EXTRACTING MOTOR UNIT FIRING INFORMATION BY INDEPENDENT COMPONENT ANALYSIS OF SURFACE ELECTROMYOGRAM: A PRELIMINARY STUDY USING A SIMULATION APPROACH

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ABSTRACT

Decomposition of electromyogram (EMG) provides a valuable means of obtaining motor unit recruitment and firing rate information. The feasibility of decomposing surface EMG signals into their constituent motor unit action potential (MUAP) trains using independent component analysis (ICA) was examined using simulated EMG data. Surface EMG signals detected with an array of nine electrodes were simulated when nine motor units were active. The electrodes were positioned in three different locations with respect to muscle fiber orientation. It was found that ICA based on an instantaneous mixing model was not able to separate all the MUAP trains due to shape variations and time delays between the surface action potentials detected at the different electrode locations. However, from certain independent components, the firing information of a very limited number of motor units could be obtained. This suggests that ICA based on an instantaneous mixing model may yield firing rate information of a small number of motor units from surface EMG signals recorded at relatively high force levels. However, to obtain more information, blind source separation techniques addressing a more complex convolutive mixing model are required. Similar results were obtained for each of three different electrode locations and orientations.

Keywords: ICA, Surface EMG, Decomposition, Motor unit

1. INTRODUCTION

The electromyogram (EMG) signal is composed of the summation of motor unit action potential (MUAP) trains from all active motor units within the electrode recording range. The EMG signal can be recorded noninvasively using surface electrodes or by an intramuscular approach using needle or wire electrodes. To obtain physiological or clinical information from the EMG signal, a wide range of quantitative EMG analysis methods have been developed (Fuglsang-Frederiksen 1989, 2002; Finsterer 2001). Among these methods, the most frequently used are measurements based on the amplitude of the EMG signal. An alternative method is to count the number of zero-crossings, turns, spikes or small segments of EMG signal per unit time to measure the muscle activity. Frequency domain EMG processing techniques are also employed. The most commonly used parameters are the mean frequency and the median frequency of the EMG power spectrum. To overcome the limitations of Fourier transform, time frequency representations can be used to obtain both time and frequency resolutions of the EMG signal, particularly during dynamic contractions (Bonato et al. 1996; Laterza and Olmo 1996; Olmo and Laterza 1999; Karlson et al. 1999, 2000;). Other EMG processing methods include fractal analysis (Anmuth et al. 1994; Gitter and Czerniecki 1995; Gupta et al. 1997), and recurrent quantification analysis (Filligoi and Felici 1999).

All of these methods have been widely applied in EMG analysis. However, the motor control information contained in the signal is not very clear. The central nervous system controls muscle force generation by adjusting the recruitment and firing rates of motor units. Therefore, as muscle force increases, the EMG interference pattern changes as motor units are recruited and the rate at which they are firing increases. Conventional EMG processing methods are not directly related to the neuromuscular control mechanisms because they can not distinguish between changes in EMG that are due to differences in motor unit recruitment and firing rate or due to some other factors such as variations in action potential shapes or sizes, and different motor unit locations, etc.

One method of obtaining recruitment and firing rate information from EMG signal is to use an EMG decomposition technique. EMG decomposition is the procedure by which the EMG signal is separated into its constituent MUAP trains. It is a complicated process that requires advanced signal processing and pattern recognition techniques. In the past three decades, many efforts have focused on developing reliable EMG decomposition techniques (LeFever and Deluca 1982; LeFever et al. 1982; McGill et al. 1985; Fang et al. 1999; Gut and Moschytz 2000). Because of high selectivity of needle or wire electrodes, almost all of the EMG decomposition methods were designed towards intramuscular EMG. Furthermore, due to difficulties in dealing with action potential superposition, these methods only address EMG waveforms where two or at most three action potentials are superimposed (Stashuk 2001). Surface detection of EMG offers several advantages over needle or wire detection. The surface electrode can be quickly and easily applied without medical supervision or discomfort to the subject. The repeatability of measurements for surface EMG is also higher. Perhaps more importantly, surface detection can obtain global information about the muscle activity and therefore contains much more information. This makes it more appropriate for the study of neuromuscular control mechanisms than EMG recorded by invasive methods, which is not representative of the activity of the whole muscle activity.

