Self-Organizing Social and Spatial Networks under What-if Scenarios

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ABSTRACT
Multi-agent models have been used to simulate complex systems in many domains. In some models, the agents move in a physical/grid space and are constrained by their locations on the spatial space, e.g. Sugarscape. In others, the agents interact in a social multi-dimensional space and are bound to their knowledge and social positions, e.g. Construct. However, many real world problems require a mixed model containing both spatial and social features. This paper introduces such a multi agent system, Construct-Spatial, which simulates agent communication and movement simultaneously. It is an extended version of Construct, which is a multi-agent social model, and its extension is based on a multi-agent grid model, Sugarscape. To understand the impact of this integration of the two spaces, we run virtual experiments and compare the output from the combined space to those from each of the two spaces. The initial analysis reveals that the integration facilitates unbalanced knowledge distribution across the agents compared to the grid-only model and limits agent network connections compared to the social network model without spatial constraints. After the comparisons, we setup what-if scenarios where we varied the type of the threats faced by network and observe their emergent behaviors. From the what-if analyses, we locate the best destabilization scenario and find the propagation of the effects from the spatial space to the social network space. We believe that this model can be a conceptual model for assessing the efficiency and the robustness of team deployments, network node distributions, sensor distributions, etc.

Categories and Subject Descriptors
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General Terms
Algorithms, Experimentation

Keywords
Network evolution, Multi-agent system, Organizational structure

1. Introduction
Multi-agent models have been used to simulate complex systems in many domains [10] such as military operations [5, 16], corporate management [14], disease transmission [3], etc. Because the models often are utilized to estimate outcomes from what-if scenarios, the realism of the models is an important issue in their development. However, while the simulated systems are organizations residing in the real world with physical and social dimensions at the same time, few multi-agent models take both dimensions into the consideration for agent interactions. Often, the agent interactions are limited to either social multi-dimensional spaces or spatial spaces, and the drivers of the interactions come from only one of the two spaces. Therefore, we present a conceptual model, Construct-Spatial, that is the integration of two well-known multi-agent models, Construct [4] and Sugarscape [6]. Whereas the agents in Construct and Sugarscape are bound to the interaction on a social dimension and a spatial dimension respectively, the agents in Construct-Spatial act in a space with features from both spaces. By combining the two different interaction spaces, Construct-Spatial can be used for what-if analyses concerning social and spatial changes simultaneously.

After we setup this conceptual model, we run two experiments to assess the impact of the integrations. The two models, one with communications and the other one without it, generated organizational performances for the two cases. Then, we compared the results to see the impact of integrating communications into the model. Similarly, we observe the influence of integrating spatial limit into the communication behavior by comparing the results with and without range limits. Next, we performed exemplary what-if analyses with the model. Specifically, we examined the impact of various agent removal scenarios within the system. We varied the scenarios by changing the agent capabilities respect to the agents' social dimension and spatial dimension. Also, we observed the propagation of the impacts caused by agent removals from the spatial dimension to the social dimension. With these conceptual experiments, we see that the models with the two dimensions can yield different outcomes that may not be obtained by simulations with only one dimension.

2. Previous Research
Sugarscape is one of the most classical grid models in multi-agent system field. The model is introduced by a book [6] written by Epstein and Axtell. They suggest a simple agent algorithm,

moving agents looking for sugar, and a simple agent interaction space, a grid world with sugar distribution. Though the agent and the environment designs were simple, they demonstrated that the models have many analogies originated from real world problems, market dynamics, disease spread, social networks, etc. They setup virtual experiments corresponding to the problems and seek insights into them by performing experiments with the model. Whereas the model and the book is a classic and thoughtful example of a multi-agent model and its virtual experiments, the agent algorithm is too simple to represent many important activities, such as cognition, learning, communication, etc, in the real world. Moreover, the experiment about social network with the model does not contain important aspects of human interactions, such as homophily [11], expertise [8], knowledge transfer, and so on. They create a social network when the two agents are near in the spatial space, which often just outputs two clustered social networks with rare connections between the two. The updated version of Sugarscape is VUScape [1]. It integrated the communication function to the agents of the original model, so the agents in VUScape exhibit more realistic communication behaviors such as posting messages to news board or broadcasting communication messages. Then, the model is used to compare the performances when different communication protocols are adopted. This is encouraging virtual experiments by displaying which communication protocols can increase the output of the organization. However, still the model does not adopt any learning or cognition related features, which has been regarded as important drivers for social interactions.

