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Classification Based on Deep Neural Cellular Automata Model

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***Abstract*—**Deep learning structure is a branch of machine learning science and greet achievement in research and applications. Cellular neural networks are regarded as array of nonlinear analog processors called cells connected in a way allowing parallel computations. The paper discusses how to use deep learning structure for representing neural cellular automata model. The proposed learning technique in cellular automata model will be examined from structure of deep learning. A deep automata neural cellular system modifies each neuron based on the behavior of the individual and its decision as a result of multi-level deep structure learning. The paper will present the architecture of the model and the results of simulation of approach are given. Results from the implementation enrich deep neural cellular automata system and shed a light on concept formulation of the model and the learning in it.

***Keywords*—**Cellular automata, neural cellular automata, deep learning, classification.

I. Introduction

NATURAL computation is a discipline that builds a bridge between computer science and natural science. Natural computations deal with the methodologies (including genetic algorithms, neural networks and cellular automata) that take their inspiration from nature for problem solving and use of computation with real life problems [1]-[4].

A cellular automaton is a discrete state system consisting of a countable set of identical cells that interact with their neighbors. The global evolution of each cell is driven from the simulation application based on a transition function govern the interactions among each cell and its neighborhoods. This system can take on any number of dimensions [5]-[7], starting from one-dimensional string of cells. The two-dimensional cellular automata model [7], [8], in the simplest way, is a grid of squares, each square having a number of adjacent neighbors. The main difficulty with the cellular automata approach is how low-level representation of the application and the coding of the problem into the cellular automata structure will be.

Deep learning [9]-[11] has emerged as one of the fastest growing machine learning paradigms in artificial intelligence and human-centric systems. The potential benefit of the deep learning is that many hidden layers of features representations can be stacked in a deep structure. It is more capable to model complex form of data and knowledge. The notion of deep learning is the use of deep information, multiple levels and multiple views of data for learning processing and problem solving algorithms. One of the consolidated findings of deep learning approaches is that they join and define learning features representation together whenever enough training data and computation capabilities are available.

The paper tries to present deep structure in the representation of cellular automata [12], [13] as well as the learning model- an approach that unifies cellular automata with the representation learning functionality known from deep learning. The structure of the rest of this paper is as follows: Next section is an introduction to neural cellular automata. Followed that, Section III presents a general view of the combination system of deep learning and cellular automata model. The application of proposed model to traffic system design is presented in Section IV with discussion of the results. The paper will be concluded in Section V.

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II. Neural Cellular Automata

Neural cellular networks are powerful tools on pattern detection and have a topology to resemble human retina [1], [14]. A neural cellular network is a system of cells in a normalized space. It can be defined on any dimension. It combines the main advantages of cellular automata and those of artificial neural networks. Neural cellular network uses only local information of cells to perform its computation on large amount of data where each cell evolves in time [15]-[17]. Every cell is related to the neighboring cells. The state of each cell changes in time and influences the output in a nonlinear manner.

The single cell output is defined as

$$y = f(x) = \frac{1}{2}|x+1| - \frac{1}{2}|x-1| \tag{1}$$

where x is in state of the cell. For $N \times M$ neural cellular networks, the state of cell (i, j) is

$$x_{ij}^{t+1} = x_{ij}^{t} + \sum A.y_{ij}^{t} + \sum B.u_{ij}^{t} + b_{ij} \tag{2}$$

where A and B are parameters, b is the bias, y_{ij}^t is the output of cell ij and u_{ij}^t is the input to cell (i,j).

$$A = \begin{bmatrix} S1S5S4 \\ S2S3S2 \\ S4S5S1 \end{bmatrix}$$

$$B = \begin{bmatrix} S6S10S9 \\ S7S8S7 \\ S9S10S6 \end{bmatrix}$$

$$b = S11$$

III. Deep Neural Cellular Automata Model (Deep NCA)

This section presents the general principles of the combination system of deep neural learning [18], [19] and cellular automata model that can be used in many fields of applications (see Fig. 1). The basic deep neural cellular automata (Deep CA) modeling principles are as follows:

(1) A grid made up of discrete cells represents space.
(2) Each cell should be in one of a finite number of fixed states.
(3) Cell may change state only at fixed, regular intervals of time.
(4) States are updated accordance to local rules operated on an interaction neighborhood.
(5) The structure of the layers is a deep structure.

