COGNITIVE DYNAMICS IN AN AUTOMATA GAS

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The problem of modeling cognitive systems has been recently considered under new point of views. The attention is no more mainly focused on the simulation of rational behaviors, but also on the importance of the individual free-will and of the apparent "irrational decisions". A possible approach for a mathematical modeling is to introduce an internal dynamical structure for the "elementary particles" that allows to define an individual cognitive dynamics at the base of the decision mechanisms. Our assumptions imply the existence of an utility potential which is the result of an evolution process, where some behavioral strategies have been selected to perform efficiently in presence of different environmental conditions. The utility potential defines a cognitive dynamics as a consequence of information based interactions and the choice of a strategy depends on the individual internal cognitive state. This is the definition of an "automata gas model", whose aim is to extend some statistical physics results to cognitive systems. We shall discuss the existence of self-organized dynamical states in an automata gas, that are the result of a cognitive behavior. We show as the introduction of a cognitive internal dynamics allows to simulate the individual rationality and implies the existence of critical conditions at which the system performs macroscopic phase transitions. The application to the pedestrian mobility modeling problem is explicitly considered and we discuss the possibility of a comparison with experimental observations.

Keywords: Cognitive Behavior; Automata Gas; Pedestrians Dynamics.

1. Introduction

Any simple decision is the result of complex processes that takes into account the available information, the previous experience and the individual propensities. The rational decision models, that are mainly derived from the game theory,[22] are not suitable to simulate the individual free-will and the existence of different strategies in each individual.[16] These phenomena

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could play an essential role to explain both the adaptation capability of cognitive systems to dynamical environments, and the existence of sudden transitions in the macroscopic dynamical states, like the develop of panic in crowded or critical conditions.[13] A possible approach to a mathematical modeling of cognitive systems may take advantage from the idea of *cognitive dynamics* recently proposed by neuroscientists.[7] This theory assumes the existence of an internal cognitive state, which creates an interface between the external stimuli and the consequent decisions and whose evolution simulates the brain activity. On one hand the introduction of a cognitive state is quite natural if one interprets the brain activity as a dynamical system, coupled with the external environment by information based interactions.[24] On the other hand the idea of propensity understands the existence of an utility function, that allows a quantification of the expected utility of a certain choice taking into account the available information and the previous experience.[5] We consider the utility function as the result of an evolution process and as a common feature to all the individuals. Any rational individual will choice the decision that maximized the estimated utility, but due to the existence of an individual cognitive state, it is not possible to define a universal rationality, since the state depends on the previous decisions and the information at disposal. Using a parallel with the concept of *Subjective Probability* introduced by B. deFinetti,[4] we can say that only a subjective rationality exists.

In the simple examples we consider, a population of automata has to decide between two possible choices.[2] Each automaton changes its cognitive state according to a Langevin's equation defined by an utility potential which depends on the external information.[25] A stochastic noise reproduces the effect of the continuous unpredictable interactions not directly related to the decision utility, but that can modify the cognitive state. The noise amplitude can be also interpreted as the individual attitude to change mind. Each cognitive state is associated to the individual propensity toward one of the possible choices and defines the decision mechanism in a probabilistic way. The decision realization means to perform a particular action, which allows to get new information and, consequently, to change the utility potential. In this way the automata perform a learning procedure that enforces the most successful choice and creates self-organized dynamical states due to coupling between physical and cognitive dynamics.[26,27]

The aim of this paper is to study some statistical properties and the presence of different strategies in an automata gas inspired by the pedestrian dynamics modeling. Such a problem has attracted the attention of physi-

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cists and mathematicians since several years ago,[3,8] due to its relevance both for safety reasons (risk control during crowd stampede and panic situations) and for improving the accessibility of urban space like stations, museums or shopping centers. In the second section we discuss a possible mathematical modeling of an automata gas for pedestrian mobility in simple urban space. The third section we apply a statistical physics approach to study the existence of critical values in the system parameters for the appearance of emergent states and we illustrate some properties of the model by using numerical simulations. Finally in the last section we discuss the problems related to experimental validations of the automata gas model by using video data recorded during the Venezia Carnival 2007.[15]

