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RCS Estimation using LSTM at High Frequency

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고주파에서 LSTM을 사용한 RCS 추정

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Abstract RCS measurements are a helpful factor in the design of communication systems, antenna systems, and aircraft, where scattering and reflection of electromagnetic waves are essential. High-frequency RCS measurement time and expenses are relatively high in large objects, such as aircraft and ships. This paper introduces an AI model to solve the above problems and increase the RCS measurement efficiency. Among AI models, Long Short Term Memory (LSTM) has the advantage of solving the long-term dependence problem. Therefore, a method of LSTM and a parallel LSTM model are proposed to increase the accuracy further and reduce time in the model of LSTM. RCS was measured using a computer simulation CST, and low-frequency band data among CST-measured data was learned using Matlab. The RCS of the high-frequency band was estimated using LSTM and the parallel LSTM model. The estimated value of the LSTM model and the value measured by CST were compared with the estimated value of the parallel LSTM model. The high accuracy was confirmed through the results within the error value of the allowable range. In addition, the time was reduced significantly using LSTM and parallel LSTM than with CST.

요 약 RCS 측정은 전자파의 산란과 반사가 필수적인 통신 시스템, 안테나 시스템, 항공기 설계에 도움이 되는 요소이다. 항공기나 선박 등 대형 물체에서 고주파 RCS 데이터를 얻기위해서는 측정 시간과 비용이 많이 들게된다. 이에 본 논문에서는 위와 같은 문제를 해소하고, RCS 측정 효율을 높이기 위하여 AI모델을 도입한다. AI 모델 중 Long Short Term Memory(LSTM)은 장기의존성 문제를 해결하는 장점을 가진다. 따라서 LSTM의 방법을 제안하며, LSTM의 모델에서 정확도를 더 높이고 시간을 단축하고자 병렬 LSTM모델을 제안한다. 컴퓨터 시뮬레이션 CST를 이용하여 RCS를 측정하고, Matlab을 사용하여 CST로 측정된 데이터 중 저주파대역을 데이터를 학습한 후, 고주파대역의 RCS를 LSTM와 병렬 LSTM 모델을 이용하여 추정하였다. 이후 LSTM 모델과 병렬 LSTM 모델의 추정값과 CST로 측정한 값을 비교하여, 허용 범위의 오차 값 이내의 결과를 통해 높은 정확도를 확인하였다. 결과는 CST로 측정하였을 때보다 LSTM과 병렬 LSTM을 사용하였을 때 시간이 크게 단축되었음을 보여주었다.

Keywords : Radar Cross Section, Long Short Term Memory, Deep Learning, Estimation, Parallel LSTM

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1. Introduction

Radar detection, tracking, and missile guidance for military purposes are essential objectives in modern warfare. One of the crucial factors is that the developed aircraft are not to be captured by enemy radar; this is because easily spotted ships, missiles, and aircraft are quickly destroyed before completing their missions. The Radar Cross Section (RCS) is a reference measure of how large an object appears on a radar signal. The RCS uses square meters (m^2) and calculates the RCS value of the object to be actually measured based on the size of the reflected wave when electromagnetic waves are emitted onto a fully reflected metal sphere with a front projection cross-sectional area of 1 . Since RCS can be reduced by applying radio wave absorption materials to aircraft when designing aircraft, RCS is a significant design variable in all industries such as communication systems, electromagnetic waves or antenna systems, aircraft, shipbuilding, etc. At this time, scattering and reflection of electromagnetic waves are the main factors [1,2].

Methods for measuring RCS include actual measurement methods and electromagnetic simulation calculation methods. The measurement method is significant for making an actual-scale model of an aircraft or ship. It is challenging to build in an anechoic chamber and perform RCS measurements. Therefore, the method used to conduct research in high frequency is a computer simulation and belongs to the indirect calculation method [3,4].

Computer simulations can be used to model objects and measure RCS using Maxwell's four equations. The RCS measurement mainly uses the MOM (Method of Moment) method. However, the MOM method models the structure by dividing the wavelength into several regions, so the system is constant. Still, as the frequency increases, the wavelength decreases, and the unknown index increases exponentially. The main frequency band, X-band, is used in aerial radar. The primary frequency of the X-band is in the 10 GHz band, which is very difficult to measure the aircraft's RCS with commercial software and current computing technologies. If it takes more than 10 hours at 1 GHz to calculate the RCS of a life-size aircraft, we can see that it is not easy to measure the RCS of a large aircraft in a high-frequency band such as 10 GHz [3,5].

