DECOMPOSITION OF MULTI-CONTACT NERVE CUFF SIGNALS INTO VELOCITY-SPECIFIC COMPONENTS

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INTRODUCTION

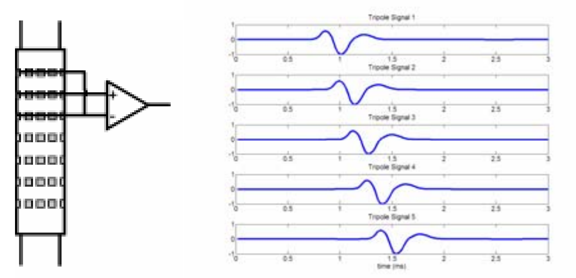
Nerve cuff electrodes are often used in neuroprosthetic systems due to their long-term stability [1]. One drawback of these devices is their poor selectivity. To compensate for this, methods have been proposed to identify the conduction velocities of action potentials (APs) traveling through a cuff. These methods are useful because different types of fibers have different velocities, such that the velocity information can be used to distinguish groups of fibers. Various techniques have been proposed to achieve this goal using measurements at two different sites, such as correlation-based methods [2] and matched filters [3]. Developments in nerve cuff manufacturing technology led to the introduction of a velocity-selective system that uses several measurements sites within a single cuff [4,5,6]. Using measurements at N sites rather than only two provides increased robustness.

In this simulation study, we propose a new algorithm that makes it possible not only to identify the velocities associated with each of the active pathways in the nerve, but also to decompose the recorded signals into separate waveforms, each one corresponding to one of the identified velocities. Using this information, it will be possible not only to determine that APs of a certain velocity are traveling though the cuff, but also to study firing frequencies, bursting behaviours, and other rhythmic activity in a velocity-specific manner.

METHODS

A traditional nerve cuff usually contains three circumferential contacts, one at each end of the cuff and the third halfway between them. The signal is then obtained from the middle contact, using the average of the other two as a reference [7]. This is known as a tripole configuration. In a nerve cuff with a higher number of contacts, more tripoles can be created by measuring the potential from each contact against the average of the contacts above and below it (Figure 1a).

The algorithm proposed here assumes that the cuff contains N tripoles, where N > 2. The neural signal at each tripole is seen as being a superposition of waveforms, each one produced by a group of fibers with a distinct conduction velocity. The two main steps of the algorithm are, first, to identify the velocities underlying the signal and, second, to decompose the signal into its constituent velocity-specific waveforms. The essence of the algorithm is to use a form of template matching in which templates are extracted from the recorded signals themselves and only retained if they are physiologically plausible. In this way, the only input required from the user is the set of tripole signals. There is no need to provide templates to the algorithm. Physiological plausibility is defined in this case as observing an identical (or very similar) signal at each consecutive tripole, with a consistent time delay from one tripole to the next (Figure 1b). Each segment of the signal is examined in turn and subjected to this criterion, enabling us to determine whether or not it corresponds to an action potential. The delay from one tripole to the next can be used to estimate the velocity. A step-by-step description of the algorithm follows.



a) b)

Figure 1: a) Tripole configuration for a multi-contact nerve cuff electrode. N-2 tripoles can be formed using N rings of contacts (each ring is averaged and treated as one circumferential contact). b) Example of the signal recorded by each tripole when an action potential traverses the cuff.

In the first part, one of the tripoles is set as the reference tripole, for example the one closest to the middle of the cuff. Then, the delays are identified from the N recorded time series as follows:

1. A window W1 of length L is made to slide over the reference tripole signal. In this study, L = 0.5ms. The window is shifted one sample at a time. The contents of W1 at each position are treated as a template to be matched to the other N-1 tripole signals.

2. In the first non-reference tripole signal, a template matching approach is used to select the best match to the contents of W1, using the norm of the difference between the signals as the error criteria. In other words, a window W2 also of length L slides over the non-reference signal, and the quantity $||W1-W2||_2$ is plotted against the delay between W1 and W2. Of the delays producing an error below a certain threshold, the delay with the smallest absolute value is recorded. Figure 2 illustrates this process.

