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Opinion dynamics and synchronization in a network of scientific collaborations

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Abstract

In this paper we discuss opinion dynamics in the *opinion changing rate* (*OCR*) model, recently proposed in Pluchino et al. [Int. J. Mod. Phys. C 16(4) (2005) 515–531]. The OCR model allows to study whether and how a group of social agents, with a different intrinsic tendency (*rate*) to change opinion, finds agreement. In particular, we implement the OCR model on a small graph describing the topology of a real social system. The nodes of the graph are scientists participating in the Tepoztlán conference, celebrating Alberto Robledo's 60th birthday, and the links are based on coauthorship in scientific papers. We study how opinions evolve in time according to the frequency rates of the nodes, to the coupling term, and also to the presence of group structures.

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1. Introduction

In the last years there has been an increasing interest in statistical physics for interdisciplinary applications. Not only biology, economy and geology but also soft sciences [2] like sociology or cognitive sciences have been involved. An effort in this sense has also been advocated in order to strengthen the scientific aspect of these disciplines [3]. At the same time, the study of complex networks, concerning both their structure and their dynamics, has seen an explosive evolution [4–6]. This field is probably only in its infancy and will likely reinforce the interdisciplinary new directions of contemporary statistical physics. Within this scenario, many *sociophysics* papers have been published and new models have been proposed for studying in particular opinion dynamics and consensus formation [7–12]. Although in many cases such models offer at the moment an oversimplified description of a real social system, they can be hopefully very useful in the long term. In this paper we discuss opinion formation mechanisms and, in particular, we study the implementation on a real social network of a recently proposed model, the *opinion changing rate* (OCR) model [1]. The latter is a modified version of the Kuramoto model [14–16] adapted to the social context. The OCR model allows to explore the possible role of synchronization in the process of opinion formation. In previous works we have

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considered a group of fully coupled agents with a different natural tendency (*rate*) to change opinion. Here we extend the study to a system of agents on a small graph representing a real social network, namely the network of scientific collaborations among statistical physicists in which Alberto Robledo is involved.

The paper is organized as follows. In Section 2 we review the main features of the OCR model. In Section 3 we explain how the network has been constructed. There we study its structural properties with a particular attention to the subdivision in community structures and we discuss the results of numerical simulations of the OCR model on the network. Conclusions are drawn in Section 4.

2. The OCR model

Many of the most popular opinion formation models have the limitation of not taking into account the individual inclination to change, a realistic feature of any individual. In fact, each one of us changes idea, habits, style of life or way of thinking in a different way, with a different velocity. There are conservative people who strongly tend to maintain their opinion or their style of life against everything and everyone. There are more flexible people who change ideas very easily and follow the current fashions and trends. Finally, there are those who run faster than the rest of the world anticipating the others. These different tendencies can be interpreted as a continuous spectrum of different degrees of natural inclination to changes.

In a recent paper [1] we showed how such a personal inclination to change, randomly distributed in a group of individuals, can affect the opinion dynamics of the group itself. Switching from the question "*Could agents with initial different opinions reach a final agreement*?" to the more realistic one "*Could agents with a different natural tendency to change opinion reach a final agreement*?", we introduced a new idea, the natural opinion changing rate, which is very similar to the characteristic frequency of an oscillator. In such a way, one can treat consensus as a peculiar kind of synchronization (frequency locking) [13], a phenomenon which has been very well studied in different contexts by means of the Kuramoto model [14–16].

The Kuramoto model of coupled oscillators is one of the simplest and most successful models for synchronization. It is simple enough to be analytically solvable, still retaining the basic principles to produce a rich variety of dynamical regimes and synchronization patterns. The most interesting feature of the model is that, despite the difference in the natural frequencies of the oscillators, it exhibits a spontaneous transition from incoherence to collective synchronization beyond a certain threshold of the coupling strength [16]. The existence of such a critical threshold for synchronization is very similar to the consensus threshold found in the majority of the opinion formation models. Thus we modified the Kuramoto model in order to study synchronization mechanisms in consensus formation. In our model, each oscillator represents an agent corresponding to a node of a given network and the topology of the network fixes the neighborhood $\mathbf{K}_i$ of every agent. The dynamics of a system of N individuals is governed by the following set of differential equations:

$$\dot{x}_i(t) = \omega_i + \frac{\sigma}{k_i} \sum_{j \in \mathbf{K}_i} \alpha \sin(x_j - x_i) e^{-\alpha|x_j - x_i|}, \quad i = 1, \dots, N, \tag{1}$$

where $x_i(t)$ is the opinion of the ith agent at time t. Here the opinions have a very general meaning and can represent the style of life, the way of thinking or of dressing etc., thus they can be usefully represented by means of unlimited real numbers $x_i \in]-\infty +\infty[\ \forall i = 1, \dots, N$. Opinions interact by means of the coupling term, where σ is the coupling strength and k_i is the degree (i.e., the number of first neighbors) of each agent. The exponential factor in the coupling term, tuned by the parameter α, ensures that opinions will not influence each other any longer when the reciprocal distance exceeds a certain threshold. This is perhaps the most remarkable feature of our model with respect to the Kuramoto model, since it allows the system to reach an asymptotic stationary state where the configuration of opinions does not vary any longer. The parameter α appears also as a factor of the sine in the coupling term and simply rescales the range of the coupling strength.[1] We typically adopted the value $\alpha = 3$, which ensures a consistent behavior of the exponential decay. Finally, the ω_i's—corresponding to the *natural frequencies* of the oscillators in the Kuramoto model—represent here the so-called *natural opinion changing rates* (*ocr*), i.e., the intrinsic inclinations of the agents to change their