In addition, expensive equipment is required for actual RCS measurement at high frequencies compared to low frequencies, which is expensive. Therefore, predicting unmeasured data based on previously measured RCS data is beneficial [4].

Various research has been undertaken to forecast given known RCS data using the Cauchy approach. However, when measured using the Cauchy technique, the inaccuracy increases as the expected frequency increases. In addition, it can be seen that it takes less time than the method of measuring RCS using the indirect method but takes at least a few seconds [6]. When the LSTM model is used, the data may be predicted by finding the rule after converting it into sequence data. Thus, it can be confirmed that unmeasured data can be effectively estimated even if all data are not measured and only measured data are present [7-10]. Therefore, in this paper, we propose a method of further reducing time while increasing accuracy by reducing errors. To solve the problem of increasing error of prediction data and taking a long time to estimate, we propose to estimate the RCS of the high-frequency band using the LSTM method. In addition, we offer a parallel LSTM model using LSTM structural rules to increase accuracy and reduce time. This paper explains the methodology in Section 2, the experiments and discussions in Section 3, the experimental results in Section 4, and the conclusions in Section 5.

2. Long Short Term Memory

LSTM is a type of artificial intelligence that addresses the issue of long-term dependence, a weakness of RNN. Long-term dependence is a problem because the more input data there is, the less past information stored in the hidden layer is delivered to the final layer. The key feature of the LSTM is that preliminary step information is stored in a memory cell before being passed on to the next step. In other words, LSTM uses the information in the present vision to calculate how much it will forget or recall the past, then adds the current information to the result and transfers it to the next time point. The LSTM does this by storing memory cell information and sending it to the next stage via forget gates, input gates, output gates, and other components. The construction of the LSTM is shown in Fig. 1.

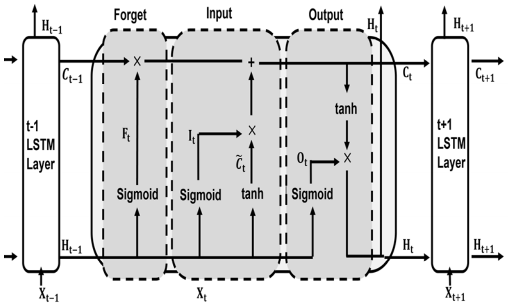

Fig. 1. Represents the LSTM structure

First, among the LSTM structures, the forget gate is a gate that decides how much previous information to forget or remember by applying the sigmoid function after multiplying the current input X_t and the past hidden layer value H_{t-1} by each weight W_f, U_f. Because the sigmoid function has a value between 0 and 1, a calculated value near 1 indicates that a lot of historical knowledge is utilized. In contrast, a calculated value close to 0 indicates that much historical information is lost. As a result, F_t may be described using the following equation.

$$F_t = sigmoid(U_f + W_f H_{(b-1)} + b_f) \tag{1}$$

The input gate is the second component, which multiplies the current time data by the previously hidden layer value multiplied by each weight and then applies the sigmoid function to the extra result to choose which information to update. Furthermore, the current time data and the previously hidden layer value are multiplied by each weight, and the tanh function is employed to generate new information at present. In other words, it is recorded in the cell based on the importance of the information at the time. This process may be described using the equation below.

$$\widetilde{C} = \tanh(U_c X_t + W_c H_{t-1} + b_c)$$

$$I_t = sigmoid(U_{in} X_t + W_{in} H_{t-1} + b_f) \tag{2}$$

The cell state is a phase in the memory cell storage process that uses the forget gate output value and the input gate output value. In other words, the memory cell value at the current moment is determined by forgetting (or remembering) as much past information as calculated in the forget gate and multiplying the information value at the current point by the significance of the input gate. The following equation can be used to compute the current memory cell state.

$$C_t = F_t C_{t-1} + I_t \widetilde{C}_t \tag{3}$$

Finally, the output gate is a step that specifies how much of the current memory cell state values are affected by the forget gate, and the input gate will be deleted and transmitted to the next layer. The equation characterizing the LSTM output value at the time is as follows: the multiplication mark signifies a pointwise operation.

$$H_t = O_t * \tanh(C_t),$$
$$O_t = sigmoid(U_o X_t + W_o H_{t-1} + b_o) \quad (4)$$

In other words, LSTM is a layer in a deep learning system. As a result, the corresponding layer has weights and biases. It can be observed that the weights and biases in the LSTM layer, together with the weights and biases in the output layer, are parameters that should be adjusted through learning. The LSTM structure may be used to estimate the next value.