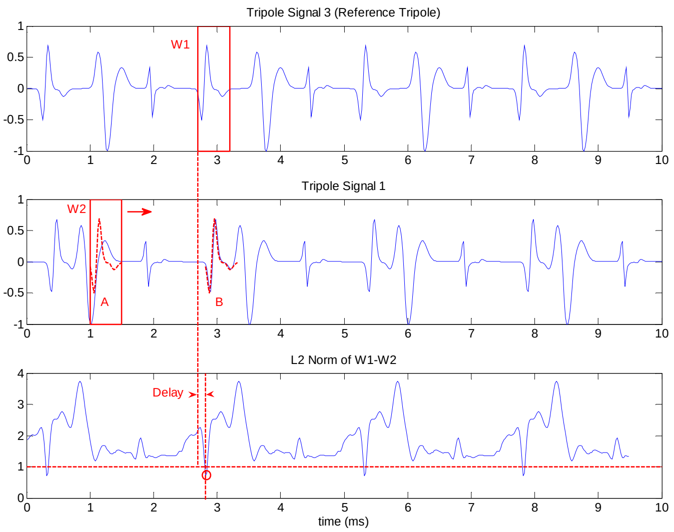


Figure 2: Delay identification process. The contents of the two windows are compared while W2 slides over the signal, and a time series of errors is created. Examples of good and bad matches, respectively, are shown at locations A and B in the middle time series of the figure. A threshold is applied to the error time series, and of the values below this threshold, the one with the closest index to the beginning of W1 is chosen. The recorded delay is the difference between the index of the selected value and the index where W1 begins. This process is repeated for each time sample as W1 slides along the reference signal.

3. Step 2 is repeated for each of the N-1 non-reference tripole signals.
4. The delays identified in steps 2 and 3 for each of the N-1 non-reference tripole signals are compared. If the delays between tripoles are approximately constant, then the contents of W1 at that position are assumed to correspond to a neural signal traveling through the cuff and the observed delay is retained. Otherwise no delay is retained. W1 is shifted one sample and the algorithm continues at step 1 until the whole time series has been examined.
5. Once W1 has been passed over the whole time series, all the delays retained are organized into groups using a histogram. The average of each delay group is computed, and converted into a velocity (this can be done directly since the distance between tripoles is known). These velocities are the ones present in the neural signal.

Step 4 is the key step of the algorithm: if the template under consideration (obtained dynamically from the reference tripole signal) can be matched to a signal traveling at a consistent velocity from one tripole to the next throughout the entire cuff, then that part of the signal is assumed to be produced by a traveling action potential. Templates that do not yield consistent delays between tripoles are rejected. The expected behaviour across the whole set of N time series is therefore used to dynamically extracts templates from one of those time series.

Once the velocities have been identified, the reference tripole signal is decomposed into separate waveforms corresponding to each velocity as follows:

6. For each time sample in the reference tripole signal, the set of windows (from the shifted versions of W1) containing that sample is examined. Each of those windows was either assigned a specific velocity in step 4, or rejected as a template. The velocity associated with the greatest number of windows from the set is assigned to the time sample, determining which velocity component it belongs to.
7. The waveform corresponding to each velocity is constructed by masking out of the reference tripole time series all the samples that were not assigned that velocity in step 6. A “remainder” signal is formed from the unassigned points.

Note that the algorithm assigns a given sample to only one waveform, and therefore the shapes of the waveforms may be distorted if the signals of different velocities overlap in the reference tripole signal.

The algorithm was applied to a simulated time series of length 10ms, with a sampling rate of 50KHz. The simulated measurements were generated with the help of a finite element model of a rat sciatic nerve. An action potential waveform was first generated using Sweeney channel dynamics [8]. Three active myelinated fibers were then simulated at three random positions within the nerve cross-section. The fibers had diameters of 5µm, 10µm, and 20µm, with corresponding velocities of 25m/s, -50m/s, 100m/s (the signs indicate the direction of propagation). In a second simulation, the component of the signal with the -50m/s velocity was time-shifted so that it overlapped with the 25m/s velocity component.

The cuff electrode used was 2.3 cm long and contained seven rings of eight contacts each [9]. The distance between each ring of contacts was 3.33 mm. The measurements from all the contacts of each ring were averaged, resulting in seven signals along the cuff. Combining these measurements into tripole configurations resulted in five tripole measurements (tripole 1 was formed from rows 1, 2, and 3, tripole 2 from rows 2, 3, and 4, etc.). The third tripole was chosen as the reference tripole.

