

ICA Based Blind Source Separation Applied to Radio Surveillance

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SUMMARY In radio surveillance systems we consider the problem of identifying interferers or illegal radios in licensed communication channels. The systems considered are receivers using arrays of antennas for spatial processing. At the output of each antenna, we have a mixture of communication signals. The mixture will depend on the distance of the source radios and the propagation environment. These signals may or may not have the same modulation type. The main four tasks in the radio surveillance system are: Separation of the source signals contained in the data mixture at the array antenna, modulation recognition to identify the illegal radio, direction of arrival estimation to pinpoint the location of the illegal radios, and demodulation to intercept the information contained within the illegal transmission. In this paper we deal with the application of the Fast ICA algorithm [3] to a uniform linear array. Our interest is to separate the independent source signals from the mixture of signals obtained at the sensors. Since the target system operates in the HF domain, where analog modulations dominate, the impinging signals are assumed analog modulated communication signals.

key words: HF, array antenna, BSS, ULA

1. Introduction

The ubiquitous expansion of information technology has been a key factor in the increase usage of radio waves. Cellular phones and handy systems have become a part of the everyday culture. While radio makes devices portable and convenient, it is also susceptible to jamming, interference, and obstruction. For these reasons, common sense rules have been established to create an environment where these problems can be avoided. Still, it is also necessary to develop technology that will make this task an easy one. In Japan, the Telecommunications Bureau of the Ministry of Public Management, Home Affairs, Posts and Telecommunications has developed a system called the DEURAS [1] (DEtect UNlicensed RADio Stations) System. It uses the MUSIC [13] algorithm for direction finding and works in the range of 0.1 to 30 MHz. This system is the present technology for monitoring unlicensed radio waves. It has been deployed in main cities across Japan. Other systems based on superresolution algorithms like UCA-ESPRIT [8], have been proposed as well, but they are limited by the number of signals they

can distinguish. Blind source separation (BSS) uses essentially the spatial diversity [6] provided by an array of sensors. It works under the assumption that the signals arriving at the array are independent. The main technology for realizing BSS is independent component analysis (ICA). ICA assumes that the signals are maximally nongaussian, thus providing some a priori information that helps simplify the source separation. ICA based source separation provides the means of detecting multiple signals, and if temporal processing is included, the method can also process coherent signals caused by multipath [11]. The purpose of this research is thus to propose a new HF radio surveillance system using ICA as well as other aiding technologies, like modulation recognition, and DOA estimation. In this paper we put emphasis in the role played by ICA and give a description of its functionality, and how it can provide a better resolution than conventional systems. For completeness we also briefly discuss the other technologies involved, stating useful results only, and providing pertinent references for the interested readers. The system proposed has to be able to adapt to changing conditions, like detecting different modulation types and swapping between different demodulation schemes as required (multimode functionality). Because of the multiple signal processing tasks involved in the radio surveillance system, it requires the multifunctionality that is available in software defined radios (SDR). We will describe the architecture of our proposed system in the following section.

2. System Architecture

The system proposed is depicted in Fig.1. The system shown is divided in four subsystems: independent component analysis (ICA), modulation recognition, demodulation, and direction of arrival (DOA) estimation. Let's consider a channel environment where several signals impinge to an array of antennas (sensors) from different directions. At the receiver, each antenna contributes a mixture of all the signals present in the radio channel. In the radio surveillance scenario, we are interested in determining illegal signals arriving from any direction, hence the need of obtaining the source signals from the mixtures received. In the proposed system, the ICA subsystem has the task of providing this source separation. There is no knowledge available regarding

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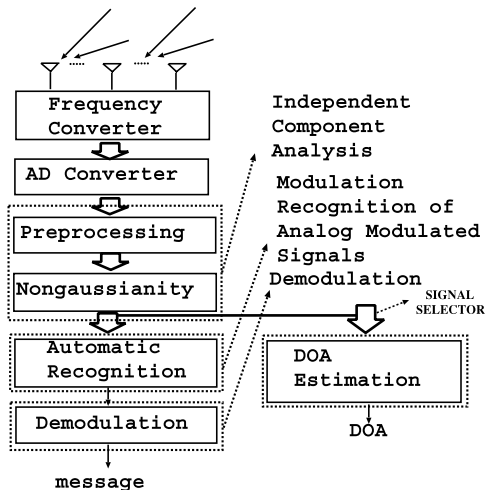


