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Separation of Multiunit Signals by Independent Component Analysis in Complex-valued Time-Frequency Domain

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Abstract— **Multiunit recording with a multi-electrode in the brain has been widely used in neuroscience studies. After the data recording, neuronal spikes should be sorted according to spike waveforms. For the spike sorting, independent component analysis (ICA) has recently been used because ICA potentially solves the problem to separate even overlapped multiple neuronal spikes into the single. However, we found that multiunit signals are recorded in each electrode channel with channel-specific delay. This situation does not satisfy the instantaneous mixture condition prerequisite for most of ICA algorithms. Actually, this delayed mixture situation was shown to degrade the performance of an ordinary ICA. In this study, in order to overcome this problem, complex-valued processing in the time-frequency domain is applied to multiunit signals by the wavelet transform. In the space spanned by the wavelet coefficients, the condition of instantaneous mixture is almost fulfilled. By application to a synthetic multiunit signal, the ICA algorithm extended to complex-valued signals makes much improvement in spike sorting performance so that even overlapped multiple spikes are successfully separated. Taken together, the complex-valued method could be a powerful tool for spike sorting.**

I. Introduction

In the brain, it is assumed that information is represented by a spatio-temporal pattern of ensemble neuronal activity (e.g. cell assembly). Therefore, simultaneous recordings of multiple neuronal activities are essential for the study of information processing in the brain. For this purpose, recordings of extracellular action potentials generated from multiple neurons (multiunit) with multi-site electrode such as tetrode have been widely used [1]. Since the multiunit signal contains multiple neuronal activities near the electrode, signal processing including detection of neuronal spikes and sorting of action potentials to the spike-generating neurons is required. Recently, many spike sorting methods based on pattern classification technique have been proposed. The method sorts the multi-channel action potential signals according to the pattern of spike waveforms. Thus the pattern classification-based method hardly separates overlapped neuronal spikes due to distortion of spike waveform, which are recorded when neighboring neurons excite synchronously. Since the synchronized neuronal activity is believed to play an important role in the brain information processing, solving the spike overlapping problem would be essential.

One of the methods to solve the spike overlapping problem is independent component analysis (ICA) [2]. It could separate overlapped signals without prior information about the multiunit signals. Actually there are prerequisite conditions for successful performance of ICA, e.g. statistical independence of the source signals and instantaneous mixture of source signals. However, from our experience that multiunit activities cannot precisely be sorted by an ordinary ICA algorithm, we found that multiunit signals are recorded in each electrode channel with a significant channel-dependent delay, and this delayed mixture situation at least partly degrades the performance of the ICA [3].

In this study, in order to overcome this delayed mixture problem, complex-valued processing in the time-frequency domain is applied to multiunit signals by the wavelet transform. It is expected that processing in the complex-valued time–frequency domain allows successful separation unaffected by the delay specific to each recording channel. Simulations using synthetic multiunit data are done to examine how performance of separation is improved by the ICA algorithm extended to complex-valued signals. Through these investigations, applicability of the spike sorting method in the complex-valued time-frequency domain is evaluated.

II. Methods

A. Complex-valued Independent Component Analysis

Assume that independent n-source signals (neuronal spikes, $\mathbf{s}(t)=[s_1(t),\ldots,s_n(t)]^T$) are recorded with an m-channel electrode ($\mathbf{x}(t)=[x_1(t),\ldots,x_m(t)]^T$), where T denotes transpose and t denotes time. If $\mathbf{x}(t)$ is generated through a spatio-temporal transformation rather than an instantaneous mixture, the following relationship holds:

$$\mathbf{x}(t) = \mathbf{A} * \mathbf{s}(t), \quad (1)$$

where $\mathbf{A}$ is a linear operator and * denotes convolution. Here, when $\boldsymbol{X}(\omega,t)$ is obtained as time-frequency representation of $\mathbf{x}(t)$ by a wavelet transformation, the following relationship is assumed to hold at least in an approximate sense [4]:

$$\boldsymbol{X}(\omega,t) = \hat{\boldsymbol{A}}(\omega)\boldsymbol{S}(\omega,t), \quad (2)$$

where $\mathbf{S}(\omega,t)$ is time-frequency representation of $\mathbf{s}(t)$ and $\hat{\mathbf{A}}(\omega)$ is Fourier transformation of $\mathbf{A}$. By these representations, the spatio-temporal mixture including time-delay is transformed into instantaneous one. Here, note that for spike sorting not all of the frequency components do

