ADAPTIVE BLIND SEPARATION OF CONVOLVED SOURCES BASED ON MINIMIZATION OF THE GENERALIZED INSTANTANEOUS ENERGY

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ABSTRACT

Generalization of the energy concept is proposed resulting in a class of novel on-line algorithms for blind separation of convolved signals. Signal separation is achieved when signal energy of the appropriated order is minimal. The resulting learning rules have the similar form as those recently discussed to be optimal for blind separation of instantaneously mixed signals. Algorithms are tested on the separation of two real-world signals. It is believed that for the first time the blind signal separation (BSS) theory is applied to the light sources localization problem. With proposed algorithms better separation quality is obtained than when using adaptive decorrelation, recently proposed separation algorithm based on entropy maximization and neural network separator based on nonlinear odd activation functions.

1. INTRODUCTION

Potential application of the BSS lies in many areas such as: antenna arrays processing, speaker separation in speech recognition, communication signal processing by performing adaptive blind equalization, remote sensing, medical imaging, astronomy, seismic signal processing, etc. [11]. We believe that for the first time the BSS theory is applied to the new problem: localization of the light sources.

BSS usually assumes a linear instantaneous mixing model: $x(t) = As(t)$ where $s(t)$ is vector of source signals A is mixing matrix, and $x(t)$ is vector of the observed i.e. measured signals. The goal is to reconstruct the source signals from the observed signals only, i.e. the mixing matrix A is assumed to be unknown. The solutions of such problem for two or more signals are given in [1], [3], [4], [8], [10], [12]. The application of those algorithms to the real-world situations is seriously limited from several reasons. The most problematic is the assumption of instantaneous mixing of the source signals. The real-world situations very often include time delays between the sources in the mixture. Also, sensors themselves influence the signals by their impulse responses. Such situation can be modeled with convolutive mixture. It is mathematically described with: $x(t) = A * s(t)$, where $*$ denotes convolution and A is the matrix of impulse responses. Solutions for such problem are given in [4], [5], [7], [9], [13], [16]-[21]. However, most of the proposed solutions are very complex in computational sense and iterative by nature, [5], [7], [9], [20]. For real time source separation adaptive i.e. sequential version of the algorithms is necessary. Such algorithms are described in [13], [16], [17], [18]. The subject of the second section are novel on-line separation algorithms that perform simultaneous minimization of the generalized instantaneous energy.

Experimental results are given in the third section. Several algorithms are mutually compared through the quality of separation of two real-world signals. Optical modulation process is described very shortly to give an idea why the light sources localization problem can be interpreted as the BSS problem. Conclusion and future work are given in section four.

2. ON-LINE SEPARATION ALGORITHMS

The on-line separation algorithms are given in [13], [16], [17], [18]. In [18] adaptive sequential procedure based on Estimate-Maximize algorithm is given. However, the signal-noise paradigm still dominates in [18]. In [17] on-line separation is performed by minimizing instantaneous energy of the separator output signals. That leads to decorrelation. The algorithm [16] separates convolved signals by maximizing entropy of the sigmoidal functions of the output signals. Here proposed algorithms are generalization of the energy criteria used in [17]. Signals will be separated when mutual information is minimal i.e. when signal energy is minimal. Here the term energy is generalized in a sense that higher-order moments or their suitable modifications should be viewed as energies of the higher order. The signal model given with figure 1. is assumed.

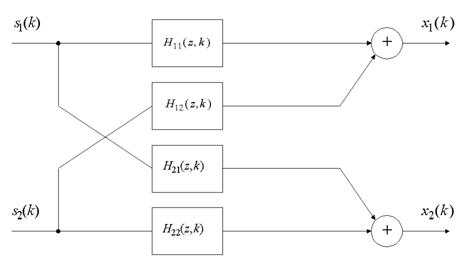

Figure 1. Convolutive signal model

For reconstruction of the source signals the feedback separation network shown on figure 2. is applied. Specifically, it has been adopted $W_{11}(z) = W_{22}(z) = 1.0$. The same structure was used in [13], [16], [17]. The reasons of using feedback network with $W_{11}(z)$ and $W_{22}(z)$ set to unity is to avoid withening effect explained nicely in [16].

