Localization of Mobile Users of Stochastic Radiation Nature by using Neural Networks

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Abstract – **Localization of narrow-band electromagnetic sources of stochastic radiation nature in far-field is considered in the paper. Artificial neural networks-based approach is applied here to allow for accurate and efficient direction of arrival (DOA) determination of electromagnetic signals radiated from an arbitrary number of stochastic sources mutually positioned at fixed angle distance or up to two stochastic sources at arbitrary angle distance. Correlation matrix, obtained by signal sampling via antenna array in far-field scan area is used to train an appropriate model based on MLP (Multi-Layer Perceptron) neural network. Proposed approach is validated on the example of neural model performing accurate and fast one-dimensional (1D) DOA estimation of angular position in the azimuth plane of two mobile users at arbitrary angle distance.**

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

I. Introduction

Suppression of negative interference impact at the signal reception terminal is one of important tasks to fulfill in the design of modern wireless communication systems. Spatial signal filtering performed by an antenna array and adaptive beamforming algorithms for optimization of radiation pattern of antenna array contribute to this suppression. These techniques are based on a direction-of-arrival (DOA) estimation and spatial localization of numerous sources of electromagnetic (EM) interference of either deterministic or stochastic radiation nature.

There are a number of algorithms in literature developed to deal with the DOA estimation problem. They are mostly based on processing of spatial covariance matrix of received signals by antenna elements. One of these techniques is the subspace-based MUSIC (MUltiple SIgnal Classification) method, best known for its super-resolution capabilities [1]. MUSIC is able to provide accurate DOA estimation but at the expense of high computational complexity due to demanding spectral search procedure. Artificial neural networks (ANNs) [2] could represent an alternative faster approach to the computationally intensive super-resolution DOA algorithms performing basic mathematical operations and calculating elementary functions.

This ability qualifies them as very suitable for determining of angular positions of source signals [3]. In [4] a novel approach combining MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function) ANNs is proposed for DOA estimation in order to detect the presence of deterministic narrow-band EM source and determine its angular coordinates (azimuth and elevation). In [5,6], an ANN approach, realized by MLP neural model, has been presented to provide a high-resolution DOA estimation. However, it was able to provide azimuth position of only few stochastic narrow-band EM sources in far-field.

Neural model for an efficient one-dimensional (1D) DOA estimation of stochastic EM sources, presented in this paper, represents an extension of previously developed models in [5,6] as it is able to provide a solution for cases when there is an arbitrary number of stochastic sources in far-field mutually positioned at fixed angle distance or where there are up to two stochastic sources placed at arbitrary angle distance. Neural model is realized again using MLP ANNs. Its training is based on the correlation matrix of received signals, obtained combing the Green function for electric field in far-field and correlation matrix of feed currents representing stochastic sources. Successfully trained neural model is able to provide accurate and fast DOA of incoming EM signal and determine azimuth coordinates of multiple sources making the model convenient for real-time application.

II. Stochastic Source Radiation Model

We represent a radiation of stochastic source in far-field by linear uniform antenna array with N elements at the mutual distance $d = \lambda/2$ (Fig.1). In this radiation model representing stochastic source, antenna elements feed currents (defined by vector $\mathbf{I}=[I_1, I_2, \ldots, I_N]$) are in general mutually correlated. The level of their correlation can be defined by correlation matrix, $\mathbf{c}^I(\omega)$, describing stochastic nature of antenna array radiation [6]:

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

Using Green function to map the domain of radiation source currents into the domain of electric field in far-field, vector $\mathbf{M}$ can be defined as:

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

where z_0 is free-space impedance, $F(\theta,\varphi)$ is the radiation pattern of antenna array elements, r_c is the distance of far-

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field point to the centre of array, k is the phase constant (k=2π/λ) and r_1, r_2, ... , r_N are the distances of far-field point from the first to the N-th element of antenna array. The electric field intensity in sampling point in far-field (sampling point is at the angles θ and φ in azimuth and elevation planes, respectively, defined by the first element of antenna array) can be calculated as:

$$E(\theta,\varphi)=\mathbf{M}(\theta,\varphi)\mathbf{I} \tag{3}$$

If M points are simultaneously observed in far-field, then more general notation can be used to describe the antenna array elements distance from particular points in far-field. In this notation $r_{i,m}$ represents the distance between i-th element ($1 \le i \le N$) in the antenna array and m-th point in the far-field ($1 \le m \le M$) (see Fig. 1).