In the other side of multi-agent simulation field, some social network models [9, 18] have been developed to investigate knowledge diffusion and structure evolution in human organizations. Among the models, Construct [4] is one of the most frequently used and validated models. Its agents interact with others based on relative similarity and relative expertise. These concepts are originated from social theories, homophily, expertise, etc. Construct is used to investigate the performance changes of a small company [14], the organizational network healing process [17], etc. Moreover, its extended version, Dynet [2], was utilized to estimate the performance of military command and control structures [12], NASA small team dynamics [15], and so on. Though Construct model has been used in many real world situations, its usage and analyses have been limited because physical proximity is important in some organizational performances and the proximity was not represented in the model. Therefore, we integrate spatial factors into the original Construct model and see the impacts of the integration.

Besides the classic models known to many researchers or the models frequently used in the real world, there are many models that are simple but useful in the investigation of team formation and organizational structure. For example, Schermerhorn and Scheutz [13] developed a multi-agent model, MATE, which can explore spatial territory with social coordination. They show that the simple social mechanism can enhance the performance of the spatial exploration. However, they just use static pairing of two agents, which is a simple method of communication, to represent the real world communication while real communication networks dynamically change, heal and evolve. Also, Gaston and desJardins [7] presented a simulation model for agent-organized networks. Their agents have cognitive functions, communications and accompanying constraints and spatial layouts, etc. Therefore, their model is closely related to ours. However, the methods and the objectives of the virtual experiments are different. They let agents evolve by two different mechanisms, structure-based and performance-based. On the other hand, we have one mechanism for agents, and change the parameters for the mechanism in three different ways. Also, we perform threat what-if analyses with our model after the evolution of our agents while they show the evolution result of the network only.

3. Method

Our research objective is creating a model with an agent's behavior inherited from two different models, Construct and Sugarscape. Therefore, we explain the differences in the agent behavior of the two models, design the general behavior of our agents, and match the behavior features corresponding to the two models. Also, the environment of the virtual world in our developed model adopts some aspects from the two models, so we described the integrated interaction space after the agent behavior. Finally, we presented a performance measure because the measure was applied to observe and assess the organizational performance during simulations.

3.1 Agent Behavior

The agents in our model, Construct-Spatial, inherited the two agent behavioral logics from the two models, Construct and Sugarscape. Though the two models simulate systems with the concept of agent behavior and its emergent structures, there are some intrinsic differences between the agents' behaviors. In Construct, agents try to communicate with each other based on their similarities and exchange their knowledge with the agents that they are interacting with. Therefore, the agents' interaction mechanism is creating a communication link from him to one of the other agents, sending his knowledge to the interacting agent and receiving the interacting agent's knowledge. In Sugarscape, agents search for better locations where they can harvest more sugar and relocate their positions to the found locations. Of course, the extended versions of Sugarscape allow agents to interact with each other, but the basic model does not. In the perspective of sugar harvest and consumption, the agents are like normal creatures that obtain nutrition, consume it and save the rest of the consumed nutrition in their bodies.

One of the discrepancies of the two models is the interpretation of knowledge and sugar. Construct agents and Sugarscape agents utilize knowledge and sugar respectively, and this shows that knowledge and sugar are equivalent because they are a benefit to the agents. However, knowledge in Construct never decays and has a permanent positive value to its agents, and there is no supply for knowledge in the model. On the other side, sugar in Sugarscape is consumed by its agents regularly and supplied at various locations in the grid world. With this gap between the two models, our model implemented mixed rules of the two original benefits. First, our agents will get benefit from a knowledge piece, not from sugar, so knowledge will be the utility for our agents. Second, the knowledge will not decay and keep its value until a simulation ends. Third, knowledge pieces will be distributed on a grid plane with different densities according to regions. These rules are designed to ensure our agent exchange knowledge as in Construct and harvest knowledge as in Sugarscape.

