Holographic neural networks*

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Abstract. *Holographic neural networks are a new and promising type of artificial neural networks. This article gives an overview of the holographic neural technology and its possibilities. The theoretical principles of holographic networks are first reviewed. Then, some other papers are presented, where holographic networks have been applied or experimentally evaluated. A case study dealing with currency exchange rate prediction is described in more detail.*

Key words: *neurocomputing, artificial neural networks, holographic neural technology, prediction problems*

Sažetak. Holografske neuronske mreže. *Holografske neuronske mreže predstavljaju jednu novu i obećavajuću vrstu umjetnih neuronskih mreža. Članak daje prikaz holografske neuronske tehnologije i njenih mogućnosti. Prvo se objašnjavaju teoretski principi na kojima se zasnivaju holografske mreže. Zatim se prikazuju neki drugi radovi koji se bave primjenom ili eksperimentalnom evaluacijom holografskih mreža. Detaljnije je opisan studijski primjer prognoziranja valutnih tečajeva.*

Ključne riječi: *neuronsko računanje, umjetne neuronske mreže, holografska neuronska tehnologija, problemi prognoziranja*

1. Introduction

Neurocomputing [4] is a technological discipline concerned with information processing systems (for example neural networks) that autonomously develop operational capabilities in adaptive response to an information environment. Neurocomputing is a fundamentally new and different approach to information processing. It is a first alternative to programmed computing, which has dominated information processing for the last 50 years.

An *artificial neural network* is a data processing structure (real or simulated) that bears some resemblance to a natural neural tissue. More precisely, it is a set of interconnected basic processing elements called neurons. For an input (called stimulus) this set automatically produces an output (response). Furthermore, the

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network can be trained to faithfully reproduce a predefined collection of stimulus-response associations. After successful training (learning), the used associations are also slightly generalized, i.e. the network produces a plausible response to a new stimulus that is similar to some of the learned stimuli.

Typical applications of neural networks include pattern recognition, classification, prediction (forecasting), control of complex systems, signal processing. Some more concrete examples are: optical character recognition, voice recognition, credit scoring, bankruptcy prediction, stock forecasting, robot control, acoustic noise filtering.

A problem suitable to be solved by neural networks has the following general characteristics. It reduces to a correspondence between some kind of stimuli and responses. However, there exists no simple mathematical model of that correspondence. Instead, concrete examples of stimuli and required responses are given. These examples are comprehensive enough to express all important aspects of the problem.

A solution obtained by neural networks has the following characteristics. It is obtained by designing a suitable network and by network training. Thus it avoids the classical algorithmic approach and programming. Unfortunately, it is a black-box solution, which does not give any explanation to its responses, decisions, etc.

There are many types of neural networks, which differ in various details including neuron structure, network topology and training algorithms. *Holographic networks* are yet another class of neural networks, which have recently been proposed [11]. Although conforming to the general paradigm, these networks are unusual in many aspects, and they provide an alternative to conventional network types [4].

The aim of this presentation is to inform the reader about holographic neural networks, its peculiarities, and its possible applications. We believe that this novel type of networks deserves more attention, and that it should play a more prominent role in the future. Apart from this introduction, the text consists of two major sections and a conclusion. *Section 2* reviews the theory of holographic networks: through this review the holographic neural process is analyzed, and its main properties are explained in more detail. *Section 3* refers to some other papers, which consider possible applications of holographic networks, or where those networks have been evaluated on experimental data; special emphasis is put on a case study dealing with currency exchange rate prediction. R

2. Theoretical issues

The main difference between holographic and conventional neural networks is that a holographic neuron is more powerful than a conventional one, so that it is functionally equivalent to a whole conventional network. Consequently, a holographic network usually requires a very simple topology consisting of only few neurons. Another characteristic of the holographic technology is that it represents information by complex numbers operating within two degrees of freedom (value and confidence). Also an important property is that holographic training is accomplished by direct (almost non-iterative) algorithms, while conventional training is based on relatively slow "back-propagation" (gradient) algorithms.

