Heterogeneous Hybrid Neural Network for Modeling Spatially Distributed Destructive Processes

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Abstract. In this paper, a hybrid model of cellular neural network based on heterogeneous spiking neurons connected with a spatial model of terrain through hierarchically ordered context is proposed. Spatial cells are considered as elements of the neural network (neurons) and events are considered as spikes at the neuron output. A discrete automaton model with integrated likelihood model supplements a hybrid spiking neuron model to determine the neuron state at specified time points based on probability or possibility of state transitions. The structure of neuron connections in the model resembles a cellular network model. The hierarchical context containing a set of transmitters allows organizing additional channels of communication between neurons and provide remote sensing data to the neural network. Neurons have controlled sensitivity to transmitters with special receptors connected to the network context. The method of modeling spatial distributed destructive processes using the proposed hybrid neural networks is presented. The proposed method and models are intended for modeling dynamic systems with different types of simultaneously arising interacting processes with respect to their spatiotemporal aspects.

Keywords: Destructive Processes, Forest Fire Spreading, Cellular Neural Network, Spiking Neuron, Discrete Automaton, Likelihood Model

1 Introduction

Natural systems include a multitude of spatially distributed interacting dynamic processes. Most of such processes arise unexpectedly, proceed fleetingly, evolve in space and time transiently, non-linearly, and have a stochastic nature. Some of them are destructive and usually characterize natural disasters (fires, floods, waterlogging, mudflows, tsunamis, etc.). Therefore, they give rise to a variety of hazards, threats, and risks to various objects [1] and often can lead to emergencies.

Decision support in situations of the development of spatially distributed dynamic destructive processes is one of the most important tasks since such processes can cause deaths, injuries, and huge damage to property and infrastructure. Since natural emergencies are poorly modeled and unpredictable, and resources for eliminating them are usually limited and should be used with maximal efficiency, well-studied classical decision support approaches cannot be used for such kind of processes [2].

Thus, people face a problem of real-time decision making in conditions of natural destructive processes, which is primarily based on modeling and forecasting. Clearly, decision support systems (DSS) must be based on information obtained by observation of spatially distributed processes, which can determine the course of the process development (temperature, humidity). The efficiency of decision support strongly depends on the availability of observations of destructive processes, their accuracy, and validity. It can be extremely difficult to obtain proper information about the process development because appropriate sensors are not always available during the process, their measurements are not always accurate, or the measuring can be a very dangerous activity. Fortunately, the images of the process itself or its result (i.e. visual observations) can be obtained by remote sensing using a wide range of vehicles from little unmanned aerial vehicles to large aircraft and ever space ships [3]. However, in real situations, such images are usually filled with large uncertainty and distortions caused by sensor noises, incomplete observations, and dynamic changes in the environment. Thus, DSS requires the ability to predict and estimate such uncertain factors using adequate models of destructive processes. We consider a class of GIS-based real-time DSS [4]. We can formulate the following requirements to the model:

- the model should describe not only the process itself but also the dynamics of its development in respect to time and space (e.g., propagation);
- each observed change in the environment must be assumed as an event;
- each event must be referenced both to a certain time and spatial location;
- events can be described with various kinds of uncertainty;
- events can be associated with complex (e.g., hierarchical) structures, which describe the environment;
- the model needs an acceptable computational complexity to be operable in real time.

2 Related Work Analysis

A number of models of destructive processes have been suggested to be used in decision support systems. The most common approach is to use graph-based models [5] and Bayesian network [6] are most often used among them. Bayesian network (also called belief network) is a probabilistic model that represents the dependency among random variables and gives a specification of joint probability distributions. This model is defined as a directed acyclic graph (DAG), which has conditional probabilities in each node. It allows evaluating unknown random variables after building an appropriate graph structure and obtaining the conditional probabilities. There are two basic types of Bayesian network models for dynamic processes: state-based and event-based [7]. These models provide the ability to perform both predictive and classification functions, as well as probabilistic reasoning, but the insufficiency of statistical data prevents its efficient use in the considered class of DSS.

Other graph-based models include varieties of semantic networks [8] and cognitive models [9]. These models have a very high representative ability; however, they are passive structures that require special formal methods of processing. Besides that, graph-based models do not contain a clear understanding of the domain structure, especially in the presence of multiple relationships between its variables; therefore, the building, use, and modification of them are quite difficult. All of the above-mentioned disadvantages do not allow using them in real-time systems.

