

Research Article

Analysis and Influence of Media Degradation Image Propagation Path Based on Image Vision

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With the rapid development of the information age, the efficiency of image information dissemination has been improved and the way of information dissemination has gradually moved from text information to image information. In the process of using equipment to take pictures, because of some objective reasons, the images taken are different from the ideal images taken by the equipment, so the interference brought by these objective factors to the images is eliminated, thus presenting a more realistic image process. In the process of network propagation, degraded images show different characteristics in the network. In the process of propagation, images degenerate again, which makes it difficult for images to be authentic or restored. In this paper, an SIR model is selected from three classical infectious disease models to simulate and reflect the propagation path and influence of degraded images and the influence of degraded images on propagation is evaluated by extracting the moderate and degree distribution of undirected network. In addition, the distribution and integration between nodes are evaluated to distinguish the average road sources. Based on the SIR propagation model, a propagation model of information timeliness is constructed. By describing the update of subjective attitude values of nodes and then defining the probability function of state transition between different nodes, the model has higher fitting and adaptability. Finally, using BA, WS, Facebook, and Sina Weibo as the base map and setting the network environment parameters, based on the SIR model, the propagation of degraded images in different network environments is analyzed and the influence results of degraded images in network propagation are obtained.

1. Introduction

With the rapid development of the information age, image information has become an important source of information. In the last century, the main media of information dissemination still stayed in words and information was basically obtained from words. Until the popularity of modern television and the slow establishment of the Internet, people's quality of life and ways have changed greatly with the development, which affects the way of information acquisition. Now, people are more willing to obtain useful and relevant information from images and often spread the information in the form of images. It is very efficient and rapid for the visual propagation of images on the network. The study in [1] mentioned the segmentation of superpixel images, which will increase a series of complexity for the

flow of superpixel images in the network. Previous studies often focus on deblurring of degraded images, such as the data-driven method proposed by Li et al. [2] to remove the blurring of images and Pan et al. [3] and others using dark channels to process degraded images. In fact, degraded images can interact with low resolution (LR) and high resolution (HR) to achieve better propagation effect on the network, as mentioned in [4].

The main way of image dissemination is to rely on the network, and the information in online social networks reflects social hotspots, influence, and other factors [5]. Bae and Lee's [6] content analysis of the 13 most influential tweets mentioned by more than 3 million users of Twitter can judge the emotional impact of these messages on users. Not only Bae but also Xiong et al. [7] established an emotional independent cascade model and analyzed the

mode and influence of social networks in emotional transmission. Mei et al. [8] help enterprises and governments standardize public opinion by extracting information from online social networks. Yi et al. [9] propose a social connection strength model to verify the importance of information in social connections. The study in [10] describes the propagation characteristics of sudden information on the Internet from the perspective of information entropy. The propagation of image information in the network is also similar to the social network information propagation model. In order to deeply understand the propagation path and influence of image information in the social network, it is necessary to establish a feedback model [11]. Liu et al. [12] established an information model NFSIR (negative feedback susceptible to infection) which introduces attenuation parameters and noise figure to study the information feedback brought by images. Most models are based on the incidence of infectious diseases. For example, a susceptibility-infection-elimination (SIR) model is established based on the classical susceptibility-infection-hibernation-elimination (SIHR) model mentioned in [13] to describe the transmission probability of images. The study in [14] analyzes influential nodes through the SIR model based on the community mediator. Both Granell et al. [15] and Melesse and Gumel [16] are based on epidemic propagation models. The former uses microscopic Markov chain to analyze the probability of information propagation, while the latter uses Lyapunov function to analyze the equilibrium point and stability. The research work on degraded images is insufficient, and the research on degraded images only focuses on the restoration of related algorithms and technologies but does not pay attention to the problem of propagation in the network. There is no comparison in various network environments. The method proposed in this paper simulates the propagation analysis of images in different network environments.

This paper analyzes the epidemic propagation model, simulates a degraded image, puts the image in four preset network environments, and analyzes its propagation path and influence in four different network environments.

2. Degraded Images and Related Theories of Image Propagation

2.1. Overview of Degraded Images. Compared with high-definition images, degraded images are low-resolution images produced by various disturbances. There are many reasons for image degradation, such as camera shaking, shooting object moving, out of focus, and so on, which will cause image blurring. Different pixels will also be lost in the process of network propagation. The propagation of images in the network is also led by degraded images.

