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2D DOA Estimation Using Beam Steering Antenna by the Switched Parasitic Elements and RBF Neural Network

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1. Introduction

An array antenna that parasitic elements are arranged on the concentric circle of a central radiating element and that each output of the parasitic elements is connected in any of release and short circuit to scan the main beam or to estimate Direction Of Arrival (DOA) is proposed [1]. The monopole on the ground plane is used for radiating and parasitic element in the many, and fixed volume is necessary as an antenna structure. For the application to portable terminals, etc., it is desirable that the antenna aperture is composed of plane and conformal shape using microstrip patch antenna (MSPA).

As DOA estimation algorithm applied to the beam scanning antenna with switched parasitic elements, beamformer, eigenvalue decomposition, and the RBF neural network are considered. The RBF neural network is almost equivalent to the MUSIC on accuracy and resolution. Calculation load for the DOA estimation is small, when it once carries out the learning. And, it is robust for trouble and manufacturing error [2]. In addition, multiple signals with the correlation can be also estimated [3]. However, the number of incoming wave must be known, because output of the network shows the estimated result directly.

When the direct sequence spread spectrum signals such as W-CDMA mobile communication and wireless LAN of the IEEE 802.11b are handled, the de-spread signal in the first demodulation is separated to the every user and every pass, and signal number handled in this stage becomes 1. Therefore, utilization of the RBF neural network becomes possible [4].

2. Beam scanning antenna with switched parasitic elements

Fig.1 shows the antenna aperture. A central radiating element and six parasitic elements on the circumference of the 0.4λ radius at intervals of 60 degrees are placed on the dielectric substrate. Circularly Polarized Wave (CPW) MSPA with 2 points feed is used, because the coupling amount is different according to the polarized wave direction. An output of 3dB hybrid coupler for CPW is connected with the common terminal of the SPDT switch. Current induced on parasitic element is controlled by setting the switch to ON/OFF, and the directivity is changed. Here, a parasitic element, that is handled as a director, is set to ON and the others are set to OFF in order to scan the beam.

3. DOA Estimation Using RBF Neural Network

Correlation matrix Rxx is estimated using the received signal vector $\vec{x}(t) = \left[x_1(t), x_2(t), \ldots., x_6(t)\right]^T$. Here, $x_n(t)$ is signal received by the time sharing every 6 beams

$$Rxx = E\left[\vec{x}(t)\vec{x}^T(t)\right] \tag{1}$$

E[·] denotes the ensemble average. It is considered that the array antenna is the system which maps arrival direction (φ,θ) in the array received signal vector. It is considered that DOA estimation is to reversely map onto the arrival direction from the array received signal vector. That is to say, DOA can be obtained from the array received signal vector if f_1 and f_2 of the reverse mapping function were able to be found.

$$\varphi = f_1(\vec{x}) \qquad \theta = f_2(\vec{x}) \tag{2}$$

In the RBF neural network, function f_1 and f_2 are approximated by the linear sum of radial basis function

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weighted.

$$f_m(\vec{x}) \cong \sum_{j=1}^{J} \omega_{mj} \exp\left(\frac{\left\|\vec{x}-\vec{x}_j\right\|}{\sigma_j^2}\right) \quad m=1,2 \tag{3}$$

$\vec{x}_j$ and σ_j^2 is central vector and spread of the radial basis function, respectively. $\|\cdot\|$ is defined as Euclidean norm. The RBF neural network solves the nonlinear interpolation problem by mapping the input space in the higher dimensional space.

