Modeling and Visualizing Individual and Global Trends of a Multi-agent System

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Abstract: This paper proposes a new model for real-time visualization of the social dynamics as a resultant of individual changes due to their mutual interactions. The model allows the dynamical visualization of both, the individual characteristics changes as well as the resultant system trends as a whole. As an application, we investigated the role of individual degrees of influence and the number of agents in the global choice of a population between two antagonistic options.

1 INTRODUCTION

Recently mathematical models have gained ground in the simulation of biological and sociological behavioral phenomena. In some fields of science these models have helped to understand the operation of other complex systems, such as the transmission of disease or the tendency of an economic system.

One of the subject of sociological research is social behavior, or collective action. The collective behavior modeling is the result of actions, decisions, or thinking of individual social actors (agents) that lead to diffusion of innovations, coordination of conventions, emergent norms, and cultural convergence. At the emergent structure of these kind of models, agents change location or behavior in response to social influences . Rather than producing homogeneity these decisions aggregate to produce global patterns of cultural differentiation, stratification, and homophilic clustering in local networks[1] (Macy and Willer, 2002) One limitation in most social influence models is the assumption that influence is only positive. However, social relations can also have negative valence, such that the state of an agent tends toward maximal distinctiveness rather than similarity.

Theory of information and social structure has the basic insight that the amount of widely shared information in a system is negatively related to the level of social differentiation in that system (Mark, 1998). In other words, high levels of shared information and high levels of social differentiation do not occur in the same societies at the same times. Social influence occurs when an individual's thoughts, feelings or actions are affected by other people. Social influence takes many forms and can be seen in conformity, socialization, peer pressure, obedience, leadership, persuasion, sales, and marketing.

Morton Deutsch and Harold Gerard (Deutsch and Gerard, 1955) described two psychological needs that lead humans to conform to the expectations of others. These include our need to be right (informational social influence), and our need to be liked (normative social influence). The informational social influence is prominent in ambiguous social situations where people are unable to determine the appropriate mode of behavior, and is driven by the assumption that surrounding people possess more knowledge about the situation. Normative social influence is "the influence of other people that leads us to conform in order to be liked and accepted by them." In many cases, normative social influence serves to promote social cohesion. When a majority of group members conform to social norms, the group generally becomes more stable.

A multi-agent system (MAS) has multiple interacting intelligent agents. They present self-organization and related complex behaviors based on agents simple parameters. They have been applied in the real world to graphical applications such as computer games and movies. Other applications include transportation, economy, networking and mo-

[1]Homophily: the tendency to interact more frequently with similar agents

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bile technologies. Usually we can visualize over simulation time only the result or emergence of these systems at the macroscopic way. The real-time visualization of agents internal parameters is necessary as we need to change some parameters at few agents to analyze the system perturbation that this carries.

This work proposes a new model that allows the analysis of a multi-agent system in order to investigate which parameter is decisive to one society decides to choose between two different concurrent concepts. A real time visualization of the individual internal parameters allows researcher to identify the individual and global tendencies of the role system.

The outline of this paper is as follows: after presenting the related work in the next section, we will present our social model with some explanation about the agents parameters and their interactions. After that, a section explaining the two kinds of MAS visualization. Some results of the simulation is explained at Section and a conclusion will be given in the last section of this paper.