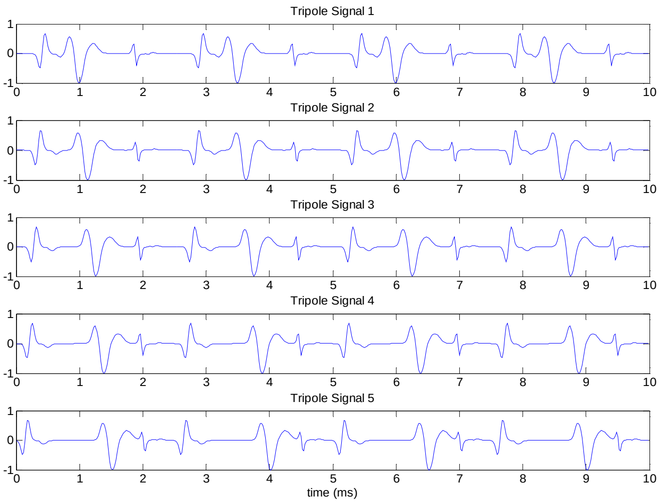


Figure 3: Tripole signals.

RESULTS

Figure 4 shows the output of the algorithm for the tripole inputs in Figure 3. In this case, the velocity components do not overlap. The estimated velocities were 25.97m/s, -55.66m/s, and 110.07m/s, corresponding to errors of 3.88%, 11.32%, and 10.07%, respectively. The decomposition of the signal into its velocity components was successful, with each action potential being correctly assigned.

Figure 6 shows the output of the algorithm for the tripole inputs in Figure 5, in which the velocity components overlap. Velocity components were identified at 27.23m/s and 100m/s. The 50m/s component was not successfully identified. Examination of the decomposed waveforms shows that the 50m/s component waveform was incorporated into the 27.23m/s waveform. The overlapping waveforms therefore degraded the performance in that one of the velocities was not identified, and there was corruption of one of the waveforms. The velocity components that were identified, however, were correct.

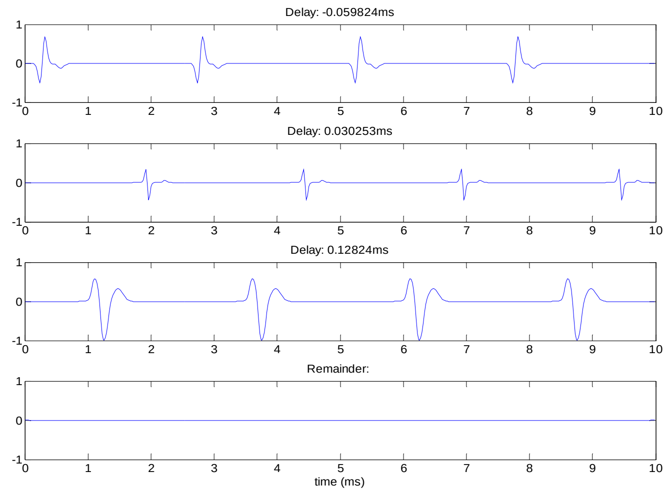


Figure 4: Algorithm output for input in Figure 3, using tripole 3 as the reference.

Figure 7 shows the output corresponding to the input in Figure 5 when the 5th tripole signal is used as the reference instead of the 3rd tripole signal. The 50m/s waveform is now correctly separated, although the algorithm was not able to estimate the velocity. This is to be expected since the overlap in the waveforms is such that no consistent delay can be observed for the 50m/s component in all five tripole signals. If, with this reference, only the last four tripoles are used, the velocity can be estimated (results not shown).

