Hybrid and Evolutionary Agent-Based Social Simulations Using the PAX Framework

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Abstract

*This paper investigates a new hybrid evolutionary agent model for agent-based social simulations (ABSS), which incorporates two decision components: (*i*) sub-symbolic (genetic) and (*ii*) symbolic (cultural). These components are coherently combined to produce a more plausible agent model. Experiments were carried out using the Plausible Agents Matrix (PAX) framework, and modeled a real dengue fever spreading scenario. They aim to analyze the qualitative and quantitative predictive power of the model. Previous work has explored the impact of structuring elements on agents' behaviors and the impacts of communication mechanisms on agents' behaviors using PAX. In this paper we investigated three types of agent models regarding to the combination of decision components: (1) agents only with genetic component; (2) agents only with cultural component; and (3) agents with both genetic and cultural components. Results show the importance of each component in the model and their synergic effects when combined.*

1. Introduction

Agent-based social simulations (ABSS) have been widely used by social scientists to understand real social phenomena. The major motivation to use agent models in social simulations is the possibility of modeling and controlling different granularity levels. Epstein and Axtell are prolific in providing reasons for use of agent-based models instead of the analytical ones [1].

Many platforms and models were proposed to support ABSS, *e.g.*, the Schelling's segregation model [2], the garbage can model [3], the Sugarscape model [1] and the Vidya platform [4][5][6]. Previous works introduced the PAX (Plausible Agents Matrix) framework [7], whose main objective is to facilitate the development of social simulations, considering modeling of spatial structuring elements [8].

In the 70s, the biologist Richard Dawkins had an insight of what he called the theory of memes [9]. If genes are physical replicators responsible by the genetic evolution, *memes* are mental replicators responsible by cultural evolution. Differently of genes, memes can change substantially along the agent lifetime.

In this paper we investigate a new model of agent, which combines two perspectives: (1) genetic – agents have genetic codes that influence their behaviors – and (2) cultural – agents have beliefs systems that also influence them behaviors. We highlight the plausibility of this model and its implication for mimicking society.

Results show interesting emergent phenomena in simulations of a real town in the countryside of Pernambuco state (Northeast of Brazil), relative to different configurations of model, namely, model with only genetic component, with only cultural component and with both genetic and cultural component. We perform a comparative analysis between simulated and real data. Finally, we investigate the influence of culture on genes distribution over population.

2. The PAX Framework

As in previous works, we have built our model and performed all simulations using the PAX (Plausible Agent Matrix) Framework. Its architecture was conceived to be as modular as possible, allowing to the social scientist to model and perform the ABSS including the following elements:

- *Environments:* structures, structural levels and environments cell's labels;
- *Entities (or objects):* the basic elements of simulations, defined by a set of spatial characteristics;

- *Entities' interaction interfaces*: set of actions that entities can invoke from others;
- *Agents*: abstract structures to implement context-specific agents.

2.1. Environments

In PAX, the environments are 2-dimensional matrices defined by different types of elements: structural level, structuring elements, environmental cell's labels. All structures in PAX are entities with spatial coordinates (i.e. placement), dimensions (i.e. width and length), and may also contain other structures in it. The placement of structures in the environment affords and can influence the choice of different agents' strategies, work as means of promotion of global order, as well as may create beneficial contexts that impact on the dynamics of social networks.

2.2. Entities

Entities are anything conceivable to be a part of the environment. They are composed by a 2-dimensional spatial coordinates, meta-location (i.e. the structure where it is located or no structure) and an entity interaction interface. As the basic class of the simulator, it is used by the user (i.e. the social scientist) to create context-specific objects. It allows the implementation of some abstract methods and the provision of an entity interaction interface (if necessary).

2.3. Entities' Interaction Interfaces

An Entities' interaction interface represents a set of rules that guide the way entities interact with each other. For this, an entity interface incorporates a set of possible actions that entities can perform over other entity and its state; restrictions may be top of which restrictions will be placed based on the current state of the entity. Therefore, when the user is designing an object and wants to include restrictions on its behavior during interactions with other entities, he may only need to implement an entity interaction interface.

