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THE PRACTICAL ASPECT OF USING THE ARTIFICIAL INTELLECTUAL TECHNOLOGY FOR BUILDING A MULTIDIMENSIONAL FUNCTION CFAR FOR SMART-HANDLED LPI RADAR

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The problem of the development of modern mobile smart-handled LPI radars using artificial intelligence technologies, the main difference of which is the construction of the CFAR function, which takes into account the influence of external and internal factors and requirements for the purpose, also distinguishes the developed radar among others in its class. The analysis of the publications was showed a great interest in modern radar systems and the lack of a unified approach to solving this problem. The purpose of the article is to reduce this gap, from collecting information from radar sensors and internal sensors to construct a generic multidimensional CFAR function and for organize its effect on the receiving and transmitting part of the radar. The application of artificial intelligence technologies in the construction of a modeling complex of LPI radars with CFAR function and their debugging in real time is covered.

Key words: Smart-Handled Radar, LPI (Low Probability of Intercept) Radar, CFAR (Constant False Alarm Rate), IoT (internet of things), artificial Intelligence, Deep learning, Signal processor, Signal-to-Noise Ratio (SNR).

Розглянуто проблему розробки сучасних мобільних інтелектуальних LPI радарів використовуючи технології штучного інтелекту, основна відмінність яких полягає в побудові функції CFAR, що враховує вплив зовнішніх та внутрішніх факторів і вимоги по призначенню, також вона вирізняє розроблюваний радар серед інших у своєму класі. Проведений аналіз публікацій показав велику зацікавленість сучасними радарними системами і відсутність єдиного підходу до розв'язання цієї проблеми. Мета статті – зменшити цю прогалину, починаючи зі збору інформації від радарних сенсорів та внутрішніх датчиків для побудови узагальнюючої багатовимірної функції CFAR та організації її впливу на приймальну і передавальну частину радару. Висвітлено застосування технологій штучного інтелекту при побудові моделюючого комплексу LPI радарів з функцією CFAR та їх відлагодження в реальному масштабі часу.

Ключові слова: Переносний розумний радар, LPI (з низькою ймовірністю перехоплення) радар, CFAR (функція постійної ймовірності хибних тривог), IoT (інтернет речей), штучний інтелект, глибоке навчання, сигнальний процесорг, коефіцієнт сигнал-шум (коеф. с/ш).

Рассмотрена проблема разработки современных мобильных интеллектуальных LPI радаров, используя технологии искусственного интеллекта, основное отличие которых заключается в построении функции CFAR, учитывающий влияние внешних и внутренних факторов и требования по назначению, также она отличает разрабатываемый радар среди других в своём классе. Проведённый анализ публикаций показал большую заинтересованность современными радарными системами и отсутствие единого подхода к разрешению этой проблемы. Цель статьи - уменьшить этот пробел, начиная по сбору информации от радарных сенсоров и внутренних датчиков для построения обобщающей многомерной функции CFAR и организации её влияния на приёмную и передающую часть радара. Освещены применения технологий искусственного интеллекта при построении моделирующего комплекса LPI радаров с функцией CFAR и их отладки в реальном масштабе времени.

Ключевые слова: переносной умный радар, LPI (с низкой вероятностью перехвата) радар, CFAR (функция постоянной вероятности ложных тревог), IoT (интернет вещей), искусственный интеллект, глубокое обучение, сигнальный процессор, коэффициент сигнал-шума (коэфф. с/ш).

Introduction

Today nobody will have surprised application of radar technologies in different industries of the economy: medicine, armament, security, agriculture, geology, IoT and others like that. Their further development is impossible without the use of artificial intelligence, cognitive technologies, deep learning, cloud computing, real-time multiprocessors, which are being rebuilt in the process of solving the problem, neural networks. All these modern technologies do not diminish the importance of knowledge of antenna theory, radio engineering, signal processing, but make them revisit, more meticulously. And a separate task, no less important - real-time setup of the complex. This is often a stumbling block, since debugging LPI radars is sometimes more difficult than designing the radars themselves, since it requires the construction of modelling complexes but often sufficient resources (time, funding) are not provided in the contract.