2.2. Overview of Image Propagation and Related Models. Picture dissemination refers to the interactive flow of information and the support of pictures. The way of image transmission has changed greatly in the ever-changing society. The advent of new social media has connected

everyone. Everyone has a good understanding of the characteristics of images, and the participation of image dissemination process is stronger, which enables images in online social networks to spread to millions of users in a short time [17]. However, the image will be distorted and the image pixel will be reduced after countless times of transmission. In order to explore these problems and the path of image propagation, researchers have carried out a lot of related research around image propagation, including image propagation modeling, image influence, popularity prediction, image traceability and other image propagation models, which can be divided into two categories: prediction model and interpretation model [18]. Prediction models mainly include independent cascade model and linear threshold (LT) model. The information cascade model is that an activated node deactivates the surrounding inactive nodes with a certain probability. The linear threshold model is used in the process of image propagation modeling. Image propagation, information propagation, and epidemic propagation models have high similarity. Therefore, the image disseminator and receiver can be divided into three categories: Susceptible state (S), which means that the image information has not been received, but there will be a great probability to spread the image after receiving the information. Secondly, the infection state (S) means that the image has been received and will be transmitted again. Finally, the immune state (R) means that no matter whether the image has been accepted or not, the image will not be propagated next time. The combination of the three states can be summarized into three common models.

2.2.1. SI Model. Susceptible S nodes and infected I nodes are combined into the SI model. The transition of these two nodes happens from susceptible node S to infected node I with an average probability of λ , which is a special feature of the model. That is, susceptible nodes will remain infected after being converted to infected nodes, as shown in Figure 1.

The proportion of susceptible node S is expressed as $S(t)$, and infected node I is expressed as $I(t)$ as follows:

$$\begin{cases} \frac{dS(t)}{dt} = -\lambda I(t)S(t), \\ \frac{dI(t)}{dt} = \lambda I(t)S(t). \end{cases} \quad (1)$$

The higher the λ value, the higher the probability of node infection and the faster the propagation speed.

2.2.2. SIS Model. The susceptible state S and infection state I are combined into the SIS model, and the probability of S node transforming into I node is λ . The sensed I node will be transformed into S node again with probability μ . The transmission process of influenza virus is similar to it [19], as shown in Figure 2.

The proportion of S nodes and I nodes is expressed by $S(t)$ and $I(t)$, as follows:

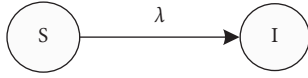


FIGURE 1: Node state transition diagram of the SI model.

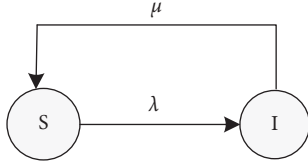


FIGURE 2: Node state transition diagram of the SIS model.

$$\begin{cases} \frac{dS(t)}{dt} = -\lambda I(t)S(t), \\ \frac{dI(t)}{dt} = \lambda I(t)S(t) - \mu I(t), \\ S(t) + I(t) = 1. \end{cases} \quad (2)$$

2.2.3. SIR Model. The SIR model is based on the SI model and has a new immune state R , from sensing node infection probability λ and node infection probability μ to immune state, and this immune state will not return to infection state. This process is similar to smallpox and chickenpox, which will produce antibodies to immunize against similar viruses after being cured [20], and its state transition diagram is shown in Figure 3.

The S-I-R transformation condition is that the image or similar image has been received before. Because of the characteristics of the network environment, the nodes in the network will have the probability to receive the same image information again. When this happens, the nodes will no longer spread the image information.

$S(t)$, $I(t)$, and $R(t)$ can be used to represent the differential of the proportion of susceptible nodes, infected nodes, and immune nodes, respectively, as follows:

$$\begin{cases} \frac{dS(t)}{dt} = -\lambda I(t)S(t), \\ \frac{dI(t)}{dt} = \lambda I(t)S(t) - \mu I(t), \\ \frac{dR(t)}{dt} = \mu I(t), \\ S(t) + I(t) = 1. \end{cases} \quad (3)$$

3. Image Propagation Network Analysis

3.1. Using Statistical Characteristics to Describe the Structural Characteristics of the Image Propagation Network. In order to better analyze the image propagation network, we can

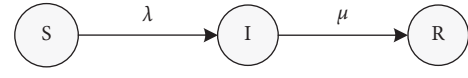


FIGURE 3: Node state transition diagram of the SIR model.

effectively describe the structural characteristics of image propagation network with the help of statistical features. In this study, the following commonly used statistical features are mainly used.