Other discrepancies of the two models are the ages of agents and the consequence of failed sugar consumption. The agents in

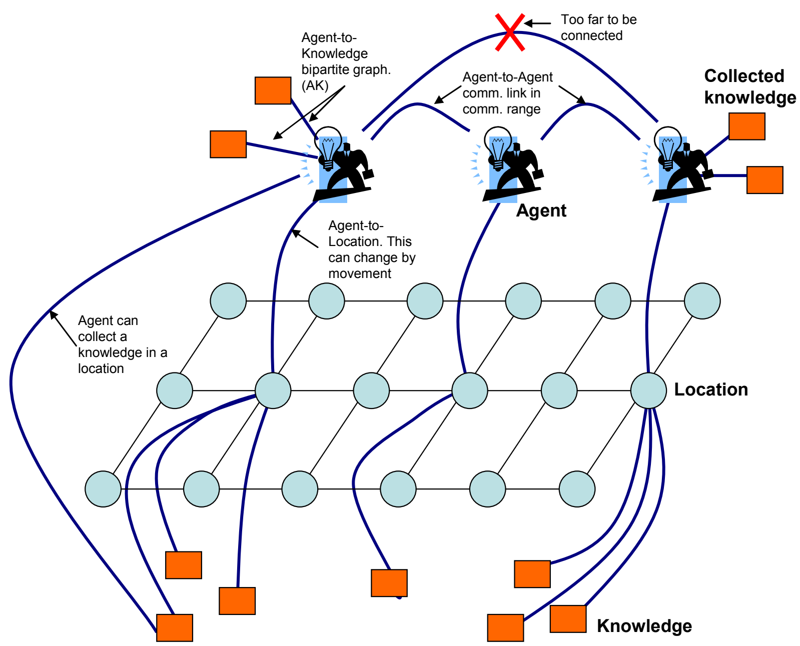

Figure 1 Simple description of Construct-Spatial

Sugarscape get older as a simulation proceeds and die when their ages exceed their pre-defined life expectancy. This is one cause of death for Sugarscape agents. The other cause of death is the insufficient sugar consumption of agents. Agents have a preset amount of sugar that should be consumed for one time tick. If an agent fails to consume that amount of sugar, it dies. On the other hand, a Construct agent never dies. The Construct agent will suffer from the lack of knowledge in its performance measure, but it does not cause the agent to be excluded from a simulation. Our agent will follow the Construct style. There will be no death for our agents, but their lack of knowledge pieces will be represented by the performance measures we defined. Also, we will isolate some agents and observe the impacts of the isolations as previous Construct simulation experiments performed instead of adopting the automatic death of agents in Sugarscape.

Agent Behavior (Agent A)

1. A searches for locations with more unknown knowledge pieces for him within A's vision range
2. A moves to the found location
3. A learns the unknown knowledge at its location
4. A searches for one of the other agents to interact with within A's communication range
5. A exchanges the unknown knowledge with the agent selected to interact with him

Algorithm 1. the agent behavior in Construct-Spatial

As we claimed that our agents will inherit the rules from both models, our agents can communicate and exchange knowledge with other agents as well as search for better locations where they get more utilities and relocate themselves to the found locations. In detail, our agent follows the logic shown in Algorithm 1.

In the above behavior description, most of the logics from Sugarscape are straight forward. For example, looking for a better location within his vision range is the same as the agent behavior in Sugarscape. Also, an agent's relocation and harvest of knowledge in a location are easy to understand if we agree on regarding knowledge in our model as sugar in the original Sugarscape model. While the agent behavior from Sugarscape is relatively simple, the agent communication behavior in our model originated from Construct requires additional descriptions. Agents in our model will select an agent to interact with based on relative similarity and relative expertise. Relative similarity is the ratio of how much the target agent has the same knowledge pieces that the source agent has. On the contrary, relative expertise is the degree of how much the target agent has unknown knowledge pieces. These two metrics comparing the acquired knowledge of two agents developed in sociology. Homophily is a natural factor for the selection of a person to meet and interact with. Also, expertise is another factor for the selection. In our model, these two metrics are the factors for agent communications.

$$P_{ij} = RS_{ij} + RE_{ij}$$

$$RS_{ij} = \frac{\sum_{k=0}^{K} AK_{ik} AK_{jk}}{\sum_{k=0}^{K} AK_{ik}}, \; RE_{ij} = \frac{\sum_{k=0}^{K} AK_{jk}(1 - AK_{ik})}{\sum_{k=0}^{K} AK_{ik}}$$