2.4. Agents

In the framework, agents are entities designed to be intelligent. Nevertheless, the framework does not supply any particular implementation of intelligent components for the agents' behavior. However, PAX provides an abstraction for perception and action, leaving it opens for the developer to include intelligent

processing routines. Therefore, the user, when implementing a specific kind of intelligent agent, is free to build an intelligent module, mapping perceptions to actions according to its needs (regarding behavior).

3. Hybrid Evolutionary Agent Model

This section explains the proposed hybrid evolutionary agent model. The model is evolutionary because the agent learning is based on evolutionary processes and it is hybrid because it combines two different evolutionary approaches.

The Darwin's Theory of Evolution and subsequent advances on Genetics applied to ethology (i.e. study of animal behaviors) show that a substantial part of human structures and behaviors are dictated by our genes In 1976, the ethologist and geneticist Richard Dawkins proposed another ground breaking theory that casts cultural evolution as an evolutionary process whose fundamental units are "mental replicators", as he coined, memes (Theory of Memes [1]).

Memes, differently from genes, are not physical structures – but virtual ones – which only exist due to the mental activity of human and other animals able to replicate symbolic expression of other individuals (frequently) of the same species. In human societies, these symbols, here referred as memes, have some evolutionary properties (or operators, in the evolutionary algorithm perspective), like mutation (i.e. random alteration) and crossover (i.e. combination with other memes). Obviously, the environment (i.e. the human mind and its communication schemes) and its morphology impose different evolutionary dynamics to memetics when compared to genetics.

We assume that two main driving "forces" – not always (but sometimes) divergent – guide the human behavior: genetics and culture. For example, the decision of a human being to marry is influenced by genetic (*e.g.* reproduction, cooperation) at the same time it is influenced by cultural (*e.g.* social reputation) factors. In this example, the same behavior (to marry) could be reinforced by the two factors, which could not be the case at all times.

The majority of traditional ABSS models present low plausibility regarding the mentioned genetic and cultural influence factors on agents' behaviors. Because of that, the proposed model incorporates these factors as decision components, aiming to increase the plausibility of produced social simulations in the behavioral dimension; regarding the quality dimensions of social simulations, see [8]. A BDI-like architecture for the hybrid evolutionary agent model is

illustrated in Figure 1. It shows the combination of the cultural and genetic components. In the illustrated BDI architecture, *beliefs* are the perception, the genetic database (B_G) and the cultural database (B_C); *desires* can be innate (D_i) or learnt (D_l); and *intentions* (or action plans) are produced by the decisor module, combining both genetic and cultural influences.
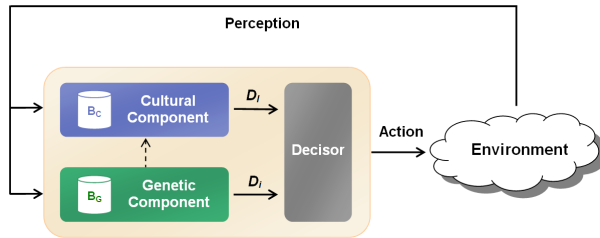

Figure 1. BDI-like architecture for the proposed hybrid evolutionary agent model.

Notice the dashed line from the genetic component to the cultural one. This means that the cultural component is influenced by genetic characteristics. For example, a tendency to communicate more or less with other individuals could be genetically coded, but this could impact on the agent´s culture.

3.1. Cultural component

The cultural component of the model is responsible for the agent cultural learning. This means that agent learning can modify its behavior along life and the acquired knowledge can be disseminated throughout society by available communication media. The cultural component provides both individual and social learning, since beliefs can be disseminated in the society and can be useful for solving problems that require participation of groups of individuals.