Fig.2 shows the principle of DOA estimation by the RBF neural network. In the pre-processing stage, triangular elements of the received signal correlation matrix Rxx are extracted and are vectorized as follows.

$$\vec{\mathrm{b}} = [\mathrm{Re}(\mathrm{r}_{12}), \mathrm{Im}(\mathrm{r}_{12}), .. \mathrm{Re}(\mathrm{r}_{16}), \mathrm{Im}(\mathrm{r}_{16}), \mathrm{Re}(\mathrm{r}_{23}), \mathrm{Im}(\mathrm{r}_{23}), .. \mathrm{Re}(\mathrm{r}_{26}), \mathrm{Im}(\mathrm{r}_{26}), .. \mathrm{Re}(\mathrm{r}_{56}), \mathrm{Im}(\mathrm{r}_{56})]^{\mathrm{T}} \tag{4}$$

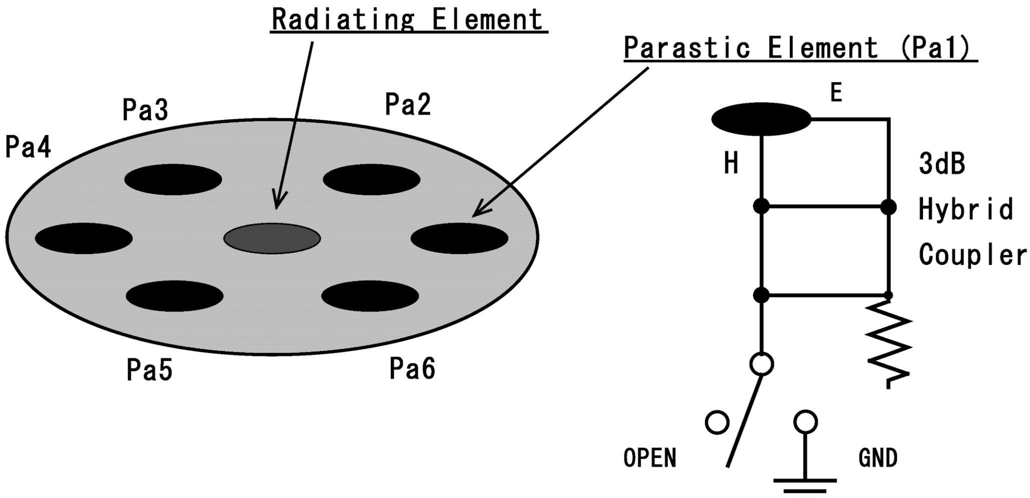

Fig.1 Antenna Aperture

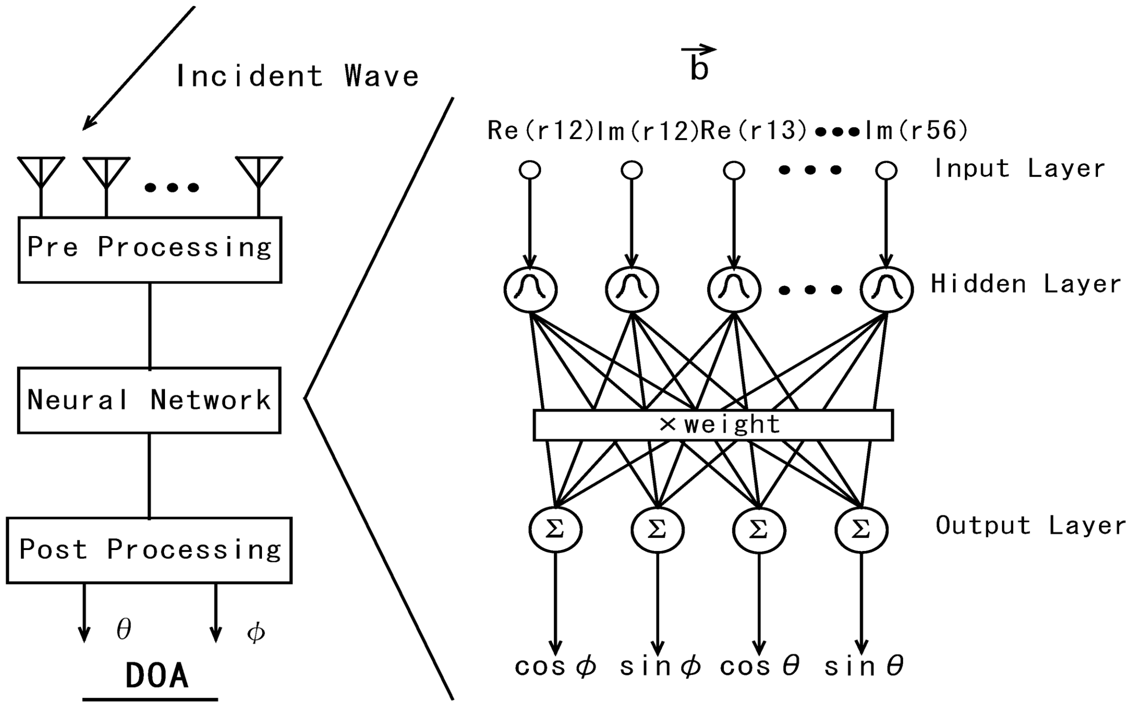

Fig.2 DOA Estimation Using RBF Neural Network

In addition, the input vector is normalized.

$$\hat{b} = \frac{\vec{b}}{\left\|\vec{b}\right\|} \tag{5}$$

The RBF neural network consists of input layer, hidden layer, and output layer. Number of nodes in the input layer is equal to the input vector dimension, and number of the nodes in the output layer is equal to number of the information output. The interpolation accuracy increases, when number of neurone J in the hidden layer which is smaller than learning data of number L increases. The input and output node have a linear response, and the hidden neurone have such nonlinear response as Formula (3).