$N = (\textbf{num. of agents in a network at the time})$

$K = (\textbf{num. of knowledge bits})$

$\mathbf{AK} = (\textbf{Adjacency matrix of Agent-Knowledge})$

$= (\textbf{links between agents and collected knowledge bits})$

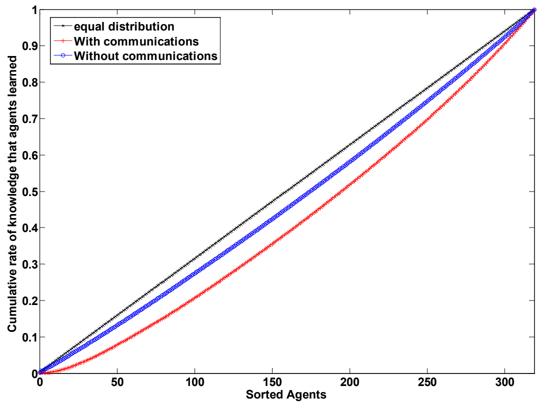

Figure 2 the Lorenz curves for knowledge distribution across the agents. When comm. was disabled, agents have only eight vision range. When comm. is up, agents have eight vision range and eight comm. range.

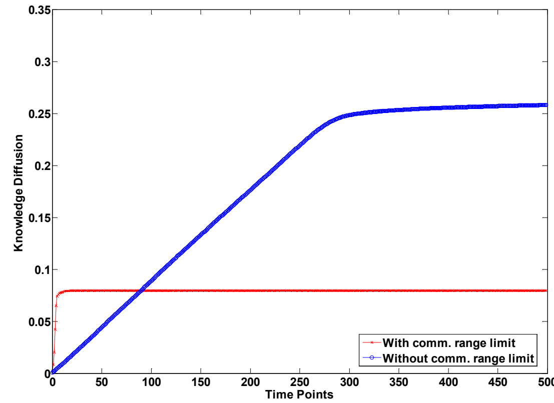

Figure 3 knowledge diffusion charts over time. When there is a comm. range, the knowledge diffusion reach plateau faster, but the plateau is lower than the case with unlimited comm. range

In the above, we described the agent behavior rules in our model, Construct-Spatial. First, we discussed the characteristics of the two different agent behavior models of Construct and Sugarscape. Then, we mitigated the discrepancy between two logics and suggested a rule that reflects the core aspects of both. Finally, we explained details of our agent behavior and the factors of decisions that agent will make.

3.2 Environment of simulation world

The environment of a simulation world is one of the important factors that represents the complex nature of the simulated society and causes the emergent behavior of agents. In Construct, the agents reside in communication world, which is not like spatial world such as the grid world in Sugarscape. There is no specification where Construct agents are, and the only perceivable part is the communication networks showing who-talk-to-whom. While Construct is about the communication world, not spatial world, Sugarscape is the simulation with a spatial grid world. Whereabouts of agents can be easily visualized in two dimensional grids, and so can the sugar distribution on the grid world. Moreover, the extended version of Sugarscape model maps the interaction network among agents on the grid world.

Our model uses a network world that looks like a grid world in Sugarscape, and the purpose of the description below is demonstrating a multi-modal and multiplex network can capture the salient features of Sugarscape model without hurting its spatial nature. First, we assume that a cell on a grid is a node in a network and a neighbor relation between two cells is a link between two cell nodes. With this assumption, we can reduce a coordination-based grid world to a network-based spatial world. After we setup a network-based spatial world, we keep the network model and include knowledge pieces and agents in the network. As we decided to use knowledge pieces instead of sugar, we found a way to represent the knowledge distribution in our network world. While Sugarscape specified the amount of sugar at a certain location as a number, we created knowledge nodes and linked the knowledge nodes to a location node. We determined to represent each knowledge piece as a unique entity because a knowledge piece is different from other pieces whereas sugar in Sugarscape is homogeneous. Also, symbolizing a knowledge piece as a network node is useful because we can consistently keep the representation of entire simulation world as a network world. Just like the knowledge representation, the location of an agent can be represented as a link between the agent and a location where the agent is. Then, we can setup our network model and still include the agents' spatial locations on a grid plane. Thus, our extended model can be fundamentally based on a multi-agent network simulation model while we are still including grid space features.