Graph-dynamic models are based on nonlinear relations supported by a developed form of associative access, which is based not only on changes of the variables states but also on changes in the configuration of relations between them [10]. Thereby, they can properly represent the dynamics but their high computational complexity prevents efficient use in real-time systems. Since the observed information frequently can be explained as event streams represented by series of time-stamped events [11], many models, which describe multitudes of events occurring jointly and simultaneously, have been studied. However, most of the proposed approaches are based on semantic meaning, causal relationships, and use the simplified notions of time and space [12].

The event trees allow modeling of a sequence of events, forming the structures of any level of complexity [13]. The event trees can be adapted to a different type of uncertainties (probabilistic, fuzzy, rough, etc.). Their limitations in terms of the considered class of DSS lay in the facts that events are strictly referenced to time points rather than to spatial locations, and the event trees are more suitable for solving the problem of classifying new events than the problem of modeling the developing processes.

We can emphasize static and dynamic models, as well as probabilistic and non-probabilistic (e.g., based on fuzzy sets or possibility theory) models [14]. Most of them are typically built through a careful, tedious, and often expensive process of knowledge engineering, which is inappropriate in real-time conditions. Moreover, taking into account above-mentioned requirements to knowledge representation, none of these models can be used due to a lack of binding to spatial locations. The only model of plausible event-tree networks [4] allows taking into account the spatial location of events and has a high representative ability. However, it is not suitable for modeling the dynamics of the process development in space and time (e.g., propagation).

Another approach based on the use of neural networks has been proposed in [15], its main advantage is the ability to provide well-developed neural network training using the results of the processes observation (optical, infrared, radar, etc.) as a training sample. This technique can be easily extended to a wide range of destructive processes.

A number of architectures of such networks were studied from binary and frequency/speed to spiking neural networks [16]. Much attention was paid to the spatially dependent configurations of such networks, including neural networks of radial distribution [15] and cellular networks [17]. The first of them have an obvious drawback, which is associated with the propagation of a signal from a certain center using the polar coordinate system. Clearly, the network configuration will depend on the choice of the starting point (epicenter), and every time the next process occurs, the network will need to be rebuilt. Besides that, such a network cannot describe the presence of a number of processes simultaneously interacting on the terrain.

A cellular neural network (CNN) is an array of cells, each of which can be represented as a dynamic system [17]. It is a kind of coupled networks with local connections only. The cells can be organized in certain two-dimensional or three-dimensional configurations, the most frequently used one is the two-dimensional network arranged in an eight-neighbor rectangular (corner) grid [18]. Each cell has an input, a state, and an output, and it interacts directly only with the neighbor cells within a certain radius. A common assumption is that the neighborhood includes the cell itself and its eight nearest neighboring cells. The state of each cell and its output depends only on the input and the output of its neighbor cells as well as on the certain initial state of the network.

Thus, CNN is the most suitable model for use with GIS, since each cell of a map can be naturally represented as a cell of the neural network. Due to its advantages such as a possibility of massively parallel computation, this type of neural networks became widespread in solving several problems, for example, image processing, statistical physics, simulations in fluid dynamics, and many other fields where events can be represented as patterns in space and/or time [17].

The above-mentioned review enables to conclude that existing graph-based and event-based models correspond very weakly to the processes of the considered class. CNN may be of interest for our research, but to solve the considered problem, it will require a combination (hybridization) with other models of neural networks. Their use for developing the models of spatially distributed dynamic processes have not been currently worked enough, but have a great interest and need more developments. Thus, the development of the model of spatially distributed destructive processes based on CNN is a topic of our interest.

3 The Methodology of Modeling Spatial Distributed Destructive Processes Using Neural Networks

A starting point for using a neural network to model destructive processes is that the vast majority of them can be described in terms of wave-front propagation based on the use of the Huygens principle (Fig.1). In accordance with it, each point of the front (the surface reached by the wave) is a secondary (i.e., new) source of spherical waves.

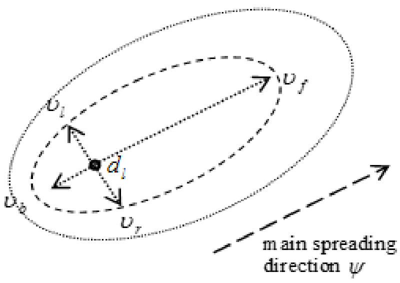

Fig. 1. The propagation of the destructive process

Let us create a cellular neural network by placing neurons at each cell of the terrain. The signals propagating from each excited neuron to the receiving neurons through their synaptic connections play here a role of the waves.

