# Public Opinion Evolution Based on the Flocking Algorithm

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*Abstract*—**Surrounded by the explosive development of information, people always present different views and attitudes towards a social event, and how to create a topic to have an impact on the public opinion evolution imperceptibly and effectively has become a promising topic. In order to have a public opinion evolution model close to reality, this paper proposes a dynamic topological network with a high degree of verisimilitude and improves the public opinion evolution algorithm based on the flocking algorithm. Moreover, we propose an innovate attempt of combining the movement-mode with the opinion-exchange algorithm. Experimental results demonstrate that the proposed network public opinion evolution model can impact the public opinion evolution with autonomous, efficient and complete convergency, while simultaneously show the powerful capability of our model in handling the problem of public opinion guidance in social networks.**

***Keywords- flocking algorithm; complex network; topic generation; opinion evolution***

## I. Introduction

With the vigorous development of the Internet and the rapid popularity of portable devices, people have become accustomed to express opinions on different things in the virtual world actively[1].

Dynamic interpersonal relationship network is one of the main manifestations of social networks. The network formed by users of social software is a network with strong dynamics and rapidly changing topological structure [2]. Complicated information makes it difficult for users to distinguish between true and false. Many hotspots often trigger reversals due to incomplete information, false facts, planned facts, and inversion of cause and effect [3]. Measuring and predicting public opinion trends from real-time social media is the long-term goal of big data analysis [4]. At the same time, how to authoritatively interpret social events, especially some emergencies, and carry out news reports in a timely, accurate, open and transparent, efficient and orderly manner, so that the public learn about the truth and avoid unnecessary misunderstandings and panic. It is a problem that all kinds of official media need to study and think [5]. During the global COVID-19 pandemic [6], analyzed the comments on social media platforms such as Twitter and showed that people's emotions are closely related to the airport closure and grounding. Establishing confidence in victory is also the focus and difficulty of the government's concern.

The flocking algorithm is essentially a bionic method application abstracted by the movement of birds, fish, and sheep in nature. Individuals in flocking movement adjust their behaviors only according to the information of neighbors, so that the overall self-organization emerges a globally coordinated behavior. The rushing-control problem is a core problem in the autonomous cooperative control of multi-agents in complex network [7].

This paper makes the following three contributions: 1) Combining the research results in the field of complex network multi-agents with the guidance of public opinion in social networks, and apply information topology and flocking control algorithms comprehensively to create a guidance for the evolution of network public opinion The model can efficiently influence the trend of public opinion in social networks; 2) By the means of network cluster control, promote communication efficiency through "new opinion leaders" and "secondary communication" at the same time, and have an impact on the evolution of users' opinions in the way of "integrating parts"; 3) We attempt to integrate group behavior and opinion exchange, and make each node's direction, neighborhood, movement trend more richer in meaning. What's more, the simulation of the evolution of multiple users' opinions verifies the independent realization of consensus guidance and coordination. Both the possibility of flocking control behavior and the stickiness between users increases, while the users keep in touch finally.

## II. Flocking Algorithm

### A. Concept and Application of Flocking

Flocking is a form of collective behavior of large number of interacting agents with a common group objective. It is usually a phenomenon that the scattered groups can produce overall synchronization effect and global coordination behavior through the interaction between individuals and neighbors in the absence of centralized control [8].

At present, flocking algorithm is mainly applied to research fields such as simultaneous fleet delivery, UAV formation control, control and management of intelligent machinery, etc.

This paper will be applied to impact the evolution of public opinion.

*B. Rules of Flocking*

In 1986, Reynolds introduced three heuristic rules that creates the first computer animation of flocking to simulating the emergence of flocking groups [9]. Each individual in this model follows the following rules:

*1) Flocking Centralization: an attempt to stay close to nearby individuals.*

*2) Avoid Obstacles: keep a certain distance from nearby individuals to avoid collisions between individuals.*

*3) Speed Matching: Try to match the speed of nearby individuals.*

*C. Control Issues of Flocking in the Evolution of Public Opinion*

If each user in the social network is regarded as a vertex in the graph, and the influence and communication relationship between each user is regarded as an edge, then the social network can be regarded as a graph, and the evolution of public opinion of users can be represented by the topology change of the graph, so as to analyze and study the guidance and control of the evolution of public opinion.

