BAYESIAN SEPARATION OF NON-STATIONARY MIXTURES OF DEPENDENT GAUSSIAN SOURCES

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Abstract

Independent Component Analysis (ICA) has been a very popular research topic in the last decade, because of its huge interdisciplinary application areas, such as communications, signal processing, biomedicine, geophysics, astrophysics and finance [1]. Despite its advantages, ICA is not a fully realistic approach for source separation, since the real world signals do possess dependencies. Thus, the independency assumption cannot always hold and dependency information should be exploited. In literature, there is a limited number of works, where dependencies are taken into account [2]. Moreover, in these works, stationary mixtures are considered. For handling the non-stationarities, particle filtering is a very suitable approach, and it has been successfully utilized for separating the *independent* sources [3]. In this work, a novel method, utilizing the use of particle filters, is proposed for separating two *dependent* (correlated) Gaussian signals from their mixture, where the mixing matrix has a non-stationary structure, as shown below:

$$\begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} 1 & a_1(t) \\ a_2(t) & 1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} n_1(t) \\ n_2(t) \end{bmatrix}, a_1(t) = \cos(\frac{\pi t}{64}), a_2(t) = \sin(\frac{\pi t}{64}) \qquad (1)$$

$$\begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

where $y_i(t)$, $x_i(t)$, $n_i(t)$, $a_i(t)$ denote the observed mixture, source, observation noise signals and the non-stationary mixing matrix elements for i = 1,2, respectively. Since particle filtering is a sequential Bayesian technique, it is very suitable for handling the non-stationarities here. Moreover, since it is a Bayesian approach, the *a priori* information about the source correlations can easily be imposed into the structure. In our method, this is accomplished by defining an additional particle set to model the correlations. Since, particle filtering can be used for non-Gaussian signals, this is a promising method for separating dependent and non-Gaussian sources. According to the computer simulations, it has been observed that the algorithm is successful in estimating the elements of the mixing matrix from the mixtures as shown below:

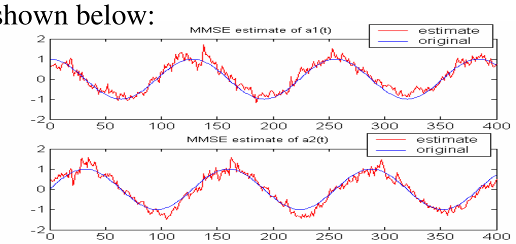

Fig. 1. Minimum Mean Squared Error Estimates of the mixing matrix elements

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