Blind Source Separation Based on a Single Observation

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Abstract. This paper deals with a novel approach to the compound signal decomposition. It takes advantage of blind source separation using the algorithm for convolution kernel compensation (CKC). We derive a version which cope with compound signals, mixtures of several source contributions, even if only a single observation is available. Our novel approach detects and separates the triggering instants of all source symbols which contribute to the processed observation. The obtained decomposition is very robust and accurate. We experimented with synthetic signals having characteristics similar to the electrocardiographic (ECG) signals. Also at signal-to-noise ratios (SNRs) as low as 0 dB, the obtained average true positive statistics for the detected source-symbol triggerings was 98±1%, average false positive statistics 2±1%, and false negative statistics 3±2%.

1 Introduction

Many natural and technological phenomena can be modelled as multiple-input multiple-output (MIMO) systems. Observing compound signals, for example, such as telecommunication, bioelectrical, seismic, speech or imaging data, successful approaches are sought to perform a thorough decomposition to the signals' constituent components. These components observed, i.e. measured, at multiple system outputs carry simultaneous information on each system input excitation, which is said to come from a source, and on the response of the transmission path between a source and an observation point, i.e., a system channel [1, 2].

On the other hand, any compound signal can be interpreted as a superimposition of signal components, which correspond to the individual source symbols generated by the MIMO input sources. These components, therefore, appear at time instants which coincide with the triggering (generating) instants of the sources. If the symbol alphabet is finite, so is the number of different observed signal components. By reformulating the model in such a way that it describes the observed signal components and their triggering instants, the characteristics of source symbols and the model transfer channels are not seen separately any more [1]. There are several benefits out of this assumption. The first of them brings unification to the interpretation of all compound signals, regardless their original sources. Secondly, decomposition of those signals can be focused on the component triggering instants, which greatly improves its accuracy, robustness, and reliability. So, the

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decomposition result is a train of triggering pulses. And finally, the observed individual signal components may be extracted from the observations by different approaches, such as spike-triggering averaging [11].

Typical observations of compound signals in practice are related to communications, bioelectrical signals, range imaging, etc. If the input source symbols can be considered spatially and temporally uncorrelated, a variety of blind source separation (BSS) techniques serve the decomposition purpose accordingly [3, 4, 5, 6, 7, 8]. When the sources tend to become correlated, more reliable solutions may be expected using higher-order statistics (HOS) [9, 10], which are also very noise-resistant. While the BSS methods cope with nonstationary signals, HOS approaches cannot. On the other hand, the number of observations must exceed the number of sources to warranty a reliable BSS operation, whereas for HOS there is no such limitation [10, 11].

Recently, a novel BSS-based method has been proposed. It makes use of the Mahalanobius distance and angle calculation which, consequently, can lead to the entire model convolution kernel compensation (CKC). As a result, the system output observations are blindly deprived of the transfer channel influence and only the source-symbol triggering pulse trains are extracted [11, 12]. It has been shown that the source symbols correlated up to 10 % and the underdetermined cases with the number of observations being as low as a half of the number of source symbols do not hinder a proper CKC-based decomposition [12].

This paper proposes a novel solution which combines the benefits of the CKC and HOS approaches. It can cope with an arbitrary underdetermined case in such a way that it generates additional observations out of the given ones. This generation must be based on nonlinear operations on the given observations–the linear ones wouldn't increase the rank of the CKC decomposition matrix. To demonstrate the idea in an extreme situation, we are going to deal with only a single observation here, so the anticipated model will be reduced to a multiple-input single-output (MISO). Adequate data model and the CKC-based decomposition are presented in Section 2. Section 3 introduces the idea of how to generate more observations out of a single one, while Section 4 explains this new concept with a short example. The influence of noise and correlated sources is discussed in the concluding Section 5.

2 Data Model

Recapitulate briefly the reconstruction of source-symbol pulse trains using the CKC-based decomposition [11, 12]. Consider the following data model:

$$x_i(n) = \sum_{j=1}^{K}\sum_{k=0}^{L-1} c_{ij}(k)t_j(n-k) + v_i(n); i = 1,\ldots,M \tag{1}$$

where $x_i(n)$ stands for the i-th observation, $c_{ij}(k)$ corresponds to the contribution of length L of the j-th source symbol in the i-th observation, and $t_j(n\text{-}k)$ denotes a sequence of triggering instants for this symbol, $t_j(n) = \sum_{l=-\infty}^{\infty}\delta(n - T_j(l))$, with unit-sample pulses placed at $T_j(l)$ lags, while $v_i(n)$ is considered i.i.d. white noise independent from the sources.