The strategy of flocking movement is used to explain the two main individual psychological behaviors in the evolution of public opinion, which are the two main social driving forces for the formation of public opinion. In the process of public opinion evolution, individuals get close to each other out of curiosity for their neighbors, but they will reject the neighbors who are too close for the protection of their own privacy. The radius of attraction parameter in the model is used to describe the social influence of individuals in the evolution of public opinion, while the radius of exclusion parameter is used to describe the self-protection strength of individuals in the process of exchange of opinions. People who consume news and curate it on Twitter show stronger opinion leadership on Twitter than people who consume news but don't curate it [10]. We can create such "opinion leaders" to make something different. Through the analysis of simulation experiments, this paper confirms that this model not only inherits the opinion dynamics characteristics of the public opinion evolution model of dynamic space network, but also reflects the influence of individual behavior on the public opinion evolution.

## III. The Public Opinion Evolution Based on Flocking Algorithm

*A. Modeling of Public Opinion Evolution Network*

The guidance model of public opinion evolution in this paper is based on complex network. In the study of flocking control, graph theory is an important analytical tool and the basis for representing each user's information. The modeling part used in this paper is introduced here.

A graph $G$ is composed of nodes and edges, denoted as $G = (V, E)$, where the vertices are $V = \{1, 2, \ldots, n\}$, mean the individuals, and edges as $E \subseteq V \times V$, which represents the adjacency relationship between individuals. $|V|$ and $|E|$ also referred to as order and size of graph respectively. In the process of network evolution, $|E|$ represents information flow network communication complexity.

The adjacency matrix corresponding to the graph $G$ is $A = [a_{ij}]$, which satisfies $a_{ij} \neq 0 \Leftrightarrow (i, j) \in E$. When the elements of the adjacency matrix of graph are not just elements 0 or 1, it is called the weighted graph. Here we define $a_{ii} = 0$, that is, the connection between the nodes themselves is meaningless.

The set of neighbor individuals of point $i$ is defined as $N_i = \{j \in V: a_{ij} \neq 0\} = \{j \in V: (i, j) \in E\}$.

*B. Collective Potential Functions*

In order to explore the potential energy of the cluster, we use a non-negative function to express $\nu: R^{mn} \to R \geq 0$, which is defined as follows:

$$\nu(q) = \frac{1}{2}\sum_i \sum_{j\neq i} \psi_\alpha\left(\|q_j - q_i\|_\sigma\right) \tag{1}$$

Let ψ_α (z) be an attractive/repulsive pairwise potential with a global minimum at z=d_α and a finite cut-off at $r_\alpha = ||r||_\sigma$. Then, the following function:

$$\psi_\alpha(z) = \int_{\mathrm{d}_\alpha}^{z} \phi_\alpha(\mathrm{s})\mathrm{ds} \tag{2}$$

In order to construct a smooth pairwise attractive/repulsive potential, an action function $\phi_\alpha(\mathrm{z})$ is incorporated in the study :

$$\phi_\alpha(\mathrm{z}) = \rho_{\mathrm{h}}(\frac{z}{\mathrm{r}_\alpha})\phi(\mathrm{z} - \mathrm{d}_\alpha) \tag{3}$$

$$\phi(\mathrm{z}) = \frac{1}{2}[(a+b)\sigma_1(z+c) + (a-b)] \tag{4}$$

where, $\mathrm{z} > \mathrm{r}_\alpha$, $\sigma_1(z) = z/\sqrt{1+z^2}$, and $0 < a \leq b$, $c = |a - b|\sqrt{4ab}$, $\phi(0) = 0$.