Fig. 1 Proposed radio surveillance system.

the characteristics of the signals involved, but in this paper we will assume that the signals are analog modulated. At the selector, we choose one of the sources obtained from the ICA, and we estimate its direction of arrival, as well as its modulation type. Once we obtain the modulation type we also demodulate the signal and obtain the message contained within. In this paper we will describe the application of the ICA algorithm to the blind source separation problem in a uniform linear array (ULA) of antennas.

3. DOA Model

The uniform linear array system considered here is depicted in the upper part of Fig. 2. It consists of a set of sensors separated by a distance d . It is assumed that the signals arriving at the array are planar waves. In the figure the angles of incidence (θ_i) are the directions of arrival (DOAs) of several waves arriving at the array.

These signals are assumed to be analog communication signals (e.g. double sideband amplitude modulation (DSB-AM), narrowband frequency modulation (NBFM), single sideband amplitude modulation (SSB), etc). The waves arrive at each antenna element (sensor) with a phase delay given by,

$$\psi_m(\theta_n) = \frac{2\pi}{\lambda} d(m-1) \cos \theta_n \quad (1)$$

where λ is the wavelength, m is the index of the array element, d is the inter-element distance, and θ_n is a directions of arrival. At the m -th antenna element we have the following signal in intermediate frequency (IF):

$$r'(k) = s(k) \exp^{j(2\pi k - \psi_m(\theta_i))} + n(k) \quad (2)$$

Now let us generalize the model and consider the N-source M-sensor MIMO IF signal model for the mixing problem:

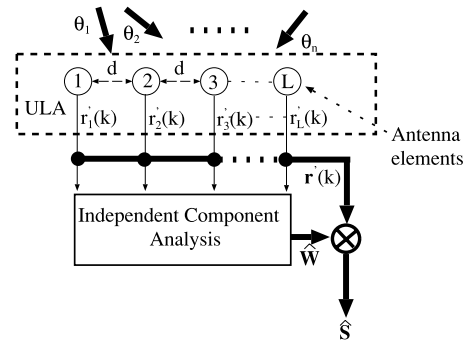


Fig. 2 DOA and ICA estimations.

$$\mathbf{r}'(k) = \mathbf{W}(k)\mathbf{s}(k) + \mathbf{n}(k) \quad (3)$$

where $\mathbf{r}'(k) = [r'_1(k), \dots, r'_M(k)]^T$ is the vector of observed signals, $\mathbf{s}(k) = [s_1(k), \dots, s_N(k)]^T$ is the vector of sources, $\mathbf{W}(k) = [\mathbf{w}_1(k) \mathbf{w}_2(k) \dots \mathbf{w}_N(k)]$ is $M \times N$ channel matrix, $\mathbf{n}(k) = [n_1(k), \dots, n_N(k)]^T$ is the additive white Gaussian noise, and k is the temporal sampling index. It will be assumed that we have more array elements than sources and that $s_n(k)$ is a zero-mean non-stationary non-Gaussian process. When the plane wave incidence is assumed, i.e. the n -th arrival is θ_n , $\mathbf{w}_n(k) = \mathbf{a}(\theta_n)$. In the following sections the index k is dropped to make the equations more readable.

4. ICA Processing

Fast ICA [3] processing is a procedure of two tasks:

- Preprocessing (decorrelate data mixtures)
- Independence and maximum nongaussianity estimation

