A Distributed simulation method of Forest fire Propagation Based on Cellar Automata model

Zhenqiang Li[1] Xuefeng Guan[1]   Huayi Wu[1]

[1]Wuhan University, State Key Lab Information Engineer Surveying Mapping & R, Wuhan 430079, Peoples R China
Email: lizq@whu.edu.cn

1. Introduction

It's critical to predict the propagation of forest fire to make better decisions in firefighting. CA(cellar automata) model has proved to be a rational approach to simulate the propagation of forest fire in many literatures mainly considering meteorological factors, land cover and geographical factors. However, the computational complexity and memory consumption of CA models is a major challenge in acquiring accurate results in time given dynamic meteorological observations and realistic geographical data in a large-scale simulation. Distributed high performance computing can provide computing and memory capabilities to solve this problem with inexpensive commodity hardware. This paper proposes a distributed simulation method of forest fire propagation using CA model.

2. Related work

CA was identified to be an effective approach to study the spatial-temporal dynamics in the complex adaptive systems through local interaction rules. The propagation of forest fire is a highly non-linear problem sensitive to kinds of factors including weather conditions, heterogeneous land cover and complex geographical condition. It is very difficult to take all those factors into account using a traditional mathematic analytic approach. A CA model was extensively used to predict the spatial and temporal behavior of wildfires considering the fire physic inspired by diffusion limited aggregation processes (Clarke, K. C., et al. 1994). Ioannis Karafyllidis et.al. (Karafyllidis and Thanailakis 1997) applied CA model to simulate forest fire spread and behavior in the case of homogeneous and inhomogeneous forests based on the fire front evolution. A. Herna ńdez Encinas et al. (Hern ández Encinas, Hern ández Encinas et al. 2007) proposed a more realistic modification of the model introduced by Karafyllidis and Thanailakis with a more accurate factor of propagation from a diagonal neighbor cell. Joseph Quartieri et al. (Quartieri, Mastorakis et al. 2010) , on the other hand, proposed a new approach which introduced an "ignition probability" in transition rules resulting in an irregular shape in contrast to fire front. However, CA models become computation-intensive and data-intensive as the simulated area's scale or the model's detail increases, which is the same with other spatial models. Besides, easy access to dynamic observations can be retrieved as the development of sensor network. It's possible to integrate those data into simulation to get more accurate results compared to predetermined or empirical model parameters, which in turn increases the computational and memory consumption.

In view of this, the objective of this work is to utilize distributed computing technology to solve large scale or highly detailed forest fire propagation CA model

integrated with dynamic observations in time to achieve more realistic simulation result.

3. Methodology

3.1 A CA based forest fire propagation model

CA models ca be described as the equation 1. It is critical to define the neighborhood of each cell and the transition rule $f_{\text{transition}}(\bullet)$. The neighborhood reflects the spatial correlation in the systems, which requires some hypothesis and simplification based on experience and experiment. The transition rule in CA models depends on the initial perception towards studying systems.

$$status_i^t = f_{\text{transition}}(status_i^{t-1}, \{status_j^{t-1} \mid j \in \text{Neighbors}\}) \tag{1}$$

As this paper floccus more on the distributed computing of a CA based forest fire propagation model, not the model itself, so the neighborhood in this paper is simply defined a 3x3 window. The transaction in this paper is described as in the equation 2.

$$if \ status_i^{t-1} = 0 \ \&\&random() < P_{burning} \quad then \ status_i^t = 1$$

$$if \ status_i^{t-1} = 1 \ \&\&burnedTick >= K\frac{area*moisture}{fuel*temperature} \quad then \ status_i^t = 2 \tag{2}$$

$$if \ status_i^{t-1} = 2 \ then \ status_i^t = 2$$

In the equation 2, status 0 stands for not burning; status 1 stands for burning; status 2 stands for burn out. The $P_{burning}$ stands for the "*probability to burn*", which can be calculated as in the equation (3-3).

$$P_{burnning} = fuel\frac{temperature}{moisture} \times$$
$$\sum_{j \in neighbors} status_j^{t-1}(2 - status_j^{t-1})(f(\Delta h) + g(\cos(\theta)|wind|)) \tag{3}$$

In the equation 3, the $f(\cdot)$ and $g(\cdot)$ are the function of *elevation difference* and *wind*. The θ stands for the intersection angle between the wind direction and neighbor cell's direction.