2. The Automata Gas Model

The automata gas model simulates an ensemble of cognitive particles moving in a given space. Using a reductionist point of view, we divided the interactions in two main classes: the physical and the cognitive interactions. By physical interactions we mean not only the effect of physical forces, but also the dynamical phenomena that can be described by Newton-like equations by assuming the existence of *social forces*.[10] The social forces simulate the effect automatic strategies, that are a direct response to external stimuli without the necessity of cognitive processes: a typical example is the collision avoidance strategy of pedestrians where the vision mechanism may be simulated by a long range repulsive force. In our model the automata have a incompressible body of dimension r_b, a social space of dimension $2r_b$ and a visual radius of dimension $\simeq 5r_b$ (fig. 1), that define the spatial scales of physical interactions. The social space is used to simulate the pedestrians attitude to avoid the physical contacts with other individuals, whereas the visual radius defines semicircle centered at the automaton velocity direction which reproduces the effect is of a frontal vision. Each automaton i tends to move at a desired velocity $\vec{v}_{0i}$ according to

$$\dot{\vec{v}}_i = -\gamma(\vec{v}_i - \vec{v}_{0i}) \quad (1)$$

where the parameter $1/\gamma$ defines the microscopic relaxation time scale of the system. We also provide the automata of an inertial mass m and we introduce inelastic collisions as a consequence of the automata body incompressibility.

The vision mechanism is realized by a topological long range interaction among the automata: each automaton focuses his attention to the other automata in the visual space, whose trajectories will enter its social space.

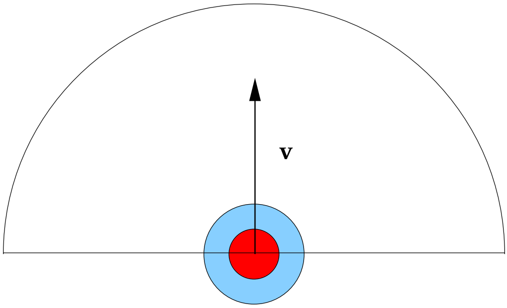

Fig. 1. Sketch of automaton physical dimensions: the dark circle is the incompressible body of radius r_b; the light circle is the social space of radius $2r_b$ and the larger semicircle is the frontal visual space of radius $5r_b$.

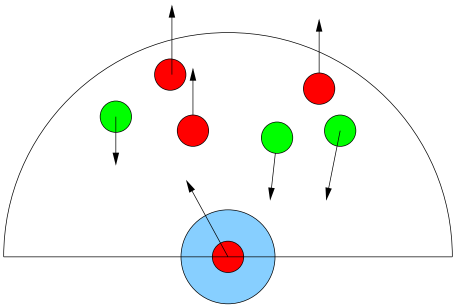

Fig. 2. Collision avoiding strategy of automata as a consequence of a local vision mechanism.

In such a case it rotates and/or reduces the velocity in order to avoid future collisions. The net result is a repulsive force among the automata coming from opposite directions, which does not satisfied the Action-Reaction principle (frontal vision). The repulsive force turns out to be proportional to the density of counteracting automata in the visual space and to the rotational velocity and deceleration rate values. Due to the long range character of local vision, the automaton has the tendency to move towards empty regions or to follow other automata moving in the same direction. This mechanism allows the formation of self-organized dynamical states: let us consider two counteracting automata flows along a narrow corridor. If the relaxation time $1/\gamma$ is not too small (in the limit $\gamma \to \infty$ the velocity is frozen along the desired direction), the collisions dynamics tends to distribute the automata population along the corridor according to maximal entropy principle (fig.

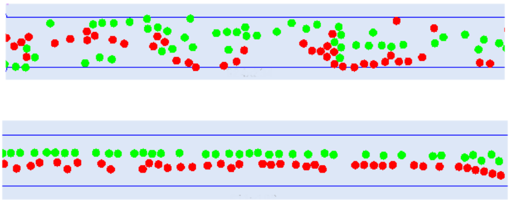

Fig. 3. Dynamics of two counteracting flow of automata moving along a corridor. When the automata interact only by means of inelastic collisions a disordered state is observed along the corridor(top); if the local vision is introduced, a two streams ordered flow appear along the corridor (bottom).

