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Blind Signal Separation (ICA) Using the Method of Convolution Mixture in the Intelligent Telecommunication Systems (COMINT) Using MATLAB

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Abstract: Modulation recognition is the main part of Smart Telecom receptors and to detect the type of signal, eliminating the interference, noise and measuring the spectrum is very useful and important. The received signals due to a variety of reasons including fading and multi-alignment phenomena and …. Are not very safe and must initially be separated and process of separation and noise eliminating to be done. For this purpose, signal separation is very important and separation of considered signal from the received signals has a great importance in the signal processing ; That one of its best applications is the elimination of telecommunication signal interference, noise elimination from the received signals and speech signals or image or information separation from solitary data and etc … Due to the extensive applications and its enormous importance, rapidly new and efficient algorithms were introduced in order to process and design them. Despite the exiting independence condition, the issue of initial resources derivation from the several signal production sources independent from each other is possible that we knew it by the name of blind signal separation. The main idea in all signal separation algorithms is the same and is the finding a criterion for measurement of a density function's non-Gaussian. This criterion must be simple and meanwhile be resistant to the solitary data and noises. In this paper blind signal separation is investigated using the method of Convolution Mixture in the intelligent telecommunication systems (Coming) and finally will be investigated via MATLAB.

Key word: Blind signal separation (ica) · Smart telecom (comint) · Convolution mixture

INTRODUCTION

Diagnosis of modulation is the main part of smart telecom receivers and is important to diagnose the signal type, interference elimination, noise and measuring the spectrum is very good. The received signals due to a variety of reasons including fading and multi-alignment phenomena and …. Are not very safe and must initially be separated and process of separation and noise eliminating to be done. For this, the act of signal separation and noise elimination must be done. The issue of signal separation composed of signals always had a special position I the process of signals ; that the noise elimination from speech signals or images also interference elimination in the telecommunication signals can be counted of its most important cases.

Due to the extensive application of this method, rapidly some efficient algorithms were offered for it. In the initials of 90s, a new question attracts the attention of researchers toitself whether by having theseveral combinations of some sources of independent signals, is there the possibility of initial sources' derivation?

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Gradually, many attentions was attracted to this issue and now the separation of blind signal became one of the active fields for researches in the field of signalprocessing. The signal separation methods. Signal separation methods are divided to two categories: classic and non-classic. In this paper, the act of separation in thesmart telecommunication systems is going to be investigated using the Convolution Mixture and finally the results from simulation are investigated by Matlab [1].

ICA using the Non-Gaussian Method: We indicate in this part that the non –Gaussian can be used as a criteria in ICA. Notice that the Non-Gaussian is important in solving the ICA and estimates the ICA model. Meanwhile, the issue of central-limit is very important.According to this theorem, distribution density function of a set of some random independent variables tend to the Gaussian densityfunction by increasing their numbers [2, 3]. Briefly, distribution density of the set of two random variables independent from each one of those variables' distributionfunctions will be closer to the Gaussian distribution. Now, suppose that view vector of follows the ICA model. [2, 4].

$$x = As \tag{2-1}$$

If, x is a linear combination of dependent components (sources). Then the distribution of independent components. i.e s_i are same. Because, the mixture's system is linear, then we can for derivation of independent sources use of linear mixture of x_i.

It means that, if y to be the estimation of one of independentsources; we can suppose it as $y = b^T x = \sum_i b_i x_i$, then b is a vector that must be estimated.

Note that now estimation of one of (s_i) s is considered by us, not their all estimation. On the other hand, because $y = b^T As$, therefore, y will be a linear mixture composed of (s_i) s. If, $b^T A$ is shown by q, we will have the following relation:

$$y = b^T x = q^T s = \sum_i q_i s_i \tag{2-2}$$

If b was one of the rows of matrix of A^{-1}; the linear combination of $b^T x$ accurately is equal with one of the independent components of s_i and q only was including a non-zero element. Practically, due to the lack of A, we can only estimate b that certainly the ideal b will not be achieved.If, there was used of central limit theorem and coefficients of q will be changed and the *distribution density function* to be considered as $y = q^T s$, because even total of two random independent variables becomes more Gaussian than them,therefore the distribution of $y = q^T s = \sum_i q_i s_i$ becomes more Gaussian than each s_i.