In simplified form, it can be described as follows. The synaptic connections between neurons should model the channels of energy or other substance transfer in real destructive processes. The necessary synaptic coefficients can be determined by environmental parameters. The neuron evaluates signals from the excited neighbor neurons and enters an excitation state itself if the activation threshold is exceeded. The neuron can be in the active state for a finite time only, after which it is permanently inactive.

The area near the process development front consists of neurons, which are exciting or already excited. During the process development, the exciting neurons are replaced by the excited ones, and thus we obtain the corresponding recurrent neural network.

The crucial point of all dynamic processes is the transfer, so the destructive processes spread the "energy" of the cell to all other cells by a certain law characterizing the amount of energy transferred. Such spreading depends on non-stationary and nonlinear physical and chemical processes arising within the terrain, which can be described analytically with high dimensional equations, so we must solve these complex equations with the exact numerical values of parameters to determine the development of the process at each moment. Since wave-front propagation of the process has a certain geometrical shape (usually elliptical or spherical), the spreading process can be characterized by its speed. The spreading speed is generally non-stationary and its value varies for different spatial directions (Fig.1). Given the fact that we cannot provide necessary completeness and accuracy of the information for solving the complex equations, we should use their approximation within the discretized spatial model as proposed in [19], and CNN can be a proper non-linear approximator. The process of energy transfer from cell to cell can be considered as the process of transmitting a signal from one neuron to another. Thus, we obtain a spatially distributed neural network, where neurons are connected with each other by synaptic connections, in which signals are multiplied by synaptic coefficients. Such a network is very loaded with synaptic connections. However, only neurons that are in the front of the process, in other words, directly involved in transmitting and receiving a signal at a given time, can take part in the process changing their states. At each moment, only one neuron layer (located at the front of the process) can transmit excitation while the second can only take (Fig.2).

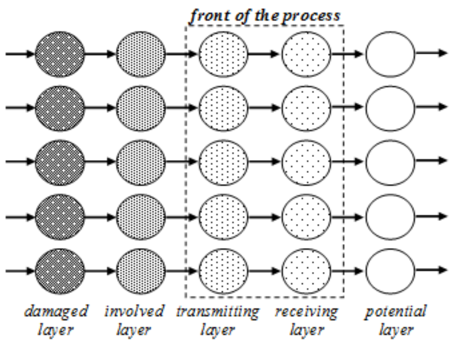

Fig. 2. The front of the process

If a neuron turns into some damaged state, it cannot be involved in the transfer process, so it stops receiving or transmitting a signal, and should be automatically excluded from consideration. Instead of this, the new neuron will be involved in the process due to its propagation. Since each neuron corresponds to a certain cell of the terrain and environment, its synaptic coefficients can be generally calculated based on the observed parameters of the cell. Note that the main problem is the inaccuracy of observed data about the process, including the parameters of each individual cell, however, they vary slightly between neighboring cells. At each step, after obtaining the observations and calculating the state of the neurons, synaptic coefficients will be corrected for neurons involved in the process of the front propagation. We can compare the calculated position of the fire front with the actual development of the process obtained by observation.

Deviations between these fronts can be minimized by correcting the state vector, which is determined by the set of environmental parameters and should be eliminated by training the neural network. The easiest way to train the network is the gradient descent method. It allows us to adjust the model in order to improve its accuracy. However, the main problem of training the neural network is the speed of training.

We will consider a typical example of forest fires. Most other types of destructive processes are similar in terms of their distribution and propagation but are described by other parameters and have other channels of energy or matter transfer. In the case of forest fires, there are heat transfer channels. Thus, the most important state parameter of a certain cell is its accumulated energy. This energy is necessary for ignition in the sense that if there is not enough energy, the cell stays in a pre-ignition state, but if the threshold value is exceeded and the accumulated energy is enough for ignition, the cell turns into a burning state. Fire propagation contour usually can be described using an ellipse, so the description of the energy transfer requires only parameters of two radiuses of the ellipse and the angle of its rotation. The main direction of spreading can be determined based on the parameters of the environment.