3.3 Performance measure

Finally, we need a measure to calculate the organizational performance. In this paper, we use the degree of knowledge diffusion.

$$KD = \frac{\sum_{i=0}^{K}\sum_{j=0}^{N} AK_{ij}}{kn}$$

The knowledge diffusion (KD) stands for the degree of how many the agents in an organization exchanged knowledge that was exclusive to certain agents before simulation begins.

4. Result

This section introduces virtual experiment results obtained from Construct-Spatial that specified in method section. First, we assess the impact of the integration of two agent interaction spaces. Mainly, we compared the result from the original model to our model and observe the difference between the two. Next, we setup a threat what-if scenario and perform virtual experiments with the scenarios and our model. In this paper, we limit the threat to the isolation of a part of the agent populations in the system, and we experiment the agent reaction to the scenario with a set of various parameters.

4.1 Effects from the integration of Construct and Sugarscape

First, we assess the impact of the integration to a grid world model. In Sugarscape, agents harvest sugar from the grid and consume it. Because the distribution of sugar is different, the agents at better location will have more sugar. While the original model did not allow agents to share the sugar with others, our model lets agents to share knowledge through communications. Therefore, we check how equally the sugar/knowledge is distributed across the agents without or with communications. According to Figure 2, the agent organization with communications show more unbalanced distribution than that without communications. This result may be surprise, but it should be noted that some agents located at key positions gained more sugar through communications than the others. Because of the agents with key communication position, the unbalanced distribution of original model got worse. Of course, the number, not the distribution, of shared knowledge under communication enabled world (3939480) is larger than the shared knowledge number under communication disabled world (3298170).

Second, we evaluate the impact of the integration of communication range limit on the grid plane. In Construct, agents are able to communicate with another agent if he is available without any limit of spatial distance. In our model, there is a communication range, so the agents have limited number of agents that he can interact with. Figure 3 shows the knowledge diffusion rate over time with comm. range limits or without. When there are comm. range limits, it appears to agents diffuse knowledge faster. This is because the agents do not have to talk to the deserted agents who are away from the knowledge hot spot. Therefore, they are diffusing knowledge faster by interacting with only agents who are near knowledge popup sites. On the other hand, as a simulation proceeds, the comm. range without limit shows better diffusion rate because they are slowly but widely diffusing knowledge including the deserted agents. Therefore, the agents with ranged comm. cannot diffuse knowledge from a certain time point, while the agents with unlimited ranged comm. can diffuse knowledge furthermore.

4.2 Isolation of agents and its impact

After we observed agent clustering and network healing process in Construct-Spatial, we setup a number of what-if scenarios to test the robustness of self-organized agent societies. Particularly, we varied the limitation of agent abilities and the places where isolations happened. This model allows agents to exhibit two behaviors, communication and movement, and the two actions are bound to the communication range and the vision range respectively. Therefore, we setup the limitation of the agent abilities by changing the two ranges of agents in three different modes. The first mode, communication intensive situation, specifies that agents can communicate with other agents at farther places (comm. range=12) while they can only see the nearer places compared to the sights of agents in the other modes (vision range=4). The second mode, neutral situation, means that agents have the same ranges for both (comm. range=8, vision range=8). The third mode is just the opposite of the first mode (comm. range=4, vision range=12). We also provide three variations of isolation places. Since the spatial grid plane that we used in this paper has two hotspots and one bridge point at the middle of the two spots, we setup one baseline and two corresponding scenarios. As the baseline of this variation, we isolate the agents at multiple random places, so there were no preferences in the isolation process in terms of spatial location. Next, we isolate agents located at the bridge point where the two hotspots intersect. Finally, the isolation happened at the two hot spot points.