Features of development of CFAR function for LPI radar

The main requirement for LPI radars, depending from the using – is invisibility to the surrounding electronic devices, low radiation power (less than 1 W), minimizing the negative impact on human health. This makes it difficult to isolate the signal from the noise, which explains the unsuccessful attempts to create a ground-based scanning radar (GRP), a mine-finding radar, a portable intelligent through the wall radar (PSTW), near- and far-range radars. The use of technology in the IoT environment is rapidly increasing as demand for such a service built into existing gadgets such as iPhones, clocks, and so on increases, allowing for unlimited access to cloud computing, which facilitates deep learning of cognitive functions. Historically, this new class of radar has been called the Low Probability of Interception (LPI) radar.

For nonlinear approach (NLFM) the CHIRP modulation as the SIDELOBE (side petals) can improve level has the greatest advantage and to receive losses <1 dB in comparison with windowing configuration. (NLFM) modulation can be considered of course as "window weightings". As a lack of nonlinear modulation in relation to linear it is possible to note difficulties with elimination of hindrances and big sensitivity to Doppler shift (providing Doppler compensation filters).

The radar has to operate from 20 m, at fine resolution, out to 96 nmi, at reduced resolution, with the same solid state transmitter, relying on waveforms and processing to achieve the necessary performance. The underlying method by which this is achieved is to use short pulses for close ranges, where the returned energy is adequate for detection, and then to integrate the power over longer pulses or sequences of pulses, preferably coherently, to allow adequate SNR for the detection of targets at longer ranges.

This leads to the use of signals with a complex signal structure. Consider the key metrics that characterize radar: resolution by distance, azimuth, area, volume.

The distance resolution on range is estimated by distance ΔD between two separately observed targets 1 and 2 located on one direction concerning the radar. Separate reception of the reflected signals from these targets it is possible if the reflected impulse from the first targets ends before, than there will be acceptances an impulse which is reflected off from the second target.

Since the reflection from the first target lasts for τ pulse time, and the signal from the second target is delayed by time $\Delta t = \frac{2\Delta D}{s}$, then the inequality of the individual receiving signals will be inequality $\frac{2\Delta D}{c} \geq \tau_{pulse}$.

Two targets will be displayed separately on the radar screen if the distance between the targets is:

$$\Delta D \geq \Delta D_{resolution} = \frac{c\tau_{pulse}}{2}.$$

With decreasing ΔD resolution, the value of the range resolution increases. Thus, to increase the resolution of the range should reduce the length of the probe pulses.

The azimuth resolution is estimated by the minimum value of the angle α_0 between the directions to two equidistant point targets 1 and 2, inat which the reflected signals from these targets are received separately. The azimuth resolving power value α_0 is determined by the horizontal antenna width α_H at half power. Thus, in order to increase the azimuth resolution, one should narrow the antenna pattern in azimuth.

The resolving area at a distance D is estimated by the size of the area limited by azimuth by the beam width α_H of the antenna at half power, and in range — by range resolution. It should be noted that the range resolution due to the finite sliding angle β is 1/cosβ times larger than the generally accepted value $\frac{c\tau_{pulse}}{2}$.

The slip angle is the angle in the vertical plane between the direction of maximum radiation from the output of the radar antenna and the sea surface.

Area resolution

$$S_{resolution} = \frac{D\alpha_H c\tau_{pulse}}{57.3 \cdot 2\cos\beta} = 0.0087\frac{D\alpha_H c\tau_{pulse}}{\cos\beta}$$

For small values of β, this holds

$$S_{resolution} = 0.0087 D\alpha_H c\tau_{pulse}.$$

Estimated expression for resolving area

$$S_{resolution} = \frac{D\alpha_H 150 c\tau_{pulse}}{57.3} \approx 2.6 D\alpha_H \tau_{pulse} \ [м^2],$$

were α_H *[град]*; τ_{pulse} *[mks]; D [м].*

Within the area resolution, point targets cannot be displayed separately on the radar screen

If $D = 50 \cdot 10^3$ *м*; $\alpha_H = 1°$; $\tau_{pulse} = 1$ *мкс, то* $S_{resolution} = 13 \cdot 10^4$ *м*^{2}.

