DOA algorithms noise performance analysis for cognitive radio systems

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In this paper the precision of variety direction of arrival (DOA) algorithms used in cognitive radio systems are investigated. The researched algorithms are MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS. The goal of this article is to achieve better quality performance in cognitive radio networks by using smart antenna arrays. Dynamic spectrum access allows secondary users to access licensed frequency bands as long as they are not interrupting primary users' transmission. Cognitive radio users must be able to identify the presence of the primary users as quickly as possible. The accuracy and relative average processing time of each algorithm depending by signal to noise ratio (SNR) with given number of antenna array elements and number of snapshots are compared and analyzed. Wide and narrow angular separation modes are used for analyzing the performance of DOA algorithms in different detection and environment conditions. The results obtained in this work give an idea of the effectiveness of the DOA algorithms and their applicability to improve quality performance in cognitive radio devices.

Изследване шумоустойчивостта на DOA алгоритми, приложими в когнитивни радиокомуникационни системи (Тодор Д. Цветков, Илия Г. Илиев). *В настоящата работа се изследва и анализира точността на различни алгоритми за изчисляване на ъглите на постъпване при детектиране на сигнали в когнитивни радиокомуникационни системи. Разгледани са алгоритмите MUSIC, Капон (MVDR), ROOT MUSIC, ESPRIT-LS и ESPRIT-TLS. Целта на предложения анализ е подобряване на качествените показатели на когнитивното радио чрез прилагане на адаптивна антенна решетка и динамичен достъп на вторичните потребители, които да използват лицензирана честотна лента без да внасят смущения в каналите на първичните потребители. Сравнени и са анализирани точността и средното относително процесорно време на всеки алгоритъм в зависимост от отношението сигнал-шум при зададени брой елементи на антенната решетка и брой на отчетите в обработваната извадка. Изследвани са комбинация от ъгли на постъпване, разположени на близко и далечно разстояние един от друг за оценка на разделителната способност при различните условия на приемане. Резултатите, получени в настоящата работа дават представа за ефективността на алгоритмите за изчисляване на ъгъла на постъпване и препоръки за тяхното приложение с цел подобряване качествените показатели на когнитивните радиокомуникационни системи.*

I. Introduction

In recent years, the number and capacity of wireless devices using licensed frequency bands is increased. This results in situations in which some radio frequency bands are heavily used, while others are only either partially or rarely occupied. Cognitive radio technology gives the opportunity for more efficient frequency usage [1].

Users who have legacy rights on the usage of spectrum bands are called primary users, while secondary users have lower priority in the same frequency bands without causing unnecessary interference to the primary users [1]. Dynamic spectrum access allows secondary users (SU) to access licensed frequency bands as long as they are not interrupting primary users' transmission. Cognitive radio users must be able to identify the presence of the primary users (PU) as quickly as possible. All secondary users must use devices with cognitive radio capabilities in order to provide the necessary quality of service for primary users and for their own requirements. Primary users can use their frequency band at anytime while cognitive radio is operating in the same band. All secondary users must constantly change their transmission parameters in order to avoid interference to the primary users.

Spectrum sensing is one of the most important goals in cognitive radio and can be classified as blind spectrum sensing or non-blind spectrum sensing. The main advantage of blind spectrum sensing is that it does not require information about a primary user's signal a priori. Examples of blind spectrum sensing methods are energy detection, wavelet detection and eigenvalue detection. When there is prior knowledge about the primary signals, then non-blind spectrum sensing techniques are used as matched filtering and cyclostationary detection. Matched filtering is optimal method in this category, but requires perfect knowledge about the primary signals characteristics. Higher implementation complexity makes it difficult to apply in cognitive handheld devices [2]. Cyclostationarity detection utilizes specific features of the primary signals, which could be considered as periodical [3]. Thus improves detector's sensing process and it can easy distinguish cyclostationary signals from stationary noise. However, this technique is not widely used due it's high computational demand and long observation times [4]. Energy detection is the most common type of spectrum sensing technique due to its implementation simplicity and does not require knowledge about the primary signal [3]. Energy detector cannot detect weak signals in noise due to noise power, which may change over time and hence is difficult to measure precisely in real time [4]. Wavelet detection has been introduced in the recent years for spectrum sensing, where wavelet filters are used for detecting the edges in the power spectral density (PSD) of the received signal [5]. Eigenvalue detection uses the largest and the smallest eigenvalues of the covariance matrix to detect the presence or the absence of the primary user [6]. It requires smart antenna array or cooperative detection sensing.