Obviously, we must first distribute the considered spatial area into cells, each of which can be in one of several states at a certain discrete point in time. The state of each cell can be defined by a certain set of parameters, including environmental parameters. Further, we need to define the appropriate type of neuron and neural network architecture. This paper is organized as follows. In section 3, the spatial model is considered, corresponding states of cells and events are described. In section 4, the model of impulse neuron used for energy transfer modeling combined with the discrete automaton model are proposed. In section 5, the cellular neural network architecture based on proposed impulse automaton neurons is described. In section 6, the implementation of the proposed model is described, and finally, in section 7, the experimental results of the research are considered and discussed.

4 The Spatial Model, States, and Events

4.1 Spatial Model

Assume that the destructive processes spread over a certain area of interest (AOI). Consider a two-dimensional Euclidean space C, which contains the AOI as an openly connected subspace $X \subseteq C$. Suppose a non-empty finite set of parameters $A = \{a_1, ...a_m\}$

and observation function f such that $f: X \times A \rightarrow V$ for each $x \in X$. Our spatial model is discretized at three levels: the lower level contains cells of equal size, the middle level consists of spatial regions of different sizes, and the upper level represents large spatial areas.

At the lower level, we impose a metrical grid of coordinate lines with size δ on C using a linear map ϕ such that coordinate lines form a set D of the cells with the size being $\delta \times \delta$, $\phi: D \rightarrow C$. Thus, space C is discretized by a grid $D=\{d_{xy}\}$ of isometric cells d_{xy}. A cell $d \in D$ is a spatial object of a minimal size associated with a set of parameters values, which is called the cell state, via an observation function $f(d, A)$. The proposed discretization assigns the equal values of the parameters to each point belonging to a certain cell d, therefore each cell $d \in D$ represents a homogeneous area of the AOI in the sense of such values, and all points of this cell are A-indiscernible: $(\forall d_1, d_2 \in D)(\forall a \in A)\left[f(d_1, a) = f(d_2, a)\right]$.

At the middle level, the subspace X can also be divided into a finite set of disjoint objects having geometric shapes, which represent the certain homogeneous areas of the AOI. Consider a non-empty subset of parameters $A_i \subseteq A$. A_i-indiscernibility relation given on the set of cells D means that all pairs of different points y,z that belong to the different cells d_m, d_n have the same values of parameters $a_j, \ldots a_m \in A_i$. Thus, we define a middle-level structural element of the spatial model as the homogeneous spatial area that is uniform in the sense of parameters' values and can be represented by the approximating set of cells. Such element is called a region, has the features of continuity and connectivity, and denoted by h. All the cells belonging to h are A_i-indiscernible.

Spatial areas can consist of a plurality of separate regions spatially distributed over X, and represent certain zones homogenous in the sense of some indicators (e.g. danger, threat, and risk), which depend on the values of parameters $A_j \subseteq A$. Thus, we define a distributed spatial area H as an upper-level structural element of the spatial model represented by the approximating set of regions. Obviously, they do not have the property of the continuity, but all regions belonging to H are A_i-indiscernible in the sense of the same values of parameters $a_l, \ldots a_p \in A_j$.

4.2 Events and States

Suppose the set of process-dependent parameters A can be divided into subsets: not changing over time (static) attributes A_S, time-varying (dynamic) attributes A_D, slowly changing (environmental) attributes A_E, $A = A_S \cup A_D \cup A_E$.

Suppose $W = \{w_0, \ldots w_i, \ldots w_F\}$ is an ordered set of the cell states, where w_0 is the initial state, w_F is the final state, and w_i is the transitional state. Suppose ϑ is a category function such that $\vartheta: D \times A \rightarrow W$. Each state $w \in W$ has two subcategories: the cell condition $w_C = \vartheta(A_S \cup A_E)$, and the cell stage $w_D = \vartheta(A_D)$, so that $w = \langle w_C, w_D \rangle$. Each random change of values of the value of some parameter $A_k \in A_D$ can change the cell condition w_C in such a way that the cell stage w_D must also change. This change is not necessary, but possible. Thus, if the cell condition w_C changes, the cell possibly goes into another state w_i. We consider each significant change of the cell parameter's value, which forces the cell to change its state, as an event, and denote it by y, so that $y : w_i \to w_j$. It is clear that the model of the destructive process can be represented as a model of dynamic change of states of a certain subset of cells covered by the process within the grid D. Their states can be evaluated during continuous observations (remote sensing) [3] that allow obtaining time-ordered sequences of events. If we associate each cell $d \in D$ with a specific neuron $g \in G$ in a neural network G spatially distributed over the grid D and connect each neuron $g \in G$ with the continuously observed parameters, we can develop the model of the destructive process propagation represented by the neural network G.