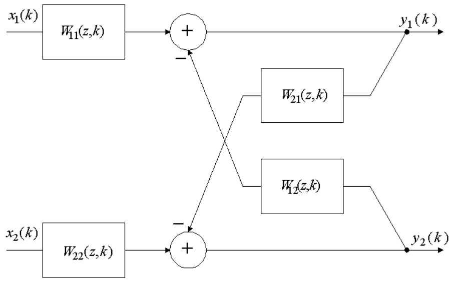

Figure 2. Feedback separation network

As already noticed, the minimization of the energy of the signal estimates is used in [17] as performance criteria:

$$\xi_i(k) = E\Big[y_i^p(k)\Big] \quad i = 1,2 \tag{1}$$

where $p = 2$. It is assumed that source signals are zero mean and statistically independent, i.e.:

$$E\Big[s_i^r(k)s_j^q(k-m)\Big] = 0\ . \tag{2}$$

for odd r and q, and for every m. Assuming that both cross-filters have the same order the input-output relations based on the figure 2. are given with:

$$\begin{aligned} y_1(k) &= x_1(k) - \sum_{m=1}^{M} w_{12}(m)y_2(k-m) \\ y_2(k) &= x_2(k) - \sum_{m=1}^{M} w_{21}(m)y_1(k-m) \end{aligned} \tag{3}$$

There is no general agreement whether second order statistics is sufficient to separate the signals or not. Some successful applications based on decorrelation criteria are reported, [5], and some with higher-order statistics also, [13], [21]. That suggests an idea to generalize the energy concept (1) by allowing the possibility $p > 2$. So the separation of signals, understood as minimization of the mutual information, is achieved when the generalized energy ξ_i be minimal. From the energy point of view the expression (1) doesn't make sense when p is an odd number. The negative energy, that can be computed from (1) when p is odd, has no physical sense. To preserve the physical meaning of the energy based criteria expression (1) is reformulated for odd p as:

$$\xi_i(k) = E\Big[y_i^p(k)sign(y_i(k))\Big] \quad i = 1,2 \tag{4}$$

or:

$$\xi_i(k) = E\Big[\sqrt{y_i^{2p}(k)}\Big] \quad i = 1,2 \tag{5}$$

Sign function in (4) ensures that $\xi_i(k)$ is always positive but it does not change the energy amount. The same role has positive square root in (5). For criteria (1), p even, gradients are given with:

$$\nabla_i(k,m) = \frac{\partial \xi_i(k)}{\partial w_{ij}(m)} = -pE\Big[y_i^{p-1}(k)y_j(k-m)\Big] \tag{6}$$

where: $i,j = 1,2, i \neq j$. The same applies for indices in all forthcoming formulas dealing with gradients and learning rules. The general learning rules are given with:

$$w_{ij}(k+1,m) = w_{ij}(k,m) - \mu\nabla_i(k,m)\ m = 1,2,\ldots,M. \tag{7}$$

Replacing the expected values in (6) with their instantaneous sample estimates and inserting them in (7) the following learning rules are obtained:

$$w_{ij}(k+1,m) = w_{ij}(k,m) + \mu y_i^{p-1}(k)y_j(k-m) \tag{8}$$

what leads to decorrelation when $p = 2$ is selected. For odd p the gradients of criteria (4) are obtained as:

$$\nabla_i(k,m) = -pE\Big[y_i^{p-1}(k)sign(y_i(k))y_j(k-m)\Big] \tag{9}$$

and for criteria (5) as:

$$\nabla_i(k,m) = -pE\Big[\big[y_i^{2p}(k)\big]^{-\frac{1}{2}}y_i^{2p-1}(k)y_j(k-m)\Big] \tag{10}$$

From (9) and (7), when expected values are replaced by their instantaneous sample estimates, follow the learning rules for odd p criteria (4):

$$w_{ij}(k+1,m) = w_{ij}(k,m) + \mu y_i^{p-1}(k)sign(y_i(k))y_j(k-m) \tag{11}$$

and from (10) and (7) for odd p criteria (5):

$$w_{ij}(k+1,m) = w_{ij}(k,m) + \mu\Big[y_i^{2p}(k)\Big]^{-\frac{1}{2}}y_i^{2p-1}(k)y_j(k-m) \tag{12}$$

Convergence of the learning algorithms is achieved under condition, [8], [15]:

$$E\Big[\nabla_i(k,m)\Big] = 0 \quad i = 1,2. \tag{13}$$

Since by assumption (2) the source signals $s_1(t)$ and $s_2(t)$ are statistically independent so will be the output signals $y_1(t)$ and $y_2(t)$ when time goes to infinity. Under this condition application of the expectation operator on the expression (6) gives:

$$E\Big[\nabla_i(k,m)\Big] = -pE\Big[y_i^{p-1}(k)\Big]E\Big[y_j(k-m)\Big] \tag{14}$$

