Joint Radar and Communication based Blind Signal Separation using a New Non-Linear Function for Fast-ICA

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***Abstract*—Joint radar and communication (JRC) is a fast emerging research field to cope up with the ever-growing applications dependent on both sensing and communication. However, frequent issues are faced for JRC systems including interference mitigation, transmission design and signal analysis. This paper focuses on blind signal separation (BSS) of spectral coexistence JRC signals for blindly extracting sensing information from the communication signal for spectrum awareness, also this BSS is used for interference mitigation by using a modified fast independent component analysis (Fast-ICA) algorithm. Furthermore, a new non-linear function is introduced for Fast-ICA which tends to have better performance of separation with low time computational complexity. The numerical analysis shows the effectiveness and practicality of the system by using modified Fast-ICA algorithm in separating JRC signals successfully compared to other separation methods.**

***Index Terms*—Blind signal separation, coexistence, Fast-ICA, interference mitigation, JRC, negentropy approximation.**

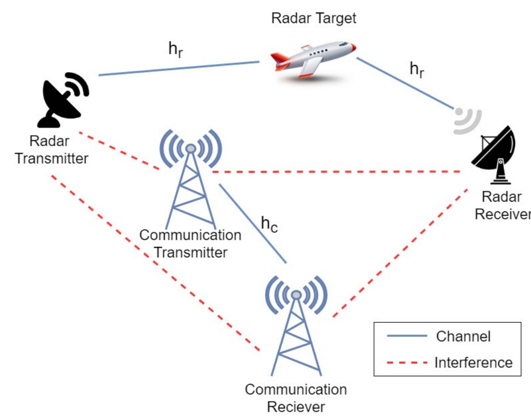

Fig. 1: Spectral coexistence system.

I. INTRODUCTION

Joint radar and communication (JRC) has become an attractive domain for future wireless networks (6G and beyond) to meet the dynamically increasing applications and to overcome spectrum scarcity. These applications require reliable sensing with high data rates at the same time [1]. There are two main types of waveforms used for JRC; radar-communication coexistence (RCC) and dual functional radar-communication (DFRC) [2]. The major work in literature for JRC, is the waveform design which is emphasized on designing a waveform that can work for both sensing and communication in parallel with harmony [3].

The main focus of this paper is spectral coexistence scenario of RCC, in which both communication and radar systems occupy the same frequency spectrum. In this architecture the major issue is mutual interference mitigation for reliable performance while maximizing the detection of both communication and radar sensing. A detailed survey of coexistence for JRC systems, where problems regarding interference mitigation are catered in [4]. Besides, new methods are proposed for interference mitigation in RCC waveforms in, [5] and [6].

Different degrees of freedom (DoF) are exploited at the transmitter and receiver, e.g. time, frequency, spatial, or power to eliminate or avoid interference. Multiple-input, multiple-output (MIMO) system is designed in [7] to provide resilience against interference. In most of the methods the feedback about the channel response is used to cancel interference from the overall received signal. A commonly used method is by successive interference cancellation method as done in [8].

Despite aforementioned studies, constant monitoring and management of blind JRC signal reception is of great concern and not been yet addressed in literature. The main motivation of using blind signal separation (BSS) in this paper includes; (a) firstly, blind acquisition of sensing data from the JRC signals especially for scenarios of radio environment map (REM), radio surveillance, electronic warfare and spectrum monitoring. The blind sensing data acquisition would mainly help in constant spectrum awareness and know how about the congested radio frequency environment around us. (b) Secondly, BSS is implemented for interference mitigation at the receivers of communication and radar, in the availability of both cases, perfect and non-perfect channel state information (CSI).

