IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 31 January 2025, accepted 16 February 2025, date of publication 20 February 2025, date of current version 28 February 2025.
Digital Object Identifier 10.1109/ACCESS.2025.3543847

RESEARCH ARTICLE

Prediction of Atmospheric Refractivity From Clutter Power Images Using a Convolutional Neural Network and a Trilinear Atmospheric Model

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This work was supported by Korea Research Institute for Defense Technology Planning and Advancement (KRIT) Grant funded by Korea Government [Defense Acquisition Program Administration (DAPA)] (Space Signal Intelligence Research Laboratory, 2022) under Grant KRIT-CT-22-021.

ABSTRACT In this paper, we propose a method for predicting atmospheric conditions from clutter power images using a convolutional neural network (CNN). The proposed refractivity from clutter (RFC) method employs a CNN model that utilizes clutter power images as input. These input data, generated by the Advanced Refractive Prediction System (AREPS) EM simulator, using four variables of a theoretical trilinear atmospheric model. The proposed RFC method outputs values for these four variables, which can be used to predict the current atmospheric conditions in a short time. This CNN model is trained on 50,000 data samples, with a training-to-validation data ratio of 4:1. Furthermore, as cross-validation, the trained CNN model is utilized to predict atmospheric conditions using actual data measured in Baengnyeongdo, and the findings show that increasing the number of data samples improves performance. These results demonstrate the capability of the proposed RFC method to predict various atmospheric conditions in real time.

INDEX TERMS Electromagnetic wave propagation, radar, deep learning, CNN, RFC, clutter power image.

I. INTRODUCTION

Long-range naval search radar systems are usually employed for early detection of distant targets, and there is growing interest in enhancing the detection capabilities of these radars [1], [2], [3]. In the maritime environment, the atmospheric refractivity, which is determined by temperature, humidity, and pressure, exhibits significant changes in time due to more active convection phenomena compared to over a land environment [4], [5], [6]. These changes in atmospheric refractivity lead to the refraction of electromagnetic wave propagation paths [7], [8]. Thus, electromagnetic waves radiated by naval long-range radar systems propagate along bent paths rather than straight lines in accordance with atmospheric conditions, which can cause substantial detection errors when identifying distant targets [9], [10]. Thus, it is important to observe the atmospheric refractivity in real time and provide correction values for detection errors to the radar systems. Generally, the atmospheric refractivity at different altitudes is measured using radiosonde equipment, but this measurement is limited to specific locations and carried out only 2−4 times a day [11], [12], [13]. Thus, it is difficult to observe the atmospheric refractivity in real time. To resolve this issue, methods for estimating refractivity from the clutter spectra gathered by the radar systems have been reported. These estimation methods use various optimization algorithms, such as a genetic algorithm, a particle swarm optimization algorithm, and a pattern search algorithm [14], [15], [16]. However, these methods are not suitable for naval applications that require real-time operation, because they spend a lot of time predicting atmospheric conditions. Recently, studies have also been conducted on

The associate editor coordinating the review of this manuscript and approving it for publication was Pavlos I. Lazaridis.

predicting atmospheric conditions according to predefined classifications by applying deep learning to collected clutter power spectra [17], [18]. However, these studies have only focused on predicting the duct conditions in real time, so it is difficult to accurately predict the various types of atmospheric conditions, such as normal, super, sub, and duct [19], [20], [21]. Therefore, a study is needed on a refractivity from clutter (RFC) method that can accurately predict the atmospheric refractive index value according to altitude, rather than predicting atmospheric conditions only based on predetermined classifications.