3. SIMULATION AND DISCUSSIONS

The following are the specs of the PC used for simulation: The CPU is an i7-11700, the RAM is 32GB, and an GPU is RTX2060. The RCS measurement simulation software is CST Studio Suite 2021. A 3D model was created and approximated on a PC using the MOM technique in a simulation application. As simulation settings, MONO-static and smaller objects were used. CST Studio Suite 2021 is proposed since the model used in the simulation is several centimeters in size, and RCS must be measured in all directions.

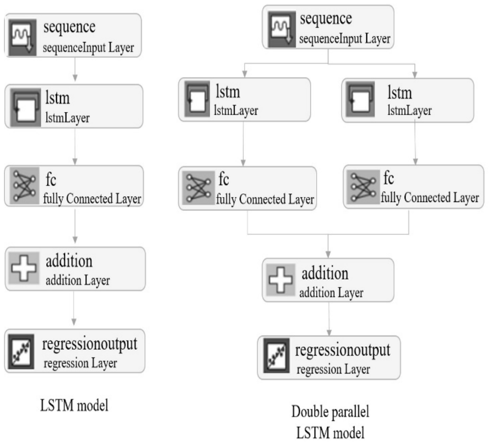

Fig. 2. Block diagram of the LSTM model and the proposed LSTM model

Based on the data obtained through CST, 70% of the data was learned, and the remaining 30% was estimated. At this time, there are two models used to teach. One used the LSTM model, and the other used parallel LSTM to obtain a more accurate estimation response. Next, Fig. 2 shows the model used for data learning and estimation as a diagram block.

3.1 Sphere

First, to demonstrate the validity of the proposed method, we used an LSTM model to measure the RCS data of a sphere with a radius of 0.1M in a band of 1GHz-10GHz at 10MHz intervals. Fig. 3 is a spherical model with a radius of 0.1 meters measuring RCS data.

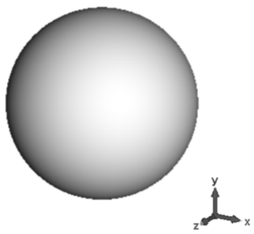

Fig. 3. Represents the spherical model with a radius of 0.1meter

The LSTM model translates sequence data into sequence data via learning to identify rules and estimate prediction data. Only 0.1 GHz - 6 GHz of data was learned using the LSTM model from the observed data, and then 6 GHz-10 GHz of data was approximated. The elapsed time was 157 seconds, and Epoch was trained at 500. Fig. 4 depicts a comparison graph between the RCS measurement and the anticipated value of the 0.1-meter-radius spherical model.

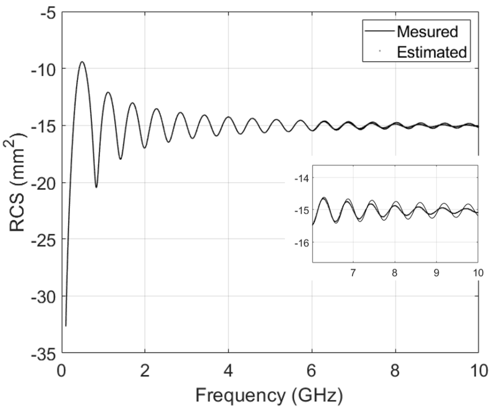

Fig. 4. Comparison graph between RCS measured and estimated values of a radius 0.1-meter sphere

The difference between the measured and estimated values is graphed, and the error is calculated using RMSE.

$$RMSE(\theta_1,\theta_2) = \sqrt{MSE(\theta_1,\theta_2)} = \sqrt{E(\theta_1,\theta_2)^2}$$
$$= \sqrt{\frac{\sum_{i=1}^{n}(x_{1,i}-x_{2,i})^2}{n}} \quad (5)$$

The error value was calculated and revealed that the RMSE value of 0.082979 was nearly identical to the observed value. Fig. 5 shows the value obtained by comparing the RCS measured value, the sphere's estimated value, and the RMSE value.

