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INTEGRATED EMG SOURCE SEPARATION OF EI AND EDM MUSCLES USING NON-NEGATIVE MATRIX FACTORIZATION

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SUMMARY

Electromyographic (EMG) signal directly represents muscle activity. When recording EMG signals of closely located muscles on skin surface the problem of source separation arises, each acquired channel records signals coming from different muscles [1]. Working on extrinsic finger extensors EI (index) and EDM (little finger) provides a system with muscles that are closely located and independently activable at low levels of force. Source separation of EMG signals is difficult to achieve since instantaneity of the mixtures recorded has been shown to be very sensitive to electrode location. Non-negative matrix factorization (NMF) has been applied to the locally integrated EMG (IEMG) signal in order to identify the mixing matrix and Integrated EMG source signals. Values of contrast between EMG activity during EI and EDM contractions was computed before and after source separation and contrast gains turned out to be significantly higher using NMF on IEMG than using a well known source separation algorithm on EMG signal directly.

INTRODUCTION

The problem of source separation in EMG arises quite often when working on closely located muscles recorded from the skin surface. This problem can be solved using blind source separation algorithms in the common linear instantaneous case provided electrode placement is optimal, we propose to use NMF in order to identify mixing matrix and estimate sources of the integrated version of EMG signal and we will compare separation quality.

METHODS

Electromyographic recordings were done on volunteers with informed consent during an alternating finger extension task of index and little fingers. On the distal third of the forearm two bipolar surface EMG channels were recorded at 2kHz and functional testing assessed good sensor response for EI and EDM extensors. Fingers were attached to force transducers at third phalanx and forces were recorded for task monitoring purposes. Recorded EMG signals were band-pass filtered between 20 and 500Hz, and integrated EMG (IEMG) was computed using a 200ms sliding window on the squared EMG such that IEMG at time t is equal to the local variance of the raw signal in the corresponding sliding window.

A contrast function was defined to compare initial contrast values and values after-separation for two different techniques; JADE [2] a well described algorithm applied on filtered raw EMG data, and NMF [3] applied on IEMG.

Let x_I be the portion of signal x during index extension and x_L the portion of the same signal during little finger extension. We define the contrast function in dB for the index finger on EMG as (Var stands for the variance operator):

$$C_{I} = 10 \log_{10} \left(\frac{Var(x_{I})}{Var(x_{L})} \right)$$

To get the contrast function on IEMG, replace the Variance with the Mean operator. The higher C_I the more specific the considered channel is to the index (EI), higher C_L values indicate a channel very specific to little finger (EDM). We define the contrast gain as the difference between these measures after source separation and before source separation. Contrast gain unit is the dB and it is computed for index (EI) and little finger (EDM).

RESULTS AND DISCUSSION

Contrast gains (Figure 1) clearly shows that NMF on IEMG improved estimated sources quality with respect to classical JADE algorithm on raw filter EMG signal. Contrasts increase by roughly 5dB and 3dB for EI and EDM respectively, with initial contrast values for the index finger that are often around 0dB the increase in percentage is huge. Index initial contrast values are much higher, then again using NMF the gain of 3dB can represent up to 50% increase even here when JADE has absolutely no effect.



Figure 1: Gain in contrast values between estimated sources and recorded signals on EI and EDM muscles using JADE and NMF algorithms respectively on EMG and IEMG data.

Looking at source instantaneity using cross-correlation between sensors during index or little finger extensions shows that instantaneity hypothesis is met for EDM source but not for EI source. Instantaneity during EDM activity enables mutual cancellation of waveforms recorded on each channel when JADE finds the optimal unmixing matrix, but instantaneity hypothesis during EI activity is not met such that EI waveforms cannot cancel each other out ending up in little finger contrast having no gain at all. NMF on its side is applied on positive IEMG signals which are envelopes of much lower frequency content blurring off the time arrival difference of EI between sensors. These lower frequency IEMGs match the instantaneity hypothesis and a mixing matrix and source estimates can be computed with a reasonable separation gain. A concrete example of source separation is shown in following Figure 2.



Figure 2: An example of source separation using NMF on IEMG signal. Dashed blue line is the recorded channel with highest C_I contrast. Red full line is the NMF estimated source with highest C_I contrast. First burst is during EI activity second burst occurs during EDM activity.

CONCLUSIONS

NMF algorithm on IEMG shows significantly higher gain than a more classical algorithm used on EMG directly. IEMG signals are envelopes of lower frequency content, hence we assume that small time arrival differences that invalidates instantaneity hypothesis when using EMG become less significant when working with IEMG. Using NMF on IEMG or any other appropriate separating method on IEMG might be more robust to the instantaneity hypothesis than working directly on EMG. Further research on this subject will focus on that specific question using different recording locations and studying their impact on separation quality.

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