A bump function is a scalar function $\rho_h(z)$ that smoothly varies between 0 and 1. Here, we use bump functions for construction of smooth potential functions with finite cut-offs and smooth adjacency matrices. One possible choice is the following bump function introduced in [11].

$$\rho_h(z) = \begin{cases} 1, & z \in [0, h) \\ \frac{1}{2}\left[1 + \cos\left(\pi \frac{(z-h)}{(1-h)}\right)\right], & z \in [h, 1] \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $h \in (0, 1)$. Using this bump function, we can define a spatial adjacency matrix $A(q)$ via its elements by:

$$a_{ij}(q) = \rho_h\left(\|q_j - q_i\|_\sigma / r_\alpha\right) \in [0, 1], \quad j \neq \mathrm{I} \tag{6}$$

*C. Analysis of Public Opinion Evolution Model*

Suppose there are a total of $n$ users, in order to impact users to spontaneously change their views and approach to an expected point of view $\gamma - agent$ without interference, to achieve the consistency of public opinion evolution and to maintain a stable state within a communication range. Choose a model design based on the Olfati multi-agent flocking control algorithm.

The equation for the change of opinion is:

$$\begin{cases}\dot{q}_i & = p_i \\ \dot{p}_i & = u_i\end{cases} \tag{7}$$

Input control for each user consists of three parts:

$$u_i = f_i^g + f_i^d + f_i^\gamma \tag{8}$$

where, $f_i^g = -\nabla_{q_i} V(q)$ gradient−based term, $f_i^d$ is a velocity consensus/alignment term that acts as a damping force, and $f_i^\gamma$ is a navigational feedback due to a group objective. The first two items are the position and speed feedback between the user $i$ and the user j in its neighborhood, which are used to realize the aggregation, separation and speed matching that emerge in a flocking during the evolution of opinions. The third item is used to adjust the viewpoint value of user I according to the expected viewpoint, to achieve the goal and avoid the divergence of the whole public opinion. In the evolution of viewpoints, it is expected that viewpoints can select one or several users as the target according to task needs or constraints, or to use virtual points as the target [12]. It has been proved that this protocol unifies all three Reynolds rules in one equation. To describe the process of evolution more closely, we define it as follows:

$$u_i = u_i^\alpha + u_i^\gamma \tag{9}$$

$$u_i^\alpha = \sum_{j\in N_i} \phi_\alpha\left(\left\|q_j - q_i\right\|_\sigma\right)\mathbf{n}_{ij} + \sum_{j\in N_i} a_{ij}(q)\left(p_j - p_i\right) \tag{10}$$

$$u_i^\gamma = f_i^\gamma(q_i, p_i) \tag{11}$$

,and we define a vector along the line connecting $q_i$ to $q_j$ , and it is given by $\mathbf{n}_{ij} = \sigma_\epsilon\left(q_j - q_i\right) = \frac{q_j - q_i}{\sqrt{1+\epsilon\|q_j - q_i\|^2}}$. The navigation feedback of the group goal is:

$$u_i^\gamma \coloneqq f_i^\gamma(q_i,\ p_i,\ q_r,\ p_r) = -c_1(q_i - q_r) - c_2(p_i - p_r),\ c_1,\ c_2 > 0 \tag{12}$$

### D. Definition of the Evolution Direction of Public Opinion

Usually, people's opinions are in a state of normal distribution, meaning that most people are neutral or slightly inclined, and a few people have extreme views. For ease of representation, we divide the viewpoint area into four parts in a two-dimensional coordinate system, $\text{positive}:\text{neutral}:\text{negative} = 1:2:1$ .

As far as the direction of the user node is concerned, the plane is divided into four parts with the lines $l_1: y = x$ and $l_2: y = -x$, and the target viewpoint is selected as the positive region(orange) along the x-axis, and the part containing the negative semi-axis is negative region(green), the remaining upper and lower parts are neutral areas(blue). The part of the dividing line is consistent with the clockwise region. This is illustrated in Fig. 1. The starting direction of each user is determined by the initial viewpoint. The smaller the angle $\theta(\theta \in [0,\ \pi])$between the viewpoint direction and the x-axis is, the closer the viewpoint is to the target viewpoint. the larger the $\theta$ value, the greater the divergence between the user's point of view and the target point of view.

