EMG SIGNAL DECOMPOSITION BY LOOPY BELIEF PROPAGATION

Volker M. Koch and Hans-Andrea Loeliger

Signal and Information Proc. Lab., Dept. of Information Technology and Electrical Engineering
ETH Zentrum, CH-8092 Zürich, Switzerland
{koch, loeliger}@isi.ee.ethz.ch

ABSTRACT

The problem of separating superimposed action potentials in electromyographic (EMG) signals is considered. Based on a graphical model (factor graph), a new EMG signal decomposition algorithm that uses loopy belief propagation is presented. Results show that the algorithm is capable of decomposing multiple superpositions in simulated and measured EMG signals.

Keywords: EMG signals, factor graphs, loopy belief propagation, signal decomposition, superposition.

1. INTRODUCTION

Anatomy and physiology: A motor unit (MU) is the smallest functional unit of the neuromuscular system. It consists of a motoneuron and all the muscle fibers that are innervated by the motoneuron. In this paper, we will sometimes refer to a MU as a source. When a motoneuron fires, all its muscle fibers contract. Motoneurons fire repeatedly over time.

EMG signals: Muscle contraction goes along with electrical activity. The analysis of the resulting EMG signals yields valuable information for clinicians and researchers. An EMG signal consists of signal contribution from the muscle fibers that are within a certain distance from the electrode. One activation of a MU results in a wave that is called a motor unit action potential (MUAP). A single MU generates a train of such similar waves, called a MUAP train. MUAPs from different MUs can overlap.

EMG signal decomposition: The task of EMG signal decomposition is to separate an EMG signal into its MUAP trains. As the level of muscle force increases, the number of active MUs increases as well as their activation rates. This leads to more overlapping MUAPs from different MUs, which makes the signal decomposition task harder. Many decomposition algorithms have been proposed. However, many practical tools are limited to a few superimposed MUAPs, e.g., only two in [1]. Refer to [2] [3] for a good overview of EMG signal decomposition methods.

New EMG signal decomposition approach: In this paper, we present a new EMG signal decomposition algorithm (outlined in [4] [5]) that is based on a graphical model (factor graph). The algorithm is capable of decomposing signals with many overlapping MUAPs, i.e., signals that might be difficult to decompose with existing tools.

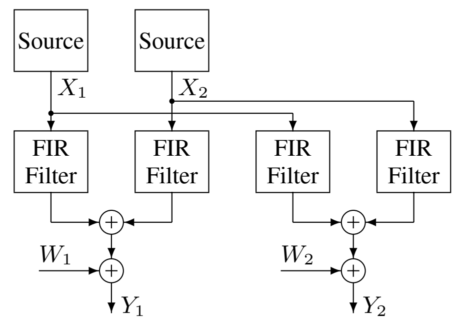

Fig. 1. Model of EMG signal generation: here shown for only two sources (MUs) and two channels (electrodes).

2. METHODOLOGY

Our EMG signal decomposition algorithm is developed by starting with an EMG signal simulation model from which a factor graph model is derived. A message passing algorithm runs on this factor graph and calculates an approximation of the maximum a-posteriori (MAP) estimate of the firing times of the MUs.

EMG signal simulation model: Fig. 1 shows a discrete-time model of EMG signals. Source (MU) i emits a discrete-time binary signal $X_i \triangleq (X_{i,1}, X_{i,2}, X_{i,3}, \ldots)$ with $X_{i,k} \in \{0, 1\}$. If $X_{i,k} = 1$, we say that MU i "fires" at time k. The source model ensures that, after sending a 1, there have to follow M zeros so that MUAPs of the same source do not overlap. M is the maximal memory of all finite impulse response (FIR) filters (see below). Each electrode picks up a noisy and heavily filtered superposition of these signals. For example, electrode j picks up the EMG signal $Y_j \triangleq (Y_{j,1}, Y_{j,2}, Y_{j,3}, \ldots)$ with