In this paper, we propose the method for predicting atmospheric refractive index values according to altitude using the clutter spectra collected in real time. To accurately predict refractive index, the deep learning with convolutional neural networks (CNN) is applied to the proposed RFC method. The CNN extracts features from images to train and is known to be highly effective and accurate in recognizing images [22]. Therefore, the proposed RFC method with the CNN can effectively estimate refractive index values according to the altitude from clutter spectrum images. However, the proposed method in conjunction with the CNN requires as much clutter spectra data as possible under various atmospheric conditions for training [23]. Such clutter power spectra can be obtained not only through measurements but also using theoretical methods. In this study, each input dataset for the proposed method is determined by combining the theoretical clutter power image and the atmospheric refractivity index values for each case. To represent as many different atmospheric states as possible, a trilinear atmospheric refractivity model is used [24]. The four variables of this trilinear model are randomly changed in a uniform distribution to arbitrarily generate 50,000 data samples, and another data sample using four variables that follow a Gaussian distribution is generated to compare the estimation performance of the CNN model according to the bias of the data. These trilinear atmospheric models are then used for the Advanced Refractive Prediction System (AREPS) to create the theoretical clutter power spectra [25]. The graphs of clutter power spectra corresponding to the 50,000 data samples stored as 256×256-pixel images, are used for training and input in the deep learning. This dataset size is based on previous research [26], which indicates that larger datasets lead to more accurate prediction. The deep learning model for predicting atmospheric conditions uses the CNN, and four variables of the trilinear model corresponding to each clutter power spectrum image are used for training. The trained CNN model takes only the clutter power images as input and outputs the four variables of the trilinear atmospheric model. To analyze the impact of the dataset size on the performance of the proposed RFC model, training is conducted according to the total dataset size, and the same CNN model is applied each time. The ratio of training data to validation data is 4:1. In the cross-validation process, to enhance the realism of the clutter power spectra, actual atmospheric refractivity data collected at Baengnyeongdo meteorological observatory are utilized. The trained CNN model predicts atmospheric conditions from clutter power spectrum images in a short time, and we found that the root mean square error (RMSE) decreases as the dataset size increases. These results demonstrate that the proposed RFC method can be applied to radar systems to predict various atmospheric conditions such as normal, sub, super, and duct in real time.

II. GENERATION OF CLUTTER POWER IMAGES

Figure 1 illustrates the propagation characteristics according to the atmospheric condition and proposed RFC method. The proposed RFC method uses deep leaning with a CNN to predict atmospheric refractivity values in real time within a maritime environment. As shown in Figure 1(a), the shipborne radar radiates electromagnetic waves parallel to the ground at an elevation angle of 0°, and the operating frequency is 2.84 GHz [27]. Herein, the path of electromagnetic waves emitted from a shipborne radar are refracted according to the atmospheric refractivity, and this refractivity N can be calculated as follows [28]:

$$N = \left(77.6 \times \frac{P}{T} + 72 \times \frac{e}{T} + 3.75 \times 10^5 \times \frac{e}{T^2}\right) \quad (1)$$

$$M(z) = N(z) + 157 \times z \quad (2)$$

where N represents the refractivity, which is calculated using the atmospheric pressure P, absolute temperature T (in Kelvins), and vapor pressure of water e. The modified refractive index M can be obtained from the refractive index N, and M takes into account the curvature of the Earth at altitude z. The atmospheric conditions are classified based on a slope of the modified refractivity in terms of the altitude. The normal atmospheric state corresponds to the slope of modified refractivity of $78 \leq dM/dz \leq 157$. A specific clutter power spectra may be observed depending on characteristics of the radar system. When the slope is greater than this normal atmospheric state, it is called a sub condition ($dM/dz > 157$). In this case, electromagnetic waves of the radar propagate in the opposite direction to the ground, reducing the clutter power spectra. On the other hand, super ($0 \leq dM/dz < 78$) and duct ($dM/dz < 0$) conditions are states in which the slope is lower than the normal atmospheric state, resulting in higher clutter power spectra [29]. These correlations allow us to determine the current atmospheric refractive index from the clutter power spectra. Thus, the proposed RFC method for predicting such conditions can be summarized in the three-step procedure shown in Figure 1(b). In the first step of the RFC method, clutter power spectrum images are used as input data. After the data are entered, the CNN determines the atmospheric refractive index value corresponding to the input clutter power image. The CNN is trained on 50,000 data samples of the clutter power images and the atmospheric refractive index values for each case. Finally, the CNN outputs predictions in the form of a trilinear atmospheric refractive index model. The details of this procedure are explained in Chapter 3.

