SCIENTIFIC COMPARISON OF CONVOLUTIONAL AND RECURRENT NEURAL NETWORKS AND THE MAXIMUM USE OF THEIR POSSIBILITIES IN PHASE ANTENNA ARRAYS FOR MONITORING ATMOSPHERIC RADIOSONDE MEANS

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This article examines the use of two main types of deep neural networks (DNN) convolutional (CNN) and recurrent neural networks (RNN), where a detailed comparison of each of them is carried out and how they can be optimally used for synthesizing a multi-lobe radiation pattern in a phased array antenna (PAA) for monitoring atmospheric radiosonde means. It is shown that a DNN can simultaneously be used as a calculator of the directions of arrival of electromagnetic waves, for example, from a pilot balloon and several unmanned meteorological probes (UMP) moving in space. When choosing between RNN and CNN, choosing the appropriate neural network depends on the type of data available and the results required. While RNNs are used primarily for text classification, CNNs help in identifying and classifying images. There are many differences between them, but this does not mean that they are mutually exclusive. RNN and CNN can be used together to take advantage of their advantages. In this article, The difference between RNN and CNN and how they can be used to monitor atmospheric sounding instruments will be considered.

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Introduction

Pilot balloons and unmanned meteorological probes are used to measure the spatial distributions of atmospheric meteorological parameters and obtain information that increases the probability of recognizing dangerous weather phenomena and the accuracy of measuring the spatial parameters of hydrometeors by radar stations [1-3].

For a phased array antenna, the position of the main lobe of the radiation pattern can be adjusted by changing the relative phases of the current present in each individual antenna element. This is the advantage of electronic scanning PAR. The implementation of multi-lobe radiation patterns for objects moving in space is a practical problem. Deep learning has recently been utilized in various research areas, including applications in electrodynamics. In the field of antenna arrays, artificial intelligence methods are used to reduce the influence of side lobes on the signal detection characteristics and identify failed elements in the phased array [4, 5]. Complex radiation patterns are training samples and are fed to the input of the CNN in the form of images and to the input of the RNN in text form. To train the DNN, the authors created an updated database, which currently contains 2,097,152 vector images obtained using a laboratory phased array 1 × 8 cross-polarization by measuring the amplitudes and phases of individual antenna elements (Each image can be represented by a text vector consisting of from the phases and amplitudes of the elements of the antenna array).

Methods and means of obtaining meteorological information by radio sounding of the atmosphere

Atmospheric physics is a unique object for teaching various approaches and methods for studying complex information systems. The most common in situ sounding is a radiosonde, which is usually a weather balloon but can also be a rocket sounder.

A modern radiosonde is a very compact radiometeorological station launched into free flight using a balloon filled with hydrogen or helium; The shell of the ball is made of thin elastic rubber or neoprene. The radiosonde consists of portable highly sensitive meters of atmospheric pressure, temperature and air humidity; an original device for encoding measurement results converted into radio signals, and a miniature radio transmitter for these signals. All the complex radiosonde equipment weighs only about 300 grams.

Currently, along with the development of traditional radar probe methods, active research is being conducted in the field of remote radiophysical and optical methods for determining the same atmospheric parameters using active and passive location tools in the microwave and optical wavelength range. It is assumed that measurements can be carried out both from the Earth's surface and from geostationary and low-orbit artificial meteorological satellites.

With the advent of satellites, atmospheric remote sensing has become a very powerful method for obtaining additional data, especially in remote areas such as deserts and over oceans, making it possible to observe the atmosphere potentially in any part of the globe.

The Radio Acoustic Sensing System (RAS) is a new remote sensing method for measuring temperature and wind profiles in the lower atmosphere. The development of RAS technology is primarily due to the rapid development of Doppler radar and acoustic technologies, as well as the development of computer hardware, software and signal processing techniques [6].

Recently, in atmospheric radiosensing systems using sound radiation, phased antenna arrays are increasingly used as antennas for acoustic and radio channels.

The use of phased arrays can significantly expand the capabilities of radiation monitoring and signal processing. In this context, they have much in common with the arrays used in radars [7].

Atmospheric radiosensing systems of the Earth receive the most accurate aerial information about the thermodynamic parameters of the atmosphere, such as temperature, humidity, pressure, wind direction and speed.