$$Y_{j,k} = \sum_{i=1}^{N_{\rm src}} \sum_{\ell=0}^{M} X_{i,k-\ell} \cdot h_{i,j,\ell} + W_{j,k}, \qquad (1)$$

where $h_{i,j,\ell} \in \mathbb{R}$ are the filter coefficients, $N_{\rm src}$ is the number of sources, and $W_j \triangleq (W_{j,1}, W_{j,2}, W_{j,3}, \ldots)$ is additive white Gaussian noise (AWGN) for channel j. An example of such an EMG signal is given in Fig. 3 (top).

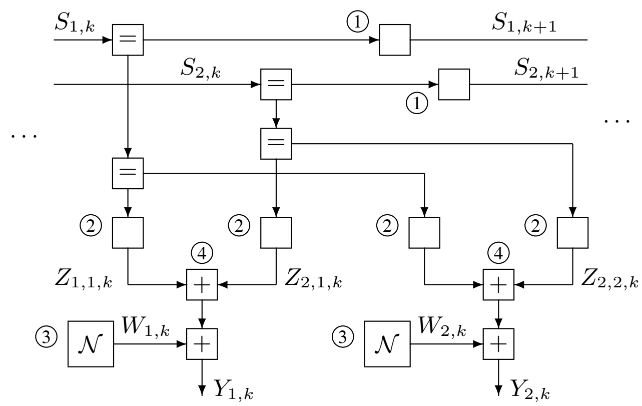

Fig. 2. Time-k section of a factor graph corresponding to Fig. 1.

EMG signal decomposition: To decompose an EMG signal into its MUAP trains, the source signals X_i are estimated based on the measured signals Y_j. Although the MAP estimate of X_i is desirable, its exact computation is very complex using any known algorithm. In fact, we do not know any algorithm that can compute the MAP estimate in a reasonable time in the case of many overlapping MUAPs.

Factor graphs and the sum-product algorithm in general: Factor graphs [6] are graphical models that may be used to derive various signal processing algorithms. The sum-product algorithm [6] (or *belief propagation* or *probability propagation*) operates by passing messages along the edges of the factor graph. If the factor graph has no loops, then belief propagation will yield MAP estimates. If the factor graph has loops (as it has in our case), then the algorithm yields only an approximation of the MAP estimates and may in fact fail to converge. However, loopy belief propagation can handle very complex models (factor graphs) and is known to give excellent results in some applications [4] [6].

Factor graphs and the sum-product algorithm for EMG signal decomposition: The diagram in Fig. 2 is a part of a factor graph, which may be viewed as the simulation model in Fig. 1 "rolled-out" in time. Fig. 2 shows only one section of the graph; the total graph consists of many such sections, one for each time index. The global function represented by this factor graph is the joint probability mass function of all variables.

The factor graph of Fig. 2 explicitly uses a state space model of the sources and the filters. In particular, the variable $S_{i,k} \triangleq (X_{i,k}, X_{i,k-1}, \ldots, X_{i,k-M})$ is the state of the FIR filters fed by source i. We assume that the vector $S_{i,k}$ can contain at most one "1", i.e., self-superpositions are not allowed. We currently do not use the average firing rates. However, our model can easily be modified to include firing statistics.

The boxes labeled ① in Fig. 2 represent the state transition probabilities $p(s_{i,k+1}|s_{i,k})$, which are defined in Table 1. The boxes labeled ② represent the deterministic functions

$$Z_{i,j,k} \triangleq \sum_{\ell=0}^{M} X_{i,k-\ell} \cdot h_{i,j,\ell}, \tag{2}$$

where $Z_{i,j,k}$ is the output of the FIR filters. The filter coefficients are assumed to be known. The boxes labeled ③ represent Gaussian distributions according to our noise model. Node ④ is a sum-constraint node, which is designed hierarchically in the case of more than two sources. In the case of many sources, several variable quantization and message approximation strategies were explored for messages through this addition node.

