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EMERGING COHESION AND INDIVIDUALIZATION IN COLLECTIVE ACTION: A CO-EVOLUTIVE APPROACH

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By means of a simple computational model, we explore a dynamic perspective of social cohesion in populations under stress. Dynamics are driven by the co-evolution of structural and cognitive dimensions. Submitted to sudden variations on its environmental conflict level, the model is able to reproduce certain characteristics previously observed in real populations in situations of emergency or crisis. A closer analysis of the results, observing both structural and cognitive together, uncovers a causal path from the level of conflict suffered by a population to variations on its social cohesiveness.

Keywords: Social cohesion; conflict; adaptive networks.

1. Introduction

Populations under stress can present surprising and powerful behaviors. From the uprising of spontaneous social protest against authoritarian regimes leading to their fall, to the emergence of unexpected solidarity among victims of terrorist attacks (see September 11th 2001 or March 11 2004 Madrid, for instance), we could mention a long list of situations where conflicting scenarios made social cohesion in human groups to emerge.

Some scholars studying different empirical cases have stressed the importance of pre-existing informal social networks in such an emergence. The role of personal networks as mobilization contexts in East-German and October's Serbian revolutions is the main interest of Opp and Gern in [26], and Araya in [2], respectively. Opp and Gern present a complete analysis on the incentives of individuals to join Leipzig's Monday demonstrations in 1989. They uncover the little influence of opposition organizations in comparison with that of personal networks of friends. Araya introduces the concept of *cooperative cascade* to describe the link between ego-centric networks' characteristics and macroscopic mobilization phenomena. Kinship structures have also been considered. In Ref. 25, Murphy studies their relationship with warfare organization patterns of a Brazilian Indian group, the Mundurucú. The Mundurucú were settled in several apart villages, spread along the upper Tapajós River. However, the setup of war parties evidenced a strong relationship among these communities, otherwise unobservable. Murphy concludes that intercommunity cooperation in warfare was facilitated by cross-cutting ties of residential affinity and affiliation by descent.

Other authors have observed that there exists also an influence in the opposite direction, that is, of mobilization over informal social networks. In Ref. 13, Gould analyzes the insurgent activity during the Paris Commune in 1871, which sprung after a mixture of political, economic and war crises. In this paper, as in later works [14, 15], he settles that organizational networks and pre-existing informal networks interacted in the mobilization process. As Gould points out, mobilization does not just depend on existing social ties; it also creates them. Although members of a protest organization may have joined because of a pre-existing social tie to an activist, they eventually also formed new social relations while participating in collective protest. In other words, opinion affinity manifested by joint mobilization led to the formation of new ties among individuals.

Summarizing, in order to analyze the emergence of cohesiveness in conflictive scenarios, we need to observe the dynamic interplay between structural and cognitive components of social cohesion during the period of activity. Notice that this conclusion illustrates perfectly what Giddens defined as "duality of structure". According to him, the social structure is simultaneously the product and the constraining environment of social action and, therefore, these two entities cannot be studied separately [11].

This paper aims at addressing this interplay in a quantitative way by modeling the co-evolution between individual behaviors (opinions) and social networks [20]. Different quantitative approaches have been developed to study the evolution of the social structure under the influence of local dynamics (e.g. strategic network formation, network evolution models and exponential random graph models) [18, 31]. However, it is only very recently that we have started to see simulation-based studies addressing the co-evolution of structure and dynamics [16, 27]. Specifically, our model's dynamics, based on the proposal by Holme and Newman in Ref. 17, make the system to evolve in a twofold way: individuals become likeminded because they are connected via the network (change is induced by the structure) and they form network connections because they are like-minded (structure undergoes change).

The model reveals to be a good framework to reproduce and study the evolution of social cohesion in a population submitted to sudden changes on its environmental conflict level. Moreover, a detailed analysis of its dynamics uncovers the counterintuitive effect of noise and the importance of the social structure at the microscopic and mesoscopic structural level.