Estimation range of (φ,θ) in the hemisphere space is 0≤φ<2π, 0≤θ<π/2. The output value near the boundary of the estimation range greatly fluctuates, when the parameter of the network is trained so that the estimation angle may appear in the output node directly until now. Then, the estimation accuracy deteriorates. Parameters of the network is trained so that the value of next trigonometric function may appear in four output node f_1~f_4.

$$f_1(\vec{x}) \cong \sum_{j=1}^{J} \omega_{1j} \exp\left(\frac{\left\|\vec{x}-\vec{x}_j\right\|}{\sigma_j^2}\right) \cong \cos\varphi \quad f_2(\vec{x}) \cong \sum_{j=1}^{J} \omega_{2j} \exp\left(\frac{\left\|\vec{x}-\vec{x}_j\right\|}{\sigma_j^2}\right) \cong \sin\varphi \tag{6a)(6b}$$

$$f_3(\vec{x}) \cong \sum_{j=1}^{J} \omega_{3j} \exp\left(\frac{\left\|\vec{x}-\vec{x}_j\right\|}{\sigma_j^2}\right) \cong \cos\theta \quad f_4(\vec{x}) \cong \sum_{j=1}^{J} \omega_{4j} \exp\left(\frac{\left\|\vec{x}-\vec{x}_j\right\|}{\sigma_j^2}\right) \cong \sin\theta \tag{6c)(6d}$$

In the post-processing stage, these 4 outputs convert into arrival direction (φ,θ).

$$\varphi = \arg\{f_1(\vec{x}) + jf_2(\vec{x})\} \qquad \theta = \arg\{f_3(\vec{x}) + jf_4(\vec{x})\} \tag{7a)(7b}$$

In the training, input vector $\vec{b}_i$ (i=1,2,…,MN) in proportion to arrival direction (φ_m,θ_n) (m=1,2,..,M, n=1,2,…,N) and network output($\cos\varphi_m$, $\sin\varphi_n$, $\cos\theta_m$, $\sin\theta_n$) are used. Matlab function of the Neural Network Toolbox applying the method of literature [5] which learns iteratively increasing the hidden layer neurone until set accuracy of the goal is achieved, was used.

