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THE PROBLEM OF DEVELOPING THE ARCHITECTURE OF MODERN COGNITIVE RADAR SYSTEM

The problem of developing the architecture of modern cognitive radar systems using artificial intelligence technologies is considered. The main difference from traditional systems is the use of a trained neural network. The heterogeneous multiprocessor system is rebuilt in the process of solving the problem, providing reliability and solving various types of problems of one class and deep learning of the neural network in real time. This architecture promotes the introduction of cognitive technologies that take into account the requirements for the purpose, the influence of external and internal factors.

Keywords: Perception-Action Cycle, Artificial Intelligence, Signal to Noise Ratio, Active Electronically Scanned Array, Environmental Dynamic Database, Signal to Noise Ratio, Radar Resource Management, multiprocessor.

Introduction

Modern radar systems operate in a wide variety of dynamically changing scenarios: the detection, tracking and classification of very small and slow targets. Such objects as drones, missiles, boats, along with a complex spectrum are important system requirements. Cognitive radars, combining many well-known and new methods, offer a promising solution to these problems. We consider the functional architecture of cognitive radar from the perspective of the user and the manufacturer.

Cognitive radar is an updated technology, the origins of which go back to science - «cybernetics», human-machine interaction, signal processing. The evolution of cognitive radar is aimed at achieving cognition, as in its natural counterparts, such as the radar capabilities of bats and dolphins, or human intellectual decision-making. This article provides an overview and trends in the development of cognitive radar systems.

Organization of cognitive computing

The term «cognitive radar» was first introduced by Dr. Simon Haikin [1], following the ideas of cognitive neurology, which is based on works of cybernetics, artificial neural networks, self-organized learning and solutions of Bayesian theory. Engineering analogues for the implementation of the main cognitive features identified by Faster: memory, attention and intelligence (PAC Perception-Action-Cycle: Cycle-perception-action) have been proposed [2]. In studies of cybernetics, Rasmussen [3], [4] described human behavior in terms of three levels: based on skills, rules and knowledge. He described behavior-based behavior as a subconscious that reflects basic signal processing and generation blocks in a radar system [5]. Rule-based behavior is used in familiar situations. The basis of parallel work is modeling and analysis of previous experience.

Build cognitive radar developers have inspired research in the field of biomimetics. Artificial intelligence is modeled on the basis of observations of living intelligence. Thus, masters of echolocation - bats and dolphins can detect and track very small prey, using complex waveforms that are changed dynamically [6]. Moreover, knowledge of the intelligence of living beings allows us to better understand living nature. It helps to create artificial intelligence, which is superior to «living» and is used in technical systems.

Information in the radar system is perceived by «smart» sensors, i.e. sensors with primary processing and control of the measurement process [7], as well as through network sensors that demonstrate «distributed intelligence» with self-monitoring capabilities, automatic solution of changes in their environment [8] , [9]. Cognitive radar has the ability to adapt to transmission in the probing process, imitating human perception as an interactive process where the cognitive entity responds to or changes its behavior as a result of external stimuli.

In traditional radar systems, the flow of information is one-way: the radar interrogates the environment by transmitting a fixed, predetermined pulse signal, regardless of any changes in the environment. Adaptive processing is performed on reception, but the results of such processing do not control any radar function for transmission. An overview of the cognitive directions of radar construction research over the last decade gives an idea of the methods being developed for a wide range of radar applications. Technical problems in the development of cognitive radars are the motivation for further work in this area. Central to these works is the idea of closed-loop data collection, where the dynamic state is interpreted as an adaptive measurement determined by Kalman filtering. This approach allows the antenna array to be adaptively directed in the direction and width of the beam, as well as to place zeros so as to reject any unwanted signals or noise outside the main particle.

A database of problems has been developed that allows comparing methods that use beam control of phased array antennas to optimize tracking, minimizing false alarms [10], [11]. Sometimes several hypotheses and filtering interactions of several tracking models are tested [12-13] to optimize performance: such as signal-to-noise ratio, interference effects, track, and detection threshold.