By iterative sum-product probability propagation in the factor graph of Fig. 2, we obtain an estimate of the variables $S_{i,k}$ for all i and k. Estimates of $X_{i,k}$ are then obtained by using the Viterbi algorithm, which is equivalent to max-product message passing (forward and backward sweep) over the source nodes ① in the factor graph. Although we used the standard sum-product algorithm, much experimentation was necessary, e.g., to find a suitable factor graph and a good message update schedule. We also experimented with different message types, various variable quantizations and message approximations, different node functions, and different noise models.

3. EXPERIMENTAL RESULTS

To test our decomposition algorithm, we started with simulated EMG signals. In this way we could generate special signals to test specific aspects of our algorithm, e.g., the decomposition of difficult superpositions. Another advantage of simulated signals is that the decomposition results are known. We have also begun to decompose real (measured) signals.

Simulated EMG signals: The upper plot in Fig. 3 shows a single-channel simulated EMG signal with a superposition of 4 MUAPs and AWGN with zero mean and a standard deviation of 20. This signal was correctly decomposed in about 30 seconds on a standard PC[1]. We simulated 1000 such EMG signals using the same MUAPs but different firing times, which were chosen at random for each signal. The decomposition results are given in Table 2.

Measured EMG signals: In measured EMG signals, the noise is not AWGN, which can make the decomposition task harder. Fig. 4 shows an example of a single-channel measured EMG signal containing a superposition of 4 MUAPs. The signal is annotated with the "firing times" of the $N_{\text{src}} = 9$ active sources. Also shown is the signal residual, i.e., the EMG signal minus the reconstructed signal. The reconstructed signal created based on the detected firing times and the MUAPs. Note that the MUAPs have very different amplitudes, especially the MUAP of MU 8 has a very low amplitude compared to the other MUAPs. All the 9 MUAPs (8 of them shown at the bottom of Fig. 4) were given to our decompo-

[1] Pentium 4 CPU with 2.66 GHz, 1 GB RAM.

Table 1. State transition probabilities (nodes ① in Fig. 2), $\varepsilon \approx 10^{-3}$.

$s_{i,k}$	$s_{i,k+1}$	$p(s_{i,k+1}\|s_{i,k})$
all zeros	all zeros	$1-\varepsilon$
all zeros	$(1,0,\ldots,0)$	ε
"1" at position n	"1" at position $n+1$	1
$(0,0,\ldots,1)$	all zeros	1
everything else		0