3.2 The parallelization of model

CA model is naturally parallelizable as a result of its own local transition rules which are suitable for space domain decomposition. There are many paradigms on the parallelization of CA model with respect to high performance computing paradigms which can be mainly classified into shared memory and distributed memory paradigms. In this paper distributed computing technology is utilized to both speed up computing and handle memory demand with inexpensive commodity hardware. As for the boundary cells residing on each computing node, the "ghost cell" strategy is taken to fulfill its local computing needs. An observation database is adopted to store dynamic observation data. Each computing node retrieves its own data iteratively through network to conduct its local computing. The whole conceptual framework is illustrated in Figure 1.
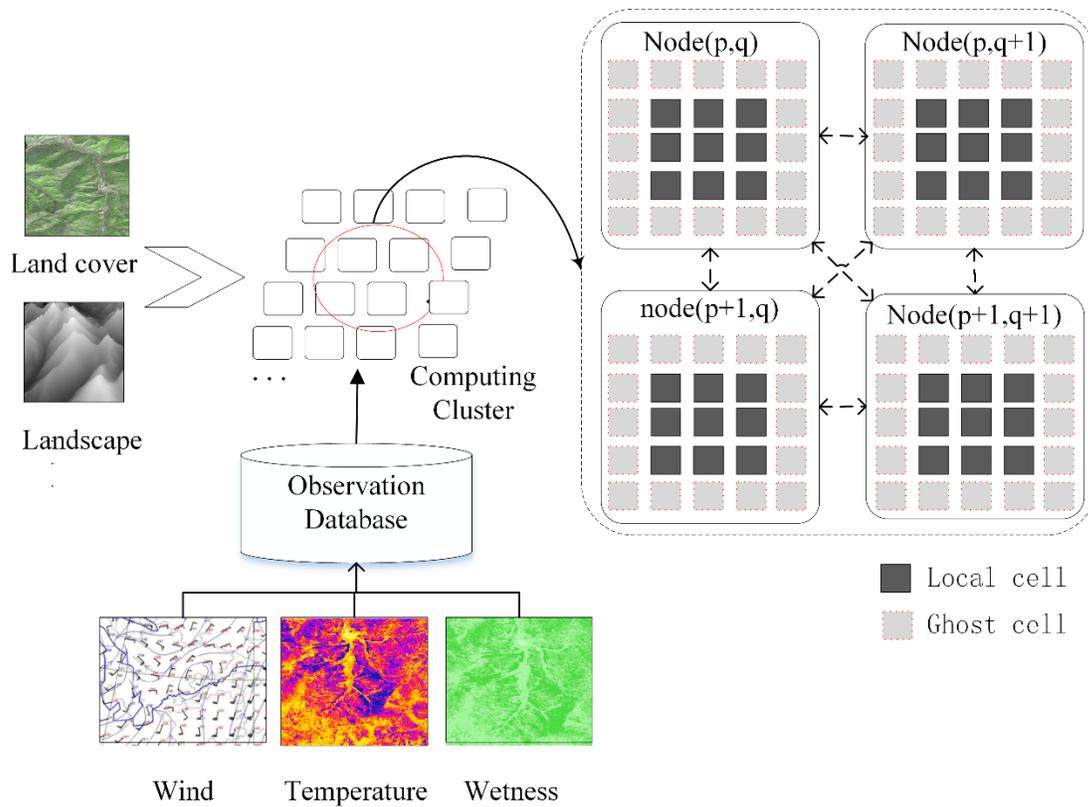
Figure 1 the framework of forest fire CA model distributed computing

The space domain decomposition split simulated area into grid topology, and each computing node is in charge of a subsection. Each computing node consists of local cells and ghost cells as shown in fig.1. The ghost cells represent the local cells on the relevant neighbor computing node. During the synchronizing process, the state of ghost cells are synchronized according to corresponding cells. The size of buffered area is related to each cell's perception window, for example the size pf cell's perception window is 3×3, and the buffered area size is 1.

The dynamic observation data is collected from sensors and stored in the observation database according to predefined schema through the so-called "Extract-Transform-Load" process. During the process, in addition to the synchronization of ghost cells' state, each node needs to load the latest dynamic observation data and update corresponding subsection's model parameters according to some rules. So it is obvious that the model parameters are dynamic and heterogeneous, which is more close to reality.

3.2 The integration of dynamic observation data

Model parameters are central to simulation results. In contrast to predefined, static model parameters in many other papers, the observation database acts as a flexible middleware to inject dynamic model parameters values into model in the runtime. Due to the sensor network, it is easier to retrieve "the neighbor data points" both in spatial and time dimension, which can be used to increase the quality model parameters' estimation.

