Neural Network-Based Phase Estimation for Antenna Array Using Radiation Power Pattern

Tetsuya Iye, Member, IEEE, Pieter van Wyk, Takahiro Matsumoto, Yuki Susukida, Shohei Takaya, and Yoshimi Fujii, Member, IEEE

Abstract—In this letter, a neural network-based interelement phase estimation method using radiation power pattern of the linear phased array is proposed. To validate the proposed method, a radiation pattern measured in an anechoic chamber is input to the neural network to estimate the initial phase errors, and to confirm practical estimation accuracy. The proposed method requires only single radiation pattern measurement and no additional measurements only for estimation. This indicates the proposed method is significantly more time-saving, compared to other conventional techniques. Furthermore, we propose a method to suppress the failure rate of estimation by recursively reinputting patterns into the neural network, and discuss its effectiveness. These results show that the proposed methods useful for phase estimation of the linear array in experiments.

Index Terms—Antenna arrays, calibration, deep learning, neural network (NN), radiation patterns.

I. INTRODUCTION

Beamforming is one of the key techniques for 5G and beyond to cope with severe path loss in millimeter-wave (mmWave) bands, and to enable reliable high-data-rate transmission [1], [2]. A beamformer equipped with phased array systems is required to generate the desired beam pattern by controlling excitation amplitudes and phases of multiple antenna elements [3], [4]. Therefore, it is essential to calibrate initial excitation errors for each antenna element caused by manufacturing errors, and/or characteristic changes in RF components with temperature or time. In the mmWave band called FR2 in 5G NR, the components are smaller due to the shorter wavelengths and various functions are integrated, making it difficult to test antenna with a connector. Instead, over-the-air tests are being conducted in anechoic chambers. In order to align the initial complex excitation coefficients of all antenna elements, the rotating-element electric-field vector (REV) method or multielement phase-toggling (MEP) method are widely used [5], [6]. The REV method, while requiring only power measurements, always gives two candidate solutions, which are technically difficult to distinguish [5]. The MEP method can extract calibration values more effectively in exchange for the accuracy compared to REV by electric field vector measurements. Various calibration methods using power or electric field measurements have been proposed [7]–[15]. All of these methods require multiple measurements and repetitive numerical calculations taking up to a few dozen minutes to derive the excitation errors from measurement results.

Recently, the application of artificial intelligence-related technologies, such as deep learning using neural networks (NNs) has been attempted in all industrial fields, including wireless communications [16]. Pattern synthesis methods for phased-array antennas have already been proposed using deep NN [17] and convolutional NN [18], although both works show no statistical results and discussion on estimation accuracy. A compressed sensing-based online calibration using NN has also been proposed, whereas it requires signal processing, indicating immediate calibration is difficult [19]. However, all the abovementioned reports lack proof of concept based on an actual experimental data. Another NN approach to calibrate both transmit and receive channels for phased array antenna by power-only measurement has been reported [20]. This method allows for simple hardware implementation using little computational power, while still requiring multiple power measurements.

In this letter, we introduce an NN-based phase estimation method for phased array using radiation power pattern as an input, which is designed to overcome the aforementioned drawbacks. The trained NN model works as an inverse function that outputs the excitation phase coefficients of the antenna elements in milliseconds in response to a radiation pattern input.

The rest of this letter is organized as follows. In Section II, the synthesis process of the radiation patterns for the training and validation of NN is described. Section III presents the architecture of the NN model for radiation pattern. Section IV describes training, validation, and experimental results for evaluation and accuracy of the NN model. We further discuss recursive application of the calibrated radiation pattern to the NN in order to improve the calibration by reducing the failure rate. Finally, Section V concludes this letter.

II. PATTERN SYNTHESIS OF ANTENNA ARRAY

Experimentally, power patterns measured by a combination of signal generator and spectrum analyzer provide more accurate single point frequency results than the patterns measured by a vector network analyzer with banded power transmission. Considering these factors, we prepare the NN model for using measured power pattern to estimate the excitation phase errors of the elements.