And y will have minimum of being Gaussian when to be equal to one of (s_i) s. this condition will be achieved when only one of (q_i) s to be non-zero. Practically, we don't know q and really don't need it. Because, since $q^T s = b^T x$, we change b and then the distribution density of $b^T x$ will be observed. It means that we suppose b as a vector that maximize the being Gaussian of $b^T x$ and we can estimate one of the independent sources.

Generally, Optimization of non-Gaussian in a n-dimensional space of b vectors, has local $2n$ maximum, i.e, two local maximums per independent source which caused by s_i hand $-s_i$. (Notice that sign of (s_i) s cannotestimated) [5-6].

Separation Using the Method of *Convolution mixture*: In this part blind separation of two filtered source will be investigated and required conditions for separation will be achieved.

Suppose that $s_1(t)$ and $s_2(t)$ are the independent unclear sources and $x_1(t)$ and $x_2(t)$ are the observed signals and also we suppose that their relation will be shown by the following equations:

$$\begin{aligned} x_1(t) &= s_1(t) + H_{12}(t) * s_2(t) \\ x_2(t) &= s_2(t) + H_{21}(t) * s_1(t) \end{aligned} \tag{3-1}$$

This relation can be written in the scope of frequency as follows:

$$\begin{bmatrix} x_1(\omega) \\ x_2(\omega) \end{bmatrix} = \begin{bmatrix} 1 & H_{12}(\omega) \\ H_{21}(\omega) & 1 \end{bmatrix} \begin{bmatrix} s_1(\omega) \\ s_2(\omega) \end{bmatrix} \tag{3-2}$$

Our purpose of finding the separator G matrix is in a form that the estimations of and only include one of the following sources. For simplicity, $G(\omega)$ will be considered as follows:

$$G(\omega) = \begin{bmatrix} 1 & -G_{12}(\omega) \\ -G_{21}(\omega) & 1 \end{bmatrix} \tag{3-3}$$

For performing the separation must the matrix of $T(\omega) = G(\omega)H(\omega)$ to be as one of the following forms:

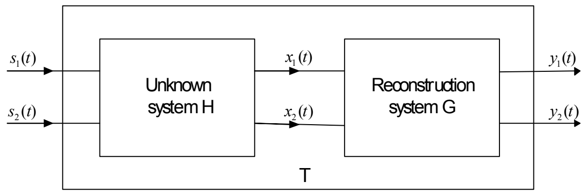

Fig. 1-3: Block of diagram of blind separation issue in the filtered state

$$T(\omega) = \begin{bmatrix} T_{11}(\omega) & 0 \\ 0 & T_{22}(\omega) \end{bmatrix} \quad (3\text{-}4)$$

$$T(\omega) = \begin{bmatrix} 0 & T_{12}(\omega) \\ T_{21}(\omega) & 0 \end{bmatrix} \quad (3\text{-}5)$$

In the first state we have: $y_1(t) = T_{11}(t) * s_1(t)$ and $y_2(t) = T_{22}(t) * s_2(t)$ and in the second state we will have: $y_1(t) = T_{12}(t) * s_2(t)$ and $y_2(t) = T_{21}(t) * s_1(t)$ that in two states the act of separation was done and in each output only one of the sources exits.

Because of that $T(\omega)$ to be in the form of (5-3) we must have:

$$G_{21}(\omega) = H_{21}(\omega) \text{ و } G_{12}(\omega) = H_{12}(\omega) \quad (3\text{-}6)$$

And because of that $T(\omega)$ to be in the form of (3-6), we must have:

$$G_{12}(\omega) = 1/H_{21}(\omega) \text{ و } G_{21}(\omega) = 1/H_{12}(\omega) \quad (3\text{-}7)$$

In the following, we will express the Polyspectrum and some of its features.

Suppose that $x_1(t),....,x_k(t)$ is the combined timeout processes. If $k_0,k_1,...,k_m \in \{1,2,...,k\}$ is a set of m indices between 1 and k, therefore the polyspectrum corresponding with these indices are stated as follows:

$$P_{x_{k_0}x_{k_1}\dots x_{k_m}}(\omega_1,\omega_2,\dots,\omega_m) = \sum_{\tau_1}\dots\sum_{\tau_m} cumul(x_{k_0}(t), x_{k_1}(t+\tau_1),\dots,x_{k_m}(t+\tau_m))\ e^{-j\sum_{i=1}^{m}\omega_i\tau_i} \quad (3\text{-}8)$$