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[1]Please notice that, due to a misprint, this factor α before the sine term is missing in formula (7) of Ref. [1].
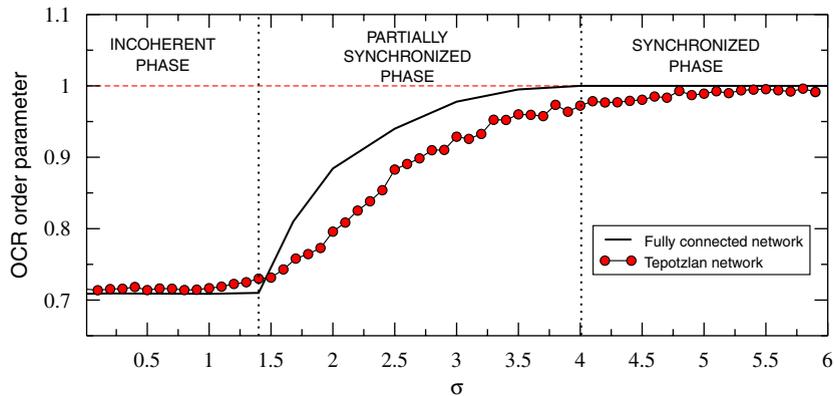
Fig. 1. Phase diagram of the OCR model. The order parameter is reported as a function of the coupling constant for a fully connected system of $N = 1000$ agents (full line) and for the scientific collaboration network under investigation (full circles). In the latter case, an average of over 100 realizations was performed. See text for further details.

opinions. For this reason we called our model: the OCR model [1]. The values ω_i's, which do not depend on time, are distributed in a uniform random way with an average ω_0. In this way we can simulate the behavior of both conservative individuals, characterized by small values of ω_i ($<\omega_0$), and more flexible people, with high values of ω_i ($>\omega_0$). Agents going against the mainstream can be also simulated, by choosing negative values for their *ocr*.

In Ref. [1], we studied the opinion dynamics of the OCR model considering a fully connected network. The numerical simulations were performed typically with $N = 1000$ agents and with a uniform distribution of the initial individual opinions x_i ($t = 0$) in the range $[-1, 1]$. The natural *ocr* ω_i were taken from a uniform distribution in the range [0,1]. By solving numerically the set of ordinary differential equations (1) as a function of the coupling strength σ, we observed a transition from an incoherent phase (for $\sigma < \sigma_c$), in which people tend to preserve different opinions according to their natural rate ω_i, to a partially synchronized phase, where people share a small number of opinions, and, finally, to a fully synchronized one (for $\sigma \gg \sigma_c$) in which all the people change opinion with the same rate and share a common social trend. In order to measure the degree of synchronization of the system, we adopted an order parameter related to the standard deviation of the opinion changing rates and defined as $R(t) = 1 - \sqrt{(1/N)\sum_{j=1}^{N} (\dot{x}_j(t) - \dot{X}(t))^2}$, where $\dot{X}(t)$ is the average over all individuals of $\dot{x}_j(t)$. From such a definition, it follows that $R = 1$ in the fully synchronized phase and $R < 1$ in the incoherent or partially synchronized phase.

In Fig. 1 we report as a full line the asymptotic (stationary) value R_∞ of the order parameter as a function of σ for a fully connected system, as reported in Ref. [1]. A phase transition occurs at $\sigma_c \sim 1.4$. A further analysis of the model showed that in the region $1.5 < \sigma < 2.5$ (belonging to the partially synchronized phase) an equilibrium between conservative and progressist components (a sort of bipolarism) can be observed. Conversely, out of this window, the system rapidly reaches a final configuration consisting of many small opinion clusters (anarchy) or in a single large cluster (complete consensus). Moreover, starting the system with all the agents sharing the same opinion and for $\sigma \sim 1.5$, one observes an interesting kind of metastability: even though we are in the partially synchronized phase, the system relaxes to the partially synchronized state only after a metastable regime, where the opinions remain synchronized. The duration of such a metastable regime was observed to diverge when the value of σ approaches 1.62.