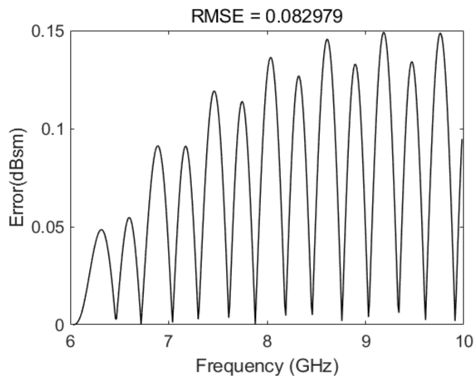

Fig. 5. Represent the estimated error between the mesured and estimated value of sphere.

3.2 Bomber

Next, the model used to measure RCS data in this paper is shown in Fig. 6. This model is B-1B and measures 40.96mm*42.75mm*6.18mm.

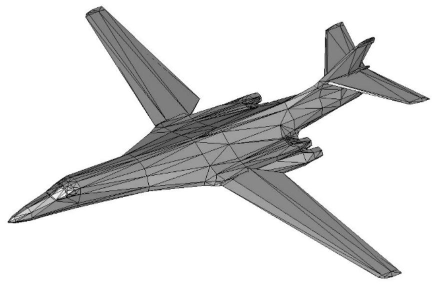

Fig. 6. Represents the aircraft model B-1B with the dimensions 40.96mm*42.75mm*6.18mm

To estimate the RCS data, data of 1.55 GHz to 14 GHz were measured at 50 MHz intervals to obtain about 620 data. A simple LPF (4th degree Butterworth filter with cutoff frequency = 0.07) was used for data stabilization. Based on this data, 70% of the learning data and the remaining 30% were estimated using the LSTM model. In each model used in learning, the epoch was trained at 500.

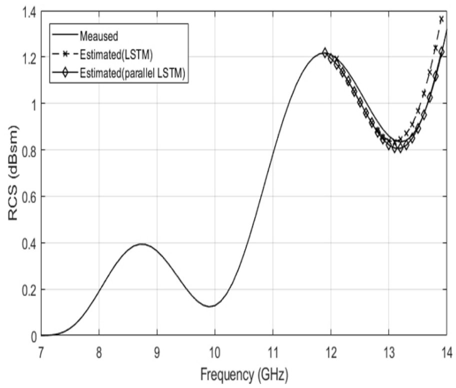

Fig. 7. Represent the comparison graph between RCS measured and estimated values of a B-1B at 45°.

Fig. 7 is a graph showing the results of estimating the response of the RCS of 12 GHz to 14 GHz by learning 7 GHz to 12 GHz using RCS data of 7 GHz to 14 GHz at an angle of 45°. In this graph, the solid line represents RCS data from 7GHz to 14GHz, the graph represented by x represents RCS estimation data from 12GHz to 14GHz using the LSTM model, and the diamond graph represents RCS estimation data from 12GHz to 14GHz using the parallel LSTM model.

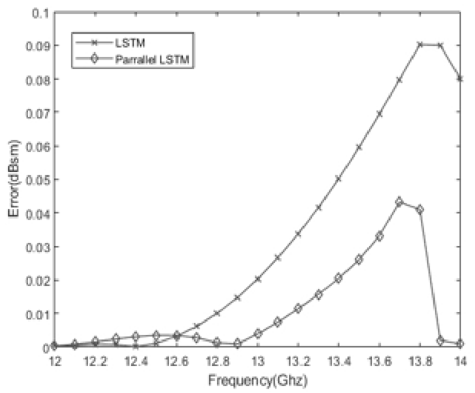

Fig. 8. Represents the estimated error between the mesered and the estimated value using LSTM and parrallel LSTM of bomber B-1B model at 45°.

Fig. 8 is a graph comparing the original RCS measurement data and the estimated data of each model. It can be seen that the difference between the measured value and the estimated value of each model remains below 0.045 dBsm. At this time, the graph indicated by x represents the difference between the measured value and the estimated value of LSTM, and the graph indicated by diamond represents the difference between the estimated value and the measured value of the parallel LSTM. If each error value is calculated as RMSE, it has values of 0.07905 and 0.0159, respectively.