In this equation, $cumul(x_{k_0}(t), x_{k_1}(t+\tau_1),\dots,x_{k_m}(t+\tau_m))$ is the cumulent of random variables of $x_{k_0}(t), x_{k_1}(t),\dots,x_{k_m}(t)$ ☻ and Polyspectrum has the following features [7]:

Feature 1: If $x_{k_0}(t), x_{k_1}(t),\dots,x_{k_m}(t)$ can be divided into two or several sub-set of independent processes,then:

$$P_{x_{k_0}x_{k_1}\dots x_{k_m}}(\omega_1,\omega_2,\dots,\omega_m) = 0$$

Feature 2: If $x_{k_0}(t), x_{k_1}(t),\dots,x_{k_m}(t)$ can be a combined Gaussian, then for $m > 1$, we have the following:

$$P_{x_{k_0}x_{k_1}\dots x_{k_m}}(\omega_1,\omega_2,\dots,\omega_m) = 0 \quad (3\text{-}9)$$

Feature 3: If $y_i(t) = \sum_{j=1}^{k} h_{ij}(t) * x_j(t) \quad i = 1,2,\dots,l$ and here, $h_{ij}(t)$ is the resultof the impact of a LTI linear filter, then per $l_0,l_1,...,l_n \in \{1,2,...,l\}$ we have the following:

$$P_{y_{l_0}y_{l_1}\dots y_{l_n}}(\omega_1,\omega_2,\dots,\omega_m) = \sum\dots\sum H_{l_0 j_0}(-\sum_{i=1}^{n}\omega_i) H_{l_1 j_1}(\omega_1)\times\dots\times H_{l_n j_n}(\omega_n) P_{x_{j_0}x_{j_1}\dots x_{j_n}}(\omega_1,\omega_2,\dots,\omega_n) \quad (3\text{-}10)$$

The act of separation canbe done based on Bi-polyspectrum and Tri-polyspectrumthat will be investigated in the following:

Separation by Bi-Polyspectrum: Theorem: suppose that $S_1(t)$ and $S_2(t)$ are two timeout processes such that:

$$P_{s_i^* s_i s_i}(\omega_1,\omega_2) \neq 0 \qquad \forall \omega_1,\omega_2, \quad i=1,2 \tag{4-1}$$

$$P_{s_i^* s_j s_k}(\omega_1,\omega_2) = 0 \qquad \forall \omega_1,\omega_2, \quad \forall i,j,k \in \{1,2\} \quad except \;\; i=j=k \tag{4-2}$$

If the following equation is established:

$$\det\{T(0) = T_{11}(0)T_{22}(0) - T_{12}(0)T_{21}(0) \neq 0 \tag{4-3}$$

Therefore, $T(\omega)$ can be in the form of (4-4) or (4-5), if:

$$P_{y_1^* y_1 y_2}(\omega_1,\omega_2) = 0 \qquad \forall \omega_1,\omega_2 \tag{4-4}$$

$$P_{y_2^* y_2 y_1}(\omega_1,\omega_2) = 0 \qquad \forall \omega_1,\omega_2 \tag{4-5}$$

Proof: According to the feature (3), we have:

$$P_{y_1^* y_1 y_2}(\omega_1,\omega_2) = \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{k=1}^{2} T_{1i}^{*}(\omega_1+\omega_2)T_{1j}(\omega_1)T_{2k}(\omega_2)P_{s_i^* s_j s_k}(\omega_1,\omega_2) \tag{4-6}$$

$$P_{y_2^* y_2 y_1}(\omega_1,\omega_2) = \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{k=1}^{2} T_{2i}^{*}(\omega_1+\omega_2)T_{2j}(\omega_1)T_{1k}(\omega_2)P_{s_i^* s_j s_k}(\omega_1,\omega_2) \tag{4-7}$$

By separation of $\omega_1 = \omega$ and $\omega_2 = 0$ and using (4-10), (4-12) and (4-13), we have the following equations:

$$|T_{11}(\omega)|^2\, T_{21}(0)P_{s_1^* s_1 s_1}(\omega,0) + |T_{12}(\omega)|^2\, T_{22}(0)P_{s_2^* s_2 s_2}(\omega,0) = 0 \tag{4-8}$$

$$|T_{21}(\omega)|^2\, T_{11}(0)P_{s_1^* s_1 s_1}(\omega,0) + |T_{22}(\omega)|^2\, T_{12}(0)P_{s_2^* s_2 s_2}(\omega,0) = 0 \tag{4-9}$$