3.1.1. Degree and Degree Distribution. Degree is described as an important attribute node and an important statistical characteristic in the network. In an undirected network [21], the degree K_i of node i is the number of edges connecting node i . Network average $\langle k \rangle$ refers to the average of all nodes in the network. The degree on the node can be divided into outgoing and incoming according to the characteristics of the degree, and the sum of the degree is the sum of the two divided degrees. For nodes that exist in degrees, the two degrees divided into out and in can be converted into outer joints and inner joints. The specific expression is as follows:

$$K_i^{\text{out}} = \sum_{j=1}^N a_{ij}, \quad (4)$$

$$K_i^{\text{in}} = \sum_{j=1}^N a_{ji}. \quad (5)$$

3.1.2. Average Path Length. The shortest path is the one with the least number of connected edges between nodes. The distance between two points is the number of sides on the shortest path. The average distance of degraded image propagation in the network can usually be expressed by L , that is, the average path length value. The analysis of the characteristics of existing networks can often be measured by the convergence and dispersion of their separated states. The specific expression is as follows:

$$L = \frac{1}{1/2N(N-1)} \sum_{a \geq b} d_{ab}. \quad (6)$$

3.1.3. Aggregation Coefficient. The aggregation coefficient refers to the ratio of edges to the number of adjacent nodes. Through the uniform distribution of the aggregation coefficient, the local characteristics of the network can be reflected [22]. The coefficients in real networks are often higher than those in random networks, and nodes gather into clusters in social networks. The clustering coefficient of node i is expressed as follows:

$$C_i = \frac{E_i}{(K_i(K_i-1))/2} = \frac{2E_i}{K_i(K_i-1)}, \quad (7)$$

where K_i is the degree of node i and E_i is the number of connected edges between neighboring nodes of node i . Users can discuss the distribution system of each node in the

network. Propagating the connection between nodes is like the communication of information between users, and information is only connected along nodes. Assuming that a propagation node j in the network propagates a message to node i at time $t + 1$ and the attitude values of node j and node i at time t are S_t^j and S_t^i , then according to the non-Bayesian social learning method, the degree value of node i is updated as shown in

$$S_{t+1}^i = S_t^i + (S_t^j - S_t^i)\phi(i, j). \quad (8)$$

If there are n propagation nodes j_1, j_2, \dots, j_n propagating information to node i at time $t + 1$ and the state value of the propagation node at time t is $S_t^{j_1}, S_t^{j_2}, \dots, S_t^{j_n}$, then the value of node i is updated as shown in

$$S_{t+1}^i = S_t^i + \frac{1}{n} \sum_{j_n \in T(i)} (S_t^{j_n} - S_t^i)\phi(i, j), \quad (9)$$

where $T(i) = \{j_1, j_2, \dots, j_n\}$ denotes the set of nodes that propagate information to node i and $\phi(i, j) \in [0, 1]$ denotes node j 's influence of attitude value on node i . If node i makes the time T unknown and the attitude value is 3, the propagating node J propagates the message to node i at the time $t + 1$; then, node i changes from unknown to propagating the probability calculation of the broadcast node as shown in

$$p_{st}^i = S_{t+1}^i + (1 - S_{t+1}^i)v_0. \quad (10)$$

The influence of $\phi(i, j) \in [0, 1]$ at node j is brought into the following formula:

$$p_{st}^i = (S_t^i + (S_t^j - S_t^i)\phi(i, j) + [1 - (S_t^i + (S_t^j - S_t^i)\phi(i, j))]v_0, \quad (11)$$

where S_t^j represents the attitude value of the node under the influence of propagation node j at time $t + 1$, $v_0 \in [0, 1]$ represents the value of information, and the value represents the quality of information. $(1 - S_{t+1}^i)v_0$ is used for node transfer. The probability p_{sc} of node i changing from the unknown state to informed state is calculated as follows:

$$p_{sc} = 1 - p_{si}. \quad (12)$$

When $(1 - S_{t+1}^i)v_0$ is brought into the node state i , it can be expressed as the following formula:

$$p_{sc} = 1 - \left\{ (S_t^i + (S_t^j - S_t^i)\phi(i, j) + [1 + ((S_t^i + (S_t^j - S_t^i)\phi(i, j))] \right\}. \quad (13)$$

If node i is in an informed state at time t , considering the social reinforcement effect [23], the user will continuously receive the same information from neighboring nodes for many times in a period of time. The benefit value generated in the propagation node with a strong social influence is recorded as the propagation probability p_{ci} , which is calculated as shown in

$$p_{ci} = 1 - (1 - p_{si})e^{-b(n-1)}. \quad (14)$$

Putting p_{si} into node state i can be expressed as

$$p_{ci} = 1 - \left\{ 1 - [S_{t+1}^i + (1 - S_{t+1}^i)v_0] \right\} e^{-b(n-1)}. \quad (15)$$

