FIRING PULSES IN ELECTROMYOGRAPHIC SIGNAL

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Abstract - An Electromyographic (EMG) signal may be modelled as a filter representing the motor unit action potential convolved with a train of neuron firing pulses. Recovery of the neuron firing pulses is difficult especially when a large number of fibres are firing at the same time. This paper presents a technique of EMG signal decomposition allowing the recovery of neuron-firing pulses. The technique has been applied to some real EMG signals and shows that the rate of firing pulses increases if a subject increases muscle effort.

1. Introduction

One model often used in myoelectric signal processing is the EMG signal as the output of a LTI system that is convolved with the neuron firing pulses. This model of an EMG signal $y(n)$ can be expressed as (1) [shaded part of Fig. 1] where $e(n)$ is the input of a LTI system representing the neuron firing pulses, $h(n) = F^{-1}[H(k)]$ is a filter representing the MUAP and $w(n)$ is the system noise

$$y(n) = e(n) \otimes h(n) + w(n)$$

[1] reported that the neuron pulses are random in nature. [2] considered the firing pulses as non-Gaussian white noise. [3] demonstrated the non-Gaussianity of the firing pulses in contracting muscle’s surface EMG signal. Upon considering a LTI system input signal as non-Gaussian white noise (random impulse train), higher order statistics techniques [4]-[8] can be applied to estimate the input impulse train. This paper uses the cepstrum of bispectrum [4] [5] approach to blind deconvolution to reconstruct the system and then to recover and characterize the neuron firing pulses from a real EMG signal.

Fig. 1: Block diagram of blind system’s input impulse reconstruction. Block belongs to dash line indicates the blind signal generation concepts.

2. System’s Input Signal Estimation

Blind deconvolution techniques allow for estimation of a system and its unknown input from a LTI system’s output signal. Generally, the problem of recovering the input signal can be overcome by designing or estimating one or more systems that can be cascaded with the original system [other than the shaded part of Fig. 1]. Let $y(n)$ be an output signal of a LTI system of which we want to estimate the input signal. Now, if the signal passes through a filter $h_i(n) [= F^{-1}[H_i(k)]]$ whose frequency domain relation with the original system $h(n)$ is

$$H(k)H_i(k) = 1 \quad \text{or,} \quad H_i(k) = 1/H(k)$$

(2)
i.e., the filter $h_i(n)$ is the inverse filter. The output of this inverse filter $z(n) = F^{-1}[Z(k)]$ can be written as

$$Z(k) = Y(k)H_i(k) = [E(k)H(k) + W(k)]H_i(k) = E(k)H_i(k) + W(k)H_i(k)$$

$$= E(k)H_i(k) + E_w(k)$$

where $Y(k)$, $E(k)$ and $W(k)$ are the frequency domain representations of $y(n)$, $e(n)$ and $w(n)$. The frequency domain inverse filter can be found from [8]

$$H_i(k) = \frac{1}{|H(k)| \exp(-j\phi(k))}$$

Thus the frequency domain inverse filter can be estimated if the frequency domain system (or its Fourier magnitude $|H(k)|$ and Fourier phase $\phi(k)$) is known. The Fourier magnitude and Fourier phase of the blind system can be estimated using either the log-bispectrum [6], [7] or cepstrum of bispectrum [5] based system recognition algorithm. Here we use the cepstrum of bispectrum approach.

[8] applied the frequency domain form as (3) to estimate the input signal from the blind system’s output signal. We also use the frequency domain form and then apply the inverse Fourier transform to $Z(k)$ to estimate the input signal $e(n)$ with noise component $e_w(n)$.

It is generally assumed in signal processing that the system noise is a random signal and, in practice, its average amplitude is smaller than the typical impulse (firing pulses) amplitude. As it is of interest to observe the nature of the firing pulses, a logical filter can be used to cut-off noise level (up to any desired level). The logical filter uses the equation

$$\hat{e}_o(n) = \begin{cases} \{z(n)\}' & \text{if } \{z(n)\}' \geq t_l \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{e}(n) = M(n).z(n) \text{ where } M(n) = \begin{cases} 1 & \text{if } \hat{e}_o(n) \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

where $r \geq 2$ is a parameter that sets the attenuation level and $t_l$ is the threshold level and $\hat{e}_o(n)$ is the resulting estimated sequence of pulses. Note that the estimated input impulses may not be the same as those of the actual system input if the threshold level is not chosen accurately and also when any system input impulse level is below the threshold.

3. Results - Application of Input Signal Estimation Theory

Three fine wire EMG (wEMG) signals were used for estimating firing pulses. The EMG signals were recorded from the Rectus Femoris (RF) muscle when the subject was seated with 30 degree hip flexion and had three different loads (0Kg, 1Kg and 2Kg) at the ankle. Applying the above method to one second duration EMG signal, three neuron firing sequences were recovered and are plotted in Fig. 2. In all cases, the cepstrum of bispectrum based system estimation followed by inverse filtering was used. Moreover, for each application of the logical filter, the attenuation level was same i.e., $r = 2$ and the threshold level was fixed.

4. Discussion and Conclusion

It is observed from Fig. 2 that the number of neuron firing pulses becomes higher when the load on the subject increases. Again, [4] reported that the shape of the MUAP in EMG signals when different loads are applied to the same muscle remains similar and differs from the
Fig. 2: Neuron firing pulses observed in the wEMG signal from Rectus Femoris muscle at hip flexion to 30 degree and the subject has (a) no load, (b) 1.13 Kg and (c) 2.26 Kg.

resting muscle’s MUAP. Therefore, it can be concluded that when a subject increases effort to do more work, the rate of neuron firing increases.

References