The BSS is used to recover or separate desired signal(s) from a mixture of unknown signal, without knowing any, or

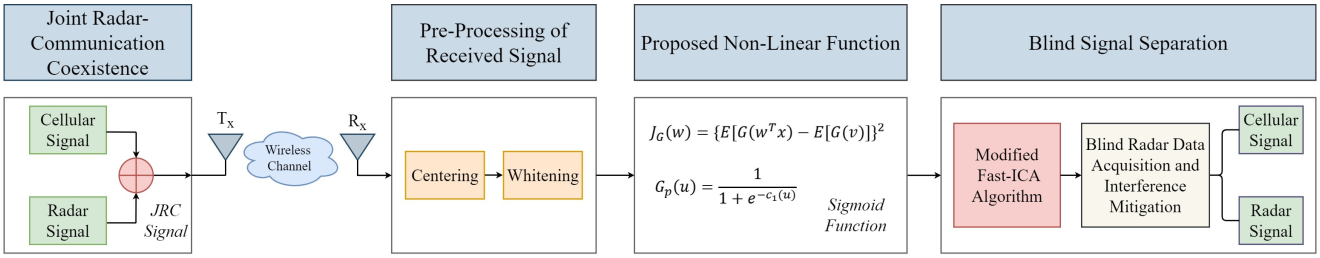

Fig. 2: Proposed framework for JRC coexistence BSS.

having minimum prior information about the source signal(s). Fast independent component analysis (Fast-ICA) is a commonly used BSS algorithm for music and voice separation [9]. There are many other methods used for BSS and its applications, one such explained in [10]. A modified Fast-ICA algorithm with a new non-linear function for estimation of negentropy is proposed in this paper. Fast-ICA is the most effective algorithm for the proposed framework compared to other algorithms such as principal component analysis (PCA) and non-negative matrix factorization (NMF) which are later compared in the results.

Wireless communication community is in an urge to modify and enhance the existing growing JRC research field, because of its importance in future wireless networks (6G and beyond). Blindly separating the signals would be helpful in acquiring sensing data from the communication signal to have a better insight over the radio environment of JRC signals. The main contributions of this paper are enlisted:

- Implementing BSS for JRC spectral coexistence signals is introduced in this paper for the very first time to the best of authors' knowledge.
- This separation is implemented for coexistence JRC signals in order to acquire the sensing data blindly from the communication signals at the receiver(s) for constant spectrum awareness and applications such as REM.
- Moreover, the same BSS method is also used for interference mitigation for perfect or non-perfect CSI availability.
- A new non-linear function for modified Fast-ICA is introduced which outperforms traditional non-quadratic functions. The new non-linear function is used for negentropy approximation of signal separation to optimize the contrast function.
- A generalized framework is proposed for blind separation of any coexistence JRC signals under the assumptions of the modified Fast-ICA algorithm.

The structure of paper is as follows. Section II presents the system model, Section III provides methodology of BSS with optimization of contrast function. Section IV gives the insights of the results. Section V ends the paper with brief conclusion.

II. System Model

In this section, system model of the proposed framework is explained. Let m-dimensional observed signals be denoted by $\mathbf{x} = (x_1, x_2, ..., x_m)^T$, while the statistically independent components of n-dimensional vector be denoted by $\mathbf{s} = (s_1, s_2, ..., s_n)^T$ and $\mathbf{A}$ is a constant $m \times n$ matrix that is to be estimated. The model of the Fast-ICA algorithm in vector-matrix representation is as follows:

$$\mathbf{x} = \mathbf{A}\mathbf{s}. \tag{1}$$

The mentioned model, (1) is effective under the following restrictions: at most only one of the independent components (ICs), s_n can be Gaussian and that matrix $\mathbf{A}$ being of a full column rank. Moreover for simplicity it is assumed that the dimensions of $\mathbf{x}$ and $\mathbf{s}$ are equal that means, $n = m$.

A. Transmitter Design

As a particular example, orthogonal frequency division multiplexing (OFDM) signal $s_1(t)$ for communication and chirp signal $s_2(t)$ for radar sensing, are considered as a spectral coexistence for JRC model.

$$s_1(t) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_m(k) e^{j2\pi t \frac{k}{N}}, \quad 0 \leq k \leq N-1, \tag{2}$$

$$s_2(t) = e^{j\pi\beta t^2/\tau}, \quad 0 \leq t \leq \tau, \tag{3}$$

where (2) represents OFDM signal with X_m transmitted data symbols and N number of carriers, (3) represents a complex linear frequency increasing chirp signal of time-domain representation that has a sweep bandwidth of β Hz with total duration of τ seconds. Both the signals are superimposed in such a way that they are allocated with the same bandwidth with spectral coexistence scenario therefore, the sampling rate f_s for both are also considered same.