Our proposition of cultural component is based on the Theory of Memes, where beliefs (or memes) are represented – in its simplest case – by reinforcement learning structures. Thus, memes survival will depend, mainly, based on their adaptability to the environment in which they are inserted.

In the proposed cultural component, memes can be generated by experience (i.e. interaction with environmental entities) and communication with other agents. Therefore, the cultural component is continually modified throughout the agent lifetime.

Communication among Agents – Communication is the main "operator" of the cultural component for memes dissemination. We can think about very complex communication mechanisms, with beliefs regulating the communication flow (e.g. communication regulated by social reputation of individuals) and highly expressive communication

protocols. However, one of the simplest mechanisms – adopted in the experiments of this work – is the interchange of reinforcement learning values (i.e. weight of connections among states) among agents that are geographically close. In all simulations of this work, communication is also regulated by genetic factors that reinforce the likelihood of genetically close agents to communicate.

3.2. Genetic component

Differently of the cultural component, the genetic one keeps immutable along the agent lifetime, that is, changes happen between generations. It is composed of the genetic memory passed on by ancestors of the agent, perpetuating behaviors of survivors through natural selection. The genetic component has a genotype, or genetic database, which will quantify agent's attributes and will code some of its behavioral tendencies.

Two genotypes of agents can be crossed-over to produce a new genotype for a descendent agent. Several combination strategies can be adopted; in the simplest case, the genetic values can be the average of the parents' genetic values. This is the strategy used in this work. Another approach used is to combine half of the two agents' genotypes. In the case of similar genes of parents, the generated gene is reinforced. An interesting consequence of that is the transformation of recessive genes into dominant ones for some individuals of the offspring. The genetic component provides learning in the population level, which may ideally converge to optimize agents' behaviors that survive by means of natural selection of genes.

4. Case of study

In a previous work, we have used the PAX framework to simulate a fictitious environment to investigate the impact of structuring elements' placement on agents' behaviors [10]. In that environment, we simulated a generic epidemic on some scenarios, aiming to assess yield impact.

Regarding the modeling of environments, the present work innovates in the following aspects: (a) scales-up to representation the level of a real town; (b) incorporates representation aspects of a real disease (i.e. dengue fever); (c) allows many more agents to be considered; and most important, (d) incorporates the hybrid evolutionary agent model commented before.

4.1. Modeling of *Iguaraci* Town

In this work, we have simulated *Iguaraci*, a small Brazilian town located in the Northeastern state of Pernambuco. Real data was collected from the official database of the state government – BDE/PE (at http://www.bde.pe.gov.br) and from demographic data from the Brazilian Institute of Geography and Statistics – IBGE (at http://www.ibge.gov.br/english). *Iguaraci* has an area of approximately 780 km^2, and a population of approximately 12,000 inhabitants, that is a population density of 15 per km^2.

In the simulated environment, we have represented *Iguaraci* as a grid of square cells of cardinality 28×28; each cell corresponds to 1 km^2 of *Iguaraci*. Based on the real geographic aspects of the town, the environment was divided in 4 structures, representing each one of the communities in the city — 2 large communities (22 per km2) and 2 small (5 per km2). As we are simulating dengue dissemination over the population, we placed in the environment health structures, i.e. hospitals and health stations. Iguaraci has 1 hospital and 3 health stations, but these structures are not sufficient to attend all its health services demand. Hence, the population has to use health services of two neighbor towns: *Afogados da Ingazeira* and *Sertânia*. For this reason, two additional hospitals were considered in the model, representing the Hospital of *Afogados da Ingazeira* (19 km away) and the Hospital of *Sertânia* (46 km away). These two towns are connected to Iguaraci by a state road, PE-292. These elements are all illustrated in Figure 2. All data from the abovementioned sources was collected in the beginning of the 2007 year.

