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DESIGN AND DEVELOPMENT OF AN EMULATED HUMAN COGNITION USING NOVEL 3D NEURAL NETWORKS

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ABSTRACT

This paper describes the development of an Emulated Human Cognition (EHC) which is designed and based on a replicated human brain with a right- and a left- hand lobe, one a deductive side and the other a generic one. Right-hand lobe consists of a newly designed Artificial Neural Network (ANN) with a multi-hidden layer topology. Left-hand lobe is a newly designed 3-dimensional cellular neural network. The input variables presented to the EHC are immediately analysed for it to decide which lobe should be activated. The EHC, when fully developed, has almost an unlimited memory capacity and is capable of immediate recall of any data in its almost unlimited memory locations. EHC has been used in several applications where neural networks have been used to establish relationship between two or more sets of variables. In this paper the EHC has been used to forecast demand for a given product.

Keywords: forecasting, 3D neural networks, artificial neural networks, cellular neural network

1 INTRODUCTION

The research reported in this paper is a continuation of the Factories of the Future programme instigated in the early 1980s supported by the EU. The programme initially concerned aspects relating to high technology manufacturing with emphasis on automation cited in (Ziarati, 1989) and (Ziarati, 1989). The programme became more focused on system integration and development of information management systems in the 1990s (EUREKA (QMIS/IBIS, 1990-95) concentrating on the development of an integrated business information system (Ziarati and Khataee, 1994). Early in the 2000s, the Factories of the Future programme put a great deal of effort into wireless communication (Ozhusrev, 1992; Ziarati and Higginson, 1992), roadmap development (Yoji et al, 1999) and value stream mapping (Tapping et al, 2002), helping the manufacturing industry to be leaner and become more efficient. In the mid 2000s focus was diverted into a new concept now known as ‘Lean Optimal’ (Ziarati and Ziarati, 2009). The development of the lean optimal system led to the development of this Emulated Human Cognition (EHC). The earlier EHC is composed of an Artificial Neural Network (ANN) and a Cellular Neural Network (CNN). The CNN was later developed into a 3 dimensional network (3-DCNN). The recent work by Urkmez et al (Urkmez et al, 2007; Akdemir et al, 2007) also led to the development of multi-hidden layer ANNs. The following sections give a summary of the emulated human cognition and make references to the multi hidden layer ANN, and the new 3-DCNN. The EHC is then given the task of predicting the demand for a given type of ship. The predicted values are very good and proof that the EHC is capable of making the right decision and has the capabilities to establish relationships between input and output data with an astonishing degree of accuracy and an acceptable level of reliability.

2 THE MAIN COMPONENTS OF THE EMULATED HUMAN COGNITION

The EHC is technically represented as a system composed of two parallel and distinct sides. One side is deductive and analytical and the other side is generic and descriptive. The deductive side is composed of a novel ANN and the generic side a novel CNN.

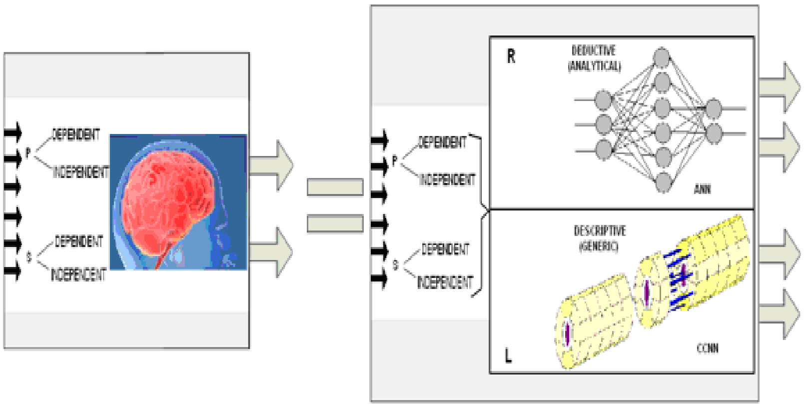

Figure 1. Description of Emulated Human Recognition

All four equations of motion were unified into one single expression and used in the modelling of all components when there is a flow of fluid (Ziarati, 1979). Using the same approach as (Ziarati, 1979) the system theory of $\sum = (U^r, X^n, Y^m, \alpha, \beta)$ was transformed into a family of $\sum_1 = (U^r, X^n, Y^m, A, B, C)$ for ANN applications. For CNN applications it was reduced to