However, there is, therefore, a high level of action potential superposition and cancellation within surface EMG signals. Furthermore, for surface recording, due to relative large recording surface, increased spatial filtering of the propagating action potential with increasing distance between electrode and source, and spatial integrating effects under the electrode, the differences in surface action potential shapes from different motor units are not as distinctive as with intramuscular recordings (Zhou and Rymer 2004). All of this makes surface EMG decomposition an extremely difficult task, especially at high force levels. Although some investigators use the term “decomposition” for surface EMG, it is only feasible at very low force levels with no more than 5 motor units contained in the signal (Chauvet et al. 2001; Xu et al. 2001).

Due to the difficulties in decomposing surface EMG using single channel recording, an alternative means of extracting information about motor unit recruitment and firing rate information from surface EMG signal is sought. In this paper, independent component analysis (ICA) (Comon 1994) of multi-channel surface EMG data was evaluated using simulated surface EMG signals. The purpose of this paper is to investigate the feasibility of using ICA to obtain information from surface EMG signal that is directly related to the control properties (recruitment and firing rate) of the active motor units.

2. METHODS

2.1 Simulation of Surface EMG

EMG signals were simulated using a previously developed mathematical model of the surface EMG signal. The model simulations are described briefly here. Further details of the EMG model are given by Lowery et al. (2000). The properties of the EMG model for this study were based on the first dorsal interosseous muscle of the hand (Milner-Brown and Stein 1975). Twenty motor units were randomly located throughout a semi-circular muscle cross-section of radius 4 mm, Figure 1. The number of fibers assigned to each motor unit increased linearly with recruitment threshold from 20 fibers in the smallest motor unit to 100 fibers in the largest. All muscle fibers were assigned a diameter of 50 μm. Muscle fiber conduction velocity increased linearly with motor unit size from 4 m/s to 5 m/s. The fibers in each motor unit were randomly distributed throughout the entire muscle cross-section and the muscle fiber end-plate zone was assumed to lie midway along the length of the muscle. Individual muscle fiber innervation points were located randomly throughout the end-plate zone. All muscle fibers were assumed to run parallel to one another and ran the entire length of the muscle, which was 100mm long. The fiber terminations were randomly distributed throughout a region of width 5 mm centered on each end of the muscle. Nine electrodes were arranged in a two dimensional electrode array, which was located 2 mm above the muscle area. The electrodes were separated by a distance of 5 mm from one another and were simulated as point electrodes. Two different electrode configurations were used for the electrode array, with the electrodes oriented at an angle of 0 degree and 30 degrees, with respect to the muscle fiber orientation, respectively. For the third configuration, all the electrodes were placed in a longitudinal array, perpendicular to the muscle fiber orientation (see Figure 1). The distance between consecutive electrodes was 2 mm. The transmembrane current density was represented by a 15 mm long multipole comprised of 150 current sources obtained from the second derivative of the transmembrane potential described analytically by Rosenfalck (1969). All current sources were initially located at the fiber end-plate to ensure that zero net charge was maintained at all times. When the fiber was stimulated, action potentials began propagating in both directions away from the point of stimulation. Upon reaching the end of the fiber, each current source remained stationary until it was partially or wholly cancelled by a source of opposite polarity, thus incorporating muscle fiber end-effects characteristic of fibers of finite length (Gootzen et al. 1991). EMG data was generated at a sampling rate of 2 kHz. The muscle fibers were assumed to be located within homogeneous cylindrically anisotropic muscle tissue. The single fiber action potential detected at each electrode when each muscle fiber was stimulated was calculated using an infinite volume conductor model for anisotropic muscle (Andreassen and Rosenfalck 1981). Each MUAP was formed by summing together the single fiber action potentials generated by all fibers in the motor unit. Mean motor unit firing rates ranged from 8 to 14 Hz. The time between successive firings of a motor unit, the interpulse interval, was assumed to have a Gaussian distribution about the mean interpulse interval (Clamann 1969). The simulated surface EMG signal was the sum of the MUAP trains generated by all active motor units. All motor units were simulated to fire independently of one another. To satisfy the conditions necessary for ICA, the simulated surface EMG signals were generated by 9 motor units, since the number of source signals should be less than or equal to the number of recording channels. Nine active motor units were randomly chosen from a pool of 20 motor units.