4.2. Modeling of Agents

In the environment described above, 12,000 agents were added, each one with an "infection" and a "wellbeing" label. The former represents the health status of the agent (i.e. if the agent is infected or not by the dengue fever), and the latter informs if the agent is "feeling good" or "feeling sick", regardless of its health status. Even if the agent is not infected, its "wellbeing" label may be set to sick. However, if the agent is infected, it always feels sick. The decision to go or not to a health unit is based on the "wellbeing" label, not in the health condition by itself. This is a hedonistic perspective, as most humans naturally subscribe to.
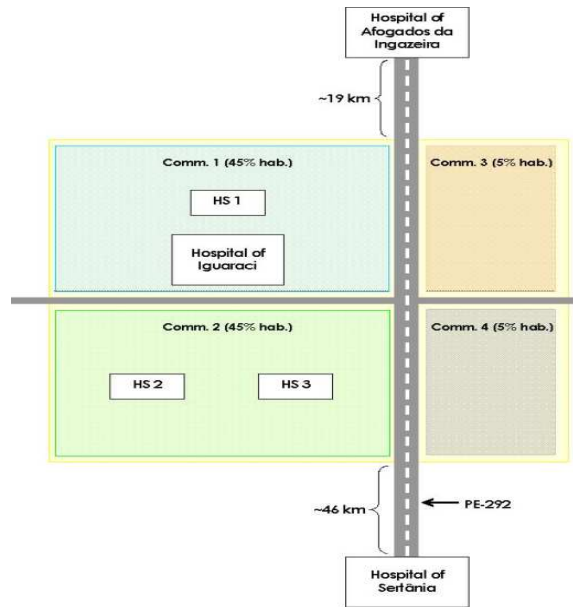

Figure 2. Schematic view of the considered environment (adapted from [10]).

We assumed that each agent in the simulation perform 5 actions in one day, thus the simulated day has 5 iterations. Total simulated time period was 1825 iterations, meaning 365 days in the real world.

The learning module of the agent in this hybrid evolutionary approach is composed by cultural and genetic components. To investigate the influence of each component in the action chosen by the agent, we simulated 3 different scenarios: (i) cultural component; (ii) genetic component; (iii) cultural and genetic components. In the environment, the agent has to move to the different structures according to the action chosen. To perform the action, the agent will face a cost, proportional to the distance from origin to destination. Therefore, this cost has an important role on the cultural learning component, once it will determine the learning reinforcement rate. The genetic component will determine the probability of an agent chose and perform an action according to its genetically coded behavior tendencies.

In the beginning of all simulations, agents do not know the best action to perform for each state. In the scenarios with cultural learning, agents learn through reinforcement learning aiming to adjust their behavior to their particular needs, considering their current state. An agent state is a combination of its current location and feeling. At a certain moment, an agent can be in one of the following locations: Community1; Community 2; Community 3; Community 4; Hospital of Iguaraci; Hospital of *Afogados da Ingazeira*; Hospital of *Sertânia*; Health station1; Health station2;

and Health station3. The possible feelings are "feeling good" and "feeling sick". For each state, an agent has a set of possible actions to chose and performs. The available actions, considering all possible states are: go to community1; go to community2; go to community3; go to community4; go to hospital of *Iguaraci*; go to hospital of *Afogados da Ingazeira*; go to hospital of *Sertânia*; go to health station1; go to health station2; go to health station3; walk inside community; go home; and, do nothing.

Regarding cultural learning, agents can communicate with each other and transmits their knowledge (i.e. values learnt by reinforcement) to other agents. The meme transmission between two agents is the main part of the cultural evolution, since the agent shares knowledge about the best options of actions to be performed in the location where they gather at each time.

Each agent's genetic code has the following genes:

- *Gene 1* – quantify the reinforcement applied to bad and good feelings (values in the interval [100.0, 600.0]);
- *Gene 2* – preference of staying at community, or the tendency to accommodate at the current community (values in the interval [-1.0, 1.0]);
- *Gene 3* – preference of walking inside community (values in the interval [-1.0, 1.0]);
- *Gene 4* – preference of doing nothing (values in the interval [-1.0, 1.0]);
- *Gene 5* – preference of backing to home (values in the interval [-1.0, 1.0]);
- *Gene 6* – probability of talking to others (values in the interval [0.0, 1.0]).