A large number of radiation patterns with constant amplitudes and random combinations of excitation phase coefficients for
multiple elements generated by random selection from a uniform distribution are used to train the NN model for calibration. The radiation field pattern of a linear array antenna can be described by complex value as follows [21]:

\[ E(\delta, \theta) = \sum_{k=1}^{N} g_k(\theta) A_k \exp \left\{ \frac{2\pi}{\lambda} \left( (k - 1) d \sin \theta - \delta_k \right) \right\} \]  

where \( \delta = [\delta_1, \ldots, \delta_N] \) is the initial phase error vector, \( \theta \) is the azimuth angle measured from the broadside, \( N \) is the number of antenna elements, \( \lambda \) is the wavelength, \( d \) is the distance between antenna elements, \( g_k(\theta) \), \( A_k \), and \( \delta_k \) are the directivity function, normalized amplitude, and the initial phase error of \( k \)-th antenna element, respectively. In this work, the use of uniform excitation amplitude \( A_k = 1 \) is assumed for all \( k \). The eight-element vertically polarized linear array antenna for 28 GHz with patch antennas evenly spaced at \( d = 6.0 \times 10^{-3} \) [\( m \)] was designed. The radiation gain pattern for each antenna element, \( g_k(\theta) \), was measured and is reported in [22]. Since the antenna elements are separated by a distance of \( \geq 0.5 \lambda \), the antenna coupling effect are neglected in this work.

We generate 1 250 000 radiation power patterns \( P(\delta, \theta) = |E(\delta, \theta)|^2 \) for a range of \(-90^\circ \leq \theta \leq 90^\circ \) in 1° step by setting random phase values \(-180^\circ \leq \delta_k \leq 180^\circ \) for \( k = 2, \ldots, 8 \) of eight elements, keeping \( \delta_1 = 0^\circ \). This is because only the relative phase difference between the elements is important for the radiation power pattern. It takes approximately 10 min to generate all the radiation patterns. The power patterns are normalized to range from 0 to 1 for training the NN. A total of 96% of the dataset is used as for training, and the remaining 4%, consisting of 50 000 patterns, is used for validation. Therefore, a real valued matrix with the size of 1 200 000 \( \times \) 181, as well as training label \( |\delta_k| \) with phase values of 1 200 000 \( \times \) 7 is prepared as an input dataset for the NN model. We note that the validation dataset is chosen uniformly at random from the total dataset. Three examples of randomly set phase patterns and corresponding radiation patterns are shown in Fig. 1(a) and (b), respectively.

III. NN Model

The NN consists of eight layers, including six hidden layers. The activation function in the output layer is the “sigmoid” function with the remaining layers using the rectified linear unit (ReLU) function. Each layer consists of a dense layer that is fully connected without dropouts. As a loss function, we use the mean squared error (MSE). The optimizer “Adam” is chosen and batch size is set to 16 384 for training. Detailed parameters for the model are summarized in Table I.

![Figure 1](image_url)  
Fig. 1. (a) Three samples of randomly chosen phase set generated from a uniform random distribution. (b) Normalized power patterns calculated for each phase values in (a) using element patterns in [22].

IV. RESULTS AND DISCUSSION

A. Training and Validation Results

The training and validation loss recorded over 1000 epochs are converged to 1.76 \( \times \) 10^{-4} and 8.01 \( \times \) 10^{-3}, respectively. Total training time was approximately 3.5 h on an Intel Core i5-8400 CPU at 2.80 GHz with 8 GB of RAM and NVIDIA GeForce GTX 1060 6 GB.

As an indicator of the performance of the learning model, we evaluate the root mean squared errors (RMSEs) of the estimated phase patterns as follows:

\[ \delta_{\text{RMSE}} = \sqrt{\frac{1}{7} \sum_{k=2}^{8} \left( \left| \delta_k - \hat{\delta}_k \right|, 360^\circ - \left| \delta_k - \hat{\delta}_k \right| \right)^2} \]

where \( \hat{\delta}_k \) is the estimated outputs of phase for \( k \)-th antenna element, and we take into account that (1) is invariant under translation of 360° of the phase factor \( \delta_k \). The averaged \( \delta_{\text{RMSE}} \) over all the test data is \( \delta_{\text{RMSE}} = 6.96^\circ \), which is comparable to the phase estimation accuracy of REV or MEP methods using 6-bit phase shifter [23], indicating sufficient estimation accuracy for practical use. The best value among the test data is \( \delta_{\text{RMSE}} = 0.616^\circ \), and the worst value is \( \delta_{\text{RMSE}} = 89.8^\circ \). The actual and predicted phase pattern and corresponding radiation patterns for the worst case, and for the case where \( \delta_{\text{RMSE}} \) has the closest value to the average obtained by the NN.

