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# Unambiguous Identification of Objects in Different Environments and Conditions Based on Holographic Machine Learning Algorithms

**Evgeny Bryndin\****Professional researcher of Engineering Research Association (AER), Russia*

**\*Corresponding author:** Evgeny Bryndin, Professional researcher of Engineering Research Association (AER), Russia, Novosibirsk.

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**Abstract**

Unambiguous provision of results in different environments and conditions by machine learning algorithms is an unresolved problem until now. Solving the problem of machine learning with unambiguous provision of results in different environments and conditions can be approached by focusing on the psychophysical holographic process of human learning. A person, with a mental concentration of attention, experimentally teaches vision, hearing, psyche and mind in a holographic way and in a resonant way to perceive, recognize and recognize phenomena, processes, objects, subjects, meanings, music and other entities in various environments and conditions. A person experimentally teaches the psyche and feelings to rationally navigate in various environments and conditions. Holographic algorithms of experienced machine learning will help neural network ensembles to unambiguously recognize objects, subjects, music, texts in various environments and conditions using a model of recognizing their own or someone else's. Machine learning simulates holographic processes of human communication memorization of entities. Searching for objects in different environments in different conditions based on experienced machine learning simulates resonant associative processes of human entity detection. By simulating holographic processes of the human psyche based on artificial intelligence of machine learning with Fourier transformation, using full parametric sequences of necessary and sufficient data of holograms of target objects, it is possible to solve the problem of their unambiguous detection in different environments and in different conditions.

**Keywords:** Holographic algorithms; Machine learning; Complex neural networks; Full parametric sequences of hologram data

**Introduction**

Machine learning includes task setting, data collection and preparation, modeling (building a predictive model and selecting its parameters), evaluation of the resulting model, implementation and support. Models must be built in accordance with dynamically changing conditions. Data preparation is associated with many resource-intensive actions - it is important not only to understand existing data and select those related to the problem being solved, but also to transform them to a format suitable for machine learning algorithms. Neural networks are a universal approximator and the model gives greater accuracy. To do this, you need to specify the quality criterion by which the optimization will be carried out. The

success of machine learning is determined by the choice of algorithm, the approach to learning, the development and implementation of the model architecture and the selection of data.

A problem in machine learning is the inability of models to work correctly on a greater variety of examples than those encountered in training [1]. For example, the network trained in images of an elephant, in which most often the elephant was against a forest background, and when tested, correct recognition of the elephant against any background is required. Working on this problem is important not only for solving practical problems, but also in general for the further development of AI. Machine learning special-

ists try to solve the problem of unambiguously providing results in different environments and conditions using particular knowledge and approaches to training, assessing the overall accuracy of the model on the test sample and on individual types of examples, using domain adaptation and large models [2-9]. Researchers have long been looking for an opportunity to train models in systematic generalization, understanding of the concepts of the part and the whole and operation with abstract concepts [10]. One of the promising approaches to increasing the generalizing ability of models is considered to be meta-learning ("learning-to-learn") [11]. High generalizability is also required in the training of agents, since the environment can be very diverse and change from the actions of the agents themselves. Important is the ability of agents to function correctly under new conditions not encountered before [12-14]. On the problems of modern machine learning, correlations in data and approaches to increasing generalizing ability [15].

Multi-modal learning seems promising. In the last couple of years, impressive results have been achieved in this area [16-18]. When training agents, it is necessary to predict the consequences of their own and other people's actions. A self-learning model, which exists, for example, in the mind of a person [19]. Researchers have always been interested in the topic of general artificial intelligence and the creation of systems that think like people [20-21]. Solving the problem of generalizing machine learning based on partial knowledge and private approaches can take a long time, and as a result, it is not effective. Nobel laureate Daniel Kahneman highlighted in thinking learning the skill of functional system-1 and using the skill of functional system-2. Learning occurs through the specialization of neurons in different areas of the brain. They band together in an ensemble and we acquire a skill. First, the skill is formed, and then its application. Functional systems for learning skill and its application work on the same ensemble of neurons. The author proposes approach to solving the problem of machine learning with an unambiguous result in different environments and conditions based on holographic algorithms, just as person teaches the skill and its use [22-23].

