Physica A 415 (2014) 220–228

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

A novel opinion dynamics model based on expanded observation ranges and individuals' social influences in social networks

Su-Meng Diao[a,b], Yun Liu[a,b,*], Qing-An Zeng[c], Gui-Xun Luo[a,b], Fei Xiong[a,b]

[a] *School of Communication and Information Engineering, Beijing Jiaotong University, Beijing 100044, China*

[b] *Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education, Beijing Jiaotong University, Beijing 100044, China*

[c] *Department of Computer Systems Technology, North Carolina A&T State University, Greensboro, NC 27411, USA*

HIGHLIGHTS

- A model to study the dynamics of the opinion evolution process is proposed.
- The observation range of an individual is expanded, and an affected individual receives social impact from supporter and opponent participants.
- A tradeoff of relaxation time can be found between high interaction intensity and low stability.
- Social influence is introduced to highlight the heterogeneity of individuals.
- The distribution of individuals' social influences when convergence is reached is the power-law.

ARTICLE INFO

Article history:
Received 4 April 2014
Received in revised form 18 July 2014
Available online 2 August 2014

Keywords:
Opinion dynamics
Social influence
Social impact
Observation range

ABSTRACT

In this paper, we propose an opinion dynamics model in order to investigate opinion evolution and interactions and the behavior of individuals. By introducing social influence and its feedback mechanism, the proposed model can highlight the heterogeneity of individuals and reproduce realistic online opinion interactions. It can also expand the observation range of affected individuals. Combining psychological studies on the social impact of majorities and minorities, affected individuals update their opinions by balancing social impact from both supporters and opponents. It can be seen that complete consensus is not always obtained. When the initial density of either side is greater than 0.8, the enormous imbalance leads to complete consensus. Otherwise, opinion clusters consisting of a set of tightly connected individuals who hold similar opinions appear. Moreover, a tradeoff is discovered between high interaction intensity and low stability with regard to observation ranges. The intensity of each interaction is negatively correlated with observation range, while the stability of each individual's opinion positively affects the correlation. Furthermore, the proposed model presents the power-law properties in the distribution of individuals' social influences, which is in agreement with people's daily cognition. Additionally, it is proven that the initial distribution of individuals' social influences has little effect on the evolution.

* Corresponding author at: Key Laboratory of Communication and Information Systems, Beijing Municipal Commission of Education, Beijing Jiaotong University, Beijing 100044, China. Tel.: +86 1051684227.

E-mail addresses: diao.simon@gmail.com (S.-M. Diao), liuyun@bjtu.edu.cn (Y. Liu), qzeng@ncat.edu (Q.-A. Zeng), luoguixun@gmail.com (G.-X. Luo), xiongf@bjtu.edu.cn (F. Xiong).

http://dx.doi.org/10.1016/j.physa.2014.07.072
0378-4371/

1. Introduction

In recent years, social network services have become the most significant medium for information sharing and dissemination. Many researchers, including statistical physicists and sociophysicists, have made significant contributions to this field. By using theoretical models and experimental methods, sociological phenomena, such as information diffusion and opinion evolution, have been elaborated and analyzed [1–3], and the idea and concept of interdisciplinary research, such as the combination of complex networks, statistical physics, and evolutionary games, have been adopted and applied [4–7].

Opinion dynamics [1,8,9] is one of the most effective methods to model the spread and evolution of opinions in a multi-agent society by using the Monte Carlo simulation method. Each individual is considered to be an agent holding continuous or discrete opinions in favor of one decision or choice, and each individual interacts with others and tries to persuade or impact others dynamically through his/her opinion.

Several opinion dynamics models have been proposed and can be classified into three main groups: (1) discrete opinions models; (2) continuous opinions models; and (3) continuous opinions and discrete actions models (CODA model). The Sznajd model [10,11] and voter model [12,13] are the most significant representations of discrete opinion models, in which individuals hold binary opinions using Ising spins [14], which are used to model ferromagnetism with ferromagnetic spins in solid-state physics. The generalization, improvement, and applications are further studied in Refs. [13,15–18]. Moreover, the innovative diffusion model combining benefit-driven evolutionary games and discrete behaviors has been proposed to investigate the dynamics of human innovative behaviors [19]. In the second group, the Deffuant model [20] and Hegselmann–Krause model [21] use continuous opinions to evaluate the performances of agents. Continuous opinions are able to quantify the desire of a specified choice for each individual. In the final group, however, each agent shows his/her discrete behavior and carries a continuous opinion updated by observing others' discrete actions [22–24]. The CODA model is a more realistic model and has been attracting increasing attention [25–29]. By differentiating between opinions and actions, the update rule of CODA allows the agents to rationally analyze the observations and their own situations, instead of simply following a flip and follow pattern with no memories. The effect of selective attention, which is described by individual relevance and time-openness, is studied to improve the interactions and updating of individuals' opinions [25]. Selective attention provides a possible explanation for the appearance of large clusters consisting of a set of tightly connected individuals who hold similar opinions. A joint evolution of opinions and trust among individuals is introduced in Ref. [27]. A bounded confidence mechanism and distant observation are introduced by opinion diffusion models in Refs. [21,29–31]. To implement Bayesian posterior estimation, however, the confidence associated with the behaviors of neighbors who represent the degree of being affected is presumed to be constant. This is somehow oversimplified. It appears that individuals in a social network are heterogeneous [32].

As a model of online opinion dynamics, update rules and evolution should take the reproduction and reflection of realistic social phenomenon into primary consideration. The distinction among update rules has the potential to bring out different perspectives and emphases. Many studies are focused on opinion interactions between neighbors, where individuals change their opinions by comparing the differences among each other. However, the process of persuasion and interaction between two adjacent neighbors is overemphasized in many models [11,17,19,28]. In contrast, individuals are more likely to take a wider perspective of their surroundings. Despite the possibly vital role of a certain opinion leader, individuals are inclined to join a discussion of several people and to accept the impact of not only conversion from differences but also enhancement from similarities.