4.3. Modeling Dissemination Dynamics of Dengue Fever

The dengue fever is a vector-borne disease, and its dissemination dynamic applied in the proposed model is based on the mosquito-human-mosquito (mainly *Aedes aegypti*) infection cycle. The agent infection occurs when a healthy agent is bitten by an infected mosquito. The mosquito infection is caused by: (i) if a mosquito bites an infected agent (i.e. horizontal transmission); (ii) if it is descendant from an infected female mosquito (i.e. vertical transmission). Ponds and other water accumulation places are deeply connected with the disease dissemination [11].

Due to the fact of only female Aedes aegypti are hematophagous (i.e. are dissemination vectors), in our model only 50% of mosquitoes are able to "bite" the agents. In this model, the intrinsic and extrinsic virus incubation period was abstracted. However, all those parameters can be easily included later.

In our model, the dissemination cycle was subdivided in: (1) hatching of the eggs – the number of eggs to hatch is proportional to de number of eggs and the rate of water inside the cell; (2) infection dissemination – 50% of the mosquitoes inside the cell can bite the agents. The number of agents bitten, at each iteration, is proportional to the number of agents and the number of mosquitoes inside de cell. If a healthy mosquito bites an infected agent, this mosquito will become infected and from now on will transmit the infection to all its offsprings; (3) mosquitoes spreading – considering that each cell is an abstraction of 1km^2 of the Iguaraci area and the fact of an *Aedes aegypti* can fly up to 100m of distance, the number of mosquitoes that will fly to a neighbor cell is a function of the cell area (i.e. 1 Km^2), the number of mosquitoes in the cell and the maximum distance a mosquito can fly; (4) *oviposition* (i.e. laying eggs) – the female mosquito needs a blood meal and water to lay its eggs. Hence, the number of new eggs in the cell is a function of number of agents, amount of water and number of mosquitoes in the cell.

The dengue disease was simulated following a Cellular Automata -like dynamics. Therefore, *Aedes aegypti* mosquitoes were not represented in the model as agents, but they were abstracted in each cell of the environment by its quantity and the percentage of infected mosquitoes. Other variable values were kept constant for each cell, namely, the number of eggs, the percentage of infected eggs and the level of water in that cell. These values were initialized uniformly for all executions and changed over time as the simulation progressed, based on neighborhood and presence of agents. Although hard-coded, most of these simulation variables could be readily obtained (and used) should a more precise simulation would be necessary. This fact only confirms the flexibility PAX as a powerful simulation tools for social problems.

5. Experiments and results

5.1. Experimental setup

As the proposed agent model has two decision components: genetic and cultural, experiments were carried out to investigate their mutual influence. Three simulation scenarios were devised: (1) agent only with cultural component; (2) agent only with genetic component; and (3) agent with both cultural and genetic component.

The performance of each scenario was inferred by its approximation power relative to real data, after one

simulated year. Population state was inspected each 7 days. All simulations have two distinct moments, of which only the second one is considered in results. The first moment is a "free run" of 3 simulated months – a period of time needed to produce a more stable population behavior. After these three initial months, one year is simulated and results observed.

To build a more realistic environment relative to public health services, 10% of population per iteration was induced to feel sick, generating extra demand to hospitals and health stations in addition to the regular infected agents demand. Each hospital or health station was allowed to have different waiting queue limits and different number of beds, which determines the number of agents that it is able to attended. In this work, we considered all simulated health units with waiting queue of size 50. The hospital of *Iguaraci* has 16 beds; the hospital of *Afogados da Ingazeira* has 96 beds; the hospital of *Sertânia* has 55 beds; each health station has only 1 bed.