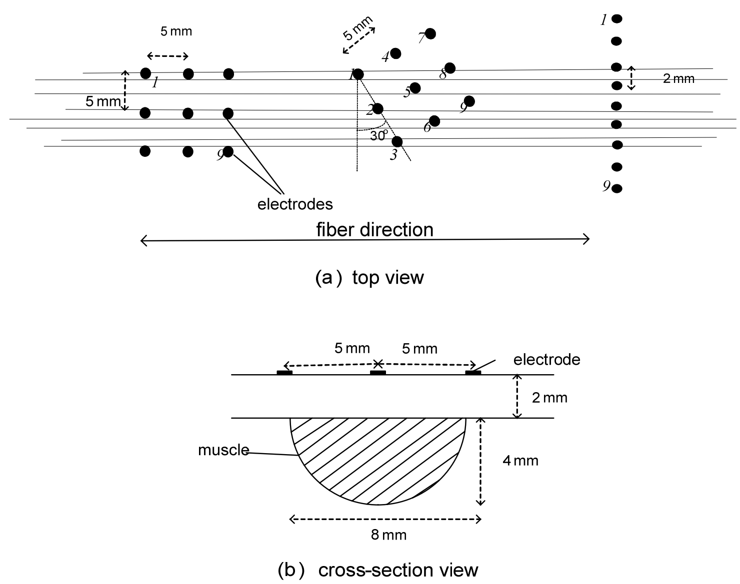

Figure 1. EMG model (a) top view illustrating the arrangement of the 3 simulated electrode configurations (b) cross-sectional view illustrating the muscle cross-section

2.2 Independent Component Analysis

For this problem the surface MUAP trains from different active motor units were the inputs to the ICA model, with surface electrodes collecting the output mixed surface action potentials or surface EMG. For a mixing model, $x = \mathbf{A}s$, where $s = \{s_1(t), \cdots s_N(t)\}$, $x = \{x_1(t), \cdots x_N(t)\}$, $\mathbf{A}$ may generally be construed as a linear time-invariant (LTI) system, there are three levels of complexity of $\mathbf{A}$:

(1) $\mathbf{A}$ is a matrix. This is the instantaneous mixing model, since only the relative attenuations of MUAP trains are accommodated.

(2) $\mathbf{A}_{ij} = a_{ij} z^{-D_{ij}}$. This is the delayed mixing model, incorporating not only the attenuations of the MUAP trains, but their travel time as well.

(3) $\mathbf{A}_{ij} = \sum_{k=0}^{L-1} a_{ijk} z^{-k}$. This is the convolutive mixing model, where the shape variations of action potential from the same motor unit collected by different electrodes are accounted for.

ICA recovers N source signals s after they are linearly mixed by multiplying an unknown system $\mathbf{A}$, $x = \mathbf{A}s$, while assuming as little as possible about the nature of $\mathbf{A}$ or the component signals. ICA aims to recover a version $u = \mathbf{W}x$ of the original sources s to make u and s identical except scaling and permutation. The key assumption used in ICA is that the sources are as statistically independent as possible. Specifically, the determining criterion for separation is a measure of independence, typically represented by some cost function. There are varieties of cost functions including kurtosis, mutual information, cross power spectra, negentropy or log-likelihood, etc., which can be shown to be mathematically equivalent in many cases. Therefore, ICA is an optimization process by finding the extremum of the cost function under the condition $u = \mathbf{W}x$. Such a system is illustrated in Figure 2. In this paper, ICA based on standard infomax algorithm (Bell and Sejnowski 1995) was employed to process the simulated surface EMG signals. It was implemented using the MATLAB ICA toolbox developed by the researchers at the Institute for Neural Computation, University of California San Diego, and made available for research and education purpose (http://www.sccn.ucsd.edu/~scott/ica-download-form.html).

