UTILIZATION OF CLONAL SELECTION ALGORITHM IN PERFORMANCE ANALYSIS OF UNITARY CAPON METHOD +

إستخدام خوارزمية الاختيارالنسخي في تحليلِ أداء طريقة Capon المتكاملة

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Abstract:

In this paper, the Clonal Selection Algorithm (CSA) is presented for extraction the direction of arrival of the several signals impinging on uniform linear arrays using a very efficient computational procedure in which the complexity of the computation can be reduced significantly by using a unitary Capon method. Using this method with CSA will enable to expect not only the higher computation efficiency but also the higher estimation accuracy of the direction of arrival angles of incident signals. A good performance was demonstrated via a number of numerical examples by using environment of Matlab 2009a program to examine the effect a number of sensor (K) and number of signal snapshots (N) on performance of the unitary Capon method based on the CSA.

Keywords: Uniform Linear Array (ULA); Unitary Capon method; Clonal Selection Algorithm (CSA).

المستخلص:

يُقدم في هذا البحث خوارزمية الاختيارالنسخي لاستخراج اتجاهات الوصول لإشارات متعددة ساقطة على مصفوفة الهوائيات الخطية المنتظمة مستعملاً إجراءِ حسابيٍ كفوءِ جداً الذي فيه يُمكنُ أَن يُقلل تعقيد الحساب بشكل ملحوظ باستعمال طريقة Capon المتكاملة. سَيُمكّنُ إستعمال هذه الطريقة مع خوارزمية الاختيارالنسخي لتَوَقُّع ليس فقط اعلى كفاءة الحسابِية لكن ايضا اعلى دقة تخمينية من اتجاه زوايا وصول الاشارات الساقطة. يُوضح الاداء الجيد للخوارزمية خلال عدد من نتائج المحاكاة باستخدام بيئة برنامج Matlab ٢٠٠٩a لفحص تأثير عدد المتحسسات (K) و عدد العينات الاشارة على اداء طريقة capon المتكاملة بالاعتماد على خوارزمية الاختيار النسخي.

Introduction:

The problem of estimating the Direction of Arrival (DoA) of the various sources impinging on a phased array has received considerable attention, in many fields including radar, sonar, radio astronomy, and mobile communications. There are many algorithms that exist to find the DoA and research is going on to increase their resolution as well as to reduce their computational complexity [1]. Unitary Capon attempts to overcome the poor resolution problems associated with the delay-and-sum method [2, 3].

The Capon high-resolution algorithm is well-known [2, 4, 5] and its performance has been studied extensively. It will be assumed in this paper that all sources are well separated (by at least a beam width or Rayleigh distance) and possess SNRs that exceed the estimation threshold. In addition it is assumed that signals are mutually incoherent (coherent sources are

+ Received on 26/9/2010 , Accepted on 6/4/2011 .

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not resolvable with the Capon algorithm), and that the total number of signals present in the data is known. In this paper, an unitary Capon method based on the Clonal selection Algorithm (CSA) [6, 7] is used to solve the problem of direction of arrival estimation with higher computation efficiency, higher estimation accuracy and speed in simulation results display.

The organization of this paper is as follows. The data formulation for DoA estimation is first introduced in Section 2. The angular spectrum of unitary Capon method is then described in Section 3. Features and principles of the CSA are discussed in Section 4. Next, in Section 5, the computer simulation results of proposed algorithm are presented. Finally, concluding remarks and observations are given in Section 6.

Data Formulation for DOA Estimation:

The *K*-element Uniform Linear Array (ULA) with an antenna spacing of Δ is depicted in Fig.(1).

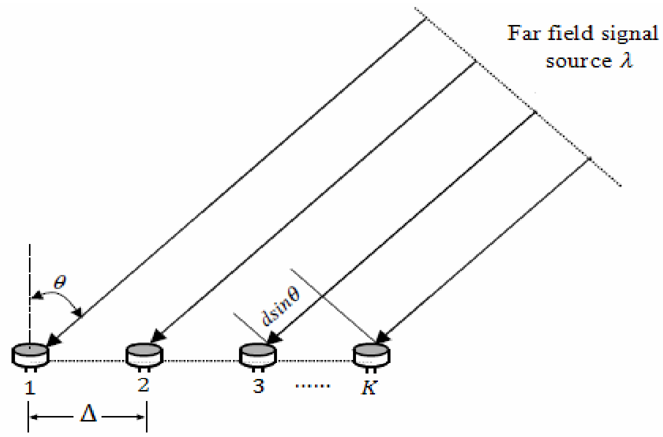

Fig. (1) Uniform linear array with far field signal source.