Social movement behaves in a regular pattern; from the institutional (macro) level to the individual (micro) sphere through the intermediate (meso) level of networks and vice versa [7]. This interaction at the meso level is complex and it is constituted both by processes of selection on the part of individual and influence by groups [30]. In other words, a mobilization begins with a mobilization potential which depends both on macrostructural factors such as demographic, economic or ideological variables and individuals predispositions and social networks structures in which they are embedded, who, in turn, change their connectivity thus affecting social groups' structure and the macrostructural framework. In particular, our analysis reveals that a moderate rate of noise (here seen as an individualistic trait) can enhance the social cohesion of a population by enabling cross interactions among the groups forming it.

The remainder of the paper is organized in three sections. The second section is devoted to the detailed description of the model, making an special insight on the influence of the social noise. Simulation results are presented and discussed in Sec. 3, focusing specially on the role of the different topological levels. Finally, the last section summarizes the work and proposes further extensions.

2. Cohesion Analysis through a Coevolutive Model

2.1. *The model*

We consider a population of N agents, connected through a variable number of undirected (bidirectional) links. Each agent i presents a h_i value, corresponding to his location in a continuous lineal social space of size L (proportional to N). Here, h_i could be seen as an opinion or positioning of individual i in relation to a certain topic (related to religion or politics, for instance). Notice that this approach has been commonly adopted in the well established literature about continuous opinion modeling [1, 8, 29].

Initially the h values of all agents are assigned randomly, following a uniform distribution along the lineal social space. Besides, the initial arrangement of the edges correspond to a topology with the same structural properties than real social networks (like large clustering coefficient and positive degree correlations, for instance). To construct such a scenario, we use a class of models proposed in Ref. 4, which are able to grow up networks with social-like macroscopical (global) properties from a microscopical (individual) definition of the linkage probability between two agents. The key element of that definition, is the social distance between the two individuals in a social space of a certain dimension $d_{\mathcal{H}} \geq 1$. By social distance, here we mean "*the degree of closeness or acceptance that an individual or group feels towards another individual or group*" [4]. Since our social space is lineal, here we use a simplified expression of the linkage probability with $d_{\mathcal{H}} = 1$:

$$r(h_i, h_j) = \frac{1}{1 + [b^{-1}|h_i - h_j|]^{\alpha}}, \tag{1}$$

where $|h_i - h_j|$ corresponds to the social distance, b a parameter controlling the length scale of the lineal social space, and α quantifies the homophily, which is everyone's preference to establish and maintain relations with people that have any common characteristic with (cultural background or political feelings, for instance) [23]. Therefore, given a certain social distance between two agents, different combinations of b and α values lead to different link probabilities, in such a way that the higher the b and the lower the homophily, the larger the probability of connection.

Our model evolves from the initial scenario in a twofold way, by redefining both the topology of the network and the positioning of the population of agents in the social space. Based on a co-evolution model proposed by Holme and Newman in Ref. 17, the two main mechanisms driving this co-evolution process are the rewiring of links and the imitation of h values among agents. Additionally, we have incorporated a third mechanism that reproduces slight shifts on each one's opinion or social position, induced by individual circumstances and daily life experiences, which usually modify individuals' knowledge in a subtle but continuous way. This third mechanism is necessarily external, since these particular characteristics are different for each individual, and do not depend on any other parameter of the model. Notice that, at the mid-long time range, these slight but continuous shifts can change significantly the social distance among two individuals, separating two agents that were once very close in the lineal social space or, on the contrary, approximating them enough to favor the creation of a new link. Consequently, the accumulation of these microscopical changes can modify the whole macroscopical scenario, by disrupting both the distribution of agents' positions along the social space and their connectivity. Taking into account this disrupting effect, and in alignment with previous literature introducing noise in a similar way [22], we have denoted this third mechanism of the dynamics as *individualization noise*.