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not have to be dealt with. In other words, we can estimate the timing of spike occurrence based only on a limited number of frequency components [5]. The complex-valued wavelet used here is a Morlet wavelet [6]:

$$\psi(t) = \pi^{-1/4}\left(e^{i2\pi f_0 t} - e^{-(2\pi f_0)^2/2}\right)e^{-t^2/2}, \qquad (3)$$

where f_0 is a central frequency. Angular frequency is related to f_0 by $\omega=2\pi f_0/a$, where a is scale of the wavelet transformation. Finally, solution of our problem is to find a separation matrix $\boldsymbol{W}(\omega_0)$,

$$\boldsymbol{Y}(\omega_0,t) = \boldsymbol{W}(\omega_0)\boldsymbol{X}(\omega_0,t), \qquad (4)$$

so that mutually independent $\boldsymbol{Y}(\omega_0,t)$ is obtained, where $X(\omega_0,t)$, $Y(\omega_0,t)$, and $W(\omega_0)$ are all complex values. In order to solve eq.(4), we use the natural gradient algorithm extended to the complex value [4]. In this study, we use ω_0=1000Hz*2π and f_0=3/2π. This ω_0 is selected because the signal-to-noise ratio of this wavelet coefficient is better in average for actual spike train data than the others within our trials [5]. In addition, the mother wavelet waveform shaped by f_0 and ω_0 is close to an actual waveform.

B. Synthetic Multiunit Signals

For evaluating performance of spike sorting, synthetic multiunit signals are subject to the analysis. In order to compose the synthetic signals, we use extracellular action potentials of multiple neurons recorded from the CA3 field of guinea pig hippocampus with a tetrode (a bundle of four stainless steel wire electrodes) [7]. Here, because we are concerned about the actual mixture process in multiunit signals, appearance of action potentials in multiple recording channels of the tetrode should be preserved in the synthetic signals. For this purpose, an action potential of each neuron is treated as a set of recorded waveforms in the multiple recording channels. The spike sorting algorithm based on a conventional pattern classification technique is used to determine which set of action potentials belongs to which neuron [1]. To improve the signal-to-noise ratio, spike waveforms are averaged over occurrences of neuronal firing. The synthetic multiunit signals are obtained by randomly aligning each set of action potentials along with the time axis, to each channel of which independent white-noise is added. Here, note that action potentials happen to be overlapped with each other. Each neuron is set to fire randomly and independently at a firing rate of 50 Hz. The number of neurons contained in the signal is four, i.e., the number of source signals is equal to that of the recording channels.

C. Quantitative measure of deviation from instantaneous mixture condition

If an m-channel signal is generated by instantaneous mixture of multiple sources, the recorded signals originated from an identical source should be the same except for their amplitude. This implies that the signal originated from the identical source exhibits a linear locus along with a straight

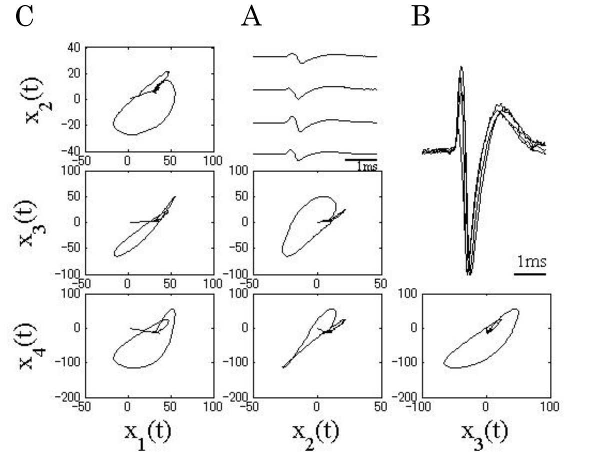

Fig.1 Typical extracellular action potential waveforms not satisfying the instantaneous mixture condition. A: Averaged spike waveform. B: Superimposed waveforms whose amplitudes are normalized. C: Loci of the extracellular potentials in the multiunit signal space. The contribution ratio of PC1 is 92%.

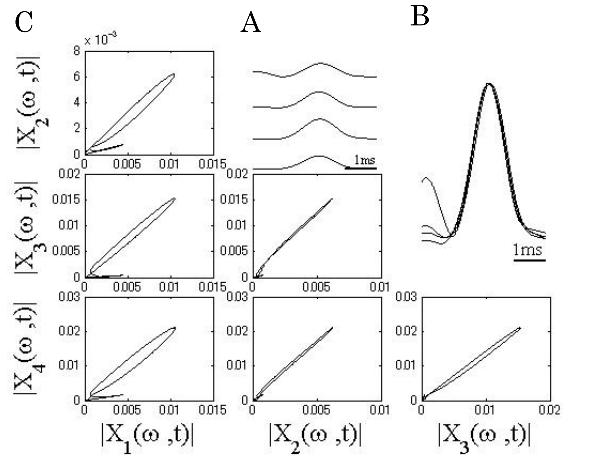

Fig.2 Typical wavelet-transformed extracellular action potential waveforms. A: Averaged spike waveform. B: Superimposed waveforms whose amplitudes are normalized. C: Loci of the wavelet-transformed extracellular potentials in the space of wavelet coefficients. The contribution ratio of PC1 is 99%.

line in m-dimensional space of recording channels. On the other hand, if there is a deviation from the instantaneous mixture condition, e.g., delay specific to each source signal, the locus should have a circular or complex shape. Therefore, linearity of the locus of the multichannel signal represents to what extent the instantaneous mixture condition is satisfied.