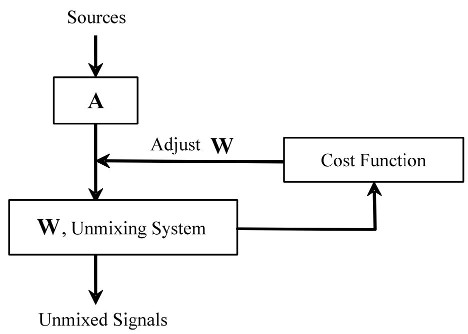

Figure 2. A source separation system

3. RESULTS

An example of 9 individual MUAP trains simulated at a single electrode is illustrated in Figure 3. The 9 MUAP trains sum linearly to yield the EMG signal detected at that electrode. Figure 4 shows simulated surface EMG signal recorded from 9 active motor units with an array of 9 electrodes oriented at an angle of 30 degrees with respect to the direction of muscle fibers. The outputs of ICA are presented in Figure 5.

Comparing the ICA outputs (Figure 5) and the input MUAP trains (Figure 4), it can be seen that the independent components do not correspond to the individual MUAP trains. Similar results were obtained after ICA based on an instantaneous mixing model for the three different electrode orientations. The correlation coefficients between the 9 input individual MUAP trains and the 9 independent components after ICA for electrode configuration 1 are presented in Table 1. The poor correlation between the input MUAP trains and the independent components conforms that ICA based on an instantaneous mixing model was not able to completely decompose the simulated surface EMG signal.

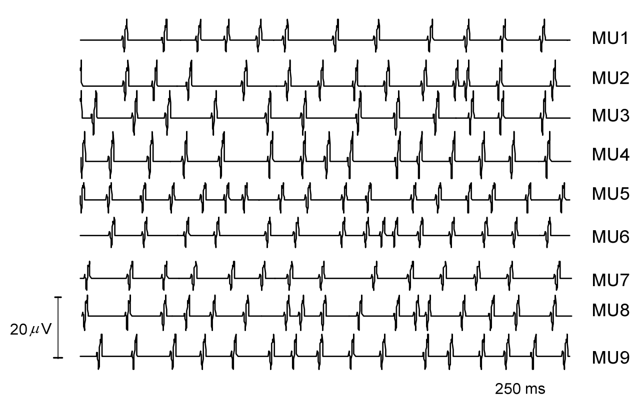

Figure 3. Simulated surface MUAP trains from 9 motor units detected at a single electrode

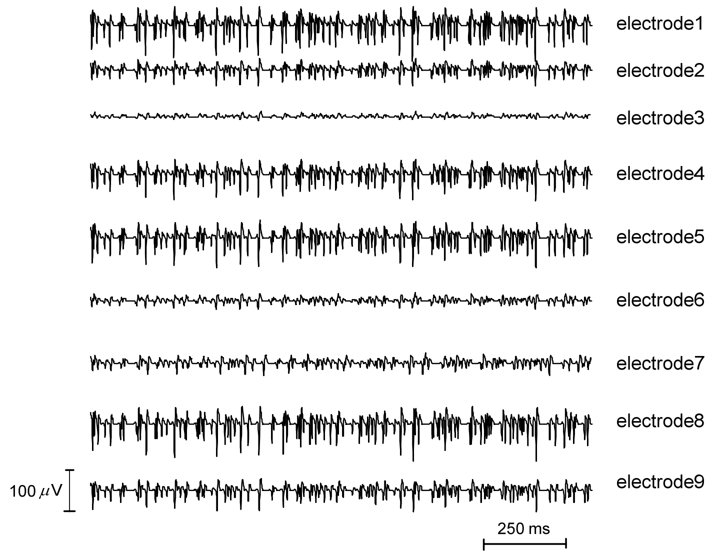

Figure 4. Simulated surface EMG signals detected from 9 motor units at 9 electrode locations using electrode configuration 2

