

Letters

■ Editor:

The Phoenix project ("Trial by Fire: Understanding the Design Requirements for Agents in Complex Environments." *AI Magazine*, Vol. 10, No. 3) presents very interesting work in forest fire simulation. I am especially glad to see recognition that the "real-time, spatially distributed, multi-agent, dynamic, and unpredictable fire environment" provides an excellent opportunity to explore a variety of AI issues, such as how complex environments constrain the design of intelligent agents. I hope more AI researchers will venture into the complex domain of forest fire management.

However, I am concerned about the fire knowledge presented in the article. In defending their use of simulation, Cohen et al. argue that their simulated fire environment is a complex environment, irrespective of whether it is an accurate model of how forest fires spread. Yet, they recognize the importance of a realistic simulation, "the point of using simulators is to create realistic and challenging worlds." Then they make the unsubstantiated claim that the "fire environment is an accurate model of forest fires." Mathematical models of fire spread have been developed that do a reasonably good job of prediction, if the models are applied within the bounds of the simplifying assumptions. That is a very big if. To state unequivocally that an accurate model of fire spread exists is somewhat of an overstatement.

Examining the fire simulation shown in figures 1 through 4, the fire appears to spread from the northwest to the southeast in a somewhat elliptical shape. This appears reasonable and is consistent with other models of fire spread. However, this would mean that the rear of the fire is in the northwest corner. The starting position of the bulldozers indicates that the rear of the fire is in the northeast corner. Something is amiss. In addition, the length to width ratio of the fire is about 1.5, indicating a mid-

flame windspeed of about 3.2 kph. For a fire in that fuel complex to grow to the size indicated in the time indicated would require a midflame windspeed of at least 6 kph, even under the driest conditions.

The authors go on to state, "Fire-fighting objects are also accurately simulated; for example, bulldozers move at a maximum speed of . . . 0.5 kph when cutting a fireline." In reality, sustained fireline production for bulldozers is variable (0.1 - 2.0 kph) depending on steepness of the slope, vegetation, and size of the bulldozer. Furthermore, although bulldozers are often used to fight large forest fires, they are rarely dispatched to initiating fires. Sending bulldozers to attack an initiating forest fire in a National Park is especially unrealistic since there are special restrictions on the use of mechanized equipment. Bulldozers often inflict more damage on the ecosystem than the forest fire!

The simulation also portrays fire bosses (the correct terminology is incident commanders) in a remote location. For initiating fires, the incident commander is always at the fire. The simulation appears to confuse the roles of a dispatcher with those of an incident commander, as well as confound tactics used on an initiating fire with tactics used against a large established fire.

I recognize that the authors are presenting work in progress and I applaud their excellent preliminary efforts. I look forward to seeing future developments. My main concern is that the authors may think they have developed a realistic fire environment already or, worse yet, they don't see a need to develop a realistic simulation. Although a realistic simulation may not be necessary to explore some of the AI related issues, such a simulation would prove all but useless for work in fire science. My hope is that joint projects can be undertaken that are mutually rewarding for the fields of AI and fire science.

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■ Editor:

Mr. Saveland's letter focuses our attention on the important distinction between accuracy and realism. We believed the Phoenix fire simulator to be accurate (with the provisos noted in our article). Mr. Saveland believes otherwise, and he is certainly better qualified than us to judge! We can allay some doubts (e.g., fire-fighting objects actually do move at variable rates, depending on ground cover, as Mr. Saveland notes they should), but basically we agree with Mr. Saveland that the Phoenix fire simulator is not accurate. But we do claim it is realistic. Realism is necessary for our research; accuracy is not. Here are some examples of the distinction: In a realistic simulation, processes become uncontrollable after a period of time; in an accurate simulation, the period of time is the same as it is in the real world. In a realistic simulation, agents have limited fields of view; in an accurate simulation, agents' fields of view are the same as they are in the real world. In a realistic simulation, the probabilities of environmental events such as wind shifts are summarized by statistical distributions; in an accurate simulation, the distributions are compiled from real-world data. When possible, we use accurate data; for example, we replaced our original hand-built map with Defense Mapping Agency data of elevation, ground cover, and so on. But the goal of our research is not to accurately simulate forest fires in Yellowstone National Park. It is to understand the design requirements of agents in real-

istic environments—environments in which processes get out of hand, resources are limited, time passes, and information is sometimes noisy and limited. Toward this end, we welcome the collaboration suggested by Mr. Saveland in his closing paragraph. Whether it proves mutually rewarding may depend on whether our goal is realism or accuracy.