The resolving volume at a distance D is estimated by the value of a volume numerically equal to the cross-sectional area of the antenna beam at this distance, multiplied by the range resolution $\frac{c\tau_{pulse}}{2}$.

Get $$V_{resolution} = D^2 \frac{\alpha_H \theta}{(57.3)^2} \cdot \frac{c\tau_{pulse}}{2} = 1.5 \cdot 10^{-4} D^2 \alpha_H \theta c\tau_{pulse}.$$

Calculation formula for volume resolution:

$$V_{resolution} = D^2 \frac{\alpha_H \theta}{(57.3)^2} \cdot 150\tau_{pulse} = 0.045 D^2 \alpha_H \theta \tau_{pulse} \ [м^3],$$

were D *[м]*; α_H *[град]*; θ *[град]*; τ_{pulse} *[mks]*.

We get:

$$V_{resolution} = D^2 \frac{\alpha_H \theta}{(57.3)^2} \cdot \frac{c\tau_{pulse}}{2} = 1.5 \cdot 10^{-4} D^2 \alpha_H \theta c \tau_{pulse} .$$

Clouds, rain, fog and snow interfere with the radar, which manifests itself in the form of false radar reflections (weather clutter, volume clutter). Thus, difficult meteorological conditions lead to a weakening of the reflected signals from the targets and the appearance of additional re-reflected interference. If the sea surface is mirrored, then the probe signal reflected from the sea surface propagates only towards the target.

With an excited sea surface, the geometry of the reflecting surface of the sea is constantly changing, part of the power of the probing signal is reflected from the sea waves, arrives not only towards the target, but also returns to the side of the locator, creating additional interference (sea clutter). The reflected signals in this case are diffuse in nature; the probability distribution of instantaneous noise values has a normal distribution, the same as that of thermal noise.

LPI Radar emites electromagnetic waves with impulse modulation low power of up to 1 watt. Depending on application , modulation can be phase, frequency, pseudorandom, noise-like, and the like. For determine goals with good resolution requires complex mathematical processing of the received signal, controlling process of formation of probing impulses, interaction with the receiving part and control of the processing of received information. Similar non LPI radars have a power of about 1 kW.

The task of collecting information from the sensors of the electromagnetic environment, the internal sensors, isolating of signal from noise at the input of the radar receiver, signal processing, using of artificial intelligence technology, deep learning, classification of signals, support of cognitive functions of radar are provided by a multiprocessor with architecture which in during of processing is rebuilt with forming a multidimensional function dependent on the application of the radar.

This feature is called: Constant False Alarm Rate (CFAR). The developer's task is to minimize false alarms at different signal, interference, and noise levels. In this article, we will focus on the formation of the CFAR function and will cover, beyond the scope of consideration, the formation of interference elements, the effect of internal noise and the methods of forming controls on the components of the radar LPI and the process of organizing calculations. The rapid growth in the number of scientific publications in domestic and foreign publications confirms the importance of the CFAR function, as well as the lack of a clear concept for its construction and the presence of a small number of practical successful applications related to the most understandable and widely using military field: marine and surveillance radars.

The main task of creating LPI radars with CFAR is to build a CFAR processor that processes an adaptive algorithm for noise detection and interference problems. This must be the original architecture. We begin the process of developing radar by formalizing radar requirements, building a complex to model a multidimensional CFAR function with sufficient resources, and generating an impact function. This dispels the myth of the ease of constructing LPI radars as a transmitter and superheterodyne receiver, as well as exaggerated affinity with basic telecommunication wireless stations.

In most real systems, the level of interference changes over time. To maintain the constant probability of false alarms, we change their threshold. A series of discrete values, each of which is the average signal level over a corresponding time interval, enters the CFAR detection circuit. The detection scheme must decide whether the signal in the study interval indicates the presence of a target or whether it is caused by external and internal noises. In most simple CFAR detection schemes, the threshold level is calculated as the average noise value over several time intervals before and after the test. We consider that the signal level in the test interval is conditioned by the presence of a target if it exceeds the signal level at adjacent intervals. This approach is called cell-averaging CFAR (CA-CFAR).

Examples of CFAR implementation

There are many options for forming a CFAR function, depending on the purpose. Basically, it comes down to determining the threshold level. For example, some algorithms average the signal at predetermined intervals before and after the test, and then take more or less of the values obtained. These approaches are called maximum-of-CFAR, GO-CFAR and least-of-CFAR, LO-CFAR.