A *holographic neuron* is sketched in *Figure 1*. As we can see, it is equipped with only one input channel and one output channel. However, both channels carry whole vectors of complex numbers. An input vector S is called a *stimulus* and it has the form

$$S = [\lambda_1 e^{i\theta_1}, \lambda_2 e^{i\theta_2}, \ldots, \lambda_n e^{i\theta_n}].$$

An output vector R is called a *response* and its form is

$$R = [\gamma_1 e^{i\phi_1}, \gamma_2 e^{i\phi_2}, \ldots, \gamma_m e^{i\phi_m}].$$

All complex numbers above are written in polar notation, so that moduli (magnitudes) are interpreted as confidence levels of data, and arguments (phase angles) serve as actual values of data. The neuron internally holds a complex $n \times m$ matrix $X = [x_{jk}]$, which serves as a *memory* for recording associations.

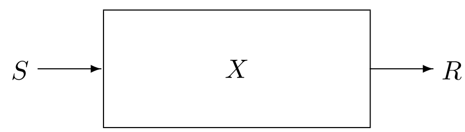

Figure 1. *A holographic neuron*

Now we will explain the *basic learning process*. Learning one association between a stimulus S and a desired response R requires that the correlation between the j-th stimulus element and the k-th response element is accumulated in the (j,k)-th entry of the memory matrix. More precisely:

$$x_{jk} \mathrel{+}= \lambda_j \gamma_k e^{i(\phi_k - \theta_j)}.$$

The same formula can be written in the matrix-vector form:

$$X \mathrel{+}= \bar{S}^{\tau} R. \tag{1}$$

Here $\bar{S}^{\tau}$ denotes the conjugated transpose of the vector S.

To accomplish *training* with multiple stimulus-response associations, the basic learning step (1) must be repeated in turn for each association. Note that all associations must be enfolded onto the same memory matrix. Each learned association will slightly disturb the other learned associations.

The *computed* response R^* to a new stimulus

$$S^* = [\lambda_1^* e^{i\theta_1^*}, \lambda_2^* e^{i\theta_2^*}, \ldots, \lambda_n^* e^{i\theta_n^*}]$$

is obtained as a matrix-vector product

$$R^* = \frac{1}{c}\, S^* X. \tag{2}$$

The normalization coefficient is usually taken as

$$c = \sum_{k=1}^{n} \lambda_k^*.$$

Now there follows an analysis of the computed response. Suppose that the associations

$$(S^{(t)}, R^{(t)}), \quad t = 1, 2, \ldots, p,$$

have previously been learned. Let us consider the k-th response element, $1 \le k \le m$. According to (1) and (2) we have:

$$\gamma_k^* e^{i\phi_k^*} = \frac{1}{c} \sum_{j=1}^{n} \lambda_j^* e^{i\theta_j^*} \sum_{t=1}^{p} \lambda_j^{(t)} \gamma_k^{(t)} e^{i(\phi_k^{(t)} - \theta_j^{(t)})} = \frac{1}{c} \sum_{t=1}^{p} \gamma_k^{(t)} e^{i\phi_k^{(t)}} \sum_{j=1}^{n} \lambda_j^* \lambda_j^{(t)} e^{i(\theta_j^* - \theta_j^{(t)})}.$$

The above formula can be rearranged in the following way:

$$\gamma_k^* e^{i\phi_k^*} = \sum_{t=1}^{p} \Lambda^{(t)} e^{i\Psi^{(t)}},$$

where

$$\begin{aligned}
\Lambda^{(t)} &= \frac{\gamma_k^{(t)}}{c} \left[[\sum_{j=1}^{n} \lambda_j^* \lambda_j^{(t)} \cos(\theta_j^* - \theta_j^{(t)})]^2 + [\sum_{j=1}^{n} \lambda_j^* \lambda_j^{(t)} \sin(\theta_j^* - \theta_j^{(t)})]^2 \right]^{1/2}, \\
\Psi^{(t)} &= \tan^{-1} \left[\frac{\sum_{j=1}^{n} \lambda_j^* \lambda_j^{(t)} \sin(\theta_j^* - \theta_j^{(t)} + \phi_k^{(t)})}{\sum_{j=1}^{n} \lambda_j^* \lambda_j^{(t)} \cos(\theta_j^* - \theta_j^{(t)} + \phi_k^{(t)})} \right].
\end{aligned}$$

Thus the chosen response element is a sum of many components. Each component corresponds to one of the learned associations.