In this paper, an opinion dynamics model considering the social influence, feedback, and accumulation of each individual is proposed by combining psychological studies on the social impact of majorities and minorities [33]. Unlike the classic models mentioned above where an individual is affected by one specified adjacent neighbor, each individual in the proposed model observes the behavior of a number of individuals before he/she updates his/her opinion and makes a decision. Moreover, the persuasion from the opposing sides are accepted and can affect the final decision, and the influence of each persuader and its closeness to the affected individual are taken into consideration in distinguishing the impact of different persuaders. In this paper, we study opinion evolution by using the proposed model. From the perspective of opinion evolution, a complete consensus is not always obtained according to the density of individuals' initial behaviors. When the initial density of either side is greater than 0.8, the enormous imbalance leads to complete consensus. In other circumstances, opinion clusters consisting of a set of tightly connected individuals who hold similar opinions appear. The impact of the observation range and individuals' social influence are analyzed. It can be seen that the observation range of individuals is significantly related to the interaction intensity and opinion stability. Both interaction intensity and opinion stability can speed up the evolution process. Extensive simulations and analysis show that the interaction intensity decreases as the observation range of individuals increases, while the opinion stability increases. Moreover, the stability tends to stabilize when the observation range is large enough. Therefore, a tradeoff between high interaction intensity and low stability is exposed. In addition to the observation range, the social influence of individuals plays a major role in the dynamics of diffusion. When opinion evolution reaches convergence, the distribution of individuals' social influence follows the power-law; however, the initial distribution of individuals' social influence has little effect on opinion evolution.

2. Proposed model

To investigate opinion evolution and the diffusion of individuals clearly and distinctly, the proposed model is simplified on some reasonable bases. When facing a certain isolated question, each individual chooses between binary strategies:

support (A) or oppose (B) [10,12]. Moreover, the outer action is a true reflection of the inner opinion for an individual in that it can be observed by others [22]. In other words, each individual updates his/her continuous opinions based on the observation of others' outer actions. To indicate the bias of an individual, the odds in favor of accepted strategy (Odd_A) is utilized [23], which is defined as a ratio between the preference of support [$p_A \in (0, 1)$] and the preference of opposition [$p_B \in (0, 1)$] with a limitation of $p_A + p_B = 1$, which is given by:

$$Odd_A = \frac{p_A}{p_B} = \frac{p_A}{1 - p_A}. \tag{1}$$

We assume that the outer action of an individual intuitively reflects the inner opinion. More specifically, an individual displays supporting behavior for an odds favor that is bigger than 1, and opposing behavior for an odds favor that is less than 1, respectively.

To make more rational decisions, rather than simply interacting with a single neighbor, each individual takes a wide perspective of his/her surroundings and observes the outer actions of a group of n individuals who are selected from the overall population. In this group, persuaders can be divided into two groups in terms of their outer actions, namely, support and opposition. The social impact of both groups can be calculated by the psychological results of the social impact of majorities and minorities [34]. All sources are presumed to be heterogeneous and their impacts vary with respect to the strength and immediacy to destinations. Therefore, the influence and closeness of each persuader are introduced to calculate the social impact on a single individual, given by:

$$SI_{i,x} = N_{p,x}^{\frac{1}{2}} \sum_{j=1}^{N_{p,x}} \frac{\inf_j}{d_{ij}^2} / N_{p,x}, \quad (x \in \{A,\ B\}) \tag{2}$$

where i is an affected individual, x is the orientation of outer actions, $N_{p,x}$ is the population of persuaders displaying the outer action x, $\inf_j$ is the social influence of the persuader j, and d_{ij} is the distance between the affected individual and the persuader. In online social networks, information disseminate along online social relationships. Therefore, the distance can be calculated as the shortest hop to reach others through online friends. As an interpretation of Eq. (2), the social impact of a group of persuaders with the same orientation on a single individual is the average persuasive intensity affected by each persuader multiplied by the square root of the group size. The persuasive intensity is presented by the social impact of each persuader weighted by social closeness, which is the inversion of the square distance. The social support impact SI_A and social opposition impact SI_B are thus obtained.

After observing the surrounding situation and being affected by others' social impact, individuals update their opinions. To overcome the ambiguity of using models where individuals interact with an adjacent neighbor [17,19], an update role considering the impact of both support and opposition is proposed. From the perspective of affected individuals, persuasion from both sides has some effect. A preference for support is expanded after being persuaded by supporters. Likewise, a preference for opposition is also expanded after being persuaded by opponents. Therefore, the approval on both supportive and opponent sides shows an upturn. The balance of preferences on both sides is actually the odds in favor of accepting a strategy. Thus, the update rules at step $n + 1$ are presented as:

$$Odd_A(n+1) = Odd_A(n) \cdot \frac{1 + P\left(SI_A, n\right)}{1 + P\left(SI_B, n\right)} = \frac{p_A(n)}{1 - p_A(n)} \cdot \frac{1 + P\left(SI_A, n\right)}{1 + P\left(SI_B, n\right)} \tag{3}$$

where $P(SI_x)$ is the proportion of the social impact of strategy x and is defined as follows:

$$P\left(SI_x\right) = \frac{SI_x}{SI_A + SI_B}, \quad (x \in \{A, B\}). \tag{4}$$

The evolution algorithms of the proposed model can be described by the following steps:

(1) In a social graph with a population of N nodes, each node i represents an individual who has a continuous opinion $p_{i,A}$ and social influence $\inf_i$ towards a topic. Assume that each individual shows binary action X_i epitomizing his major opinion.

$$X_i = \begin{cases} A, & \text{if } Odd_{i,A} \geq 0.5 \\ B, & \text{otherwise.} \end{cases} \tag{5}$$

In the initial condition at time step 0, each node takes an arbitrary opinion and influence.

