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Non-stationary sources separation based on maximum likelihood criterion using source temporal–spatial model

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ABSTRACT

In this paper, we propose a new non-stationary sources separation algorithm, which is referred to as autoregressive hidden Markov Gaussian process (AR-HMGP), in which the sources are non-stationary and temporally correlated. For the proposed algorithm, a generative model is employed to track the non-stationarity of the source where the temporal dependencies of sources are represented by autoregressive model (AR) and the distribution of the associated innovation process is described using non-stationary Gaussian process with hidden Markov model (HMM). We further explore the maximum likelihood (ML) method to estimate the parameters of the source model by using the expectation maximum (EM) algorithm. Our important findings reveal that (a) AR-HMGP algorithm outperforms the other three BSS algorithms for non-stationary sources separation, the instantaneous mixture system is also well corroborated with the effectiveness of our algorithm; (b) both independent and dependent non-stationary sources have been successfully separated; (c) the proposed algorithm is robust with respect to noise, while the other three algorithms are not.

1. Introduction

Source signals mixing has attracted a wave of attentions with various applications, such as communication system, speech system, biomedical signal processing. In particular, target signal can be easily extracted by filter if there is no spectral overlap. However, if there is spectral overlap, the filter method is invalid. In this case, blind source separation (BSS) is a good choice to solve the problem. BSS is a technique which attempts to extract a set of unknown sources mixed by an unknown mixing matrix, given only a set of their mixture signals [1].

In past several decades, BSS has been widely researched. It has been used to remove interference from communication signal [2], separate speech signals from different speakers [3,4], extract encephalography (EEG) signals [5,6], and so on. Meanwhile, many BBS algorithms are developed. There are two common types of BSS algorithms. One is based on independent component analysis (ICA) [1,3,6] and the other is based on decorrelation [7,8]. BSS algorithms based on decorrelation use covariance matrices of estimation sources with two or more lags and combine the matrices characteristics to achieve mixture system identification, and then obtain sources. Those methods are able to separate dependent sources mixtures and multi-Gaussian sources mixtures when the sources have sufficient spectral diversity. The algorithms based on ICA are invalid in this case. While the BSS algorithms based on ICA minimize the cost function constructed on the dependence of estimation sources. Those algorithms assume that sources are mutually independent and no more than one Gaussian signal exists. Under those conditions, ICA-based algorithms can separate mixtures no matter what the sources are, even all of the sources have identical spectra, which is significant for communication system – without consuming additional power and frequency resources to eliminate interference or jamming to achieve normal communication. However, decorrelation-based algorithms are invalid when the sources have identical spectra. Therefore, we need to select different algorithms according to different application environment, which brings much inconvenience for the application of BSS. The reason is mainly because of the two methods above analyse temporal structure and spatial structure of sources separately, consequently the temporal-spatial structure information has not been fully utilized. The algorithm proposed in this paper is to solve the two aforementioned cases, in which both temporal and

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spatial structure information are in consideration. Recently, there are also some others methods to address BSS, such as bounded component analysis (BCA) [9–11] and non-negative matrix factorization (NMF) [12–14]. However, since these methods are based on the geometric properties of the received signals, they are very sensitive to noise. From the practical application of the blind separation algorithm, we will no longer discuss these algorithms in detail.

Structures that have been used in BSS to explain the temporal structure of each source are often described by using autoregressive model (AR) and hidden Markov model (HMM). Both ICA-based methods [15,16] and decorrelation-based methods [15,17] can be used to separate AR sources. It is worth noting that only stationary signals can be represented by AR model. However, most of signals are non-stationary in practice. Non-stationary signals are often described by using HMM. The BSS algorithms for HMM sources can be used to separate non-stationary sources [18–20]. However, those methods are based on ICA, in which dependent sources cannot be separated. Some researchers have also studied blind separation for moving average model (MA) sources [21,22]. However, MA model is not prevalent in BSS, because it needs to estimate a back forward finite impulse response (FIR) filter, which has high computational complexity compared with the AR model.

The statistical distribution models prevalent in BSS are often described by using Gaussian mixture model [2,23], generalized Gaussian distribution (GGD) [24] and generalized hyperbolic model [25]. However, those models are used to represent stationary signals. Meanwhile, authors of [26] combined HMM with GMM to present the non-stationary characteristic and statistical characteristic of non-stationary signals respectively, which obtains a good separation result. However, the complexity of the algorithm grows exponentially with a linear increase in model order.