Now let us consider the case where the new stimulus S^* is approximately equal to one of the previously learned stimuli. Suppose that for some l, $1 \le l \le p$,

$$S^* \approx S^{(l)}.$$

Suppose also that for all j and t,

$$\lambda_j^* \approx 1, \quad \lambda_j^{(t)} \approx 1, \quad \gamma_k^{(t)} \approx 1.$$

Then the above expressions for $\Lambda^{(t)}$ and $\Psi^{(t)}$ indicate that the l-th component of the response has a relatively big confidence level and an explicit direction:

$$\Lambda^{(l)} \approx 1, \quad \Psi^{(l)} \approx \phi_k^{(l)}.$$

The other components usually have smaller confidence levels and different directions. It means, for $t \ne l$:

$$\Lambda^{(t)} << 1, \quad \Psi^{(t)} = \cdots \ ? \ \cdots.$$

It is expected that these other components will neutralize in a manner analogous to random walk. Consequently, the generated response will be approximately equal to the desired learned response, as shown in *Figure 2*.

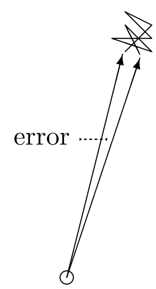

Figure 2. *Response to a learned stimulus*

An important aspect of the holographic neural technology is data pre- or post-processing. For instance, *data conversion* is needed to switch between external (real or integer) and internal (complex) representation, i.e. original application data should be transformed into arguments (angles) and vice versa. Some commonly used types of data conversion are: linear conversion (real values from a known finite range), sigmoid or arctan conversion (real values from an unknown or infinite range), step-function conversion (a finite set of values). As we will see in the next section, additional *stimulus preprocessing* procedures can be used to control the holographic process in some way.

In addition to the already presented formula (1), the holographic neural technology provides also some other more advanced learning modes. The following *enhanced learning* formula takes into account the prior knowledge accumulated within the neuron, and tries to minimize distortion of the previously learned associations. Let S again be a given stimulus, and R the desired response. The idea is to compute first the response that would already have been generated:

$$R' = \frac{1}{c}\, SX.$$

Then compute the difference between the generated and the desired response:

$$R_{\mathrm{dif}} = R - R'.$$

Finally, learn the association between the stimulus and the above difference, by using the old formula (1):

$$X \mathrel{+}= \bar{S}^{\tau} R_{\mathrm{dif}}.$$

The resulting formula, which can replace (1), is

$$X \mathrel{+}= \bar{S}^{\tau} \left(R - \frac{1}{c} SX \right). \tag{3}$$

In fact, this formula is used as default since it assures better performance than (1).

As before, to accomplish training on a set of stimulus-response associations, the enhanced learning step (3) has to be repeated for each association in the set. Note that the order of steps now becomes important, namely the first association is more distorted by subsequent encodings than the last one. Therefore, the whole learning cycle should be repeated several times in order to stabilize. So we end up with a form of *iterative* training. Still, the number of needed iterations (so called epochs) is considerably smaller than in traditional "back propagation" algorithms, i.e. according to [2] it is never greater than 20.

Holographic networks also allow a special regime called training with a *reduced memory profile*. When this regime is applied, the previously learned stimulus-response associations are gradually forgotten as training progresses. Consequently, more recently learned associations expose stronger influence on a response than older ones. The memory profile is expressed in percentages (100% - permanent memory, $< 100\%$ - reduced memory), and it is controlled through periodical re-scaling (reduction) of the entries in the memory matrix X.

Finally, let us note that holographic networks allow *incremental training*. It means that an already trained neuron can subsequently learn an aditional stimulus-response association. The latter is not true for traditional networks, where adding a new training example usually means starting the whole training procedure from scratch. Incremental training of a holographic neuron is possible for both learning formulas (1) and (3), and for any memory profile. Again, the additional learning step will slightly distort the prior knowledge. However, this distortion is not visible if a reduced memory profile is used.

3. Applications and experiments

Holographic neural networks can be applied to the same problems as the other network types. However, the process of designing a holographic application is quite specific. Namely, the network topology for most problems turns out to be trivial or very simple. Rather than with topology, the designer is much more concerned with data preprocessing. Adequate preprocessing procedures can, for instance, be used to improve accuracy in reproducing the learned associations, or to expand learning capacity, or even to control generalization properties.