More sophisticated CFAR algorithms can adaptively adjust the threshold level based on radar statistics. This is especially true for shore-based radars, where noise due to reflection from the sea surface is poorly approximated by the additive white Gaussian noise. This makes it difficult to detect objects such as submarines, yachts, swimmers, etc.

Article [1] examines critical interferences in the form of an unwanted echo called clutter. These include echoes of the earth, weather (especially rain, snow), the sea, and deliberate disturbances. Therefore, the developer of shore-based radars faces the problem of how to eliminate external interference. This article discusses troubleshooting methods such as Doppler processing and Log-FTC, and then introduces an algorithm for protection against accidental changes that are suitable in a transition state and a steady state. Also, this technique does not depend on the type of interference and center frequency.

Article [2] presents the original structure of a CFAR detector and the estimation of moving marine targets under natural interference conditions using bistatic radar scattering. Studies confirm that the amplitude of the marine target signal is distributed by Rayleigh, and the amplitude of the reflected signal from the sea is distributed by Weibul. In this situation, an adaptive approach to the formation of a statistical rule was used to suboptimal detect the unknown length of the target at sea. The purpose of this approach is to build a structure of decision-making rules to determine unknown parameters in situations where part of the statistical parameters of two hypotheses is unknown: power or length of target.

A comparison of the performance of the CFAR API and the Hauff detector with incoherent multilayer integration is investigated in [3]. For comparison, the Rolling approach was used to calculate losses. This article unifies the results of an extensive loss study of several types of detectors. This study examines the results of a comparative analysis of a Hauff detector with incoherent integration in a multilayer situation. Losses are defined as a statistical estimate using the probabilistic characteristics of detectors of both types. The efficiency of the Hauf detectors is calculated for different values of the false alarm probability with different observations in the reference window, the average interference ratio, the noise, and the probability of occurrence of a multi-path medium-length situation in the cell range. Our results show that Hauf transformation is effective if the multipath situation is reduced.

Article [4] investigates the automatic averaging (ACCA) of a CFAR detector based on ordered variable data (ODV) for heterogeneous background environments. The ACCA-ODV detector dynamically selects, by successive test checks, the appropriate set of ranked cells to estimate the unknown background level. The proposed detector does not require any prior information about the background environment and uses the variability index statistics as a form parameter to reject or accept the ordered ordered cells. For implementation, a two-tier architecture is proposed, in which both ODV-based sequential statistics match the hypotheses that are being processed simultaneously. The performance of the proposed detector is evaluated and compared with those such as OS-CFAR and modified index-CFAR (VI-CFAR) detectors in different background environments. The results show that the ACCA-ODV detector acts as a CA-CFAR on a homogeneous background and operates reliably in heterogeneous environments.

Article [5] examines the received signals in a radar system, which are always accompanied by noise and interference, such as echoes from the earth, sea, rain, birds, insects, wind gusts and atmospheric turbulence. These disturbances can cause a serious deterioration in the performance of radar systems, leading them to conclude that these echoes are targets (false alarms). To overcome this problem and make the right decision, the receiver in the radar system must achieve a constant false alarm rate (CFAR) and a maximum probability of target detection. Modern radars typically make the detection decisions automatically, using an adaptive threshold based on the CFAR architecture, where the threshold is determined dynamically based on local background noise / clutter rather than the constant value of a powerful signal.

Formation of CFAR function and its influence in modern LPI councils is impossible without the use of digital filtering. We offer its construction on a multiprocessor, which is being rebuilt in the process of operation. Using multiprocessor with neurocomputer elements allows you to achieve multiple types of signal processing in real time. The processing is easy to do in the baseband, not the bandwidth. Then the low pass filter performs the task without taking into account the external band. Increasing the signal-to-noise ratio improves the detection of targets in the middle of the noise, if this filter is consistent with the expected radar signal, even when it has distorted the signal. Doppler processing excludes signals from fixed and slow targets. The proposed filter, developed as an adaptive filter, is used for spectrum formation and interference elimination, based on the least-squares algorithm, which monitors interferences and eliminates the "blinding" of moving targets that occur during digital Doppler smoothing, which are more likely to be caused.