![Figure 2](image_url)  
Fig. 2. Actual and predicted phase patterns and corresponding radiation patterns for the worst case, and for the case where \( \delta_{\text{RMSE}} \) has the closest value to the average obtained by the NN.
Assuming that the phase of each element are uncorrelated and generated uniformly, they would be distributed in a grid pattern in a seven-dimensional hypercube at approximately \(360/(1250000)^{1/7} = 48.5^\circ\) intervals. Despite this sparsity of data set, \(\delta_{\text{RMSE}}\) in the test data can be kept below 9.2\(^\circ\) with a probability of 90\%. If we try to achieve a 10\(^\circ\) spacing in the phase space using simpler searching algorithms, we would require a data set with \(7.8 \times 10^{10}\) patterns.

### B. Experimental Data

To test the usefulness of our proposed model in actual antenna array calibration experiments, we use previously reported results [22] of uncalibrated radiation patterns of the eight-element linear array, which is the same antenna as the one assumed in this work. This experimental power pattern data is input to the NN model to confirm the estimation accuracy for the real measurement data. The obtained estimated phase pattern vector \(\delta_{\text{exp}}\) and the calculated radiation pattern, assuming the estimated phase as the initial excitation error, are presented in Fig. 3, along with the estimated phase vector \(\delta_{\text{REV}}\) and corresponding radiation pattern by REV obtained in the previous work and the uncalibrated radiation pattern measured in the experiment [22]. Although the true initial phase offset for the linear array cannot be identified in the experiment, we have confirmed that the phase offset estimated by REV is close enough to the true offset by showing excellent agreement between the calibrated radiation pattern and the ideal radiation pattern. This was done by calculating and comparing the offset estimated by MEP, which shows good agreement with the REV result. Thus, regarding the REV result as the true phase offset, the RMSE in the predicted phase is calculated to be \(\delta_{\text{RMSE}} = 11.1^\circ\). The experimental pattern contains amplitude imbalances of up to 1.4 dB [22], but the phase estimation nevertheless works as shown in Fig. 3. This indicates that even the NN model constructed without considering amplitude imbalance may be able to robustly handle the imbalance up to about 1.4 dB. This is because the phase imbalance makes a larger contribution to the radiation pattern than the amplitude imbalance.

### C. Recursive Calibration

It is shown that the trained NN can be used recursively until the estimation accuracy goes within the acceptable range as shown in Fig. 4. By inputting test radiation patterns [see Fig. 4(1)], the NN model outputs phase estimates \(\delta\) [see Fig. 4(2)]. For the test patterns, \(\delta_{\text{RMSE}}\) can be calculated using the residual phase error after calibration \(\delta'_k = \delta_k - \hat{\delta}_k\) [see Fig. 4(3)]. However, since neither \(\delta_k\) nor \(\delta'_k\) are known in the experiment and \(\delta_{\text{RMSE}}\) cannot be calculated. Therefore, we need a reference and index to evaluate the accuracy of phase estimation by the NN from experimental radiation patterns [see Fig. 4(4)]. As a reference, we propose the ideal radiation pattern obtained by setting \(\delta_k = 0^\circ\) in (1). Since the accuracy of the absolute value of experimental pattern is not always guaranteed, the difference should be quantified by comparing the shape of the remeasured pattern after calibration. For this purpose, we propose to use the correlation coefficient as a comparison index. Therefore, the degree of difference \(D_C\) for all test patterns is calculated [see Fig. 4(5)] as follows:

\[
D_C \equiv \frac{(1 - C)}{2} \quad (3)
\]