The preprocessing or decorrelation can be achieved by whitening [3], [6] (sphering) the observed data vectors. A zero-mean random vector is white, when its components are uncorrelated and have unit covariance. To whiten the random vectors in our problem we need to find a whitening transformation operator. To accomplish this, we compute the matrix $\mathbf{E} = (\mathbf{e}_1 \dots \mathbf{e}_n)$, whose columns are the unit-norm eigenvectors of the covariance matrix $\mathbf{C}_r = E\{\mathbf{r}'\mathbf{r}'^H\}$. From this we construct our matrix operator given by:

$$\mathbf{V} = \mathbf{D}^{-\frac{1}{2}} \mathbf{E}^H \quad (4)$$

where $\mathbf{D} = \text{diag}(d_1, \dots, d_n)$ is the diagonal matrix of the eigenvalues of $\mathbf{C}_r$. The whitening transformation is then given by:

$$\mathbf{z} = \mathbf{V}\mathbf{r}' = \mathbf{V}\mathbf{W}\mathbf{s} \quad (5)$$

or

$$\mathbf{z} = \hat{\mathbf{W}}\mathbf{s} \quad (6)$$

where $\hat{\mathbf{W}}$ is the whitened mixing matrix. The covariance matrix of $\mathbf{z}$ equals unity ($E\{\mathbf{z}\mathbf{z}^H\} = \mathbf{I}$). The new

mixing matrix ($\hat{\mathbf{W}} = \mathbf{V}\mathbf{W}$) obtained from whitening is orthogonal [3]. Thus the mixing matrix can be estimated from the space of orthogonal matrices. This reduces the number of parameters (n^2) needed for the estimation of the original mixing matrix ($\mathbf{W}$) to a lower number ($\frac{n(n-1)}{2}$) for the new mixing matrix ($\hat{\mathbf{W}}$). The parameter reduction (dimension reduction) is done by discarding the low valued eigenvalues from the eigendecomposition computation, thus eliminating irrelevant components and reducing the complexity of the following processes.

For independence and maximum nongaussianity, ICA has two basic principles [3]:

- **Nonlinear decorrelation**
Nonlinear decorrelation implies independence. If the signals in a set of random signals are independent, then any nonlinear transformations on them will produce uncorrelated signals (their covariance is zero). For merely uncorrelated signals the covariance will be non-zero in general.
- **Maximum nongaussianity**
Independent components are maximally nongaussian components. Sums of nongaussian random variables (central limit theorem) are closer to gaussian than the original ones.

We make use of this principles as follows: The task of $\hat{\mathbf{W}}$ is depicted in the following expression:

$$\hat{\mathbf{s}} = \hat{\mathbf{W}}^H \mathbf{z} \quad (7)$$

Each individual column of $\hat{\mathbf{W}}$ will select one signal from the mixture. In order to estimate this matrix we use approximations to neg-entropy to measure nongaussianity of the data sequences. The cost function of these approximations takes the following form:

$$J(z) = [E\{G(z)\} - E\{G(v)\}]^2 \quad (8)$$

where v is a zero mean, unit standard deviation Gaussian distributed random variable. The choices of the nonlinear functions (nonlinear decorrelation) G can be $G(u) = \frac{1}{\alpha} \log \cosh(\alpha u)$ or $G(u) = -\exp\left(-\frac{u^2}{2}\right)$ according to [2], [3]. In the simulations performed for this paper the latter function is used. The columns $\mathbf{w}_p$ of matrix $\hat{\mathbf{W}}$ are initialized with unit norm values. p is an index of column. After the initialization we do the following:

$$\mathbf{w}_p \leftarrow E\{\mathbf{z}(k)G(\mathbf{w}_p^H \mathbf{z}(k))\} - E\{G'(\mathbf{w}_p^H \mathbf{z}(k))\} \mathbf{w}_p \quad (9)$$

Here G' denotes the derivative of G . Then the following orthogonalization is performed:

$$\mathbf{w}_p \leftarrow \mathbf{w}_p - \sum_{j=1}^{p-1} (\mathbf{w}_p^H \mathbf{w}_j) \mathbf{w}_j \quad (10)$$

where $\mathbf{w}_j$ is the j -th row of matrix $\hat{\mathbf{W}}$. At the end

of the procedure the data is normalized and we obtain the matrix $\hat{\mathbf{W}}$. This matrix is the approximation of the channel matrix $\mathbf{W}(k)$ introduced in the previous section. With this matrix we can perform the final transformation and extract the estimated independent components $\hat{\mathbf{s}}(k)$ of the received signal mixture:

$$\hat{\mathbf{s}} = \hat{\mathbf{W}}^H \mathbf{r}' \quad (11)$$

The weighting vectors $\mathbf{w}$ contained in matrix $\hat{\mathbf{W}}$ can be used to select any signal from the signal mixtures at the array.

