2D Localization of Source of Stochastic EM Radiation by using Neural Networks

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Abstract – **2D localization of narrow-band electromagnetic source of stochastic radiation nature in far-field is considered in the paper. The model presented is based on artificial neural networks (ANN). This model is trained to perform accurate and efficient 2D direction of arrival (DoA) determination of electromagnetic signals radiated from some stochastic source, That changes its position in a parallel plane, to the level of a 2D antenna array, in the far-field scan area. This antenna array is used for sampling the spatial correlation matrix signal that provides the necessary information for the training model.**

Keywords – **Source localization, Mobile users, Stochastic radiation, Correlation matrix, Neural networks.**

I. Introduction

Spatial filtering of the antenna array signal and shaping the radiation characteristics, using adaptive antenna arrays, are now current techniques. They unveil the possibility to efficiently decrease the negative impact of interference, on the signal reception site, and therefore the possibility of a significant increase in the number of users of modern wireless communications as well as, the service quallity of services that such systems offer to the customers [1,2]. In parallel with the above fact, the techniques relating to the localization position of the source signal by the passive sensor array also attract the attention today because there is an increasing need for their application in geophysics, satellite communications, radio-astronomy, biomedical engineering, radar systems engineering 5G and other forms of wireless communication.

In applying the above techniques of both classes, procedures have a very important role for DoA estimation of the signal. Today the most commonly used super-resolution algorithms for DoA estimation such as MUSIC [1,2] and its modifications have a high accuracy in determining the directions of where the EM signals come from, but because of its complex matrix calculation, it requires powerful hardware resources and are not suitable for operation in real time. In papers [3-11] is shown that the alternative methods DoA estimation algorithms can be super-resolution models based on artificial neural networks [3,12 to 13]. Neural models for DoA estimation avoid complex matrix calculations, and can have an approximate accuracy of the MUSIC algorithm. They are faster than the MUSIC algorithm which makes them more suitable choice for implementation in real time [3 to 4,11].

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In the papers [4-5] su predstavljeni efficient neuron models are presented. For 1D DoA [4] and 2D DoA [5] estimation of deterministic radiation source. In papers [6-11] are presented neural models for 1D DoA estimation origin with the stochastic nature of EM radiation wave [14,15] where the stochastic sources moving along one direction in the azimuthal plane and where their positions are characterized by a single angular coordinate (azimuth).

This paper goes a step further in research in relation to the works [6-11] because it now allows the stochastic radiation source moving in 2D space (the plane), and its position is located using two angular spatial coordinates. These coordinates represent the angles of the spherical coordinate system under which the stochastic EM radiation sources comes to a rectangular planar antenna array, or in other words to the angles that are obtained using the method of 2D DoA estimation to the plane of the antenna array. A scenario is considered where a single source of stochastic radiation changes its position in the plane relative to the planar antenna array, which is located in the far zone of radiation and which is parallel to the plane of movement of the relative level of stochastic sources. This scenario, with certain approximations, and ignoring the effect of curvature of the earth's surface, can be present in passive radar and other sensors that are based on antenna arrays and mounted on satellites that are in low-earth orbit, planes or drones in order to make detection and localization of the source of radiation at the earth's surface.

II. Stochastic Source Radiation Model

In this paper, a model of stochastic radiation source in a far zone which is also applied in the works [6-11]. With this model stochastic radiation sources in the far zone presents a linear uniform radiation of the N antenna array elements that are at the distance d (Figure 1). The degree of correlation between the supply current of the elements of an antenna array that is described buy the vector $\mathbf{I}=[I_1, I_2, \dots, I_N]$) is defined by the correlation matrix $\mathbf{c}^I(\omega)$ [14,15]:

$$\mathbf{c}^I(\omega) = \lim_{T\to\infty} \frac{1}{2T}\left[I(\omega)I(\omega)^H\right] \tag{1}$$