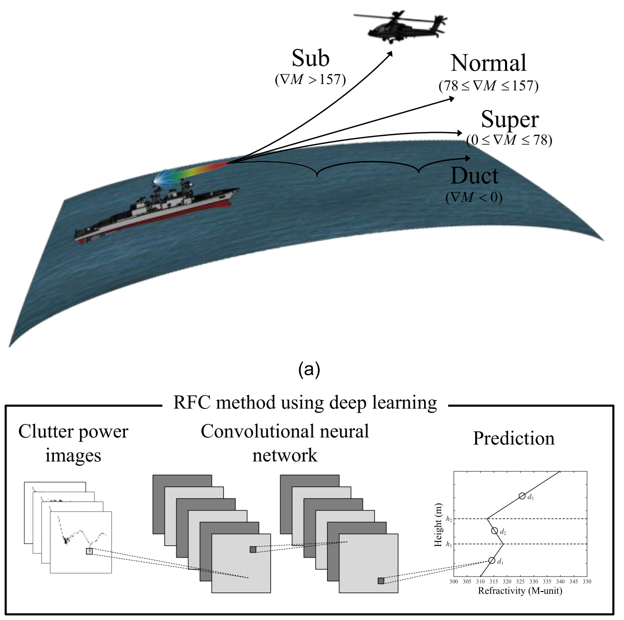


FIGURE 1. RFC method for radar system using deep learning. (a) propagation path of the radar system according to atmospheric conditions. (b) CNN-based RFC method.

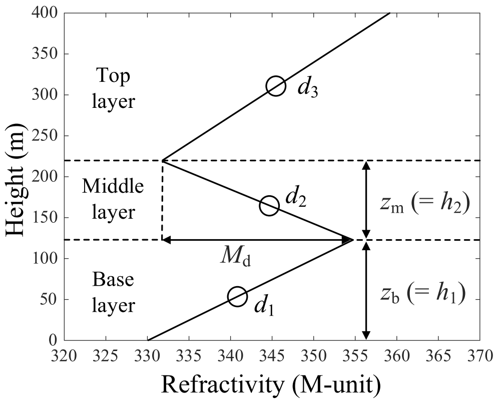


FIGURE 2. Trilinear model representing atmospheric conditions.

TABLE 1. Detailed values of the trilinear atmospheric model for the four atmospheric conditions.

condition	d_1 [M-unit/km]	d_2 [M-unit/km]	d_3 [M-unit/km]	h_1 [m]	h_2 [m]
sub	200	200	117	200	400
normal	120	120	117	200	400
super	30	30	117	200	400
duct	–200	120	117	200	400

Figure 2 presents the trilinear atmospheric model, which is a simple model capable of expressing the four atmospheric conditions (normal, sub, super, and duct). This model can be

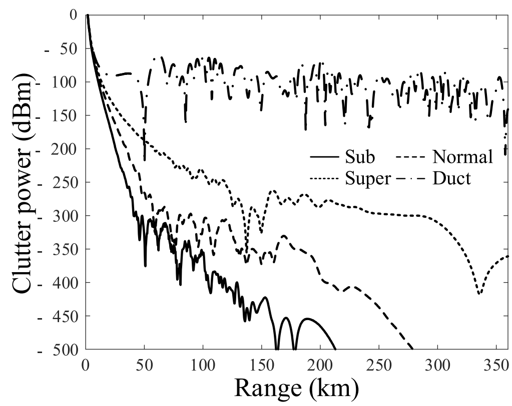


FIGURE 3. Clutter power spectra according to atmospheric conditions.

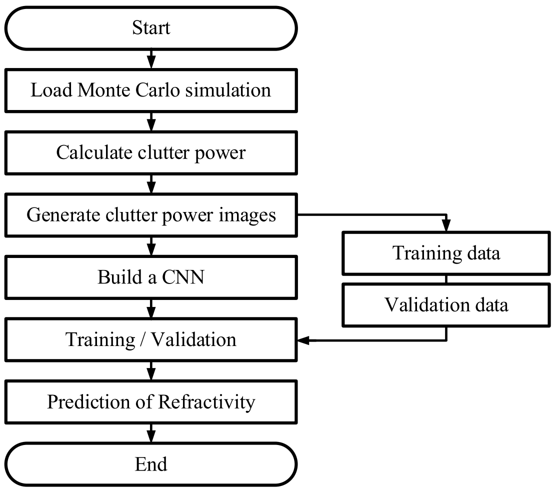


FIGURE 4. CNN model process for predicting atmospheric refractivity.