The linearity of the locus can be characterized by a principle component analysis. In this study, we used a contribution ratio of the first principal component (PC1) to quantify the linearity of the locus, i.e., the value of PC1 increases as the locus becomes more linear. The contribution ratio of PC1 is defined as follows:

$$\text{(Contribution ratio of PC1)} = d_1 \Big/ \sum_{i=1}^{m} d_i \ , \qquad (5)$$

where d_i is the i-th eigenvalue of the covariance matrix of the m-channel signal.

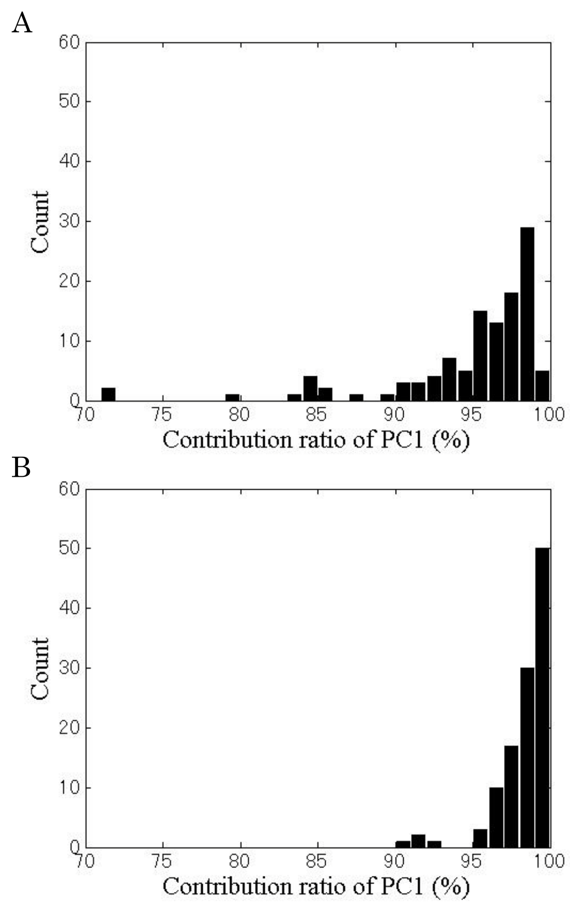

Fig.3 Histograms of the contribution ratio of PC1 (n=114). A: real-valued spike waveforms. The scores for 80 out of 114 neurons exceed 95%. B: complex-valued spike waveforms. Those for 110 out of 114 exceed 95%.

III. Result and Discussion

Previously we indicated that straightforward application of an ordinary ICA to the synthetic multiunit signals results in poor spike separation [3]. Because the synthetic multiunit signals satisfy the independence of source signals and complete condition, i.e., the number of sources equals to that of recording channels, the poor performance of spike sorting by ICA was attributed to violation of the instantaneous mixture condition [3]. This was known from the linearity analysis of the locus of the multichannel signals. Figure 1 shows a typical waveform with low linearity, where the normalized spike waveforms and peak timings are different from channel to channel. The loci of the multichannel signal seem far from linearity (Fig. 1C). The linearity in terms of the contribution ratio of PC1 is 92%. This type of waveform suggests that the instantaneous mixture condition is not satisfied at least partly due to the delay specific to each recoding site. In contrast, Figure 2 shows the wavelet-transformed version of the same waveform as in Fig.1, where the normalized spike waveforms and peak timings are almost identical over multiple channels. The loci in the space of wavelet coefficients have almost a linear shape, whose contribution ratio of PC1 is up to 99%. This improvement suggests that the delay specific to each recording site degrades the performance of separation by ICA. Figure 3 gives an overview of improvement by the complex-valued wavelet transform, which shows the histograms of the contribution ratio of PC1 for both cases. The scores for 80 out of 114 neurons under study exceed 95% for the real-valued case and 110 exceed 95% for the complex-valued case.