Here, b represents the degree of social reinforcement and n represents the cumulative number of times that node i received information at time $t + 1$. For an informed node that has not been exposed to the information again for a long time and thinks that the informed node has forgotten the information as time goes by, there is no longer possibility of spreading information, and then, it is transformed into an immune node, and its transformation probability is calculated as follows:

$$p_{cr} = 1 - p_{ci}. \quad (16)$$

If node i is a propagator at time t , then p_{ii} is the probability that node i remains propagated at time $t + 1$ and p_{ri} is the probability that node i becomes an immune node at time $t + 1$. The probability of node i maintaining the propagation state at time $t + 1$ under the influence of adjacent nodes is calculated as follows:

$$p_{ii} = S_{t+1}^i - S_{t+1}^i\beta, \quad (17)$$

where β is the aging rate of information and $S_{t+1}^i\beta$ refers to the role played by the aging rate of information in the process of state transition. In the propagation process, if node i comes into contact with the immune node at time $t + 1$, it becomes an immune node with a probability of β . Then, the probability of keeping the propagation state is $1 - \beta$. If there are n propagation nodes and m immune nodes in the neighbor node, the probability of the node remaining in the propagation state is calculated as follows:

$$p_{ii} = \prod_{j_n \in T(i)} (S_{t+1}^i - S_{t+1}^i\beta) \cdot (1 - \beta)^m. \quad (18)$$

The probability that the propagation node i becomes an immune node is calculated as follows:

$$p_{ir} = 1 - p_{ii}. \quad (19)$$

The probability of p_{ii} changing from a propagating node to an immune node is expressed by the following equation:

$$p_{ir} = 1 - \prod_{j_n \in T(i)} \left[(S_{t+1}^i - S_{t+1}^i\beta)\phi(i, j_n) \right] \cdot (1 - \beta)^{m+n}. \quad (20)$$

On the Internet, all information follows the product principle and goes through the dissemination boom until the decline law disappears. Therefore, a message will not spread indefinitely [23]. Degenerated images will change state with nodes in the process of transmission. When they reach the immune state, they will gradually exit from the propagation state. When there are no propagation nodes in the network, the whole propagation process ends. Figure 4 shows the propagation process of information timeliness changing with time.

The trend of the whole time change, that is, the image in social network from initial state to declining state, can be roughly summarized into three sections, in which the initial period is from point A to point B , the peak period is from point B to point C , and the falling period is from point C to

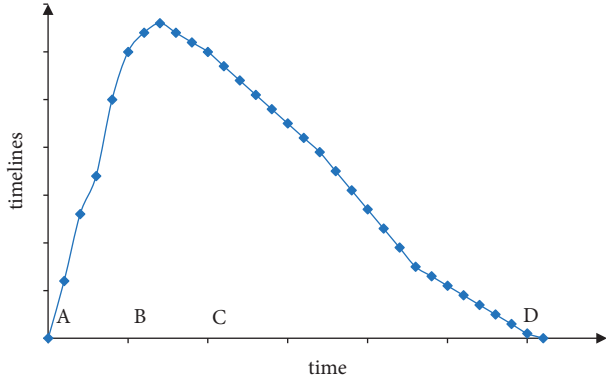


FIGURE 4: Graph of information timeliness change.

point D . The peak value can be understood as the theoretical upper limit of propagation in the current network, that is, the maximum number of infected nodes. The change rule of the degraded image can be clearly seen as a conic structure, and the three-stage pattern can be briefly understood as climbing in the initial period, reaching the maximum in the peak period and falling in the trough period, and finally approaching zero. Usually, the initial dissemination period of social network information is much shorter than the recession period [24]. The probability calculation of transforming a propagation node into an immune node considering the timeliness of information is as follows:

$$p_{ir} = S_t^i - S_t^j e^{-\lambda(t-t_s)} = S_t^i \left(1 - e^{-\lambda(t-t_s)}\right), \quad (21)$$

where $e^{-\lambda(t-t_s)}$ represents the timeliness of information in social networks at the current moment. λ denotes the information aging coefficient. In the network, when information is transmitted, the state of system users changes dynamically with time. The model is constructed on the basis of differential equations, in which four nodes and propagation probability have been proposed above, and the state transition mechanism is described as shown in Figure 5.

The information propagation rule in the SIR model can be described as that after a propagation source j publishes a message, its neighbor nodes first come into contact with the message and if they think that the message has propagation value, they will forward comments to more people with probability p_{si} . Otherwise, you will be transformed into an insider with a probability of p_{sc} . The probability that users will spread information only once is very limited. Considering the social reinforcement effect [25], in the process of information dissemination, similar information from neighbor communication nodes will be received many times. The probability of informed users spreading information will increase and become a communicator with a probability of p_{cr} or just for simple browsing. After a period of time, it gradually forgets to become immune with probability p_{ci} and the information is widely spread or loses its attraction after the upsurge, which no longer has communication value and gradually withdraws from people's field of vision and changes into immune with probability p_{ir} , after which the information will no longer be spread in any form.