5 Developing a Hybrid Neuron Model

Generally, a formal neuron is a threshold element with a single output and its activation function, which depends on a linear combination of all input signals.

Since its beginning, the neuron model has been intensively studied. However, researchers are interested in biological brain analogies only at the start of the project and soon lost interest in them. As a result, artificial neural networks turned towards solving certain tasks such as functions approximation, pattern recognition, classification problems, etc. The first generation of neurons operate only with binary signals, in the second generation the flow is in both directions and we deal with continues output values, and the third generation is the spiking neural networks (SNN), which use biologically-realistic models of neurons to carry out the computation. Thus, SNNs operate using spikes, which are discrete events that take place at points in time, rather than continuous values. The occurrence of a spike is determined using differential equations [16]. Neurons in the SNN do not fire at each propagation cycle as it happens with typical multi-layer perceptron, but rather fire only when a threshold (i.e., membrane potential) is achieved.

Consider the methodology proposed in section 2 it is clear that spiking neurons are the most convenient solution for modeling dynamic destructive processes, because:

- they work in discrete time based on events;
- their firing principle is most consistent with the simulated process of energy (matter) accumulation and transfer;
- their firing principle allows restricting the calculations to only those neurons that conform the front of the propagation process at some time point.

However, there are at least three moments, which do not allow spiking neurons to be used "as is":

- according to section 3.2, each neuron bounded to the specified spatial location (cell) should have more than two (i.e., several) states;

- according to sections 2, the cells simulated by neurons should change their states due to changes in accumulated energy (matter) that exceeds its given threshold value;
- the state transition dynamics requires information not only about the cell state parameters but also about the environmental parameters (i.e., context), which can be organized into complex hierarchical structures in accordance with section 3.1.

Thus, it requires a neuron has a finite set of states and some automaton can describe transitions between them. In other words, we need to embed the discrete automaton inside the spiking neuron model. Some environmental parameters cannot be determined directly by the observations, so in the process of monitoring. The neuron should receive the values of such parameters from the GIS. Obviously, these values can not only be distributed by cells but also within regions or other spatial areas of the AOI, that is, at higher levels of the spatial hierarchy, so the neuron must be determined in some hierarchically ordered context. Thus, we need to combine the spiking neuron with a discrete automaton neuron [20] and ensure its operating in a hierarchically organized spatial context. It is a difficult task but available to solve. Our task is to enrich this model with some properties inherent in natural neurons, and allowing it to realize new functions.

5.1 The Simplified Information Model of the Natural Neuron

Over the past decades, fundamentally new neuron network models have emerged, but artificial neural networks are still based on the idea of "wire connections", in which the brain is represented by an electrical network with a rigidly defined topology, which is formed by axons ("wires") connecting neurons. However, natural neurons work completely differently. Modern research suggests that neurons are transmitter-specific [21]. In addition to electrical connections, they receive chemical signals, and their sensitivity to such signals depends on the availability of appropriate receptors. The more receptors has a neuron to a particular transmitter and the higher is their sensitivity, the stronger is the effect of these signals. Moreover, reorganization of the network topology changes in the neuron activity can occur under the influence of neurotransmitters. More about these and other aspects can be found in [22]. We consider only information interaction between the neurons concerning the problem we are solving.

The main properties of natural neurons that we will simulate are the processes that occur in the interaction of neurons with each other and with the environment. A neuron usually has a channel to the transmission of electrical impulses from its output to the inputs of other neurons through the synaptic connection. Consider this channel main. Neurotransmitters are considered as additional (chemical) channels to information transmission. The range of neurotransmitters to which a certain neuron is sensitive is quite wide and depends on the availability of receptors. One neuron can have many types of receptors, which have the ability to capture corresponding transmitters. Usually, neurons have receptors for the transmitters, which they generate themselves. Thus, they can manage their activity through positive or negative feedbacks.

During a spike, one or more transmitters generated by the neuron can be ejected into the extracellular space. Moreover, the transmitters can be organized in certain mixes.

Conductivity and sensitivity of such channels can vary over time, and neurons themselves can influence them by injecting certain types of transmitters. Receptors to a certain transmitter are not always of the same type, they can be excitatory, inhibitory, and metabotropic. Moreover, in the advanced concepts, anti-transmitters are also considered, which allow blocking the specific receptors.