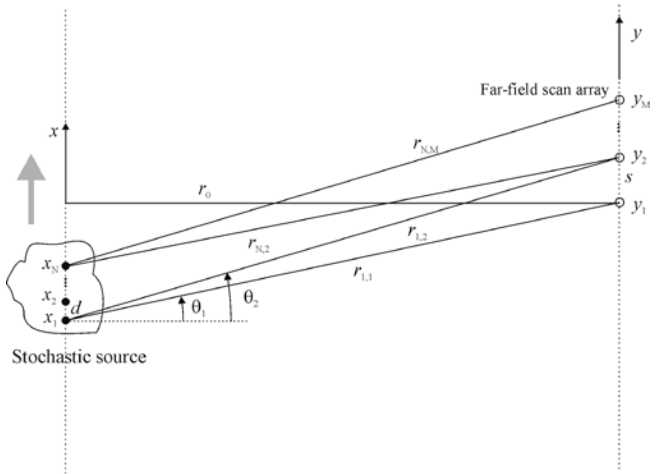

Fig. 1. The position of stochastic source in azimuth plane with respect to the location of EM field sampling points in the far-field scan area.

M points (Y_1 Y_2, ..., Y_M) in far-field, in which electric field levels are sampled, are at the azimuth and elevation plane angles (θ_1, φ_1), (θ_1, φ_1), ... , (θ_M, φ_M), determined by the first element of antenna array. The correlation matrix of signals received in these sampling points can be obtained from the correlation matrix of antenna elements feed currents as:

$$\begin{aligned}&\mathbf{C}_E[i,j]=\mathbf{M}(\theta_i,\varphi_i)\mathbf{c}^I\mathbf{M}(\theta_j,\varphi_j)^H\\ &i=1,\dots,M \quad j=1,\dots,M\end{aligned} \tag{4}$$

For the case of several stochastic sources in azimuth plane, the radiation of each source can be represented by one antenna aray with N elements as previously shown. The level of EM field in far-field sampling point, as well as the elements of correlation matrix are determined by the superposition of radiation from all sources. In accordance with this, when the number of stochastic sorces is S, vector M has a form :

$$\begin{aligned}&\mathbf{M}(\theta,\varphi)=jz_0\frac{F(\theta,\varphi)}{2\pi r_c}\cdot\\ &\cdot\left[e^{jkr_1^{(1)}}\dots\, e^{jkr_N^{(1)}}e^{jkr_1^{(2)}}\dots\, e^{jkr_N^{(2)}}\dots e^{jkr_1^{(S)}}\dots\, e^{jkr_N^{(S)}}\right]\end{aligned} \tag{5}$$

where $r_i^{(j)}$ is the distance between i-th element in antenna array, representing j-th stochastic source, and the sampling point in far-field, while the feed currents vector is:

$$\mathbf{I}=\left[I_1^{(1)}\dots I_N^{(1)}\,I_1^{(2)}\dots I_N^{(2)}\dots I_1^{(S)}\dots I_N^{(S)}\right] \tag{6}$$

where $I_i^{(j)}$ is the feed current of i-th element in antenna array representing j-th stochastic source.

