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Modeling and Simulation Using Artificial Neural Network-Embedded Cellular Automata

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ABSTRACT For the accurate prediction of a complex system, determining how to model well it is essential. A classical simulation modeling method that abstracts causality between inputs and outputs utilizing knowledge such as physical laws or operating rules is widely used. However, it may cause a problem in reliability of the model's validity if data acquisition of the actual system is difficult. Machine learning, on the other hand, is a method to represent a correlation between one set of data and another. The model can be built using the big data of the target system. It has a limitation in that it is impossible to predict accurately using the learned model if the parameters or the operating rules are changed after the model is learned. In this paper, we propose a collaborative modeling method using big data-based machine learning and simulation modeling. Specifically, a hypothetical model can be constructed through a cellular automata model (simulation modeling), and parameters and functions necessary for a hypothetical model can be simulated by learning and applying an artificial neural network model (machine learning). This paper shows that the proposed method can be applied to the traffic model to predict traffic congestion in an unsteady state.

INDEX TERMS Artificial neural network, big data, cellular automata, machine learning, modeling and simulation, traffic simulation.

I. INTRODUCTION

There are various methods to model a system for analysis and prediction. As the system becomes more complex, it is very important to determine how to abstract and model it well. In general, simulation modeling refers to a theoretical modeling method commonly used in simulation fields, and physical or operational laws are used to build a model [1]. It is possible to clearly indicate the causal relationship between the input and the corresponding output through this. The cellular automata model is a discrete model that is modelled through cells arranged in a regular grid. It is one of the widely used simulation models throughout various areas [2].

It is a useful approach for prediction, but it alone is not a perfect solution for modeling complex systems in the big data era [3]. For example, when it is difficult to acquire sufficient knowledge about a system, it is impossible to completely build a model that satisfies the objective of modeling and simulation (M&S). This is because simulation modeling is based on prior knowledge of the target system, and its completion depends on how much we understand about the system [4], [5]. For accurate modeling, extensive physical and operational knowledge of the target is needed, as well as ideal assumptions and constraints on the system. In other words, when building a simulation model, it can be valid only in a narrow range of behavior because it includes ideal assumptions. In addition, it is necessary to validate the model after the simulation model is created. If there is no data for validation or it is difficult to obtain, the reliability of the model is lowered.

Meanwhile, many M&S researchers focus on big data as a means of predicting diversified societies, and it is widely used to model and predict system behavior [6]. Data models using such big data can be built through correlation between data, and machine learning is generally based on this principle [7]. Machine learning has been widely used in various fields to predict the future behavior of a complex system, and some researchers have argued that correlation is sufficient to make strong and accurate predictions given sufficient data [8]. Contrary to these expectations, however, machine learning is not always the best way of modeling. Machine learning has some limitations, one of which is that it can represent only the correlation between data, not the causal relationship between the control input and the corresponding output.

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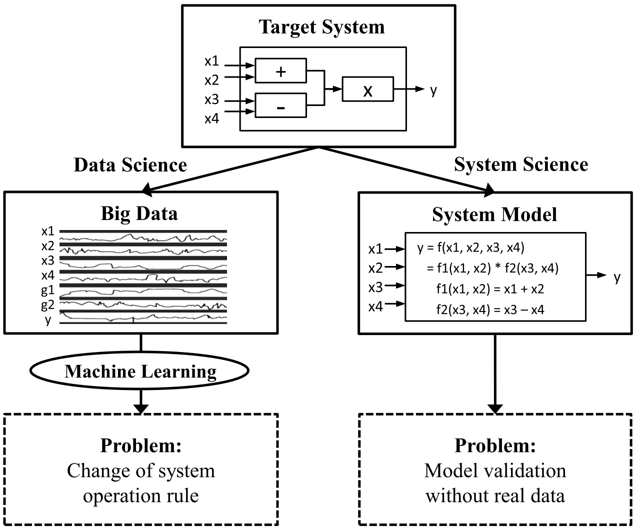

FIGURE 1. Limitation of each modeling approach.