These three mechanisms (rewiring, imitation and individualization noise) are integrated within the co-evolutive dynamics of the model, consisting on the repetition of the following two steps:

(i) Select an agent x at random and decide, with equal probability, whether to apply rewiring or imitation.

- The rewiring consists on a redefinition of all links of node x using the expression in (1).

- Imitation is implemented by selecting randomly a neighbor y of node x, and setting h_y equal to h_x.

(ii) Introduce the *individualization noise* by summing up a random quantity to the h value of each agent in the population. This random quantity is obtained from a Gaussian distribution (with mean = 0.0 and variance = 1.0) multiplied by a noise *magnitude* or *strength* factor n.

Figure 1 illustrates these dynamics. At each time step, the system evolves following one of the two possible branches of the diagram (imitation plus *individualization noise*, or rewiring plus *individualization noise*) with the same probability. Notice that this probability (or, in other words, the relative proportion at which imitation and rewiring occur) has been found to play an important role in this kind of co-evolutionary models. Vazquez and co-authors, for instance, showed that there is a phase transition towards fragmentation varying this probability [32]. In order to discard potential effects of such a transition in our particular case, we have performed additional simulations (not shown). These simulations show that the rewiring probability used in this paper ($p = 0.5$) is such that it is well below the critical value for fragmentation.

After a certain number of time steps, the system reaches a *steady-state*. In our context, this means that both the topology and the distribution of individuals' social positions along the space remain stable. The concrete topology and distribution of social positions reached at each possible steady-state depend, as we will show in the next section, on the strength of the *individualization noise*.

2.2. *Effect of individualization noise*

An important issue to deep in at this point, is the influence of the *individualization noise* over the evolution of the model. Different kinds of noise have been reported to influence enormously different opinion and cultural dynamics models.

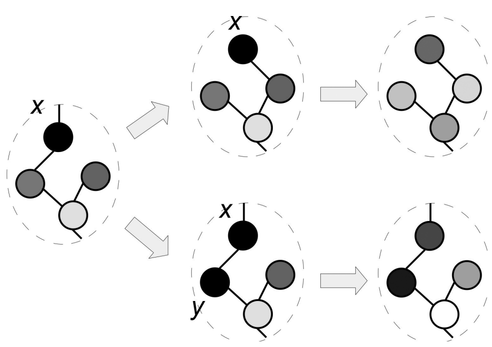

Fig. 1. An illustration of our co-evolutive dynamics, where colors indicate the h value of each individual. At each time step, the system evolves following one of the two branches. The upper branch correspond to a rewiring (of $x's$ links) plus a shift of all positions, and the lower one to imitation (y imitates x) plus position shifts.

One of the most relevant examples in the literature is Ref. 19, where the authors show that the stable cultural diversity achieved by Axelrod's model of dissemination of culture [3], can be easily fused into cultural homogeneity by introducing small random variations in agents' cultural features (what they call *cultural drift*). This result is explained by the fact that cultural drift can eventually make an agent to share cultural traits with agents belonging to completely different groups, allowing crossed social influence among previously isolated agents and, therefore, leading toward cultural homogeneity. After this observation was made, robustness to noise has become an important requirement for models trying to reproduce the emergence of opinion diversity [6, 9, 10].

More recently some authors have started to introduce noise in models to account for opinion individualization. Pineda and coauthors proposed a new version of Deffuant's bounded-confidence model where noise is used to model individuals' *free will* [28]. Specifically, in that model agents' were given the opportunity (with a certain probability) of changing their opinions to a randomly selected position in the whole opinion space. The authors found that the noise defined in such a way was able to induce a transition between a disordered state (where opinions were distributed uniformly) and an ordered one (where opinion clusters emerged). Similarly, Mäs and *et al.* used a noisy model to show how moderate rates of individualization can lead to opinion clustering [22]. In this case the noise plays the role of a uniqueness-seeking effect, which counteracts the general tendency of agents' opinions toward consensus around the average opinion in the population. More concretely, the noise is defined by a normally distributed random variable which standard deviation is higher the more homogeneous is the social context of the opinion holder (i.e. the more similar to her are the opinions of the other agents in the population). Finally, this same noise-based mechanism is used in a subsequent paper to explain the persistence of social differentiation in groups and organizations [21].