It has been shown [3] that Eq. (1) can be transformed into a multiplicative vector form as follows:

$$\mathbf{x}_e(n) = \mathbf{C}_e\mathbf{t}_e(n) + \mathbf{v}_e(n);\, n = 0,\ldots,N-1 \tag{2}$$

where subscript e designates extended vectors and matrices, $\mathbf{C}_e$ contains the observed contributions of source symbols:

$$\mathbf{C}_e = \begin{bmatrix} \mathbf{C}_{11} & \cdots & \mathbf{C}_{1K} \\ \vdots & \ddots & \vdots \\ \mathbf{C}_{M1} & \cdots & \mathbf{C}_{MK} \end{bmatrix} \tag{3}$$

with

$$\mathbf{C}_{ij} = \begin{bmatrix} c_{ij}(0) & \cdots & c_{ij}(L-1) & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & c_{ij}(0) & \cdots & c_{ij}(L-1) \end{bmatrix}, \tag{4}$$

$\mathbf{x}_e(n)$ stands for the vector of observations, and $\mathbf{t}_e(n)$ for the vector of triggering pulses, both at lag n:

$$\begin{aligned} \mathbf{x}_e(n) &= [y_1(n),....,y_1(n-M_e+1),....,y_M(n),....,y_M(n-M_e+1)]^T \\ \mathbf{t}_e(n) &= [t_1(n),....,t_1(n-L-M_e+2),....,t_K(n),....,t_K(n-L-M_e+2)]^T \end{aligned} \tag{5}$$

Extended noise vector $\mathbf{v}_e(n)$ is considered constructed in the same way. M_e in Eqs. (5) means an extension factor. If it fulfils the following inequality

$$M \cdot M_e \geq K(L + M_e - 1), \tag{6}$$

then for K different source symbols of length L and M observations the matrix $\mathbf{C}_e$ is of full column rank. This condition warranties a successful elimination of contributions of $\mathbf{C}_e$, as we are going to show in the next section.

2.1 Convolution Kernel Compensation

Recall Eq. (2). It has a typical MIMO structure. From this point of view, Ce is a convolution kernel convolving $\mathbf{t}_e(n)$ into the observations $\mathbf{x}_e(n)$. Given $\mathbf{x}_e$, if we can get rid of $\mathbf{C}_e$ the triggering instants of unknown source symbols, $\mathbf{t}_e$, would be obtained. We called this process “convolution kernel compensation (CKC)”.

Observe the following expression:

$$\mathbf{x}_e^T(n)\mathbf{R}_{\mathbf{x}_e}^{-1}\mathbf{x}_e(n) \tag{7}$$

where $\mathbf{R}_{\mathbf{x}_e}$ stands for the sample correlation matrix:

$$\mathbf{R}_{\mathbf{x}_e} = \mathbf{x}_e\mathbf{x}_e^T = \mathbf{C}_e\mathbf{t}_e\mathbf{t}_e^T\mathbf{C}_e^T + \sigma^2\mathbf{I} = \mathbf{C}_e\mathbf{R}_{\mathbf{t}_e}\mathbf{C}_e^T + \sigma^2\mathbf{I} \tag{8}$$

with $\mathbf{R}_{\mathbf{t}_e}$ denoting sample correlation matrix of source triggering trains of pulses, and the expression $\sigma^2\mathbf{I}$ represents the noise, $\mathbf{v}_e$, correlation matrix.

For easier comprehension of derivation, continue with the noise-free case. By substituting (8) into (7), we see that convolution kernel is eliminated:

$$\mathbf{x}_e^T(n)\mathbf{R}_{\mathbf{x}_e}^{-1}\mathbf{x}_e(n) = \mathbf{t}_e^T(n)\mathbf{C}_e^T\mathbf{C}_e^{-T}\mathbf{R}_{\mathbf{t}_e}^{-1}\mathbf{C}_e^{-1}\mathbf{C}_e\mathbf{t}_e(n) = \mathbf{t}_e^T(n)\mathbf{R}_{\mathbf{t}_e}^{-1}\mathbf{t}_e(n) \tag{9}$$

The expression from (7) is known as Mahalanobius distance, which, as it is clear from Eq. (9), yields only the information on source triggering instants. Actually, its value depends on the number of sources active in given time instant n. This is why we call it *activity index*.