3 (top)). When the local vision is introduced, each automaton moves to avoid collisions and the system tends to relax to a stable dynamical state which minimizes the collisions number. As a result two ordered counteracting streams appear along corridor (fig. 3 (bottom)). The stability of the self-organized solution is destroyed when the automata density along the corridor overcomes a critical threshold, simulating the appearance of a panic dynamics, but this is a consequence of physical interactions as the transition from a laminar to a turbulent regime in fluids.
In order to introduce a cognitive behavior in the automata that cannot be reduced to a Newton's like dynamics we are inspired by recent experimental results in neuroscience research,[18] that can be summarized by the following remarks:

- the decisions are always mediated by the brain activity (existence of a cognitive space);
- there is a nonlinear subjective relation between the "utility" of a decision and the probability of taking that decision: an overestimate of small advantages and an underestimate of the large advantages with respect to a linear relation;
- there is an aversion to risk.

Then we associate to each automaton a dynamical cognitive model, that is formulated according the assumptions:

- the brain activity can be represented by a dynamical system defined on a n-dimensional cognitive space;
- the utility associated to a decision introduces a landscape potential in the cognitive space whose shape depends on the external information;

- the cognitive state is stochastically perturbed;
- the possible choices E_j $j = 1, ..., n$ define a partition of the cognitive space and there exists a decision mechanism which is a function of the cognitive states $X(t)$.

The first assumption essentially states that the brain can be macroscopically described by a dynamical system.[24] The existence of an utility function in the decision mechanism has been proposed in various contexts.[5] Our point of view is to consider the utility function as a potential $V(X; I)$ in the cognitive space, whose minima are related to the perceived utility of the various decisions depending on the information I. Of course there is a strict relation between self-organization and the "information" inserted in the utility function. Indeed the definition of "interesting information" for a certain decision is a key point to model a cognitive behavior.[25]
The third assumption is quite obvious since any individual decision can be influenced by several unpredictable factors.
Finally the last assumption allows to introduce a subjective rationality since the choice probabilities depend on the individual cognitive state X and/or information level. According to hypotheses, the automaton cognitive dynamics is defined by a stochastic differential equation

$$dX = -\frac{\partial V}{\partial X}(X; I)dt + \sqrt{2T}dw(t) \tag{2}$$

where we have introduced the individual "social temperature" T (i.e. a measure of the individual influence of external random factors on the cognitive state) and $w(t)$ is a Wiener processes. The cognitive dynamics is the result of a deterministic tendency to increase the utility proportional to the "force" $\partial V/\partial X$, and of random effects to describe the great number of unpredictable factors that enter in any individual decision. When T is small, the stochastic dynamics $X(t)$ is essentially confined in a neighborhood of the potential minima and it is straightforward to associate each minimum to a particular choice and the well deepness to the choice utility. In other words, the cognitive space represents different brain areas and the utility defines the probability that a certain area is activated. The solution $X(t)$ is the evolution of the brain activity and the automaton decision will be associated to the choice E_i if

$$\frac{1}{\tau_d}\int_t^{t+\tau_d} \chi_{E_i}(X(s))\, ds = \max_{j=1,..,n}\left[\frac{1}{\tau_d}\int_t^{t+\tau_d} \chi_{E_j}(X(s))\, ds\right] \tag{3}$$

where τ_d defines the decision time-scale and $\chi_{E_j}(X)$ is the characteristic function of the set E_j: i.e. the decision is associated to the most visited

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choice during the decision time. The information dependence of the potential $V(X;I)$ simulates a common rationality in the population, that modifies the utility function when any individual get certain information I. We can distinguish three different time scales in the model: the relaxation time scale (or Kramer's time scale) τ_K of the stochastic dynamics (2), the decision time scale τ_d and the information acquisition time scale. The relaxation time scale is the time requires to the dynamics (3) to reach a stationary state. The decision time can be interpreted as a reasoning time: if $\tau_d \ll \tau_K$ then the choice depends strongly on the actual cognitive state (subjective rationality), otherwise each automaton tends to select the most useful choice among all the possibilities (objective rationality). Finally the information acquisition time scale is directly related to the dynamical properties of the automata gas, since an automaton get new information as a consequence of a physical action. In the model we assume that τ_d is shorter than the information acquisition time scale, so that a long decision time scale corresponds to a delay in the information acquisition.
We will illustrate the properties of the definitions (2,3) in the atomic decision case (the decision between two possible choices). Then the utility potential reduces to a double well potential