3. The OCR model on a real network of scientific collaboration

In this section we study the dynamical evolution of the OCR model on the topology of a real social network, namely the network of scientific collaborations shown in Fig. 2. Such a network is made of $N = 49$ nodes and $K = 117$ links. The nodes of the network represent some of the people who attended the Tepoztlán conference,
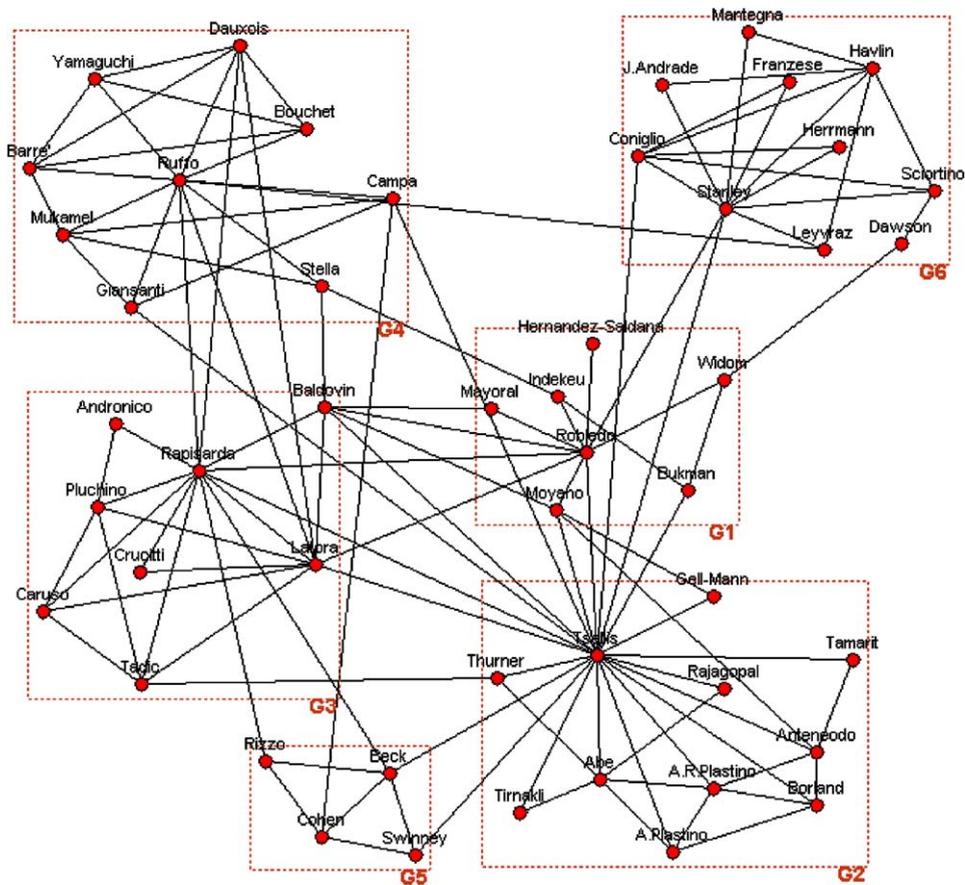
Fig. 2. The graph of the *Tepoztlán Network* (TN). The graph under investigation is inspired by Alberto Robledo's scientific collaboration network. The graph is made of $N = 49$ scientists and $K = 117$ links (between couples of scientists) representing the existence of coauthored publications. The graph shows a clear division in six communities (groups G_1, G_2, G_3, G_4, G_5 and G_6), as indicated by the six squares reporting the results of the GN algorithm [17]. See text for more details.

celebrating Alberto Robledo's 60th birthday, including also other scientists who collaborate with them. For this reason we named it the *Tepoztlán network* (TN). The graph has been constructed by using information on coauthored scientific publications from the cond-mat archive at arXiv.org and from the web engine *Google scholar*. The resulting graph is simple and unweighted [6]. In fact, a link between nodes i and j indicates that the two respective agents share at least one scientific preprint or co-editorship, which reveals the existence of a scientific collaboration. Of course, some links could likely be missing, but it is not very important here if such a network is fully realistic or not. Actually what we want to do is to see how groups of collaborating people "sharing the same opinion" or the same scientific interests evolve in time according to the natural tendency to change opinion (i.e., the natural *ocr*) of their members, the topology of the network and the strength of interaction σ.

In order to find the best modular division of the nodes of the graph into groups or communities (i.e., subsets of nodes which are more densely linked when compared to the rest of the network), we have used the Girvan–Newman (GN) algorithm for the detection of community structures [17]. This is a hierarchical divisive algorithm, based on the progressive removal of the edges with the highest score of *betweenness*, the latter being a measure of the fraction of shortest paths that are making use of a given edge. The GN algorithm produces a hierarchical tree of communities starting with a single community including all the nodes of the graph, and ending into a set of N communities of isolated nodes. But which of these nested subdivisions describes the real community structure of the network?

To answer this question it was introduced the so-called *modularity Q* [17], a variable that quantifies the degree of correlation between the probability of having an edge joining two sites and the fact that the sites belong to the same community. Actually, given an arbitrary network and an arbitrary partition of that network into *n* communities, it is possible to define a $n \times n$ size matrix **e** whose elements e_{ij} represent the fraction of total links starting at a node in partition *i* and ending at a node in partition *j*. Clearly the sum of any row (or column) of **e**, namely $a_i = \sum_j e_{ij}$, corresponds to the fraction of links connected to *i*. For a random network, which does not exhibit any community structure, the expected value of the fraction of links within partitions would be simply the probability that a link begins at a node in *i*, a_i, multiplied by the fraction of links that end at a node in *i*, a_i. So the expected number of intra-community links is just $a_i a_i$. On the other hand, we know that the *real* fraction of links exclusively within a partition is e_{ii}. So, we can compare the two directly and sum over all the partitions in the graph, thus obtaining exactly the definition of modularity:

$$Q \equiv \sum_i (e_{ii} - a_i^2). \tag{2}$$

It is easy to see that if we take the whole network as a single community, or if the network is a random one, we get the minimum value $Q = 0$; on the other hand, values approaching the maximum value $Q = 1$ indicate strong community structure. In practice, however, Q never reaches the value 1 and, for networks with an appreciable subdivision in classes, it usually falls in the range $[0.2, 0.7]$.