The connections between neurons, the sequence, and rate of their activation, the amplitude and frequency of spikes depend not only on electric impulses but also on the availability of neurotransmitters and sensitivity of receptors. Brain achieve a wide variety of activity patterns due to the sophisticated combination of neurotransmitters and neurons having different types of receptors to the same neurotransmitter. Thus, from an information point of view, the neuron can be described by the value of its membrane potential, the presence of receptors and their sensitivity, while the extracellular space containing a multitude of neurotransmitters constitute a media for transmitting additional information. Now, we can describe a model of a hybrid neuron that has not only electric but also transmitter-based inputs and outputs, and a model of its context.

5.2 The Formal Model of a Hybrid Neuron

Let Ctx be a certain context, E be energy and $\mathrm{T} = \{\tau_1, \tau_2, \ldots \tau_k\}$ - a set of transmitter types. Suppose the neuron g has a sensitivity to a certain subset of transmitters $\Omega = \{\omega_1, \omega_2, \ldots \omega_q\}$ where each transmitter ω_i has a type $\tau_j \in \mathrm{T}$.

Suppose the neuron g has a set of receptors $\Theta = \{\rho_1, \rho_2, \ldots \rho_k\}$, where each receptor ρ_l is sensitive to the certain transmitter ω_i of type $\tau_j \in \mathrm{T}$ (Fig.3). Thus, each neuron has some receptors, each of which is sensitive only to transmitters of the given type. The neuron connects to its context through these receptors. Besides that, the neuron g can have a set of effectors $\Upsilon = \{\upsilon_1, \upsilon_2, \ldots \upsilon_k\}$, where each effector υ_l can eject the certain transmitter ω_i of type $\tau_j \in \mathrm{T}$ (Fig.3).

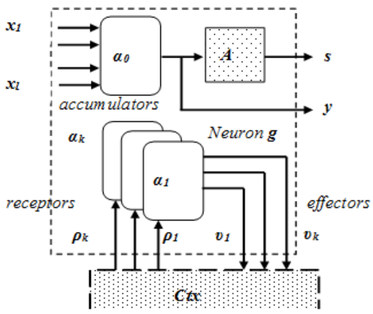

Fig. 3. Structure of the neuron g

Consider a finite set of accumulators $\mathrm{A} = \{\alpha_0, \alpha_1, \alpha_2, ...\alpha_n\}$, where α_0 accumulates a certain amount of energy E while each $\alpha_i \in \{\alpha_1, \alpha_2, ...\alpha_n\}$ accumulates transmitters ω_i of type $\tau_j \in \mathrm{T}$ if the receptor for this type of transmitters is available. Suppose the neuron g has a set of inputs $X = \{x_1, x_2, ...x_l\}$, through which energy E is transmitted to accumulator α_0 with corresponding multiplication factors (weights) $\zeta_1, ...\zeta_l$, and the output y . Transmitters ω_i can be received through receptors from the network context Ctx and accumulated in the corresponding accumulator α_i .

Consider a discrete time T . At each step $t \in T$ amount of energy (or transmitters) in each accumulator α_i can be evaluated via potential functions $U_i(t)$. If a certain threshold value λ_i is exceeded, the spike is generated, and a certain amount of energy (transmitters) is released from the accumulator and ejected to the communication channels (synaptic connection for energy and corresponding transmitter channel for the transmitter). The amplitude and duration of such spikes depend on the degree of exceeding the threshold value in such a way that the integrate estimation of the impulse area is proportional to the value of the excess with a certain factor γ_i .

The proposed model of the hybrid neuron is quite flexible, since the weights ζ_j , threshold values λ_i , and factors γ_i can dynamically change in time. Their changes depend on the state of the network context as well as on the state of the automaton A that is contained within the structure of the neuron and determines its output state $s \in W$. Finding the optimal values of these parameters is the task of training the neural network.

5.3 The Network Context Model

While the proposed formalization of the spiking neuron is a hybrid model of a natural neuron, the extracellular space is modeled using the network context. Since each event has a spatial location, the context of each neuron must be dependent on its location within the spatial model.

