Agent Perception Modeling for Movement in Crowds

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Abstract. This paper explores the integration of a perception map to an agent based model simulated on a realistic physical space. Each agent's perception map stores density information about the physical space which is used for routing. The scenario considered is the evacuation of a space given a crowd. Through agent interactions, both in physical proximity and through distant communications, agents update their perception maps and continuously work to overcome their incomplete perception of the world. Overall, this work aims at investigating the dynamics of agent information diffusion for emergency scenarios and combines three general elements: (1) an agent-based simulation of crowd dynamics in an emergency scenario over a real physical space, (2) a sophisticated decision making process driven by the agent's subjective view of the world and effected by trust, belief and confidence, and (3) agent's activity aimed at building relationships with specific peers that is based on mutual benefit from sharing information.

1 Introduction

Increasing abundance of mobile communication and sensor technologies accompanied by the evolution of mobile computational power suggests that these technologies may alter the very nature of human communication schemes and information diffusion dynamics. This may have a profound effect on the patterns of human behaviour, especially in the situations in which people rely on the availability and quality of information.

In everyday situations the existing infrastructure provides information of adequate quality and in a timely manner and people are typically capable of accessing the information and adjusting their activities accordingly. However, many of such pre-deployed systems are not as useful and effective in emergency situations, like natural disasters or terror attacks. The usual information delivery channels may be disrupted, and of importance – the information consumers may require is at an entirely different rate of update and level of detail when coping with their specific situation. A balance between providing a broad image simultaneously with the information required locally is crucial. In particular, a successful evacuation may depend on the underlying physical infrastructure as well as on coordination. The physical infrastructure adjustments tend to be quite costly. Agent based models provide a reasonable solution for agent behaviour prediction and analysis.

Agent Based Modeling is an important tool, particularly relating to recent developments in Computational Social Science [1]. For effective, realistic agent based modeling frameworks, it is of great importance to integrate cognitive models for social simulation [2]. With the recent revolution in ambient intelligence and the increasing trend of social media usage for interaction, the need of exploring social networks in social simulation is evident. Towards this, a social simulation should model the "process" influencing the buildup of a social network. Consequently, it should also analyze the "structure" a networks evolves into based on the environment and parameters describing the process. As indicated by Alam and Geller in [3], structure of a social network emerges based on the modalities of the process. One of the most important modalities of a process in social simulation (and social networking within it) is the "connectivity" between the interacting agents. The connectivity of the agents is dependent on communication as well as spatial features.

In this paper, we model an agent based framework on a real physical space. We are simulating the evacuation of the space given a crowd of agents. Agents make routing decisions towards points of attraction, where we assume once these points have been reached the agents are safe. The routing decisions are based on a novel cognitive decision model, which integrates belief, trust, and confidence and is based on agent communications. Communications occur based on the physical proximity of other agents and distant communications, simulating phone conversations. The entire process is encapsulated by the agent perception map, which is the main contribution of this work. Overall, the agent perception map (which is the agent's perception of the density of the world, or physical space) contains the routing information which is updated based on agent communications.

The contributions of this paper are: (1) a novel cognitive decision model based on trust, belief, and confidence, (2) a realistic simulation framework for crowd evacuation in an emergency scenario, (3) the encapsulation of a cognitive decision model for agent routining based on the forumulation of an agent perception map.

Based on our simulation results, we investigate the validity of our model. Some examples of our findings are that (1) the full communication model results in a higher number of pair-wise agent trusts given higher degrees of trust, (2) agents which communicate locally only are able have higher accuracy in their density perception of the world, though agents with a full communication mechanism are able to perceive more density information about the world (have more perception map information) though with slightly less accuracy, and (3) the node degree distribution of the evolved trust network exhibits the same overall shape as a real mobile phone communication network.

2 Related Work

From a networking science perspective, a number of related studies follow Kleinbergs generative model [4] that explored the emergence of spatially embedded networks and their searchability. In particular, Liben-Nowell et al. [5] investigate the functional dependence of the probability of tie existence on the distance between LiveJournal users. The effect of a distance on the cellular communication patterns was explored by Lambiotte et al. [6] at a customer level and by Kings et al. [7] at an inter-city level. Adamic and Adar [8] explore the geographic properties of e-mail exchange networks within a company, while Mok and Wellman [9] focus on how the frequency of offline face-to-face interactions decays with distance. However, these studies did not directly address the specifics of the information benefits, geography, details of cognitive processes or the evolution of trust relationships between the peers typically focusing on the network structure and the distance as the fundamental underlying mechanisms of the suggested generative models.