Paul R. Cohen
David M. Hart
Adele E. Howe

■ Editor:

"The good workman does not blame his tools."

Verol Akman and Paul J. W. ten Hagen, in their article, "The Power of Physical Representations" (*AI Magazine*, Vol. 10, No. 3), discuss a variety of important issues about the relation between the scientific enterprise of physics and recent AI research on qualitative reasoning about physical systems.

However, while doing so, they reveal serious misunderstandings about QSIM (Kuipers 1986), and indeed about the relationship between modeling and simulation. QSIM is a piece of qualitative mathematics, in support of the larger enterprise of qualitative reasoning about physical systems. QSIM provides a language for expressing models—qualitative differential equations—capable of expressing states of partial knowledge that are inexpressible in the language of ordinary differential equations. It also provides a simulation algorithm for inferring the possible solutions to a given qualitative differential equation.

Any modeler knows that if you build the wrong model, the predictions derived from that model are likely to be wrong, too. In the rocket problem, for example, if you build a model asserting that gravity is constant, independent of height, the predictions derived from that model will faithfully report that the rocket will fall back to earth, no matter what the initial velocity. In that model, there is no such thing as escape velocity.

It is straight-forward to express a model with decreasing gravity in QSIM, and such a model is one of the standard examples included with copies of QSIM we distribute to interested researchers. As one would expect, it predicts three behaviors:

fall back to earth; escape with velocity decreasing asymptotically to zero; and escape with velocity decreasing asymptotically to a positive value. Since QSIM is a mathematical language for expressing models, rather than a physical methodology for building correct models, it must be able to express both good and bad models, both true and false models, and faithfully derive their consequences, to allow other processes to discriminate among them.

In a criticism directed at this issue of expressive power, Akman and ten Hagen conjecture that QSIM will be unable to express energy conservation laws. In fact, a model including energy conservation (an undamped harmonic oscillator with monotonic, possibly non-linear, restoring force) was described as early as (Kuipers 1985). Such constraints appear in several of our published and distributed models.

Finally, Akman and ten Hagen assert that "Kuipers (1986) believes that causality can be taken as value propagation with constraints." This is incorrect.

My position on causality and QSIM starts with Karl Popper's (1935) definition of causal explanation:

To give a causal explanation of an event means to deduce a statement which describes it, using as premises of the deduction one or more universal laws, together with certain singular statements, the initial conditions.

Following this definition, I argue (Kuipers 1987) that when a set of observations about the world matches the prediction derived from a QSIM model, then the model can be considered a causal explanation of the observations. Frequently, of course, there are multiple causal explanations for a given set of observations, leading to the need for more observations to discriminate among them. (The reader should note that "causality" is a complex and multi-faceted set of issues. Causal explanation, in this sense, is largely disjoint from the issue of "causal ordering" as discussed by Iwasaki & Simon and de Kleer & Brown.)

Thus, the proper way to

view QSIM is, first, as a language for expressing models consistent with a state of incomplete knowledge, and second, as an inference tool for deriving predictions consistent with such a model. Physics, qualitative or quantitative, depends critically on mathematical methods for deriving predictions from models, both correct and incorrect. QSIM is one step toward providing the degree of expressive and inferential power necessary for qualitative physics, along with the guarantees of mathematical validity that are necessary for any science.

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References

Akman, V., and ten Hagen, P. J. W. 1989. The Power of Physical Representations. *AI Magazine* 10(3): 49-65.

Kuipers, B. J. 1985. The Limits of Qualitative Simulation. In *Proceedings of the Ninth International Joint Conference on Artificial Intelligence*. Los Altos: Morgan Kaufman.

Kuipers, B. J. 1986. Qualitative Simulation. *Artificial Intelligence* 29:289-338.

Kuipers, B. J. 1987. Qualitative Simulation as Causal Explanation. *IEEE Transactions on Systems, Man, and Cybernetics*. SMC-17(3):432-444.

Popper, K. 1935. *Logik der Forschung*. English translation *The Logic of Scientific Discovery* (1959). London: Hutchinson.

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