Once the estimate of the independent components is obtained, the system will be able to analyze each of the signals using modulation recognition to estimate the modulation type, DOA estimation to estimate the position of the source, and demodulation to recover the message embedded in the signal. The following section describes the modulation recognition system.

5. Modulation Recognition

Before explaining about the key features used in the modulation recognition algorithm, let us review some of the modulated signals used. Four modulated signal types can be processed by the system: DSB-AM with or without transmitted carrier, SSB and narrow band FM. In this section, the carrier frequency of the signal is assumed to be exactly known. From here forward, DSB-AM with transmitted carrier will be referred to as AM, and DSB-AM without carrier will be referred to as DSB.

According to Azzouz and Nandi [4], 4 key features are used to discriminate between the modulation types of interest and they are derived from the instantaneous amplitude $a(t)$ and the instantaneous phase $\phi(t)$. In our approach, however, we find that 3 key features are enough to discriminate the modulation types of interest. In this section we will give a brief explanation of these 3 key features.

The first key feature, γ_{max} is defined by

$$\gamma_{max} = \max |DFT(a_{cn}(i))|^2 / N_s \quad (12)$$

where N_s is the number of samples per segment and $a_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude at time instants $t = \frac{i}{f_s}$, ($i=1,2,\dots,N_s$), and it is defined by

$$a_{cn}(i) = a_n(i) - m_a, \text{ where } a_n(i) = \frac{a(i)}{m_a} \quad (13)$$

where m_a is the average value of instantaneous amplitude evaluated over one segment.

$$m_a = \frac{1}{N_s} \sum_{i=1}^{N_s} a(i) \quad (14)$$

γ_{max} represents the maximum value of the spectral power density of the normalized-centered instantaneous

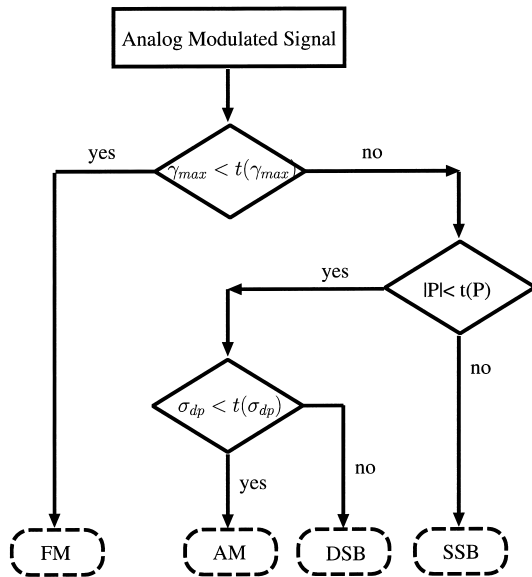


Fig. 3 Modulation recognition flowchart.

amplitude of the intercepted signal.

This value is used to discriminate between FM signals as a subset and DSB as the second subset. As the FM signals have constant instantaneous amplitude, their normalized-centered instantaneous amplitude is zero. Thus, their spectral power densities are also zero. On the other hand, DSB possess amplitude information. The second key feature is defined as

$$\sigma_{dp} = \sqrt{\frac{1}{C} \left(\sum_{a_n(i) > a_t} \phi_{NL}^2(i) \right) - \left(\frac{1}{C} \sum_{a_n(i) > a_t} \phi_{NL}(i) \right)^2} \quad (15)$$

where $\phi_{NL}(i)$ is the value of the centered non-linear component of the instantaneous phase at time instant $t = \frac{i}{f_s}$, C is the number of samples in $\phi_{NL}(i)$ for which $a_n(i) > a_t$ and a_t is a threshold for $\{a(i)\}$ below which the estimation of the instantaneous phase is very sensitive to the noise. Thus, σ_{dp} is the standard deviation of the centered non-linear component of the direct instantaneous phase, evaluated over the non-weak intervals of a signal segment. σ_{dp} is used to discriminate between AM as subset and DSB,SSB,FM as the other subset. This is due to the fact that AM signal has no direct phase information. On the other hand, the other types have direct phase information. The third key feature is used for measuring the spectrum symmetry around the carrier frequency, and it is based on the spectral powers for the lower and upper sidebands of the signal. Mathematically, it is defined as