The basic element for developing the network context is the hierarchy. Suppose each hierarchy $\Im_i$ is a triple: $\Im_i = \langle \perp_i, I_i, \prec_i \rangle$, where I_i is a set of some elements, each of which corresponds to a certain relation υ_i among them, $\prec_i$ is the order relation over I_i , and $\perp_i$ is the least element of $\prec_i$. We can build a spatial hierarchy I_S within the proposed spatial model with a set of elements like {*cells*, *regions*, *areas*} and the partial order relation $\prec_S$ over it, as well as a time hierarchy I_T with the set of elements like {*seconds*, *minutes*, *hours*, *days*...} and a full-order relation $<_T$ over it. The spatial and temporal hierarchies are the basis for building the adequate space-and-time-referenced model of observed events. The network context signature Λ is defined as a tuple $\Lambda = \left\langle A, \{\Im_i\}_{i=1}^{m} \right\rangle$, where A is a set of observed parameters and $\{\Im_i\}_{i=1}^{m}$ is a set of hierarchies $\Im_i$ induced by the corresponding relations υ_i .

Consider the model of the network context $Ctx = \langle \upsilon, \rho, \mathfrak{z} \rangle$, where υ is a set of variables that represent the observed parameters, Ω is a set of available transmitters, ρ is a set of domain-dependent restrictions, and Λ is the signature of the context. Thus, the network context contains a set of communication channels between neurons using transmitters (Fig.4). Through these channels, neurons can exchange context-sensitive information between themselves and influence each other. Variables of the context can represent available remote sensing data. Neurons can obtain necessary information from the cell context, and in case of its absence from the regional context, area context, or ever from the system context.

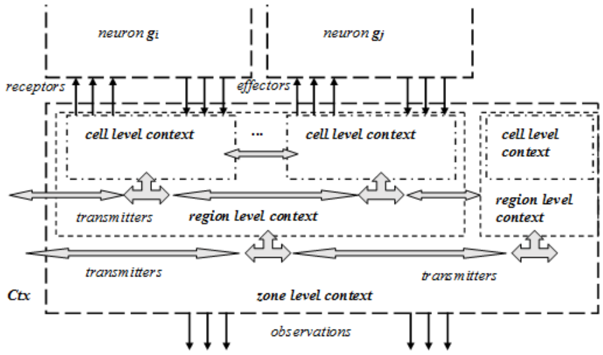

Fig. 4. Structure of the context Ctx

Various relations υ can be defined between the transmitters, as well as between the neurons (e.g. spatial, temporal, substitutability, splitting, bonding, extrusion, and so on). Moreover, special operations can be defined for the network context that allows blocking, braking or amplifying transmitters of some type or even utilizing them.

5.4 The Model of Discrete Automaton

The state $s \in W$ of the hybrid neuron g is determined by the state of automaton A contained in the neuron structure (Fig.3).

A discrete finite automaton is a 5-tuple $A = \langle W, \Sigma, \delta, w_0, W_F \rangle$ [23], consisting of:

- a finite set of states W;
- a finite set of inputs Σ;
- a transition function $\delta : W \times \Sigma \to W$;
- an initial state $w_0 \in W$;
- a set of accept states $W_F \subseteq W$.

Obviously, the set of states W, including initial w_0 and final w_F states, are usually defined by domain. The laws of energy or matter transfer during the destructive process define the transition function δ. The proposed model can use the values of transmitters, context variables, and accumulated amounts of energy (transmitters) as inputs $\varsigma \in \Sigma$.

The model described above is deterministic. However, we can also implement a non-deterministic model using the likelihood model ℓ proposed in [4] to estimate the likelihood for the transition functions δ inside the automaton.

6 Implementation of the Hybrid Cellular Neural Networks

Consider oriented connected graph $G = \langle v,e \rangle$, which doesn't contain cycles, where v is a set of spatially ordered neurons, and e is a set of bidirectional synaptic connections. Each neuron $g_{ij} \in v$ corresponds exactly to the certain cell $d_{ij} \in D$ of the spatial model. Thus, neurons are organized in certain two-dimensional configuration arranged in an eight-neighbor rectangular (corner) grid (Fig.5).

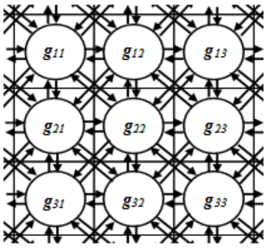

Fig. 5. Fragment of the cellular hybrid neuron network

Since various neurons of such network can have a different set of receptors and react to different sets of transmitters, as well as the discreet automata contained in them can differ in their structure, the network of such neurons will be called a heterogeneous neural network. At the same time, each hybrid neuron have not only synaptic connections but also transmitter connections reflected their heterogeneous nature.