Fig. 9 is a graph estimated based on approximately 110 data obtained by measuring 50 MHz intervals in the 1.55 GHz band at an angle of 72°. Based on this data, 70% of the data were learned using the LSTM model, and the remaining 30% were estimated. The RCS response from 1.55 GHz to 7 GHz was estimated through data from 5 GHz to 7 GHz. The data also used a simple LPF (4 degrees Butterworth filter, cutoff frequency = 0.07) for data stabilization. The solid line graph displays RCS data from 5 GHz to 7 GHz at a 45° angle, the x marker displays the LSTM model, and the diamond marker shows the parallel LSTM model.

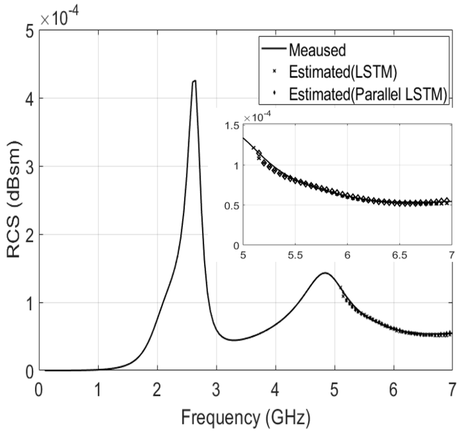

Fig. 9. Comparison graph between RCS measured and estimated values in 72°.

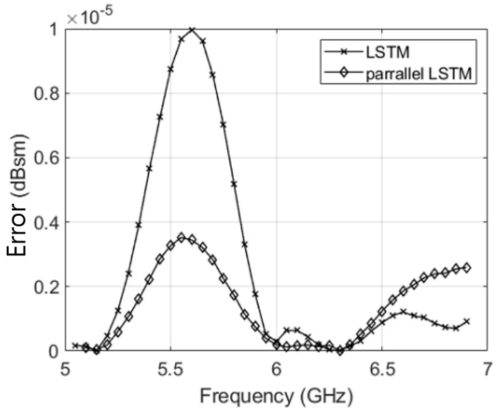

Fig. 10. Represents the estimated error between the mesered and the estimated value using LSTM and parrallel LSTM of bomber B-1B model at 72°.

Fig. 9 is a graph estimated based on approximately 110 data obtained by measuring 50 MHz intervals in the 1.55 GHz band at an angle of 72°. Based on this data, 70% of the data were learned using the LSTM model, and the remaining 30% were estimated. The RCS response from 1.55 GHz to 7 GHz was estimated through data from 5 GHz to 7 GHz. The data also used a simple LPF (4 degrees Butterworth filter, cutoff frequency = 0.07) for data stabilization. The solid line graph displays RCS data from 5 GHz to 7 GHz at a 45° angle, the x marker displays the LSTM model, and the diamond marker shows the parallel LSTM model.

Table 1 below shows that the time it took to measure the RCS using CST and the time it took to estimate it in each model were compared, and the RMSE values were compared. When calculated by CST, it takes a long time as the frequency increases, but it can be estimated to be within about 5 minutes when LSTM and parallel LSTM are used. When comparing the LSTM and the parallel LSTM, it can be seen that the Parallel LSTM is more consistent with the measured values.

Table 1. Comparison between LSTM and Parallel LSTM concerning Time and Error

Method	Angle	Frequency (GHz)	Time	Error
CST	total	1-5	100 hours	-
		5-7	50 hours	-
		12-14	225hours	-
LSTM	45	12-14	2 m 40 s	0.07905
	72	5-7	2 m 50 s	4.1149
Parallel LSTM	45	12-14	3 m 50s	0.0159
	72	5-7	3 m 40 s	1.8277

3.3 Missile

The next model to be measured is a missile, which is shown in Fig. 11. The model size is 580mm x 120mm x 120mm. The model obtained about 110 data at 50 MHz intervals of about 1.55 GHz to 9 GHz for RCS prediction. From this data, 70% of the data was learned using the LSTM model, and the remaining 30% was estimated. The RCS response of 5 GHz to 7 GHz was estimated through data of 1.55 GHz to 5 GHz.