By assumption the source signals are zero mean. The separating signals will be also zero mean i.e.

$$E\Big[y_1(k-m)\Big] = E\Big[y_2(k-m)\Big] = 0. \tag{15}$$

Applying this on the expression (14) gives that condition (13) is satisfied and that global convergence is ensured. For the odd p application of the expectation operator on (9) gives:

$$E\Big[\nabla_i(k,m)\Big] = -pE\Big[y_i^{p-1}(k)sign(y_i(k))\Big]E\Big[y_j(k-m)\Big] \tag{16}$$

Due to the (15) condition (13) is satisfied again. The same applies for gradients given with (10). It should be observed that symmetrical distribution of the source signals is not required as it is the case for some memoryless blind separation algorithms,[3], [8], or for the learning rule given in [13]:

$$w_{ij}(k+1,m) = w_{ij}(k,m) + \mu f\Big[y_i(k)\Big]g\Big[y_j(k-m)\Big] \tag{17}$$

which becomes the learning rule (8) when f and g are selected as:

$$f\Big[y_i(k)\Big] = y_i^p(k) \quad , \quad g\Big[y_j(k-m)\Big] = y_j(k-m) \tag{18}$$

It was stated in [2] that from the memoryless model standpoint a learning rule of the form $\varphi_i(y_i)y_j$ is the optimal one, what is exactly the form of our learning rules (8), (11) and (12), but this time for convolved sources. From that standpoint it appears that the concept of the generalized instantaneous energy introduced by criteria (1), (4) and (5) proves its consistency.

3. EXPERIMENTAL RESULTS

The BSS theory is applied, it is believed for the first time, on the light sources localization problem. Two real-world signals are recorded at the output of the electrooptical device called optical modulator with sampling frequency of $100kHz$. The application of the optical modulator is in detection of the polar coordinates of the light source. Time varying flux radiating from the light source is modulated by means of device called modulating disk. Photodiode detects optically modulated signal, where modulating function $s(r,\varphi,t)$ is a function of the polar coordinates of the projection of light source on the modulation disk area and also function of disk type, [6]. Here r stands for radius and φ for angle. For optical disk with fan-bladed pattern, [6], the modulating function has the form:

$$s(r,\varphi,t)=\cos\Big[\omega_0 t-\beta\sin(\Omega_M t-\varphi)\Big] \qquad (19)$$

what is canonical representation of the frequency modulated (FM) signal and β, ω_0 and Ω_M are functions of the light source coordinates and optical modulator construction constants. Deviation, β, of the FM signal (19) is directly proportional with the polar coordinate r. The sensed signal, usually photocurrent, is additionally amplified and bandpass filtered. After that it was digitally recorded. Detailed description of how optical modulation works is given in [6]. Optical modulator, the function of which is described above, fails when two or more light sources are present simultaneously in its field of view. Combining optical modulation theory, [6], semiconductor photodetection theory, [14], and linear filtering theory it is possible to derive the mathematical model of the optical modulator output signals in a case when two light sources are present in its field of view simultaneously. It is shown that linear model with memory, such as shown by figure 1., is an adequate description. Detailed derivation of the signal model is beyond the scope of this paper and will be published separately. Furthermore, optical modulator construction had to be modified by introduction of the second photodiode with photoamplifier and bandpass filter and also by introduction of the beam splitter device in order to enable the both photodetectors to see the light sources in the same system of coordinates. Assuming that photodiodes work in linear region recorded signals are linear combination of the modulating waveforms $s(r,\varphi,t)$, (19), convolved with the time varying impulse responses. Impulse responses turn to be multiplicative combination of the bandpass filters impulse response, which are stationary, and time varying fluxes radiated by the corresponding light sources. Figure 3. shows power spectrum of one measured mixed signal recorded at the output of one photoamplifier. The information about position of both light sources is present in the recorded signal. First light source, with smaller radius coordinate, has deviation of approximately $500Hz$ and is located between 22 and $23kHz$. The second signal, with larger radius, has deviation of approximately $2.5kHz$ and occupies spectrum from 20 to $25kHz$. The length of the recorded blocks of mixed signals $x_1(t)$ and $x_2(t)$ was 16384 samples. After separation determination of the coordinates of light sources is the matter of demodulation of the recovered source signals which are of the form (19).