To obtain the knowledge diffusion rate from Construct-Spatial, we replicated each of nine situations ten times and averaged the outcome of the simulations. During simulations, the isolations occurred at time point 30 and the total length of simulations was 60. As we are interested in the impacts of the isolations, we calculated the damage on the averaged diffusion rates by using the formula below.

$$kd_i = (knowledge\ diffusion\ at\ time\ i)$$

$$isolation = (time\ point\ \ when\ isolations\ happened)$$

$$(damage\ rate) = \frac{kd_{isolation-1} - kd_{isolation}}{kd_{isolation-1}}$$

4.2.1 *Isolation at different places and under different situations*

Figure 5 is the response surface from simulations of three different

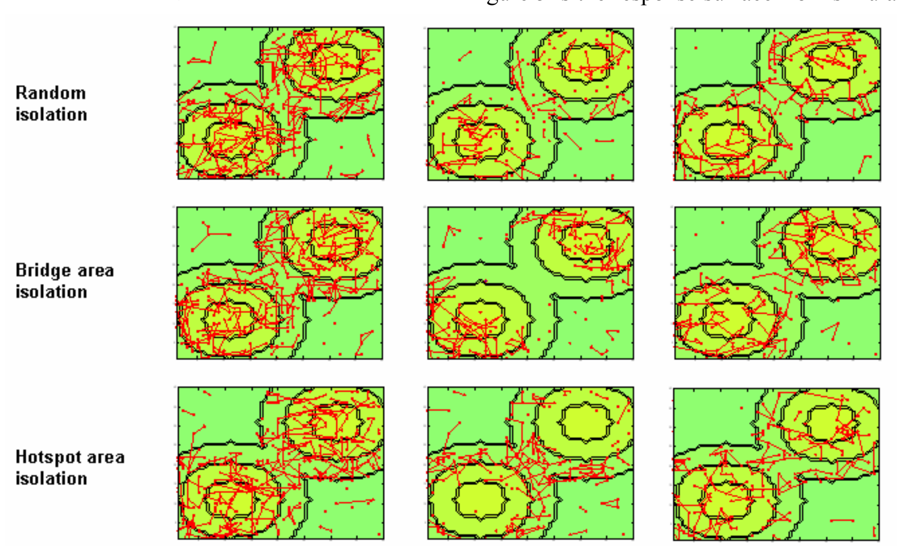

Figure 4 isolations of agents and healing process after the isolations. Agent isolations happened in three different regions, multiple random areas, the bridge area and the two hotspot areas. The isolations of different region showed different healing result in short simulation period. Snapshots at time 29, 30 when isolations happened, 59, from left to right. Three different isolation regions from top to bottom. Agents were under neutral situation where the agents have eight communication range and eight vision range

agent capabilities and three different isolation regions. The response surface shows interesting non-linear results according to the scenarios. Fundamentally, the isolation at random locations damages the diffusion rate less than the other two locations, bridge and hotspot. This suggests that the inconsistent attack toward the agents is not efficient. When we compare the efficiencies of bridge and hotspot, we found that they were different according to the situations that agents were facing. When the agents with better vision capability were isolated, the isolations at the bridge decreased the diffusion rate slightly more than the isolations at the hotspots. This result may have emerged because the agents at the bridge point connected the agents near hotspots and the isolation disconnected the communication between the two groups near the two hotspots. Also, the isolation of agents near hotspots under the vision intensive situation lightly affected the performance because the remaining agents with better visions will instantly cluster to the hotspots when the isolation happens. On the other hand, the isolations at the bridge areas were better under the communication intensive situation. The rational of the result under the communication intensive situation would be the inverse of the rational under the vision concentrated situations.

There are some limitations to this response surface analysis. It should be noted that the calculated damage is not the actual value of the cases. For example, the surface displays that the neutral situation (comm. range=vision range) minimizes the impact of the isolation, which may not be preferable in general. The neutral situation will not guarantee whether the agents can gather knowledge efficiently or not under threat-free scenarios. Furthermore, this result only shows the immediate impact of the isolations, and it does not display any over-time effects such as slower network healing after the isolation at the bridge point shown in Figure 4. Finally, this result may be sensitive to the number of isolated agents, so we setup other experiments for an analysis on isolated agent numbers.

4.2.2 Isolation at different places and under different situations

For the second what-if analysis, we varied the number of agents to isolate and see the sensitivity of the diffusion rate damage. From the previous analysis, we observed that the random isolation did not show any distinct characteristics, so we dropped the random case. Also, the neutral situation in agent capabilities did not display non-linear behavior, so we did not experiment the case. Therefore, we had four cases, the combination of two isolation place, bridge and hotspot, and two agent situation, communication intensive (longer comm. and shorter vision) and vision intensive (shorter comm. and longer vision). We replicated each case for ten times and probed the diffusion damage with the isolations of 20%, 40% and 60% agent population.