(2) For each update of node i, a group of N_p persuaders ($N_{p,A}$ supporters and $N_{p,B}$ opponents) is chosen randomly and globally. Thereby, social support impact $SI_{i,A}$ and social opposition impact $SI_{i,B}$ on node i can be calculated by Eq. (2). Especially, the distance between the affected individual and the persuader d_{ij} is calculated as the shortest hop to reach others through adjacent neighbors.

(3) The odds in favor of accepting strategy $Odd_{i,A}$ are updated by Eq. (3). This process leads to opinion dynamics or even selection jump.

(4) After each opinion update process, persuaders receive positive influence feedback based on their contributions to the social persuasiveness impact if they persuade successfully. More specifically, the influence of the affected node that changes the outer action as well as the inner opinion after one update process will be cut down and provide feedback to persuaders who convert the affected node. The feedback process is presented as:

$$\text{for each } j \in N_{p,X_j(n+1)} \quad \text{if } X_i\,(n+1) \neq X_i\,(n)$$
$$\inf_j\,(n+1) = \inf_j\,(n) + \Delta \cdot \frac{\inf_j(n)/d_{ij}^2}{\sum_{k=1}^{N_{p,X_j(n+1)}} \inf_k(n)/d_{ik}^2}. \tag{6}$$

(5) Repeat step (2) through step (4) until convergence is reached.

3. Simulation and discussions

In this section, we conduct computer simulations to meticulously investigate the evolution process and the behaviors of individuals based on the proposed opinion dynamics model. We focus on the impact of initial density, observation range and the social influence of each individual on opinion propagations.

We perform Monte Carlo simulations on an artificial network constituted by $L \times L$ square lattices with the periodic boundary condition. In this network, each node i holds a random initial value, namely, opinion $p_{i,A}(0)$ and social influence $\inf_i(0)$. In each step, every node is chosen as an affected node to update his/her opinion via Eq. (3). The observation of an affected node is a population of N_p nodes randomly selected from the entire network randomly. The distance between two nodes d_{ij} is evaluated by the shortest hops. After each interaction, successful persuaders receive social influence feedback via Eq. (6). The dynamics process runs repeatedly until it reaches convergence.

3.1. Initial density of individuals' outer actions

Without external forces acting on the system, the initial density of individuals' outer actions has a direct influence on the consensus of the final state [15,16]. Meanwhile, the introduction of social influence and social impact inversely proportional to distances causes clusters to form. The opinion evolution of individuals' outer actions with different initial densities is shown in Fig. 1(a). A phase transition at $d = 0.5$ is described. When $d < 0.5$, the system converges towards a negative status in which all individuals adopt opposing strategies, and vice versa for $d > 0.5$. Moreover, the steady states indicate that a complete dictatorship is not always obtained. As shown in Fig. 1(b), situations with $d < 0.2$ and $d > 0.8$ reach total consensus when the evolution reaches convergence, whereas $d > 0.2$ and $d < 0.8$ do not. Therefore, only enormous advantages lead to total consensus. In other circumstances, opinion clusters consisting of a set of tightly connected individuals who hold similar and stable opinions emerge and distribute themselves across the system. Additionally, the number, strength and area of clusters grow with as the differences between the initial density of support and opposition decrease. As shown in Fig. 1, the average density of final supporters when $d = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8$, and 0.9 are 0, 1, 56, 217, 511, 813, 970, 1023, and 1024, respectively.

3.2. Observation range of affected individuals

In the proposed model, affected individuals overcome blindness and make rational decisions by taking a wide perspective of their surroundings rather than following one of their adjacent neighbors. Empirically in everyday life, people are more inclined to collect relevant information before making decisions, despite the potential vital impact of one powerful leader. Additionally, the preferences of topic participants should be lessened by opponents as well as enhanced by supporters.

However, the ability and cost of information collection limit the observation range of affected individuals. To investigate the impact of the observation range on the opinion interaction process in greater detail, the number of individuals being successfully persuaded is examined. This not only attributes to the persuaders in an actual step but also reflects a cumulative impact of historical interactions. The distribution is shown in Fig. 2 when N_p equals 10, 20, 40, and 60, respectively. From an overall perspective, dramatic interactions among individuals take place at the beginning and slight decays persist until reaching convergence. Additionally, the rate of successful persuasions is closely related to N_p, the observation range of individuals. The narrower the observation an individual takes, the bigger the change that his/her inner opinion undergoes. As a possible interpretation, with a larger N_p, an individual has a wider perspective on the overall situation which is able to help him/her make an objective decision. It is also consistent with the fact that people with wide visual fields appear highly confident and rarely alter their behavior.

The differences in individuals' outer actions versus their final status are shown in Fig. 3 with an average of 100 simulations of size $L = 32$ regular lattice, while N_p equals 10, 20, 40, and 60, respectively. Similarly, significant changes occur at the very beginning, and nearly reach a stable status in 5×10^4 steps. It is found that individuals with large observation ranges N_p have the advantage of drawing to a stable status early on, while individuals with a small N_p catch up at a late stage of diffusion.