B. Channel Effect

A linear time-varying channel is considered with two radar targets present in the environment which are moving with relative velocities with some distance from the radar. The received signals at each receiver as shown in Fig. 1 is represented as

$$r(t) = \sum_{p=1}^{P} \alpha_p \mathbb{R} \left\{ x(t-\tau_p) e^{j2\pi(f_c+\psi_p)(t-\tau_p)+j\Theta+j\phi_p} \right\} + n(t)), \tag{4}$$

where the time delay between the radar transmitted and received signal is τ_p, ϕ_p is the phase error and α_p is the radar cross section (RCS). The number of targets in the environment is P, while ψ_p, ($\psi_p = \frac{2f_c v_p}{c}$) is the Doppler frequency of the target whose relative velocity is represented by, v_p and c is the speed of light. Moreover, $n(t)$ is AWGN noise with zero mean and variance, σ^2 and large-scale path-loss G between the transmitter and receiver is $G = \frac{G_T G_R \lambda^2}{(4\pi)^2 d^n}$, where G_T and G_R are the antenna gains, while n is the path-loss exponent.

III. Blind Signal Separation

The separation of the JRC signal is performed through a BSS algorithm, Fast-ICA. The main objective of signal separation is to find a representation in which the individual components can be as statistically independent as possible. The analysis block diagram is illustrated in Fig. 2, where the received signal operation consists of three stages. Starting with the pre-processing of the signal, proposing a new non-linear function for Fast-ICA to optimize the contrast function and separation of the signals blindly.

A. Assumptions

Fast-ICA has two assumptions that are necessary for separation; a) source signals being statistically independent and b) the signals must be non-Gaussian [11]. To use non-Gaussianity in Fast-ICA estimation a quantitative measure either by kurtosis or negentropy is performed. The classical measure of non-Gaussianity is kurtosis but with a major drawback of being sensitive to outliers and to external factors, leading to a larger value of kurtosis if any unsuitable value in the samples are observed. Kurtosis is defined as; $\mathrm{kurt}(y) = \mathrm{E}\{y^4\} - 3(\mathrm{E}\{y^2\})^2$, where E(.) is mean operation of random variable, y. The second critical measure of non-Gaussianity is negentropy estimation, which is discussed further.

B. Pre-Processing

The following two pre-processing techniques are performed to bring the data to a suitable and simpler format; centering and whitening. Centering is the subtraction of mean vector, $\mathbf{m} = \mathrm{E}\{\mathbf{x}\}$ from the mixed signal so that the vector becomes a zero mean variable. The centering process makes $\mathbf{s}$, of zero-mean and also because of taking expectations on both side of (1). Once the mixing matrix $\mathbf{A}$ is estimated the mean vector of $\mathbf{s}$, ($\mathbf{A}^{-1}\mathbf{m}$) is added back to the estimated $\mathbf{s}$.

Once the centering of received data is done, the centered observed variables are whitened. The observed vector $\mathbf{x}$ is transformed linearly to get $\tilde{\mathbf{x}}$, a new vector which is white. The main purpose of whitening is to make the components of the observed data uncorrelated as possible with unity variance. It can also be denoted by; $\mathrm{E}\left\{\tilde{\mathbf{x}}\tilde{\mathbf{x}}^{\mathbf{T}}\right\} = \mathrm{I}$, which represents that the covariance matrix of $\tilde{\mathbf{x}}$ is equal to an identity matrix.

C. Independent Components Estimation, Fast-ICA

The main working of Fast-ICA is to estimate a demixing matrix $\mathbf{W}$, which is the inverse of the mixing matrix $\mathbf{A}$ i.e, $\mathbf{W} = \mathbf{A}^{-1}$ and the projection of $\mathbf{w}^T\mathbf{x}$ which maximizes the non-Gaussianity of the system on a fixed-point iteration scheme. To find the ICs, estimation of negentropy is performed. The main benefit of negentropy based estimation is that it uses neural networks to implement the learning which makes the method more robust and adapt fast in real time-varying environments.

