Convolutive ICA (c-ICA) captures complex spatio-temporal EEG activity.

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[Background]

Independent Component Analysis (ICA) is a useful tool for removing electroencephalographic (EEG) artifacts such as eye-blink or eye-movement. Artifact activity that is spatially-separable and temporally independent from other EEG activity will, in a successful ICA decomposition, appear in a separate component. The ICA method is advocated because the obtained artifact components can be excluded from the EEG by a linear projection. Hence it is possible to clean EEG in its full length without loosing contaminated data segments. However, this approach still requires an expert judgment to determine which of the obtained ICA components are wanted or unwanted. In this work we show how Convolutive ICA (c-ICA) can capture more complex spatio-temporal behavior in a single component than is possible with conventional ICA. This creates components with more realistic temporal structure and furthermore assists the component inspection procedure by reducing the number of components to inspect. Convolutive ICA of EEG data has been studied by Makeig et al (2002,2003) in the complex frequency domain, here we apply a temporal un-mixing c-ICA approach which does not require windowing or frequency based representation of data.

[Methods]

The data used for the analysis was a 124 channel EEG recorded at 204.8Hz sampling rate. Electric pulses were generated at approximately 2Hz and applied to the subjects little-finger as stimulus. An eighty seconds long recording was obtained with approximately 150 stimulation epochs. DC components and slow drift were eliminated from each channel separately by high-pass filtering with a 0.2Hz transition-band around 1Hz cutting frequency. Five principal component features were extracted from the resulting data matrix for convolutive independent analysis (fig. 1).

ICA algorithm: Maximum-Likelihood instantaneous ICA (Bell & Sejnowski, 1995). **Convolutive ICA algorithm:** Maximum-Likelihood (Dyrholm & Hansen, 2003). The number of convolutive lags was set to fifty samples (0.25 sec).

[Results]

The ICA and c-ICA algorithms each resulted in five components. We illustrate the difference between the two ICA approaches by analysis of the components with the maximum correlation with the stimulus delivery. In Fig. 2 and 3 we show time series for the conventional and c-ICA for the five spatial variance components. The conventional ICA time series all follow a stereotypical time-course, hence appear as being completely time synchronized. While the c-ICA time series show non-trivial delay structure between the five spatial patterns, hence, can give rise to time variant scalp contours of activity. This is an important advantage for c-ICA because it directly, within a single component can capture delayed correlations across the features and locations. In Fig. 4 we show the cross-correlation between time series associated with two of the spatial variance features. The cross-correlation function shows two off-center peaks characteristic of two symmetrically delayed signal components. The conventional ICA algorithm captures only the “average” behavior, while the c-ICA component captures the delayed presence of one of these components.

[Conclusion]

Convolutive ICA (c-ICA) offers a more flexible representation with non-trivial temporal structure of the component time series, highly relevant for EEG analysis.

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fig. 1:

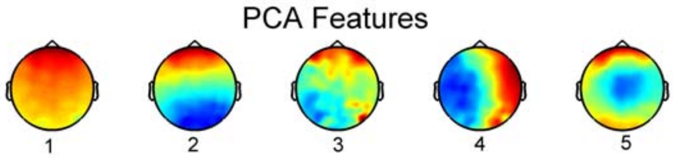

PCA Features
1
2
3
4
5

fig. 2:

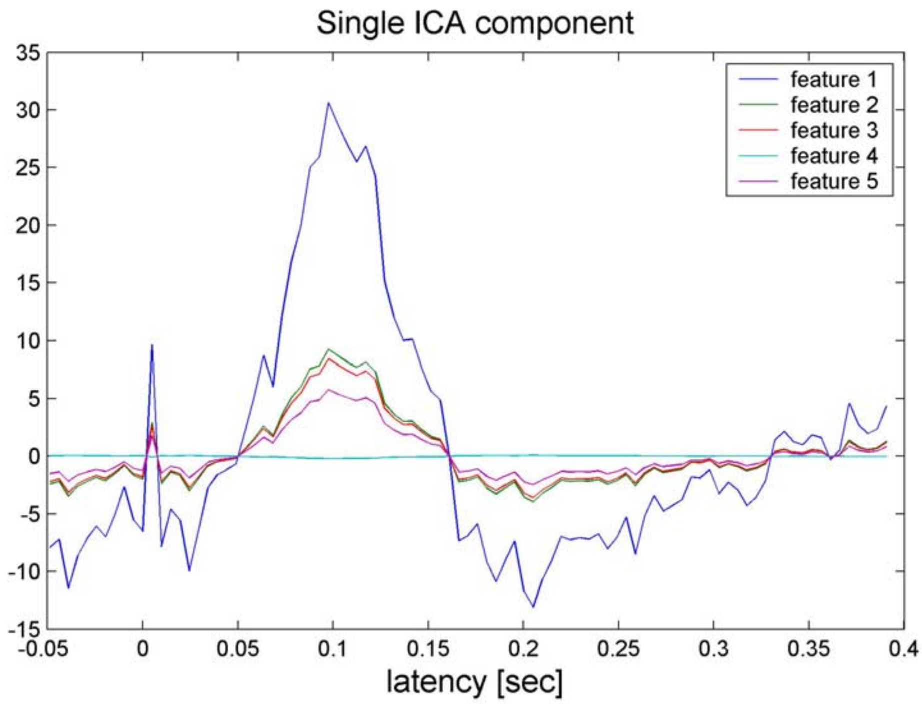
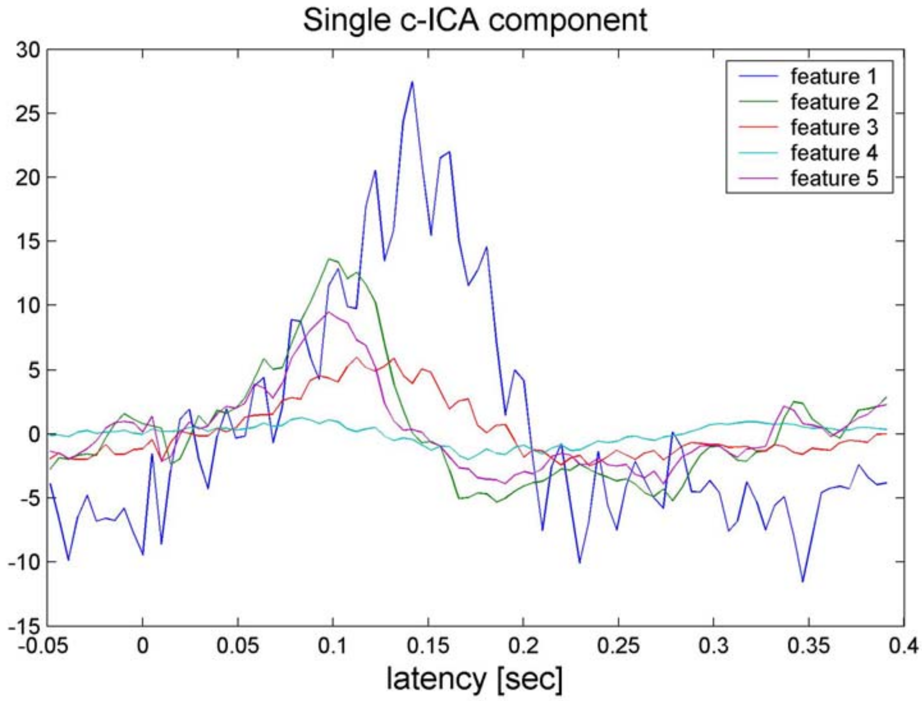
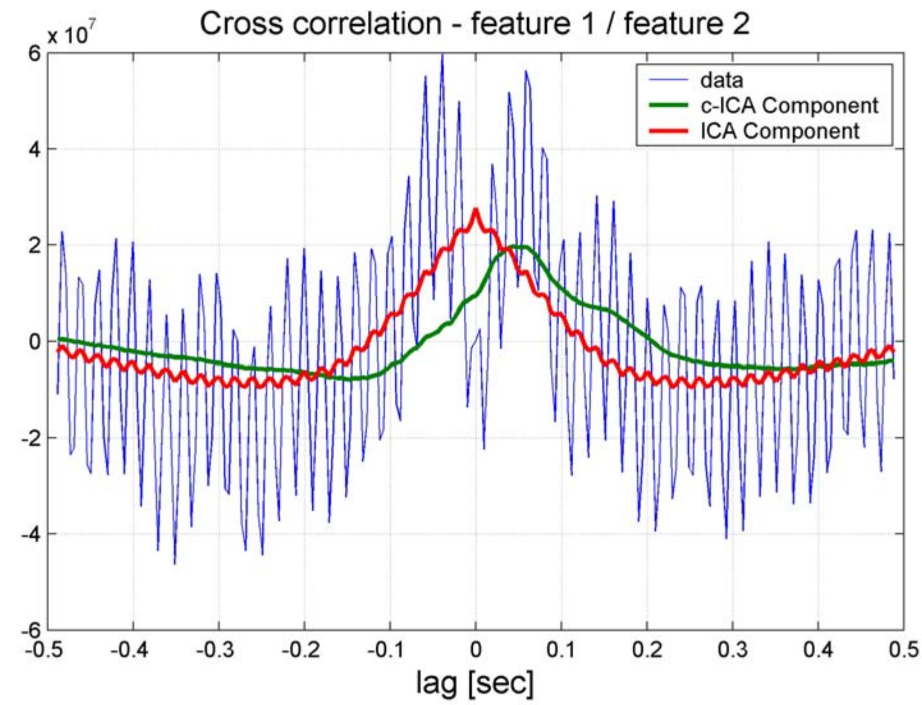

Single ICA component
feature 1
feature 2
feature 3
feature 4
feature 5
35
30
25
20
15
10
5
0
-5
-10
-15
-0.05
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
latency [sec]

fig. 3:



Single c-ICA component
feature 1
feature 2
feature 3
feature 4
feature 5
30
25
20
15
10
5
0
-5
-10
-15
-0.05
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
latency [sec]

fig. 4:



Cross correlation - feature 1 / feature 2
x 10^7
data
c-ICA Component
ICA Component
6
4
2
0
-2
-4
-6
-0.5
-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
0.4
0.5
lag [sec]