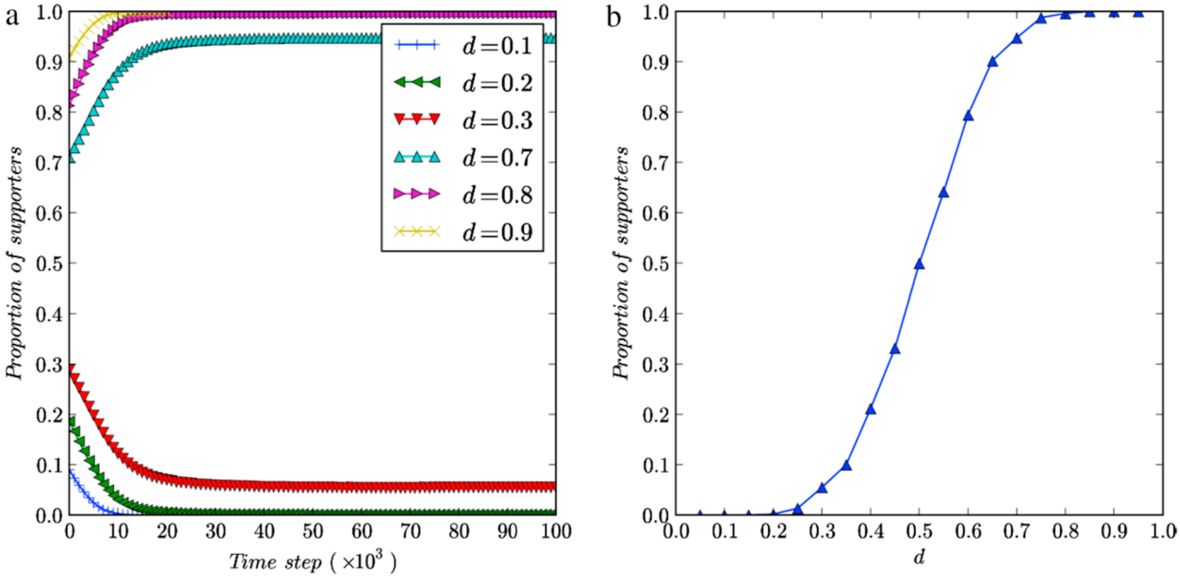

Fig. 1. (a) Opinion evolution of the proportion of supporters when initial densities of support strategy $d = 0.1, 0.2, 0.3, 0.7, 0.8$ and 0.9, respectively. (b) The distribution of the density of final supporters. Both are obtained from 200 simulations for $L = 32$ and $N_p = 30$, with $\inf_i(0)$ following uniform distributions in (0, 10).

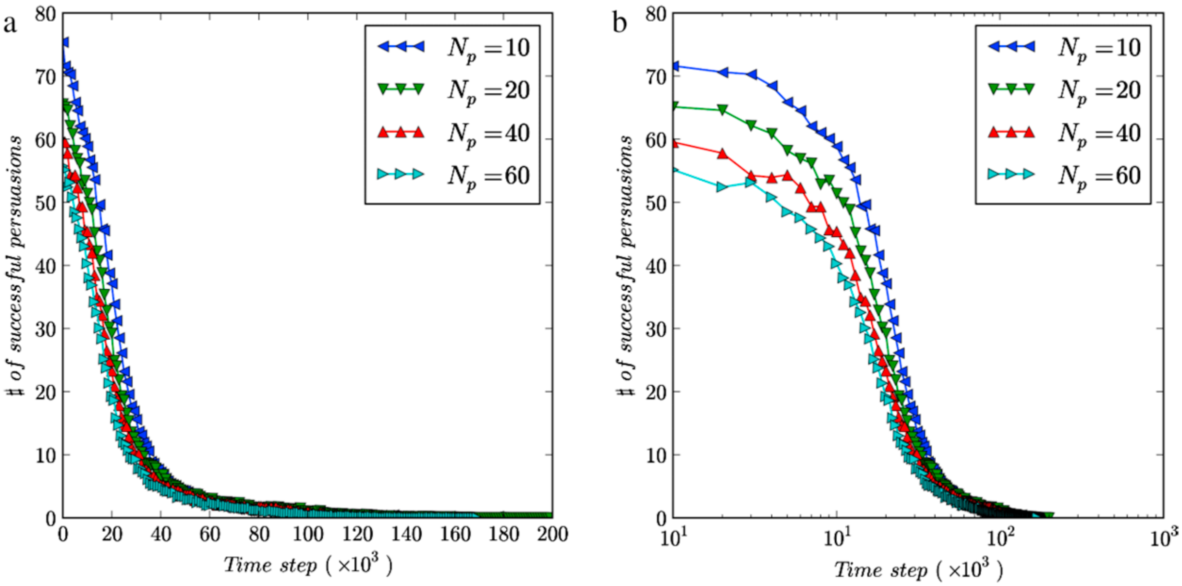

Fig. 2. The number of successful persuasions at each 10^3 time step with observation range $N_p = 10, 20, 40,$ *and* 60 for $L = 32$, obtained from 100 samples, with $p_{i,A}(0)$ and $\inf_i(0)$ following uniform distributions with an interval (0, 1) and (0, 10), respectively. Fig. 2(a) shows a linear plot and Fig. 2(b) shows a semi-log plot.

More specifically, contrary to the tendency to be successfully persuaded, individuals with a narrower observation range, i.e., a smaller N_p, have fewer similarities with the stable status at several initial steps in spite of experiencing dramatic interactions. This indicates that narrow observation ranges render individuals essentially blind, requiring more repeated attempts before being convinced of their own choices. Dramatic interactions also bring rapid attenuations later, however, as well as unstable opinions. Thus, there is a tradeoff between stability and intensity to reach convergence more rapidly. As shown in the Fig. 3, convergence is reached most rapidly when $N_p = 10$, and slowest when $N_p = 20$. Furthermore, when N_p is greater than 40, the situations are almost the same.