There are many related works in the agent-based modeling community. In many existing models (e.g., [10]) crowd dynamics are considered from a lattice gas perspective by representing the systems actors by particles interacting through forces and fields. Although such models are highly scalable, they ignore (complex) internal dynamics underlying the decision making of actors, and, thus, cannot be used in cases for which rich cognitive and affective representations are required (e.g., reasoning, human decision making).

In addition to the importance of integrating the cognitive models into social simulation in general [2], the importance of human behavioral modeling (cognitive and social) specific to the emergency situation has already been noted [11]. However, in many of these efforts, the cognitive decision making rules are either very simple [12], or investigated only on an operational level [13]. The strength of our model is mapping cognition based reasoning on the decision making related to an evacuation situation from a city. We present explicit relationships (based on well-established neurological and psychological theories) between intentions and emotions in decision making.

A few studies [14, 15] investigate the effects of information spread and emotions in crowds. In these studies, no ambient devices for communication over distance are used. Furthermore, in contrast to the model proposed in this paper, these studies do not consider trust relations and evolution of social networks.

In [16] an agent-based decision-making model in the context of crowd evacuation is proposed, which integrates existing neurological and cognitive theories of affective decision making. In contrast to our model, this model does not use crowd density as a decision criterion, and does not consider the evolution of the social networks. Furthermore, simulation in this study was performed on a smaller scale.

3 Agent Based Model

Our agent based model is simulated using Repast for High Performance Computing (Repast HPC) [17] for high performance distributed computing. It consists of multiple models defining space, mobility, perception, communication, and decision making, all formalized in the following sections.

3.1 Physical Space

Cells The physical space in which agent movement takes place is taken from a neighbourhood in a real city in Linz, Austria. A raster image of the map is incorporated into the model by first reducing it to an area of 500 cells, where each *cell* is a unit of space equivalent to 1.25×1.25 m^2 in reality. The space referred to as a cell is later used for modeling individual agent mobility and for assuring two agents do not 'step on one another' or overlap in space.

Sectors The map is segmented into 25 equally sized *sectors* for processing, where each sector is simulated by a single processor (25 processors in total). The area simulated and the division into sectors can be seen in Figure 1.

Map Generation For agent mobility on the physical space, the map has to be converted to a binary grid. In order to achieve this, streets are selected as walkable areas (agents can move here), and all other areas are considered to be non-walkable (agents cannot move here). A smoothing algorithm was run over the space, first horizontally, then vertically, to counter inconsistencies in raster. The smoothing function is a low-pass filter, with filter coefficients equal to the reciprocal of the span.

Points of Attraction For the emergency scenario simulation, we consider "points of attraction" (PoA), where an agent is considered to be "safe" once having reached these points. These PoA's are used in order to evaluate the decision making and mobility modeling. The PoA's can be seen in Figure 1 (b), illustrated by the red boxes in the corners of the space modeled. In this paper, the coordinates of the PoAs are provided manually, but in future work, our approach could easily be extended to handle random PoA generation.

3.2 Mobility

Our agent based model has the capability of modeling different transportation modes though this would result in an extra dimension of complexity in the results, so we chose to address one mode of transport for this work. Every agent requires individual basic routing information in order to move independently, assuming that all agents are pedestrian. In order to achieve this, we use the cell floor field method [18] to transfer information to the agent occupying a space at a given instant in time. This is the main reason for defining a cell (in Section 3.1). Each cell contains three variables, which are used for agent movement decision making. These are as follows.

1. **Direction**: The directions of each of the PoAs from the current cell. We refer to this feature as the direction of motion (DOM). Each DOM ranges from 0 to 355.99, calculated as the relative angle between the current cell and the cell containing the PoAs.
2. **Distance**: The physical distance to each of the sectors containing PoAs from the current sector, referred to as the hop count (HOPC). The HOPC is computed as the number of cells between the current cell and the cell of the PoAs.