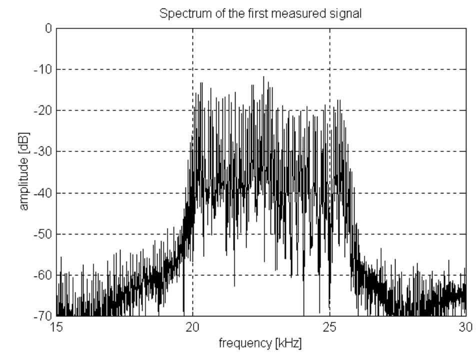

Figure 3. Power spectrum of the first measured signal

In order to measure the separation quality and to compare different separation algorithms the following separation quality criteria was used:

$$Q=10\log_{10}\frac{\sum\limits_{i=N_2}^{N_3}Y_2(\omega_i)Y_2^*(\omega_i)}{\sum\limits_{i=N_1}^{N_2}Y_2(\omega_i)Y_2^*(\omega_i)+\sum\limits_{i=N_3}^{N_4}Y_2(\omega_i)Y_2^*(\omega_i)} \qquad (20)$$

where N_1, N_2, N_3 and N_4, are frequency bin indices that correspond with frequencies of 20, 22, 23 and $25kHz$, respectively. By using (20) the separation quality is defined as the logarithm ratio of the in-band and out-of-band energy of the recovered signal $y_2(t)$. It was assumed that signal $y_2(t)$ corresponds with the source signal with smaller deviation. A number of algorithms with the learning rules (8), (11) and (12) with different values of p was applied to reconstruct the source signals. The length of the separating cross-filters has been varied in order to get as large Q as possible. Entropy maximization separator (ME) proposed in [16], and neural network separator (NN) proposed in [13], were also applied. The NN separator was used with the commonly suggested learning rule:

$$f(y_i)=y_i^2 sign(y_i) \quad g(y_j)=3\tanh(10y_j)$$

Results are summarized in table 1. Here, p means algorithms with the learning rule (8), $psig$ means algorithms with the learning rule (11), and $psqr$ means algorithm with the learning rule (12). Q is the separation quality measure (20), and M is the length of the FIR cross-filters $W_{12}(z)$ and $W_{21}(z)$. Power spectrum of the separated signal $y_2(t)$ with the best value of Q is shown on figure 4. The value of Q for the observed signals $x_1(t)$ and $x_2(t)$ is -1.74 and $-1.57dB$, respectively. It should be noticed that decorrelation criteria, $p=2$, gives $3.05dB$ worse separation quality than the best result obtained with criteria (5) and $p=9$. The entropy based separators and neural network separators with the given learning rule are inappropriate choice for separation of the sub-Gaussian signals. The FM signal produced by an optical modulator belongs to this class of signals.

4. CONCLUSION AND FUTURE WORK

A class of novel on-line algorithms for blind separation of convolved sources, based on the concept of the generalized instantaneous energy, is derived. The generalized energy should be viewed as higher-order moments or their suitable modifications. The algorithms are applied, it is believed for the first time, to the light sources localization problem. Better separation results are obtained than when using decorrelation only, [17], maximal entropy based separation, [16], or neural network separation based on the products of the certain odd nonlinear activation functions, [13]. Future work will be directed toward DSP implementation of derived algorithms. The research related to the application of the natural gradient, introduced in [1], to modify our gradients and learning rules will be carried out also.

Table 1. Separation results for different algorithms

ALGORITHM	$Q[dB]$	M
$p=2$	2.78	53
$p=6$	4.08	83
$psig=9$	4.08	43
$psqr=9$	5.83	53
ME	3.46	113
NN	0.5	103

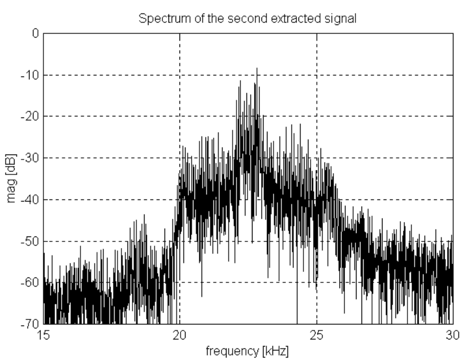

Figure 4. Power spectrum of the separated signal $y_2(t)$

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