expressed as follows [25]:

$$M(z) = M(0) + \begin{cases} c_1 z & z \leq z_b \\ c_1 z_b - M_d \dfrac{z - z_b}{z_m} & z_b < z < z_m \\ c_1 z_b - M_d + c_2 (z - z_b - z_m) & z \geq z_m \end{cases} \tag{3}$$

where the value of $M(0)$ represents the modified refractivity recorded at 0 m (sea level) and is typically set to 330 M-unit [14], and the variable $z$represents the altitude relative to the sea level. z_b and z_m denote the thickness of the base layer and the middle layer, respectively. c_1 and c_2 indicate the slopes of the base layer and the top layer, with M_d representing the duct strength. Since the propagation paths of electromagnetic waves radiated from naval radar systems are primarily influenced by the atmospheric refractivity close to the sea surface, this study focuses on predicting the refractivity in low-altitude areas. The slope d_3 (c_2) of the top layer, which represents high-altitude regions, is fixed at the standard atmospheric value of 117 M-unit/km, because the clutter data is mainly affected by a low-altitude atmospheric refraction [30]. Therefore, the four variables that need to be randomly generated in the trilinear atmospheric model are the thickness h_1 (z_b) and slope d_1 (c_1) of the base layer, and the thickness h_2 (z_m) and slope d_2 (M_d/z_m) of the middle layer. The slope and thickness values are randomly generated with a uniform distribution in the ranges of 0 m to 300 m and −200 M-unit/km to 200 M-unit/km, respectively.

Figure 3 shows the clutter power spectra for the four atmospheric conditions. In the proposed RFC process, the clutter power spectra can be obtained not only through measurement using naval radar systems but also using theoretical methods. To theoretically generate a clutter power spectrum, the propagation factor (PF) is calculated with the AREPS EM propagation simulator using the trilinear atmospheric model. The clutter power spectrum can then be obtained from the PF using the following equation [6]:

$$P_c = \frac{P_t G^2 \lambda^2 A \sigma_0}{(4\pi)^3 r^4} F^4 \tag{4}$$

$$A = \frac{r\theta_{bw} c\tau}{2} \tag{5}$$

$$F = \frac{E_r}{E_0} \tag{6}$$

where P_t represents the peak transmitted power, and G is the radar antenna's gain. The wavelength is denoted by λ, and r is the distance from the radar. A refers to the area of the sea surface illuminated by the radar pulse, and σ_0 is the normalized radar cross-section of the sea surface. In addition, θ_{bw} is the azimuth beamwidth of the antenna, c is the speed of light, and τ is the pulse width of the radar. The PF (F) is defined as the ratio of the electric field strength under the specific condition (E_r) to the free-space electric field strength (E_0). In Figure 3, the solid and dashed lines denote the clutter spectra for the sub and normal conditions, respectively, while the dotted and dash-dotted lines indicate the clutter spectra for the super and duct conditions. The detailed values for these four conditions are presented in Table 1. The radar system used in this study is assumed to be a high-power 1 MW S-band naval radar system, which can detect targets up to 360 km away. This radar antenna is mounted at a height of 30 m and operates at a frequency of 2.84 GHz [30]. As shown in Figure 3, the clutter power spectra increase from sub to normal, super, and duct conditions in that order. The strongest clutter power occurs under the duct condition, where the refraction effect is most significant.

TABLE 2. CNN architecture in the proposed RFC method.