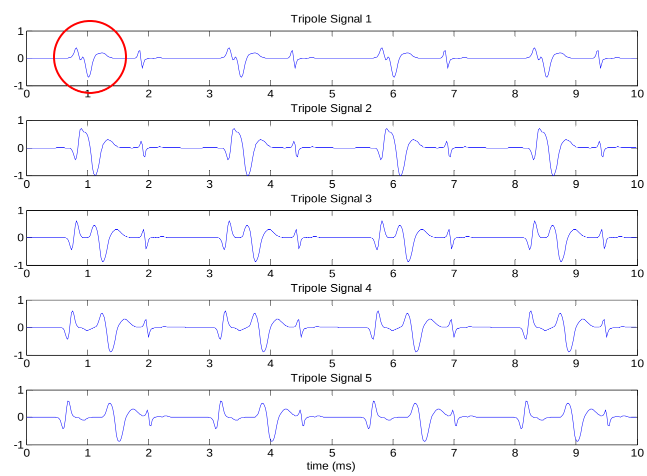


Figure 5: Tripole signals with waveform overlap. An example of overlap is circled (compare with Figure 3).

DISCUSSION

The algorithm was able to identify the conduction velocities of the action potentials with approximately 10% error, making discrimination of different groups of fibers feasible. Although overlapping waveforms made discrimination more difficult, applying the algorithm several times while varying the reference tripole was shown to have the potential to alleviate the problem. This approach will be explored further in future work.

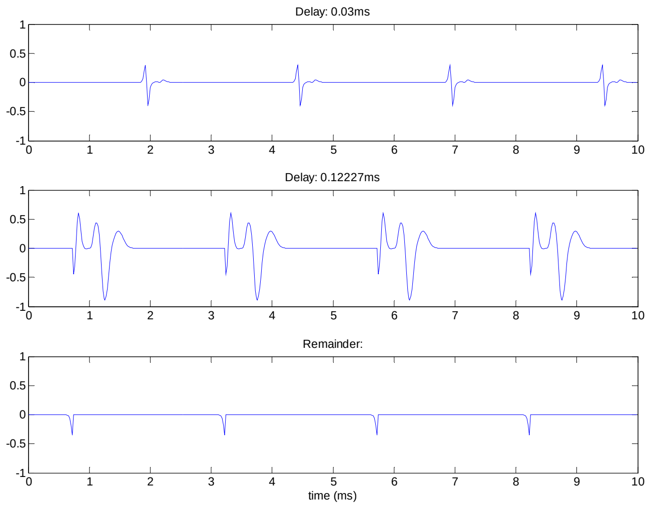


Figure 6: Algorithm output for input in Figure 5, using tripole 3 as the reference. Two of the velocity components are seen to have been combined by the algorithm (middle figure).

The advantages of the algorithm are that it can identify the velocities using a single measurement electrode, provides a decomposition of the recorded signal into velocity-specific waveforms, and does not require any input from the user other than the recordings themselves (in particular, no pre-existing templates are needed). No previously proposed algorithm combined all of these characteristics, and the decomposition aspect has not been previously investigated. Although it was not illustrated in this paper for lack of space, the algorithm is also reasonably robust in the presence of noise, in part because the tripole configuration is itself designed to reduce noise. The drawback of the algorithm is that it is slower than some of the alternatives and difficult to implement directly in hardware. Overlapping waveforms pose some difficulties, but this is true also of many of the alternative algorithms. In contrast, algorithms that addressed the issue had other drawbacks, such as a need for user-provided templates [10].

ACKNOWLEDGEMENTS

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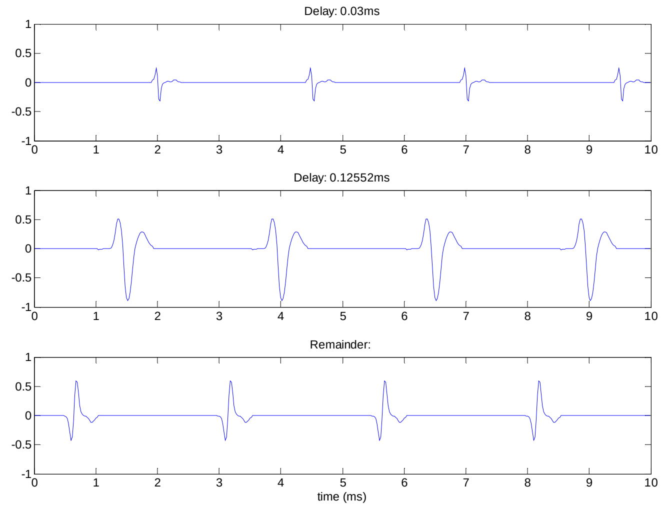

Figure 7: Algorithm output for input in Figure 5, using tripole 5 as the reference.

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