Common features of increasing adaptability: prediction of adaptive scheduling review time, adaptive choice of detection thresholds (eg, constant false alarm rate detectors) [14], and adaptive interference suppression using adaptive-spatio-temporal processing mode [15] to improve target detection. Adaptive tracking methods vary the measurement time, as well as the signals used to update the trajectory, based on the measurements obtained by the tracker. This feedback is used to control the radar so that frequent measurements are made during an unpredictable or rapid dynamic maneuver, while infrequent measurements are made during predicted periods or steady dynamics.

The simultaneous change of intra-pulse signal modulation is studied on the basis of the provided measurements on the tracker. This leads to the choice of optimal signal methods [16-17] and their adaptive extensions [18-19]. Optimization of radar signal in dynamics, to maximize performance according to specific scenarios and tasks, includes the use of some components of radar, such as antenna, radiation pattern (both transmission and reception), time, frequency, coding and polarization. The signals are selected from several classes of signals, such as linear or nonlinear frequency modulation, phase or encoding frequency, and ultra broadband signals. This also includes adapting parameters within the signal class, such as changing the pulse repetition interval, bandwidth, or center frequency [20]. The optimal signal, which maximizes the signal / noise, arises as a solution of the generalized eigenvalue on the waveform [21], developing in the framework of «joint optimization of transmission and reception by the choice of waveform. The approach was used in Bayesian theory of decision making and development, designed to optimize the system by selecting the signal at the transmitter and minimizing interference at the receiver. There are also difficulties in choosing the criteria of optimality and accurate distribution of interference.

According to the IEEE, the definition of «cognitive radar» is a radar that has the ability to learn: «Radar system, which automatically generates a constant perception of the target scene and takes appropriate action. It can use short-term and long-term memory to increase the performance of a given function. Compared to adaptive radar, cognitive radar is trained to adapt operating parameters as well as processing parameters, and can do so over longer periods of time.”

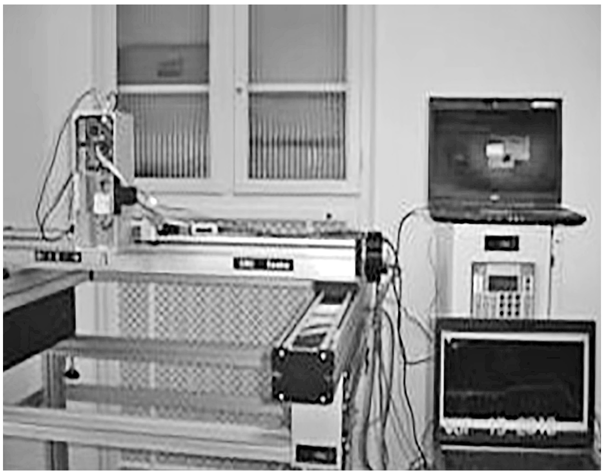

Fig.1. FMCW Radar Imaging Cognitive Ability Modeling Complex with Deep Learning Package.

Cognitive radar differs from traditional active radar due to the following features: development of rules of conduct for self-organization through a process called experiential learning, which is the result of long-term interaction with the environment. According to Charlish, cognitive radar is a radar system that acquires knowledge and understanding of the work environment through online assessment and training from databases that contain contextual information. Cognitive radar uses this knowledge to improve information: search, data processing and management of radar resources. With the development of cognitive radars began a new era in the creation of modern radar systems. The number of publications on the development of cognitive radar architecture with artificial intelligence is increasing avalanche. Artificial intelligence is used in the construction of neural networks, methods of deep learning, signal processing, pattern recognition, classification. It should be noted that elements of cognition in the construction of radars have always been presented (power, pulse width, repetition rate, modulation, etc.). There is also the ideology of the neural network, and accordingly their in-depth training (multiprocessor with restructuring). The explosive growth of the latest developments in radar systems is related to public demand (defense, security, medicine, subsurface sounding, mine search, unmanned aerial vehicles) and the ability to meet them: the use of artificial intelligence technology and the development of a new component base.

Cognitive radar methods use mimic elements of human cognition, such as the cycle of perception-action, deep learning, intelligence and the use of existing knowledge [22]. Cognitive radar vision methods use radar spectrum [23], [24], radiation optimization [25], tracking [26-28], beam control [29], interference reduction [30], network [31], resource management [32] .