2 RELATED WORK

Computer Graphics area has been extensively working with complexity of MASs systems. Works like the modeling of flock of birds(Reynolds, 1987)and (Resnick, 1994) was the forerunners of the recent works like (Vigueras et al., 2010), (Narain et al., 2009) . For modeling the flock, instead to use a bottom up approach based on agent-level interaction, Reynolds was able to produce highly realistic flight formations using very simple rules that imposed relatively small computational demands. He did not model the flock, nor did he model isolated birds. He modeled their interaction, at the relational level. Agent-based models of human social interaction are based on this same theory-building strategy. Like flocks of birds, recently simulations of human crowds processes are highly complex, non- linear, path dependent, and self-organizing (Ondrej et al., 2010); (Guy et al., 2010); (Prazak et al., 2009). We may be able to understand these dynamics much better not by trying to model them at the global level but instead as emergent properties of local interaction among adaptive agents who influence one another in response to the influence they receive . Simulation of societies as complex non-linear systems, which are difficult to study with classical mathematical equation-based models has been used to simulate agent interaction with applications ranging from economy, biology and sociology areas (Helbing, 2009; Newman, 2003). Usually, groups modelling through interactions is aplicated to crowd behavior simulation, Qiu et al. (Qiu and Hu, 2010) presenedt in their work a unied and well-dened framework for modeling the structure aspect of different groups in pedestriancrowds. Both intra-group structure and inter-group relationships are considered and their effects on the crowd behavior are modeled. As result it was presented that different group sizes, intra- group structures and inter-group relationships can have signicant impacts on crowd behaviors Villamil et al. (Villamil et al., 2005) presented a work to simulate social groups formation and interaction based on simple rules and agents progression. The competitive behaviors of those groups in the context of behavioral animation was also simulated. As the work presented here, psychological and physiological characteristics of group and its effect on traffic characteristics (speed, inter-distance, array of group) was not analyzed. As Villamil et al. work, this article also present a simulation with sociological connotation. But, in this case, we are not interested in groups displacement in a scene. Influence area, for example, do not has the same meaning in terms of local distance inside the scene where one agent can influence other. It can be considered an analogy to the level of influence of person on a big population through television. In this case, the simulation presented here differs from crowd simulation because it does not consider personal distance as a preponderant factor to interaction.

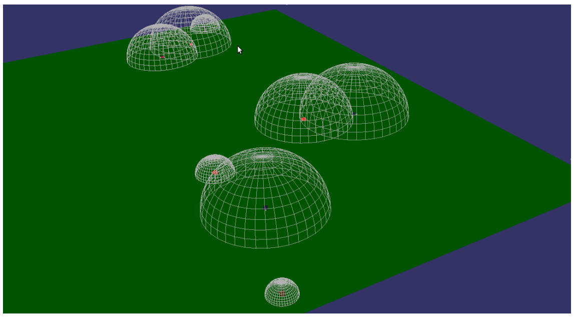

Figure 1: Simulation scene. The agents move around and interact.

3 INDIVIDUAL COMPETITIVE MODEL

Simulation is based on a system where agents graphically represented by a cube get around a scenario randomly. At the beginning agents are positioned randomly and move continuously changing their routs during the simulation (Figure1).

3.1 Agents Parameters

Each agent has social individual characteristics described as follows:

- Influence (I). The capacity or power of persons or things to be a compelling force on producing effects on the actions, behavior, opinions of the others was modeled in terms of magnitude. Influence is based on popularity (either directly or indirectly) or success or some combination of the two and is not only related to a direct interaction. It was represented by a bounding hemisphere around the cube. The circle area that forms the base of the hemisphere is directly proportional to the influence of the agent. So, the most influent agent of simulation has its hemisphere with a diameter equal to the scenario width. Influence parameter has threshold between 0 and 1.
- Communicability (v). Agents communicability represents the speed of exchange of thoughts, messages, or information, using some way such as speech, signals, writing, or behavior. In our model, the communicability of each agent is represented by its velocity, with which it run about the simulation space. The number of interactions involving a specific agent is proportional to its velocity. Communicability parameter also has a threshold between 0 and 1.
- Status (S). Accounts for the position, or opinion, of each agent with respect to two concurrent or antagonistic concepts (products, teams, ideas, etc.) In our model, $1 \leq S^i \leq -1$, for each agent i, where larger proximity to the extremes indicates greater conviction for one or other concurrent concepts. A threshold $0 < S_t < 1$ of this parameter divides the set of agents in three groups:

$$G_+ = \{A^i;\ S_t \leq S^i \leq 1\} \tag{1}$$

$$G_0 = \{A^i;\ -S_t < S^i < S_t\} \tag{2}$$

$$G_- = \{A^i;\ -1 \leq S^i \leq -S_t\} \tag{3}$$

In this paper, $S_t = 0.5$, in such a way that G_0 is empty.

