BLIND SEPARATION OF EMG AND ENG CUFF ELECTRODE RECORDINGS

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ABSTRACT

ENG signals recorded by cuff electrodes are usually contaminated by EMG activity from nearby muscles. Blind source separation is demonstrated as a method of separating these signals for use with FES applications.

INTRODUCTION

Nerve cuff electrodes can record Electroneurographic (ENG) signals elicited from cutaneous mechanoreceptors. Furthermore, this signal can be related to specific stimuli and as a result can be used as a command and control signal in functional electrical stimulation (FES) applications [1]. Unfortunately, electromyographic (EMG) interference contaminates the ENG signal and is typically removed by high-pass filtering. However, experiments with cuff electrodes have demonstrated that EMG activity is dependent on which muscles are active [2]. Therefore as the ENG signal primarily indicates changes in state, the EMG activity could be used as an independent control signal. Consequently, this paper demonstrates blind source separation as a method of separating EMG and ENG signals recorded by nerve cuff electrodes, so that they can be used independently as command and control signals in FES applications.

THEORY

Blind source separation [3] is a neural network based method that separates a linear mixture of statistically independent source signals received by different sensors, by the use of high-order statistical moments in the learning algorithm.

The EMG and ENG signals are considered as independent signals $x_1(t)$ and $x_2(t)$ respectively. The true-tripole electrode/amplifier arrangement [4] is modified to provide two bipolar channels of data $s_1(t)$ and $s_2(t)$ respectively i.e. the output of the algorithm. Therefore it can be shown that $s_1(t)$ and $s_2(t)$ are linear equations equal to:

$$s_1(t) = \frac{(a_{11} - w_{12}a_{21})x_1 + (a_{12} - w_{12}a_{22})x_2}{1 - w_{12}w_{21}}$$

$$s_2(t) = \frac{(a_{21} - w_{21}a_{11})x_1 + (a_{22} - w_{21}a_{12})x_2}{1 - w_{12}w_{21}}$$

Which is stable whilst $w_{12}w_{21}<1$. Furthermore, Jutten and Herault proposed a learning rule of the form:

$$\frac{dw_{ij}}{dt} = \mu_i \phi(s_i)\varphi(s_j)$$

Where $i,j = 1,2$, $\mu = 1/\tau$ is the adaptation gain, $\phi(s)$ and $\varphi(s)$ are odd non-linear functions containing the power terms necessary for the learning algorithm.

RESULTS

Data was recorded from a cuff implanted around the digital nerve of a human subject, whilst the index finger was stroked. Figure 1 shows a portion of this data, along with the separated EMG and ENG signals.

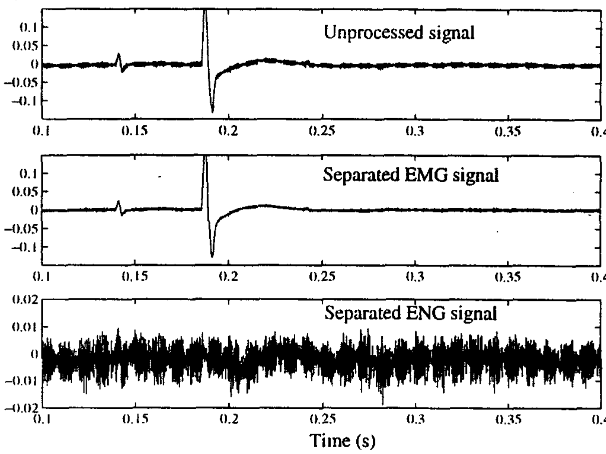

Figure 1: Unprocessed ENG data (top) containing EMG and ENG signals, separated EMG (middle) and separated ENG (bottom).

ACKNOWLEDGEMENTS

Dr Morten Haugland, for providing the experimental data. Support for this research comes from the EPSRC (UK).

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