As in previous studies of opinion dynamics models [10,11,22,29], the relaxation time, i.e., the time steps needed to reach convergence where all individuals perform stable outer actions, depends on the model's parameters. Monotonous variations are mostly founded, such as the parameter of lattice size, initial opinion densities and so on; however, an extreme is obtained

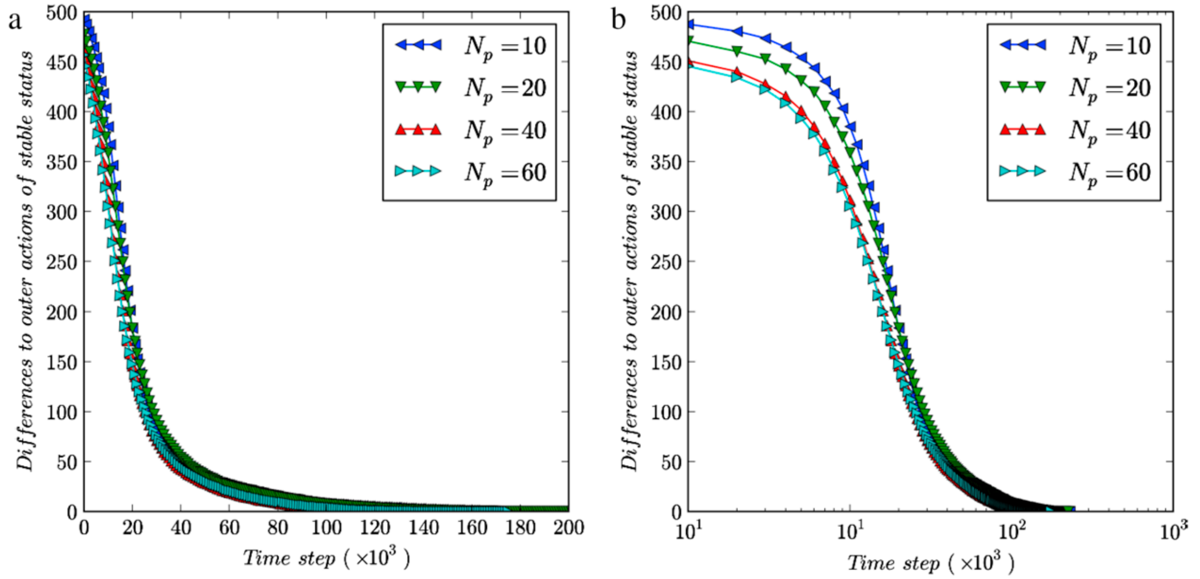

Fig. 3. The differences in individuals' outer actions to these in stable status at each 10^3 time step with observation range $N_p = 10, 20, 40,$ *and* 60 for $L = 32$, obtained from 100 samples, with $p_{i,A}(0)$ and $\inf_i(0)$ following uniform distributions with an interval (0, 1) and (0, 10), respectively. Fig. 3(a) shows a linear plot and Fig. 3(b) shows a semi-log plot.

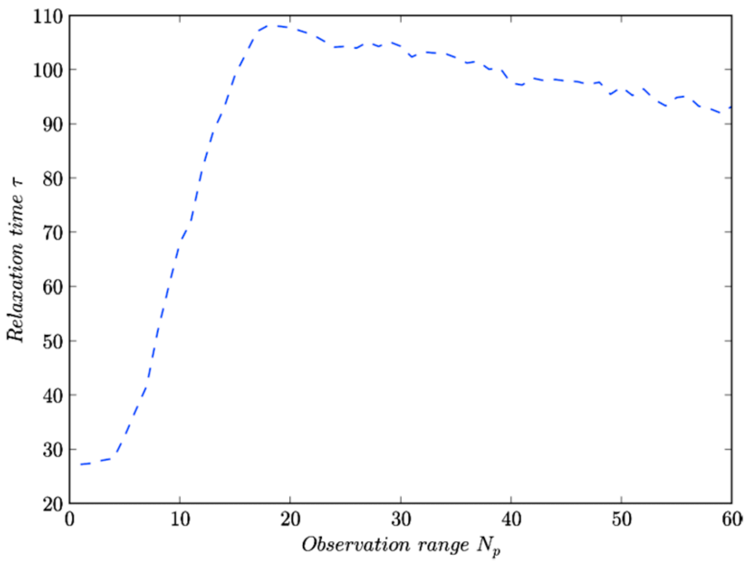

Fig. 4. Average relaxation time τ, over 500 samples, versus observation range N_p for $L = 32$, with $p_{i,A}(0)$ and $\inf_i(0)$ following uniform distributions with an interval (0, 1) and (0, 10), respectively.

in proposed model. The plot of Fig. 4 shows the distribution of the average relaxation time τ versus observation range N_p, over 100 samples of $L = 32$ square lattice.

This is the result of the tradeoff between the interaction intensity of a smaller N_p and the stability of a greater N_p. Extensive simulations over 100 samples per N_p clearly suggest that the observation range plays a significant and vital role in the distribution of relaxation time. As analyzed above, the interaction intensity decreases as the observation range of each individual increases. In addition, the stability where an individual is confident in his/her choice increases monotonously as the observation range and the objectivity of an observation increase. Furthermore, the rising tendency decreases gradually and the stability scarcely varies when N_p is large enough. As a result, the interaction intensity leads the evolution when N_p is small. The stability accelerates this process when N_p is large and brings forth more and more gentle changes, which is consistent with the simulation results where the relaxation time obtains its maximum value near $N_p = 20$ for $L = 32$ in Fig. 4.