3.2 Agents Interaction

Agents influence each other in response to the influence they receive. One agent can influence other when the other is inside its bounding hemisphere. Influence level (I) can be modified at each interaction as shown in Equations (4) for i-agent and (5) for j-agent. Modeling interaction between two agents is not a simple task. Moreover, there are an enormous variety of ways those interactions can take place. Here, we adopt the simplest possible premisses to attain mathematical expressions for those relations. We expected that, even being simple, such a model can express the most basic characteristics of social interactions. In what follows, we present the formulation of our model with respect to the change of our basic variables (I, v and S) when two agent A^i and A^j interact with each other.

For influence, we suppose that the change of influence of agent A^i is proportional to the influence of A^j, being positive when both agents have the same directions of opinion (S^i and S^j with the same signs), and negative when they have opposite directions of opinion (S^i and S^j with opposite signs). The adopted proportionality constant is $1/N$. The same is supposed for agent A^j. Then, the influence degree I^i_{n+1} in time $n+1$ after a relation with agent A^j is given by

$$I^i_{n+1} = I^i_n + \frac{I^i_n}{N}\frac{S^iS^j}{|S^iS^j|} \tag{4}$$

$$I^j_{n+1} = I^j_n + \frac{I^j_n}{N}\frac{S^iS^j}{|S^iS^j|} \tag{5}$$

Adopting a quite similar approach for the other variables S and v, we have

$$S^i_{n+1} = S^i_n + \frac{S^j_n I^j}{N} \tag{6}$$

$$S^j_{n+1} = S^j_n + \frac{S^i_n I^i}{N} \tag{7}$$

$$v^i_{n+1} = v^i_n + \frac{v^i_n}{N} I^j \frac{S^iS^j}{|S^iS^j|} \tag{8}$$

$$v^j_{n+1} = v^j_n + \frac{v^j_n}{N} I^i \frac{S^iS^j}{|S^iS^j|} \tag{9}$$

where, after each relation, the direction θ for the velocity actualization is taken randomly in the range $0 \leq \theta < 2\pi$. According to above equations, an interaction between two agents belonging to antagonistic groups is always taken as a destructive interference for both agents, since it causes a reduction of all three variables S, v and I. On the other hand, an interaction with agents of the same group increases these variables, and are taken always as a constructive interaction. Equations represent the dichotomic characteristic of the model, where agents Status tend to 1 or -1 depending on the influences they receive over simulation.

The above equations rule the dynamics of the set of agents, that are put to run with their respective velocities, into a simulation ambient. When a agent A^i gets inside a circle of influence of agent A^j (with radius I^j) the variables of A^i are actualized according to the above equations. As time passes by, transitions of agents between groups G_+ and G_- take place. The objective of this paper is to study the asymptotic behavior of this hypothetical society, to see its final equilibrium state. The possible results includes the victory of G_- (with the extinction of G_+), the victory of G_+ (with the extinction of G_-) , and the coexistence of both G_+ and G_-.

For a better understanding of the system trends we developed two kinds of real-time visualization: one concerning the total agents displacement (Window 1), their interactions, and their influence area and its variation in a scenario (Figure1).

The other one is related to individual internal parameters (Window 2) (Figure2). Usually, simulations involving MASs are analyzing by changing initial parameters and observing the trends of the system as a role. In this case, changes of individual parameters during simulation are not possible to identified in real time.

To analyze agents dynamical internal parameters, each agent is represented by a sphere positioned at RGB color space. The individual parameters, Influence (I), Communicability (v), Status (S), is represented by chromaticities of the red, green, and blue additive primaries, and can produce at real-time any chromaticity that is the triangle defined by those primary colors. Normalized values of these parameters were changed to fit on the corespondent values of RGB. Influence was defined on the red threshold chromaticitie, Communicability was defined on the green and Status was defined on blue. Spheres change their color and position during simulation as agents parameters change. Figure 2 shows a simulation timestep where all agents parameters are uniformly distributed on the RGB color space.