Noise definition in our model is somehow related to the two described above. On one side, it is independent of the social context of the opinion holder (as in Ref. 28). On the other hand, in accordance with [22], it is defined by a normal distribution since small opinion changes are much more likely than large ones. Moreover, also as in Ref. 22, we keep all agents' positions within the interval [0,L] by not applying individualization noises if such boundaries would be crossed otherwise.

Being our individualization noise defined by a Gaussian distribution with a fixed mean and variance, we center our attention on the unique parameter that can be tuned: its magnitude. In the context of our study, the magnitude corresponds to the average range of changes experimented by individuals' social position due to the *individualization noise*. Strong *individualization noise* implies sudden changes of individual's social positions along the social space. On the contrary, weak noises correspond to quite stable opinions.

Taking this into account, we can easily predict the behavior of the model for extremal values of the noise magnitude. On one side, too much *individualization noise* would result in a noise-dominated scenario, where agents would be almost completely isolated due to the difficulty to maintain links among them. On the other hand, too low noise intensity would exercise no significant effect over the dynamics, which would be controlled by the other two mechanisms (imitation and rewiring). Keeping this in mind, some questions arise: what are we to understand as "too weak" or "too strong" noise? And, how does the noise influence the dynamics for intermediate strength values between these limits?

In order to address these questions, we have analyzed the influence of different noise magnitudes over three topological measures, namely the density within clusters (ρ), the average degree ($\langle k \rangle$) and the average Clustering Coefficient (Cc). In Fig. 2, we present the evolution of these measures for a given set of initial conditions and different values of the noise strength. For extremal values of the noise magnitude, results corroborate predicted behaviors. Unexpectedly, however, we observe that the case corresponding to an intermediate noise strength leads to steady-states with the highest average degree.

Such a surprising result can be related, in our particular case, to the capacity of a moderate individualization noise to introduce heterogeneity within the different groups. This internal diversity favors the inter-group linkage without breaking them into isolated agents.

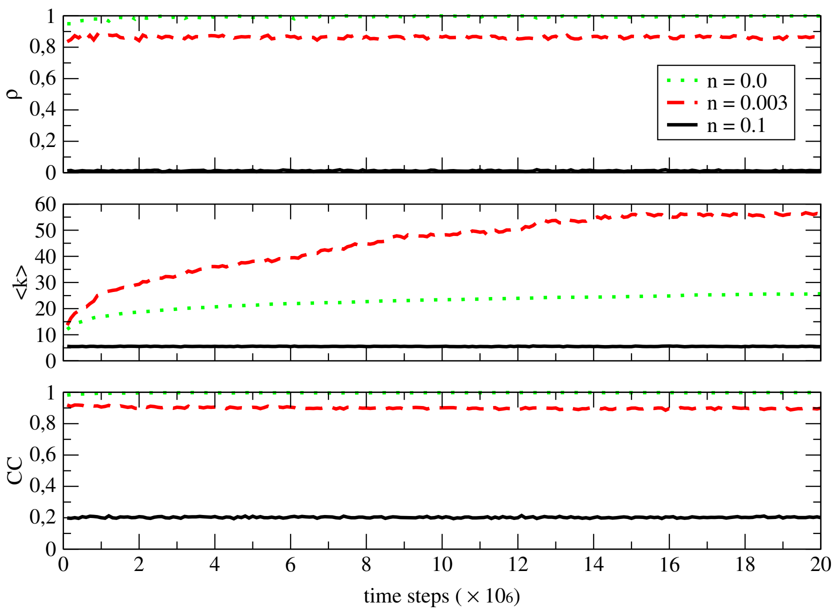

Fig. 2. Influence of noise magnitude over model dynamics. Evolution of the density within clusters (ρ), the average degree ($\langle k \rangle$) and the average Clustering Coefficient (Cc), for two different values of the noise strength (representative of strong and intermediate noise strength). The case without noise ($n = 0.0$) is also shown, for comparative purposes. Population size N, size of the opinion space L and homophily α were set to 1000, $N/5$ and 6, respectively. Results were averaged among 25 independent realizations.