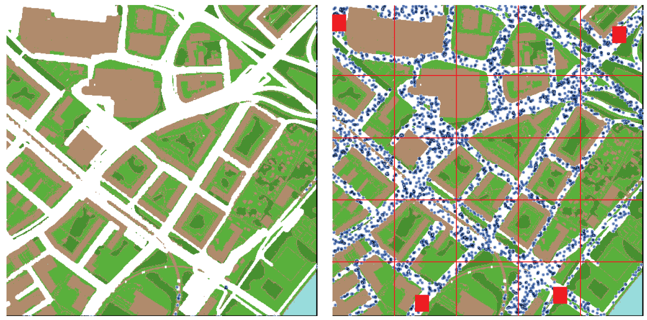

Fig. 1. View of the physical space (also referred to as the world) divided into 25 sectors. The sectors are necessary for efficient processing. Each sector is processed by an individual processor, and the agent decision making and perception of the world (described in the next section) is based on these 25 sectors. All white patches represent streets and are walkable by agents. All other are non-walkables by agents. In (b), a view with 5000 agents distributed uniformly over the space is visualized, with the points of attraction shown near the corners with red boxes.

3. **Route**: The route is the sequence of sectors that need to be traversed by agents in order to reach each of the PoAs.

An agent makes a routing decision based on a PoA selection, formalized next.

Routing Decision If we define a point of attraction, poA, as a series of sectors forming a route (R), we can formalize this as $R = \{ID_{j_1}, ID_{j_2}, ...ID_{j_N}\}$ where ID_{j_i} is the identifier for sector j_i. The subscript of j denotes the index of the process in the route j. We assume N processes form a given route. We compute the average density for each route as

$$\rho(poA_j) = \sum_{e=1}^{N} \rho(ID_{j_e})/N. \tag{1}$$

The average density is then also weighed in conjunction with distance (d) as:

$$\omega(poA_j) = \rho(poA_j) * d(poA_j) \tag{2}$$

The point of attraction selected, poA^*, is chosen to be the one with the minimum weight over the route. Formally,

$$poA^* = poA_j with min(\omega(poA_j)). \tag{3}$$

Speed We assume an agents' speed is affected by the density in its current vicinity. Therefore, an agent's speed is density based where the agent is assumed to know the density of it's current region (or sector). The formulation for speed is based on the free flow speed and is given by the following equations:

$$speed\_on\_density = v_o * (1 - N_{agents}/N_{walkables}) \tag{4}$$

$$speed = max\{v_{min}, speed\_on\_density\} \tag{5}$$

where $v_o = 1.36$, $N_{agents}/N_{walkables}$ is the density of a sector and $v_{min} = 0.0136$. Note that speed is not constant and is defined by *speed_on_density*.

3.3 Perception

Each agent maintains a perception of the surrounding world and updates it by collecting information through his "sensors" (i.e. personal observation) and receiving information via communication from his peers. The perception may be correct or not. The peers may transfer information by physical proximity interactions, or based on distant communication means (for example phone calls) with trusted peers (or friends).

Given this overview, we define a perception map for each agent, where each agent has a perception of the density in each of the sectors in the world, where the sectors are the 25 shown in Figure 1. Therefore each agent has a perception map containing 25 density values, which are updated continuously over time. In the case of an emergency scenario, the critical feature is the density so that an agent can reach an exit as quickly as possible. Additionally, the information source, time of reception and reliability assessment is stored by each agent. These maps are updated through (1) personal observation (described next) and (2) communication with other agents (described in Section 3.4).

Personal Observation The personal perception of an agent corresponds to its natural ability to observe its surroundings. Within a perceptible capability (e.g. visual and auditory range), an agent is considered to estimate the density around herself accurately. This personal observation acts as the *default* density perception of an agent of its current region, unless "outside" information is received, either through implicit dispersion due to sharing based on physical proximity communication, or explicit influence based on distant communication, in which case the decision model (Section 3.5) is used to update the agent perception map.

3.4 Communication

Physical Proximity Communication Within an interaction range of radius R, all agents can interact with each other and share information about their own perception. The information exchange occurs, however, based on the decision model in Section 3.5 assuming a radius of range, $R = 25$ cells.