$$P = \frac{P_L - P_U}{P_L + P_U} \quad (16)$$

Where, $P_L = \sum_{i=1}^{f_{cn}} |X_c(i)|^2$ and $P_U = \sum_{i=1}^{f_{cn}} |X_c(i + f_{cn} + 1)|^2$. Here, $X_c(i)$ is the Fourier transform of the signal, $(f_{cn} + 1)$ is the sample number corresponding to the carrier frequency, f_c and f_{cn} is defined as

$f_{cn} = \frac{f_c N_s}{f_s} - 1$. The ratio of P is used to discriminate between SSB as a subset and AM, DSB, FM as the second subset, since $|P|$ at infinite SNR ought to be 1 for SSB signals (+1 for LSB and -1 for USB), and 0 for AM, DSB and FM. A functional flowchart to discriminate and classify different modulation types of interest according to the explanation in previous section can be illustrated as in Fig. 3.

6. DOA Estimation

Up to this point we have introduced the application of ICA and modulation recognition to the radio surveillance system. Still it is important to discuss the role of the DOA estimator. Let $\mathbf{a}(\theta)$ be the steering vector, and let $\mathbf{w}$ be the spatial signature of the array antenna of the surveillance system. Our interest is to maximize the power spectrum or beamforming spectrum $P(\theta)$ at a given angel of arrival θ . This power spectrum [16] is given by:

$$P(\theta) = \frac{1}{\mathbf{a}^H(\theta) \mathbf{R}_{rr} \mathbf{a}(\theta)} \quad (17)$$

Here $\mathbf{R}_{rr}$ is the autocorrelation of the array input data ($\mathbf{r}'$). This power spectrum is based on the technique developed by Capon [16] that minimizes the contribution of undesired interferences by minimizing the output power while keeping the gain along the look direction to be constant. The DOAs can be estimated by checking for peaks in the spectrum and a desired look direction can be chosen to steer the array.

7. Demodulation

Demodulation is determined by the modulation recognition subsystem. The latter will pass information about the modulation type to the demodulation subsystem, and this will provide the proper demodulation algorithm in accordance with the information received. If for example, the signal is determined to be narrowband FM, then this information will be passed to the demodulation unit, and this unit will provide the proper algorithm (e.g. a phase locked loop, etc) to demodulate the signal. Figure 4 shows a scheme of the relationship between modulation recognition and how the demodulation process is determined.

For each of the modulation types recognized, the system assigns a particular method for demodulation. In the case of AM and DSB, a Costas loop performs demodulation. For FM, a PLL with a loop filter with sufficient bandwidth is used to extract the phase information. In the case of SSB, carrier recovery is also required to accomplish coherent demodulation. But SSB has asymmetrical frequency characteristics that defy an efficient estimation of the carrier, and thus it is a complex task that still requires some research. If we could

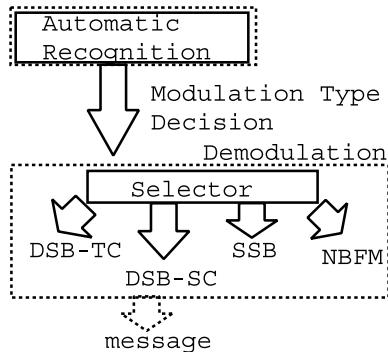


Fig. 4 Demodulation subsystem.

estimate the carrier, the SSB signals could be demodulated by multiplying the estimated carrier with the received signal and by filtering the result with a low pass filter. Carrier tracking need to be taken into account as well. For that purpose, a PLL similar to the ones described previously could be used. The estimation of unknown carrier frequencies is a problem that also requires further study. The interested reader is directed to [15]. The interested reader can obtain further details about PLLs, Costas loops, and general synchronization and demodulation techniques from [12], [14]. The next section shows a simulation of the signal resolution of the ICA estimator as used on a ULA antenna.