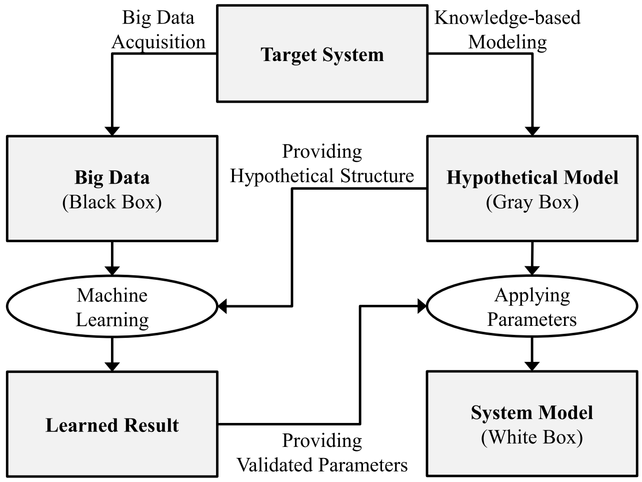

FIGURE 2. Concept of proposed work.

Models created through machine learning cannot cope with system emergencies and changing situations. That is, if the model parameters and structure/behavior are changed after learning the model, accurate prediction using the current model is impossible. Another limitation is that we cannot cope with unexpected events. In the real world, the complexity and uncertainty of a system can cause unexpected events. These are typically not included in the data set that we can obtain; when these events occur, the current model dependent on the original data set cannot accurately predict unexpected events [1].

These two approaches have limitations. Figure 1 illustrates the limitations through a simple example. When modeling a target system with x1, x2, x3, x4, and y as input and output, shown at the top of Figure 1, the simulation modeling method is available, as shown on the right side of Figure 1. The system model can be built through mathematical knowledge of the target system, but it is valid when the value output through the model is validated through the data of the actual system. On the other hand, if machine learning is performed using the data on x1, x2, x3, x4, and y obtained by operating the system, as shown on the left side of Figure 1, it is possible to get an accurate model that outputs y when inputting x1, x2, x3, and x4 values. However, when the system operation law is changed, such as replacing multiplication with division, there is a limit that the output y cannot be accurately predicted by the machine learning model learned through the existing data.

In this paper, for accurate modeling of a complex system, a method for first establishing a hypothetical model and then validating the constructed hypothetical model through machine learning is proposed, as shown in Figure 2. Specifically, the hypothetical model of the system is composed of cellular automata, and the transition function required for them is learned through an artificial neural network (ANN) model with big data obtained from the observation/operation of the actual system [9]. At this time, parameters and functions obtained through learning can be applied to a hypothetical model modelled as cellular automata. It allows for solving the validation problem of simulation modeling, and the operational change problem of machine learning can be solved at the same time.

Several studies have applied machine learning to cellular automata [10]–[12]. They have been mainly used to predict urban development. To predict the next state of a cell representing each region of a city, the cell transition was calculated using an ANN model [13]. Although they make valid predictions about urban development by applying ANN to cellular automata, they do not accurately reflect the characteristics of each cell because only one ANN is learned and applied to the transition functions of all cells. This can lead to low accuracy in prediction. In addition, there is a limit to expressing a dynamic system that varies moment by moment. Therefore, this paper proposes a machine learning-based cellular automata model that effectively reflects characteristics of geographic information system (GIS)-based simulation. Each transition function of cells can be learned through one ANN model independently using the proposed modeling method. As a result, features for each cell can be reflected, and dynamic systems that change in real time are more accurately simulated using narrow time interval data.

This paper is organized as follows. Section 2 discusses background knowledge about cellular automata and machine learning. Then, section 3 proposes an ANN-embedded cellular automata modeling method. Section 4 presents a case study that applies the proposed method to the traffic simulation. Finally, section 5 summarizes the conclusions.