1) Negentropy Estimation: Negentropy is based on the concept of information-theoretic quantity of the differential entropy $H(y)$, whereas the entropy of any random variable is amount of information that the observed variables gives, this entropy H for a discrete random variable Y is represented as

$$H(Y) = -\sum_i \mathrm{P}(Y = a_i)\log P(Y = a_i), \tag{5}$$

where a_i are all the possibles values Y can get. Further, (5) is generalized so that it can be denoted for continuous random variable values, known as differential entropy which is represented as $H(y) = -\int f(y)\log f(y)dy$, with probability density of $f(y)$ of a random vector y. Furthermore, differential entropy is normalized to get the negentropy $J(y)$ which is defined as $J(y) = H(y_G) - H(y)$, where y_G is Gaussian random variable with same covariance matrix as of y.

An objective function for the Fast-ICA algorithm is defined that can approximate the negentropy. This approximation is based on maximum-entropy principle which is given by

$$J(y) \approx \sum_{i=1}^{P} k_i[\mathrm{E}\{G_i(y)\} - \mathrm{E}\{G_i(v)\}]^2, \tag{6}$$

where the k_i's are positive constants, the Gaussian variable v and random variable y both having zero mean and unit variance while G_i denotes non-quadratic functions. For using a single non-quadratic function the approximation of (6) is represented as $J(y) \approx [\mathrm{E}\{G(y)\} - \mathrm{E}\{G(v)\}]^2$.

2) Contrast Function Optimization: From the above equation a contrast function is obtained for estimation of the ICs, so the new framework for the approximation is given by

$$J_G(\mathbf{w}) \approx [\mathrm{E}\{G(\mathbf{w}^T\mathbf{x})\} - \mathrm{E}\{G(v)\}]^2, \tag{7}$$

where, $\mathbf{w}$ is the weight vector that is constrained so that $\mathrm{E}\{(\mathbf{w}^T\mathbf{x})^2\} = 1$. For finding one IC, (7) is maximized by using $y_i = \mathbf{w}^T\mathbf{x}$. When calculating several ICs, the same one unit Fast-ICA algorithm is used for several units with different weight vectors to be specified ($\mathbf{w}_1, \ldots, \mathbf{w}_\mathrm{n}$). A robust approximation of negentropy depends on the wise selection of the non-quadratic function G that grows slowly. The following non-linear functions $G(.)$ and their derivatives $g(.)$ are frequently used in the Fast-ICA algorithms [11]

$$\begin{cases} G_1(u) = \frac{1}{a_1}\log\cosh(a_1 u), & g_1(u) = \tanh(a_1 u), \\ G_2(u) = -\frac{1}{a_2}e^{-\frac{1}{2}a_2 u^2}, & g_2(u) = ue^{-\frac{1}{2}a_2 u^2}, \\ G_3(u) = \frac{1}{4}u^4, & g_3(u) = u^3, \end{cases} \tag{8}$$

where $1 \le a_1 \le 2$ and $a_2 = 1$. In this paper, a new non-linear function is introduced, called the sigmoid function and is defined as

$$G_p(u) = \frac{1}{1 + e^{-a_4 u}}, \qquad a_4 \approx 0.5 \tag{9}$$

The proposed $G_p(u)$ gives better and robust approximation with less time computational complexity and improves the convergence property, compared to the other $G_i(u)$ mentioned above. While choosing $G_3(u)$, leads to kurtosis-based approximation which is not a robust measure of non-Gaussianity as discussed earlier. The computational speed of the separation is a main factor for JRC applications such as for vehicle-to-vehicle communication. Therefore, selection of a non-linear function that is simple, fast and with better performance than the traditional non-linearities is crucial [12]. The time computational load is calculated for each non linear-function mentioned in (8) and (9), while running the algorithm fifteen times for each non-linear function. The comparison of each function regarding for the time taken for the algorithm to converge is calculated and shown in Table I. Moreover, the modified Fast-ICA algorithm used in this paper is summarized in Algorithm 1 using a fixed-point iteration method.

TABLE I: Time complexity comparison

Non-Linearities	Average runtime (s)
$G_1(u)$	0.512
$G_2(u)$	0.628
$G_3(u)$	0.813
$G_p(u)$	0.321

Algorithm 1 Modified Fast-ICA Algorithm

Input: The mixed JRC signals $\mathbf{x}$.
Output: The separation matrix $\mathbf{W}$.