Although ICA was not able to fully decompose surface EMG, an interesting finding was that the independent components contained information from several of the active motor units. For some of these outputs no useful information could be obtained because the level of waveform superimposition was high, similar to the original surface EMG. However, several independent components contained distinctive, high amplitude spikes that corresponded to the occurrence of each action potential from a single motor unit, Figure 5, IC9. These spikes were much more distinguishable than the surface action potentials in the original EMG signals and therefore distinguishable from one another. Based on these sharp spikes, the firing rate information from a single motor unit could be obtained. This process is illustrated in Figure 6. Figure 6 (a) shows the individual MUAP train from one motor unit (MU5) recorded by one electrode at electrode configuration 1. Due to the large amount of action potential superposition and cancellation, it was not possible to identify the occurrence of the MUAP train from the original surface EMG, Figure 4. However, on the appropriate output of ICA (IC9), the occurrence of action potential train could be identified by the sharp individual spikes, as shown in Figure 6 (b). In this manner, firing rate information for that motor unit could be obtained. This is also suggested by the correlation coefficients between the independent components and the individual MUAP trains (Table 1), where IC9 and MUAP train from MU5 have the maximum cross-correlation value. Examples of a single MUAP train and independent component which yielded a high cross-correlation value for electrode configuration 2 and 3 are compared in Figure 6 (c)-(f). Figure 7 shows the action potentials from the same motor unit collected by 9 electrodes for 3 different configurations.

Table 1: The correlation coefficients (CC) between each independent component (IC) and input individual action potential train (MU)

CC	MU1	MU2	MU3	MU4	MU5	MU6	MU7	MU8	MU9
IC1	0.1461	0.1463	0.1880	0.1555	0.0956	0.2853	0.3610	0.2302	0.3345
IC2	0.1685	0.1260	0.2159	0.1470	0.1121	0.3032	0.4039	0.1564	0.3429
IC3	0.1691	0.1401	0.2132	0.1810	0.1531	0.3172	0.4061	0.2104	0.3194
IC4	0.0945	0.1398	0.1775	0.1487	0.4758	0.2722	0.1712	0.2796	0.2068
IC5	0.1500	0.1701	0.1793	0.1547	0.3141	0.3163	0.2672	0.3168	0.2378
IC6	0.0934	0.1312	0.1462	0.1159	0.5691	0.2013	0.1742	0.3677	0.2460
IC7	0.0991	0.1460	0.1565	0.1205	0.3027	0.2119	0.1955	0.3304	0.2252
IC8	0.1190	0.1441	0.1706	0.1637	0.1910	0.2123	0.2311	0.2543	0.2520
IC9	0.0866	0.0837	0.0762	0.0722	***0.7605***	0.1730	0.1832	0.3548	0.0640

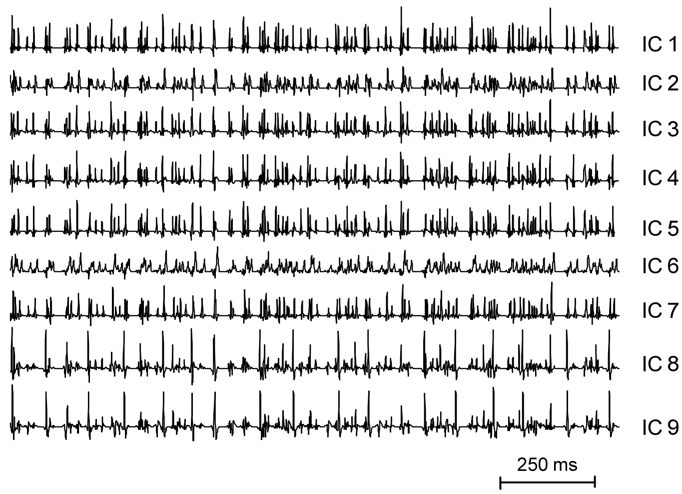

Figure 5. Independent components (ICs) obtained from simulated surface EMG signals detected at 9 electrodes using electrode configuration 2