Suppose we deal with orthogonal sources and n_0 indicates the time instant where one of them generates a symbol (its contribution appears in the observation). Then vector $\mathbf{t}_e(n_0)$ is all zero except the element which belongs to the generated symbol, say the i-th, and equals 1. Besides, matrix $\mathbf{R}_{\mathbf{t}_e}$ is diagonal, and so is $\mathbf{R}_{\mathbf{t}_e}^{-1}$. It is then straightforward that

$$p_{n_0,i}(n) = \mathbf{x}_e^T(n_0)\mathbf{R}_{\mathbf{x}_e}^{-1}\mathbf{x}_e(n) = \mathbf{t}_e^T(n_0)\mathbf{R}_{\mathbf{t}_e}^{-1}\mathbf{t}_e(n) = r_{i,i}t_{e,i}(n_0)t_{e,i}(n) = r_{i,i}t_{e,i}(n) \quad (10)$$

where $r_{i,I}$ denotes the i-th diagonal element of $\mathbf{R}_{\mathbf{t}_e}^{-1}$, and $t_{e,i}(n)$ stands for the train value at lag n for the i-th source symbol. Evidently, taking all possible n's into account, Eq. (10) produces a sequence $\mathbf{p}_{n_0,i}$ whose values equal the i-th source-symbol triggering pulse train to a constant amplitude factor, $r_{i,i}$. So, all repetitions of that symbol are detected.

The values of activity index indicate those lags n_i where individual sources contribute their symbols. If we select such n_i's that cover all different source contributions, a thorough decomposition is done and all source-symbol triggering pulse trains, $\mathbf{t}_i$; $i\in[1,K]$, are separated.

Once the triggering instants of the signal components, i.e. the source-symbol pulse trains, are known, also the components themselves can be obtained–for example, by using the spike-triggered averaging throughout the given observations.

3 An Upgrade of the CKC-based Decomposition Using a Single Observation

Suppose the data model from Eq. (1) represents a MISO instead of a MIMO system–so, only a single observation $x_1(n)$; $n=0,\dots,N$-1, is available. The necessary condition (6) for a thorough decomposition can, therefore, not be met.

Now, try to increase the number of observations artificially as follows. Assuming every observed sample $x_1(n)$ an independent random variable, new observations may be generated using higher-order moments of these variables. Also cross-moments may be applied by combining the variables at different observation lags. In the continuation, we will talk only the moments at a given lag, actually meaning the dot-operations (according to MATLAB) with the given shift of the observation repetitions. This will give additional, artificial observations; however, it will also produce additional, artificial source symbols. For instance, taking the second-order, zero-lag moments, all the observation samples that comprise superimpositions of several source activities will generate new artificial sources whose activity is determined by pair-wise logical products of the superimposed source activities. Such artificially introduced source symbols will be called cross-symbols, $s_{ij}(n)$, if i and j are two intersecting, superimposed sources in the observation sample n, $s_{ij}(n)=s_i(n)\cdot s_j(n-d_{ij})$, where d_{ij} is a time shift between the triggerings of sources i and j.

Any zero-lag higher-order moment can generate one additional (artificial) observation. How about the nonzero lags? Suppose source triggers with a minimum distance of T_{min} between the adjacent symbols. Suppose also those source symbols contribute signal components whose length in observation equals L, $L<T_{min}$. It is necessary, then, to limit the lags respected in higher-order moments to $\Lambda=T_{min}-L$. This assumption is correct with all possible applications mentioned in Section 1.

Remember we have only a single observation available, $\mathbf{x}_1$. Hence, all additional, artificial observations will be derived from it. Denote them by $\mathbf{y}$ and a set of indexes: the number of indexes is going to be equal to the order of moments applied, and the values of indexes are going to define the shifts among the combined observation repetitions. Make this more comprehensible by a short example; let

$$x_1(n)=\left[a_0,a_1,a_2,a_3,a_4,a_5,a_6\right]$$

be an observation which can be further designated as $y_{\{0\}}(n)=x_1(n)$.

Second-order moments at zero lag will be calculated as:

$$y_{\{0,0\}}(n)=\left[a_0^2,a_1^2,a_2^2,a_3^2,a_4^2,a_5^2,a_6^2\right]$$

giving the first artificial observation whose sample values equal the squares of the values in $\mathbf{x}_1$. Further non-zero lags are possible, such as:

$$y_{\{0,1\}}(n)=\left[a_0a_1,a_1a_2,a_2a_3,a_3a_4,a_4a_5,a_5a_6,0\right]$$

with the second repetition of $\mathbf{x}_1$ shifted anticausally by one sample. Also $y_{\{0,-1\}}(n)$ is feasible, but because $y_{\{0,-1\}}(n)=y_{\{0,1\}}(n)$ no new observation is obtained.