$$V(X,I) = X^2 \left(\frac{X^2}{4} + \frac{X}{3}(X_A - X_B) - \frac{X_A X_B}{2} \right) \qquad X_{A,B} > 0 \qquad (4)$$

where the stable fixed points $-X_A(I), X_B(I)$ represent the two possible choices. The cognitive space partition is defined by $E_A = \{x \,/\, x < 0\}$ and $E_B = \{x \,/\, x > 0\}$. For given values X_A and X_B, we have considered an automata population in a stationary cognitive state. In the figure 4 we plot the probability of choosing B as a function of the utility $-V(X_B)$, for $X_A = 1$ constant. The circles refer to a short decision time, whereas the diamonds refer to a long decision time in. We remark as in the first case the empirical probability is quite sensitive to the utility changes when the utility is small and tends to saturate to 1 in a smooth way when the utility increases; on the contrary in the second case we see a threshold effect, since the population changes sharply from one choice to the other as the utility changes. According to eq. (4), the utility potential is a function of the relevant macroscopic information. We are interested in the case when two opposite strategies are present in the population: a cooperative strategy that tends to increase gradually the utility if the majority of the population tends to cooperate and a selfish strategy that suddenly decreases the utility if too many people take the same decision. The relevant information is the population fraction $P_{A,B} = N_{AB}/N$ that takes the same choice A or B

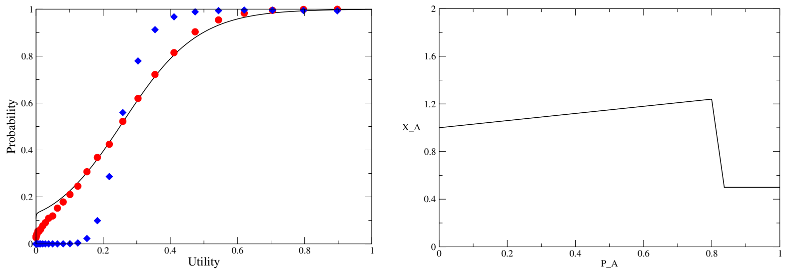

Fig. 4. Left figure: choice probability in the case of atomic decision as a function of the utility $-V(X_B)$; we have considered a population of 10^4 independent automata performing the cognitive dynamics (2) where $T = .1$ and the utility potential is defined by (4) ($X_A = 1$ constant). The circles refer to a short decision time (2.5 arbitrary times units), whereas the diamonds refer to a long decision time 250 time units; the continuous curve is the mean field estimate using the Kramer's transition rate theory (see eq. (9)). Right figure: dependence of the utility potential fixed point on the cooperative population fraction; the increasing behavior is related to a cooperative strategy, whereas the fast decrease introduces a selfish strategy in the population. The parameters are $P_* = .8$ and $a = 20$ (cfr. eq. (5)).

and we introduce the strategies in the model by varying the fixed point positions according to

$$X_A(P_A) = \begin{cases} X_A^0(1 + cP_A) & \text{if} \quad P_A \le P_* \\ \max\left(X_A^0(1 + cP_* - a(P_A - P_*)), X_m\right) \end{cases} \tag{5}$$

where the parameter c defines the cooperation degree and a the strength of the selfish strategy (fig. 4 (right)). P_* and X_m are respectively the congestion threshold and a minimal value for the fixed point position (an analogous definition holds for X_B). The different slopes in fig. 4 reflect also the different character of the two strategies: the cooperative strategy is a behavioral strategy that has been selected since it is advantageous in many situations, whereas the selfish strategy is an individual safety strategy that an automaton applies in possible dangerous situations. Under this point of view the automata are quite sensitive to danger due to crowding. In the application to pedestrian dynamics, such a model would like to describe the cooperative phenomena observed in experimental data,[11] like herding effects or streams in crowd dynamics, but also the possibility of appearance of critical states in particular congested situations.