Considering the model of sources, we always hope that the model can represent different signals perfectly, as well as the number of parameters as small as possible. Since AR model represents the temporal structure of signals with linear complexity, we select AR model as our source model frame. The innovation of AR model is described by using non-stationary Gaussian process, where HMM is employed to represent the non-stationarity. The effectiveness of the proposed approach for tracking non-stationarity is shown in section IV that small AR model order and small number of innovation state already has a great performance. The estimation of model parameters is an incomplete data issue with latent variables. The typical solution is based on maximum likelihood criterion (ML). There are two common algorithms of ML. The first is Markov chain Monte Carlo algorithm (MCMC) [27,28] and the second is expectation maximum (EM) algorithm [23,29,30]. Considering EM algorithm is simple and converges faster than MCMC [31], EM algorithm is employed in this paper to realize BSS. The main contributions of our work are summarized as follows.

- Considering both temporal and spatial structure information of sources.
- Solving the problem of non-stationary sources separation for dependent sources and sources with similar spectrum.
- Exploiting the structure of non-stationary source signals (temporal–spatial) in the ML criterion leads to better performance.

The remainder of this paper is organized as follows. Section 2 introduces three models used in this paper, including system model, sources distribution model and observations distribution model. Next, the proposed algorithm is described in Section 3. Section 4 demonstrates our experimental results, and conclusions are drawn in Section 5.

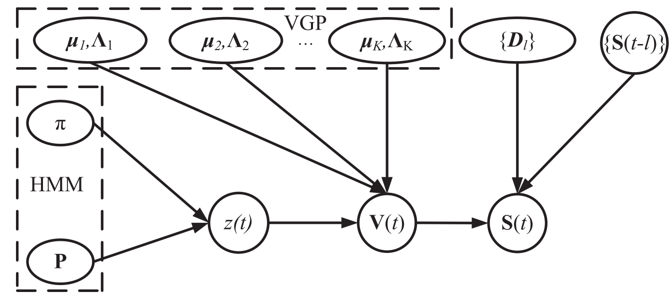

Fig. 1. The structure of sources (ellipse stands for model parameters whereas circle stands for variable).

2. Models

2.1. System model

Instantaneous mixture model is given by

$$\mathbf{X}(t) = \mathbf{A}S(t) \tag{1}$$

where $\mathbf{S}(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^T$ denotes N sources vector, $\mathbf{A} \in R^{M\times N}$ denotes mixture matrix, $\mathbf{X}(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T$ denotes M observations vector, $[\cdot]^T$ denotes transpose operator. BSS aims at constructing a demixing matrix $\mathbf{W}$ to obtain $\hat{\mathbf{S}}(t) = \mathbf{W}X(t)$, which is an estimation of $\mathbf{S}(t)$, possibly with different order and scale. To simplify the analysis, we only discuss the case $N = M$, reducing dimension method [32] can be used to transform over-determined mixture ($M > N$) to determined mixture ($M = N$).

2.2. Sources distribution model

In this paper, a temporal–spatial structure model is employed to represent sources, where the temporal dependencies of each source is described by using AR model and the distribution of associated innovation process is described by using non-stationary Gaussian process (HMGP), where HMM is employed to represent the non-stationarity. Assuming there are sources, their vector AR model is given by Boudjellal et al. [17]

$$\mathbf{S}(t) = \sum_{l=1}^{L} \mathbf{D}_l \mathbf{S}(t-l) + \mathbf{V}(t) \tag{2}$$

where $\mathbf{D}_l = diag[d_{1l}, d_{2l}, \ldots, d_{Nl}]$ denotes the coefficient matrix of vector AR model, L denotes the order of vector AR model, $\mathbf{V}(t) = [v_1(t), v_2(t), \ldots, v_N(t)]^T$ denotes the vector of innovation process.

The model is envisioned as a generative model with three layers, as depicted in Fig. 1. First, a state sequence $(z(1), z(2), \ldots, z(T))$ is generated by Markov process, where $z(t) \in \{1, 2, \ldots, K\}$. Afterwards, the innovation process is generated by Gaussian distribution process associated to the state sequence. At last, the sources are generated according to the vector AR model. There are two limitations for the generative model that need to clarify:

(1) It is first order Markov process, i.e. the state at time t, $z(t)$, only depends on the state at time $t-1$, $z(t-1)$

$$\Pr(z(t)|z(t-1), z(t-2), \ldots, z(1)) = \Pr(z(t)|z(t-1)). \tag{3}$$

(2) The value of innovation process at time t, $\mathbf{V}(t)$, has no dependency with other variables but the state at time t

$$f_{\mathbf{V}|\mathbf{z}}(\mathbf{V}(t)|z(t), \Xi) = f_{\mathbf{V}|\mathbf{z}}(\mathbf{V}(t)|z(t)), \tag{4}$$

where Ξ represents the set of variables except $z(t)$.

The initial state probability of Markov process is $\pi_k = \Pr(z(1) = k)$, the transition probability from state i to state k is $p_{ik} = \Pr(z(t) = k|z(t-1) = i)$, $i, k = 1, 2, \ldots, K$. According to Eq. (4), the