Abstract: Nowadays, multiple-input multiple-output (MIMO) transmission becomes an essential technology for wireless communication systems. Because the MIMO transmission performance heavily depends on the propagation channel characteristics, those channel parameters have been investigated through various radio measurements. In this paper, we propose a parameter estimation refinement method based on the nonlinear conjugate gradient (NLCG) approach. In our proposal, the accurate propagation parameters are obtained with a few iterations without falling into the local maximum points of the likelihood function. The proposed method was evaluated through a computer simulation, and the results showed that the residual signal power ratio (RSPR) of the channel reconstructed was improved by approximately 17% compared with the space-alternating generalized expectation-maximization (SAGE) algorithm. The proposed method is expected to be utilized for channel measurements in the future work.

Keywords: EM/SAGE, MIMO channel, nonlinear conjugate gradient, propagation parameter estimation, radio propagation

Classification: Antennas and Propagation

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1 Introduction

Multiple-input multiple-output (MIMO) transmission becomes an essential technology for wireless communication systems owing to the ceaseless demand for higher capacity of data communication. Recently, although the millimeter wave band is planned to be utilized for the fifth generation mobile wireless system [1], its applicability to the MIMO transmission is still an issue of great interest. To solve the issue, MIMO channel soundings have been conducted in various environments. The propagation parameters based on the geometry-based stochastic channel model (GSCM) are estimated from measured data by high-resolution parameter estimation algorithms such as the expectation-maximization/space-alternating generalized expectation-maximization (EM/SAGE) algorithm [2]. Because the parameter estimation is a large-scale multidimensional search problem, each propagation parameter of each multipath component is estimated sequentially in an iterative fashion in the SAGE algorithm. However, it has the disadvantage that degrades the convergence speed of the estimation. Furthermore, it requires additional calculation amount to improve the accuracy because the estimation accuracy depends on the resolution setting of the discrete parameter search process.

To solve the issues, we proposed the nonlinear conjugate gradient- (NLCG)-based parameter estimation method [3]. In our proposed method, the parameter search vector is calculated from the current partial derivative of the likelihood function concerning each propagation parameter. Then, the search step length toward the vector is decided based on the Strong Wolfe (SW) criteria [4] by a heuristic way. Therefore, our proposed method can obtain a near-optimal estimation result within a few iterations. However, it has a risk that the estimation result may fall into the local maximization points depending on the initial parameter conditions. In this paper, we solve the problem by combining the SAGE algorithm and the NLCG algorithm. In our proposal, the parameters are roughly estimated by the beamformer-based parameter search in initial iterations, and then the parameters are refined by the NLCG algorithm. We evaluated our proposal through a computer simulation, and the result showed that it significantly improved the residual signal power ratio (RSPR) of the estimation compared with the SAGE algorithm.

2 Application of the nonlinear conjugate gradient approach to the propagation parameter estimation

The GSCM assumes that the propagation channel consists of $L$ plane waves. The $l$-th path is defined by the propagation parameter vector $\theta_l = [\tau_l, \phi_{R,l}, \phi_{T,l}, \gamma_l]^T$. Here, $\tau_l$ is the propagation delay, $\phi_{R,l}$ is the angle of arrival (AoA), $\phi_{T,l}$ is the angle of departure (AoD), and $\gamma_l$ is the path weight. The received signal is modeled by the
Next, we explain the details of the NLCG-based search method. The gradient obtained without falling into the local maximum points of the likelihood function.\footnote{\text{NLCG algorithm.}} By combining the two methods, near-optimal solutions can be obtained from the global optimization viewpoint. Then, the estimated parameters are re-estimated by the beamformer-based search from the M-step of the estimation. As with the SAGE algorithm, the procedure consists of E-step and M-step. In E-Step, the expected signal component of the \( l \)-th path \( x_l \) is estimated using the estimation result of the previous iteration. In M-step, the parameters that maximize the log-likelihood function of the estimating path are shown as follows.

\begin{align}
\text{E-step: } x_l^{(ir)} &= s_l(\hat{\theta}^{(ir)}) + \beta \left( x - \sum_{l=1}^{L} s_l(\hat{\theta}^{(ir)}) \right) \\
\text{M-step: } \hat{\theta}^{(ir+1)} &= \arg \max_{\theta} \left[ -||x_l^{(ir)} - s_l(\hat{\theta})||^2 \right] \tag{3}
\end{align}

Here, \( x \) is the measured data. In our proposal, both the beamformer-based parameter search \footnote{\text{2}} and the NLCG-based search refinement \footnote{\text{3}} are used at M-step. In the first iterations, the parameters are estimated by the beamformer-based search from the global optimization viewpoint. Then, the estimated parameters are refined by the NLCG algorithm. By combining the two methods, near-optimal solutions can be obtained without falling into the local maximum points of the likelihood function.

Next, we explain the details of the NLCG-based search method. The gradient vector \( \Delta \theta \) that maximizes eq. (3) is obtained as follows \footnote{\text{5}}.

\begin{align}
\Delta \theta_l &= \nabla \left[ -||x_l^{(ir)} - s_l(\hat{\theta})||^2 \right] = 2R_s \left\{ \frac{\partial s_l^{(ir)}(\hat{\theta})}{\partial \theta_l} (x_l^{(ir)} - s_l(\hat{\theta})) \right\} \tag{4}
\end{align}

The procedure of the NLCG-based search method is as follows.