The behavior of deep neural cellular automata model depends not only on the present cell's state but also on the past sequence of states. To model the proposed deep neural cellular system, it is necessary to specify both cells' dynamic (states and state transitions rule) and the cell's deep level. In the proposed model, cells may act together.

The overall architecture of the proposed deep cellular neural automata model is shown in Fig. 1. The phrase "***act together***" implies certain deeply level among cells. Namely, if cell *O* ***acts towards*** cell *Q*, then *Q* also acts towards cell *O*. A deep neighbor's function is *N (O)*, which is a group of cells that act together toward a cell *O*.

The relation between cell *O* and its function *N (O)* induces a map from the cell space to the power set of cell space and each cell *O* can communicate with its deep cells *N (O)* and exchange cell's information with. If we denote the cell as O (i, j) at the position (i, j) with state S (O) = {1, 2… K} for O ∈ U.

The specific process of proposed model includes the following steps: (1) Define levels of deep information and establish related structure model. (2) Per cell of study, give the universe of units *U*. (3) Per characteristics of deep level; build a set of deep relations for units.

Deep neural cellular automata model is hierarchical multilevel structures defined by cells universe *U*, function *N (u), u ∈ U* and deep level *L*. The proposed model describes a segment of cells characterized by their tasks and states. Let *S* be a finite set of states, we denote by S [O] be state of unit O*[i, j]*. The configuration of deep neural cellular automata is a function from O*[i, j]* to *S* that represents 2-dimension lattice over set of states *S*. The transition rule related to cell *O* (individual cell) is defined to get a decision model based on cell *O* itself and its neighbors *N (O)*. Note that, the transition rule makes it possible the cell to predict the next local state; however, the global model state may be different from all the local predicted ones due to unpredictable interactions in and with the deep environment.

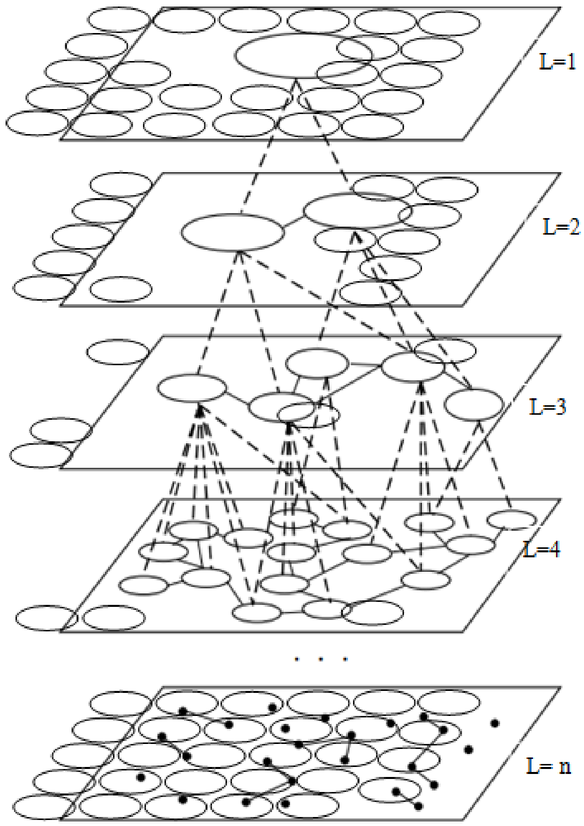

Fig. 1 Deep Structure (L is deep level)

The sequence of configurations for deep neural cellular automata is S_0. . . S_n and we observe the change of states of cells in those configurations. The transition rule of each cell *O*[i, j] in deep neural cellular automata is a map from $S_t(O)$ to $S_{t+1}(O)$ as:

$$\forall y, \mathrm{N(O, y)} = 1, \mathrm{S(t+1)(O)} = \sigma(\mathrm{g\ (St(y), St(O))}) \quad (4)$$

where $\sigma(x) = (1+e^{-x})^{-1}$ is the sigmoid function. Each cell *O* has an associated transition rule that defines the next combinational actions in the behavior of this cell's state.