Let us explain this argument more accurately. When the individualization noise is weak or absent, the combined action of imitation and rewiring leads the model to a steady-state where individuals tend to coincide in a unique h value (social position) and, therefore (because of the rewiring action), to conform a unique connected component. On the contrary, when the magnitude of the individualization noise is extremely high, differences between h values of agents (social distances among them) grow such quickly that cannot be counteracted by the imitation mechanism and, when those distances are too large to maintain links between neighbors, groups are progressively dissolved toward a completely disconnected scenario. In an intermediate situation, the noise intensity is high enough to maintain a wide variety of h values, but the differences introduced among these values are small enough to keep agents linked and, in some cases, to establish new links with agents belonging to other groups.

Notice that a moderate individualization noise in our model and Klemm and coworker's cultural drift in Ref. 19 act in a parallel way, since both of them facilitate the interaction between otherwise isolated components. Sort to say, they "liquefy" an stable scenario composed by separated components (cultural regions for the cultural drift, opinion groups in our case).

3. Results and Discussion

3.1. *Experiment*

By using the described model as a framework, we have conducted a simulation experiment to study social cohesion and its interplay with extremal changes on the social environment. Such an experiment comprises two crisis cycles (sudden increases of the social temperature followed by longer reactionary periods). Each one of the crisis cycles has consisted on a short period (about 50,000 time steps) of high social temperature, followed by a fall to extremely low temperature (reproducing an habitual reactive behavior of populations after an emergency situation) and, finally, a progressive recovery toward normality.

In order to run the described experiment, we need to be able to simulate different social temperatures in our model. Such changes on the social temperature, has been modeled as variations on the value of the b parameter (the one controlling the length scale of the social space). This solution can be justified as follows. When some kind of emergency strikes a population, social distances that separate individuals do not change, but the necessity to face the new critical scenario makes them less important than in a quiet situation. This temporal relativization of social distances is nothing but a change on the length of the scale they are "measured" against. Consequently, an appropriate way to introduce in our model the effect of emergencies and posterior relaxations of the conflict level, is to increase the value of b (making distances relatively smaller) and, after a relatively short number of time steps, decrease it back. In our case, the b values chosen to represent each period are 0.5 for "normal" social temperature, 2.0 for highly conflictive situations and 0.25–0.35 for the reactionary intervals.

Furthermore, we also want to monitor the evolution of social cohesiveness under these environmental changes. For this purpose, we have used three different macroscopical observables, namely: the average degree $\langle k \rangle$ (average number of neighbors), the clustering coefficient (a weighted measurement of the number of triangles) and the number of disconnected components or independent groups G composing the whole network. While first and second parameters signal intra-group cohesion, the third one corresponds to inter-group cohesiveness. Note that, taken jointly, these three are good indicators of the social cohesiveness, since the more cohesive is a population, the higher are their average degree and clustering coefficients, and fewer separate groups it presents.