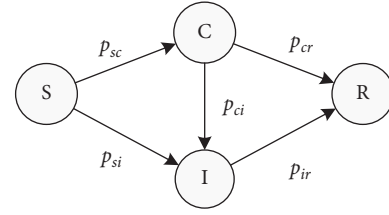


FIGURE 5: Node state transition diagram.

4. Experimental Simulation Analysis

4.1. Data Preparation

4.1.1. Data Background. Firstly, a degraded image is prepared as the material of the model experiment. The degraded image refers to the pixel size of the popular network image, and the pixel distribution of the degraded image size is shown in Table 1.

According to the distribution ratio in Table 1, the original image with a pixel size of 1920×1080 is selected as the experimental target as shown in Figure 6.

Then, the degradation image required by the experiment is obtained by degrading the image in Figure 6 as shown in Figure 7.

We use PyCharm to build python running environment, the NetworkX toolkit to generate BA scale-free network and WS small-world network, and use Sina and Facebook networks to simulate the SIR model. Specific network parameters are shown in Table 2.

In order to verify the effectiveness of this model, simulation experiments are carried out in different network environments and the changes of each node in the network with time are analyzed. Through the conclusions of Table 1 for the network environment for the real image propagation simulation, Table 2 is also a simulation environment and the purpose of the experimental environment and the real image propagation network environment is highly similar.

The degree $\langle k \rangle$ of nodes exists in the homogeneous network, β refers to the probability of the susceptible body transforming into an infected body, γ refers to the probability of the infected body transforming into a susceptible body, and the effective transmission rate is λ :

$$\lambda = \frac{\beta}{\gamma}. \quad (22)$$

$p(t)$ denotes the density of infected individuals in the network at time t , and when the network size tends to ∞ , it is determined by the average field theoretically available:

$$\frac{\partial p(t)}{\partial t} = -p(t) + \lambda \langle k \rangle p(t) [1 - p(t)]. \quad (23)$$

Formula (23) is equal to 0, and the steady-state density p of infected individuals is obtained:

$$p = \begin{cases} 0, & \lambda < \lambda_c, \\ \frac{\lambda - \lambda_c}{\lambda}, & \lambda \geq \lambda_c. \end{cases} \quad (24)$$

The propagation threshold is as follows:

TABLE 1: Picture pixel distribution proportion.

Pixel size	Baidu (%)	Weibo (%)	Facebook (%)
690 × 544	4	1	2
1024 × 576	14	6	9
1280 × 720	33	38	37
1600 × 900	8	5	4
1920 × 1080	36	43	44
2560 × 1080	5	7	4



FIGURE 6: Original image.



FIGURE 7: Degraded image after processing.

$$\lambda_c = \frac{1}{\langle k \rangle}. \quad (25)$$

When the critical value of infected individual size gradually decreases in the uniform network, the information will not spread in a large area. Affected by weak nodes, they quickly become infected people, resulting in a large amount of information dissemination. At the initial time, it is

assumed that there are propagation nodes in the network and the rest are unknown nodes. Susceptible individuals are easily influenced by infected individuals and quickly become infected, resulting in a large amount of information dissemination. At the initial time, it is assumed that there is a propagation node in the network and the rest are all unknown nodes. Set the parameters as follows: $\lambda = 2$, $\nu_0 = 0.5$, $b = 0.2$, $\phi(i, j) = 0.5$, and $\beta = 0.1$. The degraded images are brought into the SIR model for simulation analysis. For three different states S , I , and R on the BA network and WS network, the state change curves of different nodes with time are obtained as shown in Figures 8 and 9.

According to the propagation curve of the network diagram in Figures 8 and 9, the propagation law of the network is basically the same as that of the SIR model. In the initial stage, some nodes enter the propagation mode. With the increase in propagation time, the number of propagation nodes also increases. In the stage of information explosion, the propagation nodes increase to the maximum and the decline speed of unknown nodes accelerates. After the propagation reaches the peak, the degraded image slowly goes downhill and the propagation node and unknown node tend to zero, while the immune node r is close to 1. The peak value of propagation node in BA network is around 5, while the peak value of propagation node in WS network is around 7, which indicates that the information propagation speed in BA network is faster than that in WS small-world network. For degraded images, the probability of being infected in four network environments under SIR model is shown in Figure 10.

For degraded images, the probability of infected persons in four network environments under SIR model is shown in Figure 11.