To develop a cognitive radar system that adapts in real time, the multiprocessor must be an integral part of the simulation tool. It helps to analyze the behavior of the radar at the simulation stage. The post-process stage consists of two steps. In the first step, a radar sensor and a proven circuit are developed using non-adaptive settings. In the second step, the multiprocessor is tested and configured, replacing the Front-end sensor. Pre-recorded raw datasets that include all radar parameters are optimized. Such datasets use the same measurement for all parameters of environment, target, and trajectory. At this stage of development, the feedback cycle is closed by obtaining an interval of coherent processing of raw data relating to the selected optimal parameters in real time.

The modeling complex consists of an adaptive radar sensor that perceives the environment with optimized radar parameters and a multiprocessor that tracks the target and selects the optimal radar parameters for each new measurement. The sensor consists of an adaptive signal generator, a radar interface, an ADC and a real-time signal converter and a display. The controller consists of a Kalman filter tracker and an optimizer that selects both optimal signals and real-time processing parameters based on the latest measurements. Multiprocessor processing is simulated in Matlab and runs on an Ubuntu Linux PC.

The radar data processing system consists of three modules: FPGA, workstation and graphics processing unit. FPGA provides primary signal processing and hardware management. Its most important role in signal processing is to perform digital down-conversion of the received signal so that the true baseband can be transmitted to the workstation for further processing. Subsequent implementation of the appropriate filter on the FPGA can be useful for freeing resources on the graphics processor for its other tasks: filtering, discrete Fourier transform, and processing the constant rate of false alarms (CFAR). The detection task is implemented on a graphics processor. The CPU is an Intel multi-core processor.

LabView National Instruments support control functions. In addition, LabView can be used to write FPGA software. Simulation on FPGA Xilinx, RF-path on on-a-chip is used. The shell is written in Python for the C ++ library. Algorithms are tested on flexible radar equipment. We use digital transceiver systems - such as Universal Software Radio Peripheral (USRP).

In recent years, research on cognitive radar design has been conducted covering a wide range of programs, using many different methods based on previous advances in Bayesian theory, information theory, theoretical solutions, approaches, including fuzzy logic, rule-based systems, metaheuristic algorithms and Markov solutions. processes, dynamic programming, optimization and game theory.

Future systems are learning the ability to predict the behavior of radars in the operational environment and to adapt its transmission in the available spectrum. Radar cognition in this case is based on two main concepts: spectrum probing and spectrum distribution. The sounding spectrum is aimed at recognizing the frequency used by other systems and occupying the same spectrum in real time.

System performance is measured in terms of standard metrics such as target detection probability and false alarms, root mean square error in tracking systems, and classification accuracy in automated target recognition systems - cognitive systems require additional metrics that quantify performance gains and achievement use of system resources. Two key issues for cognitive radar research are the development of assessment and assessment tools, as well as experimental testing of the methodology.

A related but unique problem with the cognitive design of radar is experimental testing, as the shape of the transmitted signal and the settings are adapted during operation. With more sophisticated modeling, new development and qualification processes can be developed, including software testing that will help test cognitive radars.

Cognitive radars are evaluated through simulations, or using pre-recorded data. The infrastructure of testing, calibration and debugging tools is being developed in parallel. For example, SPC Quantor has developed real-time tests for cognitive radars. Reliability of modeling and computational errors is an important issue that should be investigated [33].

Radars differ in their qualitative and quantitative parameters. A typical approach is to determine the number of worst cases and make them work in the worst cases. This is true for non-cognitive radar systems that do not change the configuration depending on the current environment, because a single radar configuration is used. Cognitive radars change their configuration, rebuilding the neural network and learning or self-learning to solve various problems within certain limits. Moreover, with the development of neural network design tools, cognitive radars will have better characteristics and lower design costs and the ability to self-improvement.

The power of the transmitter should not exceed the limits imposed by regulatory requirements, because there is unwanted radiation due to the nonlinearity of the transmitter and a sharp increase and decrease in radar pulses [34]. Especially in cognitive systems, dynamic reconfiguration of the transmission spectrum is not always easy to implement and can lead to out-of-band transmissions, which cause a slight spectral expansion outside the designated radar band.

