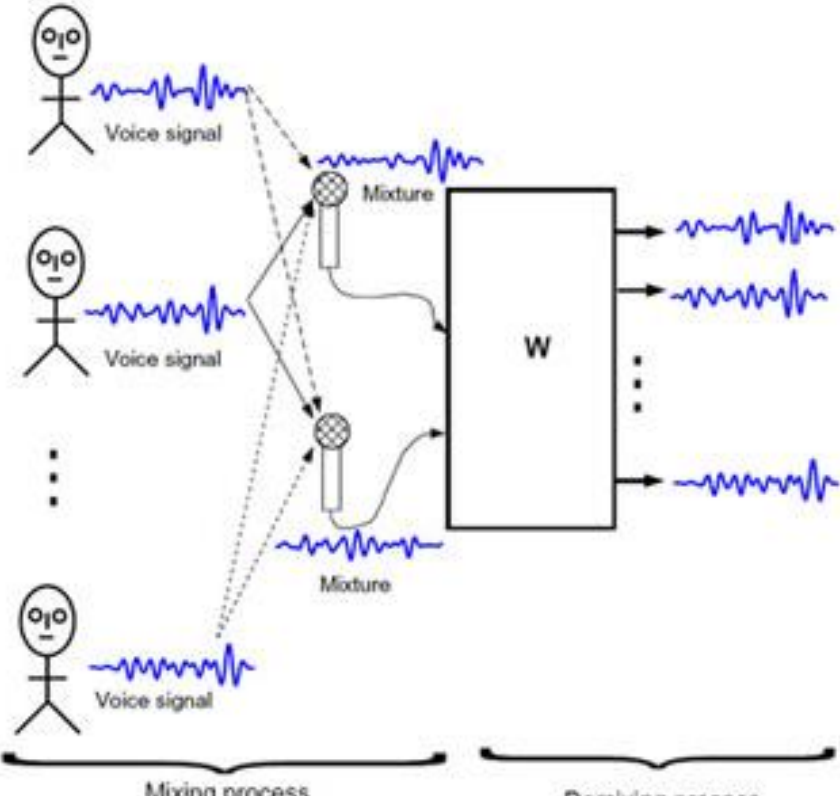
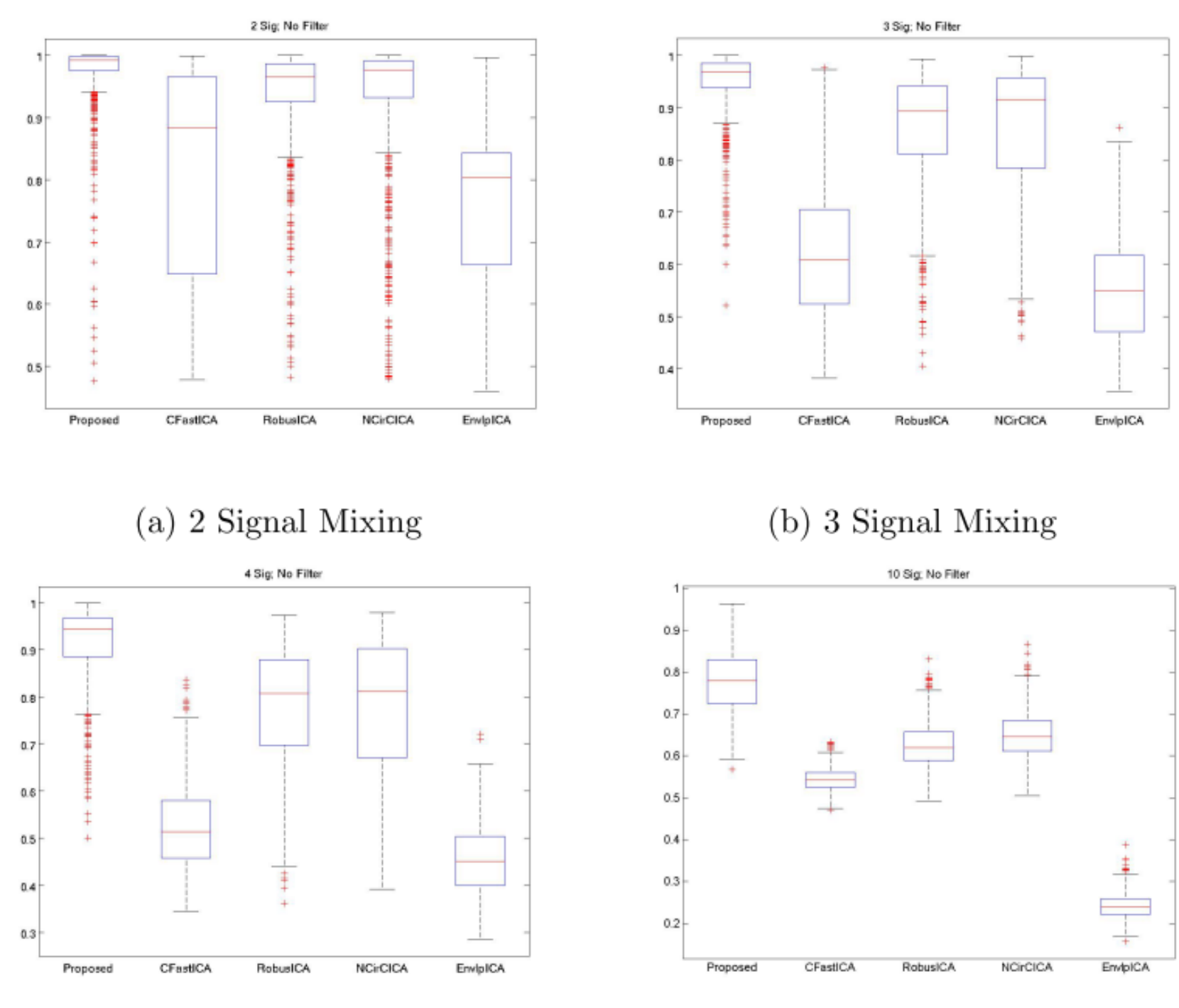


# Complex Independent Component Analysis with Real Mixing

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Introduction	Motivation
<ul style="list-style-type: none"> <li>Extended from cocktail party / ICA problem</li> <li>Complex observations <math>\mathbf{x}</math> are real mixtures <math>\mathbf{A}</math> of independent circular complex sources <math>\mathbf{s}</math></li> </ul>  <p>Mixing process:  <math>\mathbf{x} = \mathbf{A}\mathbf{s}</math>  <math>\mathbf{A} \in \mathbb{R}; \mathbf{x}, \mathbf{s} \in \mathbb{C}</math></p> <p>Demixing process:  <math>\hat{\mathbf{s}} = \mathbf{W}\mathbf{x}</math>  <math>\mathbf{W} \in \mathbb{R}</math></p>	<ul style="list-style-type: none"> <li>Based on Central Limit Theorem, sum of independent random variables is more Gaussian than the original variables.</li> </ul> $\mathbf{y} = \mathbf{w}^T \mathbf{x} = \mathbf{w}^T \mathbf{A}\mathbf{s} = \mathbf{z}^T \mathbf{s}$ <ul style="list-style-type: none"> <li><math>\mathbf{z}^T \mathbf{s}</math> is more Gaussian than any of the <math>s_i</math> and will become least Gaussian when it equals one of <math>s_i</math> (only one element of <math>\mathbf{z}</math> is non-zero).</li> <li>Cost function should be a measure of Non-Gaussianity.</li> </ul>
Method	Result
<ul style="list-style-type: none"> <li>Cost Function – Normalized Kurtosis Function</li> </ul> $K(\mathbf{y}) = \frac{E\{ \mathbf{y} ^4\}}{E^2\{ \mathbf{y} ^2\}} - 2$ <p>Where <math>\mathbf{y} = \mathbf{w}^T \mathbf{x}</math> and <math> \mathbf{w}  = 1</math></p> <ul style="list-style-type: none"> <li>Cost function is optimized based on Quasi-Newton Optimization</li> <li>The independent sources are the local maximums of the cost function if super-Gaussian sources are assumed.