1. Set the sub-iteration number \( k \) to 0 and calculate the initial parameter search vector \( \theta_0^{(0)} = \Delta \theta_0^{(0)} \) by eq. (4).
2. Update the propagation parameter vector as \( \hat{\theta}_l^{(k+1)} = \hat{\theta}_l^{(k)} + \alpha^{(k)} d_l^{(k)} \) and the expected signal of the \( l \)-th path defined in eq. (3). Here, \( \alpha^{(k)} \) is the step length that is decided based on the SW criteria \footnote{\text{4}}.
3. If the estimation converges, set \( \hat{\theta}_l = \hat{\theta}_l^{(k+1)} \) and quit the procedure.
4. Otherwise, calculate the new gradient \( \Delta \theta_l^{(k+1)} \) by eq. (4). Next, update the parameter search vector as \( d_l^{(k+1)} = \Delta \theta_l^{(k+1)} + \frac{|\Delta \theta_l^{(k+1)}|^2}{|\Delta \theta_l^{(k)}|^2} d_l^{(k)} \) and return to Step 2.

### 3 Simulation evaluation

The proposed method was evaluated through a computer simulation. The simulation parameters are shown in Table I. In the simulation, MIMO channel data were generated by the superposition of 10 plane waves, whose propagation parameters were randomly set. Then, the parameters were estimated from the data by the SAGE algorithm or the proposed method. We assumed a 12-element circular array for both the Tx and Rx array antennas. To clarify the influence of the initial parameter setting errors on the performance, random errors were added to the real
parameters, and they were used for the initial parameters of the estimation. The error followed the normal distribution, and five standard deviation conditions were investigated as shown in Table II. $W_t = 0.5$ (delay bin), which corresponded to the half of the delay sampling interval, and $W_a = 12^\circ$, which corresponded to the antenna array beamwidth. The number of trials was 100 for each error condition. In the SAGE algorithm, the delay search resolution of 1 (bin) and the angular search resolution of 1° were used. For the evaluation, the root mean squared errors (RMSEs) of the estimated parameters and the RSPR $R_{RS} = \frac{\|x - \sum_{i=1}^c s_i e^{j\theta_i}\|^2}{|x|^2}$ were compared between the SAGE algorithm and the proposed method.

### 4 Simulation result

The RMSE cumulative distribution functions (CDFs) of the delay and angular estimation results are shown in Fig. 2. The angular estimation result includes both the AoA and AoD estimation results. In the SAGE algorithm, the delay and angular CDF curves stopped decreasing around 0.5 (bin) and 0.5°, as marked by (1). This is because the estimation accuracy was limited by the resolutions of the parameter search. On the other hand, the RMSE decreased up to $10^{-3}$ (bin) and 0.05° using the proposed method. The result shows that the NLCG algorithm worked properly for the parameter estimation refinement, and it significantly decreased the RMSE.

There was another region where the RMSE became significantly large as marked by (2). Those large RMSEs were caused by path detection failures. During the iteration process, one actual path can be regarded as several adjacent paths owing to the imperfect parameter estimation result. Because the actual path numbers and the estimation path numbers were the same in this evaluation, weak paths tended to be ignored, which increased the RMSE as a result. However, the
influence of the path detection failure on the MIMO channel has to be carefully investigated.

Fig. 3(a) shows the angular delay power spectrum (ADPS) of the simulation data of Case A. The estimated paths and ADPS of the residual signal component (RSC) \( r = x - \sum_{l=1}^{L} s_l(\theta_l) \) are also shown in Figs. 3(b) and (c). Although the estimated paths looked similar in both the SAGE algorithm and the proposed method, a considerable RSC remained in the SAGE algorithm case. The RSPR for all initial parameter error cases are summarized in Fig. 3(d). For reference, the result of the case when only the NLCG was applied without the beamformer-based search is also shown. In the SAGE algorithm, the RSPR was greater than 23% under every error condition. These values are not negligible in terms of the signal reconstruction accuracy. If only the NLCG is used, although the RSPR was smaller than 3% in Cases A, B, and C, it started increasing when the errors exceeded \( W_t \) and \( W_a \). This is because the estimation result fell into the local maximum points. In our proposed method, it was smaller than 6% in all cases. The reason for the slight increase of RSPR is thought to be the influence of the path detection failure. The result confirmed the effectiveness of our proposal.
5 Conclusion

In this paper, we proposed the parameter estimation refinement method based on the NLCG algorithm. By combining the NLCG with the SAGE algorithm, the accurate propagation parameters are obtained with a few iterations without falling into the local maximum points of the likelihood function. The simulation results showed that a propagation delay RMSE of $10^{-3}$ (bin) and an angular RMSE of 0.05° could be achieved under the appropriate conditions. The average RSPR was smaller than 6% in all initial parameter error conditions, and they were significantly improved by more than 23% of the RSRPs of the SAGE algorithm. The application of the method to actual measurement data will be the future work.

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