A. Pre-Processing
1: **Centering:** $\mathbf{x} - E\{\mathbf{x}\}$; $\mathbf{x}$ has zero mean.
2: **Whitening:** $\mathrm{E}\{\tilde{\mathbf{x}}\tilde{\mathbf{x}}^T\} = \mathbf{I}$.

B. Blind Signal Separation
3: **Choose** proposed $G_p(u)$, sigmoid function.
4: **Initialize** number of ICs, **m**. Set counter p=1.
5: **Initialize** random $\mathbf{w}_p$, $\mathbf{w}_p = \mathbf{w}_p / || \mathbf{w}_p ||$.
6: **Calculate** $\mathbf{w}_p$, $\mathbf{w}_p = \mathrm{E}\{\mathbf{x}\, g(\mathbf{w}_p^T \mathbf{x})\} - \mathrm{E}\{g'(\mathbf{w}_p^T \mathbf{x})\}\, \mathbf{w}$.
7: Run $\mathbf{w}_{p+1} = \mathbf{w}_{p+1} - \sum_{j=1}^{p} \mathbf{w}_{p+1}^T \mathbf{w}_j \mathbf{w}_j$.
8: **If** $|\mathbf{w}_{p+1} - \mathbf{w}_p| < \epsilon$ not **converged**, go to step 6.
9: **Let** $p = p + 1$, if $p < n$, return to step 4.
10: **end**

IV. Results and Discussion

In this section, performance of the modified Fast-ICA algorithm is discussed for blind JRC signal separation. A spectral coexistence system is considered where the receivers of radar and communication are independently located with independent channel access. Whereas, the simulation parameters for the OFDM and chirp depending on the radar sensing and communication requirements [13], are listed in Table II.

To examine the effectiveness of the signal separation under the mentioned assumptions, spectral coherence between both the source signals is obtained. For the two signals to have minimum correlation and maximum independence between them the value of $C_{s_1s_2}(f)$ from (10), should lie as minimum as possible between $0 \le C_{s_1s_2}(f) \le 1$, shown in Fig. 3.

$$C_{s_1s_2}(f) = \frac{|G_{s_1s_2}(f)|^2}{G_{s_1s_1}(f) G_{s_2s_2}(f)}, \tag{10}$$

TABLE II: List of simulation parameters

Parameter	Value
Carrier frequency (f_c)	28 GHz
Bandwidth (β)	100 MHz
Cyclic prefix (CP) size	1/4
FFT size (N)	2048
Chirp duration (τ)	2.4 μs
Subcarrier spacing (Δf)	60 kHz
Radar target range	50m and 35m
Radar target velocities	0ms^{-1} and 22ms^{-1}

whereas $G_{s_1s_2}(f)$ is the cross-spectral density between s_1 and s_2, while $G_{s_1s_1}(f)$ and $G_{s_2s_2}(f)$ is the autospectral density.

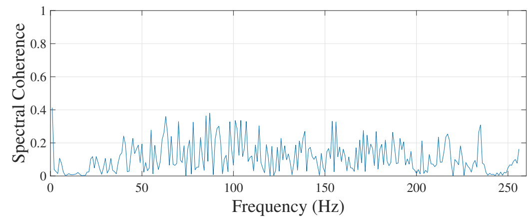

Fig. 3: Coherence estimation of both source signals.

At the receivers of both radar and communications, the paper focuses on two aspects, in situations where BSS are being used, which are discussed in the following sections.

1) BSS for Radar Data Acquisition: The main purpose for blind acquisition of radar data from communication signal is to use this information in further applications related to REM, radio surveillance, spectrum monitoring and electronic warfare. The separation results show that the proposed framework is robust in separating both the signals. In JRC, the primary focus of communication signal is to communicate radar sensed parameters to the surrounding receivers. Separation of spectral coexistence OFDM and chirp is performed and separated OFDM signal can be seen in Fig. 4 (a) while symbol error rate for OFDM signal is computed and shown in Fig. 4 (b).

2) BSS for Interference Mitigation: To overcome problems related to interference in JRC coexistence at each receiver, in both cases when perfect or non-perfect CSI is available. The separated signals at receivers are used to cancel the interference from the other unwanted signal. Once the interference mitigation is done, the radar parameters are estimated. The Doppler-range matrix is estimated from 2D-FFT process, in which the observed delay from the transmitted and received signal is used to calculate the range and velocity of the target. Fig. 5 shows the estimated distance and velocity of the targets.