Assume that L waves with the complex envelopes $s_1(t), s_2(t), \ldots \ldots s_k(t)$ are incident on the array along the angles $\theta_1, \theta_2, \ldots \ldots \theta_L$, respectively. Then, the array input vector $\boldsymbol{x}(t) = [x_1(t), x_2(t), \ldots \ldots x_K(t)]^T$ is expressed as [8]

$$x(t) = As(t) + n(t) \quad (1)$$

$$A = [a(\theta_1), a(\theta_2), \ldots \ldots\ a(\theta_L)] \quad (2)$$

$$a(\theta_i) = [\ \exp\left\{-j\frac{2\pi}{\lambda}\Delta\left(1-\frac{K+1}{2}\right)sin\theta_i\right\}, \ldots \ldots \exp\left\{-j\frac{2\pi}{\lambda}\Delta\left(K-\frac{K+1}{2}\right)sin\theta_i\right\}\ ]^T \quad (3)$$

$$(i = 1,2,3, \ldots . L)$$

$$s(t) = [s_1(t), s_2(t), \ldots \ldots s_L(t)]^T \quad (4)$$

where $a(\theta_i)$ is the array response vector of the i^{th} wave with the phase reference at the center of the array, A is the array response matrix, λ is the wavelength of the carrier, and $n(t)$ is the internal noise. Here, it is assumed that each antenna element is isotropic and there is no mutual coupling effect among antenna elements.

Using the weight vector $w = [w_1, w_2, \ldots \ldots w_K]^T$, where T is transpose ,the array output $y(t)$ and the array output power $(Pout)$ are given by

$$y(t) = w^H x(t) \quad (5)$$

$$Pout = \frac{1}{2}E[|y(t)|^2] = \frac{1}{2}w^H R_{xx} w \quad (6)$$

$$R_{xx} = E[x(t)x^H(t)] = ASA^H + \sigma^2 I \quad (7)$$
$$S = E[s(t)s^H(t)] \quad (8)$$
where R_{xx} is the correlation (covariance) matrix of the array input, S is the correlation matrix of L sources, σ^2 is the noise power, I is the identity matrix, and $E[\cdot]$ denotes expectation operator [8].

Angular Spectrum of Unitary Capon Method:

The array output power contains contributions from the desired signal along the look direction as well as the undesired ones along other directions of arrival. To minimize the contributions of the undesired signals, the array output power is minimized while maintaining the gain along the look direction to be constant. This is the principle of Capon method and it is written in the following form [8].
$$\min_w \left(p_{out} = \frac{1}{2} w^H R_{xx} w\right) \quad \text{subject to } w^H a(\theta) = 1 \quad (9)$$
Thus, the angular spectrum of Capon method is expressed as the output power by the optimum weight vector, which is given by [9]
$$P_{CP(\theta)} = \frac{1}{a^H(\theta) R^{-1}{}_{xx} a(\theta)} \quad (10)$$
Using an appropriate unitary matrix Q_K $\left(i.e., Q_K Q^H{}_K = I\right)$ like the following matrix for an example of $K = 2M$ (even), the array response vector $a(\theta)$ is transformed into the real-valued vector $d(\theta) = Q^H{}_K a(\theta)$ [8].
$$Q_K = \frac{1}{\sqrt{2}} \begin{bmatrix} I_M & jI_M \\ \Pi_M & -j\Pi_M \end{bmatrix}, \qquad \Pi_M = \begin{bmatrix} 0.. & 0 & 1 \\ 0.. & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1.. & 0 & 0 \end{bmatrix} \epsilon R^{M\times M} \quad (11)$$
where I_M denotes the identity matrix of dimension M. Via this transformation, the problem formulation of Unitary Capon method is derived as follows.
$$\min_w \left(p_{out} = \frac{1}{2} w^H Q_K Q^H{}_K R_{xx} Q_K Q^H{}_K w\right) \quad \text{Subject to } w^H Q_K Q^H{}_K a(\theta) = 1 \quad (12)$$
$$\min_v \left(p_{out} = \frac{1}{2} v^T R_{yy} v\right) \quad \text{Subject to } v^T d(\theta) = 1 \quad (13)$$
Here, R_{yy} is the real-valued matrix defined by $R_{yy} = Re[Q^H{}_K R_{xx} Q_K]$, , and v is a real-valued vector generated from $Q^H{}_K w$. Then, the angular spectrum of Unitary Capon method is given by [8].
$$P_{uc(\theta)} = \frac{1}{d^T(\theta) R^{-1}{}_{yy} d(\theta)} \quad (14)$$
As found from (14), Unitary Capon method requires the inverse matrix of R_{yy}. Normally, R_{yy} is calculated using N_s snapshots: $x(1), \cdots, x(N_s)$, which is given by [8]
$$R_{yy} = \frac{1}{N_s} \sum_{m=1}^{N_s} Re[Q^H{}_K x(m) x^H(m) Q_K] \quad (15)$$