Other parameters relative to communication were: global communication (i.e. the governmental broadcast mechanism used to instruct population on how to combat dengue) reaches 60% of population per iteration; the instructed agent, called a "conscientious" agent, is capable of remove 5% of water of water pools in every location it visits; 1% of the population is initialized as conscientious. In local communication (i.e. communication between two agents) conscientious agents instructs others. The percentage of agents that an agent can locally communicate is determined by genetic factors.

The number of confirmed cases of dengue fever infection in the end of 2006 was 1. In the end of 2007, this number grows to 19. Thus, simulations were initialized with 1 infected agent and arbitrary dengue fever dissemination spots; this including concentration of mosquitoes and water pools in the town.

After one simulated year, we expected to analyze the approximation power of each model configuration in a qualitative perspective, even using quantitative real data. The analysis will be focused basically on the percentage of sick individuals and the approximation of models to this number, as well as the population behavior over time in a cultural and genetic perspective.

The genetic component has two parameters: mutation rate and crossover rate. The mutation rate determines the probability of an agent to have its genetic code mutated per iteration, situation in which one of its genes is randomly modified. The crossover rate is the probability of an agent to crossover with other, generating a child agent. We have used a mutation rate of 0.5% and a crossover rate of 0.25%.

Agents have a minimum and maximum initial lifetime. They are initialized randomly in this interval. The minimum and maximum initial lifetimes of an agent are 50 and 80 years, respectively. Diseases have negative effect on agents' lifetimes as "natural" selection helps on the dissemination of robust genetic characteristics and cultural habits. Simulations were carried out using an Intel® Core™ 2 Quad q 6600 64 bits processor of 2.4 GHz with 4 GB of RAM. Results were averaged over 10 distinct runs.

5.2. Simulation results

We conducted two types of investigations for each scenario: (1) qualitative confrontation of the model with real data; (2) verification of influence of the cultural component over the genetic one.

The first type of investigation was carried out through simulations parameterized with real data, with its qualitative results confronted with real data after a simulated time. The second type of investigation was carried out through the generation of genetic histograms. Obviously, this investigation was only conducted when the genetic component is enabled. The mentioned genetic histogram aims to capture the distribution of genes values over the population. Each agent has six genes, so consequently six genetic histograms were generated. Therefore, we compared the six genetic histograms when the cultural component is disabled and enabled.

Figure 3 shows the population size over time. Since reproduction is enabled only when the genetic component of agents are also enabled, we observe a growth only in scenarios with genetic component. Of course, we could assume a reproduction mechanism even when only cultural component is enabled, but this would be somehow incoherent with real scenarios, since we basically see in the real world genetic motivations in reproduction, even if determined cultural symbols are indirectly benefited with reproduction. Notice in Figure 3 that the cultural component has little influence over the reproduction (a genetic-based mechanism), denoted by a similar growth. Reproduction of agents only happen when the genetic component is enabled, thus the little influence of the cultural component towards population growth.
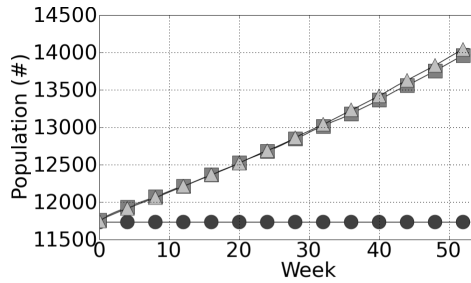
Figure 3. Populational growth over time (circles-cultural; squares-genetic; triangles-both components).

Figure 4 shows the cumulative number of infected agents over time. One can perceive the inconsistence of the agent model with only cultural component enabled and the influence of genetic characteristics on disease dissemination. Real data informs that, in the end of 2006, Iguaraci has a cumulative number of sick agents equals to 1, and in the end of 2007 equals to 19. Therefore, the best model, regarding quantitative terms is the one with cultural and genetic components.
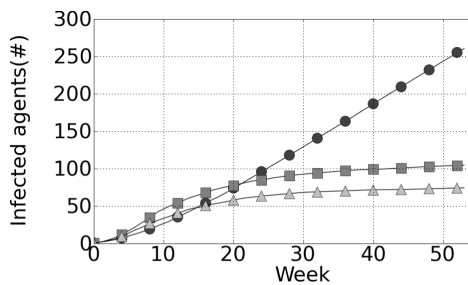
Figure 4. Cumulative number of infected agents over time (circles-cultural; squares-genetic; triangles-both components).