II. PRELIMINARIES

A. CELLULAR AUTOMATA

The cellular automata model is a discrete model that deals with modeling of mathematics, physics, complex systems, biology, and microstructures. It is defined in cells arranged in regular grid form, as shown in Figure 3 [2]. Each cell may have a finite number of states, and the lattice is defined as a finite number of dimensions. For each cell, neighbor cells can be defined as cells that are one space apart in all directions from the corresponding cell. In addition, the state of each

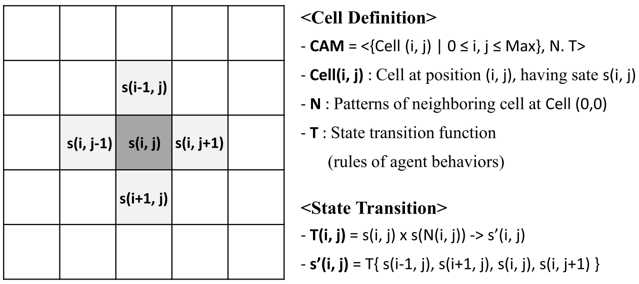

FIGURE 3. Definition of cellular automata.

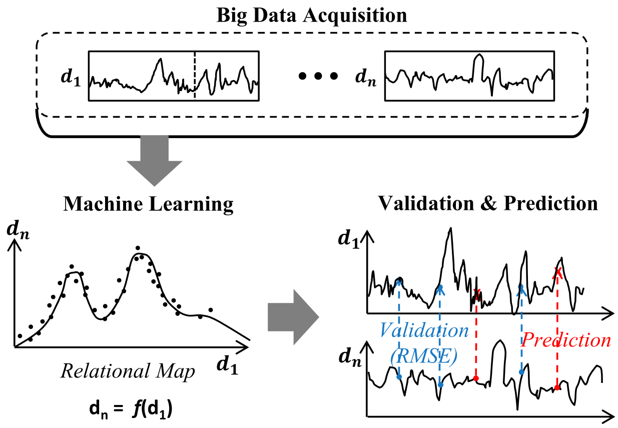

FIGURE 4. Use of machine learning in M&S.

cell when time is zero is defined as an initial state. The new generation is created from the previous generation by the state transition function, which is a mathematical function that specifies the new state of the cell, that is, the behavior rules of the cells, depending on the state of each cell and its neighbors.

Generally, the rule is the same and static for each cell and applies simultaneously to all cells of each generation. The contents of the cellular automata and state transition functions are shown in Figure 3. Cell (i, j) is a cell in position (i, j), having a state s(i, j), where N represents a neighboring cell pattern in cell (0, 0), and T represents a state transition function (i.e., an agent's behavior rule). The state of each cell can be defined according to the kinds of problems, such as traffic problems, water pollution problems, and fire diffusion problems.

B. ARTIFICIAL NEURAL NETWORK

Machine learning is a field of artificial intelligence in which the computer is given the ability to learn without explicit programs [7]. The user can map the association relationship between one set of data (d1) and another (dn) using a machine learning algorithm, as shown in Figure 4. After learning, we can verify the validity of the model learned using general performance indicators such as root mean square error (RMSE) [14]. A given data set d1 can then be used to predict the future value of the data set dn. Machine learning methods include ANN and genetic algorithms. In this paper, an ANN model was applied to the proposed method.

The ANN model is a statistical learning algorithm inspired by the neural network of biology. It is a model in which artificial neurons, which form a network by combining synapses, change the binding intensity of synapses, called weights, through learning and have problem-solving abilities. These adjustable weights, which mean the strength of connections between neurons, continue to change during training or learning using data. When learning the ANN model, a gradient descent method that calculates the actual slope using the back-propagation algorithm is used. The algorithm simply differentiates the cost function with respect to the factor of the network and then changes the factor slightly in the slope direction [9]. The ANN model has been widely applied to predict and simulate the future across various fields [15]–[18].

III. ANN-EMBEDDED CELLULAR AUTOMATA MODELING METHOD

In this chapter, we propose details of a cellular automata modeling and simulation method in which big data-based machine learning is embedded.

A. MOELING PROCESS

The process of constructing and simulating an ANN-embedded cellular automata model is shown in Figure 5. First, it is necessary to analyze the target system to be simulated and acquire the knowledge and information necessary for the hypothetical model according to the objective of the simulation. Then, it is necessary to obtain the big data of the target system through operation or observation of the actual system. Once knowledge and data are obtained, the cellular automata are used to construct a hypothetical model of the target system. In the present paper, the target system of the modeling and simulation is assumed to be a geographic information system, and the cellular automata consist of a terrain to be simulated.