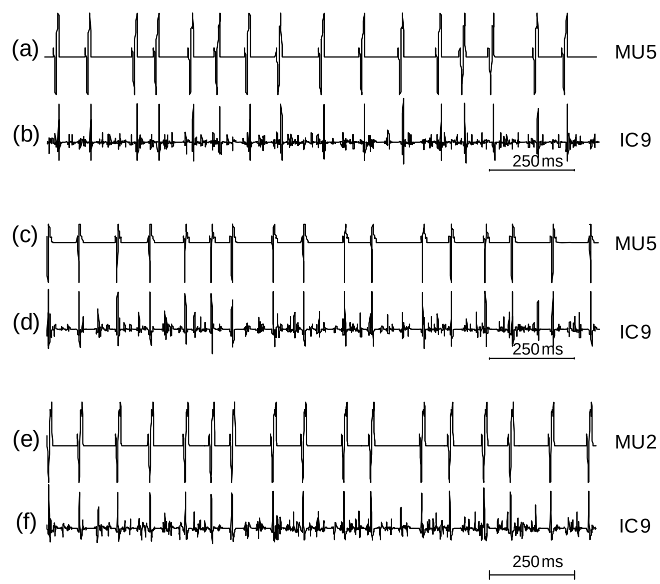

Figure 6. Comparison of the independent component and the corresponding single MUAP train for three different electrode configurations with (a) and (b) for configuration 1, (c) and (d) for configuration 2, and (e) and (f) for configuration 3

4. DISCUSSION

Varying motor unit recruitment and firing patterns provide direct access to the nervous system control mechanisms which govern muscle contraction and modulate force output. However, the extraction of motor unit recruitment and firing rate information from surface EMG signals is impeded by superposition and cancellation between action potentials. Although action potential superposition can be reduced using high spatial filtering techniques (Reucher et al. 1987a, 1987b; Disselhorst-Klug et al. 2000; Farina and Cesson 2001), it is extremely difficult to identify a sufficient number of action potentials to study neuromuscular control mechanisms during moderate to high force level contractions. One possible means of overcoming this problem is to use ICA to distinguish individual MUAP trains. The feasibility of using ICA to process surface EMG signals based on multi-channel surface EMG simulation was explored in this paper.

In processing the simulated EMG data, the surface EMG was considered as an instantaneous mixing model. The result showed that ICA technique based on an instantaneous mixing model was not able to completely separate the constituent MUAP trains (Figure 5). In fact, the surface EMG signals were reorganized such that most of the outputs of ICA were comprised of information from the constituent MUAP trains and therefore contained information from some or all active motor units.

Although applying ICA based on an instantaneous mixing model has been successfully applied to still images and fixed sources, there are some questions concerning the assumptions required to apply it to biomedical signals, in particular surface EMG. The shape of observed surface action potential is primarily determined by the relative locations of the recording electrodes with respect to the active muscle fibers, the material properties of the volume conductor and the shape of transmembrane action potential. The MUAP can be viewed as a convolution between the transmembrane action potential and a weighting function which describes the properties of volume conductor (Plonsey 1974). For the same motor unit recorded at different electrode locations, the weighting function will be different at each electrode while the current source remains the same. Furthermore, the conduction velocity of muscle fiber action potentials is appropriately 3.5~6.5 m/sec (Ekstedt and Stalberg 1973). This makes the time delay between EMG channels longer than that for the other biomedical signals, e.g. nerve action potentials, which have conduction velocity around 50-100 m/sec (Dorfman 1989). When the electrodes are placed along the muscle fibers, the action potential shape variations are relatively small, but the time delays between the signals at different electrodes become more significant, Figure 7 (a), (b). On the other hand, when the electrodes were positioned perpendicular to the muscle fiber direction, there is little or no delay between the signals detected at different electrodes. However, the action potential shape variations become more significant, Figure 7(c).