Combining Eqs.(3) and (4) with Eqs. (5) and (6) that correspond to the case of several stochastic sources, it is possible to determine the intesity of EM field in the sampling point in far-field, as well as the elements of correlation matrix $\mathbf{C}_E$. It should be also pointed out that in the case of unknown level of correlation between antenna elements feed currents, its correlation matrix can be obtained by measuring the intensity of electric field in the sampling points in near-field.

III. Neural Network Model

The neural model based on MLP ANN is developed with the purpose to perform the mapping from the space of signals described by correlation matrix $\mathbf{C}_E$ to the space of DOA in azimuth

$$\boldsymbol{\theta}=f(\mathbf{C}_E) \tag{7}$$

where $\boldsymbol{\theta}$ is azimuthal angles vector of stochastic sources, $\boldsymbol{\theta}=[\theta_1, \theta_2, \dots, \theta_S]$ and S is number of stochastic sources. In the observed case elevation coordinates of radiation sources is neglected. The architecture of developed neural model is shown in Fig.2. Its MLP network can be described by the following function:

$$\mathbf{y}_l=F(\mathbf{w}_l\mathbf{y}_{l-1}+\mathbf{b}_l) \quad l=1,2 \tag{8}$$

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:

$$F(u)=\frac{e^u-e^{-u}}{e^u+e^{-u}} \tag{9}$$

In order to perform mapping it is sufficient to take only the first column of correlation matrix and therefore $\mathbf{y}_0$ = $[Re\{\mathbf{C}_E[1,1]\}\ Im\{\mathbf{C}_E[1,1]\},\dots,\ Re\{\mathbf{C}_E[1,M]\}\ Im\{\mathbf{C}_E[1,M]\}]$. Also, $\boldsymbol{\theta}$ is given as $\boldsymbol{\theta}=\mathbf{w}_3\mathbf{y}_2$ 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 and biases values during the training allows ANN to approximate the mapping with the desired accuracy.

IV. Modeling Results

The training of ANNs is conducted for the case of four equidistant sampling points in far-field scan area, at the mutual distance d = λ/2, located 100 m from stochastic sources (Table I). Angular position in the azimuth plane of two mobile users (S=2) at arbitrary angle distance has to be determined. By using Eq.(4) and (5) for N=4 and M=4, 861 and 276 uniformly distributed samples are generated for training and testing, respectively, in the range [-80° 80°] at the working frequency of 7.5 GHz. Each stochastic source can be described by antenna array with four vertical dipole (N=4). The feed currents of two dipoles are mutually uncorrelated so that $\mathbf{c}^I$ is the unit diagonal matrix. Levenberg-Marquartd method with prescribed accuracy of 10^{-4} is used as a training algorithm. The testing results for six MLP models with the lowest average case error are shown in Table II, and MLP2-16-8 is chosen as representative neural model. The neural model simulation of testing samples set shows a very good agreement between the output values of neural model and referent azimuth values for all sources (Fig.3, Fig.4 and Fig.5). In addition, a good agreement with results obtained by MUSIC algorithm can be observed.

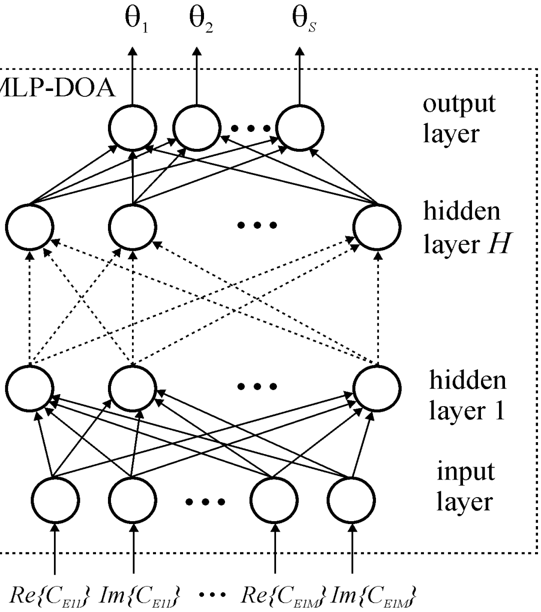

Fig. 2. Architecture of MLP neural model for DOA estimation of stochastic EM source signal in azimuth plane