Cognitive radar architecture

The cognitive radar architecture is built through the extension of the perception-action cycle by introducing an evaluation process that forms a perception-evaluation-action cycle (PEAC). The purpose of this additional step is to emphasize the assessment of the currently perceived situation supported by artificial intelligence. It is done regarding the purpose of the sensor and depends on the purpose certain perception results will lead to very different actions, such as observation, where the overall picture is important. When observed, all identified targets will receive an equal share of available resources.

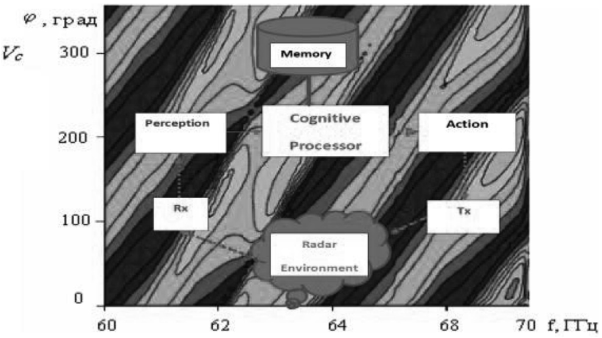

Fig.2. Functional diagram of the cognitive radar.

The radar sensor, which operates in PEAC, consists of a programmable sensor that provides data processing and data evaluation, and management of resources generated depending on recently received environmental information. In future systems, much of the intelligence will be located in a multiplatform cloud. Cognitive radar responds intelligently to real-time scenario variations.

A software-defined sensor is a system that performs radar measurements, ie emits, receives and processes electromagnetic signals in accordance with the requirements of the sensor in order to obtain new information in its environment. A software-defined sensor requires hardware capabilities (eg, instantaneous bandwidth, operating bandwidth, waveform, polarization, etc.) to meet resource management requirements.

Radio compatibility is achieved by methods relating to the emission of radar signal or signal processing. Methods of reducing interference from other radio frequency systems are achieved by dividing in time, frequency, space or signal modulation. Consider the main measures that allow coexistence: waveform, illumination in radar images, adaptive zeroing of interference, frequency adaptation, dynamic adaptation of the search circuit and the level of radiation power, detection of interfering samples in the receiving signal, suppression of interfered samples in the radar signal [35].

A Doppler shift around a target appears if the target contains moving, vibrating, or rotating parts and can be observed externally. For example, the wings of birds, the wheels of cars, the arms and legs of people walking, as well as the rotors of helicopters and tank tracks have a unique Doppler spectrum, which is observed using a radar system with a fairly high Doppler resolution. The spectrum of Doppler shift strongly depends on such parameters as the angle of illumination, the absolute velocity of the target and the composition of the underlying surface.

To adjust the detection thresholds according to the actual background, it is necessary to determine and assess the level of interference. This assessment can be performed on a one-time basis or over a long period of time by studying the characteristics of the obstacles. The mapping features can be characterized by its spatial composition, amplitude statistics and Doppler spectrum. This allows you to reliably adjust the detection thresholds according to the characteristics of the interference, while maintaining a low level of false positives and providing the ability to detect targets against the background of interference.

Multi-beam radiation on the sea surface is characteristic of marine radars. The imposition of a direct and reflected path on the sea surface leads to the appearance of zones with attenuation and loss of target detection, as well as to errors in altitude measurement. By detecting fading situations, tracking can be more resistant to detection errors by changing the transmission frequency and thus avoiding the fading situation.

Active grating and electronic scanning antennas, which are the latest in modern radar systems, provide great flexibility in the direction of the beam and waveforms.

The various actions that require resources from the system are called tasks. Each task is an implementation of the radar function that the sensor is capable of. Examples of such tasks: search tasks, tracking tasks, classification tasks, visualization tasks, environmental detection tasks, externally assigned search and tracking tasks ordered by a higher system.