\[
C = \frac{\sum_{\theta=0}^{90} (P(\theta) - \bar{P}) (I(\theta) - \bar{I})}{\sqrt{\sum_{\theta=0}^{90} (P(\theta) - \bar{P})^2} \sqrt{\sum_{\theta=0}^{90} (I(\theta) - \bar{I})^2}} \quad (4)
\]

where \(P(\theta)\) is the pattern after phase calibration, \(I(\theta)\) is the ideal pattern, and \(\bar{P}\) and \(\bar{I}\) are the averaged values of calibrated and ideal patterns, respectively. \(D_C\) calculated for all test patterns is shown in Fig. 4(a), where a smaller value indicates greater similarity. We use this data to evaluate whether an estimation has failed, based on a threshold RMSE \(\delta_{\text{RMSE}}\). To achieve this, we introduce a polynomial fitting function

\[
f(x) = \sum_{i=1}^{n} C_i x^i \quad (5)
\]

chosen such that \(f(0) = 0\). The real coefficients \(C_i\) are determined by Lasso regression fitting with \(D_C\) data-points in Fig. 4(a). In this work, we set \(n = 6\) in (5), with the coefficients \(C_1 = C_2 = 0.0, C_3 = 1.098 \times 10^{-6}, C_4 = -2.004 \times 10^{-8}, C_5 = -8.264 \times 10^{-11}, C_6 = 2.838 \times 10^{-12}\). The resultant fitting curve \(f(\delta_{\text{RMSE}})\) is given by the solid orange line in Fig. 4(a).

As can be seen by broken black line and dot-dashed green line in Fig. 4(a), if the threshold \(\delta'_{\text{RMSE}}\) is set to 15\(^\circ\), the estimation is considered to be successful for the outputs satisfying \(D_C < f(\delta'_{\text{RMSE}})\) and unsuccessful for the outputs satisfying \(D_C \geq f(\delta'_{\text{RMSE}})\). For samples determined to be failed estimations, the radiation pattern with the residual phase error \(\delta'\) [see Fig. 4(7)] is reinput to the NN [see Fig. 4(8)]. Then, the NN estimates the residual error of the inputs and outputs the estimated value \(\delta''\) [see Fig. 4(9)]. This output value is subtracted from the original residual error \(\delta''_k = \delta'_k - \hat{\delta}'_k\) [see Fig. 4(10)]. By comparing the pattern formed by the second-order residual phase error \(\delta''_k\) with the ideal pattern [see Fig. 4(4)], \(D_C\) is evaluated again [see Fig. 4(5)]. If \(D_C < f(\delta''_{\text{RMSE}})\), the estimation is successful and the recursive application of the NN is completed, otherwise the process (7)(8)(9)(10)(4)(5)(6) is repeated until \(D_C < f(\delta''_{\text{RMSE}})\) is realized. As shown in Fig. 5, each time the estimation by the NN is repeated, the number of failure decreases, i.e., the estimation failure rate is suppressed. For \(\delta''_{\text{RMSE}} = 15^\circ\), it indicates that if the input to the NN is repeated four times, the data where \(D_C \geq f(\delta''_{\text{RMSE}})\) will be 1\% of the total.
IYE et al.: NEURAL NETWORK-BASED PHASE ESTIMATION FOR ANTENNA ARRAY USING RADIATION POWER PATTERN

Fig. 4. Schematic diagram of the NN architecture, along with (a) relationship between $D_C$ and $\delta_{\text{RMSE}}$, and the recursive calibration workflow.

Fig. 5. Suppression of estimation failure rate by recursive application of NN for each tolerance threshold setting.

Fig. 6. (Left panel) Real residual phase error $\delta_k'$ and the residual error predicted by the NN $\hat{\delta}_k'$ for each antenna index $k$. (Right panel) Radiation patterns calculated with the first-order residual error $\delta_k'$ (broken red line) and second-order residual error $\delta_k''$ (solid blue line), respectively, compared with the ideal pattern (dotted black line).