TABLE I
THE VALUES OF ANTENNA ARRAY PARAMETER WHICH USED IN SAMPLING PROCESS

Frequency	f = 7.5 GHz
Number of sources	S = 2
Number of antenna array elements per one source	N = 4
Sampling points distance from source trajectory	r_0 = 100 m
Number of sampling points	M = 4
Mutual distance of the sampling points	$s = \lambda/2$ (0.02 m)

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

MLP model	WCE [%]	ACE [%]
MLP2-16-8	1.81	0.42
MLP2-14-14	2.26	0.42
MLP2-18-14	2.67	0.39
MLP2-20-10	2.71	0.38
MLP2-16-16	3.27	0.39
MLP2-16-11	3.76	0.41

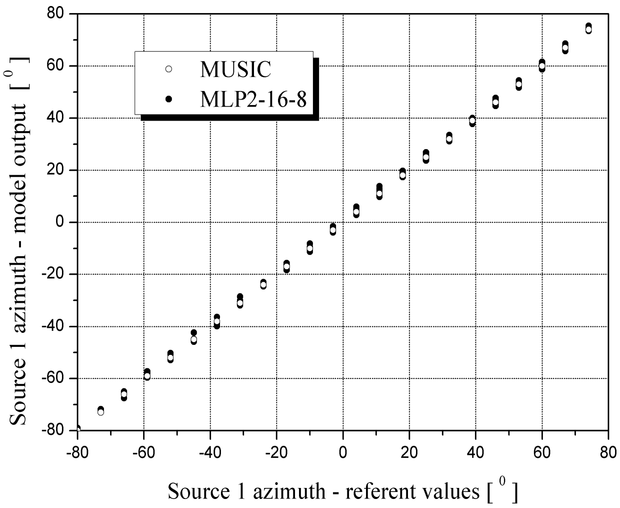

Fig. 3. Comparison of MLP2-16-8 model output 1 (azimuth of source 1) with MUSIC and referent azimuth values

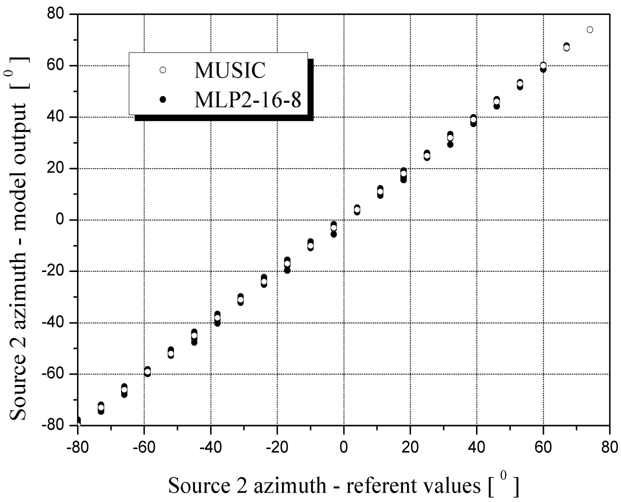

Fig. 4. Comparison of MLP2-16-4 model output 2 (azimuth of source 2) with MUSIC and referent azimuth values

V. CONCLUSION

The neural network-based approach for DOA estimation of electromagnetic radiation of stochastic sources is presented in the paper. Only the first column of correlation matrix obtained by simple signal sampling in far-field scan area by linear uniform antenna array is used as an input of developed neural model. Neural model ability to accurately and efficiently determine the 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 location in azimuth plane for up to two stochastic sources placed at arbitrary angle distance Future research will be focused to the more general DOA estimation of multiple stochastic sources at arbitrary angular distance.

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