8. System Simulation

In this section we show the results of using Fast ICA on the mixture of signals obtained from a uniform linear array (ULA) antenna. The condition parameters used in the simulations are presented in Table 1. The signals used are analog modulated signals from the set: Double Sideband Amplitude Modulation DSB-AM (with and without transmitted carrier), Narrowband Frequency Modulation NBFM, and Single Sideband Amplitude Modulation SSB-AM. We assume that the signals have been downconverted from HF (3–30 MHz) to IF and sampled for digital signal processing. The signals are incoherent. We will use three scenarios to show the source separation as applied to the ULA. The Fast ICA algorithm computes matrix $\hat{\mathbf{W}}$, which contains the necessary weighting vectors to select and resolve the signals contained in the signal mixture from the sensors. The scenarios shown below, portray how the algorithm is able to resolve two signals arriving from different directions. The beam patterns are plotted for each of the scenarios. The algorithm was capable of providing the proper array weighting vectors to resolve each signal individually.

The analog modulated signals impinging on the array are shown in Fig. 5.

- Scenario 1: In this scenario the signals arrive at the array at angles of 40° (AM) and 120° (DSB). The

Table 1 Simulation conditions.

SNR	30 dB
signal segment length	1024 samples
Sampling frequency	64 kHz
Bandwidth of Bandpass signals	3 kHz
Intermediate frequency	20 kHz
Number of impinging signals	2
DOAs used	$(40^\circ 120^\circ)$ or $(40^\circ 50^\circ)$
Number of array elements	8

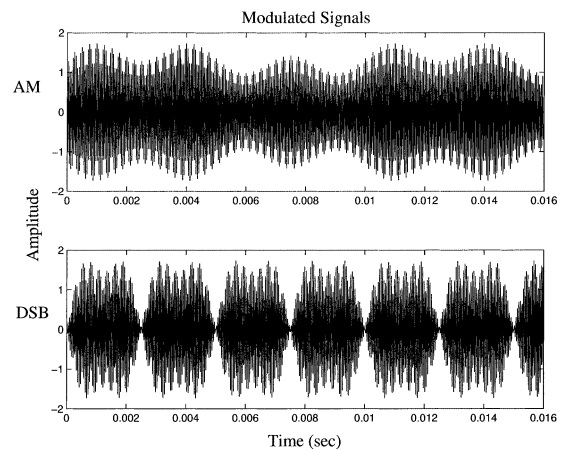


Fig. 5 Modulated signals impinging on the array.

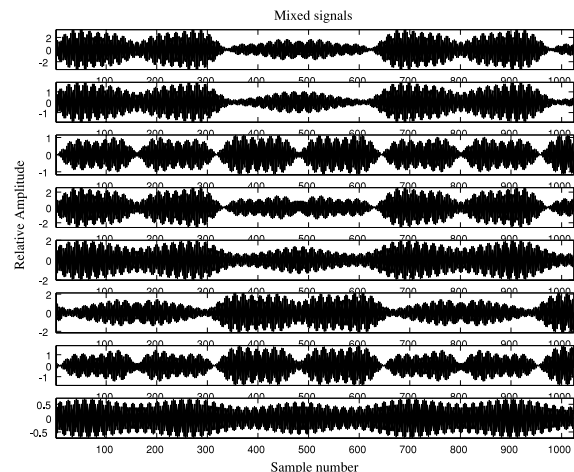


Fig. 6 Array mixtures for signals impinging at 40° and 120° .

mixtures at each of the array elements are shown in Fig. 6. The received mixtures are whitened according to equation 5. The whitened mixtures are shown in Fig. 7. The source signals are then extracted according to equation 7 and are plotted in Fig. 8. And their beam patterns are shown in Fig. 9.