We have already mentioned that added artificial observations introduce new source symbols as well. Actually, they contribute new signal components which consist of non-linear combinations of the responses to the original source symbols. Whenever a superimposition of two or more source contributions appear in an observation sample, the artificial observations based on higher-order moments need also additional, artificial sources to be modelled by MIMO. Exemplify this statement by a concrete situation. Suppose we have two components, $c_{ij}(n)=[a_1,a_2,a_3]$ and $c_{ik}(n)=[b_1,b_2,b_3]$, superimposed in our observation, so that:

$x_1(n)=[a_1,a_2,a_3,0,a_1,a_2+b_1,a_3+b_2,b_3,0,b_1,b_2,b_3]$

It is obvious that $c_{ij}(n)$ appears alone first, then at location 4 it overlaps with $c_{ik}(n-1)$, while at location 9 $c_{ik}(n)$ appears alone. Using the triggering train of pulses, $\mathbf{t}$, a matrix form follows:

$$x_1(n)=\left[a_1,a_2,a_3,b_1,b_2,b_3\right]\begin{bmatrix}1,0,0,0,1,0,0,0,0,0,0,0\\0,1,0,0,0,1,0,0,0,0,0,0\\0,0,1,0,0,0,1,0,0,0,0,0\\0,0,0,0,0,1,0,0,0,1,0,0\\0,0,0,0,0,0,1,0,0,0,1,0\\0,0,0,0,0,0,0,1,0,0,0,1\end{bmatrix}=\mathbf{C}\cdot\mathbf{t}$$

Let us now construct the artificial observation with second-order moments at zero lag:

$$y_{\{0,0\}}(n)=[a_1^2,a_2^2,a_3^2,0,a_1^2,a_2^2+2a_2b_1+b_1^2,a_3^2+2a_3b_2+b_2^2,b_3^2,0,b_1^2,b_2^2,b_3^2]$$

The original observation and the added artificial one can be described by a unified matrix form:

$$\begin{bmatrix} x_1(n) \\ y_{\{0,0\}}(n) \end{bmatrix} = \begin{bmatrix} a_1, a_2, a_3, b_1, b_2, b_3, & 0, & 0 \\ a_1^2, a_2^2, a_3^2, b_1^2, b_2^2, b_3^2, & 2a_2b_1, & 2a_3b_2 \end{bmatrix} \begin{bmatrix} 1,0,0,0,1,0,0,0,0,0,0,0 \\ 0,1,0,0,0,1,0,0,0,0,0,0 \\ 0,0,1,0,0,0,1,0,0,0,0,0 \\ 0,0,0,0,0,1,0,0,0,1,0,0 \\ 0,0,0,0,0,0,1,0,0,0,1,0 \\ 0,0,0,0,0,0,0,1,0,0,0,1 \\ 0,0,0,0,0,1,0,0,0,0,0,0 \\ 0,0,0,0,0,0,1,0,0,0,0,0 \end{bmatrix} = \mathbf{C} \cdot \mathbf{t} \tag{11}$$

Both the convolution kernel **C** and the triggering pulse trains change by adding artificial observations. From Eq. (11), it is clear how new sources are artificially introduced and what is their role (see the two bottom rows in **t**).

Eq. (11) also explains the most important contribution of added artificial observations: the rank of convolution kernel **C** increases. When dealing with finite alphabet of source symbols, e.g. *K*, it can be shown that with adequate number of artificial observations the convolution kernel matrix **C** obtains full column rank. This leads to a signal decomposition which is Bayesian optimal, as defined in the preceding section [13].

The only problem of this kind of approach is that the decomposed source-symbol triggering trains split among several artificial sources. Whenever there are superimpositions of source-symbol contributions within an observation, every type of superimposition is decomposed to its own triggering pulse train. Consequently, the triggerings which appear in those trains disappear from the trains of the sources whose symbol contributions overlap.

There are practical cases where this effect is not disturbing. This certainly is true for the observations with non-overlapping contributions, such as electrocardiograms (ECG) or, partially, images. We are going to elaborate our approach with non-overlapping assumption in the next section.