When looking at the behavior of these observables during the experiment, shown in Fig. 3, we observe two phenomena. First we notice that, for the same value of b, the social cohesiveness after each emergency situation is higher than before them. Second, we observe a memory effect on the cohesion of the system in the period between crises. Although the cohesiveness diminishes as a response to social temperature cooling, when the situation comes back to normality, the cohesiveness

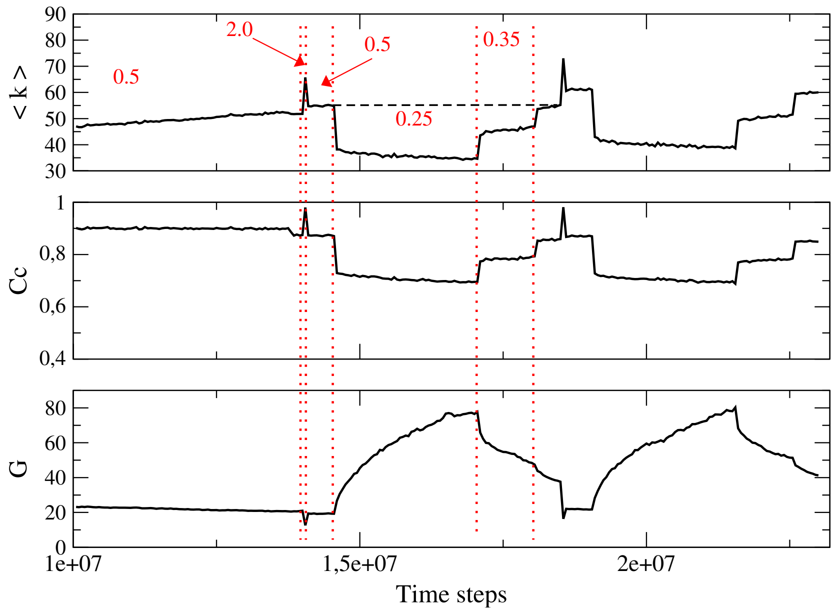

Fig. 3. Evolution of social cohesiveness during the experiment. Vertical dashed lines in red indicate regions delimited by their b value, which are indicated also in red. Values of sizes N and L, as well as homophily α, were kept as in Fig. 2. The noise magnitude was set to the intermediate value 0.003. Two important phenomena are observed: An increase on the average cohesion after each crisis, and a memory effect in the period between crises (represented here by a horizontal dashed line in black). Results were obtained by averaging 25 independent realizations.

also recovers its "normal" value (that one corresponding to $b = 0.5$ just after the crisis).

The first result agrees with the observation made in the introduction in the sense that the structure of the system changes during the conflict period. Moreover, it can be positively contrasted with observations of other real social systems. When a population has been submitted to a stressing situation, it is quite usual to find higher levels of cohesion than before the crisis. In some sense, this phenomenon could be seen as a sort of *reminiscence* of the high rates of cohesion characterizing the emergency situation.

3.2. *Analyzing mesoscopic and microscopic dynamical aspects of social cohesion*

Up to this point, our model has revealed its capacity to reproduce how changes on the social temperature (which is a macroscopical variable related to the social environment) induces changes on the cohesiveness of a population of individuals (here measured in terms of macroscopical observables).

Nevertheless, in the introduction we have pointed out that the analysis of the concept of social cohesion from a dynamical viewpoint demands a more complete scope of the problem, also including the behavior of different variables at meso and micro levels during the conflict period. In order to deep in this issue, we have studied how our model's dynamics modifies the distribution of agents' positions (h_i values) along the lineal social space and, consequently, how the social structure of the population is transformed.

In general, when plotting the distribution of agents' opinions in the social space at a steady-state (see Fig. 4 for two particular examples), we find that agents are grouped around certain positions of the space, and that there are quite regular separations among these concentrations. Taking into account the dependence of the linkage probability on the social distance, we deduce that these concentrations of opinions in the social space correspond, structurally speaking, to groups of agents densely connected. Besides, the observed separations tend to a unique value that we have called *critical social distance* $d_c(h_i, h_j)$, which is the maximum social distance at which connectivity between two groups of agents is possible. In other words, is the distance making the link probability close enough to zero as to have just one expected link between the two groups. Notice that, in accordance with this definition, d_c (and the corresponding r) depends very much on the particular scenario. For instance, if we had one single agent on one side and the rest of the population $(N - 1)$ on the other, r would take the value $1/(N - 1)$. However, for a scenario with two groups of equal size $N/2$, we would need $r = 1/(N^2/4) = 4/N^2$.