If we apply such a method to the TN, we find that the best subdivision is the one in six groups G_1, G_2, G_3, G_4, G_5 and G_6 shown in Fig. 2. This division has the considerable modularity value of $Q = 0.534$. We report the detailed list of the members of the six groups in Table 1. It is noticeable that such a subdivision reproduces quite well (even if not exactly) the real scientific groups of the Tepoztlán collaboration network, at least according to our perception. Thus in the following we will adopt it in order to characterize clusters of agents sharing the same opinion in the context of the OCR model. Now let us integrate model (1) numerically over the TN.

In this case the $x(t)$'s become the opinions of the $N = 49$ agents of the TN at time t and the ω's represent their natural *ocr*. Of course it would be difficult to hazard any hypothesis about the conservative or progressist natural inclinations of the TN people, thus we will randomly choose the ω's from a uniform distribution $\omega_i \in [-0.5, 0.5]$. Finally, as already pointed out before, $\mathbf{K}_i$ and k_i represent, respectively, the neighborhood and the degree of node *i*th.

First of all, starting from a uniform distribution on opinions into $[-1, 1]$, we have verified that also in this case a transition from an homogeneous phase toward a synchronized one occurs around the critical value $\sigma_c \sim 1.4$ of the strength of interaction. Such a behavior is visible in Fig. 1, where we plot with full circles the order parameter R_∞ versus σ for the OCR model on the Tepoztlán network, averaged over 100 realizations and compared with that one obtained for the fully connected network (full line) discussed before. Notice that, in the TN case, the transition is smoother and the curve fluctuates more than the other one. This is due to the small number of nodes of the collaboration network, $N = 49$, if compared to that one of the fully connected system, $N = 1000$. In the next paragraph we will see that a narrow window $1.5 < \sigma < 2.5$ inside the partially synchronized phase results to be the most interesting region of the diagram.

Table 1
List of the six groups G_1, G_2, G_3, G_4, G_5 and G_6 of the Tepoztlán Network, as resulting from the GN algorithm for the detection of community structures [17]

Group 1 (G1)	Bukman, Hernandez-Saldana, Indekeu, Majoral, Moyano, Robledo, Widom
Group 2 (G2)	Abe, Anteneodo, Borland, Gell-Mann, A. Plastino, A.R. Plastino, Rajagopal, Tamarit, Thurner, Tirnakli, Tsallis
Group 3 (G3)	Andronico, Baldovin, Caruso, Crucitti, Latora, Pluchino, Rapisarda, Tadic
Group 4 (G4)	Barré, Bouchet, Dauxois, Campa, Giansanti, Mukamel, Ruffo, Stella, Yamaguchi
Group 5 (G5)	Cohen, Beck, Rizzo, Swinney
Group 6 (G6)	J. Andrade, Coniglio, Dawson, Franzese, Havlin, Herrmann, Leyvraz, Mantegna, Sciortino, Stanley

The groups are the same as those indicated by dashed squares in Fig. 2. See text for details.