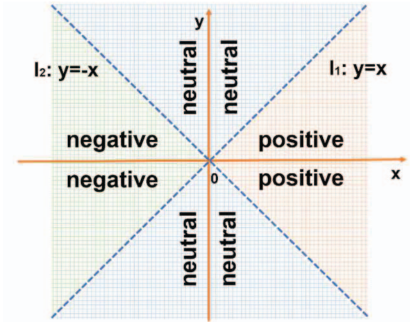



Figure 1. Direction of user-node diagram.

In terms of the location of user nodes, in order to facilitate observation, we select the first quadrant as the positive region(orange), the third quadrant as the reverse region(green), and the second and fourth quadrants as the neutral region(blue). The part of the dividing line is consistent with the clockwise region. This is illustrated in Fig.2. The starting position of each user$(x,\ y)$is determined by the initial point of view:

$$x = cos(\frac{3}{4}\pi - \frac{opinion}{1} \times \frac{\pi}{2}) \times \mu \tag{13}$$

$$y = sin(\frac{3}{4}\pi - \frac{opinion}{1} \times \frac{\pi}{2}) \times \mu \tag{14}$$

Among them, opinion is the initial opinion value of each user. Under normal circumstances, we take $opinion \in [-1,\ 1]$, μ is a random radius, which aims to represent the user's opinion truthfully and uniformly in the coordinate system. The angle between the viewpoint direction and the line $l_1: y = x$ is the upper right direction $\omega(\omega \in [0,\ \pi])$. The smaller the viewpoint is, the closer the viewpoint is to the target viewpoint. The larger the value of ω, the greater the difference between the user's viewpoint and the target viewpoint. The line $l_2: y = -x$ indicates a neutral point of view when the angle is 0, that is, when the line $l_1: y = x$ is at the left corner of the direction is 0, it indicates that the point of view is completely opposite.

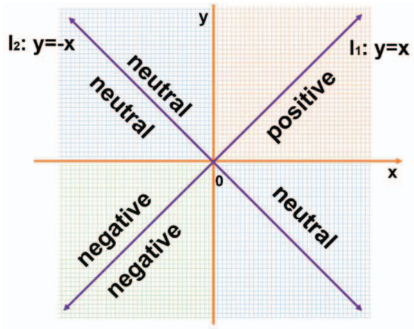



Figure 2. Location of user-node diagram.

## IV. Simulation Results and Analysis

In this paper, we used the sentiment score data of users' tweets about COVID-19 on Twitter, and selected 1,500 pieces of data on March 01, 2021. This is illustrated in Fig. 3.

According to the data set, the emotional score of each user's tweets is between [-1, 1]. "-1" means that the user is extremely depressed and is not optimistic about the epidemic; "+1" means that the user is in a very good mood and can actively face the epidemic; "0" means that the user is calm and neither sad nor happy.

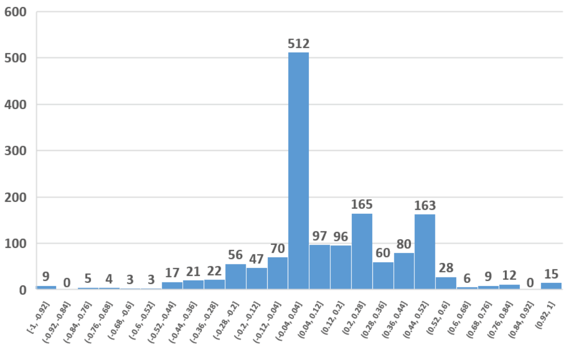
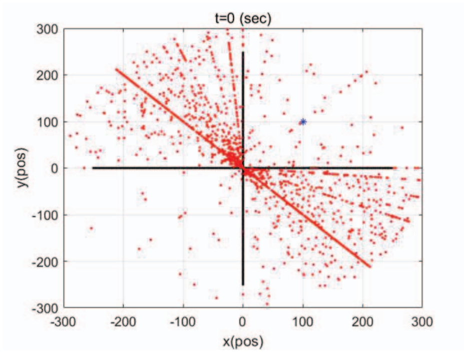