The Clonal Selection:

The feature of the clonal selection theory includes sufficient diversity, discrimination of self and non self and long-lasting immunologic memory.

1 Immune Cells

Lymphocytes are the most important cells in the immune system. B lymphocytes (B cells) and T lymphocytes (T cells) are the major groups of immune cells which are responsible for adaptive immune response and the immunologic attributes. B cells play a large role in the humoral immune response, and apply to make antibodies against antigens, perform the role of Antigen Presenting Cells (APCs) and eventually develop into memory B cells after activation by antigen interaction. T cells play a central role in cell-mediated immunity. They can activate and direct B cells and recognize only antigen that is bound to cell-membrane proteins called major histocompatibility complex (MHC) molecules through a unique antigen-binding molecule [10].

2 Antibodies (Ab) and Antigens (Ag)

Antibodies which are produced by a kind of white blood cell are used by the immune system to identify and neutralize foreign objects, such as bacteria and viruses. An antigen originally defined as any molecule that binds specifically to an antibody, the term now also refers to any molecule or molecular fragment that can be bound by an MHC molecule and presented to a T-cell receptor. “Self” antigens are usually tolerated by the immune system; whereas “Non-self” antigens are identified as intruders and attacked by the immune system [10].

3 The Clonal Selection Principle

The clonal selection theory [10, 11] interprets the response of lymphocytes in the face of an antigenic stimulus and is shown in Fig. (2).