The join value over the hidden units between deep layers is

$$S(\mathrm{O}) = \frac{1}{\mathrm{V}} e^{-E(O)} \quad (5)$$

$$V = \sum_n \sum_m e^{-E(O)} \quad (6)$$

where V is a normalization constant and E(n, m) is the impact of state O(n, m). The impact of state O(n, m) can be computed as

$$E(\mathrm{O}) = -\sum_{i=1}^{N} \sum_{j=1}^{M} W_{ij} n_i m_j - \sum_{j=1}^{H} b_j m_j - \sum_{i=1}^{N} c_i n_i \quad (7)$$

where b and c are unit biases. The learning function of a weight w can be achieved as:

$$\Delta w_{ij} = \eta \frac{\partial \log S}{\partial w}$$

$$\Delta w_{ij} = \eta(\langle m_i n_j \rangle S^0 - \langle m_i n_j \rangle S_{\vartheta}^{\infty} \tag{8}$$

where η is a learning rate.

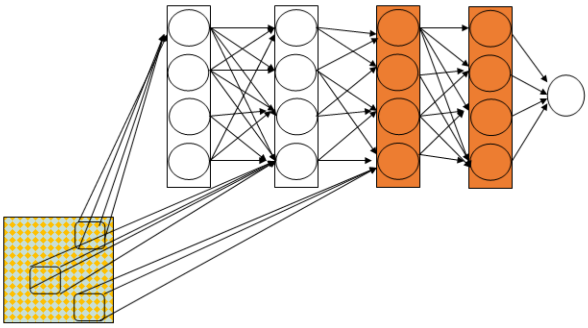

Fig. 2 Deep 1-D neural cellular networks

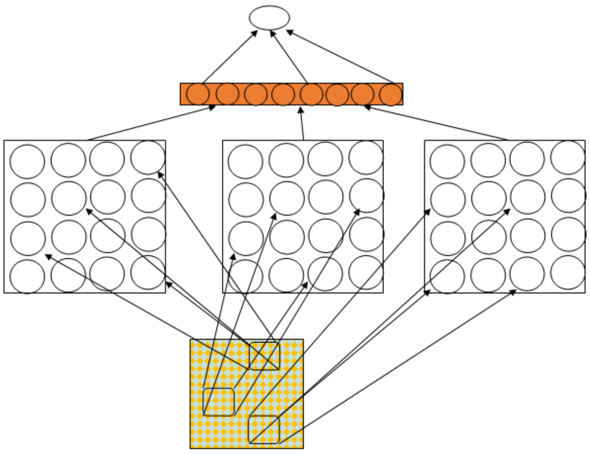

Fig. 3 Deep 2-D neural cellular network model

The output of the active function at node O is

$$Y(O) = f(S(O)) = \frac{1}{1+e^{-X(O)}} = \frac{1}{1+e^{-W_O S(O)}} \tag{9}$$

Input neurons cannot be neighbors to each other. Our algorithm for neural cellular automata learning contains the following key components: (1) Extracting set of multi-level deep features according to layers of deep neural cellular automata. (2) Estimating the inter-nodes similarities under all these feature sets. (3) Partitioning each layer of the model under selected feature set.

To formulate the deep learning task, the similarity function between the input data K and the training data x is denoted as I(K, x). The learning goal is to learn a similarity function *I* that can always produce the similarity values satisfying the following inequality:

$$I(x, K1) > I(xK2)$$

where K1 and K2 are both training and location of K1 is above location of K2 in ranking list of training dataset.

IV. Applications

In order to show the effectiveness of the approach, deep cellular neural automata model and comparative models are evaluated on real life datasets. The experiments will be done with limited number of data, so we use hardware environment as: Intel (R) Core (TM) i5-3210M CPU @ 2.50 GHz. The software environment is MATLAB 2014b and Java code for some classification methods. For the SVM classifier, we used 10-fold cross-validation for determining the parameters of SMV kernel. To avoid bias in the evaluation process, we used the same fixed size 50x50 to extract sub-images from dataset.

V. Conclusion

The paper presented a hybrid state machine decision-making, which is based on system investigated the behavior of cellular automata and deep computation. Because the model uses multilevel decision, which is incremental, it can show how the cell/environment interaction can be adapted and guide to global solution process. Since the learning is implemented in the form of deep process, the learning model is at least reconcilable with current models of AI mechanism. The number of deep levels used in general model of deep neural cellular automata is two. It is because the idea of multi-thinking at levels will be explained while in simulation of traffic model, we use four levels. we can use levels as much we can by depending on levels of thinking in the application. The proposed model needs to be adapted to show how it can response in emerging way with unscripted scenario and how it can involve multiple parts of process and contingency.

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