In the zone of far-field electric field strength at the selected sampling point is calculated in a way

$$E(\theta,\varphi) = \mathbf{M}(\theta,\varphi)\mathbf{I} \tag{2}$$

where $\mathbf{M}$ represents the scaning with Green's function

$$\mathbf{M}(\theta,\varphi) = jz_0 \frac{F(\theta,\varphi)}{2\pi r_c}\left[e^{jkr_1} \quad e^{jkr_2} \dots \; e^{jkr_N}\right] \tag{3}$$

In the equations (2) and (3) θ and φ represent the spatial position of the corners of the first antenna element of the antenna array that represents the source in relation to the selected sampling point, $F(\theta,\varphi)$ is the radiation characteristic of the antenna element, r_c the distance between the selected point from the center of the antenna array, z_0 is the impedance of free space, k is the phase constant ($k=2\pi/\lambda$) while r_1, r_2, ... , r_N represent the distance selected point from the first to the N-th antenna element respetivly (Fig. 1). When at the reception we use a planar antenna array rectangular dimensions M × P, sampling points will be in positions of planar antenna elements and a series of them will be $K=M\cdot P$. In our scenario (Fig. 1) receiving planar antenna elements that represent a set of sampling points are arranged in x-y level which is pararalelna level where the generation source S relative moving relative to the receiving antenna array. The distance between the elements of the receiving antenna array along the x axis is s, while the distance between the elements along the y axis h. The distance between the level of the planar receiving antenna array and the plane in which the mobile generation source S is r_0. Introduced the assumption that the linear antenna array, which is modeled stochastically source at the beginning of the movement oriented along the x axis and in d << r_0 ignored changes its orientation when moving sources. When copying (3) is applied to each sampling point individually, the appropriate distance between the n-th element of the antenna array that represents the stochastic radiation source S and the sampling point at the position sensor (m,p) of a planar reciever array is

$$r_{mp}^{(n)} = \frac{1}{\cos\varphi_{mp}} \sqrt{r_0^2 + \left[r_0 \cdot \tan\theta_{mp} + (n-1)\cdot d\right]^2} \tag{4}$$

where r_0 is the distance between the planes of the planary antenna array at the receving end, and the plane in which the stochastic source S is moving while θ_{mp} and φ_{mp} are spatial angles relating to the position of the first antenna element in relation to the source (m,p) sensor position and they are

$$\theta_{mp} = \arctan\left[\frac{(m-1)\cdot s}{r_0} + \tan\theta_{11}\right] \tag{5}$$

$$\varphi_{mp} = \arctan\left[\frac{(p-1)\cdot h}{r_0} + \tan\varphi_{11}\right] \tag{6}$$

whereby θ_{11} and φ_{11} spatial angles relating to the position of the first antenna element sources relative to a reference $(1,1)$ position of the sensor. The angles θ_{11} and φ_{11} also represent the angular position (θ,φ) stochastic source S in relation to the linear receiving antenna array so that the $\theta_{11} = \theta$ i $\varphi_{11} = \varphi$.

Correlation matrix signal in the sampling points is defined like so

$$\tilde{\mathbf{C}}_E[i,j] = \mathbf{M}(\theta_{\left(\left[\frac{i}{P}\right]+1\right)\left(i-\left[\frac{i}{P}\right]\right)}, \varphi_{\left(\left[\frac{i}{P}\right]+1\right)\left(i-\left[\frac{i}{P}\right]\right)})\mathbf{c}^I\mathbf{M}(\theta_{\left(\left[\frac{j}{P}\right]+1\right)\left(j-\left[\frac{j}{P}\right]\right)}, \varphi_{\left(\left[\frac{j}{P}\right]+1\right)\left(j-\left[\frac{j}{P}\right]\right)})^H, \tag{7}$$

$$i = 1,\dots,K \quad j = 1,\dots,K \quad K = M\cdot P$$

On the basis of the equations (4)-(6) is determined by the vector **M** is given in equation (3), then in accordance with the angular position of stochastic energy sources to the sampling point, the elements of the correlation matrix. If the array elements are normalized with respect to the first element of the matrix

$$\mathbf{C}_E = \frac{1}{\tilde{C}_{E11}} \cdot \tilde{\mathbf{C}}_E \tag{8}$$

in our scenario is obtained correlation matrix that does not depend on the value of r_0 , r_c , $F(\theta,\varphi)$ i N. For training the neural network of that model made enough to take only the first type of matrix C_E ($[C_{E11}, C_{E12}, \dots, C_{E1K}]$) because it turned out that the first type contains sufficient information to determine the angular position of the radiation source [5,6].

