Time-lagged Independent Component Analysis

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Instantaneous mixing model

• **Problem**: m independent sources s_m are mixed into n signals x_n

$$x_n = As_n \tag{1}$$

where A the mixing matrix and s_m are unknown.

• **Solution**: to recover the sorces s_m from this model we estimate a separating matrix W, which is inverse to A under the condition that all sources are stochastically independent and $n \ge m$

$$s_m = Wx_n \tag{2}$$

• Whitening the data x(t) is a preprocessing step of TICA. It is used to decorrelate the data x(t) to achieve independence after this step.

• **Attention**: When x(t) is uncorrelated it doesn't mean x(t) is independent.

• The first step is subtracting the mean of x(t).

$$\tilde{x} = x(t) - mean(x(t)) \tag{3}$$

• Step two is computing the covariance matrix of x(t).

$$C = cov(x(t)) = E\{x_i(t)x_j(t)\}$$
 (4)

• Step three is the diagonalization of *C*.

$$C = V \Lambda V^T \tag{5}$$

• With step four we receive the principal components

$$y(t) = V^T \tilde{x}(t) \tag{6}$$

• The last step is to normalize the principal components y(t), such that C=I

• We obtain whitened(normalized) data z(t) with

$$z(t) = \Lambda^{-\frac{1}{2}} y(t) \tag{7}$$

TICA

• To achieve stochastical independence for data x(t) we use TICA for whitened z(t). For that we are using a time lag τ .

• The first step is to compute a time-lagged covariance matrix

$$C_{\tau}^{z} = E\{z(t)z(t-\tau)^{T}\}\tag{8}$$

TICA

• The second step is making the covarience matrix symmetric.

$$\tilde{C}_{\tau}^{z} = \frac{1}{2} [C_{\tau}^{z} + (C_{\tau}^{z})^{T}]$$
 (9)

Step three is the diagonalization of the symmetric covariance matrix.

$$\tilde{C}_{\tau}^{z} = V \Lambda V^{T} \tag{10}$$

TICA

• With the last step we receive the separating matrix W and the independent sources s(t).

$$W = V^T \tag{11}$$

$$s(t) = Wx(t) \tag{12}$$

The AMUSE algorithm

• **Step on:** Whiten the data x(t) to obtain z(t).

• **Step two:** Apply TICA to z(t).