Cognitive users may reduce the interference level to the licensed users by implementing smart antenna arrays. In this case the secondary users will optimize their transmit beamforming to satisfy the primary users' quality of service (QoS). Due to the higher technical and computational complexity that idea is most suitable for centralized cognitive radio networks with communication nodes (base stations). Direction of arrival (DOA) can be combined with GPS estimation and database exchange according to IEEE 802.22 standard [7].

In this paper the precision of various direction of arrival (DOA) algorithms used in cognitive radio networks is studied. The goal of the proposed analysis is to improve quality performance by using smart antenna arrays. The investigated algorithms are MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS. The comparison is made by using the number of array elements, number of snapshots, SNR and processing time.

The rest of this paper is organized as follows. In the section II is described the system model. Section III introduces a quick review of DOA algorithms. Simulations and results are presented in Section IV followed by conclusions in Section V.

II. System Model

M element antenna array is receiving signals from L uncorrelated sources. The spacing between array elements is d. All transmitters are emitting in narrowband. N is number of snapshots taken from antenna array. Figure 1 shows a simple cognitive radio network with two primary base stations (PBS).

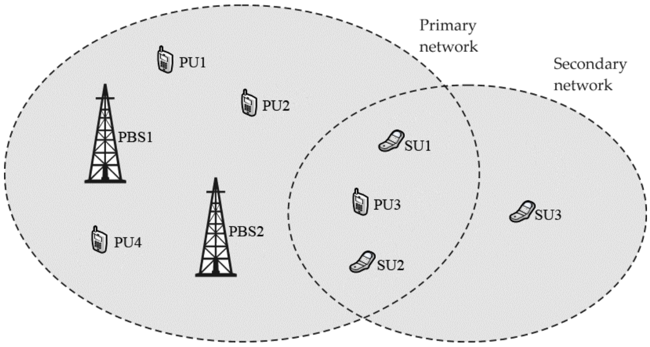

Fig.1. Dynamic spectrum sharing of a cognitive radio network.

Given an existing primary radio network with two primary base stations (PBS) and four primary users (PU), where three secondary users (SU) try to sense and share the same spectrum through space separation. Secondary users should not violate the quality of service (QoS) requirements of the primary users and meet their own QoS constraints. Cognitive users may use smart antenna arrays to minimize the interference to the licensed users. In this case the secondary users will locate and track signals of the primary users through DOA techniques and will dynamically adapt their antenna pattern to enhance the beamforming process without interrupting primary users' transmission.

The received signal $x(t)$ can be expressed as an amount of signals from all transmitters and linearly added $w(t) \in \mathbb{C}^M$ additive white Gaussian noise (AWGN) [8]:

(1) $$x(t) = \sum_{k=1}^{L} a(\theta_k) s_k(t) + w(t),$$

where $x(t) \in \mathbb{C}^{M}$ is complex baseband equivalent received signal vector at the antenna array at time t.

(2) $$x(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^T .$$

$s_k(t)$ is incoming plane wave from the k th transmitter at time t with angle of arrival θ_k, $a(\theta_k) \in \mathbb{C}^{M}$ is array response vector to the same angle of arrival. A single observation $x(t)$ from the antenna array is known as a snapshot. The received signal $x(t)$ can be written in matrix notation as:

(3) $$x(t) = A(\Theta)s(t) + w(t),$$

where $A(\Theta) \in \mathbb{C}^{MxL}$ is array response matrix for each angle of arrival.

(4) $$A(\Theta) = [a(\theta_1), a(\theta_2), \ldots, a(\theta_L)],$$

here $a(\theta_L) \in \mathbb{C}^{M}$ is array response vector for each angle of arrival. Θ is matrix of vectors for all angles of arrival and can be written as:

(5) $$\Theta = [\theta_1, \theta_2, \ldots, \theta_L]^T .$$

$s(t) \in \mathbb{C}^{M}$ is received signal vector in amplitude and phase from each transmitter at time t.

(6) $$s(t) = [s_1(t), s_2(t), \ldots, s_L(t)]^T .$$

The set of array response vectors for all possible angles of arrival is $A(\Theta)$ and is also known as an array manifold. In the most of algorithms for estimating the angle of arrival, array response matrix $A(\Theta)$ must be known for each one of the elements in the vector matrix Θ [9].