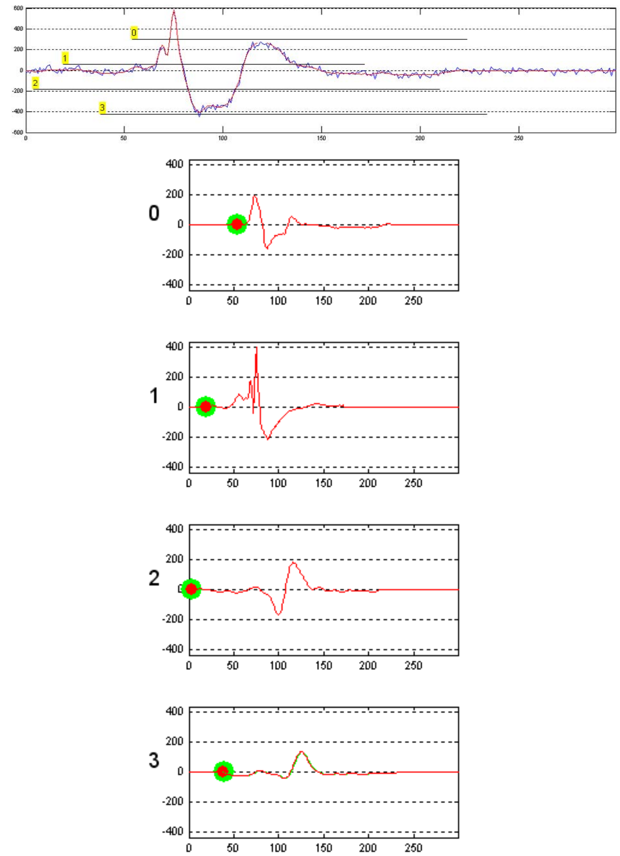

Fig. 3. Single-channel simulated EMG signal annotated with the correctly detected "firing times" and durations of the $N_{\mathrm{src}} = 4$ active sources as well as the signal reconstructed from the detected firing times (top) and the corresponding MUAP trains with correct (big marks) and detected (small marks) firing times (bottom).

sition algorithm, which found four firings in the given time frame. We believe that this decomposition result is correct.

Complexity of computation: The complexity of the computation of one iteration is linear in the length of the EMG signal, the number of MUs, the length of the MUAPs, and the number of channels. This is due to the fact that the number of messages to be calculated grows linearly with these parameters.

Superpositions consisting of many MUAPs: As a final note, we were able to decompose superpositions consisting of 16 different given MUAPs if no noise was added. In general, this is a trivial problem when the MUAPs are known: one can simply peel-off the MUAPs one after the other. However, it is still important to note that our algorithm is able to deal with this problem without explicitly programming such a peel-off approach. If noise is introduced to such difficult superpositions the decomposition fails.

4. DISCUSSION

Estimation and tracking of MUAP shapes: In this paper, the number of MUs as well as the corresponding MUAPs are assumed to be initially known and constant over time. We plan to extend our model and algorithm to estimate the number of MUs as well as the shapes with our message passing approach. In the case where MUAPs do not change much over time, e.g., in some short term recordings, the slight variations of the MUAPs from one MU can be viewed as noise. However, if long-term recordings are to be decomposed, the MUAPs from one MU might change substantially over time. In this case it is necessary to track the MUAP changes. We have already implemented such an adaptive algorithm. It works good for simple simulated signals but needs to be improved for more complex or measured signals.

Firing statistics: Superimposed MUAPs can be resolved either by using waveform information only or by additionally using firing statistics. In its current version, the only a-priori information to decompose EMG signals is that MUAPs from the same source do not overlap and the state transition probabilities as described in Section 2. Besides that, the decomposition is based on the EMG signals and the MUAP waveforms only; average firing frequencies are currently not used since they can be misleading, e.g., in the case of repetitive discharges (doublets or multiplets), which often occur in dynamic contractions. However, in other cases, e.g., when there are high levels of noise and many active MUs with similar waveforms, the use of average firing frequencies might be useful or even necessary. Our model and algorithm can easily be extended to incorporate firing statistics.

Noise and noise models: Although the noise in measured signals is not AWGN, we mostly used an AWGN model. This corresponds to a least-squares fit of the estimated signal to the measured signal. However, we have experimented with other noise models, e.g., logistic distributions. So far we found that the AWGN model works best. But further research has still to be done.

MSE minimizing algorithm: Our decomposition algorithm tries to minimize the MSE between the EMG signal and the reconstructed signal. However, the "optimal" solution based on the MSE (the decomposition that yields the smallest MSE) may not be the correct one. One reason for this is that noise or artifacts might be identified as parts of MUAPs. Using average firing frequencies and

Table 2. Decomposition results for 1000 signals. One signal is shown in Fig. 3. A MUAP is "correct", if it is detected and classified correctly.