4 Simulation Results

To exemplify the derivation from Section 3, we decided to simulate an artificial observation with characteristics similar to the ECG signals. We synthesised the following:

1. four random generated source contributions with lengths L = 8, 10, 5 and 7 samples, respectively;
2. random appearance of these source contributions in the generated observation, so that their intermediate mean distances were 50, 1000, 500, and 3000 samples, respectively, while actual appearances were Gaussian distributed around these values with standard deviation of 2 samples;

3. the generated observation with length of 10000 samples;
4. artificial observations up to the power of p=3 and shift Λ=4 (according to the assumptions in Section 3).

Thus, the simulated observation contains four different source contributions. The one belonging to the first source is most frequent and could be understood as normal systoles. The other three could be interpreted as different abnormal heart beats, i.e. extrasystoles and possible pathological changes.

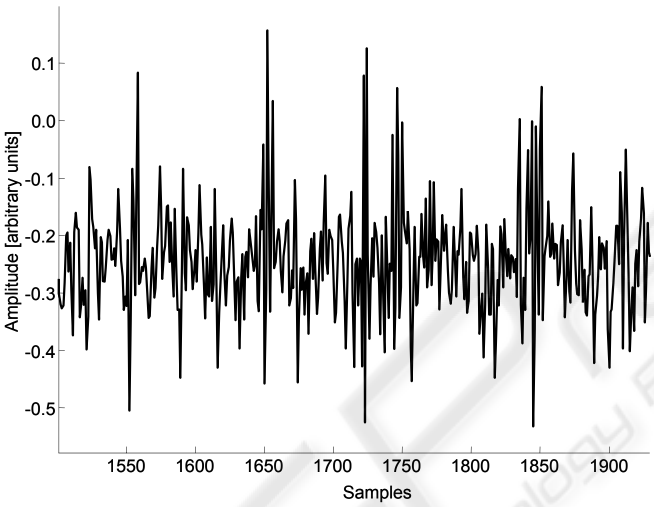

Fig. 1. The generated synthetic observation contaminated with 0 dB additive zero-mean Gaussian noise. Only a part of the generated signals is depicted.

The total number of artificial observations was 20. We set the number of extended observations to M_e=2 (Eq. (6)). Using our CKC approach [11, 12], we verified the accuracy of the decomposed triggering pulse trains for the four simulated sources. Simulations were performed in 10 Monte Carlo runs with different levels of additive Gaussian noise, so that the SNRs were 20, 15, 10, 5, and 0 dB. An example of the processed observation with 0 dB additive Gaussian noise is depicted in Fig. 1. Fig. 2 illustrates the decomposition results in the form of the detected triggering pulse trains for the first source. Trains in black were decomposed at different SNRs, as indicated. The bottom train of Fig. 2 (in grey) is the original triggering pulse train for the first source.

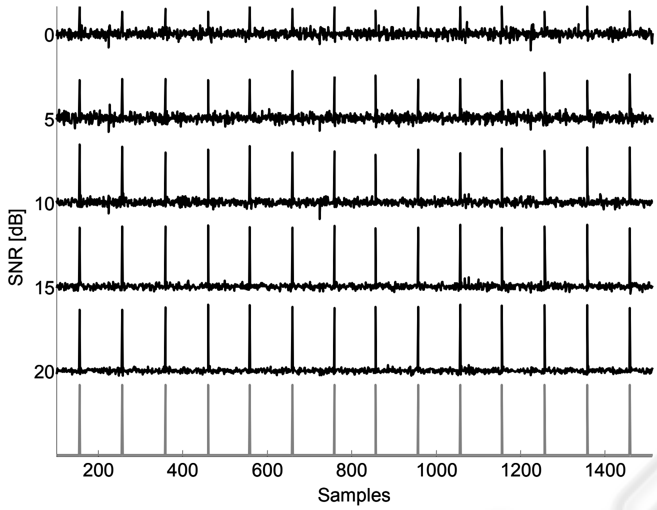

Fig. 2. Reconstructed triggering pulse sequences of source 1 at different SNRs (black) and original simulated pulses (grey at the bottom). Only a part of the reconstructed pulse sequences is depicted.

A more detailed analysis of the obtained results versus different SNRs is given in Tables 1, 2, and 3. Table 1 describes percentages of correctly detected triggering instants for all four sources (true positive statistics). A triggering instant was considered correctly detected when the decomposition returned the exact position of an original source triggering. Tables 2 and 3 collect percentages of false positive and false negative statistics, respectively.