Layer number	Layer type	Characteristics
1	image input	size: 256×256×1
2	convolution	size/filter: 5×5/32, padding: same, L2 regularization weight/bias: 0.01/0.001
3	batch normalization	-
4	relu	-
5	maxpooling	size: 2×2, stride: 2
6	dropout	rate: 0.1
7	convolution	size/filter: 5×5/32, padding: same, L2 regularization weight/bias: 0.01/0.001
8	batchnormalization	-
9	relu	-
10	max pooling	size: 2×2, stride: 2
11	dropout	rate: 0.1
12	convolution	size/filter: 5×5/32, padding: same, L2 regularization weight/bias: 0.01/0.001
13	batch normalization	-
14	relu	-
15	max pooling	size: 2×2, stride: 2
16	dropout	rate: 0.1
17	convolution	size/filter: 3×3/32, padding: same, L2 regularization weight/bias: 0.01/0.001
18	batch normalization	-
19	relu	-
20	max pooling	size: 2×2, stride: 2
21	dropout	rate: 0.1
22	convolution	size/filter: 3×3/32, padding: same, L2 regularization weight/bias: 0.01/0.001
23	batch normalization	-
24	softmax	-
25	fully connected	size: 4
26	regression	-

III. ESTIMATION OF ATMOSPHERIC REFRACTIVITY USING THE CNN

Figure 4 provides a detailed flowchart of the proposed RFC method using the CNN. To estimate the atmospheric refractivity, this proposed RFC method is performed through the following process: first, the trilinear atmospheric models are used to generate the clutter power spectrum dataset using the AREPS EM simulator. Herein, four variables of the trilinear model (d_1, d_2, h_1, and h_2) are randomly generated with a uniform distribution for the Monte Carlo simulation. The obtained clutter spectra are then stored in the form of images. In these clutter images, the spectrum is expressed as a solid black line on a white background, and 50,000 image samples according to arbitrary refractivity models are prepared in advance for training and validation purposes. Once the training is completed, the CNN model uses only clutter power