Distant Communication Distant communication corresponds to the interaction between agents without spatial consideration, such as phone calls and messaging. For the simulations, we assume an agent attempts to contact another towards which she has maximum trust. Once the communication takes place, the perception maps *of both agents* would be updated based on the decision model (Section 3.5). It is possible the communication does not take place, if the receiving agent has already reached a PoA

3.5 Decision Model

Very generally, an information source influences the confidence of an information receiver about the density in a region in proportion to the receivers trust to the source: the more the receiver trusts the source, the more it adopts the sources opinion on the density [19]. In emergency situations, people usually have little time and limited access to information to elaborate well possible decision options. Furthermore, available information is often contradictory, partial and outdated. Under these circumstances people often use cognitive shortcuts, such as based on trust. Given this reasoning, we formulate a decision model for our simulations.

The decision making of an agent consists of evaluating the time required for reaching each known exit. The agents estimation of the total time for each decision option (i.e., a path to an exit) depends on the agents estimation of its average speed for each sector on the path to the exit:

$$total\_time_{ag}(path) = \sum_{s \in path} \frac{l_{ag,s}(t)}{v_{ag,s}(t)} \tag{6}$$

The agents estimation of the length of the section $l_{ag,s}(t)$ of the path confined within sector s and of the average speed in the sector $v_{ag,s}(t)$ are updated based on the agents own observations and information about the crowd density in the sector received from other agents.

Information about the densities of regions are updated by decision making model. The higher the confidence value of the obtained information and the higher the trust of the agent to the agent-informer, the higher would be the effect of the obtained information on the agents beliefs:

$$B^*_{\rho_r,j} = \frac{C_{\rho_r,i} T_{j,i} B_{\rho_r,i} + C_{\rho_r,j} B_{\rho_r,j}}{C_{\rho_r,i} T_{j,i} + C_{\rho_r,j}} \tag{7}$$

where $T_{j,i}$ is j's trust towards i, and $*$ represents the value at the next iteration. Furthermore, $T_{j,i}$ is updated as:

$$T_{j,i}* = T_{j,i} + \alpha(C_{\rho_r,j} \frac{1}{1 + e^{-\gamma |B_{\rho_r,j} - B_{\rho_r,i}| + \beta}} - T_{j,i}) \tag{8}$$

where B is the belief, T is the trust, C is the confidence, and α, β, and γ are constants. We assume $C_{\rho_r,i}$ is the confidence agent i has about the about the density in region ρ_r. We assume an agent i communicates this density information to another agent j.

Agent js confidence is then updated as follows:

$$C^*_{\rho_r,j} = \frac{C_{\rho_r,i} T^*_{j,i} + C_{\rho_r,j} T^*_{j,j}}{T^*_{j,j} + T^*_{j,i}} \tag{9}$$

We assume every agent fully trusts themselves, therefore $T^*_{j,j} = 1$.

For simulation results, we assume $\alpha = 0.8$, $\beta = 5$ and $\gamma = 10$. Note, α is the rate of change of trust - a personality characteristic indicating the agents ability or willingness to change its state. β and γ are the steepness and threshold parameters of the logistic function, respectively. The values $\beta = 5$ and $\gamma = 10$ were chosen experimentally to reflect the following dynamics of trust:

- the agents gain high values of trust (> 0.7) slowly;
- a low level of trust (< 0.3) grows slowly with every positive experience;
- the average trust values ([0.3, 0.7]) vary rapidly.

Motivation for Trust Agents associate trust with every relationship they have. Trust is an attitude of an agent towards an information source that determines the extent to which information received by the agent from the source influences agents belief(s). It takes values in the interval [0, 1]. The higher the trust to an agent, the higher the extent to which information provided by that agent is used in the decision making ([19]). The trust to a source builds up over time based on the agent's experience with the source. In particular, when the agent has a positive (negative) experience with the source, the agent's trust to the source increases (decreases). An information experience with a source is evaluated by comparing the information provided by the source with the agent's beliefs about the content of the information provided. The experience is evaluated as positive (negative), when the information provided by the source is confirmed by (disagree with) the agent's beliefs. This assumption is supported by many experimental evidences, which demonstrated that trust correlates positively with similarity of agents (e.g., similarity of interests) [20, 21].

4 Experiments and Results

4.1 Simulation Scenario

For simulation results, we generate 5000 agents randomly, spread evenly over the walkable areas on the map (world). Therefore, each sector gets a fraction of agents equal to its walkable count over the total walkable area count. Our results are evaluated based on two scenarios.