QoS resource management techniques use quality measures to optimize overall system performance for this metric and available resources. Therefore, this approach requires a good understanding of the quality measures used. Especially when a large number of different tasks are used, which will certainly be the case in future cognitive radars, it is necessary to find a strong balance between individual tasks and mission needs. The advantage of the QoS approach is that even in dense scenarios, the available resource is distributed among the tasks still to maximize system performance, and no predetermined priority, which may or may not be applied in the current situation, should be used to resolve conflicts. However, adaptive rules as well as the QoS approach require more environmental information to adapt the waveform to the evolving situation, taking into account the various influences implemented in the model used to assess the expected performance of the system. In addition, for QoS it is necessary to keep a list of all active tasks of the radar sensor.

The hardware capabilities needed to take advantage of modern resource management capabilities are high if you use the full potential of algorithms. In this case, you need a fully flexible interface that allows you to configure all available parameters (such as waveform, parameters, and viewing directions) within the physical boundary of the external interface. However, to speed up the process of optimizing resource management, the available degrees of freedom can be limited in advance, for example, by limiting the repetition rates of the selected pulses. If the limit is chosen adequately, the decrease in productivity is insignificant.

Deep learning of the cognitive radar neural network

Probably, today only the lazy are not engaged in machine learning. But when we look at cognitive radar software, we are talking about deep learning. This is when the feedback covers the entire radar.

The backpropagation algorithm is an extension of the perception of multilayer neural networks. Thus, the backpropagation algorithm uses three or more levels of processing units (neurons). In a typical 3-tier network architecture for a backpropagation algorithm, the leftmost layer of ones is the input layer that receives the input data. Later, this is a hidden layer, where processing blocks are linked to the layers before and after it. The rightmost layer is the output layer. The levels are fully interconnected, which means that each processing unit is connected to each unit at the previous level and at the next level. However, the units are not linked to other units in the same layer. Backpropagation networks are not fully interconnected, which means that any number of hidden layers can be used. [31].

Traditional event detection in cognitive imaging radar is based on batch or offline algorithms: it is assumed that there is one event in each radar information stream. The stream is usually processed using a preprocessing algorithm that requires a huge amount of computation. Neural networks can easily cope with such tasks with the appropriate deep learning. This is an analogue of information processing tasks "on the fly" as they become available.

Neural networks are also an effective method for diagnosing faults based on nonlinear mapping of input and output data, parallel processing and a high degree of self-organization and self-learning ability [36]. In the structure of closed-loop neural networks the only suitable connections are between the outputs of each level and the input of the next level [37]. A backpropagation neural network is one known method for creating a trained machine or system that can provide a final classification decision through a series of learning processes. It can be developed using the tools provided in MATLAB, but sometimes this leads to different detection and recognition accuracy of objects for each experiment [30–31].

We achieve troubleshooting by rebuilding the computational resource of the neural network. Moreover, a quick response occurs by changing the course of the computing process and in case of failures, readjustment of the network with a change in its resource. It is possible to draw an analogy with a living intellect, where homeostasis is provided at the hormonal level and a quick response to changes in the external environment by nervous signaling.

We always willingly or unwillingly use bionic models. Now it has resulted in a separate science of imitation of nature - biomimetics. Creating a model in biomimetics is half the battle. To solve a specific practical problem, it is necessary not only to check the presence of the model properties of interest to practice, but also to develop methods for calculating the predetermined technical characteristics of the device, to develop synthesis methods that ensure the achievement of the indicators required in the problem.

And therefore, many bionic models, before they receive technical implementation, begin their life on a computer. A mathematical description of the model is constructed. Based on it, a computer program is compiled - a bionic model. On such a computer model, various parameters can be processed in a short time and design flaws can be eliminated.

Traditionally, deep learning algorithms update the weight of the network, while the architecture of the network is selected manually using the trial-and-error method. This study proposes two new approaches that automatically update the structure of the network, as well as studying its weight. The novelty of this approach is parameterization, where depth or additional complexity is constantly encapsulated in the space of parameters that give additional complexity.

Deep learning includes several levels of nonlinear information processing. This allows us to study architectures that implement functions through repetitive compositions of simpler functions, thereby exploring levels of abstraction with the best generalization and representation.