In terms of $M \geq L$ and $N > L$ the following matrix formations are proposed by [8]:

(7) $$X = [x(1), x(2), \ldots, x(N)],$$

(8) $$S = [s(1), s(2), \ldots, s(N)],$$

(9) $$W = [w(1), w(2), \ldots, w(N)],$$

where $X \in \mathbb{C}^{MxN}$, $W \in \mathbb{C}^{MxN}$ and $S \in \mathbb{C}^{LxN}$. They can be written as:

(10) $$X = A(\Theta)S + W .$$

III. DOA Estimation Algorithms

A. Capon (MVDR)

The Capon's minimum variance method is also known as MVDR (Minimum Variance Distortionless Response). This method constrains the beamformer gain to 1 in the desired direction and minimizes the output power from all other directions. Spatial spectrum of Capon can be written as [10]:

(11) $$P_{Capon}(\theta) = \frac{1}{a^H(\theta)R_{xx}^{-1}a(\theta)},$$

where $a(\theta)$ is array response vector for angle of arrival, $[\ ]^H$ denotes Hermitian (complex conjugate) transpose. DOAs are estimated by a spatial spectrum scan, where peak values correspond to the actual received angles of arrival θ. The Capon's minimum variance method estimates the inverse signal covariance matrix R_{xx}^{-1}, unlike the delay-and-sum method also known as conventional beamforming method (CBF). In addition, MVDR presents better resolution in most cases with slightly higher computational cost.

B. MUSIC

The Multiple Signal Classification (MUSIC) algorithm was first proposed by Schmidt in [11] and it can be used to estimate multiple signal characteristics like azimuth, elevation, range, polarization, etc. This is accomplished when the array response matrix $A(\Theta)$ is known for all possible combinations of transmitter's signal characteristics [8]. They are estimated with calibration or analytical computation of each response for every array element.

The MUSIC's algorithm key feature is that the desired steering vectors of the received signals in the signal subspace are orthogonal to the noise subspace [12]. The signal and noise subspaces are estimated by eigendecomposition of the incoming signal covariance matrix R_{xx}. The MUSIC spatial spectrum is calculated as follows [12]:

(12) $$P_{MUSIC}(\theta) = \frac{1}{a^H(\theta)Q_nQ_n^H a(\theta)} .$$

A peak in MUSIC spatial spectrum is formed, when the steering vector $a(\theta)$ of the incoming signal become orthogonal to the one of the eigenvectors Q_n

in the noise subspace, which corresponds to the real received angle of arrival. In practice, $a(\theta)$ is not fully orthogonal to the noise subspace due to imperfections in calculation of Q_n. This flaw is minimized by increasing the number of snapshots used in the estimation of covariance matrix R_{xx}. The MUSIC's algorithm main disadvantages are that it is unable to differentiate angles of arrival in correlated signals and its high computational cost. Its main advantages over the conventional methods are that it achieves better resolution in DOA estimation and it can be applied in a variety of array geometries.

C. ROOT MUSIC

The ROOT MUSIC algorithm was first proposed by Barabell [13]. He managed to improve the ordinary MUSIC algorithm by reducing its computational complexity and increase its resolution threshold in DOA estimation especially at low SNRs. This is accomplished by finding the roots of a polynomial instead numerical search in spatial spectrum for orthogonal basis as in the MUSIC algorithm. ROOT MUSIC is only applicable for uniform linear array, which is its main disadvantage.

D. ESPRIT

The Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) was first proposed by Roy and Kailath [14]. It is based on the fact that the steering vector of the received signal at one array element has a constant phase shift from the previous element. This is done by using structures of matched pairs (or doublets) of the sensor array with identical displacement vectors [14]. The ESPRIT achieves significantly less computational and storage costs as compared to MUSIC algorithm, which does numerical search in spatial spectrum for orthogonal basis. Narrow spaced signals and low SNRs are also an issue in MUSIC.

IV. Results

Results estimations are simulated in MATLAB environment. Comparison between DOA algorithms is achieved by averaging 100 trials for each simulation. Two largely ($\theta_1 = -10°$ and $\theta_2 = 20°$) and two closely ($\theta_3 = 50°$ and $\theta_4 = 60°$) angle spaced signals are used in different signal to noise (SNR) scenarios with 500 snapshots and 12 array elements.