## Holographic Psyche of Man

### Holographic structure of memory

A holographic model of the psyche explains how the brain stores a huge amount of information in a small space. Stanford University neurophysiologist Carl Pribram views the brain as a hologram [24]. Memory, as one of the central functions of the brain, has a distributed character, and each part of the brain contains the whole. Each biological structure, starting from the cell level, is the source of a wide range of fields. All vibrations or vibrations of internal organs are coherent. It is coherent radiation that creates the holographic image. In a biological organism, coherent fields form a dynamic spatiotemporal interference structure-hologram. The radiation of each organ is considered as a reference relative to all other organs. The holographic model of the psyche explains the fact of instant recognition. The wave principle of holography allows you to imagine a mechanism that can almost instantly extract from storage the information that is encoded using such a wave process. Any place in the brain can trigger information waves, for this it is enough to

reproduce in this place a pattern of activity similar to what occurs in it when the corresponding wave passes. The wave function can be analyzed using the Fourier transform. There are similarities between storing information in holographic memory and in a hologram, which can also be analyzed using a Fourier transform. Holographic memory establishes associative links between different parts of non-uniformly stored information.

Russian scientist, academician P. P. Garyaev, the creator of a new science - wave genetics - in his book "Wave Genome" notes: "Human memory has a clearly expressed and well-studied holographic nature." Academician Kaznacheev writes: "Today, a paradigm begins to emerge, proclaiming that our brain is a hologram. German physiologist and physicist Hermann von Helmholtz showed that the ear is also a frequency analyzer, and also perceives wave information. Studies have found that our sense of smell organ is also based on osmotic frequencies. It follows from the works of the Russian scientist Nikolai Bernstein that human physical movements are encoded in the form of Fourier wave forms. The brain, which analyzes movements, breaks them down into frequency components according to the holographic principle.

### Holographic vision

Numerous experiments conducted by Pribram showed that brain cells associated with vision respond to wave forms of images. The brain uses the Fourier mathematical method - the same method as in holography, namely, remembering visible images in the form of a wave form. Neurons have tree branches, and when the electrical signal reaches the end of one such branch, it propagates further in the form of waves. Because neurons are closely adjacent to each other, diverging electrical waves are constantly superimposed on each other. Neural holograms are created. They define our mental images. The experiments of Academician N.P. Bekhtereva showed that brain activity is carried out in accordance with quantum laws. The human brain is the organ that generates wave holographic structures adequate to the forms of the outside world according to quantum laws. The holographic model of brain function was formulated by K. Pribram and physicist F. Westlake. The source of holographic recording construction is wave processes and impulses arising during the operation of nerve cells, while information is encoded on a set of neurons interacting with each other. The holographic model perfectly describes the properties of the distribution of information in the neural networks of the brain. Currently, there is not a single method that shows the distribution of information at any point in the information storage with as much clarity and certainty as the mathematical apparatus of holography does. The brain selects only information that requires close attention and response. Neurophysiologists Russell and Karen Devalois jointly established that "the spatial frequency coding displayed by cells in the visual cortex is best described as the Fourier transform of the target object. This explains the brain's ability to recognize objects at different angles and sizes than in the original stored memory. Parameters of neural systems of the human brain based on digital holography will be able to find application in pattern recognition systems, in speech and handwritten text recognition tasks, as well as in information and intelligent systems.

## Sound hologram

Based on a holographic model of the brain, Argentine physiologist Hugo Zucarelli investigated the auditory system that allows the creation of holograms of sound. Zucarelli revealed that the human ears themselves make a sound. These natural sounds are the reference wave used to recreate the holographic image. The ability to create an image of a particular thing or process is the main property of a hologram. Indeed, a hologram is a virtual image that has arisen where there is none, and no devices are able to detect the presence of any energy anomaly or matter in place of the hologram. The senses of the holographic psyche indicate the presence of this virtual image. The universe is one large hologram, part of which is a person, his psyche and his consciousness.

## Target Image Localization Recognition Systems

In general, setting the recognition problem boils down to the following. The object subject to localization recognition, we will call its image, is in the environment of other images. The target image and the entire image in which it is included will be considered as optical signals. They are represented as two-dimensional wavefield distribution functions. The correlation pattern recognition algorithm is based on the calculation of the image correlation function represented by the  $f_o$  function and the entire image represented by the  $f_i$  function. Let's designate the correlation function of the image and image as  $\phi_{oi}$ . If the analyzed image contains the desired image, then the correlation function has a pronounced correlation maximum (correlation peak), by the position of which the image can be localized in the image field [25]. Using the known properties of the correlation functions and the Fourier properties of the transformation, the calculation of the correlation function can be reduced to simpler operations with Fourier images, since the Fourier transformation of the correlation function is the Fourier product of the image of one of the functions to the complex Fourier conjugate image of the other. This statement is proved by the Wiener-Hinchin theorem.