7 Experiment Result

To examine the validity and efficiency of the proposed model, we have conducted an experiment based on the collected retrospective information on series of large-scale forest fires, which had been taken place in Tsyurupinsk and Golopristan forestries, Ukraine, on July 20-31, 2007. To determine the fire front during the process of fire propagation, we evaluate the state of each cell within the terrain model based on remote sensing. We consider the set of cells' state $W = \{w_0, w_1, w_2, w_3, w_4, w_5\}$ and the neuron automata as it is shown in Fig.6. The likelihood $l \in \ell$ of state transitions was estimated based on flame and smoke observations in the corresponding cells.

The blurring representation of the discretized terrain containing a fire front is shown in Fig.7. The fire front is represented by the sets of ignited, burned, and fading cells highlighted on the terrain with the sets of burnt and free of fire cells on a background.

We have modeled the ongoing processes of the forest fire propagation based on the plausible event network [4] and the proposed hybrid cellular neural network. The models were developed on Pentium i5-7400 computer with 3-3,5 GHz processor and 16 GB RAM. The corresponding software was developed using Visual C++.

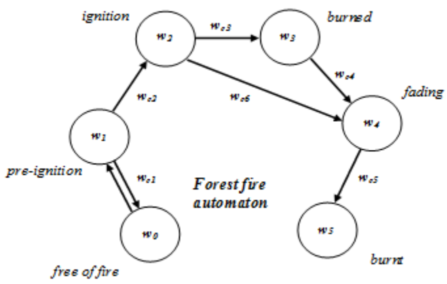

Fig. 6. The forest fire automaton

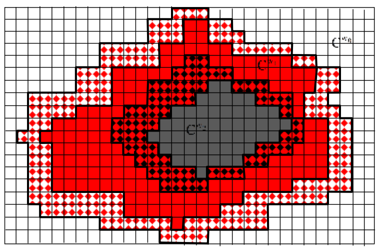

Fig. 7. The fire front representation

The experimental results show that the method can achieve an accuracy of fire front recognition up to 96% (Fig. 8), which shows the rate of correctly detected images (true positive) from the test set. Obviously, the results depend on the cell size and the number of simultaneous points of ignition (*n*). It is clear that the proposed model provides higher accuracy of the fire front recognition while winning in time. Even in the most difficult conditions, it provides the transition simulation time less than 100 ms in the entire range of possible cell sizes above 7 m. Thus, the proposed model provides acceptable performance and is acceptable for solving the practical forest fire fighting problems in near-real time GIS-based DSS.

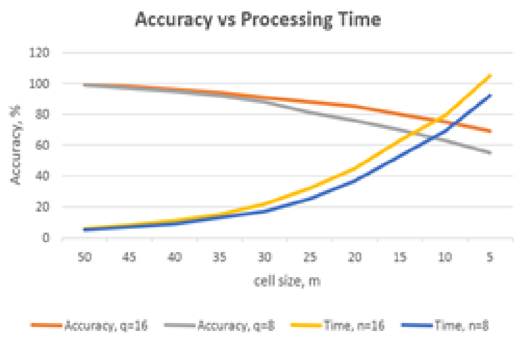

Fig. 8. Influence of the cell's size on the modeling time and accuracy

8 Conclusion

In this paper, a hybrid model of cellular neural network based on heterogeneous spiking neurons connected with a spatial model of terrain through hierarchically ordered context is proposed. A feature of the proposed model is the ability to exchange with not only spikes through synaptic connections but also performing other interactions through the proposed mechanism of transmitters/receptors.

The hierarchical context containing a set of transmitters allows organizing additional channels of communication between neurons and provide remote sensing data to the neural network. Neurons have controlled sensitivity to transmitters with special receptors connected to the network context. Spatial cells are considered as neurons and events are considered as spikes at the neuron output. A discrete automaton model with integrated likelihood model supplements a hybrid spiking neuron model to determine the neuron state at specified time points based on probability or possibility of state transitions. The method of modeling spatial distributed destructive processes using the proposed hybrid neural networks is presented. The main feature of this method is the possibility of assimilating data obtained by remote sensing during the development of the destructive process. The proposed models can be used in conjunction with the model if we consider the event sequences localized in space as sequences of neuron states, and the signature of the event model as the context of a neural network. The proposed models and method are intended for modeling dynamic systems with different types of simultaneously arising interacting processes with respect to their spatiotemporal aspects, and was tested on forest fires. The advantage of the proposed method is its possible conjunction with any mathematical models describing the destructive process, and serves to refine them by observing data, which increases the accuracy of the models.

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