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3. Statistical Properties

In order to study the statistical properties of the automata gas model (2,3) we consider the evolution of the probability density $\varrho_i(X,t)$ for each automaton i in its cognitive space. Then we define the global distribution function

$$\varrho(X,t) = \frac{1}{N}\sum_{i=1}^{N} \varrho_i(X,t) \tag{6}$$

where the sum runs over the automata population. Assuming that the information I in the utility potential (4) is functional of the distribution $\varrho(X,t)$, the cognitive dynamics decouples from the physical dynamics (of course this is a simplification to allow an analytical approach). The information $I = I(\varrho(X,t))$ introduces a coupling among the automata and it is possible to justify a system of nonlinear Fokker-Planck equations for the distributions ϱ_i under the assumption of a generalized law of large numbers[21]

$$\frac{\partial \varrho_i}{\partial t} = \frac{\partial}{\partial X}\frac{\partial V}{\partial X}(x, I(\varrho))\varrho_i + T_i \frac{\partial^2 \varrho_i}{\partial X^2} \qquad i = 1, ..., N \tag{7}$$

Using the double well potential (4), we get the self-consistent stationary solution of the system (7)

$$\varrho(X) = \frac{1}{N}\sum_{i=1}^{N} K_i \exp -\frac{V(X, I(\varrho))}{T_i} \tag{8}$$

where K_i are normalization constants. For each automaton the transition rate between the regions $E_A = \{x\,/\,x < 0\}$ and $E_B = \{x\,/\,x > 0\}$ associated to the possible choices is estimated by the Kramer's theory[9]

$$\pi_{AB} = \frac{|\omega_A \omega_0|}{2\pi} e^{V_A/T_i} \qquad \pi_{BA} = \frac{|\omega_B \omega_0|}{2\pi} e^{V_B/T_i} \tag{9}$$

where $\omega_{A,B,0}$ are the fixed point eigenvalues of the vector field $-\partial V/\partial X$. π_{AB}^{-1} and π_{BA}^{-1} define respectively the average time spent in the regions E_A and E_B (the Kramer's time scale τ_K). When the decision time τ_d is small compare, we can approximate the population fraction P_A according to

$$P_A = \int_{-\infty}^{0} \varrho(X)\, dX \tag{10}$$

This assumption can be numerically verified as it is shown in fig. 4 (left) where the formula (10) has been used to get the continuous curve. On the contrary when $\tau_d > \tau_K$, the most useful choice becomes more and more favored according to the decision mechanism (3); in the limit $\tau_d \to \infty$ all the automata will take the same decision according to

$$P_A = \begin{cases} 1 & \text{if} \quad \int_{-\infty}^{0} \varrho(X)\, dX > \frac{1}{2} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

We explicitly study the dependence (5) in the utility potential, assuming that the automata have the same social temperature $T_i = T$. Then from the solution (8), we get the self-consistent equation for P_A

$$P_A = K \int_{-\infty}^{0} \exp\left(-\frac{V(x; P_A, P_B)}{T}\right) dx \qquad P_B = 1 - P_A \tag{12}$$

If we set $X_A^0 = X_B^0 = X^0$ (i.e. there is no a priori preferred choice), the trivial solution $P_A = P_B = 1/2$ always exists, but other solutions are possible. An explicit calculation can be performed by using the transition probabilities (9)

$$P_A = \frac{1}{1 + \frac{\omega_A}{\omega_B} \exp\left(\frac{V_A - V_B}{T}\right)} \tag{13}$$

where

$$\frac{\omega_A}{\omega_B} = \sqrt{\frac{X_A(P_A)}{X_B(P_B)}} \tag{14}$$

and $V_{A,B}$ are the utilities of the two choices. The equation can be solved by using a fixed point principle and a bifurcation phenomenon is observed at $c = c_*(T)$, when the following condition holds

$$\left.\frac{\partial}{\partial n_A}\right|_{P_A=1/2} \frac{\omega_A}{\omega_C} \exp\left(\frac{V_A - V_C}{T}\right) = 4 \tag{15}$$

In the fig. 5, we plot P_A in the stationary state, as a function of the cooperation degree c, comparing Monte Carlo numerical simulations together with the analytical curve obtained from eq. (13). The existence of a bifurcation phenomenon means that a cooperative state emerges in the population only if the cooperative degree is sufficiently big for a fixed value of the social temperature. We have the limit $T \to 0$ as $c_* \to 0$, so that the automata tends to cooperate when the social temperature is small, but the time requires to relaxed to stationary state becomes extremely long according to the Kramer's estimate (9). These results are true for a small decision time τ_d, whereas the τ_d increasing causes a sharp transition to a high cooperative state. As a consequence the congested situations are also more probable, so