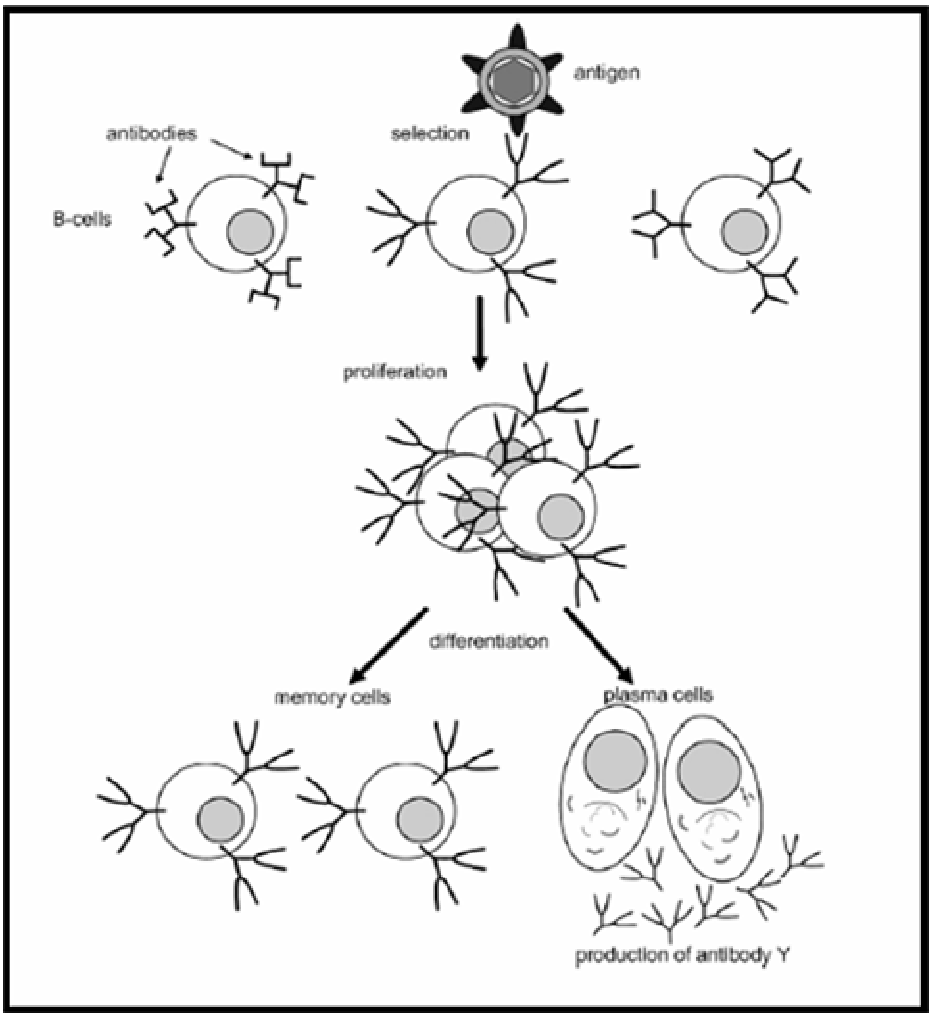

Fig. (2) The clonal selection principle.

4 The Clonal Selection Algorithm (CSA)

The CSA inspired by the clonal selection theory of acquired immunity is one of the common algorithms of the artificial immune system [11]. The concept of the CSA is shown in Fig. (3).

Begin
Construct the initial population of antibodies
Repeat
Evaluate antibodies to calculate their affinities
Select the *n* best affinity antibodies and clone them
Maturate the clones and evaluate them
Allow the best antibody from each subpopulation to survive
Replace the *d* lowest affinity antibodies with new antibodies randomly produced
Until A termination criterion is satisfied or the maximum generation number is reached
End

Fig. (3). A simple CSA [11]

The CSA starts by randomly generating the initial population (N_{pop}) of antibodies in a given bounds for the problem considered. Each antibody which means a candidate solution is represented by a binary string of bits. The bit string length is suitably selected by the user corresponding to the problem for obtaining a reasonable precision. The antibodies are evaluated over an affinity (fitness) function and ranked in decreasing order of affinity. The first n antibodies are selected for cloning operation. The number of clones (N_c) generated for all these n selected antibodies is given by [11]

$$N_c = \sum_{i=1}^{m} round(\frac{\beta N_{pop}}{i}) \quad (16)$$

where β is the multiplying factor, N_{pop} is the initial population and round $(.)$ is the operator that rounds its argument toward the closest integer.
A proposed flow chart of the CSA applied for signal parameter estimation is shown in Fig.(4). Data is obtained measuring the complex responses of the antenna array elements.