Although in-depth training is useful, keeping multiple layers can be problematic. First, when more layers, weight, space, and computational complexity are higher; second, when there are more free parameters, there is a higher risk of retraining; third, if the network is deep, there is the problem of disappearing gradients when the error spreads over many layers.

There have been many approaches to optimizing the network architecture - from early incremental methods of bringing hidden modules one after the other (or starting from a large network and reducing it) to more sophisticated modern approaches such as evolutionary algorithms or reinforced learning and stimulus style techniques. The purpose of the study is to study network architecture based on data. The main difference is that instead of searching in discrete space for all architectures that have parameterized models in such a way that the very notion of complexity or depth is itself continuous, making the model differentiated from beginning to end.

Two methods are proposed for constructing and studying the structure of a deep neural network, where the complexity of the network at the level of a hidden block or layer is encoded by continuous parameters. These parameters are adjusted together with the network weights during the gradient descent, which implies a slight change in the structure of the network together with the network weights. The first method in tunnel networks associated with each hidden block is a continuous parameter. If this parameter is not active, the block simply copies its input to its output to bypass nonlinearity, effectively increasing the depth of the network. In the second method, the perceptron has parameters associated with each layer, indicating whether further nonlinear processing is required. We start with one layer first, and when training with a gradient descent, when necessary, this parameter can become active, which causes the creation of another complete layer, increasing the depth of the network.

Experiments on synthetic double-helix data like tunnel networks and novice perceptrons can be adapted to different sizes for different complexity of problems using the same set of hyperparameters, adapting the number of units for the tunnel networks and the number of layers for the initial perceptrons. With regard to real problems of recognition of numbers and images, we observe that tunnel networks achieve better performance, providing a better regularized model and using fewer parameters compared to backbone networks. Also, novice perceptrons showed comparable or better performance. Compared to tunnel networks, novice perceptrons appear to grow larger and shrink less. By setting the learning rate in descending order, it is observed that different layers grow at different rates and are used in different ways. Combined with regularization, this allows tunnel networks to keep some of the unused upper layers linear, thus effectively removing them from the network at the end.

Deep learning is an AI function that mimics the workings of the human brain in such a way that it processes data and creates patterns for use in decision making [35]. Cognition is a fundamental feature of natural intelligence. Sensory cognitive networks provide new technological support to dramatically increase the quantity and quality of information that can be collected and transmitted in complex adaptive systems. Their application can significantly increase the level of intelligence in the design and implementation of the system to the levels at which the effects of cognition will begin to manifest themselves. Cognitive abilities can be thought of as a shared sensory network. The detection system learns to detect changes not only in signal levels, but also in the shape and parameters of the sensor signal, which is a more difficult task. The architecture can significantly reduce resource consumption without sacrificing change detection performance. Experiments prove that a neural network-based change detection system is feasible for developing sensor network applications and can be successfully implemented on available technology platforms.

Designing cognitive radars has several stages. At the first stage we develop user requirements. The second is the formalization of user requirements. Next, we develop a model of radar operation, check the receipt of the declared quality characteristics of the radar. In the fourth stage, we conduct in-depth training of the generated neural network with an inverse loop, for which the radar is calibrated. Based on the calibration results, the development of the developing cognitive radar system is adjusted. Consider in more detail the calibration of 3D-Imaging radar, developed and manufactured in SPC «Quantor» on the example of obtaining a 3D image of the internal structure of the multilayer material.

The possibility calibration of is studied in the exploring of material properties to the example of multilayer structure, depending on the distance between the sample and the antenna using an absorber. The results of preliminary studies indicate the possibility of measuring the thickness of the material. On the calibration, a small metal plate and several measurement cycles for averaging the noise were used. It is shown that the accuracy of measurements is influenced by the width of the radiation pattern, the number of measurement cycles at one point, the accuracy of positioning and moving the head during the measurements, and the time interval between the calibrations.

We have developed algorithms and have obtained the required accuracy. We will try to test the radar system, having previously calibrated it.