After that, machine learning is performed using the collected big data. In the present paper, a state transition function of a cell required for a hypothetical model can be learned using an ANN model. Figure 6 shows how the transition function in the proposed method differs from the general cellular automata model. In general, an ideal transition function occurs according to a fixed rule by reflecting the state of neighbor cells, but in this study, the transition is performed by receiving not only the state of neighbor cells but also the geographical information, the disturbances (temperature, weather conditions, etc.), as input. In other words, we can expect more accurate prediction of the state of the next cell when the characteristics of the terrain and real-time weather information are reflected in the ideal model stage by stage (Figure 6). At this time, the transition function does not have the same rules for each cell or does not change over time but depends on the location/time change of the cell. In addition, the transition rules are not deterministic according to the data or learning state but involve uncertainty. When the transition is determined using domain knowledge, as before, there is a need to prove it for the reliability of

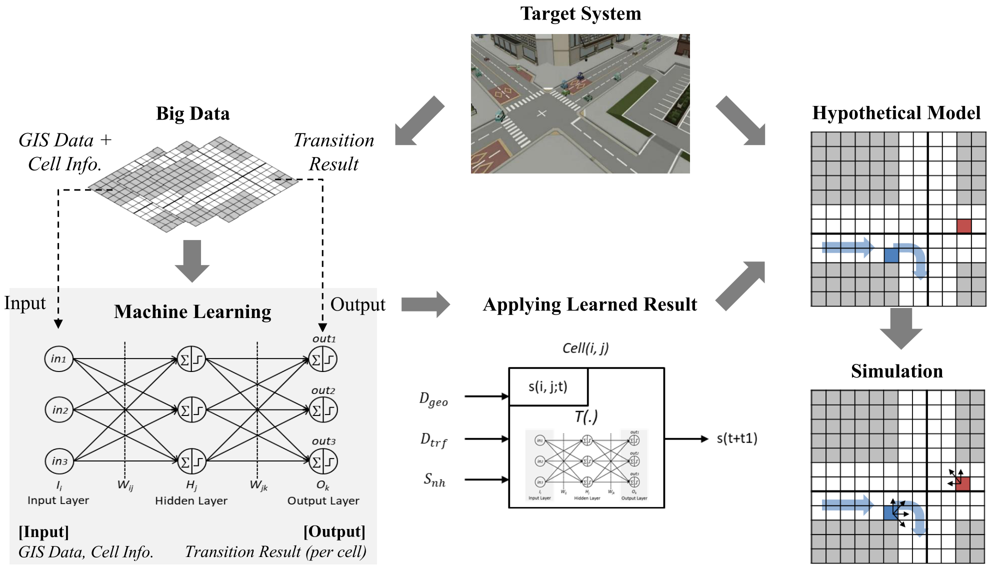

FIGURE 5. Overall process of proposed method.

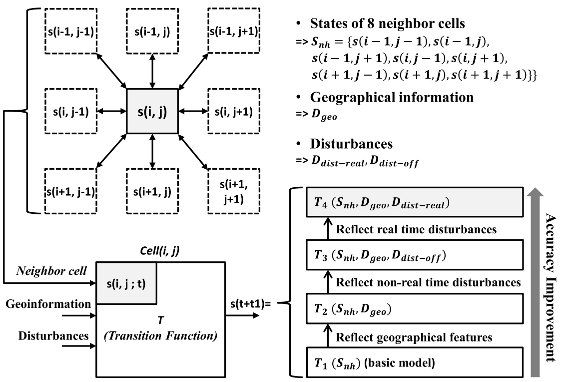

FIGURE 6. Transition function of ANN-embedded cellular automata.

the model. However, when it is learned through big data, the model reliability can be ensured based on the actual data.