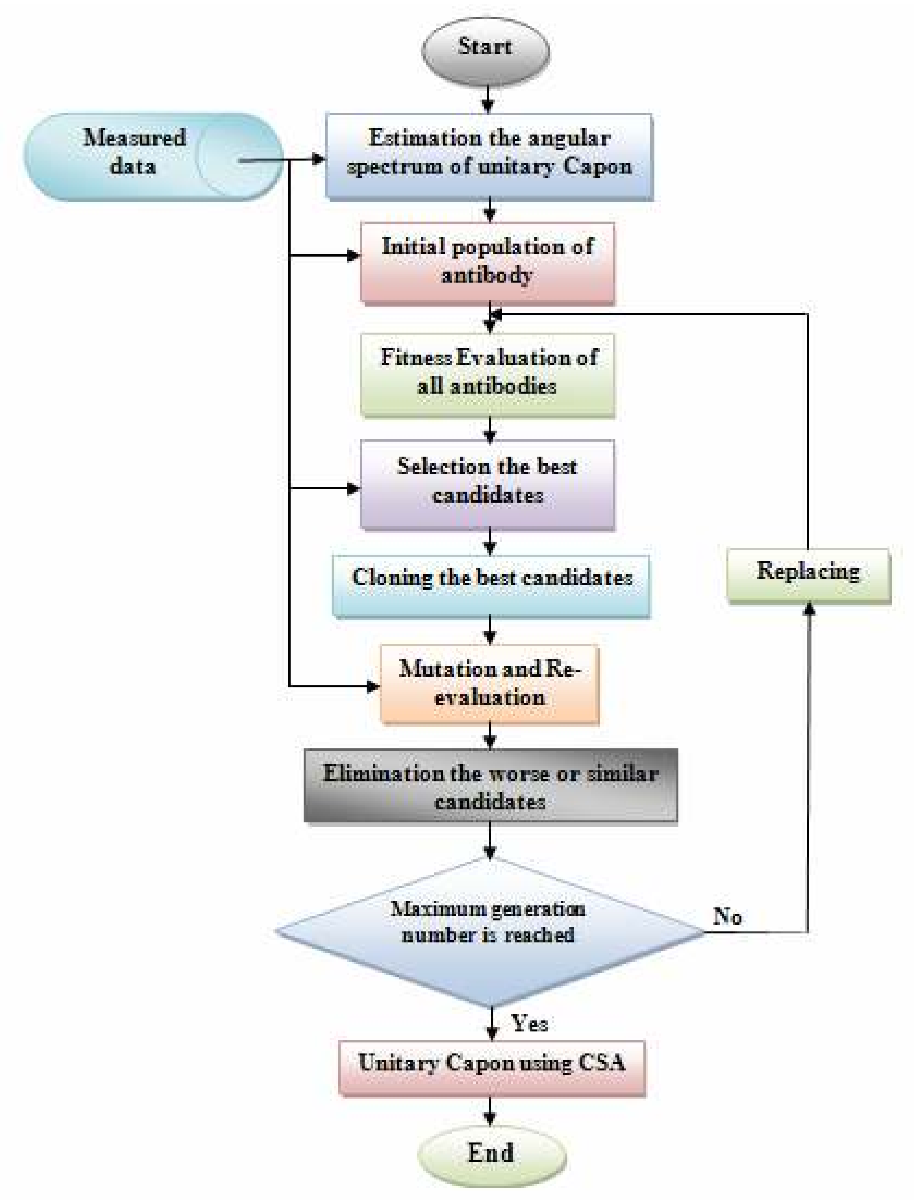

Fig. (4) The proposed flow chart of unitary Capon based on CSA.

<u>Computer Simulation</u>:

In this section, the computer simulation results are given to illustrate the performance of the unitary Capon method based on CSA. The noisy signal model is formulated from (1). $n(t)$ is treated as a zero mean Gaussian white noise with variance σ^2. The ULA of omnidirectional passive sensors are considered in this paper. The distance between any two elements (Δ) of the ULA is half a wavelength; in addition to the incident signals are mutually incoherent. The CSA is executed 100 times in order to conclude on the accuracy and reliability of the results. Different cases examine the effect a number of sensor (K) and number of snapshots (N) on performance of the unitary Capon method based on the CSA.

For two largely-spaced targets with assumptions number of sensors $(K = 15)$, number of snapshots $(N = 60)$ and suppose the target with 5dB additive noise is impinging on ULA from azimuth of 50^o and 100^o degrees. The unitary Capon searches for the peak are illustrated in Fig. (5), from the graph, it is easily shown that two emitter signal is available due to the two peaks in the spectrums. When the unitary Capon is implemented by using CSA (unitary Capon-CSA), it gave the result for two targets in direction 50^o and 100^o degrees is (50.0079^o) and (100.0019^o) degrees.

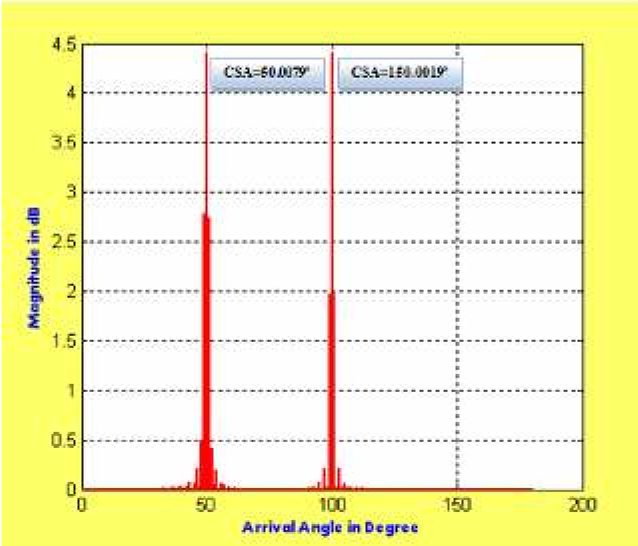

Fig. (5): Unitary capon-CSA for two targets 50^0, 150^0 with K=15, N=60.