A more realistic approach would therefore be to approximate surface EMG signal using a convolutive mixing model. Although ICA based on an instantaneous mixing model has previously been shown to be able to decompose simulated surface EMG signals (Nakamura et al. 2001), the authors assumed several conditions to satisfy the necessary assumptions. In particular, only three motor units were active and there was no time delay between observed signals at each channel. However, for real surface EMG recording, these conditions are very difficult to meet. Our results, based on a more realistic EMG model, suggested that to completely decompose the surface EMG signal, blind source separation algorithms addressing a more complex convolutive mixing model are needed.

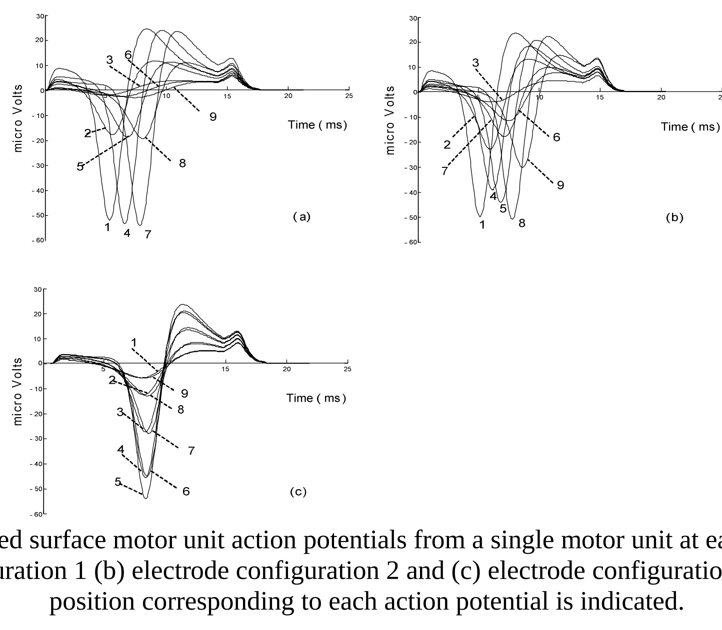

Figure 7. Simulated surface motor unit action potentials from a single motor unit at each electrode in (a) electrode configuration 1 (b) electrode configuration 2 and (c) electrode configuration 3. The electrode position corresponding to each action potential is indicated.

However, although ICA of an instantaneous mixing model is not a suitable tool for complete surface EMG decomposition, useful information can still be derived. Some outputs of ICA contained distinctive spikes which corresponded to the occurrence of individual action potentials from a few motor units. These independent components, which are time-locked to the individual MUAP trains, can be used to obtain the firing rate information from these motor units. This suggests that the firing rate information of a small number of motor units could be obtained from surface EMG signals containing highly superimposed MUAPs.

Finally, this study was based on model simulation, where the details of the motor unit pool, the motor unit properties and their location of the individual muscle fibers with respect to the electrodes have been obtained from data reported in the literature. With experimental surface EMG recording, these physiological details are largely unknown. The influence of artifacts and noise effects are also a consideration.

Although ICA has been successfully applied to the some biomedical signals (Wubbeler et al. 2000; Brown et al. 2001; Jung et al. 2001), the analysis of surface EMG using ICA is still in its infancy. This paper presents the results of a preliminary study in this direction. How much useful information can be obtained from ICA of surface EMG signals remains an open question. Further surface EMG simulations and more complex ICA algorithms are required to examine this question in more detail. However, due to the difficulties in dealing with surface action potential superposition to obtain motor unit recruitment and firing rate information, the use of multi-channel recordings in combination with blind source separation techniques looks promising.

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