4. Experiment and discussion

A simple prototype system is implemented based on MPICH3 in C++ programing language. The performance of different size grid topology has been tested to explore the scalability and efficiency of distributed computing of forest fire CA model. The result is illustrated in fig.2 and fig.3.
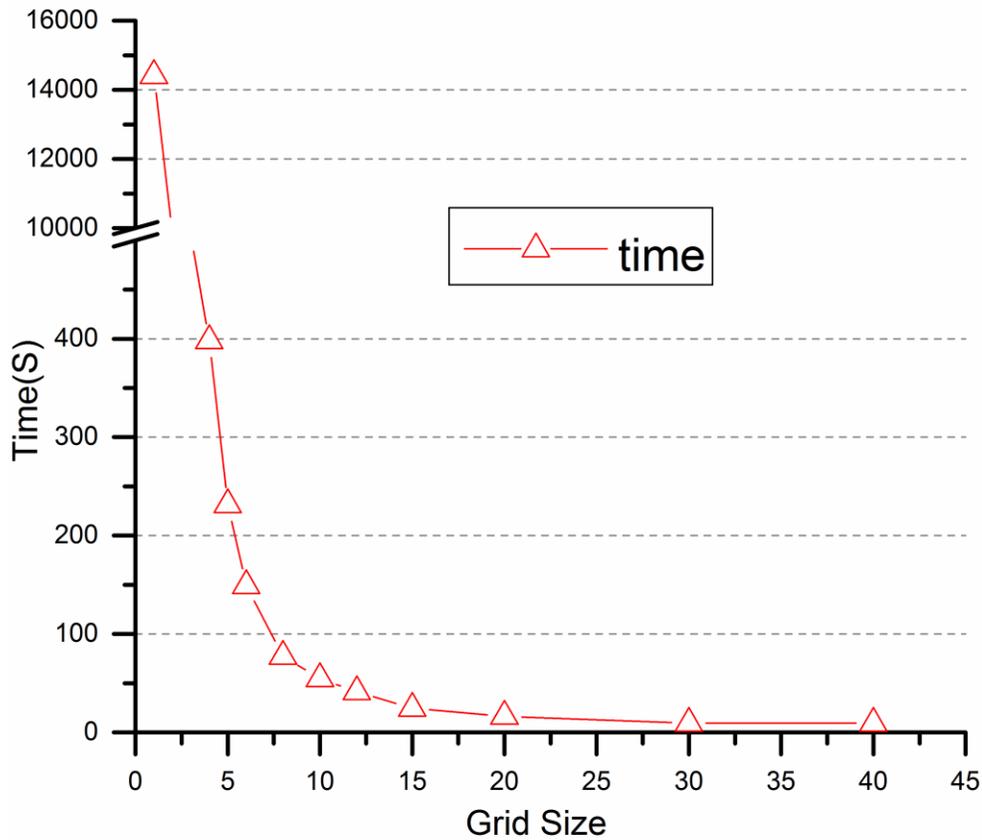
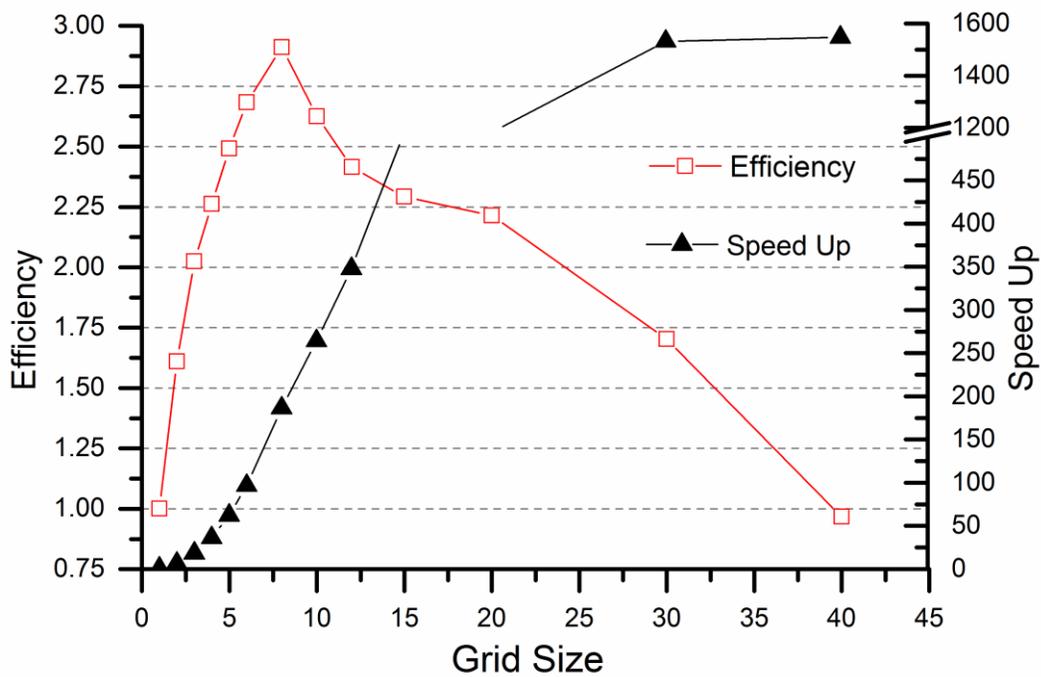Figure 2 the computing time of different grid size