Through the analysis of Figures 10 and 11, in the simulated SIR model, the probability of network infection and nonstandard small-world network infection decreases rapidly with the extension of time and basically reaches the lowest level at 8 ms. However, XinLang and Facebook have a slower decline, and there is a probability that some people will be infected in the end. For infected nodes, XinLang and Facebook are both close to 1, indicating that degraded images will always spread to users' information circle over time in social networks. In the process of social network information dissemination, users' positive attitude will promote information dissemination, while negative attitude will inhibit information dissemination. In order to study the influence of user attitude on information dissemination, the initial user attitude is set to $[-0.5, 0]$, $[0, 0.5]$, and $[0.5, 1]$ under the condition of keeping the above parameters unchanged. By analyzing Figure 12, it can be seen that the node model with positive attitude in the propagation process has faster propagation speed, wider propagation range, and shorter peak time than the node model with negative attitude.

The maximum speed of maximum infection rate (MIR) is to spread the network together with the number and proportion of nodes in the process of information dissemination, which can measure the influence of the whole network in the range of nodes. Figure 13 shows the changes

TABLE 2: Parameter settings.

Network name	Number of nodes	Average number of edges	Average	Degree correlation coefficient	Clustering coefficient
BA	2000	5991	3	-0.0758	0.02117
WS	2000	5100	2.5	-0.01472	0.26179
XinLang	4167	12954	2.4	-0.4271	0.07627
Facebook	8156	60603	7.1	-0.1464	0.3571

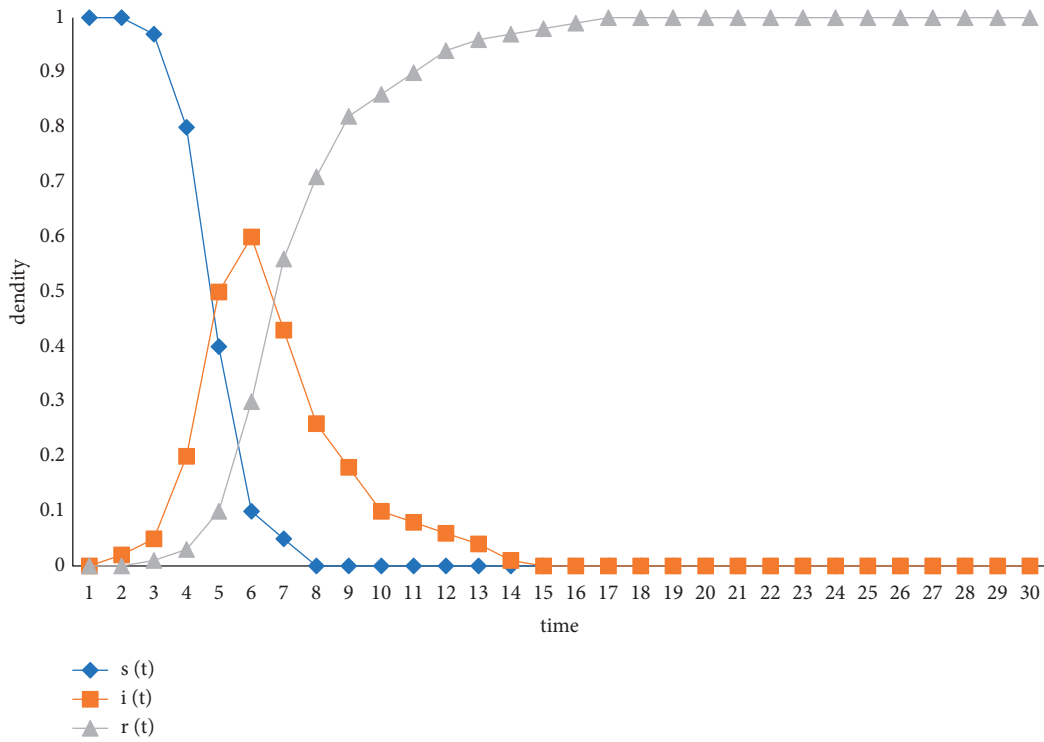


FIGURE 8: SIR model of the BA network.