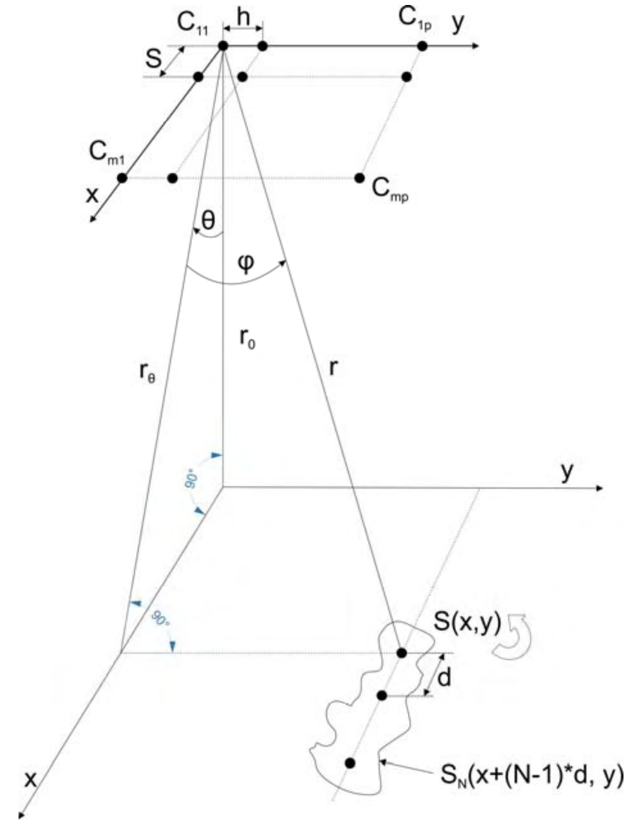

Figure 1. The position of stochastic source in x-y plane with respect to the location of EM field sampling points in the far-field scan area.

III. Neural Network Model

The neural model based on MLP ANN [12,13] is developed with the purpose to perform the mapping from the space of signals described by correlation matrix $\mathbf{C}_E$ to the 2D DoA space

$$[\theta \;\; \varphi]^T = f(\mathbf{C}_E) \tag{9}$$

where $[\theta \;\varphi]^T$ is vector of spatial angles of arrival of the stochastic source radiation. The architecture of developed neural model is shown in Fig.2. Its MLP network can be described by the following function:

$$\mathbf{y}_l = F(\mathbf{w}_l \mathbf{y}_{l-1} + \mathbf{b}_l) \quad l = 1,2 \tag{10}$$

where $\mathbf{y}_{l-1}$ vector represents the output of (l-1)-th hidden layer, $\mathbf{w}_l$ is a connection weight matrix among (l-1)-th and l-th hidden layer neurons and $\mathbf{b}_l$ is a vector containing biases of l-th hidden layer neurons. F is the activation function of neurons in hidden layers and in this case it is a hyperbolic tangent sigmoid transfer function:

$$F(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}} \tag{11}$$

In order to perform mapping it is sufficient to take only the first column of correlation matrix and therefore $\mathbf{y}_0$ = **[**$Re\{\mathbf{C}_E[1,1]\},\ldots, Re\{\mathbf{C}_E[1,K]\}, Im\{\mathbf{C}_E[1,1\},\ldots, Im\{\mathbf{C}_E[1,K]\}$]. Also, output of the neural network model is given as $[\theta\ \varphi]^T = \mathbf{w}_3\mathbf{y}_2$ where $\mathbf{w}_3$ is a connection weight matrix between neurons of last hidden layer and neurons in output layer. The optimization of weight matrices $\mathbf{w}_1$, $\mathbf{w}_2$, $\mathbf{w}_3$ and biases values during the training allows ANN to approximate the mapping with the desired accuracy.