As a proof of concept, we perform a recursive calibration on the worst estimated result of $\hat{\delta}$ (lower panel of Fig. 2) in the test pattern is used for the recursive calibration, and the results are summarized in Fig. 6. With the residual error $\delta_k' = \delta_k - \hat{\delta}_k$ shown by the solid line in the left panel of Fig. 6, the radiation pattern is calculated and shown by the broken red line in the right panel of Fig. 6. When this pattern is input again to the NN, the estimation result $\hat{\delta}_k'$ is obtained as shown by the broken orange line in the left figure of Fig. 6. In this case, the RMSE decreases from $\delta_{\text{RMSE}} = 89.1^\circ$ to $\delta_{\text{RMSE}} = 5.37^\circ$. Also, the difference $D_C$ decreases from $4.62 \times 10^{-1}$ to $1.80 \times 10^{-4}$. The calculation result of the corrected pattern is shown as the solid blue line in the right panel of Fig. 6, and it can be seen that the phase calibration works well by comparing the calibrated pattern and the ideal pattern shown by the dotted black line. Therefore, the worst-case estimation result is corrected by a single recursive calibration cycle.

V. CONCLUSION

An NN-based phase estimation method for a linear antenna array was designed. The interelement excitation phase errors in the array are estimated via a trained NN, using radiation pattern measured by a power-only measurement as an input. To validate the proposed method, a radiation pattern measured in an anechoic chamber is input to the NN to estimate the initial phase errors, and it is confirmed that the estimation accuracy is comparable to the conventional methods using 6-bit phase shifter. Our method requires only single radiation pattern measurement before calibration, indicating that the method is significantly more time-saving, compared to other conventional calibration methods. Furthermore, we propose a method to suppress the failure rate of estimation by recursively reinputting patterns into the NN, and confirmed its effectiveness by comparing calibrated pattern and ideal pattern quantitatively. These results show that the proposed methods are useful for experimental phase calibration in a linear array.

ACKNOWLEDGMENT

The authors would like to thank S. Iwasaki from Kozo Keikaku Engineering Inc. and E. Sato from Toyohashi University of Technology for valuable discussions on NN modeling.
REFERENCES

[1] W. Roh et al., “Millimeter-wave beamforming as an enabling technology for 5G cellular communications: Theoretical feasibility and prototype results,” IEEE Commun. Mag., vol. 52, no. 2, pp. 106–113, Feb. 2014, doi: 10.1109/MCOM.2014.6736750.

[2] M. Khalily, R. Tafazolli, P. Xiao, and A. A. Kishk, “Broadband mm-wave microstrip array antenna with improved radiation characteristics for different 5G applications,” IEEE Trans. Antennas Propag., vol. 66, no. 9, pp. 4641–4647, Sep. 2018, doi: 10.1109/TAP.2018.2845451.

[3] T. Murakami et al., “Research project to realize various high-reliability communications in advanced 5G network,” in Proc. IEEE Wireless Commun. Netw. Conf., Seoul, South Korea, 2020, pp. 1–8, doi: 10.1109/WCNCC45663.2020.9120477.

[4] S. Han, C. I., Z. Xu, and C. Rowell, “Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G,” IEEE Commun. Mag., vol. 53, no. 1, pp. 186–194, Jan. 2015, doi: 10.1109/MCOM.2015.7010533.

[5] S. Mano and T. Katagi, “A method for measuring amplitude and phase of each radiating element of a phased array antenna,” Trans. Electron. Commun. Jpn., vol. J-65-B, pp. 555–560, 1982, doi: 10.1109/MCOM.2015.7010533.

[6] G. A. Hampson and A. B. Smolders, “A fast and accurate scheme for calibration of active phased-array antennas,” in Proc. IEEE Antennas Propag. Soc. Int. Symp. 1999 Dig. USNC/URSI Nat. Radio Sci. Meeting, 1999, vol. 2, pp. 1040–1043, doi: 10.1109/APS.1999.789490.

[7] R. Sorace, “Phased array calibration,” IEEE Trans. Antennas Propag., vol. 49, no. 4, pp. 517–525, Apr. 2001, doi: 10.1109/8.923310.

[8] R. Long, J. Ouyang, F. Yang, W. Han, and L. Zhou, “Fast amplitude-only measurement method for phased array calibration,” IEEE Trans. Antennas Propag., vol. 65, no. 4, pp. 1815–1822, Apr. 2017, doi: 10.1109/TAP.2016.2629467.