$$\frac{dX}{dt} = -X + A*Y + B*U + I \qquad (1)$$

2.1. Artificial Neural Network (ANN)

A good description of this type of ANN is given in (Ozhusrev et al, 2003). The ANN in 2007 was re-configured by adding additional hidden layers (Urkmez et al, 2007; Yucel et al, 2007) making these types of NN much more efficient and reliable. The ANN models reported in the latter references were based on the earlier work by Ziarati, Ucan and Bilgili who published several papers on the subject; a summary of their findings are given in (Urkmez e ak, 2007; Yucel et al, 2007; Akdemir et al, 2008; Urkmez et al, 2008).

In 1998 a new kind of artificial intelligence tool was proposed called Cellular Neural Networks (CNN) where the connections between neurons are restricted with their neighbours only (Chua and Yang, 1988). This type of NN is one of the most popularly used and is described in detail later in this paper. The work on the NN led to the development of Genetic Cellular Neural Networks (GCNN). A typical artificial model of a neuron is shown in Fig. 2.

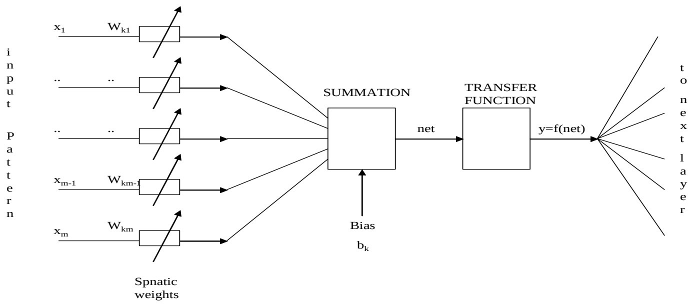

Figure 2. General Block Diagram of a Neuron

GCNN is a slight variation of the Cellular Neural Network which includes the application of Genetic Algorithms (Davis, 1991; Kozek et al, 1988). This network uses less stability parameters than Back Propagation-Artificial Neural Networks (BP-ANN) and hence should be better suited to fast changing scenarios experienced in real distribution systems. Details of GCNN for forecasting demand are provided by Ziarati et al (Ziarati et al, 2003).

A general CNN neighbourhood structure is shown in Fig. 3. The CNN structure is well suited for the computation of tabulated inter-related data. The CNN normalised differential state-equation can be described by matrix-convolution operators as follows:

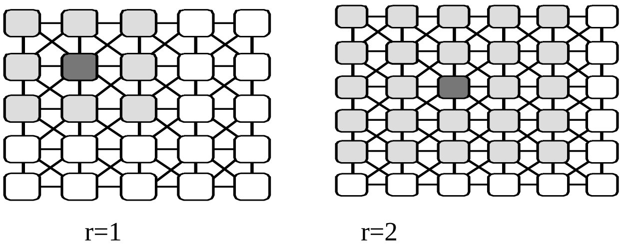

Figure 3. General Block Diagram of a CNN

$$\frac{dX}{dt} = -X + A*Y + B*U + I \qquad (2)$$

where U, X, Y are input, state and output of an M x N matrix, while I is an offset vector. The feedback and feed-forward connections are represented by matrix A and B.

2. GENETIC ALGORITHM (GA)

Genetic Algorithm is a learning mechanism that abides by the rules of genetic science. The algorithm has been successfully applied in a number of cases such as image processing, geophysics, etc. (Davis, 1991; Kozek et al, 1988). It uses a binary coding system to search for optimum values of A, B, I. The underlying principles of GA were first published by Holland (Holland, 1962). The mathematical framework was developed in the 1960s and was presented in his pioneering book in 1975 (Holland, 1975). In optimisation applications, they have been used in many diverse fields such as function optimization, image processing, market research and product marketing, system identification and control and so forth. In machine learning, GA has been used to learn syntactically simple string IF-THEN rules in an arbitrary environment. A high-level description of GA was introduced by Davis. (Davis, 1991).