Generally speaking, holographic networks are very suitable for those problems where stimuli are long vectors with symmetrically (uniformly) distributed arguments. A longer stimulus vector assures a greater learning capacity, i.e. a greater number of stimulus-response associations that can be learned. Symmetry in arguments assures accuracy in reproducing the learned stimulus-response associations. Long stimuli are usually obtained by discretization of continuous functions or digitalization of images. Symmetry of long vectors can be improved by adequate preprocessing, so called *stimulus symmetrization* based on the sigmoid function [12].

There are few demo examples in [2] that illustrate the applicability of holographic networks to problems dealing with *continuous signals* and *images*. The examples include: satellite control, image filtering, recognition of a detail in a large picture.

Holographic networks can also be applied to *classification* problems. However, some difficulties may arise if the number of attributes used for classification is small. Then it is necessary to artificially enlarge the stimulus vector, by a preprocessing procedure called *stimulus expansion*. The standard expansion procedure [12], based on higher order product terms, may prove inadequate for an extremely short stimulus. A more suitable expansion method, based on sines and cosines, has been proposed in [6]. The same paper also introduces a new symmetrization method, and evaluates both methods on the iris flowers benchmark classification problem. Other examples of classification with holographic networks have been described in [10, 5]; the concrete problems considered there comprise credit scoring and neurological diagnosis.

It has been suggested in [1] that holographic networks can be applied to *data compression*. Namely, a holographic neuron can be used to memorize the set of values from a file (stimulus: the value identifier, response: the value itself). After training, the neuron should be able to approximately reproduce any value. If the memory matrix inside the neuron happens to be smaller than the original file, we can speak about (lossy) data compression. This idea has been explored experimentally in [8]. The obtained results indicate that the considered holographic compression method works well only for very regular (smooth, redundant) files.

We believe that holographic networks are very suitable for *prediction* (forecasting) problems, specially if the considered system is dominated by short-term trends. Namely, a natural training regime for such problems is incremental training with a low memory profile (knowledge should be constantly revised). The recommended regime can easily be realized with holographic networks, but much harder with traditional network types. To illustrate this, we now present original results dealing with currency exchange rate prediction.

In our experiments we used authentic data from "Zagrebačka banka" (Bank of Zagreb) comprising the exchange rates of seven currencies (ATS, CHF, DEM, FRF, GBP, ITL, USD) for each working day between 1st October 1992 and 1st October 1993. To eliminate unwanted effects of the domestic inflation, we chose ATS as the reference currency and expressed the other six currencies in terms of ATS. Some basic statistical parameters are shown in *Table 1*.

currency	mean	standard deviation	minimum	maximum
ATS/CHF	0.1278	0.0024	0.1236	0.1322
ATS/DEM	0.1421	0.0000	0.1415	0.1422
ATS/FRF	0.4843	0.0063	0.4774	0.5040
ATS/GBP	0.0577	0.0013	0.0550	0.0612
ATS/ITL	131.4096	5.0543	119.9376	142.1060
ATS/USD	0.0879	0.0036	0.0815	0.1016

Table 1. *Statistical parameters for the exchange rates data*

The described data were interpreted as a set of stimulus-response pairs. In each pair, the stimulus consisted of exchange rates for five consecutive days, and the response comprised the next-day rates. A suitably sized holographic neuron was chosen. The stimulus-response examples were presented to the neuron in chronological order. Each example was first used for testing (i.e. prediction), and then for additional training. The mean absolute prediction errors were recorded. The whole procedure was repeated with different levels of memory profile. The obtained results are summarized in *Table 2*. The same table also contains comparable results which would have been obtained by the traditional moving averages prediction method [9].

prediction method	memory profile	mean absolute prediction error ATS/ CHF	ATS/ DEM	ATS/ FRF	ATS/ GBP	ATS/ ITL	ATS/ USD
holographic	100%	0.0004	0.0000	0.0021	0.0004	1.6089	0.0007
	80%	0.0004	0.0000	0.0021	0.0004	1.6089	0.0007
	20%	0.0004	0.0000	0.0021	0.0004	1.5986	0.0006
	10%	0.0004	0.0000	0.0023	0.0004	1.3994	0.0006
	5%	0.0003	0.0000	0.0012	0.0003	0.6818	0.0006
	3%	0.0003	0.0000	0.0008	0.0003	0.6766	0.0006
	2%	0.0003	0.0000	0.0008	0.0003	0.6748	0.0006
	1%	0.0003	0.0000	0.0008	0.0003	0.6738	0.0006
moving averages	n/a	0.0005	0.0000	0.0010	0.0004	0.9930	0.0008

Table 2. *Prediction of exchange rates*

As we can see from *Table 2*, the performance of our holographic prediction method depends on the memory profile used. With a high memory profile (persistent memory) the results are in some aspects worse than those obtained by moving averages. With a low memory profile (short-term memory) the holographic method clearly outperforms moving averages. Some other results based on the same data set are available in [7].