A common problem with atmosphere radiosonding radars is the effect of reflection of the antenna beam from the underlying surface of the earth in the near zone at the beginning of the flight of an aerological radiosonde and in the far zone at a great distance from the observation point.

The method of comparing amplitudes in angular coordinates is used for automatic tracking of radiosondes. Therefore, reducing the side lobe level (SLL) of the antenna pattern and accurate angular scanning is an important task in modern radar design [8].

The use of radar stations with phased antenna arrays in aerological sounding systems of the atmosphere significantly increases the technical characteristics of the radio channel and ensures reliable automatic tracking in the near zone at high angular velocities of the aerological probe. When designing a radar station, it is possible to significantly reduce the level of side lobes of the phased array antenna pattern and the influence of reflections from the underlying surface under operating conditions [8].

Convolutional Neural Network (CNN)

CNNs have recently become one of the most appealing Architectures for machine learning computational systems [9, 10] solving object detection [11], picture classification and face recognition [12].

The benefit of CNN over other categorization algorithms is that CNN is learned with more information rich features to categorize objects in images and has a high ability to summarize the attributes over many examples in the learning population.

Complex radiation patterns are images of an updated database from three sources of electromagnetic waves of atmospheric radio sounding devices and are fed to the input of the CNN, these inputs are images of diagrams to be classified in the output of the neural network into two categories, either multidirectional or not multidirectional.

The CNN is thematically divided into two architectural parts: The former learns which attributes are best to extract from images (learning the attributes of the input pattern), while the latter learns how to categorize the attributes into different types of categories (Fig. 1) [13-15].

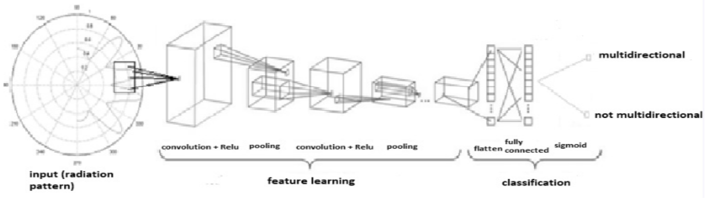

Fig. 1. CNN architecture for separating training samples

To process an image from a database representing a specific radiation pattern of a phased antenna array for reception from one of the three radio channels of atmospheric radio sounding means, for example, shown in Figure 2. 3,246,303 input neurons are required since the image has a size of 901×1201×3 (901 pixels by 1201 pixels with 3 pixels, for example, red, green, and blue, corresponding to one of the three radio channels of the atmospheric radio sounders). Thus, it is necessary to provide 901×1201×3 = 3,246,303 input neurons. Each matrix has a size of 901 by 1201 pixels, for a total of 901×1201 records. This array is then finally generated three times, each for a notional red, blue, and green radio channel ("color channel").

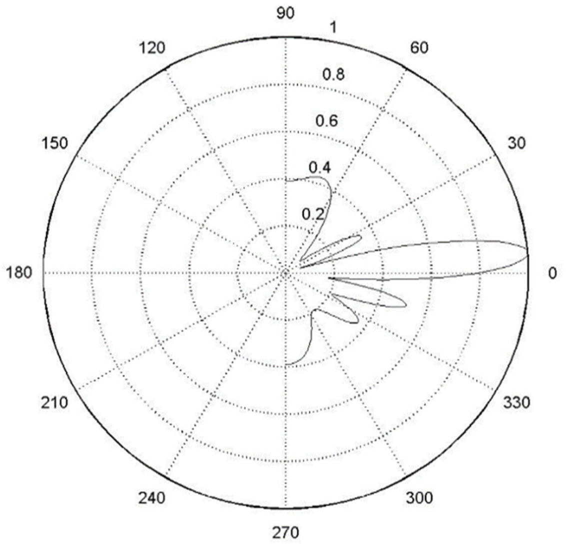

Fig. 2. One of the images in the database representing a particular phased array antenna pattern

Recurrent Neural Network (RNN)

RNNs are the neural networks that are programmed to handle consecutive values. It is used for: natural human language processing, written text analysis, machine translation of text, text generation, number generation, etc. In RNN, the result of each step is used as input for the next step., Because of this, the recurrent neural networks can handle a series of time events or sequences to produce a computational result. RNNs are considered to be an evolution of unidirectional perceptron networks by adding feedbacks. Each feedback loop has a unit delay element, due to which the signal flow can be considered unidirectional. With the help of feedback, information can be accumulated and used in signal processing.