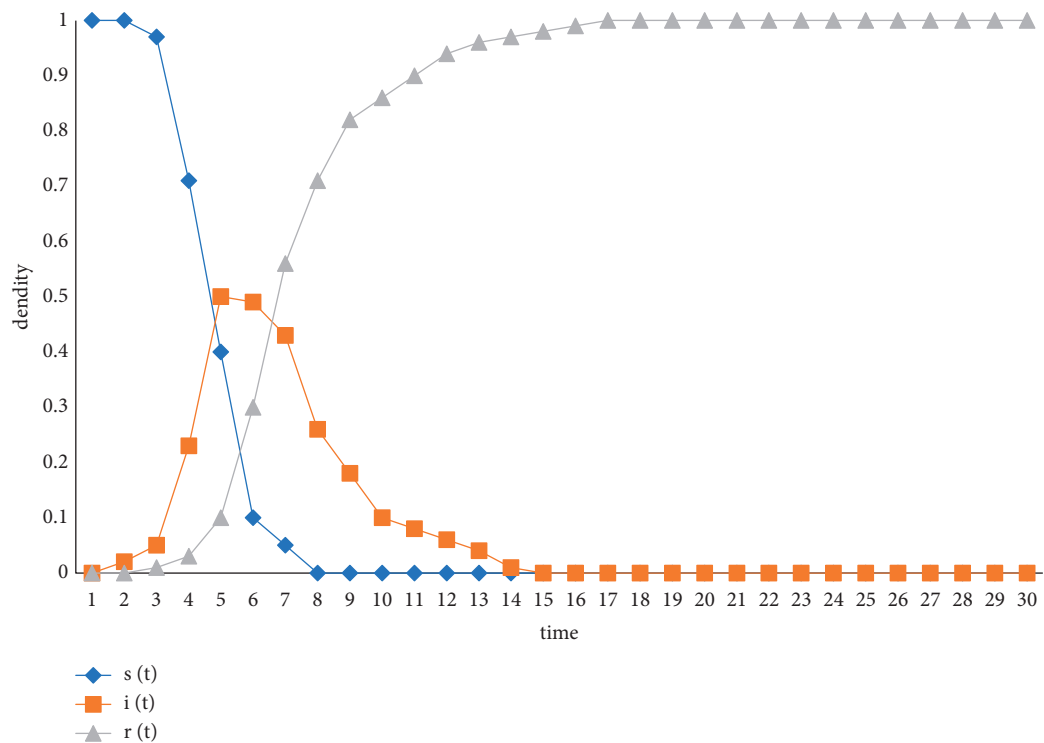


FIGURE 9: SIR model of the WS network.

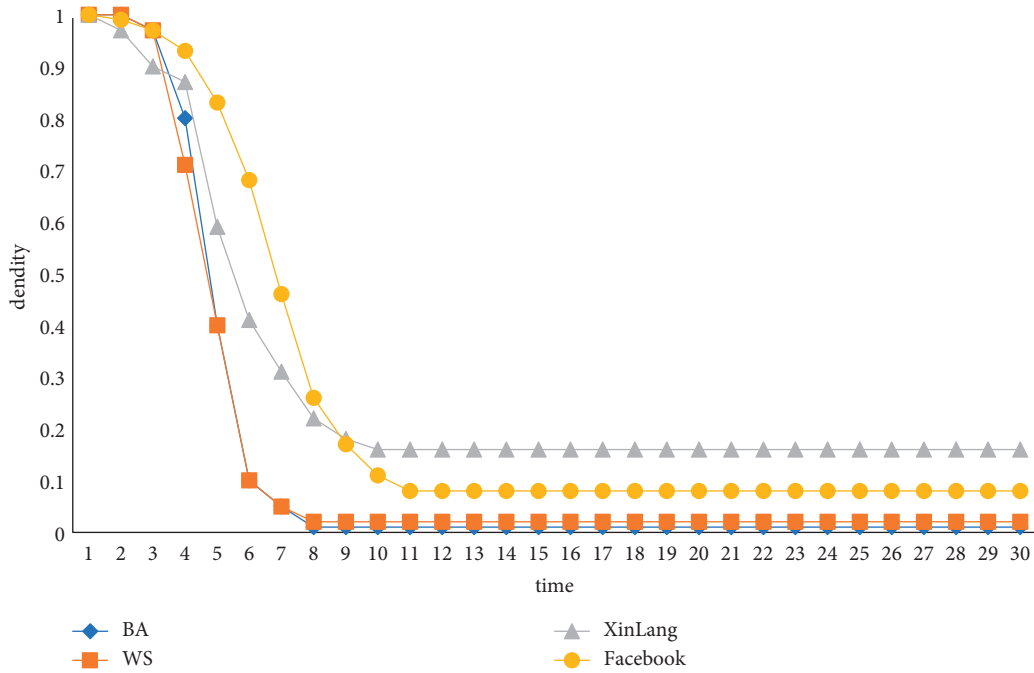


FIGURE 10: Comparison of $s(t)$ under four networks.