MUSIC and Capon (MVDR) power spectrum results for different SNR scenarios are shown in Fig.2 and Fig.3 respectively.

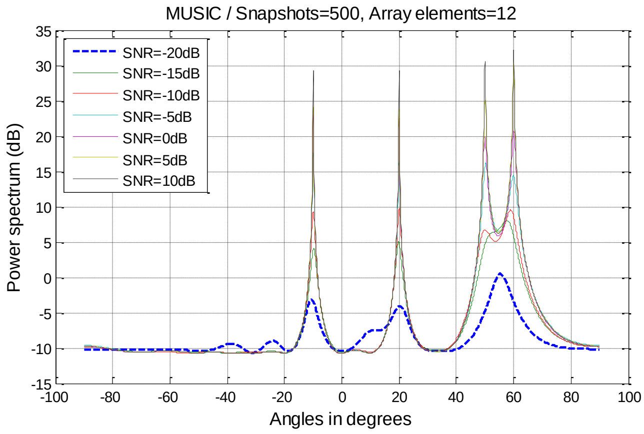

Fig.2. MUSIC performance for different SNR scenarios.

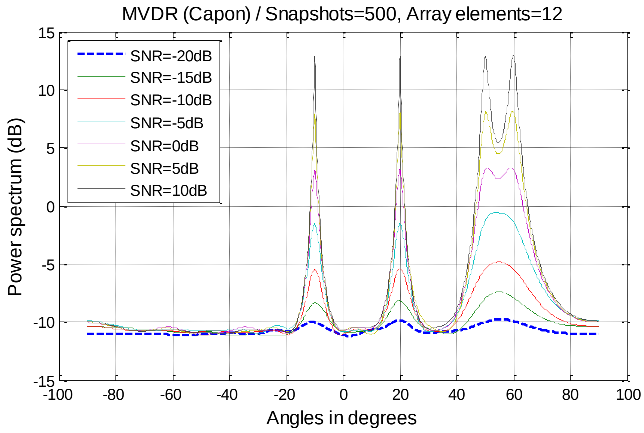

Fig.3. Capon (MVDR) performance for different SNR scenarios.

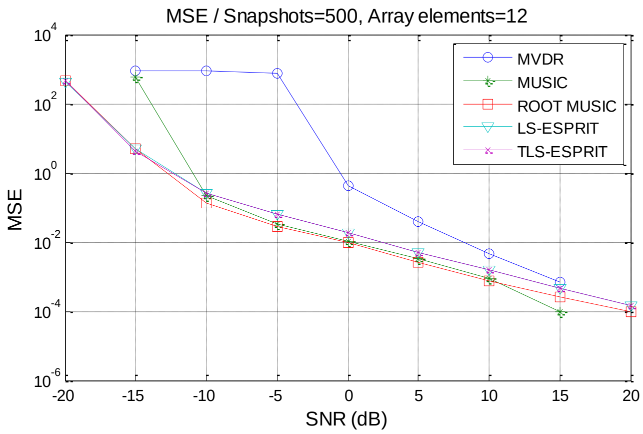

Fig.4. Mean Squared Error by MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS as a function of different number of SNR.

Even under lowest SNR, MUSIC algorithm shows distinguishable peaks with largely spaces signals $\theta_1 = -10°$ and $\theta_2 = 20°$. Same peaks for Capon (MVDR) method could be distinguished under SNR levels with at least 10dB higher. Peaks for closely spaced signals $\theta_3 = 50°$ and $\theta_4 = 60°$ in MUSIC algorithm become distinguishable for SNR values larger than -10dB. Same peaks for Capon (MVDR) method could be distinguished once again under SNR levels with at least 10dB higher.

Fig.4 shows mean squared error by MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS depending on the SNR. It is noted that MUSIC gives high values of mean squared error for -15dB SNR. Its spectral resolution of 0.1° and low SNR value explain this result. In this case a higher spectral resolution of 0.01° could be used. This will help to reduce mean squared error levels given by MUSIC, so they will drop further to the values of ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS. The computational complexity increases through the use of higher spectral resolution, which leads to increasing number of iterations and takes more processor time.