Before carrying out the measurements, we set:

1. The horn and the sample close the absorber to reduce the reflections;

2. We measure the signal without a sample;

3. We place the sample (5-10) mm and begin to measure;

4. Very carefully, a thin conductive film is pasted from above and measurements are taken;

5. Very gently flip back with a conducting medium and measure.

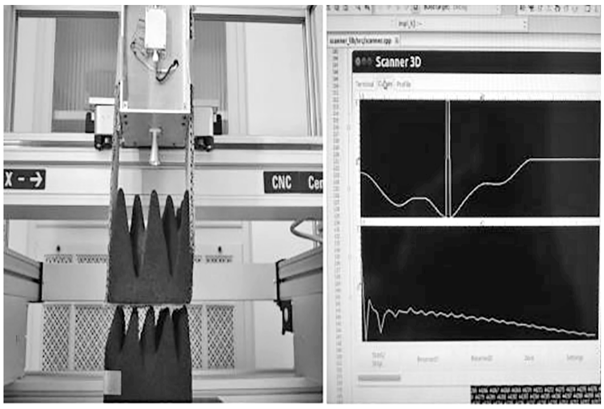

Fig.3. Implementation of 3D scanning of small objects by cognitive FMCW 3D-Imaging Radar terahertz range.

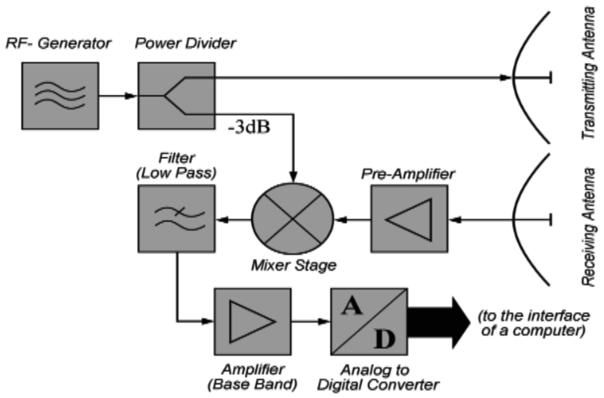

Fig.4. Functional diagram of 3D Imaging FMCW Terahertz Radar.

If all done carefully, there should be a shift of even a fraction of a millimeter. Scan must be disabled. We will make a point of 50 measurements.

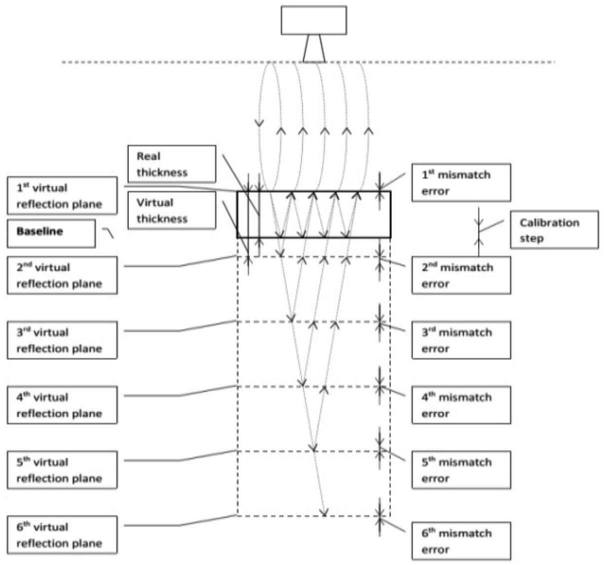

Fig.5. Propagation of radar radiation in a multilayer material.

1. Different materials have a different permittivity and different velocity of phase of electromagnetic wave. This gives that real thickness between upper and lower plane of samples is equivalent to virtual thickness between real upper and virtual lower plane in air. We can estimate equivalent virtual thickness between metal planes in air and then correct result for real material.

2. In real materials we have a multiple reflection. This gives several spectral lines for one thickness of the sample.

3. Reflections from virtual metal planes do not fully correspond to reflections from real metal planes during calibration. There are numerous errors of discrepancy between virtual planes and the nearest calibration levels. This gives multiple errors in the spectral lines and creates some difficulties in estimating the thickness.