4. Array Radius

Trial manufacture of the aperture using the Diclad substrate (dieletcric constants of 2.6 and thickness of 1.6mm has been planned. In this time, the radius of circular MSPA becomes 0.175λ, and the array radius is not made small than 0.35λ. DOA estimation error by Interferometer has been evaluated as the array radius was made to increase from 0.35λ to 1λ. Mean squared error of 288 directions of φ=0,10,…350° for θ=10,20,… 80° defined by Formula (8) was used.

$$E = \frac{\sqrt{\sum_{i=1}^{36}\sum_{j=1}^{8}\left\{\left(\Delta_{i,j}^{\varphi}\right)^2 + \left(\Delta_{i,j}^{\theta}\right)^2\right\}}}{288} \tag{8}$$

$\Delta_{i,j}^{\varphi}$ and $\Delta_{i,j}^{\theta}$ is estimated error of φ direction and θ direction, respectively. It was assumed that the signal which modulated the random sequence by the π/4 shift QPSK emitted, and number of the snapshot was made to be 100, and SNR was made to change from 0dB to 30dB. Method for electromagnetic analysis of the aperture is same as reference [6]. Simulation result by Interferometer is shown in Fig. 3. Estimated error becomes smallest, when the radius is 0.4λ.

5. Simulation

The array radius was made to be 0.4λ, and DOA was estimated by the RBF neural network. Input vector of 324 directions, ϕ=5,15,…,355° for θ=5,15,…, 85°, and corresponding network output (cosφ, sinφ, cosθ, sinθ) as learning data set were used. For DOA estimation, incidence angles of φ=0,10,…,350° for θ=10,20,…,80° was set. This incidence angle is the middle of the learning points. Spread of the radial basis function of the hidden layer neurone was set at identical 0.24. Fig. 4 shows the estimated error compared with the Interferometer. It is proven that the estimated error is rapidly improved, when the RBF neural network is used. In the simulation using MATLAB ver. 6.5, calculation load for DOA estimation including 288 directions using Interferometer with two-dimensional search of every 1° is 3556Mflops. Contrarily, it becomes 8.3Mflops, when the neural network is used. The calculation load can be shortened under 1/400.

6. Conclusions

A method for estimating DOA in the hemisphere space using RBF neural network was proposed. Arranging parasitic elements on the concentric circle of the radiating element, the antenna aperture is constituted. Applying circularly polarized wave circular microstrip patch antenna to the radiating element and parasitic elements, the planar aperture was consisted. By opening and short-circuiting output of parasitic element, the beam scanning is achieved. The new post-processing method was added in order to realize DOA estimation of the hemisphere space using the RBF neural network with high accuracy. Grounding procedure and circular array radius were optimized on the basis of beamformer approach (Interferometer). Comparing the proposed method with beamformer, the effectiveness of the proposal method was confirmed

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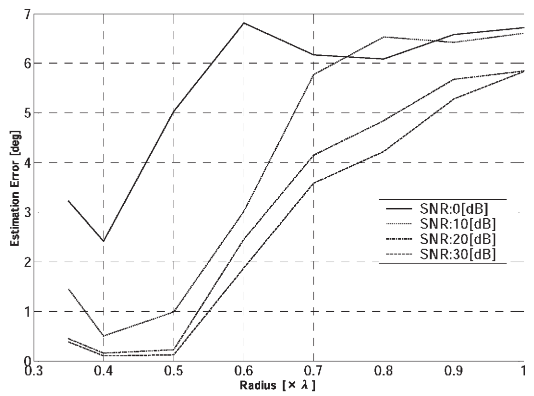

Fig.3 Accuracy of DOA Estimation vs. Array Radius

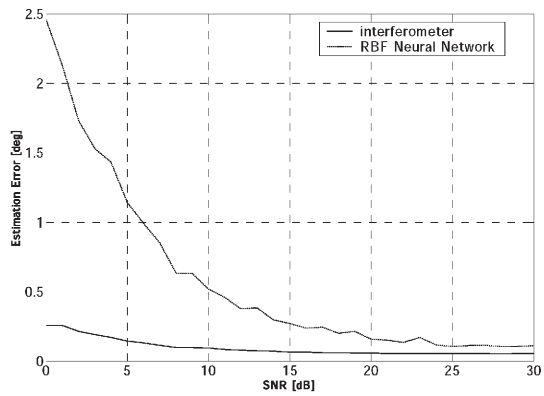

Fig.4 Comparison of DOA Estimation