Figure 4 shows an example of separation performance when the real-valued and complex-valued ICAs are applied to the synthetic multiunit signal, where the separated components $\mathbf{y}(t)$ obtained by fastICA [8] and $|\boldsymbol{Y}(\square,t)|$ by the complex-valued ICA are given. Each component of $\mathbf{y}(t)$ is supposed to represent a single neuronal activity. However, there observed significant cross-talk events from the other components. Due to the cross-talk events, serious spike detection errors are caused (open triangles). The similar result was obtained by the natural gradient ICA algorithm [9]. In contrast, the complex-valued ICA successfully separates the neuronal activities even for the overlapping case. In order to evaluate the performance of ICA for spike sorting quantitatively, we investigated the number of single neuron separated from 10 sets of synthetic multiunit data by using the fastICA algorithm and our complex-valued ICA. The averaged numbers of neuronal spike trains were 2.8 and 3.4 for the fastICA and the complex-valued ICA, respectively. This results shows that the performance of complex-valued ICA improves that of the fastICA.

IV. Conclusion

In this study, the spike sorting algorithm is proposed, which consists of complex wavelet transformation and complex-valued ICA. Here, for the purpose of spike sorting, only a single frequency component is used for ICA, which makes an algorithm very simple. This effectiveness was confirmed by improvement in the linearity of loci of neuronal spike waveform in the multichannel signal space. The complex-valued ICA together with the wavelet transformation successfully separated the synthetic multiunit signals into the single neuronal activities even when overlapping takes place. One of future subjects will be to apply our algorithm to actual spike train data, in which various kinds of noise are included. Such robustness of our algorithm is necessary to be clarified.

According to the neurophysiological studies, neuronal dendrites in the central nervous system exhibit complex spatio-temporal dynamics such as passive and active propagation of action potential dependent on the dendritic linear and nonlinear electrical properties [10]. Consequently, extracellular potential near the dendrites could change in a complex manner. Such phenomena may underlie non-instantaneous mixture of multiunit signals. In this sense, the complex-valued ICA for spike sorting is worth investigating further especially in more noisy situations as well as applications to actual signals.

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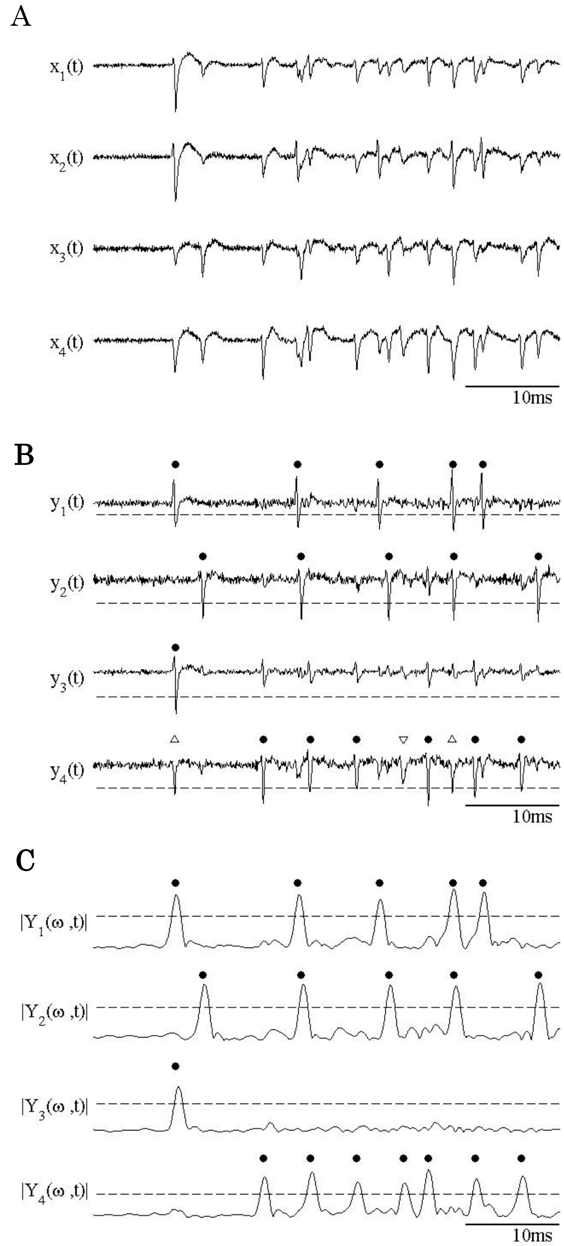

Fig.4 A: Synthetic multiunit signal (**x**(t)). B: Separated neuronal signals (**y**(t)) obtained by the fastICA. Dashed lines indicate the threshold level for spike detection. Symbols near the spikes indicate correct answer (filled circle), false positive (upward triangle), and false negative (downward triangle) spikes, respectively. C: Separated neuronal signals (|**Y**(ω,t)|) obtained by the complex-valued ICA.