Figure 6 is the diffusion damage change according to the percentage of isolated agents. Whereas the communication intensive agents suffered more when the 20% and the 40% of the agents were isolated, the vision intensive agents received significant damage when the 60% of agents were removed. This means that an agent with longer communication range is more robust than an agent with longer vision range. In this model, there are only two ways to collect knowledge: gathering from a location or through a communication. The number of isolated agents does not affect agents' knowledge gain from a location. However, the knowledge gain through communications was influenced by the number of casualties. After 60% isolation, communication oriented agents can still find agents to communicate with because their comm. ranges are longer. On the contrary, vision oriented agents cannot find other agents to interact with because the population density decreased and the number of agents within their short comm. range dropper. Therefore, the communication oriented agents were robust against the higher casualty rate.

Additionally, Figure 6 implies that the best strategy to

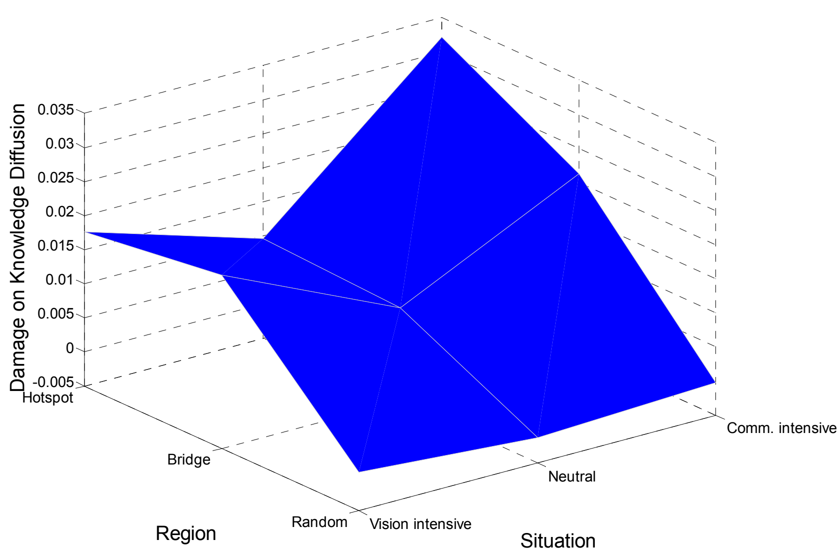

Figure 5 a response surface obtained by varying the isolation regions and the agent situation. Three different regions, isolations at the two hotspots, the bridge and multiple random places, were tested. Also, three different situations, communication intensive (comm. range = 12, vision range=4), neutral situation (comm. range = 8, vision range=8) and vision intensive (comm. range = 4, vision range=12), were examined. Each isolation removed 40% of agents.

destabilize these self-organizing societies is attacking the weakness of the agent capabilities. In the figure, there are two tendencies in the diffusion damage. When isolating the vision intensive agents, it would be preferable to isolate the agents near the bridge point. On the other hand, the isolation of communication intensive agents would be efficient when it occurs near the two hotspots. The reason why we isolate vision intensive agents near the bridge point is that the rest of vision oriented agents will not be able to communicate with each other if the agents near the bridge point are removed. Their communication range is limited, so the two groups near the hotspots are difficult to communicate with each other unless they have agents who are relaying their communications. This tendency is true to the opposite side. Once we isolate the communication intensive agents from the hotspots, the rest of the communication agents will take long time to settle on the hotspots again because their vision range is limited. Then, the overall knowledge gain from the grid plane decreases, and so does the knowledge diffusion. Though the communication network may not be damaged much, the overall decrease of the knowledge inflow will hurt their performance.

These experiments and interpretations suggest that the agents bounding to both social and spatial dimensions exhibit different characteristics when the agents have different capabilities in the dimensions. Furthermore, the threat what-if scenarios damaged the performance of the organization differently when the social ability and the spatial ability of the agents differ. Based on these analyses, we claim that the agent behaviors in the social and the spatial dimensions should be considered simultaneously when we utilize multi-agent models to estimate the impact of what-if scenarios.

