Denoising Techniques using Component Analysis for Simultaneous EMG and fMRI Motor Studies

B. J. MacIntosh[1,2], A. Martel[1,2], S. J. Graham[1,2]

[1]Imaging Research, Sunnybrook & Women's CHSC, Toronto, Ontario, Canada, [2]Medical Biophysics, University of Toronto, Toronto, Ontario, Canada

Introduction

Motor fMRI studies routinely employ complimentary measurement to aid in assessment of brain activity. Examples include measuring reaction time or tracking motion with external monitoring. Another example is electromyography (EMG), which measures bio-potentials arising from muscle contraction. In motor fMRI studies where precise movement timing is required, or where movement information may not be intuitive, EMG would be highly beneficial. For instance, recent stroke motor recovery studies (Ward, Brown et al. 2003) investigate recovery of brain function but none have sought independent measure of motor output. Compensatory behaviour such as co-contraction (Lamontagne, Richards et al. 2000) may represent a significant confound. To date, successful combination of EMG and fMRI has been in an interleaved manner only (Liu, Dai et al. 2000). Although improved fMRI-compatible electronics are required to enable continuous EMG recordings, the goal of this work is to illustrate how novel component analysis techniques (i.e. principal and independent component analysis, PCA and ICA, respectively) can be used in additional post-processing to extract muscle EMG signals in the presence of fMRI induced signal contamination.

Methods

FMRI and EMG data were collected simultaneously in 15 healthy normal participants (12 men, 3 women). T_2^*-weighted Blood oxygenation level dependent (BOLD) images were collected with TR/TE/FA = 1000 ms/ 30 ms/ 50° using single shot spiral k-space trajectories and a whole-body MRI scanner (3.0 T/94 configuration, GE Medical Systems). Subjects performed either an ankle (N=12) or wrist (N=3) flexion task (inter-task interval of 20 s) with Ag/AgCl surface electrodes measuring EMG from the tibialis anterior or wrist flexors, respectively. A custom designed pre-amplifier was situated within 25 cm of the muscle and the differential voltage EMG signal was converted to light and transmitted via fiber optics outside the magnet room for digitization using LabVIEW software.

Three post-processing techniques were tested as a means to eliminate MRI-induced structure noise in EMG data: 1) ICA (Hyvarinen and Oja 2000), 2) PCA and 3) PCA followed by ICA (referred to as PIA). EMG time series data were arranged into individual movement trials, time-locked to the MRI acquisition. Components (PCs or ICs) were selected automatically by comparing the ratio of the mean to standard deviation in the power spectra, a technique that separates structured MRI-induced signals from stochastic EMG signals. EMG contrast-to-noise ratios (CNR) between mean muscle burst and mean baseline were used to compare the 3 techniques.

Results

Fig 1 shows an A) activation map, B) average filtered EMG data after each component analysis technique, and C) EMG (raw and PCA+ filtered) and BOLD time series data from primary motor cortex (M1) for a representative subject. Across all subjects, ICA removed 7 ± 9.4 % of the total variance in the data, only converging to a solution in 6 of 15 subjects, while PCA removed 80 ± 23.9% of the data. After PCA, ICA (i.e. PIA) removed 17 ± 6.4 % and converged in all subjects. Computed CNR values (EMG task : baseline ratio) showed statistically significant incremental improvement between raw data, ICA, PCA, then PIA techniques (see Table 1).

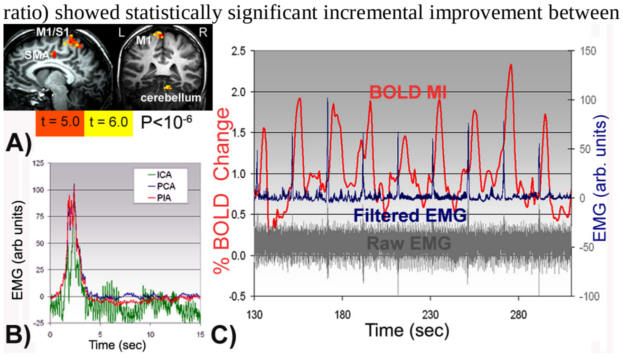

Fig 1. shows A) fMRI activation B) average filtered EMG time series for each technique and C) BOLD (left axis) and raw and filtered EMG (right axis) time series data for a single participant during event-related ankle fMRI (inter-task interval 20 s).

		Average	Std Dev	t-test	
Task	**ON (s)**	1.19	0.45		
Duration	**OFF (s)**	2.60	0.64		
Percent	**ICA**	0.07	0.094		
Variance	**PCA**	0.80	0.239		
Removed	**PIA**	0.17	0.064		
	RAW	1.67	0.551		
CNR	**ICA**	2.15	1.219	0.0681	**ica>raw**
Values	**PCA**	2.83	1.416	0.0074	***pca>ica**
	PIA	3.09	1.592	0.0019	***pia>pca**

Table 1. Component analysis techniques show significant incremental improvement in mean EMG CNR (task : baseline) for N=15, as shown by t-tests (* indicates significant difference between denoising techniques).

Discussion

These results show automated component analysis denoising techniques contribute to high quality EMG data during simultaneous fMRI by removing residual MRI-induced contamination. Of the three techniques, the computationally most intensive routine, PCA followed by ICA (i.e. PIA), was the most effective at reducing MRI contamination in the EMG data. Using ICA alone to remove MRI contamination was not a suitable technique because the combined stochastic EMG muscle signal and structured gradient noise did not permit convergence to linearly independent components.

In conclusion, even after careful electronics design, residual gradient contamination is likely to be evident in the EMG data. This prevailing confound can be overcome with the appropriate post-processing component analysis techniques. However, due to proximity to imaging gradients, EMG data from wrist flexors (N=3) was far worse than ankle EMG data (data not shown). We are currently investigating real-time PCA correction of EMG data that might permit successful measure of small muscles (e.g. flexor digitorum superficialis) as well as EMG biofeedback fMRI experiments.

References

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