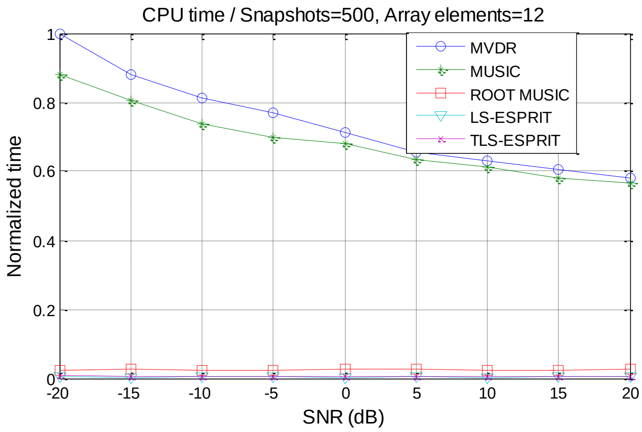

Fig.5. Normalized CPU time for different number of SNR by MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS.

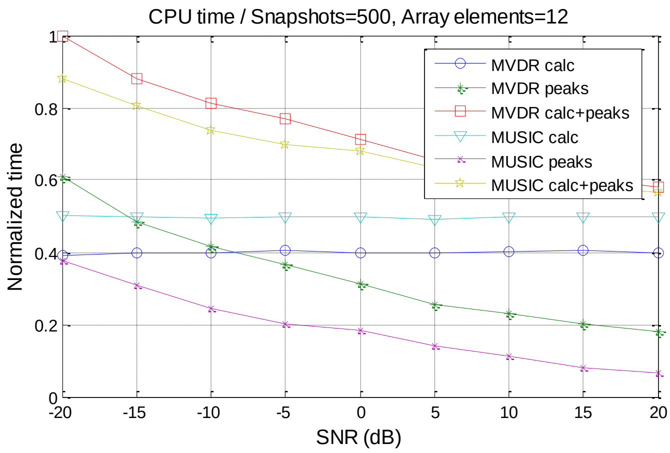

Fig.6. Normalized CPU time for different number of SNR by MUSIC and Capon (MVDR).

Fig.5 and Fig.6 shows normalized CPU time for different numbers of SNR by MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS. Fig.5 shows decreasing normalized CPU time in MUSIC and Capon (MVDR) algorithms by increasing SNR. This improvement is caused by peak function seen in Fig.6. MUSIC and Capon (MVDR) algorithms are two-stage process. The first stage estimates power spectrum for various angles, where the second stage chooses the peaks as the angles of arrival. Peak function performance is improved by increasing SNR, which shows the key role played by the function for finding peaks in reducing normalized CPU time for both methods. Proper selection of this function can improve accuracy and reduce the computational complexity of MUSIC and Capon (MVDR) algorithms, which saves limited resources (battery power, computation power etc.) and leads to an extension period of activity in cognitive handheld devices using these two methods.

The Capon's (MVDR) algorithm is a conventional beamforming method for DOA estimation and can be used in cases where there is no prior knowledge about the primary signals. MUSIC, ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS are subspace based methods for DOA estimation and they are executed when detector known information about a primary user's signal a priori.

MUSIC and ROOT MUSIC perform best for varying SNR scenarios. MUSIC and Capon (MVDR) utilize the highest computational time and generate the highest iterations than the other methods. This makes them less effective for a frequently spectrum scans when they are used in cognitive handheld devices with limited resources. ROOT MUSIC algorithm makes a direct calculation of the signal spectral components instead of numerical search for maxima like MUSIC. This drastically reduces his computational complexity and makes it more suitable for use in cognitive radio systems. ESPRIT-LS has the lowest computational complexity as compared to all other methods discussed so far. There is significantly better performance than Capon (MVDR), but withdraws to the MUSIC and ROOT MUSIC. ESPRIT-TLS improves the performance of ESPRIT-LS with slightly higher computational cost. ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS are most suitable for use in cognitive radio systems for DOA estimation, when detector know information about a primary user's signal a priori.

V. Conclusions

This paper presents results of direction of arrival (DOA) estimation using MUSIC, Capon (MVDR), ROOT MUSIC, ESPRIT-LS and ESPRIT-TLS algorithms in cognitive radio networks. The comparison is made by using the number of array elements, number of snapshots, number of SNR and processing time. Wide and narrow angle spaced signals are used in different detection and environment conditions for analyzing the quality performance and resolution threshold. The expected increase in accuracy and performance is observed with increasing the SNR value for all considered algorithms.

The simulation results in this article show the effectiveness of DOA estimation algorithms for improving quality performance in cognitive radio systems.

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