[9] G. He, X. Gao, and H. Zhou, “Fast phased array calibration by power-only measurements twice for each antenna element,” Int. J. Antennas Propag., vol. 2019, 2019, Art. no. 6432149, doi: 10.1155/2019/6432149.

[10] T. Takahashi, Y. Konishi, and I. Chiba, “A novel amplitude-only measurement method to determine element fields in phased arrays,” IEEE Trans. Antennas Propag., vol. 60, no. 7, pp. 3222–3230, Jul. 2012, doi: 10.1109/TAP.2012.2196961.

[11] C.-N. Hu, P. Lo, C.-P. Ho, and D.-C. Chang, “Automatic calibration using a modified genetic algorithm for millimeter-wave antenna modules in MIMO systems,” Int. J. Antennas Propag., vol. 2020, 2020, Art. no. 4286026, doi: 10.1155/2020/4286026.

[12] H. Steyskal, “On antenna power pattern synthesis,” IEEE Trans. Antennas Propag., vol. AP-18, no. 1, pp. 123–124, Jan. 1970.

[13] H. Schjaer-Jacobsen and K. Madsen, “Synthesis of nonuniformly spaced arrays using a general nonlinear minimax optimisation method,” IEEE Trans. Antennas Propag., vol. AP-24, no. 4, pp. 501–506, Jul. 1976.

[14] H. Steyskal, R. A. Shore, and R. L. Haupt, “Methods for null control and their effects on the radiation pattern,” IEEE Trans. Antennas Propag., vol. AP-34, no. 3, pp. 404–409, Mar. 1986.

[15] Z. He, Z. Hua, L. Hongmei, L. Beijia, and W. Qun, “Array antenna pattern synthesis method based on intelligent algorithm,” in Proc. IEEE Int. Conf. Electron. Inf. Commun. Technol., 2016, pp. 549–551, doi: 10.1109/ICEICT.2016.7879764.

[16] C. Zhang, P. Patras, and H. Haddadi, “Deep learning in mobile and wireless networking: A survey,” IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2224–2287, Jul.–Sep. 2019, doi: 10.1109/COMST.2019.2904897.

[17] J. H. Kim and S. W. Choi, “A deep learning-based approach for radiation pattern synthesis of an array antenna,” IEEE Access, vol. 8, pp. 226059–226063, 2020, doi: 10.1109/ACCESS.2020.3045464.

[18] R. Lovato and X. Gong, “Phased array antenna beamforming using convolutional neural networks,” in Proc. IEEE Int. Symp. Antennas Propag. USNC-URSI Radio Sci. Meeting, 2019, pp. 1247–1248, doi: 10.1109/URSI.2019.8888573.

[19] C. Shan, X. Chen, H. Yin, W. Wang, G. Wei, and Y. Zhang, “Diagnosis of calibration state for massive antenna array via deep learning,” IEEE Wireless Commun. Lett., vol. 8, no. 5, pp. 1431–1434, Oct. 2019.

[20] Z. Sarayloo, N. Masoumi, H. Shahi, E. H. Mirza Alian, S. S. Naeini, and M. N. Ahmadabadi, “A convolutional neural network approach for phased array calibration using power-only measurements,” in Proc. 28th Iranian Conf. Elect. Eng., 2020, pp. 1–6, doi: 10.1109/ICEE50131.2020.9260769.

[21] R. Mailoux, Phased Array Antenna Handbook, 3rd ed. Norwood, MA, USA: Artech House, 2017.

[22] T. Iye, K. Tsuda, and Y. Fujii, “An experimental study of 28 GHz analog beamforming with a uniform linear array,” in Proc. 25th Int. Conf. Adv. Commun. Technol., 2021, pp. 100–103, doi: 10.23919/ICACT51234.2021.9370840.

[23] T. Takahashi, “Statistical radiation pattern analysis and calibration technologies for phased array antennas,” IEICE Trans. B, vol. J100-B, no. 9, pp. 748–763, 2017, doi: 10.14923/transcomj.2017API0001.