We enter the operator  $F$  as the Fourier operation of the transformation, and  $F_o$  and  $F_i$  are Fourier images of the functions  $f_o$  and  $f_i$ , respectively. The algorithm can be implemented by the holographic conjugate filtration method proposed by Vander-Lugt.

In this method, three operations are performed sequentially by optical means.

1. Fourier transformation from light distribution on input placard containing analyzed image.
2. Multiplying it by the complex-conjugate spectrum of the desired image.
3. Inverse Fourier transform that forms the correlation function of image and image.

In the Fourier plane, a Fourier hologram is recorded. It is a picture of the interference of the reference and object waves. The intensity distribution  $I(x, y)$  in this picture has the form:

$$I = |T + R|^2 = T^2 + R^2 + TR^* + T^*R = T^2 + H^2 + T + T^* \quad (1)$$

The last term contains complex conjugate spectrum  $T^*$  of image recorded on hologram. Where  $H$  is the wave amplitude in the reference wave field  $R$ , and  $T$  is the Fourier image of the placard (medium). We will present to the system input our original image  $t$  in the context of some other image  $s$ , that is, let the input signal be represented by the sum of  $t + s$ . Since our optical system is linear, it reacts with the sum of two signals with the sum of two corresponding responses. That is, at the output of the system, a sum of two functions will be formed: the autocorrelation function of image  $t$  and the cross-correlation function of functions  $t$  and  $s$ . The autocorrelation function of image  $t$  will contain an autocorrelation peak emitted against the background of the "smeared" function of cross-correlation  $t$  and  $s$ . The position of this peak will represent the position of the image  $t$  in the input plane. Thus, the described system allows not only to select a certain signal from the context (that is, among other signals), but also to indicate its localization in space.

A filtration method called the Joint Fourier Transform method was developed. Two signals are simultaneously received at the system input: the original image and the analyzed image. The intensity distribution  $I$  in the interference pattern will be as follows:

$$I = |T + F|^2 = T^2 + F^2 + TF^* + T^*F \quad (2)$$

The co-Fourier transform correlator and the Vander-Lugt correlator allow you to extract the desired signal from the context.

The dynamic nature of writing and reading correlation functions makes it easy to ensure the process of recognizing the localization of the target image in real time. To this end, sequential search of correlation functions of the analyzed image with an array of images of different scale and orientation is carried out.

Localization recognition systems help to build complete parametric sequences of necessary and sufficient hologram data of the target image for machine learning of a complex neural network with Fourier transformation.

## Complex Neural Network Based on Fourier Series for Recognition Tasks

The architecture of a complex artificial Fourier neural network has an array of neurons  $m \times n$  where  $m$  is the number of Fourier decomposition descriptors and  $n$  is the dimension of the input vector. Weights in the first layer have the physical meaning of the frequencies with the highest energy, and weights in the second layer have the meaning of Fourier series coefficients. Thus, the number of inputs at each neuron of the output layer is  $m \cdot n$ , which corresponds to the number of Fourier series coefficients. Creating an array of neurons requires the use of large computational resources. In recognition tasks at the output, neural networks receive an belonging function, the value of which lies in the range from zero to one. Fourier transform for pattern recognition is used to obtain it. The network recognizes binary images. It takes complex numbers at the input, after which it approximates the function of belonging to the image. Before recognition, algorithms are used to binarize and bring the target image to the general form. Then it is supplied

completely to the artificial neural network with Fourier transformation. Separately, real and imaginary components are supplied full of parametric sequences of necessary and sufficient data of holograms of the target image, after which the image is recognized. The unambiguity of image recognition in different environments and different conditions is proved by the *uniqueness theorem*.

*Uniqueness theorem.* The integrable function uniquely defines the coefficients of the Fourier series or Fourier transform. The complete set of Fourier series coefficients or Fourier transform uniquely defines the corresponding function. To process speech and other signals, a complex recurrent neural network is used. Time domain convolution is used for frequency domain multiplication. This is how the Fourier transform is mainly used in machine deep learning with a model of reinforcement of one's own or another's.

## Conclusion

In solving the problem of unambiguous detection of objects in different environments and conditions based on holographic algorithms, the main attention should be paid to controlled machine learning based on examples based on classification. Building a good machine learning model requires experience in the development process, from data management, model selection and optimization to maintenance.

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## Conflict of Interest

No Conflict of interest.

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