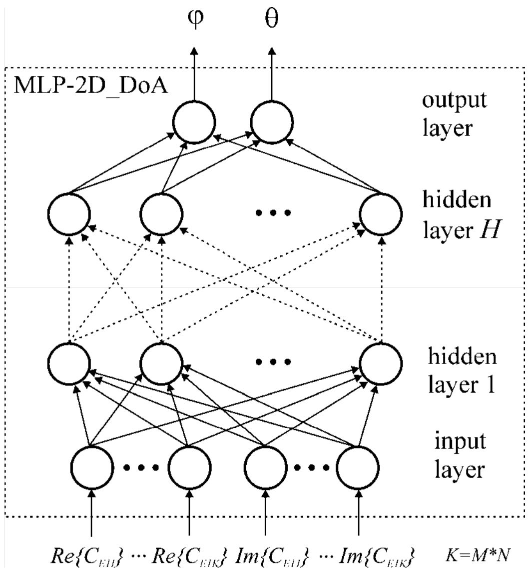

Figure 2. Architecture of MLP neural model for 2D DOA estimation of stochastic EM source signal in x-y plane plane

The general designation for this defined MLP neural model is MLPH-N_1-…-N_i-…-N_H where H is the total number of hidden layers used MLP network, while N_i is the total number of neurons in the ith hidden layer.

IV. Modeling Results

Neural model with the architecture presented in the previous section modeled the hypothetical scenario of stochastic radiation source described in section II, where the stochastic source antenna represents a series of two elements with uncorrelated currents supply a sampling signal in a far zone is carried out in nine points that are distributed the equidistant spacing in the form of a rectangular planar set of dimensions 3 x 3. For the characteristic radiation element antenna array origin is taken isotropic characteristics. The feed currents of two elements are mutually uncorrelated so that $\mathbf{c}^I$ is the unit diagonal matrix. Table 1 provides the values of parameters of the scenarios that were used to generate samples for training the neural models. For the realization of the training model used is the Matlab software development environment. Sets of samples for training and testing MLP models were generated by using equation (3) and (7). Any combination of angles θ and φ which is defined by the distribution patterns associated with the vector of 18 elements, represents the first type of signal correlation matrix (9 elements for the real part , and 9 elements in the imaginary part of the complex value of the first type correlation matrix).

TABLE I

THE VALUES PARAMETERS WHICH USED IN SAMPLING PROCESS

Frequency	f = 22 GHz
Number of antenna array elements per one source	N = 2
Sampling points distance from source trajectory	r_0= 600 km
Number of sampling points along x axis	M = 3
Mutual distance of the sampling points along x axis	$s = \lambda/2$
Number of sampling points along y axis	P= 3
Mutual distance of the sampling points along y axis	$h = \lambda/2$

TABLE II

TESTING RESULTS FOR SIX MLP NEURAL MODELS WITH THE BEST AVERAGE ERRORS STATISTICS

MLP model	WCE [%]	ACE [%]
MLP2-15-11	2.52	0.38
MLP2-12-12	2.74	0.39
MLP2-18-14	2.78	0.38
MLP4-13-13	2.79	0.37
MLP2-20-10	2.80	0.38
MLP2-18-7	2.79	0.38

For the model training , a set of 14641 samples with uniform distribution θ and φ angles in the range [-30° 30°] with a 0.5° step. Quazi-Newton method with prescribed accuracy of 10^{-4} is used as a training algorithm. For the testing of the model a set has been generated of 7396 samples with uniform distribution θ and φ angles in the range [-30° 30°] with a 0.7° step. The testing results for six MLP models with the lowest average (ACE) and worst case error (WCE) are shown in Table II, and MLP2-15-11 is chosen as representative neural model. The neural model scattering diagram of testing samples set shows a very good agreement between the output values of neural model and referent θ and φ values (Fig.3 and Fig.4).