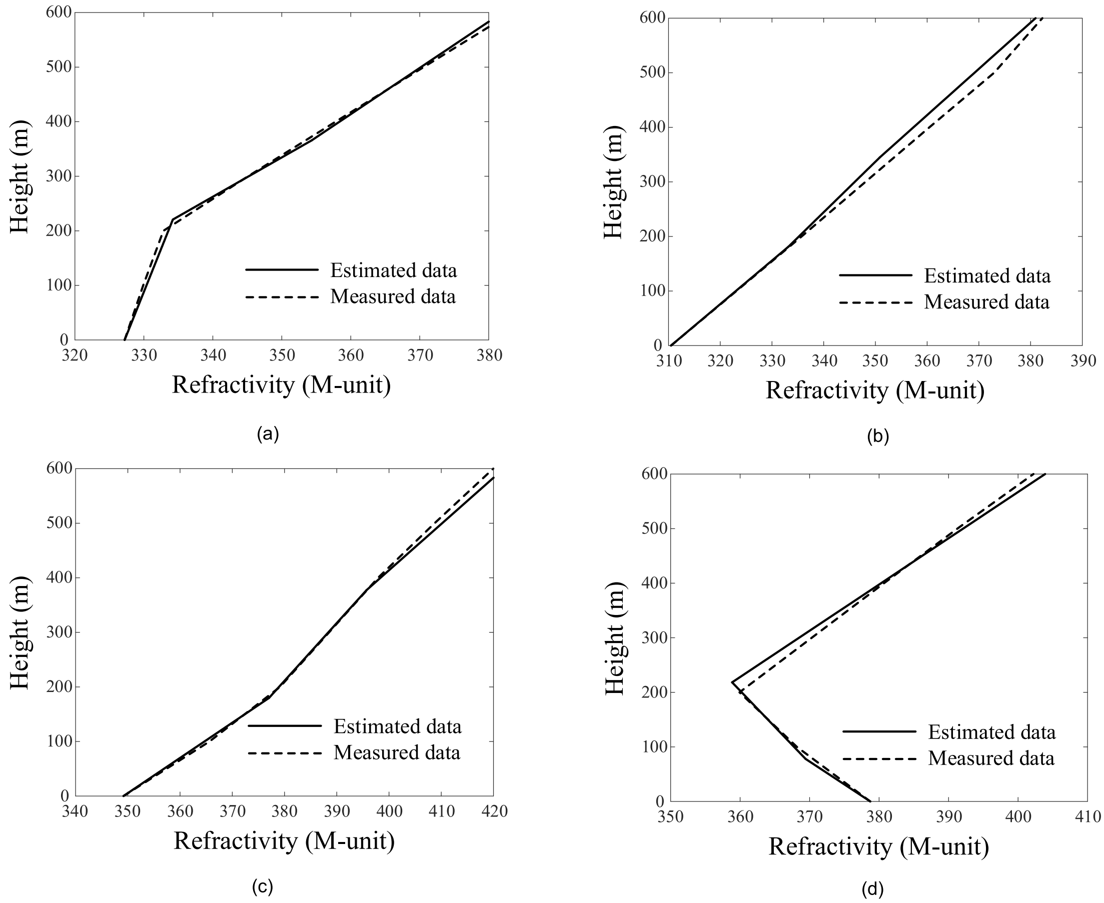


FIGURE 5. RFC results using the real atmospheric refractivity data. (a) February 16, 2022, (b) January 23, 2022, (c) September 5, 2022, (d) October 8, 2022.

TABLE 3. RMSE values of four cases according to dataset size.

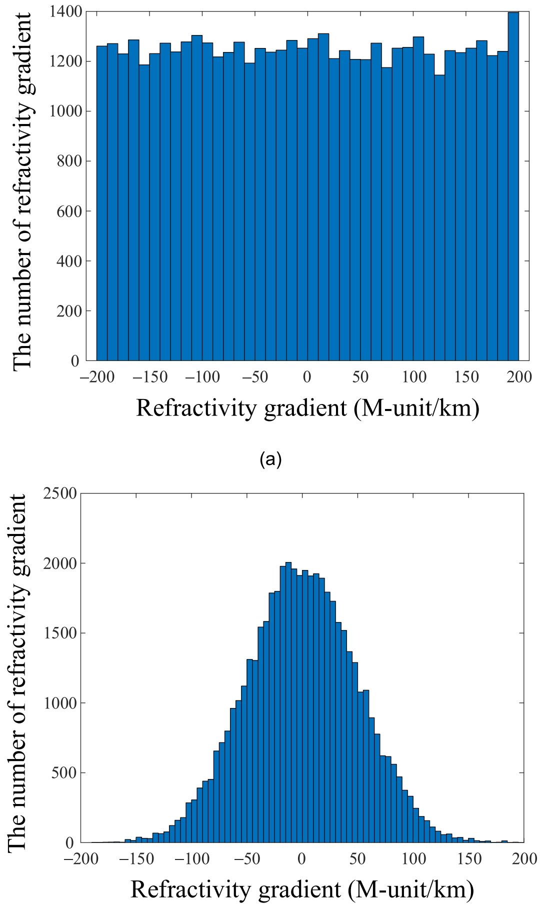
Number of data samples	RMSE of (a) [M-unit]	RMSE of (b) [M-unit]	RMSE of (c) [M-unit]	RMSE of (d) [M-unit]
5,000	5.75	10.24	13.11	8.09
10,000	7.12	5.35	7.27	5.80
30,000	2.75	3.20	3.80	2.52
50,000	0.74	2.24	1.11	1.10

TABLE 4. Error analysis based on the distribution of data samples.

Number of data samples	Average M-unit RMSEs using a uniform distribution	Average M-unit RMSEs using a Gaussian distribution
5,000	18.66	24.02
10,000	16.74	22.36
30,000	15.48	19.12
50,000	14.15	19.60

images as the input, and it outputs the four variables of the trilinear atmospheric model d_1, d_2, h_1, and h_2 to predict the atmospheric conditions.

Table 2 represents the 26-layer CNN architecture used in the proposed RFC method and illustrates how the input clutter power images is processed through each layer to achieve accurate predictions of atmospheric refractivity. This architecture is implemented in a MATLAB environment [27] using an Intel Core i5-12500 CPU and an NVIDIA GTX 1650 GPU. The input image is expressed as range (km) on the horizontal axis and as the clutter power (dBm) on the vertical axis. This image data is represented as $256 \times 256 \times 1$ pixels, where 256×256 represents the image size, and '1' indicates that the image is grayscale. This image format is then used for training the CNN. The first layer of the architecture processes $256 \times 256 \times 1$-pixel images as input and is connected to a convolutional layer with a size of 5×5. This convolutional layer uses 32 filters to enable the model to learn various features from the input images. To maintain the input and output dimensions of the convolutional layer, "same" padding is applied. Furthermore, to prevent overfitting, L2 regularization is applied to the weights and biases. The weight and bias L2 factors set at 0.01 and 0.001, respectively. A batch normalization layer follows each convolutional layer to enhance stability during training, and a ReLU activation function adopts nonlinearity characteristics. To reduce the computational load, a max pooling layer with a size of 2×2 and a stride of 2 is used, and to further prevent