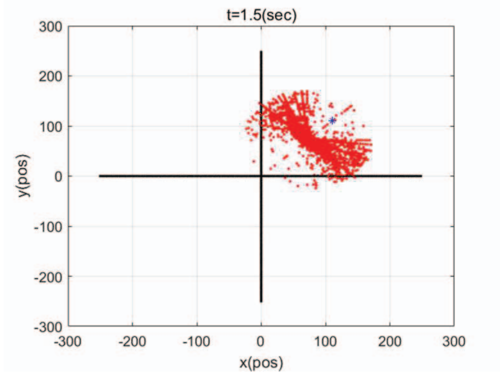

Figure 3. Distribution map of user twitter sentiment score data.

As shown in Fig.4, the results of user opinion evolution are simulated in a two-dimensional plane. Fig.4 (a) is the initial distribution state of user opinions without influence. Users' opinions are basically distributed in the neutral region. The number of users in the positive region was more than that in the negative region, and the number of users close to the neutral mood was the largest, accounting for 34.13%.

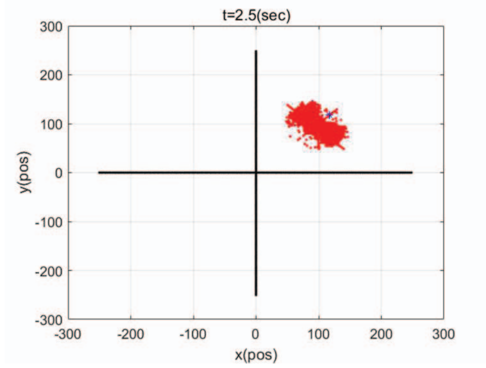
Fig.4 (b) and Fig.4 (c) are the diagrams of the effect process, and Fig.4 (d) is the diagrams of the affected results. The experiment shows that after the flocking algorithm is used to impact public opinion, all users' opinions are gradually closer to the target opinions spontaneously, and the communication links are constantly increasing, and finally a relatively regular network is formed. At this point, there are communication links between adjacent nodes, which are evenly distributed in space and reach the focusing state.



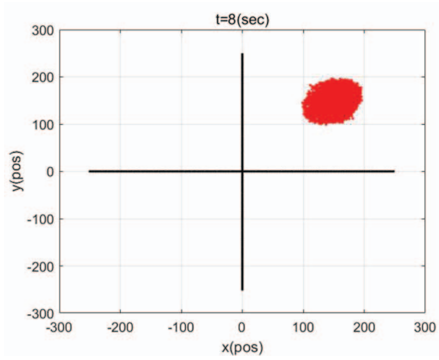

(a) Initial position.




(b) t = 1.5(sec).




(c) t = 1.5(sec).




(d) t = 6(sec).

Figure 4. Flocking algorithm public opinion evolution renderings.

In the process of group aggregation, all users' views converge, diverge and converge again in a series of processes from the initial disordered state, and finally reach the state of aggregation. This process we can through the cluster radius function $R(t) = \max_{i\in\mathcal{V}} \|q_i(t) - q_c(t)\|$ is analyzed. As shown in Fig.4, when $t = 0$, since all points are distributed according to the actual situation, the distance between nodes is far and the gravitational attraction is large. The radius of the farthest point from the center point reaches 309.39. When opinion leaders appear, people's opinions are easily affected by them at the beginning, so the value of aggregation radius drops rapidly. In the constant change of public opinions, opinions tend to converge, and the aggregation radius reaches the minimum value of 43.40 when the iteration reaches 259 times. However, due to the differences of each person, a high degree of consistency will not be maintained. People's opinions will be scattered again until a real balance is reached, and the aggregation radius will increase slightly to 59.58.