The problem in DoA estimation techniques is composed in case closely-spaced targets (approximate targets**)** that are discussed in next paragraph. For case of two closely spaced targets, with the same previous assumptions in directions of 70^o and 72^o degrees is impinging on ULA. The unitary Capon-CSA is given the result for two targets in direction 70^o and 72^o degrees is (70.0713^o) and (72.0914^o) degrees as shown in Fig. (6). As the K is increased to 20 and 25, the unitary Capon-CSA will succeeds in limiting two peaks as shown in Fig.(7) with angles of (70.0073^o) and (72.0081^o) and Fig.(8) with angles of (70.0011^o) and (72.0013^o). It clear that unitary capon method with CSA succeed in distinguishing between the closely spaced targets with good computing efficiencies compared with other techniques of DoA estimation.

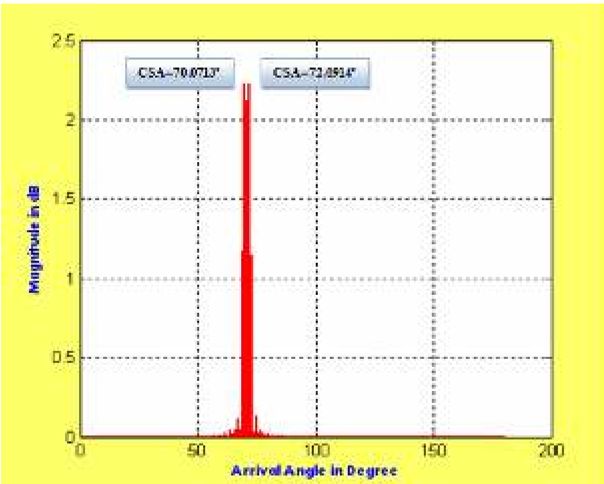

Fig. (6): Unitary capon-CSA for two closely-spaced targets 70^0, 72^0 with K=15, N=60.

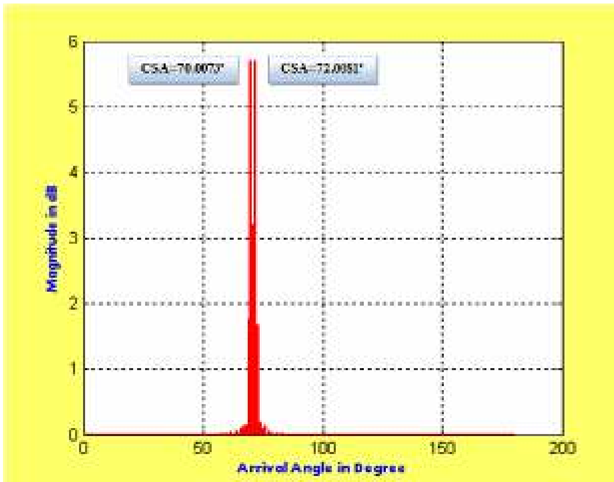

Fig. (7): Unitary capon-CSA for two closely-spaced targets 70^0, 72^0 with K=20, N=60.

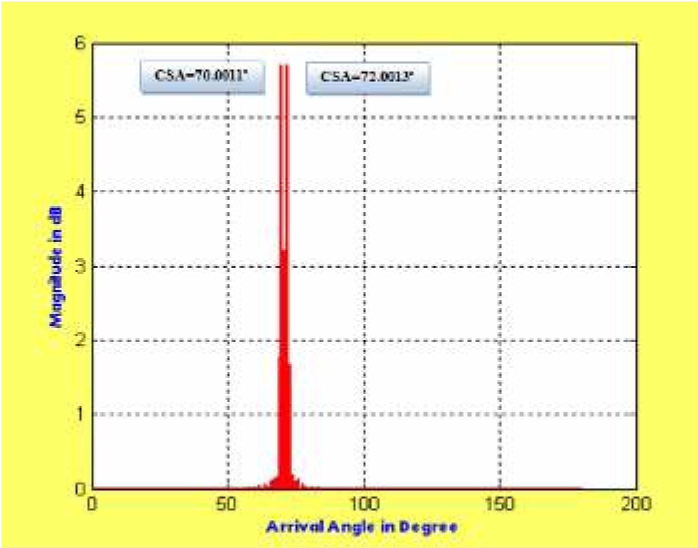

Fig. (8): Unitary capon-CSA for two closely-spaced targets 70^0, 72^0 with K=25, N=60.