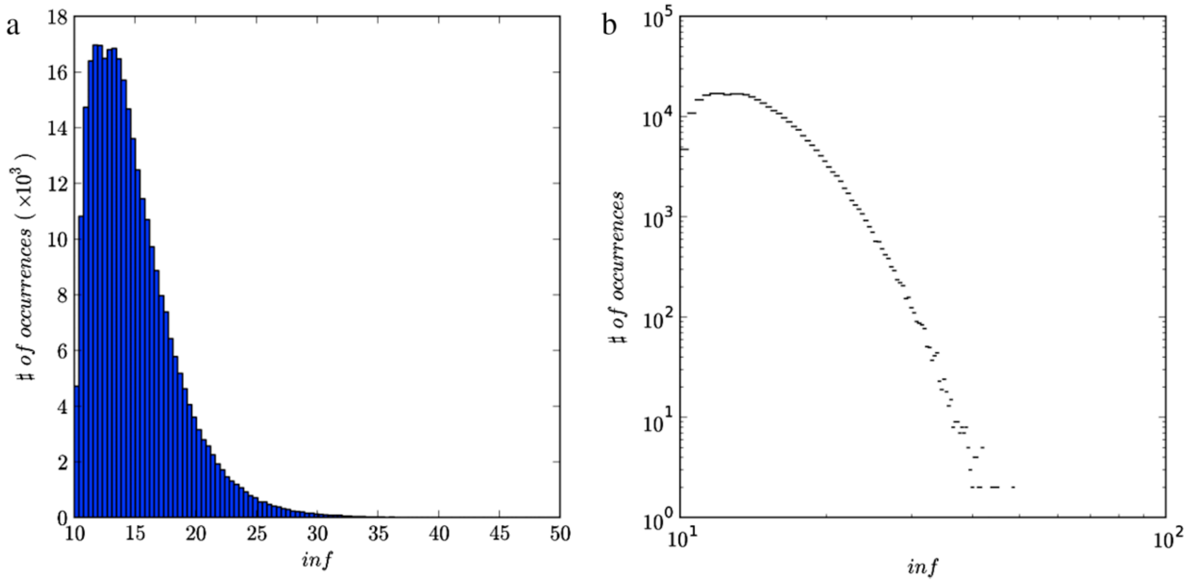

Fig. 5. Histogram of individuals' social influence when opinion evolution reaches convergence for $L = 32$ and $\Delta = 3$, obtained from 300 samples, with $p_{i,A}(0)$ following uniform distributions with an interval of $(0, 1)$ and $\inf_i(0) = 10$. Fig. 5(a) shows a linear plot and Fig. 5(b) shows a log–log plot. The power-law characteristic is presented.

3.3. Social influence of persuaders

Modeling based on decision-based queuing process, Barabasi [35] proved that human activities follow a power-law distribution. According to the following empirical and theoretical studies [36–38], the interval time of a message being released and then commented upon and interacted with by society also exhibits power-law characteristics, as does the degree distribution.

In the proposed model, we assume that individuals, whether they are supporters or opponents, can obtain some benefit from spreading an opinion. Moreover, this benefit is proportional to the contribution to a successful persuasion. This is directly reflected in social influence, which is introduced to highlight the heterogeneity of individuals and reproduce realistic online opinion interactions. As a cumulative effect, an individual gains positive feedback by successful persuasion, causing a snowball effect in social influence. As shown in Fig. 5, the distribution of individuals' social influence presents power-law characteristics. Most individuals are largely unable to influence others, and even more may not positively impact a successful persuasion. Nevertheless, a small proportion of individuals have a relatively large power to make a persuasion successful. In other words, the accumulation of successful persuasions makes success both easier and more frequent.

When social influence and its feedback mechanism are introduced, analyzing the contribution of each individual is quite straightforward. Note that the present model does not consider individual differences before a topic is embarked upon. Although all have equal probability of being selected as a persuader and the square lattice network is regular, a minority of individuals stand out and are raised above the crowd.

To discover the impact of early opinion leaders on opinion evolution, a simulation of truncated Gaussian social influence with fixed expectations is presented. The plot of Fig. 6(a) exhibits the statistics for successful persuasions and the differences with stable status in each step, where $N_p = 30$, $\mu_{\inf} = 10$ and the standard deviation $\sigma_{\inf}$ equals 0.1, 2, and 40, respectively. A smaller $\sigma_{\inf}$ sharpens the bell-shaped probability curve, whereas a greater one flattens it. That is to say, initial social influence value centers upon $\mu_{\inf}$ and is inclined to remain constant when $\sigma_{\inf}$ is equal to 0.1. It becomes dispersed and scattered when $\sigma_{\inf}$ is equal to 40 and is inclined to be uniformly distributed. As shown in Fig. 6(b), initially there are only minor differences for distributions with different values of $\sigma_{\inf}$, which is attributed to early opinion leaders. Intuitively, when initial social influence is scattered, early opinion leaders can easily lead the direction of discussions in a certain extent. This explains the advantage of situation with large $\sigma_{\inf}$ in the beginning. Without outside intervention, however, some opinion leaders arise gradually and spontaneously, causing the curve with a small $\sigma_{\inf}$ value to catch up later. In the current simulation, the average relaxation time when $\sigma_{\inf}$ equals 0.1, 2, and 40 is 102, 105, and 103, respectively. Overall, the degree of dispersion of initial social influence has little impact on opinion evolution.