After the electrodynamic formalization of the electromagnetic field, we construct an operator equation of the first kind, where the nucleus is a Green function. We display the instantaneous characteristics of the observed object, the set of values of which determines the image. This is the information that underlies the training and recognition of radar information.

Today, there are many options for building CFAR algorithms based on linear and nonlinear operations. Analysis of publications confirmed the complexity of building LPI radars. The impasse of the situation is seen in the non-systematic consideration of the design of modern radar systems. The key problem is the generalization of the CFAR function, the construction of a modeling complex to work out the options for constructing the function, the allocation of computing resource to implement the function in real time. The CFAR processor architecture is offered as a specialized module synthesized for multiple FPGA Xilinx Virtex VII configurations.

The optimum choice of architecture is ensured by its maximum approximation to the class of solved problems. To implement the CFAR function, the architecture of a fault-tolerant real-time m-cluster multiprocessor for multidimensional signal processing [6] with a high-speed radio channel is developed. High performance and reliability are achieved through the use of high-speed radio to exchange between individual clusters, channel modulation and fault-tolerant technologies. Such an architecture is optimally oriented to solve multidimensional field processing problems in radar. The spatial orientation of the information sources most fully reflects the natural parallelization of the tasks being solved in the multiprocessor whose architecture corresponds to this class. A set of functional modules designed for radar field processing has been developed, which is characterized by a large amount of information. The central unit generates CFAR functions, organizes deep learning, provides diagnostics and initial start-up. There are three stages of the operation of the CFAR calculator, aimed at managing the process of obtaining information and the formation of probing signals through the CFAR interface: the task of recognizing the radar situation, developing a decision strategy, implementing the decision.

The dynamics of the change of the radio frequency field of the radar can be analyzed in the abstract space of states – the phase space in which you can enter coordinates describing the state of the system, such as the electromagnetic field strength of points at different distances from the antenna at each time. We plot the trajectory in the phase space, indicating the direction of field change along the phase trajectory over time. Note that the introduction of such a phase space makes it easier to analyze the field if you move from a normal coordinate space to a phase space. For example, if the propagation of oscillations in the space-time diagram of variables x, t is represented by a curve line, then on the phase plane P, x (where P is the Power, x is the Coordinate), such motion is represented by a point and a line respectively (first order curve). In phase space it is also easier to analyze the stability of the solution of the wave propagation problem and to investigate the problem of stability and instability of the system. The basis for the classification of the wave propagation and their models is the condition of the reproduction of solutions under given initial conditions. Analysis of the radar system shows that over time, the phase trajectories of certain areas of space concentrate around some points - the system seems to be drawn to these points in the course of its development. The points attracting the trajectory are called attractors. An example of an attractor would be the propagation of energy from the antenna to the target and in reverse order. Power and distribution are constantly changing, but the energy flow is generally stable in space and does not go beyond certain limits.

To better understand the radar's internal links and, most importantly, the links between the information gathering systems, namely, the sources of noise, both internal and external, the effects of random and directional interference, antenna information and others, we will examine the "reticular" aspect of the radar LPI. Depending on the course of the radar situation, the information content of the radar and its computing environment changes. The radar system has reticular property due to the fact that its processors of different architecture and computing power have many contacts with external sources of information, the ability to scale the number of computers and links). In the course of training, different computers have different activity (priority when processing interrupts), blocking connections after operator intervention, or receiving a directional interference. The role of the arbiter in the reticular system of the radar takes on a central module that interacts directly and indirectly with almost all radar structures and systems, affecting its various functions. One of the most important is the radar activation function associated with the process of changing the radar environment.

The assumption is made that functional metastable structures of the neural network phase space are model representations of the radar system. It is noted that the process of relaxation of the system initiates the reflection of metastable structures of model representations of images in the cognitive space in the form of functional modes. Cognitive memory space is defined as the phase space of functional image modes. The mechanism of influence of functional modes on the process of forming model representations of images is investigated and of creation of model representation of an image with consideration of chaotic change of parameters of system with time is studied.