Moreover, system user can select some agent by a mouse clic at the visualization Window 1 and observe its position and internal parameters trends at visualization Window 2. This is the first step to predict the future behavior of the system based on present. As we know, simulation models like this, tend to grow large in size and complexity, and may be difficult to understand which is the cause of system result. For example, only one agent with large influence can modified throw interactions all other agents parameters very quickly. And, in this way, we can ask us: what would happen with the role system if we decrease only this agent parameter during the simulation? And, on the other hand, if we choose a group of agents and increase Influence parameter, or their Communicability? Would it be sufficient to reverse the big influence of this agent?

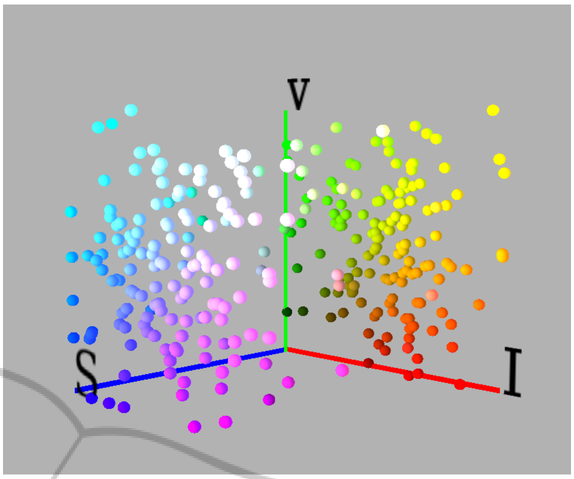

Figure 2: Visualization window 2. At this point of simulation there is much more agents with parameter $S < 0$. Communicability (v) seems to be uniformly distributed.

4 RESULTS AND DISCUSSION

In this section, we present computational experiments to get conclusions under two mains aspects: asymptotic behavior and the role of extremism over the asymptotic results.

4.1 The Role of Influence I

Although simulation designs were used experimental rather than post- hoc statistical controls to identify underlying causal processes, statistical of the results were also done to system analysis. ABMs require replications that demonstrate the stability of the results. Replications include variation in parameters that are theoretically arbitrary or of secondary interest. Agents S parameter means its position with respect to two concurrent antagonistic concepts that can be a product, teams, ideas or political parties. S limits are -1 and . The closer these limits, the more convinced about the concept becomes the agent. As result it was analyzed the impact of Influence parameter to the agents choices. How the agents choices change based on their interactions with others more influents?

The first result is related to system convergence. If the number of influent agents is big, faster all agents choose a side convinced. To investigate this, v and I parameters were lock as they initiate. It was performed 10 simulations for different I parameter averages. Initial Is were distributed with a 0.2 average and with a standard deviation of 0.1 meaning not influent agents. Also it was done more two set of simulations with Is distributed with a 0.5 average (medium influ-

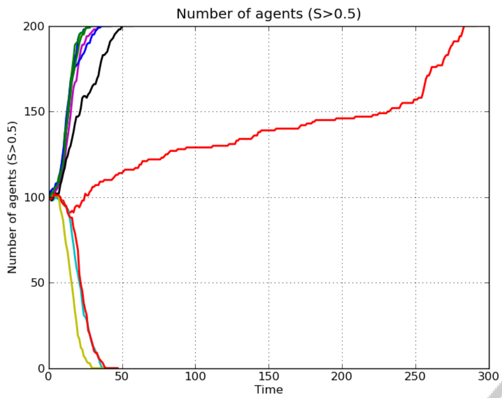

Figure 3: Agents parameter *I* with an average of 0.7.

ent agents) and *I*s distributed with a 0.7 average (influent agents). The standard deviation was maintained at 0.1 for all simulations. We can observe that simulations that has agents more influents like the ones at Figure 3 converge much quickly (9 simulation of 10 converges before frame 50) . And, on the other side, simulations with not influents agents converges slowly and agents change their Ss much times.