Table 1. Percentage (mean ± standard deviation) of accurately recognized triggering pulses (true positive statistics) versus SNR.

SNR	20 dB	15 dB	10 dB	5 dB	0 dB
Source 1	1.00±0.00	0.98±0.02	0.98±0.02	0.99±0.01	0.98±0.01
Source 2	1.00 ± 0.00	0.96 ± 0.01	1.00 ± 0.00	1.00 ± 0.00	0.97 ± 0.01
Source 3	0.99 ± 0.02	1.00± 0.00	0.99 ± 0.02	0.99 ± 0.02	1.00 ± 0.00
Source 4	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00	1.00 ± 0.00

Table 2. Percentage (mean ± std) of misplaced pulses (false positive statistics) versus SNR.

SNR	20 dB	15 dB	10 dB	5 dB	0 dB
Source 1	0.00± 0.00	0.02 ± 0.02	0.02 ± 0.02	0.01± 0.01	0.02 ± 0.01
Source 2	0.00± 0.00	0.04 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	0.03 ± 0.01
Source 3	0.01± 0.02	0.00± 0.00	0.01 ± 0.02	0.01 ± 0.02	0.00 ± 0.00
Source 4	0.00± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00

Table 3. Percentage (mean ± std) of missed pulses (false negative statistics) versus SNR.

SNR	20 dB	15 dB	10 dB	5 dB	0 dB
Source 1	0.01± 0.01	0.04 ± 0.01	0.04 ± 0.02	0.03 ± 0.01	0.04 ± 0.02
Source 2	0.01 ± 0.01	0.04 ± 0.03	0.03 ± 0.03	0.03 ± 0.02	0.03 ± 0.01
Source 3	0.01 ± 0.02	0.01 ± 0.02	0.02 ± 0.03	0.03 ± 0.04	0.02 ± 0.03
Source 4	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00

It is obvious that our method is very robust. The worst percentage of the recognised source triggering instants for the first source is 98%, for the second source 96%, for the third source 99%, and for the fourth source 100%. As we can see from the tables, even an extremely high noise with SNR=0 dB does not decrease the successful rate of the recognised triggering pulses, regardless the triggering frequency as well.

5 Discussion and Conclusions

We have derived an approach which makes a MIMO system decomposition possible based only on a single observation. It is applicable in the cases with orthogonal, or at least close-to-orthogonal, sources whose inter-triggering distance is lower bounded. As already mentioned, an obvious application is ECG signals. The systoles cannot overlap, and there is always an inter-systole gab which warranties that also the extended observations would not cause severe overlappings. Referring to the original MIMO decomposition from [11, 12], two important differences must be reported here:

1. Nonlinear procedures for generation of artificial observations influence additive noise which is presumed zero-mean and, thus, prone to elimination by averaging of the signal samples. Consequently, the observations obtained with the even powers contain additive noise which is not zero-mean any more. This effect decreases the algorithm's robustness.
2. In the MIMO decomposition from [11, 12], it is enough to locate a firing of a single source, say n_0, and $\mathbf{x}_e(n_0)$ can readily be used to extract the complete pulse train for the source symbol in question (Eq. (10)). The statement equally holds for all sources in the newly proposed approach described in this paper, so for the cross-symbols as well. This means that the firing positions of a source symbol will not be detected when using $\mathbf{x}_e(n_0)$, if n_0 is a time instant where this source symbol overlaps with any of other symbols. To detect a single source symbol's triggering instants, it is important to find such n_0 where this symbol appears alone. On the contrary, each point of a multiple source activity would be recognised as a firing of that artificial source which was generated by the overlapped multiple source symbols.

To cope with the two problems, special noise-reduction techniques must be implemented and additional post-processing stages are needed to fuse the detected pulse trains which belong to the same original source symbol. Both needs further investigation and explanation which goes beyond the scope of this paper.

Our simulation confirmed that even from a single observation and in very noisy environment a reliable separation of several sources is feasible using the CKC approach. Source-symbol triggering instants can be recognised in more then 98% of cases even when SNR goes as low as 0 dB. This is a very important conclusion for some practical implementations. Analysing ECG signals, for example, a low number of observations, if not only a single observation, is available. Nevertheless, the proposed approach improves significantly the chances of different types of abnormal heart beats to be recognised and separated from the normal systoles, while for all the beats their fiducial points can be determined with high precision.

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