Figure 5 shows the non-cumulative (i.e. instantaneous) percentage of sick agents over time. It indicates that the model with only cultural component enabled is insufficient to approximate real data. When the genetic component is enabled, the model produces a more accurate approximation. The cultural component seems to refine the behavior of agents when the genetic component is enabled, since more tuned results are found with this scenario.

Figure 6 shows the cumulative number of attended agents in health units (hospitals and health stations), and Figure 7 shows the instantaneous percentage of sick individuals over time. In both, it is clear that the model with cultural and genetic components enabled represents a mean term between the other two extreme models (i.e. with only cultural or genetic components).
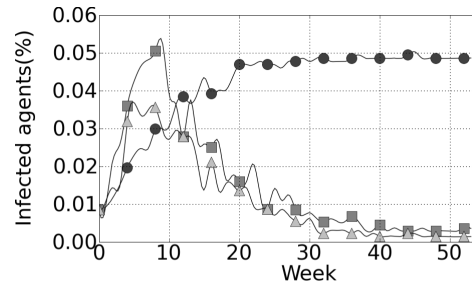

Figure 5. Instantaneous percentage of infected agents over time (circles-cultural; squares-genetic; triangles-both components).
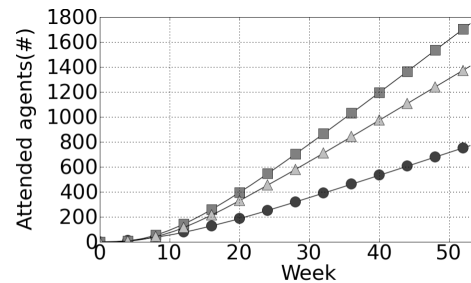

Figure 6. Cumulative number of attended agents over time(circles-cultural; squares-genetic; triangles-both components).
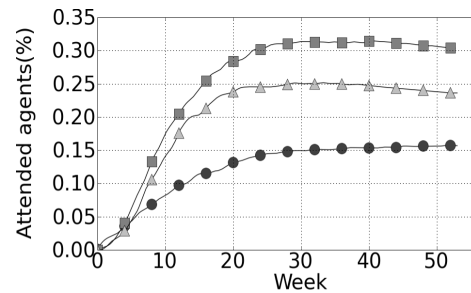

Figure 7. Instantaneous percentage of attended agents over time (circles-cultural; squares-genetic; triangles-both components).

To better understand the influence of the culture on the genetics of agents, we built histograms for each gene type (with and without cultural component enabled). They show the value distribution for that particular gene over the population. In our simulation we have six gene types.

Two example histograms can be seen in Figure 8 and 9. They are for gene 2 (without and with cultural component, respectively). We observe that the presence of the cultural component only refines the genetic convergence. This refinement may be due a faster convergence in the genetic code.

Notice the genetic convergence to values between 0.6 and 0.2. This means that the population prefers migrate to others communities instead of stay for long times at a specific community.