When learning such a transition function using an ANN, external factors such as GIS data, neighboring cell information, and weather information can be used as input parameters, as shown in Figure 6. As output parameters, information about the next state of the current cell can be used. When the transition functions of all cells are learned using the ANN, the learned result (weight of the neuron or ANN model) can be applied to the cellular automata, which produces a hypothetical model. Then, the simulation can be run by simultaneously executing the completed cellular automata model with T(i, j) of all cells per unit time.

B. CHARACTERISTICS OF PROPOSED METHOD

The proposed ANN-embedded cellular automata method has the following characteristics. First, the space variant transition is not expressed collectively for the entire cell, but the transition can be expressed differently depending on the individual cell. For example, the features of the geography that vary depending on the location can be reflected in each cell. The next point is a time variant that can reflect the time-varying features of the transition function. It also has stochastic characteristics. In the case of traffic simulation, it is important to reflect the stochastic characteristics in the model and the transition function using machine learning because a driver's decision can be stochastic rather than decisive. The proposed method can reflect nonlinear features of the system, which are advantageous to apply to real systems because many systems actually have nonlinear features. In addition, it is possible to apply and reflect much additional information through big data obtained from the actual system.

IV. CASE STUDY: TRAFFIC SIMULATION

This chapter provides a case study that applies the proposed method to actual traffic simulation. The traffic model is constructed through the cellular automata, and the simulation is performed by learning the transition function using the ANN model. The learned model can be used to predict flow and congestion in abnormal traffic situations such as accidents and bottlenecks after validation of the model using actual data [19].

A. OVERVIEW OF TRAFFIC SIMULATION

Traffic simulation has been studied widely through various methods and can be very complicated to model according to the simulation objectives [20]–[22]. However, in this paper, to show the validity of the proposed method, it is abstracted and simply modelled as shown in Figure 7. In transportation systems, cellular automata consist of areas to simulate. Each cell of the cellular automata represents a specific location and size, and a cell was defined as a road of 5 m x 5 m in this paper. It may have geographic information such as whether it is a road or not, whether it is possible to drive, whether there is a traffic light, whether there is an obstacle, and other traffic information such as vehicle information around the current cell. The state of each cell can be defined as having a value of 0 or 1 using the presence or absence of a vehicle located in the cell. At this time, it is assumed that there is only one car in each cell.

At first, when a hypothetical model for a transportation system is established through cellular automata, there is no

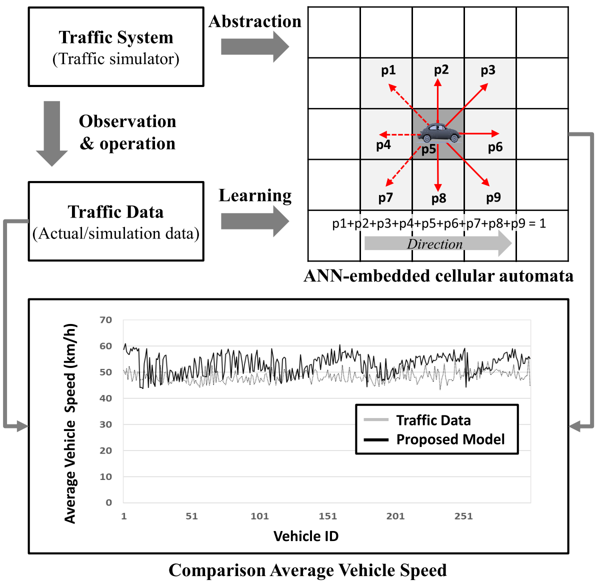

FIGURE 7. Simplified traffic system for applying proposed work.

TABLE 1. Simulation conditions.