3.1. Evolution of an initial state of synchronized opinions

In Fig. 3 we show the time evolution of the Tepoztlán network community for $\sigma = 2.0$ and for an initial state with all the members sharing the same opinion $x_i(0) = 0 \ \forall i$. The natural *ocr* have been randomly chosen again in the range $\omega_i \in [-0.5, 0.5]$. In panels (a) and (b) we plot the evolution of the opinions and of the opinion changing rates over 100 time steps (please notice that the uniformly distributed natural *ocr* ω_i also represent the initial conditions for the *ocr* variables $\dot{x}_i(t)$). We can see that, after an initial short metastable transient in which both the opinions and the opinions changing rates stay synchronized (in fact $R(t) \sim 1$, as shown in panel (f)), the system rapidly clusterizes with a branching process strongly affected by the topology of the network. The respective asymptotic stationary configurations of clusters are shown in panels (d) and (e). Finally, in panel (c) the step-by-step modularities Q for both the opinion clusters configurations (dashed line) and the *ocr* clusters configurations (full line) are also reported. From the value $Q = 0$ that characterizes the metastable configuration with only one large cluster, both modularities increase to a value $Q \sim 0.44$ in the asymptotic stationary state (d) and (e). It is important to notice that these two final configurations, since they are time invariant, must necessarily consist of the same number of clusters (even if arranged in a different order) with the same people inside, otherwise they would be dynamically unstable.
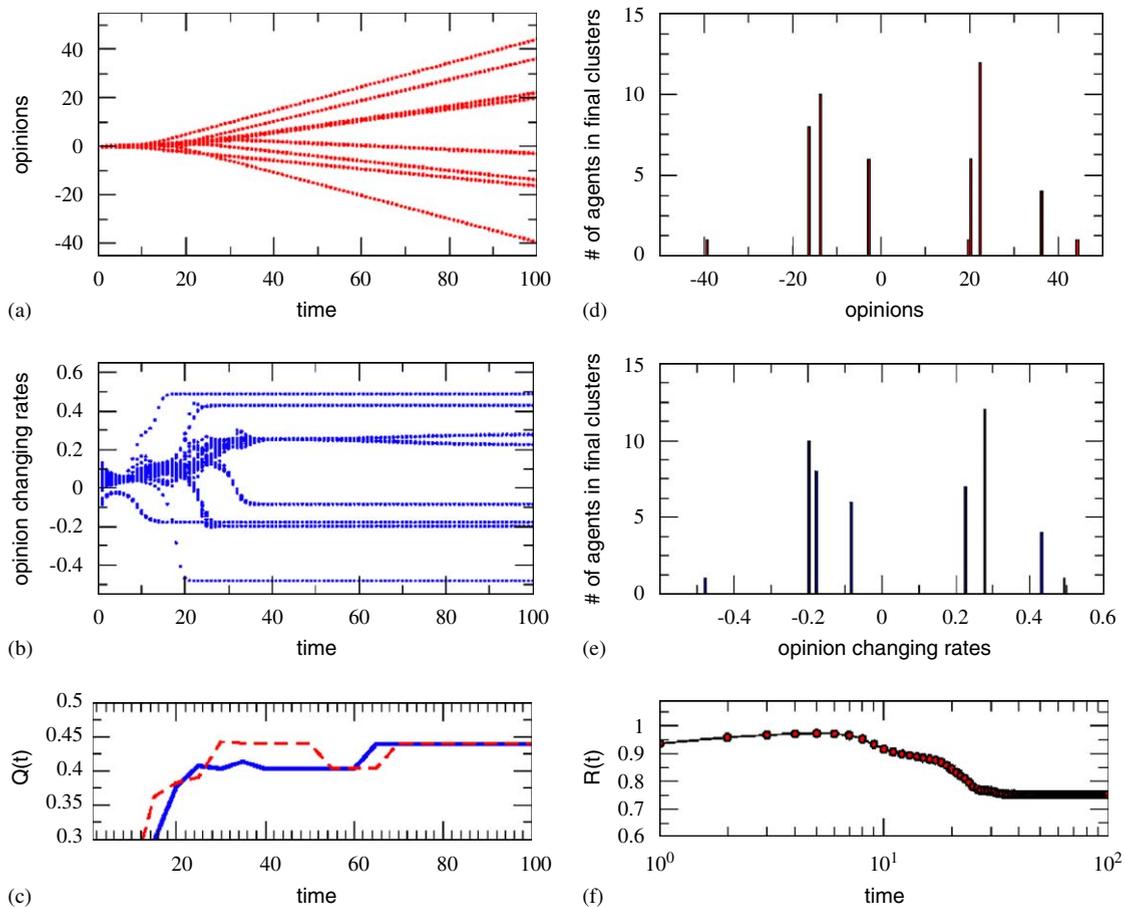

Fig. 3. Dynamical time evolution of groups synchronization in the OCR model on the Tepoztlán Network for $\sigma = 2.0$ (one realization). Starting from a metastable synchronized initial condition in the opinion space, in panel (a) groups are spontaneously formed with components similar to that ones of the previous figure. In panel (b) the corresponding ocr time evolution is plotted. The modularity $Q(t)$ defined in Eq. (2) is plotted vs time in panel (c) for the opinions (dashed line) and ocr (full line). In (d) and (e) the asymptotic cluster distribution of panels (a) and (b) are plotted, respectively. Finally in panel (f) the time evolution of the order parameter R is plotted. See text for further details.

Table 2
Asymptotic clusters configuration shown in Fig. 3(e)

Group 1 (0.49)	Sciortino (0.49)
Group 2 (0.43)	Abe (0.49), Campa (0.42), Rajagopal (0.38), Tirnakli (0.28)
Group 3 (0.28)	Andronico (−0.28), Baldovin (0.34), Caruso (−0.20), Crucitti (0.21), Latora (0.40), Pluchino (0.32), Rapisarda (0.34), Tadic (0.41), Beck (0.07), Cohen (0.40), Rizzo (0.08), Swinney (0.42)
Group 4 (0.23)	Bukman (0.17), Indekeu (0.36), Widom (0.47), Stella (0.19), Dawson (−0.07), A.R. Plastino (0.15), Mukamel (0.26)
Group 5 (−0.08)	Barré (−0.07), Bouchet (0.01), Dauxois (0.28), Giansanti (−0.12), Ruffo (−0.16), Yamaguchi (0.12)
Group 6 (−0.17)	J. Andrade (−0.46), Coniglio (−0.11), Franzese (−0.32), Havlin (−0.04), Herrmann (−0.21), Leyvraz (−0.37), Mantegna (0.21), Stanley (−0.21)
Group 7 (−0.20)	Anteneodo (−0.20), Borland (−0.24), Gell-Mann (−0.23), Tamarit (−0.40), Thurner (−0.30), Tsallis (−0.19), Hernandez-Saldana (−0.28), Majoral (−0.27), Moyano (−0.03), Robledo (−0.17)
Group 8 (−0.48)	A. Plastino (−0.48)