- Scenario 2: As for this scenario the signals arrive at the array at angles of 40° (AM) and 50° (DSB). And as in the previous scenario, we can proceed in a similar fashion and obtain the mixtures at the array output, the whitened mixture, the ICs, and their beam patterns as shown in Fig. 10,

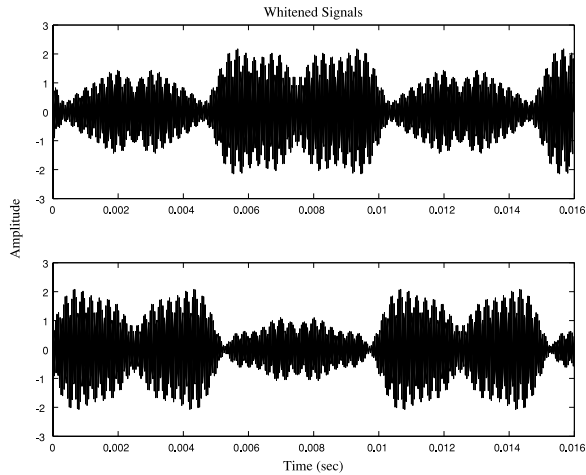


Fig. 7 Whitened mixtures for signals impinging at 40° and 120° .

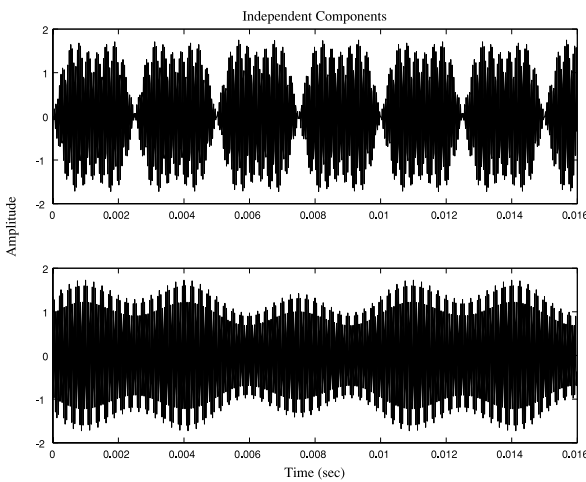


Fig. 8 ICs for signals impinging at 40° and 120° .

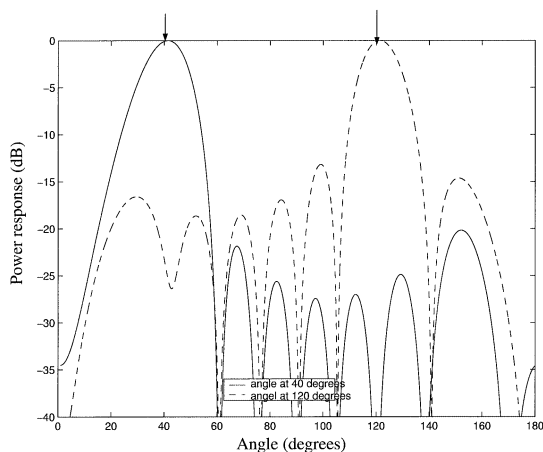


Fig. 9 ULA beampattern for signals impinging at 40° and 120° .

Fig. 11, Fig. 12, and 13, respectively.

The two scenarios show that it is possible to resolve signals impinging from different angle separations. A

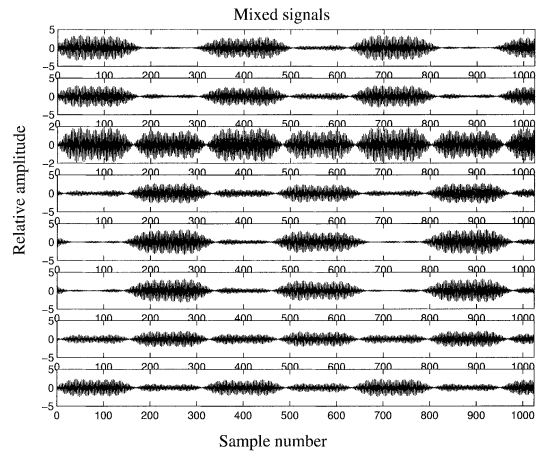


Fig. 10 Array mixtures for signals impinging at 40° and 50° .