Fig. 11. Represents the missile with the dimensions 580 mm x 120 mm x 120 mm

Similarly, in this missile model, the response of the RCS of 5 GHz to 7 GHz was estimated using the LSTM model and the parallel LSTM model. In each model, Epoch trained at 500 and took 2 minutes 45 seconds and 3 minutes 30 seconds. Fig. 12 is a graph comparing each model estimated when the theta of the missile model is 24°. The solid line represents the RCS data calculated with 1.55 GHz to 5 GHz CST STUDIO, the graph represented by x means the RCS estimation data using the LSTM model, and the RCS estimation data using the parallel LSTM model indicated by a diamond.

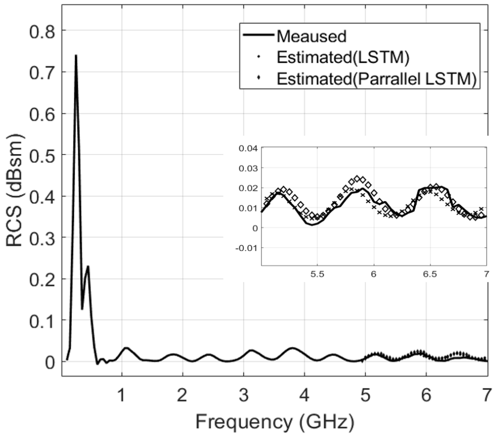

Fig. 12. Comparison graph between RCS measured and estimated values in 24°

Fig. 13 is a graph comparing the original RCS measurement data and the estimated data of each model. It can be seen that the difference between the measured value and the estimated value of each model remains below 0.012 dBsm. At this time, the graph indicated by x represents the difference between the measured value and the estimated value of LSTM, and the graph indicated by diamond represents the difference between the estimated value and the measured value of the parallel LSTM. If each error value is calculated, it has RMSE values of 0.0055035 and 0.0044496, respectively.

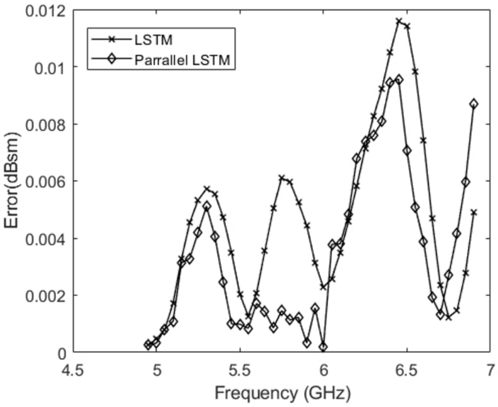

Fig. 13. Represents the estimated error between the mesered and the estimated value using LSTM and parrallel LSTM of missile at 24°.

It can be seen from Table 2 below that the speed of the LSTM model and the parallel LSTM model is much faster than the CST calculation, and the error of the LSTM model and the parallel LSTM model is reduced when the parallel LSTM model is used.

Table 2. Comparison between LSTM and Parallel LSTM concerning Time and Error

Method	Frequncy(GHz)	Time	Error
CST	1-5	100hours	-
LSTM	5-7	150hours	-
		2 m 45 s	0.0055035
Parallel LSTM		3 m 30 s	0.0044496

4. Conclusion

RCS is one of the essential parameters for designing communication systems, antenna systems, and aircraft, where the scattering and reflection of electromagnetic waves play an essential role. Electrically large objects such as aircraft and ships are complex and inefficient.

This research estimates low-frequency band RCS data for high-frequency RCS data using LSTM and discusses methods to address this issue. The LSTM model and the parallel LSTM model were proposed to predict the RCS in the high-frequency band based on the RCS of the existing data. Measurement data through simulation and prediction data using the LSTM model were visualized and compared. This data confirmed that the graph shape of the estimated RCS data and the RCS data measured through result analysis were similar. Furthermore, as can be seen, RMSE's calculation of the error value revealed accuracy that was within the acceptable error range.

Compared to the Cauchy approach, which was used to estimate the high-frequency band RCS, it is also possible to estimate multiple bands simultaneously, greater high-frequency bands, and with less time. We set the primary goal of predicting RCS values using AI. The results show that the estimates are almost consistent with the measurements, confirming high accuracy and that the time is also significantly reduced.

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〈Research Interests〉
Radar Signal Processing and Sensors

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〈Research Interests〉
Radar systems, Electromagnetic signal processing, Remotesensing, Artificial intelligence.