4.2 The Role of Extremism

Extremism denotes how close, in average, a group is to on of the extrems $= 1$ or -1. To this investigation, more than 400 simulations where made, with group G_- configured as in the previous Section, only varying the number of agents N as well as the extremism S of one group in relation to the other. In this section we will denote $N = N_+/N_-$ and $S = S_+/S_-$. We considered 20 values for each of these parameters and made the 400 corresponding simulations. With that we obtain a 20x20 grid where the maximum and minimum value for two axis are 2 and 0 respectively. Each point in the grid is a relation beween the parameters of G_+ and G_- (G_+/G_-). For example, the central point(1, 1) of the grid is the equal distribution of parameters, where the number of agents is 100 and the extremism is 0.5 for both groups. To score the results, we measure $T(N,S) = V/t$, where t is the convergence time of the corresponding simulations. To differ between the victory of G_+ from the victory of G_-, we make $V = 1$ and $V = -1$, respectively.

As the result we have a surface that displays the behavior of the system for different values of number of agents an extremism considering two opposite groups. From that surface we can see that group G_+ wins for smaller values of S and greater values of N, while the opposite occurs for the cases of victories of G_-. Moreover, some region of draws occurs between. The overall result is easier to see from the curve levels, showed in (Figure 4). There we can see the curve $T(N,S=0)$ passing by the point (1, 1) as a confirmation that, when G_+ and G_- have the same values for N and S simultaneously, the convergence time tends to infinite (draw). In the same figure, others curve levels can be seen, for positive and negative values of $T(N,S)$. Another conclusion we can take is about the minimum value that the relations for a equilibrium or a negative convergence (G_+). Its possible to note that the the minimum relation value for a negative convergence is the same for number of agents $N = 1$ and S: 0.6. In other words, adding N and S in the same proportion causes the same effect in convergence time and pole. Other data that must be explained is the quantity of levels in the positive z value side of the surface. That is because in lower relation values G1 is very less competitive than G_- causing a very low time positive conversion, and in the negative z value side, G1 even being superior in values, is competing with a medium group, of medium variables. We consider so far this data irrelevant. We can conclude that the N and S has the same weight in two competing groups scenario. Thats because the minimum relations nedded for G1 to converge is the same.

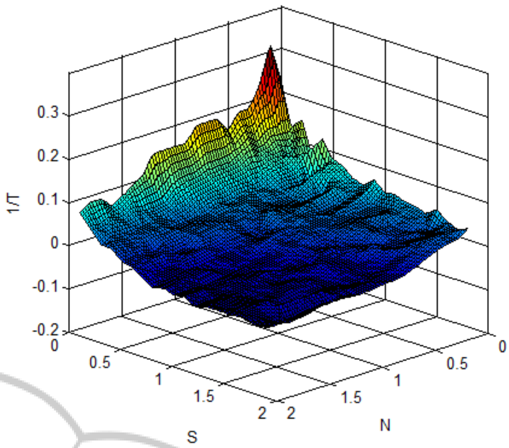

Figure 4: Function T(N,S), as a function of *N* e *S*.

5 CONCLUSIONS

In this paper, we introduced a new model for visualizing dynamics of social evolution in real time. It is applicable to any set of interacting individuals which is modeled as a multi-agent system, as the one proposed here as an example. Moreover, it permits to follow individual evolution of specific agents selected while the simulation is running (by user interaction).