The interesting result of the simulation is that the clusters of panels (d) and (e) show a good overlap with the real communities of the TN shown in Fig. 2. This can be verified comparing the groups' structure of Table 1 with that one reported in Table 2, representing the final clusters configuration of the *ocr* plotted in panel (e). In correspondence with each group in Table 2 the *ocr* value of the cluster is reported, together with the natural *ocr* of each member of the cluster itself (notice that the *ocr* of each cluster is rather close to the average of the ω's of its members). It is important to stress that people in each final cluster, evidently due to the strong influence of the network topology on the mutual interactions, manage to maintain synchronized opinions *despite* their different natural inclinations ω_i (see panel (a)). On the other hand, during the branching evolution, people with similar ω_i tend to merge together in the same cluster while people with very different ω_i tend to escape from a given cluster (see panel (b)). The competition between these two opposite effects can explain why some of the groups well distinct in Table 1, merge in Table 2 (e.g. G1–G2 or G3–G5), why new groups come up (see Group 2 in Table 2) and why agents with a very high absolute value of ω run alone at the extremes of the *ocr* range. Consequently, the resulting modularity of the asymptotic clusters configuration shown in Table 2 ($Q\sim0.44$) is smaller than the modularity of the "real" configuration ($Q = 0.53$).

We checked that even if the details of the simulation of Fig. 3 change for different runs with different random realizations of $\omega_i \in [-0.5, 0.5]$, and the final modularity can vary too, the global picture described before remains qualitatively the same, provided that the interaction strength would stay around $\sigma = 2.0$. For values noticeably higher or lower than 2.0 the system, respectively, either remains synchronized forever or quickly explodes in very small clusters.

3.2. Evolution of the coauthorship groups in the opinion space

In this subsection we want to explore what happens if we start the system with six different clusters of synchronized opinions corresponding to the six real communities of the TN, in order to see how the OCR dynamics affects the stability of the groups. Of course, in this case also, the details of the simulations will depend on the initial distribution of the ω's. But, again, we are mainly interested in studying the global picture emerging from the dynamical competition between the different natural *ocr* of the agents in each group and the opinion constraints imposed by the topology of the network.

In the simulation shown in Fig. 4 we set again $\sigma = 2$. Then we chose, for each one of the six groups of Table 1, a different initial opinion, common for all its members, while the natural rates ω's were randomly selected in the range $[-0.2, 0.2]$. The initial opinion of each group is reported in Table 3. Like in the previous section, in panels (a) and (b) of Fig. 4 we show the time evolution of the opinions $x_i(t)$ and the ocr $\dot{x}_i(t)$, while in panel (c) the respective modularities are plotted. Finally, in panels (d) and (e), we show the asymptotic clusters configuration for both the opinions and the *ocr*, and in panel (f) the time behavior of the order parameter $R(t)$ is reported.