Since that according to the equation of (4-9), i.e. $P_{s_i^* s_i s_i}(\omega,0) \neq 0 \; \forall \omega$, it is concluded that equations of (4-14) and (4-17) will be established when:

$$\det\begin{bmatrix} |T_{11}(\omega)|^2\, T_{21}(0) & |T_{12}(\omega)|^2\, T_{22}(0) \\ |T_{21}(\omega)|^2\, T_{11}(0) & |T_{22}(\omega)|^2\, T_{12}(0) \end{bmatrix} = 0 \quad \forall \omega \tag{4-10}$$

In a specific state, per $\omega = 0$, we have:

$$T_{11}(0)T_{12}(0)T_{21}(0)T_{22}(0)(\det\{T(0)\})^{*} = 0 \tag{4-11}$$

And because $\{T(0)\} \neq 0$, therefore:

$$T_{11}(0)T_{12}(0)T_{21}(0)T_{22}(0)=0 \tag{4-12}$$

At least, one of the terms of this multiplication should be equal to zero. if $T_{11}(0) = 0$, therefore we find from (4-11) that $T_{12}(0),T_{21}(0)\neq 0$, then according to (4-9) and (4-17), we conclude that $T_{22}(\omega) = 0\ \forall\ \omega$, and from (4-9) and (4-16) will be achieved that $T_{11}(\omega) = 0\ \forall\ \omega$, then we have $T_{11}(\omega),T_{22}(\omega) = 0\ \forall\ \omega$, i.e, T will be in the form of (4-5). A similarargumentgives theresult that if $T_{22}(0) = 0$, we have again $T_{11}(\omega),T_{22}(\omega) = 0\ \forall\ \omega$ and if $T_{12}(0) = 0$ or $T_{21}(0) = 0$, therefore $T_{12}(\omega),T_{21}(\omega) = 0\ \forall\ \omega$ will be in the form of (4-4).

We observed that for separation, must have $P_{s_i^* s_i s_i}(\omega_1,\omega_2)\neq 0$ that we conclude (s_i) s should be non-Gaussian and also density function of them shouldn't be symmetric. Also for derivation of sources, must be a reversible T.

The estimated signals in the output of G-filter are as following:

$$\begin{aligned} y_1(t) &= x_1(t) - G_{12}(t) * x_2(t) \\ y_2(t) &= x_2(t) - G_{21}(t) * x_1(t) \end{aligned} \tag{4-13}$$

By applying the*Feature .3*, we have the following equation:

$$\begin{aligned} P_{y_1^* y_1 y_2}(\omega_1,\omega_2) &= P_{y_1^* y_1 x_2}(\omega_1,\omega_2) - G_{21}(\omega_2)P_{y_1^* y_1 x_1}(\omega_1,\omega_2) \\ P_{y_2^* y_2 y_1}(\omega_1,\omega_2) &= P_{y_2^* y_2 x_1}(\omega_1,\omega_2) - G_{12}(\omega_2)P_{y_2^* y_2 x_2}(\omega_1,\omega_2) \end{aligned} \tag{4-14}$$

And using (4-12) and (4-13), this equation is as follows:

$$G_{12}(\omega_2) = \frac{P_{y_2^* y_2 x_1}(\omega_1,\omega_2)}{P_{y_2^* y_2 x_2}(\omega_1,\omega_2)} \tag{4-15}$$

$$G_{21}(\omega_2) = \frac{P_{y_1^* y_1 x_2}(\omega_1,\omega_2)}{P_{y_1^* y_1 x_1}(\omega_1,\omega_2)} \tag{4-16}$$

Suppose that the separator filters are as follows:

$$\begin{aligned} G_{12}(\omega) &= \sum_{k=r_1}^{r_2} a_k e^{-j\omega k} \\ G_{21}(\omega) &= \sum_{k=q_1}^{q_2} b_k e^{-j\omega k} \end{aligned} \tag{4-17}$$

Using these filters, y_1 and y_2 are as follows:

$$\begin{aligned} y_1(t) &= x_1(t) - \sum_{k=r_1}^{r_2} a_k x_2(t-k) \\ y_2(t) &= x_2(t) - \sum_{k=q_1}^{q_2} b_k x_1(t-k) \end{aligned} \tag{4-18}$$