The social model for social evolution of interacting agents proposed here and used as an example of

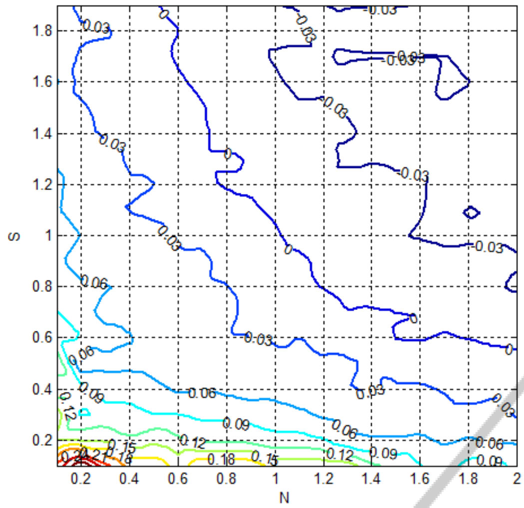

Figure 5: Surface that represents the behavior of the system for diferent parameters of *N* and *S*.

application of the visualization model is based on very simple assumptions. In fact, all the interactions are based on proportionality of the considered types of interacting parameters. This makes some of the results of a social evolution quite predictable in terms of common cense most of humans have in terms of society behavior. The application of the visualization method to such case showed consistent results according to those common cense, which gives validation to the proposed method inside the scope of the considered case.

As a future work, the visualization model shall permit to interfere on the evolution of a MAS in real-time by the possibility of modification of individual parameters to interfere on the system's fate before the asymptotic state is achieved. We intend to improve the user interaction to permit select an agent or a group of agents and change their parameters during simulation and analyze how the system as a whole would react. In this way, we could know what agents or groups of agents are crucial to desired certain convergence of the system. We also are working to improve *S* parameter to consider it as a *n*-dimensional vector to make it possible to include other agents characteristics and choi ces related to its gender, work, hobbies, etc.

REFERENCES

Deutsch, M. and Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology*, 51:629–636.

Guy, S. J., Chhugani, J., Curtis, S., Dubey, P., Lin, M., and Manocha, D. (2010). Pledestrians: a least-effort approach to crowd simulation. In *Proceedings of the 2010 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, SCA '10, pages 119–128, Aire-la-Ville, Switzerland, Switzerland. Eurographics Association.

Helbing, D. (2009). Managing complexity in socio-economic systems. *European Review*, 17:423–438.

Macy, M. W. and Willer, R. (2002). From factors to actors: Computational sociology and agent-based modeling. *Annual Review of Sociology*, 28:143–166.

Mark, N. (1998). Beyond individual differences: Social differentiation from first principles. *American Sociological Review*, 63(3):pp. 309–330.

Narain, R., Golas, A., Curtis, S., and Lin, M. C. (2009). Aggregate dynamics for dense crowd simulation. *ACM Trans. Graph.*, 28:122:1–122:8.

Newman, M. E. J. (2003). The structure and function of complex networks. *SIAM REVIEW*, 45:167–256.

Ondrej, J., Pettre, J., Olivier, A.-H., and Donikian, S. (2010). A synthetic-vision-based steering approach for crowd simulation. *SIGGRAPH '10: ACM SIGGRAPH 2010 Papers*.

Prazak, M., Kavan, L., McDonnell, R., Dobbyn, S., and O'Sullivan, C. (2009). Moving crowds: a linear animation system for crowd simulation. In *Proceedings of the 2009 symposium on Interactive 3D graphics and games*, I3D '09, pages 9:1–9:1, New York, NY, USA. ACM.

Qiu, F. and Hu, X. (2010). Modeling group structures in pedestrian crowd simulation. *Simulation Modelling Practice and Theory*, 18(2):190 – 205.

Resnick, M. (1994). *Turtles, termites, and traffic jams: explorations in massively parallel microworlds*. MIT Press, Cambridge, MA, USA.

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *SIGGRAPH Comput. Graph.*, 21(4):25–34.

Vigueras, G., Lozano, M., Orduña, J. M., and Grimaldo, F. (2010). A comparative study of partitioning methods for crowd simulations. *Appl. Soft Comput.*, 10(1):225–235.

Villamil, M. B., Oliveira, L. P. L., and Musse, S. R. (2005). A model for generating competitive groups based on virtual agents progression. In *International Conference on Computer Animation and Social Agents*, pages 133–138. Hong Kong Polytechnic University.