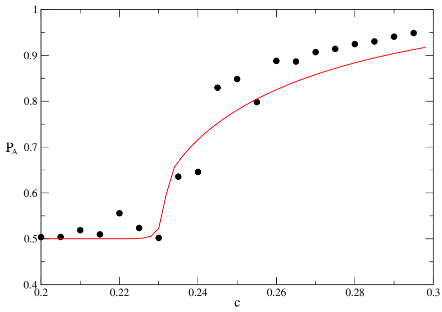

Fig. 5. Left figure: stationary value of the population fraction P_A in the case of atomic decision as a function cooperation degree c; we have considered the same parameters as in fig. 4 The circles refer to a short decision time (2.5 times units), whereas the continues curve is obtained from the Kramer's approach (13).

that we can observe the effects of the selfish strategy. This is illustrated by fig. 6 (right) where we plot the evolution of the P_A for different cooperation degrees when the decision time is long (250 time units). We observe that the transition to cooperative states emerges also for $c \leq c_*$, but as c increases, the appearance of congested states causes oscillations in the P_A values, since some automata feel the convenience of changing their decision.[28] The oscillations increase their amplitude according to the cooperative degree up to transition to a chaotic regime in the P_A dynamics (fig. 6), where the population majority changes her decision at random times. Moreover we remark the critical dependence of the cognitive dynamics on the c value. This behavior corresponds to a frustrated dynamics, in which the population is not able to relax to stationary state. When the cognitive dynamics is coupled with the physical dynamics the chaotic behavior may give rise to macroscopic transitions of the systems toward new stationary equilibria, but also to critical congested states which can decrease the system efficiency and create dangerous situations (for example the flux reduction across a bottleneck in pedestrian dynamics[14]) A semi-quantitative explanation of the numerical simulations plotted can be achieved by using a discrete version balance equation for the P_A fraction

$$P_A(t + \tau_d) = P_A(t) - \pi_{AB} P(t)\tau_d + \pi_{BA}(1 - P_A(t))\tau_d \tag{16}$$

where π_{AB} and π_{BA} are the transition probabilities (9). In the figure 6 (right), we show the P_A evolution for different c values, using the same parameters as in the numerical simulations. We observe as the nonlinear map (16) and the cognitive dynamics (2)have the same chaotic regime as

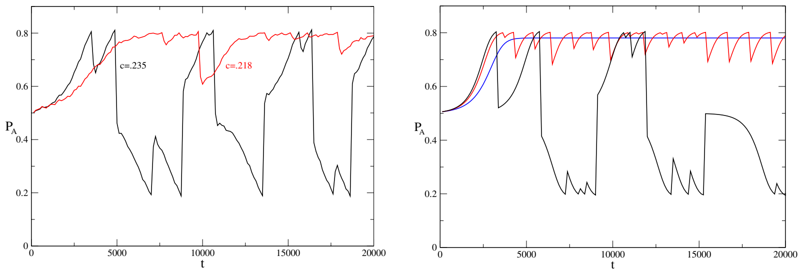

Fig. 6. Left figure: Evolution of the P_A population fraction at different value of the cooperation degree when the automata use a long decision time ($\tau_d = 250$ arbitrary time units) and a congestion threshold $P_* = .8$; the other parameters are the same of fig. 4. We observe the transition to a chaotic frustrated dynamics as the c increases, so that the automata are not able relax to a stationary cognitive state. Right figure: Dynamics of balance equations (16) for a time step $\tau_d = 250$; the transition probabilities are computed according to the Kramer's theory (9) using eq. (5) with the congestion threshold $P_A = .8$ in the utility potential (4). The different curves (blue, red, black) refer to increasing values of the cooperative degree.

when c increases. This result points out that an average approach describes the macroscopic behavior of the system as the transition to a deterministic chaotic regime, where the individual stochastic dynamics can trigger fluctuations that are then amplified up to create collective phenomena.