1. **proximity comm**: The first evaluation of our models considers a scenario where communication only occurs based on physical proximity interactions. In this scenario there are no distant communications (defined in Section 3.4).
2. **full comm**: The second agent based model simulation considers a full communication model, where agent interactions occur both based on physical proximity as well as distant communications.

Of the many features simulated, we found the most critical to be the trust formations, the agent perception maps, as well as the distribution over exits, which is the focus of the results presented.

4.2 Trust Development

In order to evaluate the development of trust across the agents, we consider a network of trust. The nodes of the network are agents and the directed edges symbolize trust, where the weight of an edge is the amount of trust an agent has towards another. In order to understand the overall amount of trust in the

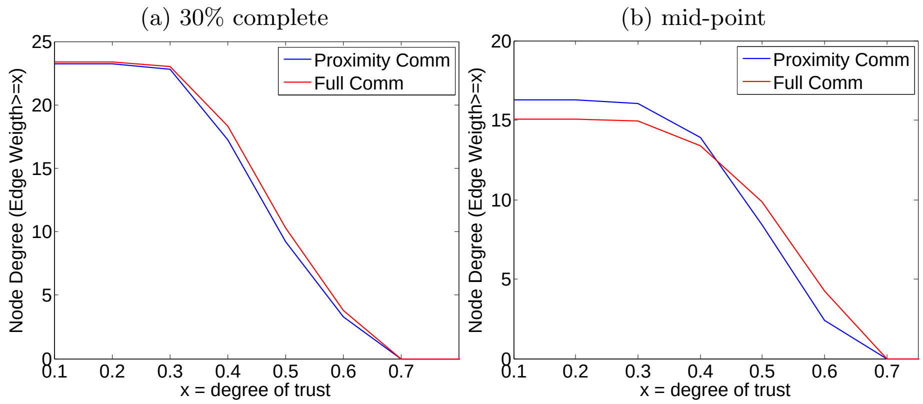

Fig. 2. The average agent node degree in the trust network plot as a function of degree (or amount) of trust. The network consists of agents as nodes and edges representing the degree of trust. In (a) the node degree is plot at the 15th iteration of the simulation (over a total of 50 simulations). In (b) the node degree is plot at the mid-point. In both cases, we can see there is a higher node degree for higher degrees of trust (indicating there is more trust in a full communication network). However, there is a higher node degree for lower degrees of trust given proximity only communication.

network, we consider the overall average node degree as a function of the degree of trust. More specifically, we consider the node degree for which the edge weight is greater or equal to x, as a function of x, where x is the degree of trust. These results are shown in Figure 2, where (a) is approximately the $1/3$ point in time of the simulation and (b) is the mid-point of the simulation. We consider these points in time since these are the critical points at which agent interactions have taken place and the decision for PoA selection is vital at these instances. After the mid-point many of the agents reach their chosen PoA and therefore the simulation is stabile and the trust dynamics are no longer visible. Overall, the results in Figure 2 indicate that a full communication mechanism results in a higher number of pair-wise agent trusts given higher degrees of trust.

In Figure 3 we further make a comparison of (a) the overall distribution of the network of trust node degree from our agent based framework to (b) that of a real-life mobile phone data collection. The details of the mobile phone data collection and network data analysis can be found in [22]. In Figure 3 (b) we consider the overall static network of phone communications of the participants in the dataset and plot the average node degree as a function of the number of calling events (edge weight). Both plots in (a) and (b) are presented on a log-log scale. Very generally we observe their shapes to be similar, serving as a validity check for our trust model. We can conclude the network of trust developed by our agent based model generally follows a similar trend to a real phone communication network, where we assume phone communications occur between trusting individuals, with information exchange as is the case for the trust network.