Condition	Value
Simulation area	Four-lane road, 4km
Cell size / number of cells	5m x 5m / 3200
Simulation time / interval	600 sec / 0.2 sec
Number of vehicles	300

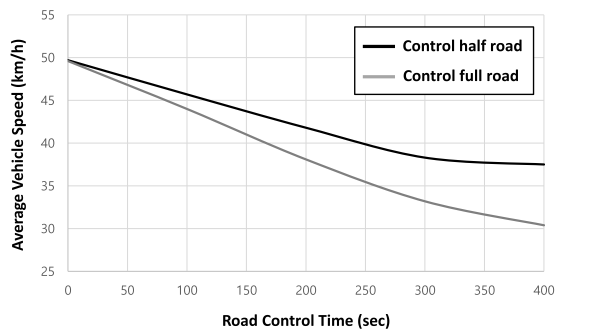

FIGURE 8. Simulation result of traffic control situation.

rule for how the transition in each cell is made. The transition function T(i, j) can be obtained as a stochastic value through learning of an ANN using validated data. It is a function that outputs a probability that a vehicle of each cell moves to a neighbor cell in the current state. It has a state value (0 or 1) of a neighbor cell, geographic information, and traffic information as inputs. An output having a probability value between 0 and 1 can be obtained by learning with the moving result of the cells. In the case study, a feed-forward neural network consisting of 8 input layers, 5 hidden layers, and 6 output layers was used for learning.

When the state transition for all cells is learned through the ANN, the cellular automata model is completed by applying the learned weights to the pre-established hypothetical model. To simulate the completed model, T(i, j) of all cells are simultaneously executed per unit time. In each cell, each vehicle moves to a neighbor cell with the highest probability value every unit time. This enables simulation of the flow of cars on the entire road. Table 1 describes the detailed conditions and variables used in the traffic simulation of this paper.

B. SIMULATION RESULT

Before using the previously constructed traffic model, it is necessary to demonstrate how accurately the learned model reflects the actual traffic simulation. In this paper, simulation data obtained from a Jeju Airport simulation is used due to determine difficulties in acquiring actual traffic data having a short time interval. The airport simulator can be used to acquire data when the road conditions in front of the Jeju Airport change. The graph on the right in Figure 7 shows the results of comparing the average car speed predicted through the proposed model and Jeju Airport data. The average speed predicted through the traffic model is 51.0 km/h, and the original data is 48.2 km/h. The RMSE value is 4.3. As a result, we can see that the proposed traffic model has a valid prediction result.

The following is an experiment on the flow and congestion prediction in an abnormal traffic situation using the validated traffic model. The experiment assumes a situation in which a road is controlled due to an accident situation rather than a normal traffic situation. It predicts the change in the average speed when a particular lane is controlled due to an accident and the change according to the control time of the road. Figure 8 also shows the experimental results of the flow and congestion prediction in an accident situation. The X-axis of the graph represents the road control time, and the Y-axis represents the average speed of the car. It also shows the change in the average speed when two lanes and four lanes are controlled, respectively. Understandably, we can see that the longer the time and the more lanes are controlled, the slower the average speed becomes. In addition to this simple experiment, the proposed model can be utilized in various abnormal traffic conditions. That is, big data acquired in a normal traffic situation and a machine learning-embedded cellular automata model can be used to predict traffic conditions when it is difficult to observe in actual situations.

V. CONCLUSION

For accurate modeling of complex systems, this paper identifies the limitations of simulation modeling and machine learning and proposes a simulation modeling method in which machine learning is embedded by combining two methods. The simulation modeling has a limitation in that the model reliability is low when there is sufficient data for validation at the prediction time, whereas machine learning has a limitation in that it is difficult to predict when system structure and behavior change. Therefore, we first present a method for establishing a hypothetical model through machine learning using big data. Specifically, the hypothetical model of the system is constructed through the cellular automata, and the transition function required for the cellular automata is learned through the ANN model, which is a method of machine learning with big data obtained from the observation/operation of the actual system. At this time, parameters and functions obtained through machine learning can be simulated by applying them to a hypothetical model represented as cellular automata. That is, an ANN using big data is embedded in the structure of cellular automata, and more accurate and improved results can be derived when predicting the target system. In addition, it can be seen as an improved modeling method in which the validation problem of the simulation model is solved through machine learning, and the problem of system structure and rule change is solved through a hypothetical model made from simulation modeling. This paper shows that the proposed method can be applied to traffic congestion prediction in an abnormal state (accident, delay, etc.) using a model acquired from normal-state data. In the future, more accurate prediction can be expected using deep learning techniques, and it can also be applied to various spatial problems such as fire simulation and disease spread simulation.

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