Forming a generalized multidimensional CFAR function

The effectiveness of the radar recognition system as a whole depends directly on the efficiency of the technical means and its mathematical support - software-implemented algorithms for constructing descriptions of classes of objects and phenomena in sign language. The obtained radar information is divided into groups of similar but not identical phenomena. We create a radar image of the object against the background of distorted information in real conditions. The characteristic property of the images is manifested in the fact that after getting acquainted with the finite number of manifestations of the object, we learn about any number of its representatives. Also, when teaching a radar neurocomputer (rebuilding multiprocessor) at different observation sites, the same objects are classified equally and independently of each other. The objective nature of the basic property of the images allows us to model the recognition process.

As a result of deep learning, the recognition system acquires the ability to respond with the same reactions to all objects of the same image and different - to all objects of different images. It is very important that the learning process be completed only by displaying a finite number of objects, without any "clues".

The objects of training are radar objects, interference, radar specifications. It is also important that only the objects themselves and their affiliation with the image are indicated in the learning process. The training is followed by the process of recognizing new objects, which characterizes the actions of the already learned system. Automation of these procedures is a problem of pattern recognition training.

The most comprehensible to us is the spatial-temporal interpretation of tasks. Hence the problem of learning pattern recognition has received its geometric (spatial) and temporal (dynamic) interpretation. Any radar image resulting from the observation of an object in the course of training or testing can be represented as a vector, and hence as a point of some space.

If it is claimed that radar images can be uniquely assigned to one of two (or more) images, then it is claimed that in some space there are two (or more) areas that have no common points, and the images shown are points from these areas. Each such area can be assigned a name, that is, give a name to the corresponding image.

During deep training, points randomly selected from these areas are presented and information is given to which area these points belong. No additional information about these areas, ie the location of their borders, is reported during the training.

The purpose of the training is either to construct a surface that separates not only the points shown in the learning process, but all other points belonging to these areas, or the construction of surfaces that limit these areas of points so that each of them is only one point insult. That is, deep learning is about constructing such features from image vectors that would be, for example, positive at all points of one and negative at points of another image.

Due to the fact that the areas do not have common points, there are always a whole lot of such separating functions, and as a result of training one of them must be built. If the displayed images do not belong to two, but to a larger number of images, then the task is to build on the points shown in the course of training, separating all the areas corresponding to these images from each other. This problem can be solved, for example, by constructing a function that takes over the points of each area the same value and the points over the different areas different.

A deep learning mechanism is used to build the CFAR function. First of all, we solve the problems of object classification. Let there be some set of investigated objects $\Omega = \{\omega\}$, each of which is determined by the vector of its values in the phase space of some m given signs:

$$\omega_1 \to \bar{x}^1 = \{x_1^1, x_2^1, \ldots, x_m^1\};$$

$$\omega_2 \to \bar{x}^2 = \{x_1^2, x_2^2, \ldots, x_m^2\};$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots;$$

$$\omega_t \to \bar{x}^t = \{x_1^t, x_2^t, \ldots, x_m^t\}.$$

We divide objects into homogeneous classes (their number can be specified or may be unknown), which we call clusters, and methods for finding them - by cluster analysis. There is no training sample in this case, that is, it is unknown to which classes the objects in the set belong $\Omega = \{\omega\}$. We define patterns of structure of objects in clusters. In particular, a "compactness hypothesis" can be used as a similar pattern, ie the requirement that objects belonging to the corresponding classes be located in a given characteristic space $\bar{x} = \{x_1, x_2, \ldots, x_m\}$ "compactly". This means that the "distance" between objects assigned to this class is no more than specified.

Other requirements may be formulated in the automatic classification, namely, the generated classes in the sign space must be spaced apart at certain distances. Essentially, with the help of a multidimensional function defined on an arbitrary grid, we construct some sign or a generalized image of a class, by which one can uniquely determine the belonging to one of two points of a point in the phase space of measurements of the values of some predefined features.

To separate the sets of points of two different visions, we use hyperplanes or their sets, but only if the sets of points of the visions are so far apart in the phase space of the signs that a separating hyperplane can be constructed between them. When this is not present, then we move on to a new signs space. As a rule, we are going to add new signs to existing ones and to increase the dimension space of the signs space. In this case, to obtain a guarantee of separation reliability, it is necessary to significantly add the number of training sample points.