The effect of N on the unitary Capon-CSA is demonstrated in this paragraph. As the N is increased to 120 and 180 instead of 60 with survival K=15 (constant). The unitary Capon-CSA will also improve its performance to limit two targets as shown in Fig. (9) with angles of (70.0086°) and (72.0098°), and Fig. (10) with angles of (70.0021°) and (72.0032°). It is also evident that using more snapshots improves the resolution of the algorithm in detecting the incoming targets closing to real value of the target; this is achieved, however, at the expense of computational efficiency and hardware complexity of the sensor array.

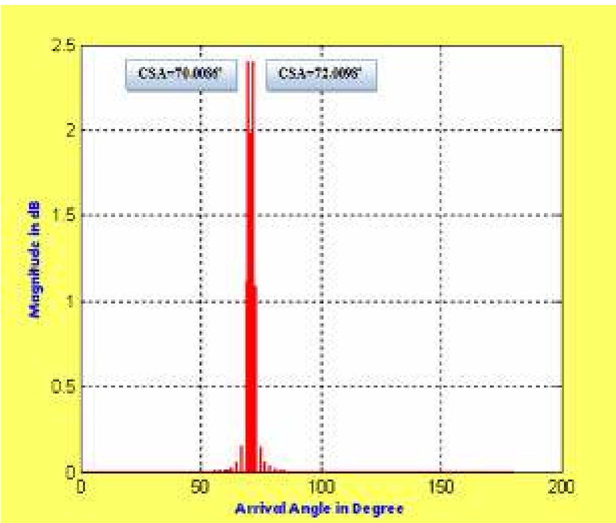

Fig. (9): Unitary capon-CSA for two closely-spaced targets 70^0, 72^0 with K=15, N=120.

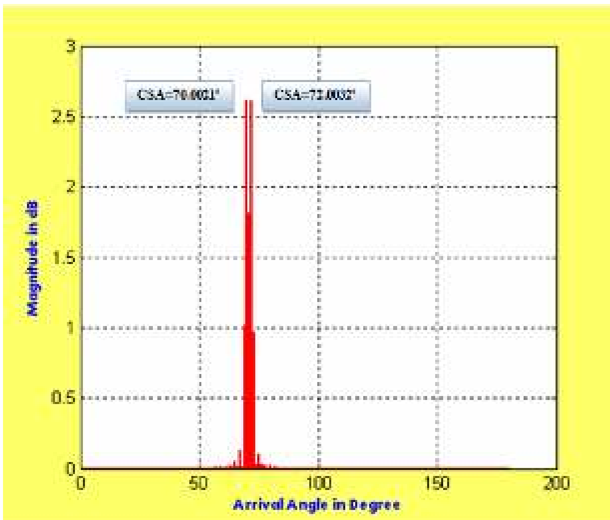

Fig. (10): Unitary capon-CSA for two closely-spaced targets 70^0, 72^0 with K=15, N=18

Conclusions:

This paper showed improvement of the accuracy of unitary Capon method based on CSA for signals by simulation in various situations. The most important conclusions can be summarized as follows:

1. The efficiency of the unitary Capon-CSA increases with the increasing number of sensors (K) as shown in Figures (7, 8). This is achieved, however, at the expense of computational efficiency and hardware complexity of the sensor array.
2. The efficiency of the unitary Capon-CSA increases with the increasing number of snapshots (N) as shown in Figures (9, 10), the performance improves significantly as the emitter sources move away from each other.
3. In case incoherent signals, the CSA succeeds in giving reliable results of unitary Capon without the need of any spectral search for angles (coherent sources are not resolvable with the Capon method).

As the future works, other estimators of direction of arrival will be given by using CSA and comparative study between them.

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