Using the MLP2-15-11 model a simulation has been conducted for tracking the movement of the hypothetic source of stohastic radiation on earth's surface in a square area in size 800×800 km. The source has changed its position along the test trajectory, which has been set by the function $y = 3\cdot10^{-6}\cdot(x\text{-}10^5)^2\text{-}3\cdot10^5$ where x and y are relative latitude and longitude expressed in meters. Evaluation paths of origin was carried out by sampling time correlation matrix of the 69 points shown in Figure 5. A satisfactory agreement can be observed between the values of the source positions which war estimated by the neuron model and the referent source trajectory.

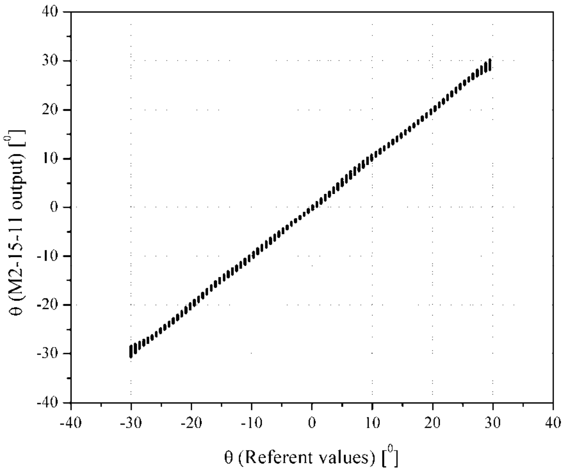

Figure 3. Scattering diagram of MLP2-15-11 model θ output

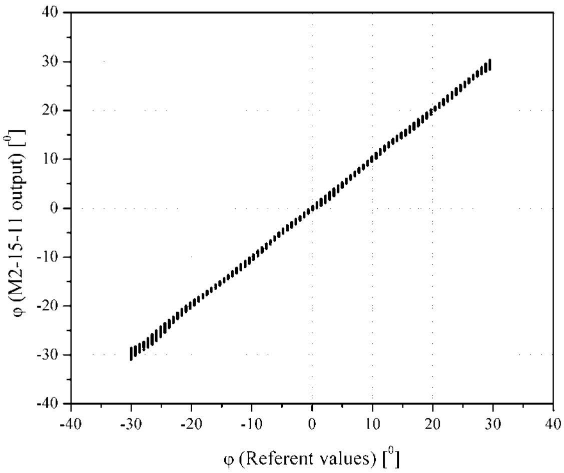

Figure 4. Scattering diagram of MLP2-15-11 model φ output

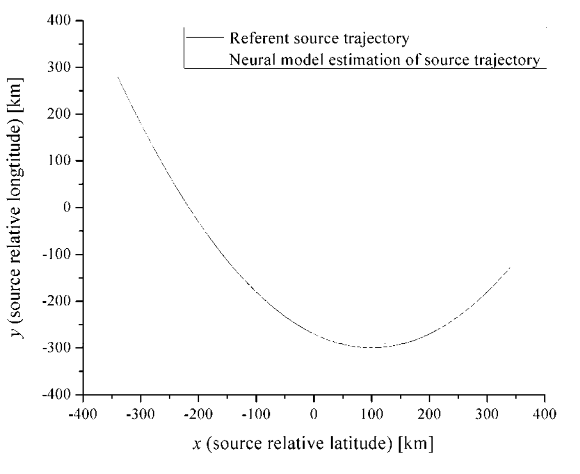

Figure 5. A simulation of localization and tracking the movement of the hypothetic source of stochastic radiation on earth's surface with the MLP2-15-11 model

V. CONCLUSION

Neural model ability to accurately and efficiently determine the 2D location of the stochastic source is illustrated on one example. As proposed neural model avoids intensive and time-consuming numerical calculations it is more suitable than conventional approaches for real-time applications. At the moment, neural model is capable to determine the 2D location in a plane for one stochastic source. Future research will be focused to the more general 2D DOA estimation of multiple stochastic sources.

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