3) Modified Fast-ICA: The performance of the JRC signal separation is done by calculating normalized mean squared error (NMSE), as shown in Fig. 4 (c). For the traditional Fast-ICA algorithm from (8), $G_2(u)$ is considered whereas, for the modified algorithm $G_p(u)$ from (9) is considered. It is observed that with increase of SNR the performance of system is getting better with less errors. Moreover, the modified Fast-ICA outperforms traditional Fast-ICA and PCA.

Considering a JRC coexistence system, at each receiver the blind separation from the mixed signal is performed and

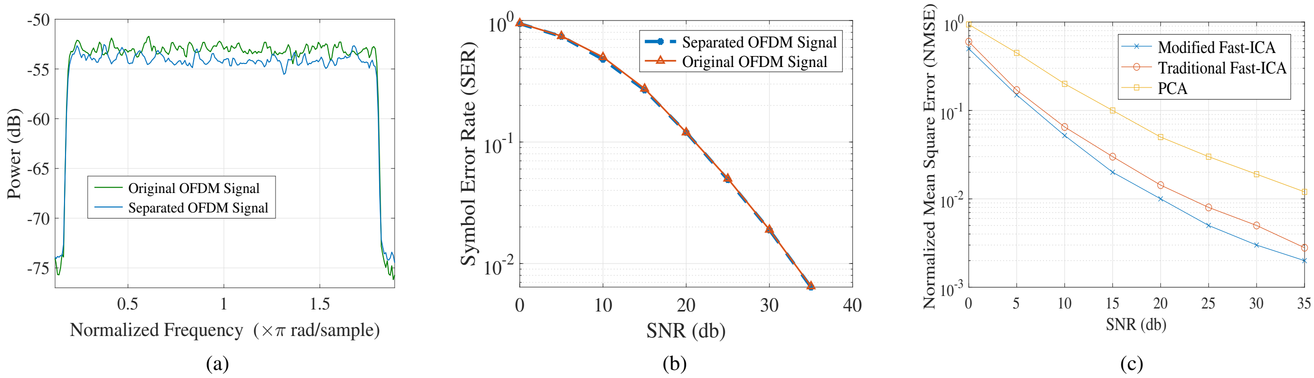

Fig. 4: (a) Original and separated OFDM signal, (b) SER of original and separated OFDM signal and (c) NMSE of signal separation for the modified Fast-ICA, traditional Fast-ICA, and PCA.

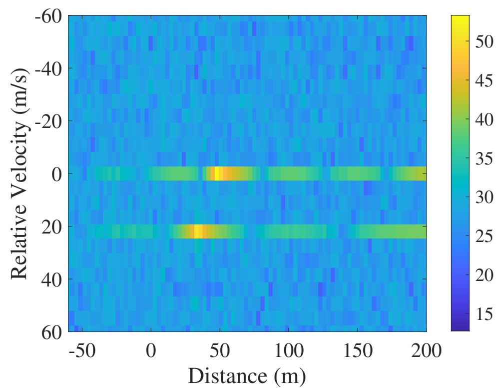

Fig. 5: Velocity-distance plot for the estimated targets.

the desired signal is extracted. For communications receiver in non-ideal channel, equalization is performed to remove the effect of the channel from the mixed signal however, the investigation of this estimation is not the scope of this paper that is why it is not discussed in detail. For the radar receiver, the channel information acts as a medium of different information about the target velocity, distance, angle, etc. In this way the coexistence of JRC signals can be used blindly to acquire information about the sensed environment and also for the mitigation of interference at the radar and communication receivers.

V. Conclusion

Acquiring data from blind signals play an important role in wireless communication applications related to spectrum awareness. BSS has been introduced for the first time in the domain of JRC signals for blindly acquiring radar parameters from communication signal and also for interference mitigation of spectral coexistence scenarios. Furthermore, a new non-linear function is introduced for negentropy estimation, the results show the robustness of the modified Fast-ICA algorithm with less time computational complexity and with better separation of JRC signals. In future networks these contributions would help in keeping better insight of the radio environment with better blind reception of information.

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