</li> <li>Single/Multiple unit Gram-Schmidt decorrelation is used to prevent different weight vectors <math>\mathbf{w}_j</math> from converging to the same maximum.</li> </ul>	 <p>(a) 2 Signal Mixing      (b) 3 Signal Mixing</p> <p>(c) 4 Signal Mixing      (d) 10 Signal Mixing</p>
Simulation	Discussion and Future Works
<ul style="list-style-type: none"> <li>The complex sources are simulated by             <ul style="list-style-type: none"> <li>- Generating independent real Rayleigh signals.</li> <li>- Apply Hilbert transform to get imaginary part.</li> </ul> </li> <li>Separation performance of the proposed method are compared with other methods including complex-fastICA method<sup>1</sup>, robust ICA<sup>2</sup>, and non-circular fastICA method<sup>3</sup>.</li> </ul> <p><small>1. A. Hyvarinen, etc. Neural Networks, 2000    2. V. Zarzoso, etc. IEEE T. Neural Networks, 2010            3. M. Novey, etc. IEEE T. Neural Networks, 2008</small></p>	<ul style="list-style-type: none"> <li>The proposed method outperforms other existing complex ICA methods.</li> <li>When the number of sources increases, the performance of source separation drops, but our method still provides a reasonable separation compared with others.</li> <li>The proposed method can be applied to the EEG/MEG sensor data to get underlying brain network at the sensory level.</li> </ul>