Let us follow the time evolution of the opinion clusters in panel (a) of Fig. 4 along 200 time steps. One can see that groups G1 and G2 merge at $t\sim120$, due to their initial position and to their similar average *ocr*. Almost immediately a fast agent (Campa, with $\omega = 0.16$) leaves the group G4 and goes ahead to its natural
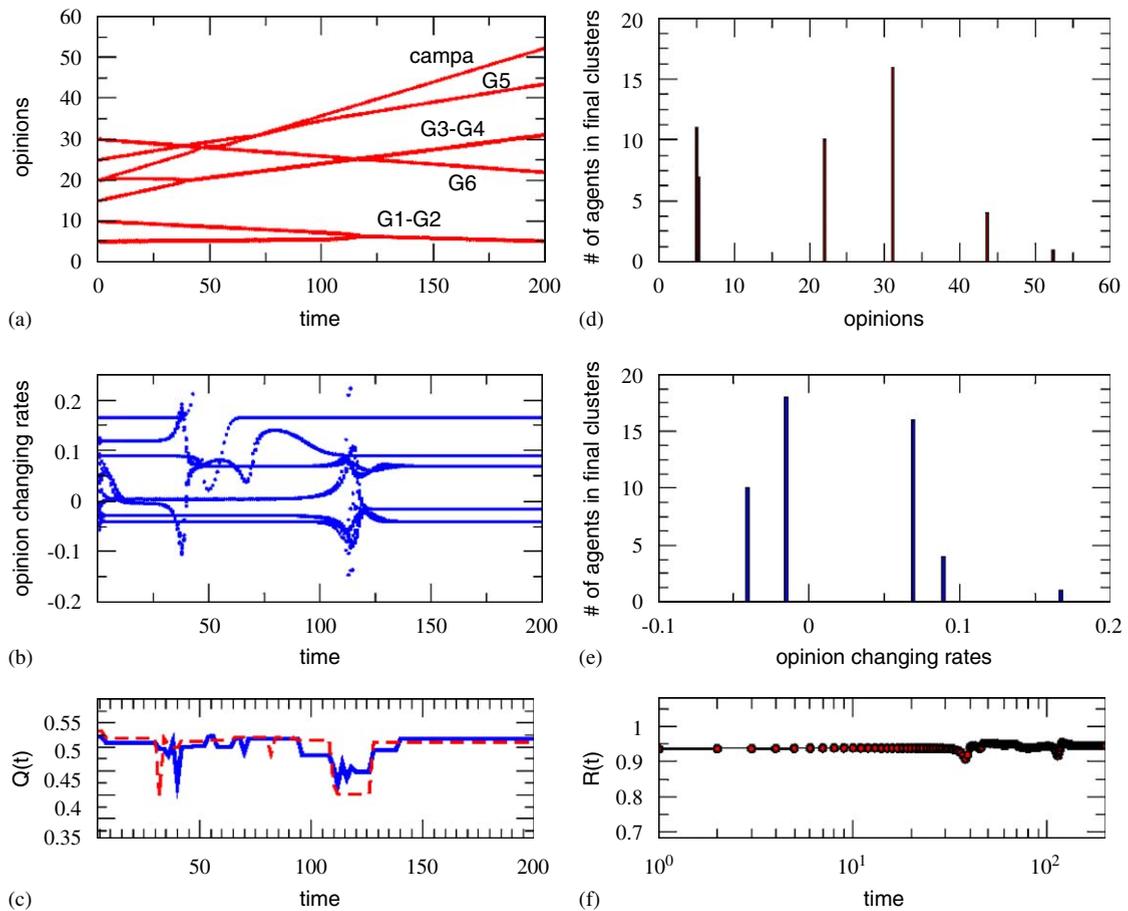
Fig. 4. Time evolution of the OCR model on the Tepoztlán collaboration network. In the opinion space (a) the agents start into six synchronized groups corresponding to the six communities of Table 1, from G1—at the bottom with $x(0) = 5$—to G6—at the top with $x(0) = 30$—(see also Table 3). On the other hand, the agents' natural rates (i.e., the initial conditions in panel (b)) are randomly chosen. See caption of the previous figure and text for further details.

Table 3
Initial position of the six real groups in the opinion space, see Fig. 4(a)

G1: $x(0) = 5$	Bukman, Hernandez-Saldana, Indekeu, Majoral, Moyano, Robledo, Widom
G2: $x(0) = 10$	Abe, Anteneodo, Borland, Gell-Mann, A. Plastino, A.R. Plastino, Rajagopal, Tamarit, Thurner, Tirnakli, Tsallis
G3: $x(0) = 15$	Andronico, Baldovin, Caruso, Crucitti, Latora, Pluchino, Rapisarda, Tadic
G4: $x(0) = 20$	Barré, Bouchet, Dauxois, Campa, Giansanti, Mukamel, Ruffo, Stella, Yamaguchi
G5: $x(0) = 25$	Cohen, Beck, Rizzo, Swinney
G6: $x(0) = 30$	J. Andrade, Coniglio, Dawson, Franzese, Havlin, Herrmann, Leyvraz, Mantegna, Sciortino, Stanley

ocr, resisting alone until the end of the simulation (see Table 4). Meanwhile, what remains of G4 merges with G3 at $t = 38$, and at $t = 120$ the new resulting group survives to the collision with G6, already survived to previous superpositions with G5 and Campa around $t = 50$. On the other hand, looking at panel (b), the ocr follow a more pronounced branching evolution, where the agents rearrange their *ocr* until a final stationary state is reached. However, as previously stressed, the asymptotic configurations shown in panels (d) and (e) must be the same. Notice that the two main rearrangements in panel (b), around $t \sim 50$ and $t \sim 120$, correspond to the main cluster collisions in panel (a) and also to the sudden falls of modularity in panel (c).

Table 4
Final positions and configurations of the clusters in Fig. 4(d)

Group 1: $x(200) = 5.05$	Bukman (0.07), Hernandez-Saldana (−0.11), Indekeu (0.15), Majoral (−0.10), Moyano (−0.01), Robledo (−0.07), Widom (0.19), Abe (0.20), Anteneodo (−0.08), Borland (−0.09), Gell-Mann (−0.09), A. Plastino (−0.19), A.R. Plastino (0.06), Rajagopal (0.15), Tamarit (−0.16), Thurner (−0.12), Tirnakli (0.11), Tsallis (−0.07)
Group 2: $x(200) = 21.95$	J. Andrade (−0.18), Coniglio (−0.05), Dawson (−0.03), Franzese (−0.13), Havlin (−0.01), Herrmann (−0.08), Leyvraz (−0.14), Mantegna (0.08), Sciortino (0.20), Stanley (−0.08)
Group 3: $x(200) = 31.02$	Andronico (−0.11), Baldovin (0.13), Caruso (−0.08), Crucitti (0.08), Latora (0.16), Pluchino (0.12), Rapisarda (0.14), Tadic (0.17), Barré (−0.02), Bouchet (0.00), Dauxois (0.11), Giansanti (−0.04), Mukamel (0.10), Ruffo (−0.06), Stella (0.07), Yamaguchi (0.05)
Group 4: $x(200) = 43.54$	Cohen (0.16), Beck (0.02), Rizzo (0.03), Swinney (0.17)
Group 5: $x(200) = 52.33$	Campa (0.16)