Thus, a "memory" is implemented in the network, which fundamentally changes the nature of its work and allows you to analyze any data sequences in which it is important in what order the values are (for example, speech, text, image, etc.). As a result, the order of the signals plays a significant role in the problem [16]. A RNN may contain fewer parameters compared to a multilayer perceptron network that performs the same task. However, the RNN learning algorithm that adapts the values of synaptic weights is more complicated due to the dependence of signals at the current time on their values at previous moments [17]. RNNs work with given values. They take certain fixed inputs and return the same fixed output. Recurrent networks explore values according to well-defined principles (Fig. 3).

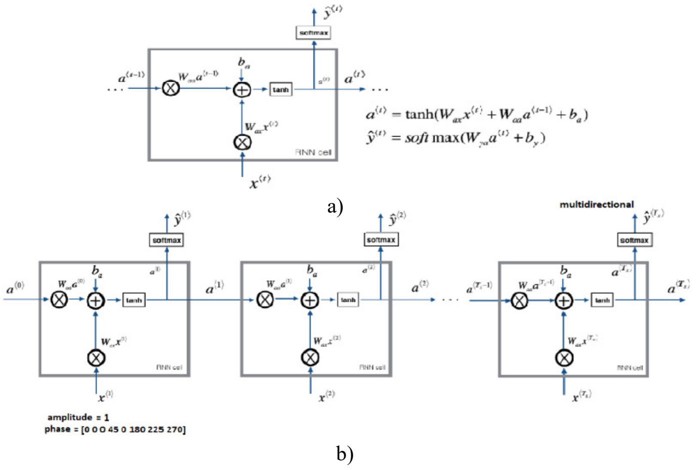

Fig. 3. a) Basic cell of the Recurrent Neural Network. Takes as input x⟨t⟩ (current input) and a⟨t−1⟩ (previous hidden state containing information from the past) and outputs a⟨t⟩, which is passed to the next RNN cell and also used to predict y ⟨t⟩; b) The basic model of the Recurrent Neural Network.

CNN or RNN: which is better?

The RNN is trained to detect patterns in time and the CNN is trained to recognize patterns in space. RNSs are designed to utilize serial data when the current step has some relationship with previous steps. This makes them ideal for applications with a time component (audio, time series data) and natural language processing. CNNs are well suited for extracting local and location-invariant traits, while RNNs are better when the classification is determined by long distance semantic dependency rather than some local key phrases. The big argument for CNN is that they are fast. a CNN model may be sufficient and even better computationally. But each network has its own effectiveness depending on the usage and type of input data that the neural network is feeding on.

Phased array laboratory bench

Figure 4 shows a phased antenna array in the laboratory of the Department of Technical Electrodynamics and Antennas, consisting of 8 elements arranged horizontally, the distance between each two elements is 0.19 m. To obtain the best radiation pattern for reception at (0.38 m), frequency 800 MHz [18, 19].

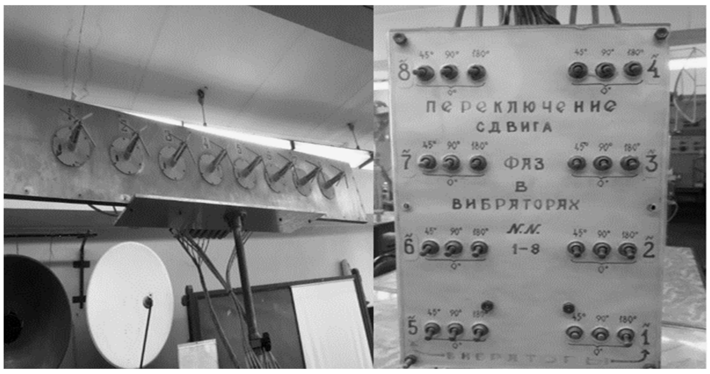

Fig. 4. Photograph of a laboratory phased array antenna

A discrete phase shifter is connected to each element, as shown in the figure. Note that for each element there are 3 positions for phase angle values (45º, 90º, 180º). The possible phase angle values for each element in the laboratory will be: 0º, 45º, 90º, 135º, 180º, 225º, 270º, 315º, 360º. Fragments of images from the updated database of the laboratory phased array antenna pattern are shown in Figure 5.