4. Conclusions

An opinion dynamics model has been proposed to investigate the evolution of individuals' opinions combined with psychological studies on the social impact of majorities and minorities. The model was built based on the following

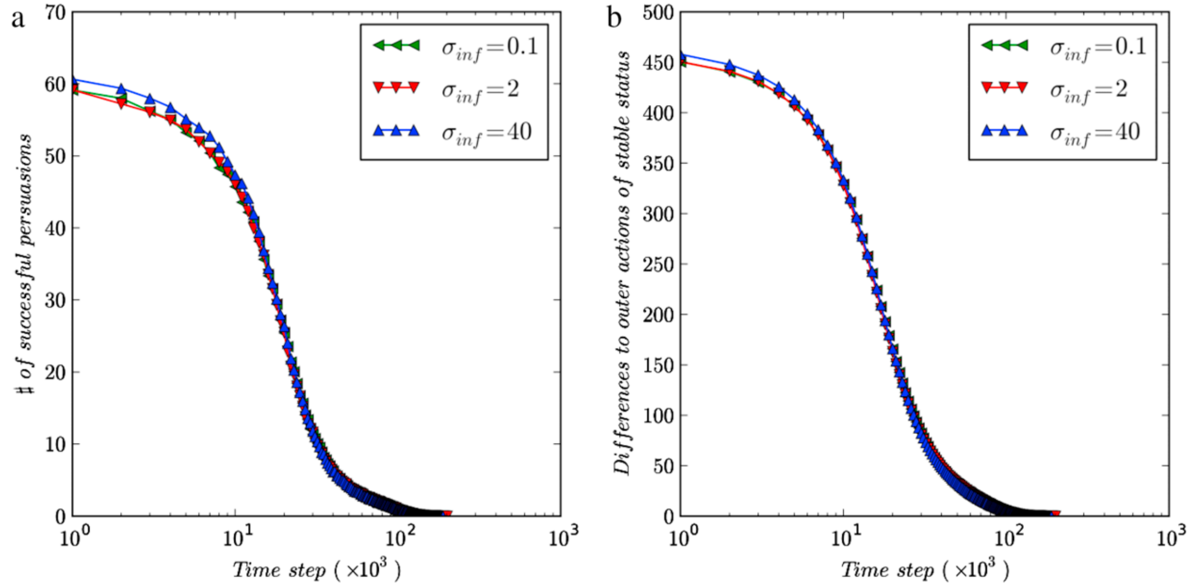

Fig. 6. (a) Semi-log plot of the number of successful persuasions at each 10^3 time step. (b) Semi-log plot of the differences of individuals' outer actions to those in stable status at each 10^3 time step. Both are obtained from 500 samples, for $L = 32$ and $N_p = 30$, with uniform distributed $p_{i,A}(0)$ and truncated Gaussian $\inf_i(0)$ of interval (0, 20) with fixed expectations $\mu_{\inf} = 10$, and varied standard deviations, $\sigma_{\inf} = 0.1$, 2, and 40, respectively.

assumptions: (i) individuals had broad observation ranges, and their preferences concerning both supporting and opposing strategies expanded after observation; (ii) individuals were heterogeneous in their power to lead the spread of opinion, and they gained influence feedback when performing successful persuasions. These assumptions were distilled from realistic phenomena and are consistent with people's intuition.

The proposed model leveraged the odds in favor of a supporting strategy to identify the preference of individuals. It was able to describe the social impact of a certain individual based on social influence and distance. Additionally, individuals updated their inner opinions through observation and evaluation based on previous psychological studies. By extensive simulations, the following features were found.

First, we analyzed the effects of the initial density of individuals' outer actions. From the perspective of opinion evolution, a complete consensus was not always obtained. When the initial density of either side was greater than 0.8, the enormous imbalance led to complete consensus. Otherwise, opinion clusters consisting of a set of tightly connected individuals who held similar and stable opinions appeared and distributed themselves across the network due to the introduction of social influence and social impact, which was inversely proportional to distance. The number, strength and area of clusters increased as the differences between initial supporters and opponents decreased.

Second, by expanding the observation range, affected individuals were able to overcome blindness and make rational decisions. Numerous results indicated that the number of successful persuasions and the differences in stable status were significantly related to the observation range. From another perspective, they reflected the interaction intensity and opinion stability of individuals who were able to accelerate the evolution process. An interesting phenomenon was discovered: the effect of an increased observation range was twofold and could strengthen individuals' opinion stability while weakening the interaction intensity among individuals. As a result, an extreme was obtained with regard to the tradeoff between high interaction intensity and low stability. Moreover, the rising tendency of opinion stability gradually slowed, and the speed of opinion evolution tended to be stable.

Finally, the effect of social influence was analyzed. In the proposed model, individuals were able to obtain influence feedback from successful persuasions that were proportional to their contributions, reflecting the cumulative impact of historical interactions. When opinion evolution reached convergence, the distribution of individuals' social influence followed the power-law. More specifically, a small number of individuals were relatively powerful in successfully persuading others, while the minority scarcely impacted persuasions. Furthermore, a simulation of truncated Gaussian social influence with fixed expectations and variable standard variances was presented and showed that the initial distribution of social influence had little effect on its evolution. Attributed to early opinion leaders, minor advantages were exposed in the beginning. Some opinion leaders rose gradually and spontaneously, but those without an initial advantage were still able catch up and maintain the same trend of evolution until convergence was reached.

In summary, we provided a general framework to model opinion dynamics and diffusion with regard to group discussion, persuasion, and human social influences. This model presents rich phenomena and was able to provide some explanations for individuals' behaviors and opinion evolution in a realistic light. Therefore, it was indeed effective to model opinion dynamics and would be helpful to further studies and researchers.

Acknowledgments

This work was partially supported by the Fundamental Research Funds for the Central Universities 2013YJS010, the National Natural Science Foundation of China under Grant 61172072, 61271308, the Beijing Natural Science Foundation under Grant 4112045, the Beijing Science and Technology Program under Grant Z121100000312024, the Academic Discipline and Postgraduate Education Project of the Beijing Municipal Commission of Education, and partially supported by North Carolina A&T State University.