We propose the following formalization for the *critical social distance*:

$$d_c(h_i, h_j) = \lim_{r \to 0} d(h_i, h_j) = \lim_{r \to 0} b \sqrt[\alpha]{\frac{1}{r(h_i, h_j)} - 1} \approx \frac{b}{\sqrt[\alpha]{r(h_i, h_j)}}. \tag{2}$$

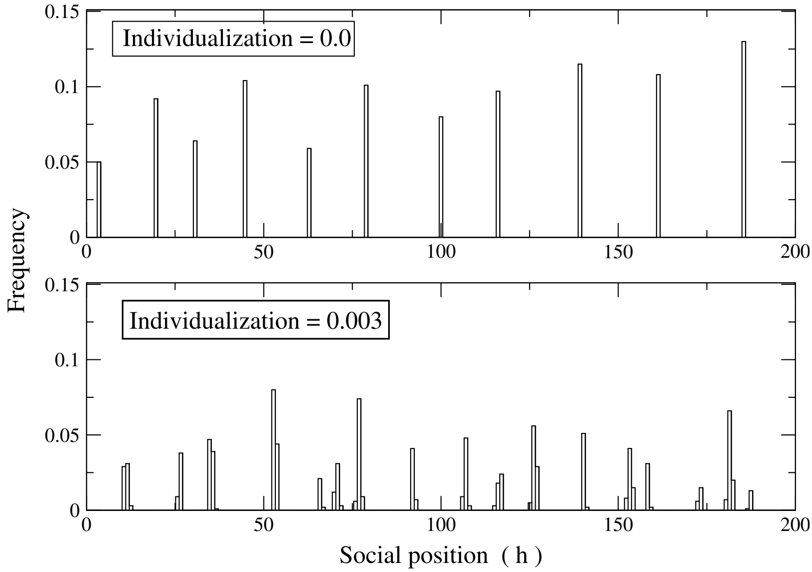

Fig. 4. Distribution of agents' positions along the lineal social space, in a steady-state, without individualization noise (top) and with a individualization noise of magnitude 0.003. Although both cases present quite regular separations between groups (see text for an explanation), the internal distribution of each group differs. In the bottom case, we appreciate the heterogeneity within groups introduced by the individualization noise.

From this definition, it is straightforward that links are established only among agents separated by a distance smaller than $d_c(h_i, h_j)$. Moreover, the combined effect of imitation and rewiring makes that any agent located in a social position shorter than $d_c(h_i, h_j)$ from any group tend to link to that group, and that two groups tend to merge if they are near enough from each other. Consequently, in the steady-state not only the distance among groups, but also their number and size, is related to the critical social distance. The larger the $d_c(h_i, h_j)$, the fewer separated groups and the larger the distance among them.

Furthermore, by taking a look to expression (2), we realize that *the critical social distance* depends on b. Since this variable controls the *social temperature* in our model, we can trace a causal path from variations on the social temperature to structural and knowledge changes experimented by the population during a crisis period. With this idea in mind, we can interpret the behavior of the cohesiveness during the experiment (shown in Fig. 3) in terms of reductions and increases of the critical distance, induced by changes on b (that is, the social temperature).

At the beginning of the experiment, before the first crisis, the critical distance is defined by the original b value (0.5). When the b value becomes 2.0, the critical distance also increases and, consequently, all agents come across other ones that were previously out of their range. Globally, this means that the population tend to reorganize into fewer but larger groups, whose opinions are separated each other by greater social distances. However, as this process is interrupted abruptly (due to the briefness of emergency situations), some agents are "surprised" halfway between various groups. After a short transitory period, a new steady-state is reached. In this new stable scenario, agents conserve many neighbors of the period before the crisis and have incorporated new ones due to those agents bridging different groups after the emergency. Consequently, the resulting groups are larger than before the crisis and, because of their high internal connectivity, the average degree and the clustering coefficient also keep higher. This phenomenon is what we have previously called *reminiscence* of the crisis over the social cohesiveness.