(a) mid-point (b) real data

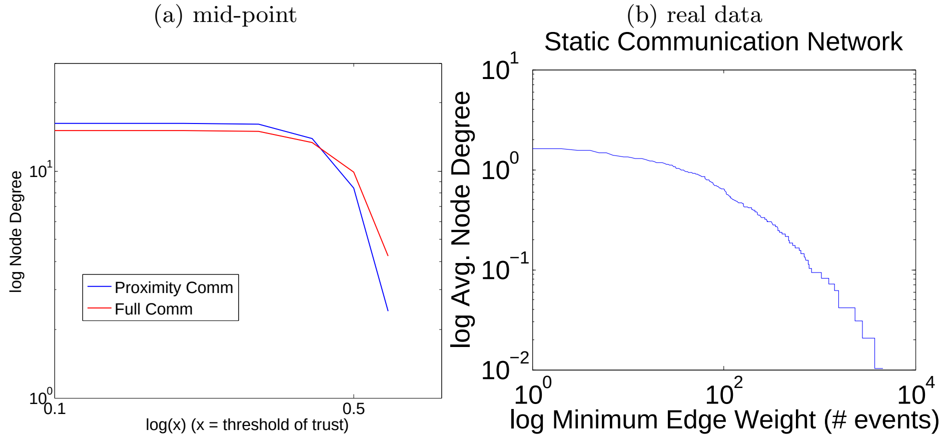

Fig. 3. Comparison of the average node degree as a function of edge weight for (a) the agent based model trust network at the mid-point of the simulation (b) the node degree of a real communication network taken from a large scale mobile phone data collection. This result serves as a general validity check to determine whether the network shape corresponds to that of a similar real-network.

4.3 Perception Maps

In order to evaluate the agent perception map data, we evaluate the *degree* to which each agent's perception of world is similar to the actual world information, which is the density of a sector. For this evaluation, we accumulate over all of the agents, the difference between the actual density and the perceived density ($|\rho_{actual} - \rho_{perceived}|$) for which the difference is greather than a threshold, Th. The results presented in Table 1 are computed over the total number of agents, iterations and sectors, resulting in the evaluation of the overall number of perception maps in the simulation.

Overall, we find that agents which communicate locally only are able have higher accuracy in their density perception of the world, though agents with a full communication mechanism, including both local and distant communications, are able to perceive more density information about the world (have more perception map information) though with slightly less accuracy.

4.4 Exiting Behavior

We plot the number of agents per point of attraction over time in Figure 4 to see how agents distribute themselves differenly in both simulation strategies. We observe that in the full communication simulation scenario, before the mid-point there is a more even distribution of agents to the PoAs (labeled as exits in the figure). This difference is subtle and can ben seen by the difference in the green curve between the figures at the mid-point.

Th	(a) Proximity Communication $\lvert\rho_{actual} - \rho_{perceived}\rvert$	(b) Full Communication $\lvert\rho_{actual} - \rho_{perceived}\rvert$	(b)-(a) $difference$
0.005	3764170	3742735	-21435
0.01	4219515	4206839	-12676
0.02	4903318	4907265	3947
0.03	5128701	5133970	5269
0.035	5228494	5239598	11104

Table 1. The number of perception maps with $|\rho_{actual} - \rho_{perceived}| < Th$, where the difference between the perceived density by an agent and the actual density is evaluated over different thresholds. The number of perception maps are computed over all the agents, sectors, and time steps. These results indicate that the full communication model results in overall more informed perception maps (as seen by $Th = 0.035$). However, when considering the least amount of error in the perceived density ($Th = 0.005$), the proximity only communication is more effective.

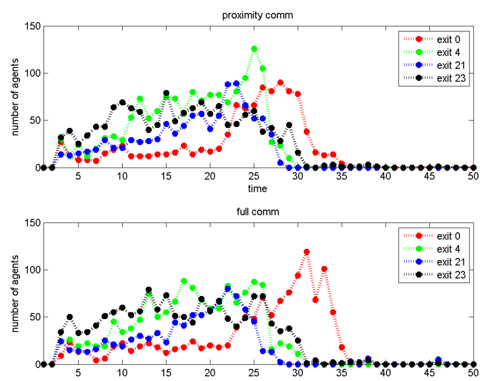

Fig. 4. The number of agents having reached a PoA (labeled as exit x) over time. In the full communication scenario, before the mid-point, the four points of attraction are more evenly reached. This can be seen by the spreading of agents from the PoA in green (exit 4) to other PoAs.

5 Conclusion

We present an agent based simulation framework to model the dynamics of agent perception and explore the effect of communication on crowd dynamics in the context of evacuation. We present a new model defining a belief, confidence and trust mechanism which forms the basis for agent movement decision making based on the agent density perception map. We have found a full communication model to be advantageous to a local communication model since agents can have a larger overall number of agent perceptions about the world, and can result in a larger number of highly trusted pairwise relationships.

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