By *Fourier transform* of taking inverse from equations (4-12) and (4-13), we have the following equations:

$$\begin{aligned} &cumul(y_1^*(t), y_1(t+\tau_1), y_2(t+\tau_2)) = 0 \quad \forall \tau_1,\tau_2 \\ &cumul(y_2^*(t), y_2(t+\tau_1), y_1(t+\tau_2)) = 0 \quad \forall \tau_1,\tau_2 \end{aligned} \tag{4-19}$$

By placement of y_1 and y_2 from the equation (4-17) in this equation, these following formulas are resulted:

$$\sum_{k=r_1}^{r_2} a_k cumul(y_2{}^*(t), y_2(t+\tau_1), x_2(t+\tau_2-k)) = cumul(y_2{}^*(t), y_2(t+\tau_1), x_1(t+\tau_2)) \quad (4\text{-}20)$$

$$\sum_{k=q_1}^{q_2} b_k cumul(y_1{}^*(t), y_1(t+\tau_1), x_1(t+\tau_2-k)) = cumul(y_1{}^*(t), y_1(t+\tau_1), x_2(t+\tau_2)) \quad (4\text{-}21)$$

These two equations respectively are linear than (a_k)s and (b_k)s. therefore, we can obtain a repetitive method by replacement between these two formula that each stage includes the solving a systemoflinearequations. Estimation of cumulents also will be done by the following equation:

$$cumul(y_i{}^*(t), y_i(t+\tau_1), x_j(t+\tau_2-k)) = E\{y_i{}^*(t) y_i(t+\tau_1) x_j(t+\tau_2-k)\}$$
$$\approx \frac{1}{L}\sum_{t=1}^{L} y_i{}^*(t) y_i(t+\tau_1) x_j(t+\tau_2-k) \qquad i,j \in \{1,2\} \quad (4\text{-}22)$$

Separation by Tri-Polyspectrum: In this case also, a similar theorem to the Bi-polyspectrum is as follows:

Theorem 2: If $S_1(t)$ and $S_2(t)$ are two combined timeout processes:

$$P_{s_i^* s_i s_i s_i^*}(\omega_1, \omega_2, \omega_3) \neq 0 \qquad \forall \omega_1, \omega_2, \omega_3 \quad i = 1,2 \quad (5\text{-}1)$$

$$P_{s_i^* s_j s_k s_l^*}(\omega_1, \omega_2, \omega_3) = 0 \quad \forall \omega_1, \omega_2, \omega_3 \quad \forall i,j,k,l \in \{1,2\} \;\; except \;\; i = j = k = l \quad (5\text{-}2)$$

$$P_{y_1^* y_1 y_1 y_2^*}(\omega_1, \omega_2, \omega_3) = 0 \quad \forall \omega_1, \omega_2, \omega_3 \quad (5\text{-}3)$$

$$P_{y_1^* y_1 y_2 y_2^*}(\omega_1, \omega_2, \omega_3) = 0 \quad \forall \omega_1, \omega_2, \omega_3 \quad (5\text{-}4)$$

The proof of this*theorem* is similar to the *theorem.1* and here we indicate it. Theadvantage of use of Tri-polyspectrum in spite of Bi-polyspectrum is this that, it is not required the density function of S to be asymmetric,because:

$$P_{s_i^* s_i s_i s_i^*}(\omega_1, \omega_2, \omega_3) = F_i^*(\sum_{j=1}^{3} \omega_j) F_i(\omega_1) F_i(\omega_2) F_i^*(-\omega_3) cumul(y_i{}^*(t), y_i(t), y_i(t), y_i{}^*(t)) \quad (5\text{-}5)$$

And existing *Cumulent* in this equation is non-zero. Using (4-13) and third feature ofpolyspectrum is achieved that:

$$P_{y_1^* y_1 y_1 y_2^*}(\omega_1, \omega_2, \omega_3) = P_{y_1^* y_1 y_1 x_2^*}(\omega_1, \omega_2, \omega_3) - G_{21}{}^*(-\omega_3) P_{y_1^* y_1 y_1 x_1^*}(\omega_1, \omega_2, \omega_3)$$
$$P_{y_2^* y_2 y_2 y_1^*}(\omega_1, \omega_2, \omega_3) = P_{y_2^* y_2 y_2 x_1^*}(\omega_1, \omega_2, \omega_3) - G_{12}{}^*(-\omega_3) P_{y_2^* y_2 y_2 x_2^*}(\omega_1, \omega_2, \omega_3) \quad (5\text{-}6)$$