4. Experimental Validation Problems and Virtual Experiments

The validation of complex systems models is still a very debated problem.[1] This is not only due to the difficulty in defining relevant parameters suitable for quantitative experimental measures, but also to the intrinsic unrepeatable nature of the experiments. The usefulness of a complex system model is mainly in its capability of reproducing virtual experiments in silico that show analogous emergent properties and macroscopic states as the real systems. The virtual experiment results should be robust with respect of an entire class of microscopic interactions so that the validation process can be simplified to verify that the microscopic interactions are compatible with the experimental observations. We have performed virtual experiments with the automata gas model to study the interaction between the cognitive dynamics (2) and the physical dynamics, in simple environments. Referring to fig. 7, we consider two populations of automata moving in counterwise through two couples of parallel bottlenecks. The decision mechanism (3) is introduced to choose among the possible paths using the flows and the den-

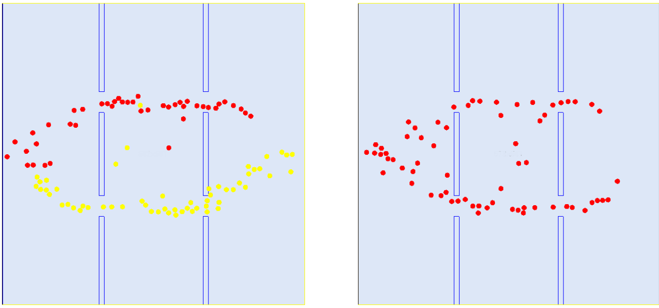

Fig. 7. Left figure: snapshot of a simulation for two automata population moving in a counterwise way through two couples of bottlenecks (the red automata move from the left to the right, whereas the green ones move from the right to the left). The automata perform a cooperative strategy with a short decision time so that a self-organized state emerges and the two populations choose different path to reach their goal. The remark there still exist few automata that do not cooperate. Right figure: a single population of cooperative automata use all the possible paths to reach the goal.

sity at the bottlenecks as relevant information. In fig. 7 (left), we show the effect of a cooperative behavior for a short decision time and a moderate population density. It is clear the formation of a self-organized state in the system when the cooperative degree overcomes a certain threshold, so that the populations choose different paths to reach their goal. Due to the probabilistic nature of the decision mechanism, there are still few automata that do not cooperate with the majority. These automata allow the system to respond efficiently to environmental changes: e.g. if one of the two population disappears, we observe a fast relaxation to a state where the automata uses all the possible paths (fig. 7 (right)). An increase of the population density strengthens the cooperative behavior and we get a completely organized state (fig. 8 (left)). But the introduction of a selfish threshold in the density destabilizes the cooperative state and a chaotic decisional regime emerges, in which the automata switch from one path to another according to the fluctuations in the density at the bottlenecks (fig. 8 (right)). The numerical simulations point out as the cognitive dynamics (3) is able to explain the formation of self-organized states in simple situations, that recall analogous phenomena experimentally observed in pedestrian dynamics.[11] At this purpose we have performed a video recording campaign during the Venetian Carnival 2007 to study the crowd dynamics in urban spaces.[15] We have developed a software to detect semi-automatically the individual dynamics from video recording by following the single head movements

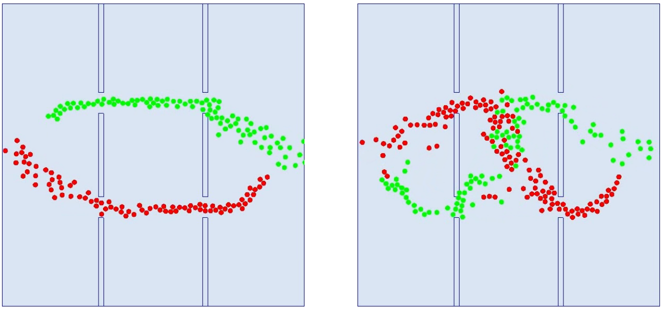

Fig. 8. Left figure: a complete coordinate state at high automata density: the system efficiency is maximal. Right figure: after the introduction of a selfish strategy the populations switch randomly from one path to another.