(a)

(b)

FIGURE 6. Histogram of the atmospheric refractivity of the training data. (a) Uniform distribution (proposed), (b) Gaussian distribution.

overfitting, a dropout layer with a ratio of 0.1 is included. The last two of the five convolutional layers are downsized to a size of 3 × 3 to capture localized features. This adjustment improves the performance of the model in identifying small and detailed patterns in the clutter power images, which is important for accurately estimating the four variables (d_1, d_2, h_1, and h_2). The architecture culminates with a softmax layer, used for multiclass classification tasks, followed by a fully connected layer corresponding to the four variables to be predicted. Finally, a regression layer calculates the error, and the output is defined as a 4 × 1 array, where each element corresponds to one of the four variables in the tri-linear refractivity model (d_1, d_2, h_1, and h_2). From the four variables, we can estimate the atmospheric refractivity based on the altitude. By means of this procedure, the proposed RFC method can predict all four atmospheric conditions: normal, sub, super, and duct.

Figure 5 presents the predicted refractivity results from the clutter power images according to the given atmospheric refractivity data by measurement. These data are recorded at the meteorological observatory in Baengnyeongdo in 2022 [31], and this observatory is equipped with radiosonde systems capable of monitoring atmospheric conditions up to an altitude of over 30 km. The observed data include measurements of pressure, temperature, and humidity, which are used for calculating atmospheric refractivity. The atmospheric refractive indices in Figures 5(a) to 5(d) were measured on February 16, January 23, September 5, and October 8, 2022, respectively. The RMSE values of estimations made using the proposed RFC method for each case are summarized in Table 3. When training with 50,000 data samples, the trained CNN takes 2.7 milliseconds to predict four variables of the trilinear atmospheric refractivity model from a single clutter power image. In addition, the RMSEs are 0.74, 2.24, 1.11, and 1.10 M-unit, respectively. This result demonstrates that the proposed RFC method can estimate the atmospheric refractivity with low error in real time.

Figure 6 illustrates the distribution of the atmospheric refractive index data used for training. As we mentioned in Figure 4, the proposed RFC model was trained using data generated from a trilinear atmospheric refractivity model in which all four variables have uniform distributions. Therefore, the average gradient of the refractivity is also uniform, as shown in Figure 6(a). To compare the estimation performance according to the bias of the data samples, we also built a CNN model trained on data with non-uniform characteristics, where the average atmospheric refractive index of the training data follows a Gaussian distribution, as shown in Figure 6(b).

Table 4 provides the average RMSEs according to the amount of training data used. At this time, 800 samples (measured on Baengnyeongdo in 2022) are repeatedly tested to validate the performance of estimation, and average RMSEs are listed. When using 5,000 uniform data samples for training, the average RMSE for 800 measured data samples is 18.66 M-unit. On the other hand, when the data samples are increased to 50,000 for training, the average RMSE decreases to 14.15 M-unit. In addition, under the same condition, when using 50,000 Gaussian distributed data samples for training, the average RMSE is 19.60 M-unit.

IV. CONCLUSION

In this paper, we investigated the RFC method that estimates the atmospheric refractivity from clutter power spectrum images. The proposed RFC method used a CNN model that utilizes clutter power images as input, and the CNN was trained on 50,000 data samples. The outputs were given as four variables of a trilinear atmospheric refractivity model. For the four dates in 2022, the proposed RFC method estimated the atmospheric refractivity with RMSEs of 0.74, 2.24, 1.11, and 1.10 M-unit, respectively. In addition, when the number of data samples increased from 5,000 to 50,000, the average RMSE decreased to 14.15 M-unit. These results demonstrated that the proposed RFC method can estimate current atmospheric conditions using the clutter power spectrum in real time. These results can be applied in various long-distance communication fields such as the satellite broadcast, global positioning system (GPS), and AM/FM broadcast.

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