Finally, let us note that a software package called the *HNeT system* is now available, which enables easy experimenting with holographic networks and rapid application development. The first version of the HNeT system [1] was designed for a PC with MS-DOS and a transputer expansion card. The present version runs under MS Windows and consists of two separate products: HNeT Discovery [2] and HNeT Professional [3]. HNeT Discovery is an emulator that serves for experimenting, prototyping and evaluation. HNeT Professional is a library of subroutines that can be used together with MS Visual Basic or Visual C++ for application development.

4. Conclusion

Holographic neural networks are in some aspects superior to traditional network types. For instance, they are more suitable for prediction problems, thanks to technical feasibility of incremental training with a reduced memory profile. Also, holographic networks assure quicker convergence during training, and are easier to use.

The most important phase in designing a holographic application is choosing adequate data preprocessing. Therefore, it is important that a diversity of preprocessing procedures are available, so that conflicting requirements of various applications can always be accommodated. Many procedures have already been proposed and experimentally tested. At this moment, a more reliable mathematical analysis of the existing methods is needed.

Holographic neural networks are still an obscure technology. There are not many papers or books that treat or even mention this type of networks. One of the reasons may be the reluctance of the traditional "connectionist" neurocomputing community. However, the situation could change very soon, thanks to the software support that is now available for holographic networks.

References

[1] AND CORPORATION, *HNeT Neural Development System, Version 1.0*, Hamilton, Ontario, 1990.

[2] AND AMERICA LTD., *HNeT Discovery Package - Version 1.3 for Windows*, Oakville, Ontario, 1993.

[3] AND AMERICA LTD., *Using the HNeT Professional Development System*, Oakville, Ontario, 1993.

[4] R. HECHT-NIELSEN, *Neurocomputing*, Addison-Wesley, Reading, Massachusetts, 1990.

[5] R. HO, J. G. SUTHERLAND, I. BRUHA, *Neurological fuzzy diagnoses: holographic versus statistical versus neural methods*, in: Frontier Decision Support Concepts (V. L. Plantamura, B. Souček and G. Visaggio, Eds.), John Wiley and Sons, New York, 1994, 155–169.

[6] R. MANGER, B. SOUČEK, *New preprocessing methods for holographic neural networks*, in: Proceedings of the International Conference on Artificial Neural Nets and Genetic Algorithms - ANNGA'93 (R. F. Albrecht, C. R. Reeves and N. C. Steele, Eds.), Springer-Verlag, Vienna, 1993, 190–197.

[7] R. MANGER, M. MAUHER, *Using holographic neural networks for currency exchange rates prediction*, in: Proceedings of the 16th International Conference on Information Technology Interfaces - ITI'94 (V. Čerić and V. Hljuz-Dobrić, Eds.), University Computing Centre, Zagreb, 1994, 143–150.

[8] R. MANGER, *Holographic neural networks and data compression*, Informatica, **21**(1997), 667–676.

[9] A. F. SIEGEL, *Statistics and Data Analysis*, John Wiley, New York, 1988.

[10] B. SOUČEK, J. G. SUTHERLAND, G. VISAGGIO, *Holographic decision support system: credit scoring based on quality metrics*, in: Frontier Decision Support Concepts (V. L. Plantamura, B. Souček and G. Visaggio, Eds.), John Wiley and Sons, New York, 1994, 171–182.

[11] J. G. SUTHERLAND, *Holographic model of memory, learning and expression*, International Journal of Neural Systems **1**(1990) 256–267.

[12] J. G. SUTHERLAND, *The holographic neural method*, in: Fuzzy, Holographic and Parallel Intelligence (B. Souček, Ed.), John Wiley and Sons, New York, 1992, 30–63.