3. THREE DIMENSIONAL CELLULAR NEURAL NETWORKS

The development of this Network was started at Dogus University with support from Istanbul University. The Model shown in figure 3 was fully developed at TUDEV Institute of Maritime Studies (now Piri Reis University) in 2008 and tested in 2009. The model can be presented as a 3-dimensional table or a cylinder. In the model used here, CNN is composed of three-dimensional shaped cells. Some cells are placed at the inside of a cylinder. These are called inner cells. The other cells are placed around the cylinder and called the outer cells. In forecasting applications for instance, the outer cells will be used to process the independent variables (demand factors). The inner cells will be used to process the dependent variables - predicted parameter - i.e. demand for a product. Each horizontal ring represents values of variables at a given moment in time. 3-DCNN has the following dynamics for each inner cell $C_{mn}(k)$. For a given time n, the m^{th} independent variable is represented by $C_{m,n}$ and it is placed at the m^{th} outer cell of the n^{th} time segment. Its state equation is written as follows;

$$\frac{dx_{m,n}(k)}{dk} = -x_{m,n}(k) + A_{outercells}(m,1).y_{m,n-1}(k) + A_{outercells}(m,2).y_{m,n}(k) + B_{outercells}(m,1).u_{m,n-1}(k) + B_{outercells}(m,2).u_{m,n}(k) + I \quad (3)$$

For the inner cell of the segment n;

$$\frac{dx_{p,n}(k)}{dk} = -x_{p,n}(k) + \sum_{r=0}^{p} A_{innercells}(r,1).y_{r,n-1}(k) + A_{innercells}(r,2).y_{r,n}(k) + \sum_{r=0}^{p} B_{innercells}(r,1).u_{r,n-1}(k) + B_{innercells}(r,2).u_{r,n}(k) + I \quad (4)$$

At the steady state condition; $y_{m,n} = f(x_{m,n})$

where $x_{m,n}$ is the state, $u_{m,n}$ is the input and $y_{m,n}$ is the output of the cell $C_{m,n}$. k is number of iteration, m,n are cell indexes, p is number of the outer cells for any ring. There are $p+1$ cells in each horizontal ring since the index of the inner cell is zero. f is PWL activation function. A and B are the weight matrices including the weight coefficients between the corresponding cells. I: denotes the offset (bias) value of each cell in the network.

3-DCNN must be trained with sample data for obtaining the weight coefficients a_n, b_m and offset coefficient I as has been the case with CNN. In GA applications there are often two equations used. In the first equation, all outputs of the cells are compared to the desired values and the sum squared error is calculated with cost function according to following equation.

$$\cos t_s(a_n, b_m, I) = \sum_{m=1}^{T}\sum_{n=0}^{p}(y_{mn} - d_{mn})^2 \quad (5)$$

where y_{mn} is actual output d_{mn} is desired output of the cell C_{mn}, T is number of the segments, p is number of the outer cells and s is chromosome number. Fitness value of each chromosome is calculated as;

$$fitness_s(a_n, b_m, I) = \frac{1}{\cos t_s(a_n, b_m, I)} \quad (6)$$

4. EMULATED HUMAN COGNITION

In the experiment conducted the EHC was given a set of data and based on the data provided it can chose either the ANN or the 3-DCNN lobe. In this paper, only the result of one application in which EHC chose the 3-DCNN is presented. However, the full results are available, and if need be, will be presented at the Conference. In this application EHC was tested to see if it can forecast the Dead Weight Tonne, (DWT) for a particular type of a ship such as 'Bulkers' worldwide. As reported earlier the EHC opted for using the 3-DCNN. The aim of this application is to predict the DWT world fleet demand in total in the future by considering the historical data of DWT world fleet. In the training stage of 3DCNN, the genetic algorithm finds the optimum values of the matrices $A_{innercells}$, $A_{outercells}$, $B_{innercells}$, $B_{outercells}$ and I. There are 37 parameters to be optimized in this example. Each chromosome in genetic algorithm includes the binary codes of 37 parameters and each chromosome includes 296=37*8 bits since each parameter has been coded with 8 bits. At the beginning of the genetic search 60 random chromosome were created. Then, the best chromosome was found at the 78^{th} generation. The templates of the best chromosome are;

$$Aoutercell = \begin{bmatrix} 0.531 & -0.325 \\ 0.006 & -0.012 \\ 0.312 & 0.287 \\ 0.319 & 0.281 \end{bmatrix} \qquad Ainnercell = \begin{bmatrix} 0.431 & 0.281 \\ -0.087 & 0.606 \\ 0.687 & -0.131 \\ 0.469 & 0.562 \\ -0.381 & -0.519 \end{bmatrix}$$

$$Boutercell = \begin{bmatrix} 0.431 & 0.281 \\ -0.088 & 0.606 \\ 0.688 & -0.131 \\ 0.469 & 0.562 \end{bmatrix} \qquad Binnercell = \begin{bmatrix} -0.275 & -0.619 \\ 0.412 & 0.300 \\ -0.512 & -0.438 \\ 0.688 & -0.788 \\ -0.231 & 0.469 \end{bmatrix}$$