Another interesting observation is that in almost all results we have noticed little influence of the cultural component on the genetic component, which can be understood as robustness of the genetic evolution.
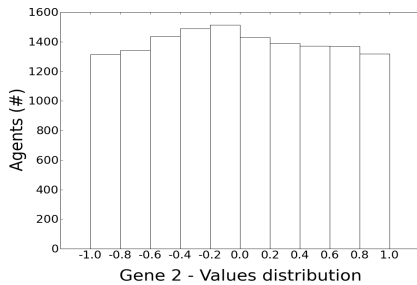

Figure 8. Gene 2 values distribution over population *without cultural component enabled*.
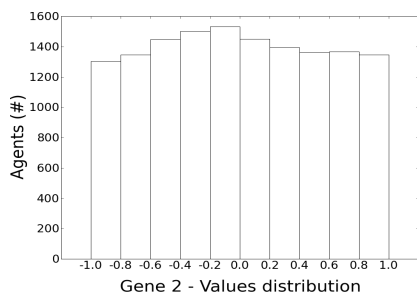

Figure 9. Gene 2 values distribution over population *with cultural component enabled*.

6. Conclusion and future work

In this paper we presented a new model of hybrid evolutionary agent which combines two perspectives: genetic and cultural. We tested three different model combinations, namely, only with the genetic component enabled, only with the cultural component enabled and with both components enabled. Experiments used real data, which was compared quantitatively and qualitatively with the produced simulated ones.

To sum up we highlight the following results:

- The cultural component has little influence over the reproduction, since the population with only genetic component and with both genetic and cultural components showed similar growth;
- Model with only cultural component enabled showed to be completely inconsistent with real disease dissemination;
- Configuration with both cultural and genetic component enabled performed best among the three tested models in approximating real phenomena of dengue fever dissemination;
- In almost all results, the cultural component has little influence over the genetic component, denoting a robustness of genetic evolution; even

thou not large, this influence is an important counter intuitive finding as one would expect only genetics affecting culture;

- The cultural component seems, most of times, to be refining the genetic-motivated behavior.

In the future we plan to put together more aspects of real populations in order to produce even more realistic results. Finally we stress the great flexibility and realism of PAX framework when processing the introduced hybrid evolutionary agent model (i.e. the combination of genetic and cultural characteristics).

7. References

[1] J. M. Epstein and R. L. Axtell, *Growing Artificial Societies: Social Science from the Bottom Up*. The MIT Press, 1996.

[2] T. Schelling, *Micromotives and Macrobehavior*. Norton, 1978.

[3] M. Cohen, "A Garbage Can Model of Organizational Choice", *Administrative Science Quarterly*, 17, 1972, pp. 1-25.

[4] M. Pita, S. Madeiro and F. B. de Lima Neto, "Vidya: a god game based on intelligent agents whose actions are devised through evolutionary computation," in *Proc. of the IEEE Symposium on Computational Intelligence and Games*, IEEE Press, 2007, pp. 352-359.

[5] M. Pita and F. B. de Lima Neto, "Simulations of Egoistic and Altruistic Behaviors Using the Vidya Multiagent System Platform," in *Proceedings of the Genetic and Evolutionary Conference*, 2007, pp. 2927-2932.

[6] M. Pita and F. B. de Lima Neto, "Simulations of Disease Dissemination Using the Vidya Multi-agent Systems Platform," in *Proceedings of the 1st Brazilian Workshop on Social Simulation*, 2008, pp. 109-120.

[7] M. Pita and F. B. de Lima Neto, "Impact of Structuring Elements on Agents' Behavior in Social Simulations," in *Proceedings of the IEEE Symposium Series on Computation Intelligence* (Symposium on Intelligent Agents), 2009, pp. 106-113.

[8] P. Andrade, A. Monteiro, and G. Câmara, "Entities and relations for agent-based modelling of complex spatial systems," in *Proceedings of the First Brazilian Workshop on Social Simulations*, pp. 52–63, 2008.

[9] R. Dawkins, The Selfish Gene (*30th anniversary edition*). Oxford University press, 2006.

[10] F. B. de Lima Neto, M. Pita and H. Serrano B. Filho, "Impact of Communication on Agent-Based Social Simulations Using the PAX Framework" in *Proceedings of the IEEE International Conference on System, Man and Cybernetics*, IEEE Press, 2009, (In-Press).

[11] M. J. Lehane, *The Biology of Blood-sucking Insects*. Cambridge University Press, 2005.