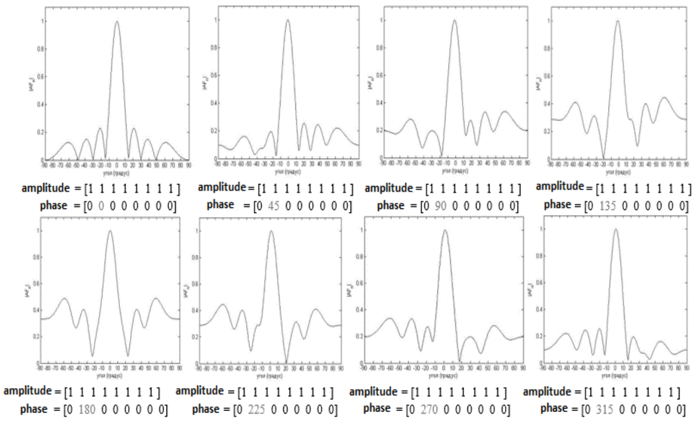

Fig. 5. Normalized Directional Patterns with Phase Change on the Second Element of the Antenna Array

To implement the formation of a multi-lobe radiation pattern, a homogeneous rectangular phased antenna array with a size of 1 × 8 antenna elements is used. It was shown in [20] that the main lobe of the elevation pattern should have a sufficient beamwidth to increase the directivity of the antenna and contribute to better angular resolution in beam steering at the smallest transverse dimensions of the antenna (Fig. 6).

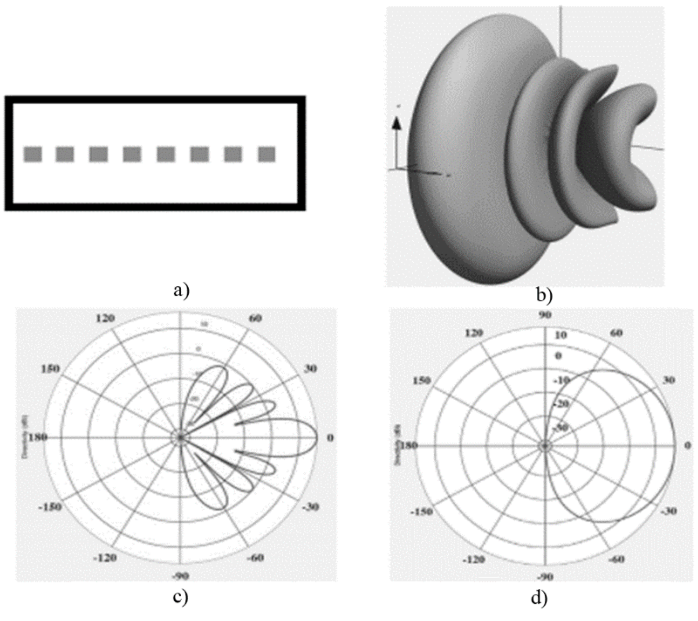

Fig. 6. a) Model of a laboratory phased antenna array 1×8; b) Three-dime ional radiation pattern; c) Directivity pattern in the azimuthal plane; d) Radiation pattern in the vertical plane

The results of experimental studies at the laboratory bench of the department show that it is possible to develop the well-known approach [20] in relation to the applied problem of synthesizing simultaneously several main lobes of the phased array antenna radiation pattern in the atmosphere radio sounding tool, changing only the values of the phase angles in accordance with the capabilities of the laboratory bench (Fig. 7).

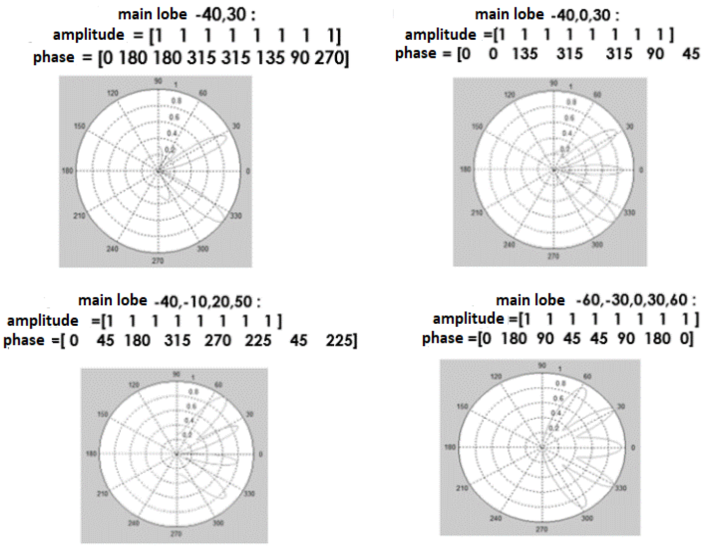

Fig. 7. Fragments of multi-lobe radiation patterns of a laboratory phased antenna array

Of course, there are other phase angles that can be used to obtain multiple main lobes, so the experimental work was to try all possible phase angles of a phased array antenna and form the required multi-beam radiation pattern.