At this point, agents are "trapped" within their groups (i.e. their opinions are too much different from those of other groups to establish cross-links). Moreover, in this second stable period, the individualization noise plays a central role by opening very little internal discrepancies between members of the same group, that allow the creation of new groups when the social temperature gets "colder" (b drops down to 0.25). Later, as the population recovers its "normal" social temperature (and, therefore, the b value increases again), the critical distance grows up and little groups tend to merge and recover the stable configuration reached just after the crisis, presenting the second phenomenon pointed above, a memory effect. Finally, during the second cycle, the system presents the same behavior than in the first one: A higher cohesiveness than before and a memory effect.

4. Conclusion

In this work we have developed a simple model as an analytic tool to explore a dynamic perspective of the concept of *social cohesion*, integrating the already-stated structural component [24] with a cognitive, cultural one. Given a certain initial scenario, the model evolves under the influence of the conflict level of the environment by redefining, simultaneously, the social structure and the knowledge or opinions (represented as positions in a social space) of a population of agents. We argue that, beyond static perspectives, the social cohesion of a population should be expressed in terms of these changes experimented both at structural and cognitive dimensions as a response to conflict increases.

By means of only three simple mechanisms, the dynamics of the model reproduces the behavior of real social populations under a highly conflictive situation. We have showed this in a twofold way. First we have studied numerically how changes on a variable of the system representing the *social temperature* (degree of conflict) conditions the evolution of three observables than can be easily related to social cohesion (average degree, clustering coefficient and number of isolated components). Second, we have deepened in dynamic aspects of social cohesion by tracing the causal path among different topological levels. Changes on social temperature happen at an institutional level, influencing relationships among agents (microscopical level), and these changes at the individual level modify the size and composition of groups conforming the social population (mesoscopic or intermediate level).

Although having demonstrated its utility as a tool to analyze the concept of social cohesion, there are some aspects of the model that could be explored in order to make it closer to particular case studies. In the following, we point out two of these possible extensions of the model.

The initial conditions of our experiment, determined by a topology and a distribution of agents' opinions, can be defined in many different ways. In this case, we have chosen a simplistic initial scenario (synthetic social-like topologies and a uniform distribution of opinions) in order to show that, even starting with such simple conditions, our model is able to reproduce certain phenomena related to social cohesion and its dependence on variations on the social temperature. Nevertheless, each one of the two components of the initial scenario can be modified separately. For example, we could use an empirically obtained social network as the initial topology, but we could also start out the experiment with a distribution of opinions representing a scenario of preexistent coalitions or opinion groups.

Another possible extension of the model is related to the observables used to quantify the evolution of the social cohesion. Although the three structural observables used in this work are too simple to represent population's cohesion separately, analyzing the evolution of their behaviors jointly has helped us to understand the dynamical processes taking place in the model. Nevertheless, for the sake of simpleness and clarity, it would be interesting to define a unique (necessarily more complex) structural observable, based on previous studies like [33] and [24]. Furthermore, in accordance with the aim of this work of enriching the structural approach to social cohesion with a cultural component, it would also be interesting to define an observable related to the distribution of opinions in the social space (based on the largest social distance in the system, for instance).

Finally, current online communication platforms open new sociological research possibilities. The eruption of social networking sites like Twitter or Facebook and their undiscussed key role in recent civil mobilizations (wave of protests in the Arab world, the M15 movement in Spain [5, 12]) and riots (England, summer 2011) provide an unprecedented chance to empirically test theoretical models relying both on underlying bond topologies (who holds stable relations with whom) and on information dynamics (who is actually communicating with whom).

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