Figure 3 the speed up and efficiency of model's distributed computing

As shown in fig.2, as the gird process topology size increases, the time declines fast at first; then it goes steady. This is because the total communication between all processes increase all the time. For a computing cluster, the network is kind of shared resource, when the total message amount reaches the cluster's network parallel processing limit the message processing degenerates to kind of sequential processing. As a result, though the workload for each process goes lower and lower, the total time won't go down.

In the fig.3, it shows the efficiency and speed up tendency as the gird process topology size increases. The efficiency geos up sharply at first then goes down with different speed but slower than that it goes up with.

In order to explore the dynamic data's effect on simulation evolution process, a simulated dynamic model parameters are incorporated. The result is illustrated in fig.4.
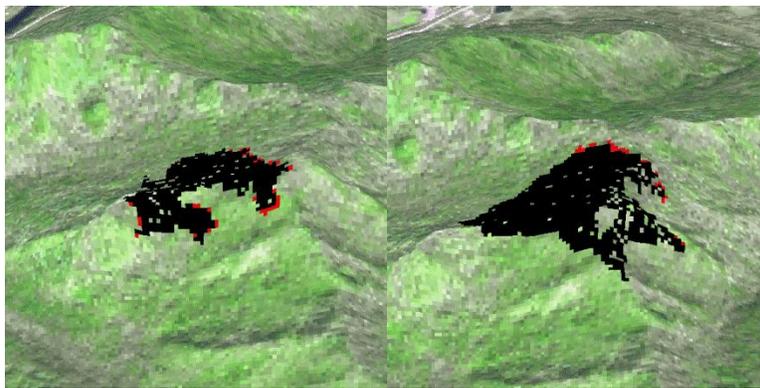

Figure 4 different simulation result with different wind parameter

The left figure shows the simulation result with wind parameter value 5, in the contrast, it's 15 in the right figure, and the other parameters are the same. As the wind became stronger, the fire spread faster, which fulfils people's basic intuition.

5. Conclusion

In this paper, the forest fire CA model is parallelized according to space domain decomposition. A prototype system has been implemented to testify the efficiency and scalability of distributed forest fire model. More realistic simulation result can be acquired using dynamic "near real-time" observation data. In this work, CA based forest fire propagation model is split into regular lattices, which guarantees the balancing between computing nodes implicitly. Besides, "near real-time" observations are integrated to update model parameters and achieves more realistic results Future work may involve with integrating machine learning algorithms for example, artificial neural network, into model parameters calibration to relieve the effects of the errors in dynamic observation data.

6. Reference

Clarke, K. C., et al. (1994). "A cellular automation model of wildfire propagation and extinction." Photogrammetric EngineerWuhan Univ, State Key Lab Informat Engn Surveying Mapping & R, Wuhan 430079, Peoples R Chinaing and Remote Sensing **60**(11): 1355-1367.

Hernández Encinas, A., et al. (2007). "Simulation of forest fire fronts using cellular automata." Advances in Engineering Software **38**(6): 372-378.

Karafyllidis, I. and A. Thanailakis (1997). "A model for predicting forest fire spreading using cellular automata." Ecological Modelling **99**(1): 87-97.

Quartieri, J., et al. (2010). "A Cellular Automata Model for Fire Spreading Prediction." Latest Trends on Urban Planning and Transportation: 173-178.