And by applying the terms of (5-3) and (5-4), we have the following equations:

$$G_{12}(\omega_3) = \frac{P_{y_2 y_2^* y_2^* x_1}(-\omega_1, -\omega_2, \omega_3)}{P_{y_2 y_2^* y_2^* x_2}(-\omega_1, -\omega_2, \omega_3)} \quad (5\text{-}7)$$

$$G_{21}(\omega_3) = \frac{P_{y_1 y_1^* y_1^* x_2}(-\omega_1, -\omega_2, \omega_3)}{P_{y_1 y_1^* y_1^* x_1}(-\omega_1, -\omega_2, \omega_3)} \quad (5\text{-}8)$$

Again like the previous state, we can find a repetitive method for computing the G_{12} and G_{21} by deplacement between the formulas.

For the filters of equation (5-5), wehave the following equation by Fourier transform of taking inverse from equations (5-7) and (5-8):

$$\sum_{k=r_1}^{r_2} a_k cumul(y_2(t), y_2^*(t+\tau_1), y_2^*(t+\tau_2), x_2(t+\tau_3-k))$$
$$= cumul(y_2(t), y_2^*(t+\tau_1), y_2^*(t+\tau_2), x_1(t+\tau_3)) \quad (5\text{-}9)$$

$$\sum_{k=q_1}^{q_2} b_k cumul(y_1(t), y_1^*(t+\tau_1), y_1^*(t+\tau_2), x_1(t+\tau_3-k)) \quad (5\text{-}10)$$
$$= cumul(y_1(t), y_1^*(t+\tau_1), y_1^*(t+\tau_2), x_2(t+\tau_3))$$

We observe that have linear equation systems compared to a_k and b_k andthen (τ_i) s are favorable, the number of equations can be considered more than the variables. We can convert these algorithms as a recursive form using the assumptions of [8-9].

Now, we offer a sample of simulation of this algorithm:

Suppose that $S_1(t)$ and $S_2(t)$ are two separate independent sources of 16-QAM, then we consider H_{12} and H_{21} as two *non-causal*and *non-minimum phase* FIR filters which you observe their impact response in Figures of 4-2 and 4-3.

We suppose SNR is 20dB, then if separator filters of G_{12} and G_{21} to be in the form of equation (5-5) or $r_1 = q_1 = -5$ and $r_2 = q_2 = 5$, totally we have 22 coefficients that must be calculated.We used of values of $\tau_1 = \tau_2 = 0$ and $-12 \le \tau_3 \le 10$ in the simulation.

Simulation Using Matlab: Simulation of these algorithms is with MATLAB that is a powerful program with a high processing speed and minimum error rate.

The similar software which in order to simulate the telecom systems are used such as MICRO WAVE, HFSS and due to the need to a communication link among the several software have a low processing process and