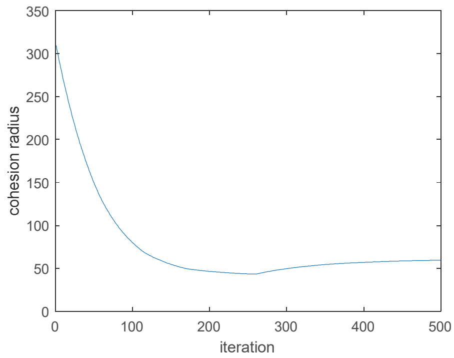



Figure 5. Condensation radius between user nodes.

For further observation, we define the velocity mismatch function $K(v)=\frac{1}{2}\sum_i \|v_i\|^2$ to represent the kinetic energy of the particle system in the moving coordinate system. The normalized velocity mismatch is indicated by $\tilde{K}(v)=K(v)/n$. In actual evolution, users' views will change under the influence of others. Different sounds around them seem to give users an invisible appeal. The stronger the appeal, the easier the user's views will be changed, that is, the faster the opinion changes, which is consistent with the fact that force is proportional to acceleration in physics.

As shown in Fig.6, when the external influence on the user is equal to the gravitational force and the repulsion force of the user's own internal thoughts, the point of view evolves to a position of equilibrium, that is, the gravitational force is equal to the repulsion force and the acceleration is 0. At this point, the speed at which the user's speed changes the idea reaches the peak, and all the values of the views continue to converge in the current direction of motion. After users follow the trend for a period, they will begin to listen more to their inner thoughts. Although their thoughts are consistent with the general trend, the change speed of their thoughts will obviously slow down. In Fig.6, after the iteration to 185 times, the repulsive force of opinions is greater than gravity, and the direction of acceleration is opposite to the direction of speed, so the speed decreases.

Finally, through constant adjustment, people's ideas and expected direction of public opinion tend to be in line with each other, and their minds and behaviors will be the same. They tend to keep in line with the speed of the created point, and develop steadily.

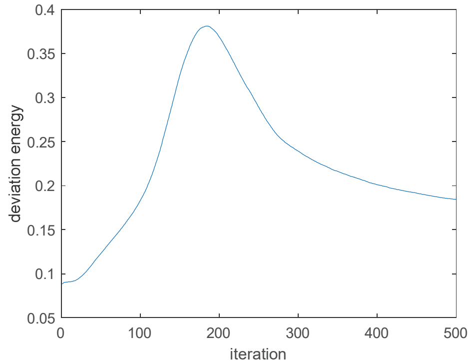



Figure 6. User opinion deviation energy.

## V. Conclusion

This paper discussed the way to affect the public opinion evolution in social networks, and applied the flocking emergence mechanism and algorithm of the complex network neighborhood to public opinion evolution, which could make the public gradually change their ideas and finally realize the change of the direction of public opinion by taking advantage of people's convergence and psychology of seeking differences without imposing intervention. By combining public opinion propagation with algebraic graph theory and flocking algorithm, a public opinion evolution algorithm integrating parts is designed, which could quickly and efficiently affect public opinion to the expected direction, and the feasibility and effectiveness of the control algorithm are verified by simulation. At the same time, new meanings were given to the coordinates, directions and modes of movement of each point, and a new two-dimensional evolution model was designed, which was consistent with the wind direction of public opinion overall, and highly consistent with the actual trend of public opinion for individuals by seeking common ground while reserving differences. Exploring "grassroots stars" and "opinion leaders" and subtly way to affect the direction of public opinion of the event was an innovative way to regulate the joint efforts of sub-media and affected core values, extending to network terminals and serving the people in close distance, forming an effective path to enhance the guidance of public opinion of new mainstream media.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