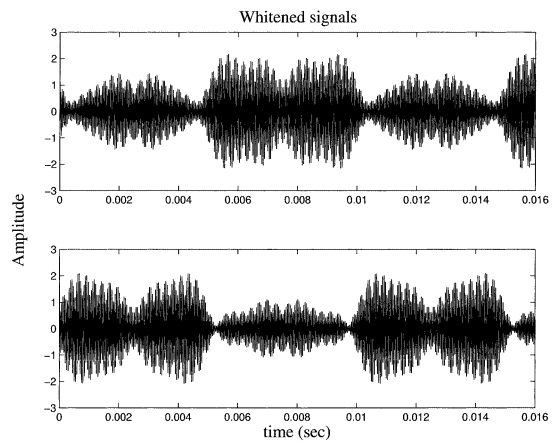


Fig. 11 Whitened mixtures for signals impinging at 40° and 50° .

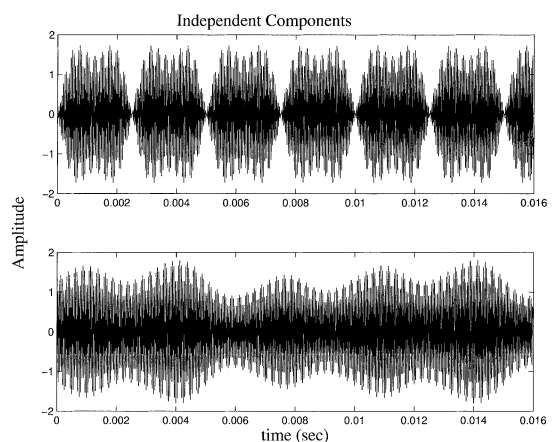


Fig. 12 ICs for signals impinging at 40° and 50° .

closer look at the whitened mixtures in Figs. 7 and 11 show the interesting result that they are identical and so are their independent components in Figs. 8 and 12. In Fig. 14 we see the result of the demodulation after the modulation recognition of one of the signals.

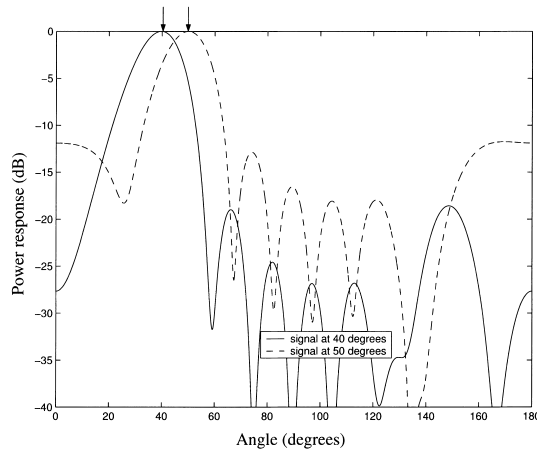


Fig. 13 ULA beampattern for signals impinging at 40° and 50°.

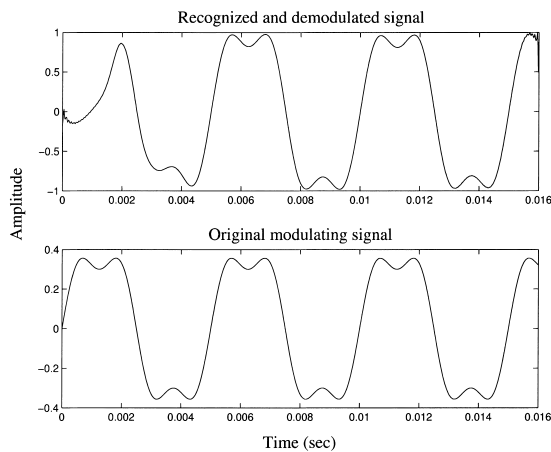


Fig. 14 Demodulated signal compared to original.

9. Conclusions

The ICA algorithm has been introduced herein, to provide a solution to the blind source separation problem in radio surveillance. The algorithm is capable of resolving signals impinging from different angles from a mixture of signals from a ULA antenna under the conditions and assumptions presented. From the beampatterns shown in this paper it is also concluded that the algorithm can also resolve closely located sources, providing proper weighting vectors for each of the signal components involved.

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