To form the radiation pattern, the phase angle of the first element is set to zero, and the remaining elements change their values (0º, 45º, 90º, 135º, 180º, 225º, 270º, 315º). Number of radiation patterns that can be generated: 1×8×8×8×8×8×8×8 = 2,097,152.

Thus, a large number of patterns are introduced into the neural network for the final classification into two classes, then the neural network is trained to classify these patterns and test other patterns after a deep analysis of the DNN.

Conclusion

The article presents a method of forming a multi-lobe radiation pattern of a phased antenna array in relation to means of radio sounding of the atmosphere. On the example of a rectangular phased antenna array with a size of 1 × 8 antenna elements, the procedure for generating a database for CNN and RNN is shown and fragments of training samples are presented. A model of CNN and RNN and the process of building an artificial neural network are presented. It is shown that in the presence of intelligent control of the amplitudes and phases of the PAR elements, it is possible to form a multibeam radiation pattern and simultaneously receive information from several unmanned meteorological probes and a pilot balloon. Although RNN and CNN have several differences, they are not completely mutually exclusive.

In fact, you can use them together to improve efficiency. This can be especially useful when the input data needs to be classified as visually complex with temporal characteristics. Since CNN can only process spatial data, you will have to use RNN to process temporal data. The experimental results obtained on a laboratory stand showed the possibility of forming up to five main lobes in the radiation pattern of a laboratory eight-element phased array. It has been experimentally proven that the number of main lobes can be up to (N/2) + 1, and for an odd number of PAA elements (N + 1)/2, which is possible only when creating a PAA with a phase calculator using neural network models and deep learning algorithms. learning. The results of this study are supposed to be used in the formulation of laboratory work on the methods of forming the radiation pattern of SMART antennas, which is planned to be delivered at the Department of Technical Electrodynamics and Antennas in the next academic year.

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НАУЧНОЕ СРАВНЕНИЕ СВЕРТОЧНЫХ И РЕКУРРЕНТНЫХ НЕЙРОННЫХ СЕТЕЙ И МАКСИМАЛЬНОЕ ИСПОЛЬЗОВАНИЕ ИХ ВОЗМОЖНОСТЕЙ В ФАЗОВОЙ АНТЕННОЙ РЕШЕТКЕ ДЛЯ МОНИТОРИНГА СРЕДСТВ РАДИОЗОНДИРОВАНИЯ АТМОСФЕРЫ

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Аннотация

В данной статье рассматривается использование двух основных типов глубоких нейронных сетей (ГНС) - сверточной (ССН) и рекуррентной (РНС), где проводится детальное сравнение каждой из них и способы их оптимального применения для синтеза многолепестковой диаграммы направленности в фазированной антенной решетке (ФАР) радиозондов зондирования атмосферы (РЗА). Показано, что ГНС может одновременно использоваться в качестве вычислителя направлений прихода электромагнитных волн, например, от аэростата-пилота и нескольких беспилотных метеорологических зондов (БМЗ), перемещающихся в пространстве. При выборе между РНС и СНС выбор подходящей нейронной сети зависит от типа имеющихся данных и требуемых результатов. Если РНС (рекуррентные нейронные сети) используются в основном для классификации текстов, то СНС (сверточные нейронные сети) помогают в идентификации и классификации изображений. Между ними существует множество различий, но это не означает, что они взаимоисключающие. Можно также использовать RNN и SNN вместе, чтобы использовать их преимущества. В этой статье мы рассмотрим разницу между РНС и СНС и способы их использования для мониторинга приборов зондирования атмосферы.

Ключевые слова: *фазированная антенная решетка, глубокое обучение, свёрточная нейронная сеть, рекуррентная нейронная сеть, многолепестковая диаграмма направленности, шар-пилот, беспилотные метеорологические зонды.*

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