References

[1] C. Castellano, S. Fortunato, V. Loreto, Statistical physics of social dynamics, Rev. Modern Phys. 81 (2009) 591–646.
[2] R. Axelrod, D. Dion, The further evolution of cooperation, Science 242 (1988) 1385–1390.
[3] K.D. Harris, C.M. Danforth, P.S. Dodds, Dynamical influence processes on networks: general theory and applications to social contagion, Phys. Rev. E 88 (2013).
[4] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, D.U. Hwang, Complex networks: Structure and dynamics, Phys. Rep. 424 (2006) 175–308.
[5] G. Abramson, M. Kuperman, Social games in a social network, Phys. Rev. E 63 (2001).
[6] M.E.J. Newman, Spread of epidemic disease on networks, Phys. Rev. E 66 (2002).
[7] R. Hegselmann, U. Krause, Truth and cognitive division of labour first steps towards a computer aided social epistemology, JASSS 9 (2006).
[8] C.M. Bordogna, E.V. Albano, Statistical methods applied to the study of opinion formation models: a brief overview and results of a numerical study of a model based on the social impact theory, J. Phys.: Condens. Matter. 19 (2007).
[9] M.H. Zheng, L.Y. Lu, M. Zhao, Spreading in online social networks: the role of social reinforcement, Phys. Rev. E 88 (2013).
[10] K. Sznajd-Weron, J. Sznajd, Opinion evolution in closed community, Internat. J. Modern Phys. C 11 (2000) 1157–1165.
[11] N. Crokidakis, F.L. Forgerini, Consequence of reputation in the Sznajd consensus model, Phys. Lett. A 374 (2010) 3380–3383.
[12] V. Sood, S. Redner, Voter model on heterogeneous graphs, Phys. Rev. Lett. 94 (2005).
[13] R.A. Holley, T.M. Liggett, Ergodic theorems for weakly interacting infinite systems and voter model, Ann. Probab. 3 (1975) 643–663.
[14] E. Ising, Beitrag zur theorie des ferromagnetismus, Z. Phys. 31 (1925) 253–258.
[15] K. Sznajd-Weron, Sznajd model and its applications, Acta Phys. Polon. B 36 (2005) 2537–2547.
[16] Y.S. Tu, A.O. Sousa, L.J. Kong, M.R. Liu, Sznajd model with synchronous updating on complex networks, Internat. J. Modern Phys. C 16 (2005) 1149–1161.
[17] N. Masuda, Voter models with contrarian agents, Phys. Rev. E 88 (2013).
[18] S. Galam, Application of statistical physics to politics, Physica A 274 (1999) 132–139.
[19] Y.T. Lin, X.P. Han, B.H. Wang, Dynamics of human innovative behaviors, Physica A 394 (2014) 74–81.
[20] G. Deffuant, D. Neau, F. Amblard, G. Weisbuch, Mixing beliefs among interacting agents, Adv. Complex Syst. 3 (2000) 87–98.
[21] R. Hegselmann, U. Krause, Opinion dynamics and bounded confidence: models, analysis and simulation, JASSS 5 (2002).
[22] A.C.R. Martins, Continuous opinions and discrete actions in opinion dynamics problems, Internat. J. Modern Phys. C 19 (2008) 617–624.
[23] A.C.R. Martins, C.D. Pereira, R. Vicente, An opinion dynamics model for the diffusion of innovations, Physica A 388 (2009) 3225–3232.
[24] A.C.R. Martins, Bayesian updating rules in continuous opinion dynamics models, J. Stat. Mech. Theory Exp. (2009).
[25] X.M. Si, Y. Liu, F. Xiong, Y.C. Zhang, F. Ding, H. Cheng, Effects of selective attention on continuous opinions and discrete decisions, Physica A 389 (2010) 3711–3719.
[26] A.C.R. Martins, C.D. Kuba, The importance of disagreeing: contrarians and extremism in the coda model, Adv. Complex Syst. 13 (2010) 621–634.
[27] A.C.R. Martins, Trust in the CODA model: Opinion dynamics and the reliability of other agents, Phys. Lett. A 377 (2013) 2333–2339.
[28] A.C.R. Martins, Discrete opinion models as a limit case of the CODA model, Physica A 395 (2014) 352–357.
[29] L. Deng, Y. Liu, F. Xiong, An opinion diffusion model with clustered early adopters, Physica A 392 (2013) 3546–3554.
[30] J.C. Dittmer, Consensus formation under bounded confidence, Nonlinear Anal. 47 (2001) 4615–4621.
[31] B. Shen, Y. Liu, Effects of confidence scale and network structure on minority opinion spreading, Internat. J. Modern Phys. C 21 (2010) 1001–1010.
[32] C. Steinfield, N.B. Ellison, C. Lampe, Social capital, self-esteem, and use of online social network sites: A longitudinal analysis, J. Appl. Dev. Psychol. 29 (2008) 434–445.
[33] A. Nowak, J. Szamrej, B. Latane, From private attitude to public-opinion: a dynamic theory of social impact, Psychol. Rev. 97 (1990) 362–376.
[34] B. Latane, S. Wolf, The social impact of majorities and minorities, Psychol. Rev. 88 (1981) 438–453.
[35] A.L. Barabasi, The origin of bursts and heavy tails in human dynamics, Nature 435 (2005) 207–211.
[36] Q. Yan, L.R. Wu, L. Zheng, Social network based microblog user behavior analysis, Physica A 392 (2013) 1712–1723.
[37] W.G. Yuan, Y. Liu, J.J. Cheng, F. Xiong, Empirical analysis of microblog centrality and spread influence based on bi-directional connection, Acta Phys. Sinica 62 (2013).
[38] Q. Yan, L.L. Yi, L.R. Wu, Human dynamic model co-driven by interest and social identity in the MicroBlog community, Physica A 391 (2012) 1540–1545.