The main task of training is not to keep all the available information about the object, but to minimize the irrelevant, highlight the most informative and leave only the essential, that is, what can only be called information about the object, not just a random set of data. Sets of image points can also be reliably separated in spaces with fewer features when the surfaces of the sets are of rather complex configuration and do not intersect. For this case, we write an algorithm for constructing a separating hypersurface in the form of a multidimensional function defined on an arbitrary grid. But first, let's write an algorithm for determining a multidimensional function on an arbitrary grid, which we will use to construct the function itself. To do this, we:

1) We set the points of the grid of ordinates in the multidimensional coordinate space - the number of these points and the values of the coordinate vector of each point;

2) Determine the values of the parameters for all components: Green's function for solving the wave equation from grid points plus elements of the polynomial kernel.

Let some arbitrary grid of ordinates $\bar{P}$ be given in the form:

$$\bar{P} = (P^{(1)}, P^{(2)}, ..., P^{(N)})$$

The system of randomly arranged at R^n different unique points is given in the form:

$$P^{(k)} = (P_1^{(k)}, ..., P_n^{(k)}) \in R^n,\ k = \overline{1, N}$$

Define as follows on the grid $\bar{P}$ a multidimensional function $\sigma(\bar{P}; \bar{\lambda}; P)$, which at points of the grid takes some already set values: $r_i, i=\overline{1,N}$:

$$\sigma(\overline{P};\overline{\lambda};P^{(i)}) = r_i,\ i=\overline{1,N}, \tag{1}$$

and has a simple look - as a sum of some functions:

$$\sigma(\overline{P};\overline{\lambda};P) = \sum_{i=1}^{N}\lambda_i G_{m,n}(P-P^{(i)}) + \sum_{|\alpha|\le m-1}\nu_\alpha P^\alpha, \tag{2}$$

where $P^\alpha = P_1^{\alpha_1}\cdot P_2^{\alpha_2}\cdot\ldots\cdot P_n^{\alpha_n}$, $P^* = (P_1,\ldots,P_n)$, $P_k^{\alpha_k}$; k - coordinate in α_k – degree, $\sum\limits_{|\alpha|\le m-1}$ – the sum of all possible combinations: when $\alpha = 0$ – is the free ratio.

When $\alpha = 1$ – this is a free coefficient + components in linear form $\nu_0 + \sum\limits_{k=1}^{n}\nu_k P_k$, at $\alpha = 2$ – sum at $\alpha = 1+$ components at quadratic form $\sum\limits_{k=1}^{n}\sum\limits_{l=1}^{n}\nu_{kl}P_kP_l$ etc, (total $\frac{(n+m-1)!}{n!(m-1)!}$ components);

$$G_{m,n}(x-P) = \begin{cases} \|x-P\|^{2m-n}\ln\|x-P\|,\ n=2k \\ \|x-P\|^{2m-n},\ n=2k-1 \end{cases},$$

$$\|x-P\| = [\sum_{i=1}^{n}(x_i-P_i)^2]^{\frac{1}{2}},$$

$$P = (P_1,P_2,\ldots,P_n)^*,$$

$$x = (x_1,x_2,\ldots,x_n)^*.$$

The continuity of Green's $G_{m,n}(x-P)$ functions requires that the condition $m > n/2$ be satisfied. By summarizing the variation theory of constructing multidimensional functions on a chaotic grid to simple algebraic conditions, we can consider finding the coefficients of a multidimensional function as a solution of some system of linear equations. To do this, we simply introduce a continuous linear indexing for the coefficients ν of formula (2). Then we find the values of the coefficients

$$\lambda_i, i=\overline{1,N} \text{ and } \nu_l, l=\overline{1,\vartheta},$$

where

$$\vartheta = C_n^m = \frac{(n+m-1)!}{n!(m-1)!},$$

by solving two algebraic conditions: and, where $\vartheta = C_n^m = \frac{(n+m-1)!}{n!(m-1)!}$ to solve two algebraic conditions:

1) coincidence of values of multidimensional - function at given points $\overline{P}$ (1);
2) and the orthogonality of the polynomial kernel functions at each other at the same points. In matrix form it has the following generalized form:

$$C\cdot\overline{\lambda} = \overline{r},$$

where the matrix C has dimension

$$(N+\vartheta)\times(N+\vartheta),$$

$$\text{or } \overline{\lambda} = (\lambda_1,\lambda_2,\ldots,\lambda_N,\nu_1,\nu_2,\ldots,\nu_\vartheta)^*,$$

$\overline{r} = (r_1,r_2,\ldots,r_N,0,0,\ldots,0)^*$ – vectors of dimension $N+\vartheta$ each, $*$ – is the sign of transposition,

$$P^{(i)} = (x_1,x_2,\ldots,x_n)^*, i=\overline{1,N}.$$

For the system to have a solution, a condition is required $N \ge \vartheta$.Consider constructing a separating hypersurface in the form of a multidimensional function defined on an arbitrary grid. Suppose two sets of m - measurable points X and Y with the number of points M and L respectively:

$$X = \{\bar{x}^1, \bar{x}^2, ..., \bar{x}^M\}, \; Y = \{\bar{y}^1, \bar{y}^2, ..., \bar{y}^N\},$$

where

$$\bar{x}^i = \{x_1^i, x_2^i, \ldots, x_m^i\}, \;\; i = \overline{1, M}, \;\; \bar{y}^i = \{y_1^i, y_2^i, \ldots, y_m^i\}, \; i = \overline{1, L}.$$

We find a multidimensional function on an arbitrary grid that can sufficiently reliably divide sets of points X and Y, that is, divide into two intersecting regions by two sets in some multidimensional space of phase features, which are initially represented as two arbitrary sets of multidimensional points. The automatic construction of such a rule is the algorithm of machine learning. This is achieved by constructing a surface that separates not only the points shown in the learning process, but also all other points belonging to these areas.

To construct a multidimensional function on an arbitrary grid, we define a grid $\bar{P}$ of N_n – dimensional points and the values of the function in them $r_i, i = \overline{1, N}$. Due to the fact that we have not determined the direction from which to build the separating hypersurface, we have the opportunity to do so in the direction of each of the *m* coordinates. To do this, we use the value of one of the **m** coordinates as the value of a multidimensional function, and we use all other *(m-1)* coordinates as the values of points to determine the grid of ordinates with the dimension *n = (m-1)*. With this approach, there are only **m** options for constructing a multidimensional function on an arbitrary grid. In addition, it can be built both from the side of the set X, checking for Y and vice versa. You can also try moving around the points of one set, searching for the closest points of the other and finding some averages and already, on them to look for a hypersurface. In total, we have at least *2m + 1* options for constructing a multidimensional function of which we choose the most acceptable.

Conclusions

In this article, we have considered the construction of a multidimensional CFAR function for LPI radars and have made a comparative analysis of the most typical variants of the function construction based on materials of domestic and foreign publications in scientific publications. [1-5] They also noted a small number of practical implementation of theoretical developments. This is due to the complexity of forming a multidimensional CFAR function, the requirements for creating a computing environment, which is formed on the basis of a real-time multiprocessor, which is reconstructed in the process of processing radar information with wireless high-speed backbone, conveyor computing, neural networks, parallels. In addition, information for CFAR function formation is collected at all levels of the radar LPI: antennas, transceiver unit, primary and secondary processing units and, accordingly, primary processing influence generation, signaling probe generation, and radar receiver. The laboratory is testing the CFAR processor on a crystal (SoC). This is a promising direction for the development of a key element for LPI radars and the ability to modularly formulate a line of destination radars.

Formalizing a recognition system to investigate and analyze the real processes of collecting, processing, and visualizing radar images whose mathematical models we are not yet able to build is very important when building radars and learning in the application process. To date, a formal apparatus designed to construct mathematical models of sufficiently complex phenomena and processes adequate to simulated phenomena or processes has not yet been developed, which opens up great prospects for the best solution of the problem as it is sufficient to accurately quantify the development of processes solely on the basis of accumulated information about processes.

Another feature of smart radars using artificial intelligence technologies is the ease of use, just like using smartphones. This will simplify the work of professional users of LPI radars (marine radar operators, subsurface sensing, etc.) and will allow for the introduction into everyday life, such as the IoT segment.

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