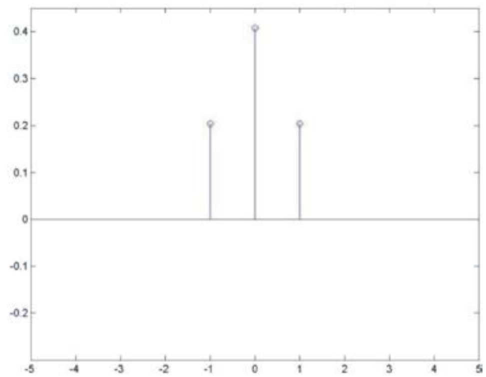

Fig. 6-1: Response of the h_{12} filter impact

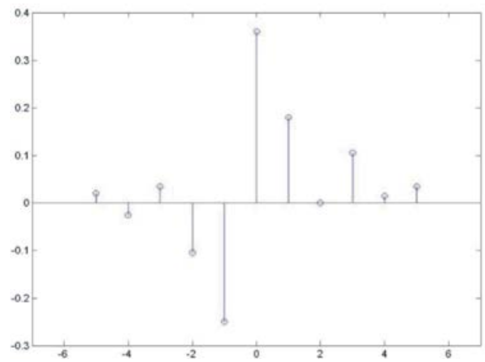

Fig. 6-2: Response of the h_{21} filter impact

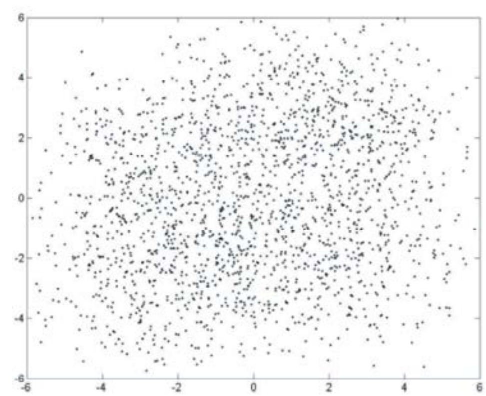

Fig. 6-3: Observation signals in the output 1

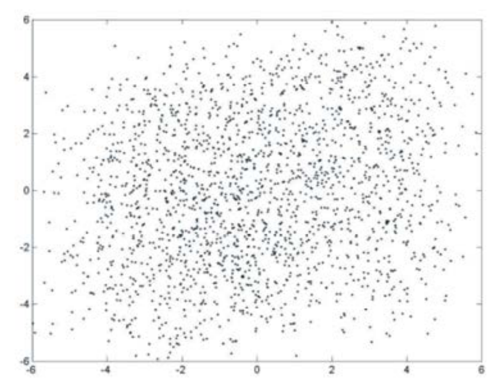

Fig. 6-4: Observation signals in the output.2

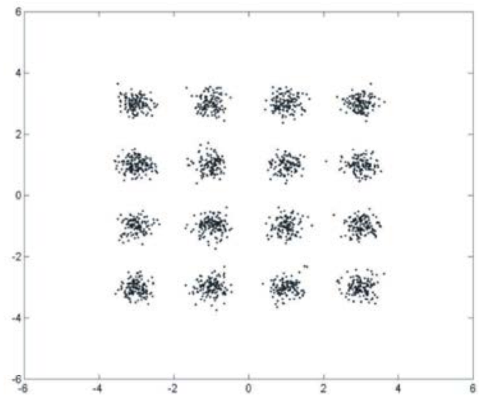

Fig. 6-5: The estimated signals in the output.1

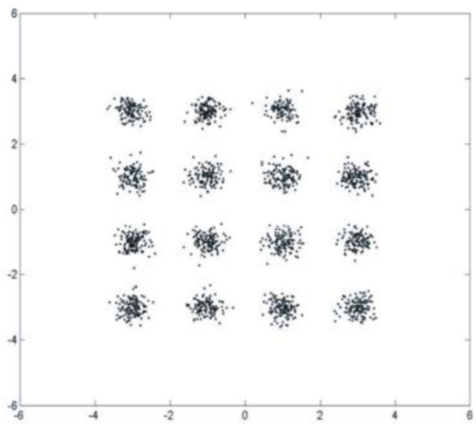

Fig. 6-6: The estimated signals in the output 2

higher error rate and time delay and have not solely the ability of simulation of whole system, but this software has such an ability.

CONCLUSION

The separation of considered signal from the received signals, is very important in the signal processing,especially in the smart telecom systems that which the accuracy of data and information is very important.

That from its best applications is the interference removal in the telecommunication signals, noise removal from the received data and speech signals or image and information separation from solitary data, etc. Due to theextensive applications and its most significance importance, rapidly many new efficient algorithms to process and design them were offered. Despite the existence of independence condition, the extraction of initial sources from the several independent signal producer signal is possible that we knew it asblind signal separation. The main idea is the same in all signal separation algorithms and is the finding of acriteria to measure the being non-Gaussian of a density function.

That in this paper, method and algorithms related to it was evaluated and fully explained. The main condition of density function is this that the criteria must be as far as possible simple and be resistant to the solitary data as one of the most important parts in the field of signalprocessing.

In this paper, blind signal separation was investigated by the method of Convolution Mixture in COMINT and relations and method of signal estimation and production of gradient coefficient was expressed and simulated and results from this algorithm and its method is this that the accuracy and base of this algorithm is more appropriate than other algorithms and also was known that the speed of processing and very high accuracy and very strong mathematics are the main reason of their superiority to the other methods of gradient and estimation of possibility density function and normal distribution function of a signal and finally results from the simulation were investigated via MATLAB.

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