Original and 3-DCNN output data values of this application are presented in Tables 1 and 2 respectively.

Table 1. Original data

Years	World Seaborne Total Dry Bulk Mil. Tones	World Seaborne Total Bulk Mil. Tones	World Seaborne Grand Total Mil. Tones	World Fleet Total Bulk Mil. DWT	World Fleet Grand Total Mil. DWT
1985	1461	2861	3631	499	**590**
1986	1415	2846	3636	478	**568**
1987	1332	2689	3635	471	**564**
1988	1410	2913	3907	469	**563**
1989	1595	3274	4173	475	**572**
1990	1598	3200	4164	489	**588**
1991	1625	3190	4201	502	**604**
1992	1596	3252	4345	514	**619**
1993	1616	3416	4554	520	**627**
1994	1673	3491	4658	528	**637**
1995	1784	3643	4877	529	**640**
1996	1816	3776	5121	548	**708**
1997	1910	3969	5432	559	**725**
1998	1897	3959	5443	570	**742**
1999	1894	3998	5566	573	**750**
2000	2040	4214	5913	586	**767**
2001	2096	4325	6022	601	**787**
2002	2170	4380	6209	607	**800**
2003	2291	4643	6553	618	**819**
2004	2469	4939	6954	634	**843**
2005	2564	5121	7258	670	**890**
2006	2703	5313	7615	715	**950**
2007	2790	5397	7852	758	**1013**

Table 2. 3-DCNN forecasting results

Years	World Seaborne Total Dry Bulk	World Seaborne Total Bulk	World Seaborne Grand Total	World Fleet Total Bulk	World Fleet Grand Total
1985	1460	2859	3631	499	**589**
1986	1416	2859	3628	479	**570**
1987	1334	2703	3625	473	**564**
1988	1409	2925	3893	471	**564**
1989	1592	3283	4162	477	**573**
1990	1599	3209	4156	491	**589**
1991	1625	3200	4192	504	**605**
1992	1597	3262	4337	515	**619**
1993	1616	3424	4545	521	**628**
1994	1673	3498	4650	529	**639**
1995	1782	3648	4867	530	**642**
1996	1815	3780	5111	549	**708**
1997	1908	3971	5422	560	**725**
1998	1897	3960	5440	571	**742**
1999	1894	3999	5561	573	**750**
2000	2037	4213	5904	587	**766**
2001	2094	4323	6019	601	**787**
2002	2168	4378	6203	607	**800**
2003	2288	4639	6547	618	**819**
2004	2465	4931	6948	634	**843**
2005	2561	5113	7255	669	**889**
2006	2699	5302	7611	714	**949**
2007	2787	5385	7852	756	**1011**
2008	2907	5558	8175	789	**1058**
2009	3013	5699	8479	825	**1109**
2010	3126	5846	8787	841	**1142**

5. CONCLUSIONS

It should be noted that the application was chosen at random from several available set of data (Urkmez e ak, 2007; Yucel et al, 2007; Akdemir et al, 2008; Urkmez et al, 2008). The comparison of the actual values for World Seaborne Tonnage and World Fleet DWT and the predicted values are remarkably good. This elucidates that the 3-DCNN is a good model and as part of the generic (descriptive) lobe of the EHC, it managed to make the right decision and use the 3-DCNN to carry out the millions of iteration to produce output values which are in good agreement with the actual values and better than the results reported in earlier papers. The merit of a 3-dimensional network is that it can be arranged to have a specific kind of input for each of its given ring. For example, one of the rings could be the primary values of the input and the next ring could be the secondary values. The same concept can be applied to dependent and independent values. The difference between CNN and 3-DCNN is that the rings forming the cylinder can be the time series for each given values of input and output values and hence 3-DCNN can be used in time series applications.

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