5. Conclusion

Multi-agent models are utilized to reason about various real world problems. Some of the problems are related to team coordination and cooperation through communications, and others are related to optimization of logistics and spatial distribution. However, in the real world, it is often observed that the communication and the spatial distribution are correlated to each other and affect the team performance together. Therefore, only modeling one aspect of the two different spaces may not yield comprehensive thoughts about the simulated systems. Furthermore, the impact of integrating the two spaces, social multi-dimensional space and spatial space, has not been discussed many times. Thus, we setup a model, Construct-Spatial, which inherits the characteristics of the two models, Construct and Sugarscape. Construct is a model for agent communications without spatial distributions, and Sugarscape is a model for agent movement and spatial clustering without communications. By mixing the agent behavior and the environment of the two models, we generated the agents who are moving, communicating and bound to a spatial and a social multi-dimensional space simultaneously.

After the model specification, we perform largely two virtual experiments. First, we explore the impacts of the integration of the two worlds. To assess the impact of adding communication to the grid world model, we examined the knowledge diffusions with or without the communication functions of the agents. Because some of the agents are positioned at critical social positions, the communication facilitates the unbalanced knowledge distribution across the agents. However, the amount of knowledge possessed by the agents increased when the agents were able to communicate. Additionally, we monitored the case with and without

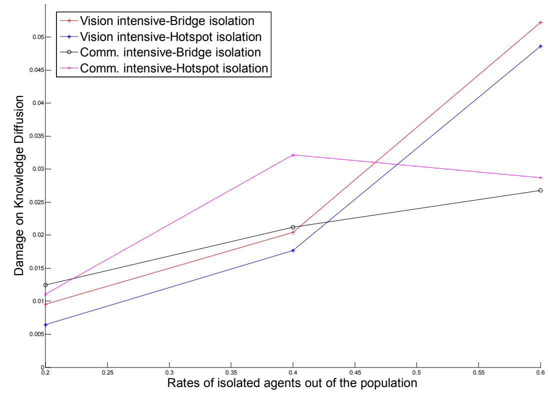

Figure 6 the changes of knowledge diffusion damage when the number of isolated agents changes. The four lines represent four different combinations of two isolation places, hotspots and bridge, and two agent capabilities, communication intensive and vision intensive.

communication range limits to assess the influence of adding a spatial factor to the social network model. When communication range is limited, the agents end up communicating less, and so less information diffuses than when range is unlimited. This is because the agents with unlimited range will include all of the agents in their interaction list and diffuse knowledge to them. With the first virtual experiments, we found out that the integration of the two worlds may make knowledge diffuses slower and less compared to the social model and forces agents to have on average more knowledge, even though the variance, the amount known per agent, is higher.

Next to the assessment of the integration, we created a number of threat what-if scenarios. We limited our threat scenarios to the isolation of a set of agents near a specific location. For example, we isolated 40% of agents that are near the two hotspots, the bridge point or random places. Also, we varied the characteristics of the agents by changing their vision ranges and communication ranges. With this virtual experiment setup, we see which agent type is more robust against the what-if scenario and which isolation area is more effective to destabilize the organization of the agents. The result of the experiment suggests that the isolation of the vision oriented agents near the bridge point and the communication oriented agents near the hotspots result in lower information diffusion. This is an interesting result because it suggests that a weak spot in an organizational structure is a function of both the type of agents and the geospatial distribution of resources, in this case, knowledge. For instance, if we isolate the vision oriented agents near the bridge point, the isolation can dichotomize the agents into two clusters that cannot communicate with the other cluster. On the other hand, such an isolation with communication oriented agents will not produce good damage because the communication oriented agents will eventually regroup the whole agent society by utilizing its long range communication capability. We interpret the isolations of the communication oriented agents near the two hotspots in the similar way. The isolations of such agents near the hotspots will damage their performance greatly because they will not cluster near the hotspots again quickly because their vision ranges are limited. Furthermore, we observed similar results when we varied the number of isolation agents out of their population.

Construct-Spatial and the above virtual experiments are still at their conceptual level. However, their applications are very obvious and promising. For instance, we can create a multi-agent model that simulates the disruption of a communication network that is distributed spatially and socially. Also, the model can be an interesting analogy to the small sensor network when the network is dispersed over a region and whose sensors have limited capability of communication or movement. Furthermore, as our future challenge, we will develop this model and equip it with more sophisticated and realistic functions of agents and environments. Then, the development will turn this conceptual model into a realistic model that can be validated with the datasets gathered from real world organizations.

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