In Table 4 we report the detailed composition of the asymptotic opinion clusters of panel (d), together with their position in the opinion space. Comparing it with the starting configuration of Table 3, we see that the real groups of the TN are quite stable, at least for $\sigma = 2$, despite the random choice of the natural changing rates of their members. Apart from one agent of group G4, and apart from a couple of fusions (G1–G2 and G3–G4), the structure of the groups seems to have been preserved by the dynamics, surviving to various collisions in the opinion space. This is confirmed by the final modularity $Q = 0.51$, not much smaller then the original one $Q = 0.53$, and also by the constant behavior of the order parameter in panel (f). Changing the initial distribution of *ocr*, the evolution of the each member can change, but the qualitative behavior is the same.

4. Conclusions

In this paper we have discussed opinion dynamics in a real social network, by considering the OCR model introduced in Ref. [1]. In particular, we have investigated a network of scientific coauthorship, inspired to Alberto Robledo's collaborations. The results demonstrate that the topology of the network is a fundamental ingredient in the opinion dynamics and in the evolution of the composition of scientific groups. The use of the OCR model seems very promising for studying the dynamics of opinion formation. Further analysis with different kinds of networks are in order to draw more definitive conclusions.

References

[1] A. Pluchino, V. Latora, A. Rapisarda, Int. J. Mod. Phys. C 16 (4) (2005) 515–531.
[2] L.D. Kiel, E. Elliot, Chaos Theory in the Social Sciences, University of Michigan Press, 1996;
    L. Tesfatsion, Economic agents and markets as emergent phenomena, PNAS 99 (2002) 7191–7192;
    J.M. Epstein, R. Axtell, Growing Artificial Societies, MIT Press, Cambridge, MA, 1996;
    W.B. Arthur, S.N. Durlauf, D.A. Lane, The Economy as an Evolving Complex System II, Addison-Wesley, Reading, MA, vol. XXVII;
    R. Axelrod, J. Conflict Resolut. 41 (1997) 203;
    S. Fortunato, On the Consensus Threshold for the Opinion Dynamics of Krause-Hegselmann, cond-mat/0408648 at ⟨www.arXiv.org⟩, Int. J. Mod. Phys. C 16(2) (2005), to appear.

[3] In praise of soft science, Nature 435(7045) (2005) 1003 (editorial).

[4] R. Albert, A.-L. Barabási, Rev. Mod. Phys. 74 (2002) 47.

[5] M.E.J. Newman, SIAM Rev. 45 (2003) 167.

[6] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, D.-U. Hwang, Phys. Rep. 424 (2006) 175 and refs. therein.

[7] D. Stauffer, Sociophysics Simulations (2003) in 'Computer Simulations', co-published by the IEEE CS and the AIP D. Stauffer, Sociophysics Simulations II: Opinion Dynamics, 2005, arXiv:physics/0503115.

[8] R. Hegselmann, U. Krause, J. Artif. Soci. Soc. Simulation 5 (3) (2002) jasss.soc.surrey.ac.uk (paper 2).

[9] K. Sznajd-Weron, J. Sznajd, Int. J. Mod. Phys. C 11 (2000) 1157;
    G. Deffuant, D. Neau, F. Amblard, G. Weisbuch, Adv. Complex Syst. 3 (2000) 87;
    S. Galam, Physica A 336 (2004) 49 and refs. therein.

[10] E. Ben-Naim, P. Krapivsky, S. Redner, Physica D 183 (2003) 190.

[11] A.T. Bernardes, D. Stauffer, J. Kertsz, Eur. Phys. J. B 25 (2002) 123–127;
    M.C. Gonzales, A.O. Sousa, H.J. Herrmann, Int. J. Mod. Phys. C 15 (1) (2004) 1–13;
    D. Stauffer, Montecarlo simulations of the Sznajd model, J. Artif. Soci. Soc. Simulations 5 (1) (2002).

[12] S. Fortunato, V. Latora, A. Pluchino, A. Rapisarda, Int. J. Mod. Phys. C 16 (2005) 1535;
    A. Pluchino, V. Latora, A. Rapisarda, Eur. Phys. J. B 50 (2006) 169.

[13] S. Boccaletti, J. Kurths, D.L. Valladares, G. Osipov, C.S. Zhou, Phys. Rep. 366 (2002) 1.

[14] Y. Kuramoto, in: H. Araki (Ed.), International Symposium on Mathematical Problems in Theoretical Physics, Lecture Notes in Physics, vol. 39, Springer, Berlin, 1975.

[15] Y. Kuramoto, Chemical Oscillations, Waves, and Turbulence, Springer, Berlin, 1984.

[16] S.H. Strogatz, Physica D 143 (2000) 1.

[17] M. Girvan, M.E.J. Newman, Paroc. Natl. Acad. Sci. USA 99 (2002) 7821;
    M.E.J. Newman, M. Girvan, Phys. Rev. E 69 (2004) 026113.