Number of signals	1000
Number of completely correct decomposed signals	942
Correct-signal rate	94.2%
Number of simulated firings	4000
Number of correct MUAPs	3875
Correct-MUAP rate	96.9%
Number of missed MUAPs	125
Missed-MUAP rate	3.13%
Number of false (additional) MUAPs	83
False-MUAP rate	2.08%

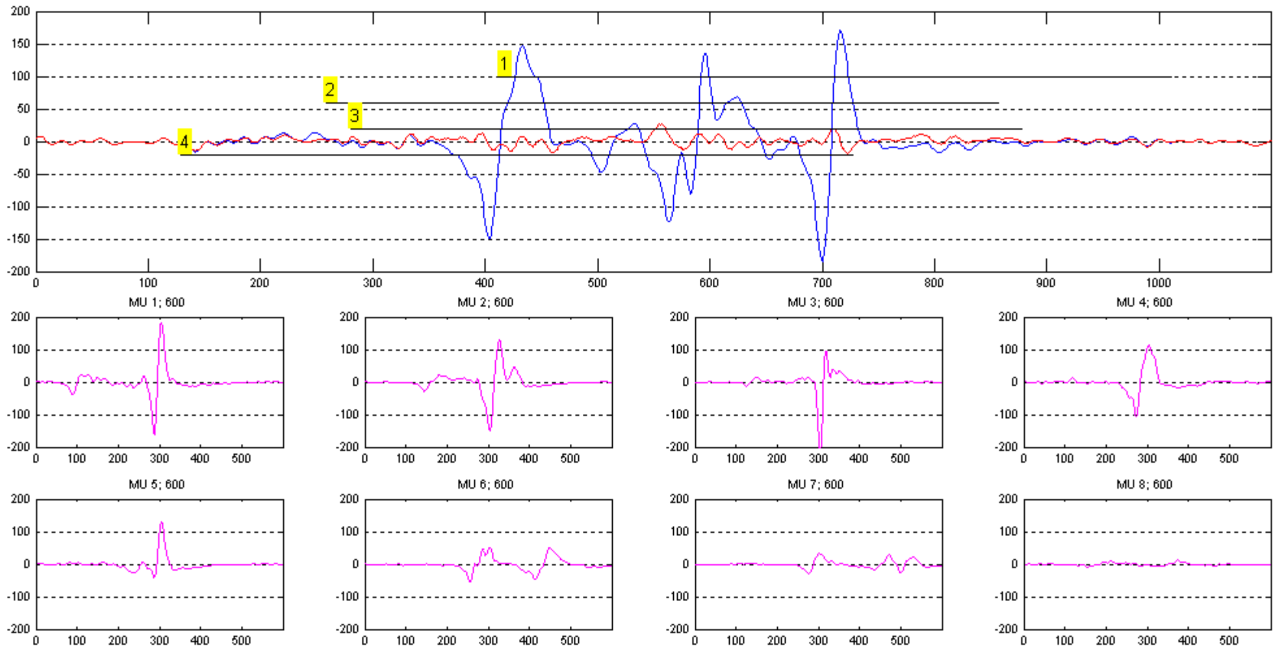

Fig. 4. Single-channel measured EMG signal annotated with the "firing times" and durations of the $N_{\mathrm{src}} = 9$ active sources (only 4 in this time frame) as well as the residual (top) and the MUAPs of 8 of the 9 sources (bottom). Source of the EMG signal: Kevin McGill.

other knowledge about the nature of EMG signals might be helpful to restrict the search space to the most probable decomposition results.

Multi-channel EMG signals: Multiple electrodes measure EMG signals at slightly different locations at the same time. Combining information from multiple channels can improve the decomposition result. Our algorithm is capable of dealing with multiple channels in a natural way. Fig. 2 shows how the equal nodes integrate the information coming from two channels.

5. CONCLUSIONS

In this paper, we presented a new EMG signal decomposition approach based on a graphical model (factor graph) and a loopy message passing algorithm (sum-product algorithm). We have demonstrated that the new decomposition algorithm works even for many overlapping action potentials. However, to use the algorithm in a clinical environment, the factor graph model and the algorithm have to be further extended. At this stage, our algorithm might already be used as a plug-in for an existing decomposition algorithm to deal with difficult superpositions.

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