Fig. 9. Left figure: snapshot of the software interface developed to detect the individual dynamics from a video recording during the Venetian Carnival 2007.

taking into account the corrections due to the projection effects (fig. 9). We have analyzed the trajectories of $\simeq$ 400 pedestrians moving across San Marco square from a 3 minutes video. Many people were moving forming little groups so that there is a strong correlation among their dynamics. We have divided the individuals into two main classes according to the velocity to distinguish the people that effectively cross the area from people that stop inside the area. Our analysis refers to the first class which contains approximately 70 % of the individuals ,whose trajectories are the result of the moving strategies to avoid collisions. In such a way we were able to have information on the pedestrian microdynamics in a moderate crowded situation. In fig. 10 (left) we report the distance distribution between each individual and his nearest neighbor (red curve) compare with a random distribution in the same area (blue curve). We observe as the distribution

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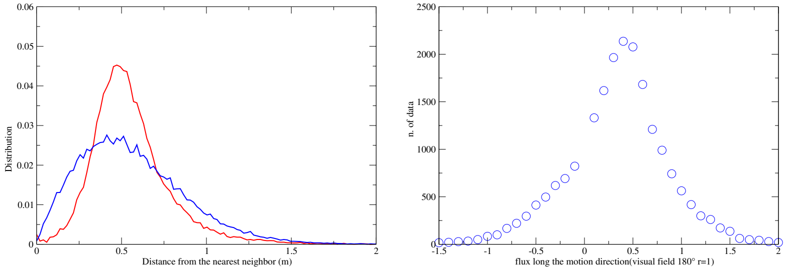

Fig. 10. Left figure: distance distribution between each individual and his nearest neighbor (Red curve) compared with a random distribution of the same number of individuals in the considered area (Blue curve). Right figure: flux distribution projected along the velocity direction for each individual in a semicircle visual space of radius $\simeq 2\ m$; the peak at .5 pedestrian per second indicates the presence of streams in the pedestrian dynamics.

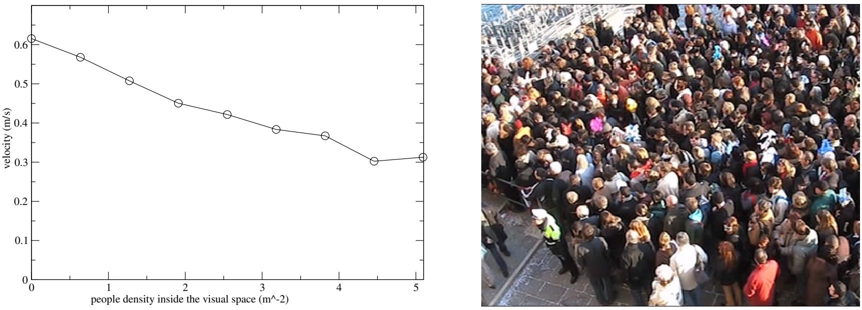

Fig. 11. Left figure: individual velocity dependence on pedestrian density in the visual space: the linear behavior means that no criticality is present in the dynamics. Right figure: snapshot of a video recording at the entrance of a bridge along Riva degli Schiavoni: stop and go density waves can be observed in the crowd.

indicate the presence of correlated structures among moving individuals and the presence of a peak at distance $\simeq .5\ m$, that can be correlated with the existence of a social space as in the automata gas model (fig. 1). The effects of a collision avoiding strategy have been studied by the flux distribution in a visual radius semicircle of dimension $\simeq 2\ m$; the results are reported in fig. 10 (right) where one can observe as the flux is peaked at a positive value denoting that people tend to move forming streams. Finally we have look for crowding effects by measuring the dependence of the individual velocity from the density in the visual space; the results are plotted in fig. 11 (left) where we do not observe any substantial deviation from a linear dependence. These data are consistent with other data previously published in the literature.[6,17] Therefore we have not any congestion effect in the analyzed data. Then we have considered very crowded situations like congestions due to bottlenecks (fig. 11 (right)), fortunately during the Venetian Carnival people do not show any evidence of selfish strategy and we can only observe the formation of stop and go waves typical of granular flow dynamics at bottleneck.[12,20] This was not the case during the 2006 Muslim pilgrimage in Mina/Makkah (Saudi Arabia), where a big disaster happened due to crowd stampede and an analysis of video recordings had pointed out the appearance of a discontinuous change in the individual behavior.[13]

5. Conclusions

In this paper we show as an automata gas, whose cognitive dynamics may realize opposite strategies, could be very useful to model the emergent dynamical states and the critical phase transitions of biological or social systems that are difficult to describe using the paradigm of Nash equilibria. Although there are still many problems to be solved to define a validation procedure, the effort of the scientific community in this direction could be very profitable for new ideas and applications of the complexity science.

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