4. Some calibration levels must be presented lower than baseline to estimate positions of virtual metal planes.

5. We try to fix existing mathematic problems and to get a mathematical tool for universal measurement device.

6. We check the additional measurement configuration. For calibration, we use a special sample with a higher accuracy – Plexiglas.

As a result of the measurement cycle, a frequency dependence of the attenuation in the microwave channel $D(f) = U_{\mathrm{ref}}(f)/U_{\mathrm{inc}}(f)$ is obtained.

Unknown parameters of the dielectric structure are determined by procedure of global minimization of discrepancy between the measured attenuation in channel $D(f)$ and one calculated theoretically $D_{\mathrm{th}}(f, \mathrm{p})$

$$F(\mathbf{p}) = \sum_{f} \left| D(f) - D_{th}(f, \mathbf{p}) \right|^2 .$$

Here $D_{\mathrm{th}}(f, \mathrm{p})$ is defined according to the formula

$$D_{th} = \left| k_0 + k_1 \frac{V - V_c}{(1 - k_3 V)(1 - k_3 V_c) - k_2 V V_c} \right|^2 ,$$

and $k_0(f), .., k_3(f)$ are complex coefficients, which are determined experimentally using reference samples and describe properties of the microwave channel; f is the frequency of sounding waves; $V_C(f)$ is the complex reflection coefficient (CRC) of the reference arm 3; $V(f,p)$ is a theoretically calculated CRC of the dielectric structure, which depends on a vector of the structure parameters p (thickness of layers and electrical parameters of materials).

We consider that in free space extends a plane electromagnetic wave and normally incident on the infinite (M-1)-layer medium with flat boundaries. The CRC $V(f, p)$ is related of the CRC of the structure in free space $V_S(f, p)$ through the scattering matrix of the antenna $\mathbf{S}$, which is determined experimentally:

$$V = S_{11} + \frac{S_{21} V_S}{1 - S_{22} V_S} .$$

The CRC of the structure in free space depends on the thickness and electrophysical parameters of structure layers:

$$V_S = V_S(f, h_1, .., h_{M-1}, \varepsilon_1, .., \varepsilon_M, \mathrm{tg}\delta_1, ..., \mathrm{tg}\delta_M),$$

where h_m, ε_m, $\mathrm{tg}\delta_m$ is thickness, permittivity and loss tangent of m-th layer. The CRC of the plane wave from dielectric plane-layered medium $V_S(f,p)$ is determined by the known formulas:

$$V_S = \frac{W_0 - Y_1}{W_0 + Y_1},$$

$$Y_m = W_m \frac{Y_{m+1}(\exp q_m + 1) + W_m(\exp q_m - 1)}{W_m(\exp q_m + 1) + Y_{m+1}(\exp q_m - 1)},$$

$$Y_M = W_M,$$

$$W_m = \sqrt{\varepsilon'_m / \mu_0};$$

$$q_m = 2j \cdot 2\pi f \cdot h_m \sqrt{\varepsilon'_m \mu_0 (1 - \sin^2 \theta)};$$

$$\varepsilon'_m = \varepsilon_0 \varepsilon_m (1 - j \cdot \mathrm{tg}\delta_m),$$

where ε_0, is permittivity and μ_0 is the permeability of free space.

During the setup process, we do not need to change the distance between the signal and the base line, but we need to will move the device and perform a calibration at the center of each step. This calibration process is simpler and can be performed in automatic mode without an additional table with a micrometer.

Conclusions

This article provides a summary of the development of modern radar systems. It is shown that with the development of Artificial Intelligence technologies, modern radars use deep learning neural networks, as a result, radars have become cognitive. There is no alternative to satisfy the consumer in terms of quality indicators using old technologies. Scientific, technological, information base is ready for such challenges. The need for modern radars is also huge: medicine, security, defense, the Internet of things, and others. Scenarios are becoming more complex and require creative solutions. Cognitive radar is one potential solution that has long been discussed in the literature.

It has been shown that cognitive radars can coexist in a congested spectrum, including with random and intentional interference, and be invisible. Cognitive radar systems can adapt to a changing environment using internal and external sources of information. It is possible to control the resources of the radar, and therefore, the radars are inherently fault-tolerant.

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