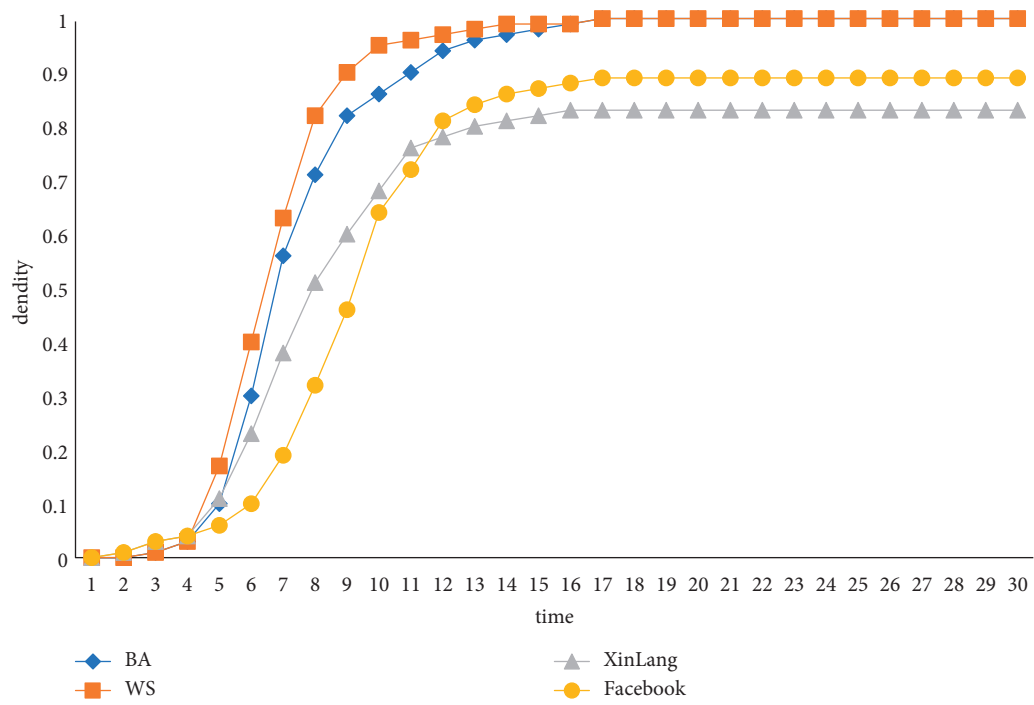


FIGURE 11: Comparison of $i(t)$ under four networks.

of the maximum infection ratio in different network environments, where the horizontal axis V is the information value and the vertical axis is the maximum infection ratio. Analysis of Figure 13 shows that the maximum infection ratio increases with the increase of V , that is, the higher the

value of information, the wider its spread range. In the whole experiment, the initial propagation node is set as one. If the propagation node is added, the propagation speed will increase and the corresponding time to reach the propagation peak will also decrease.

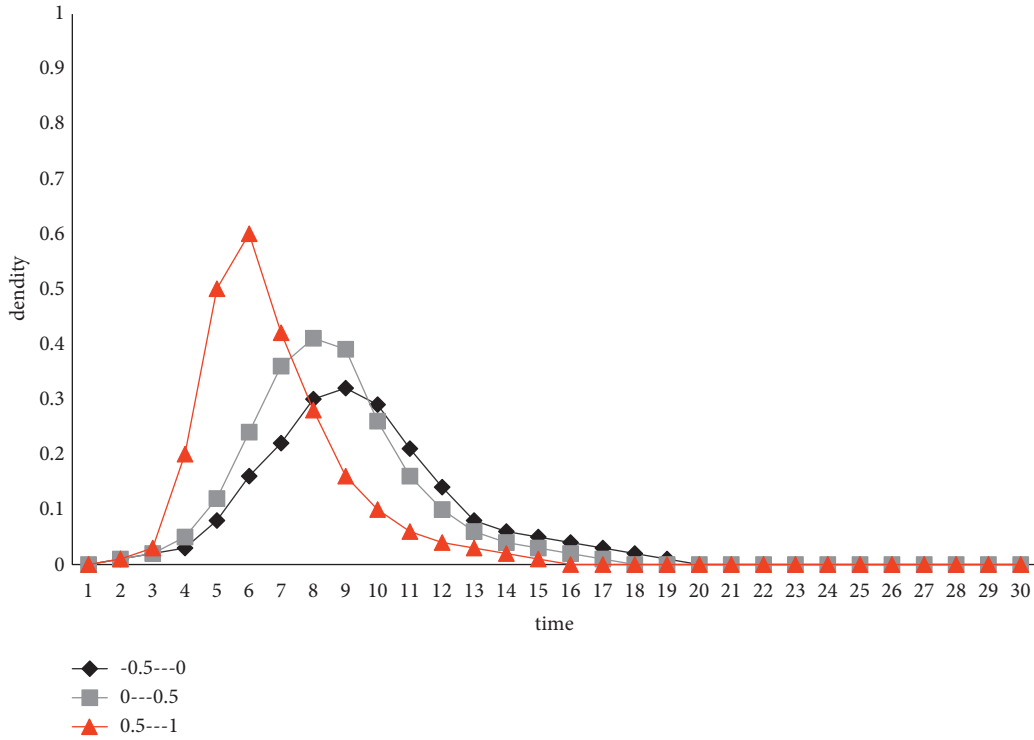


FIGURE 12: Influence of node attitude value on propagation.

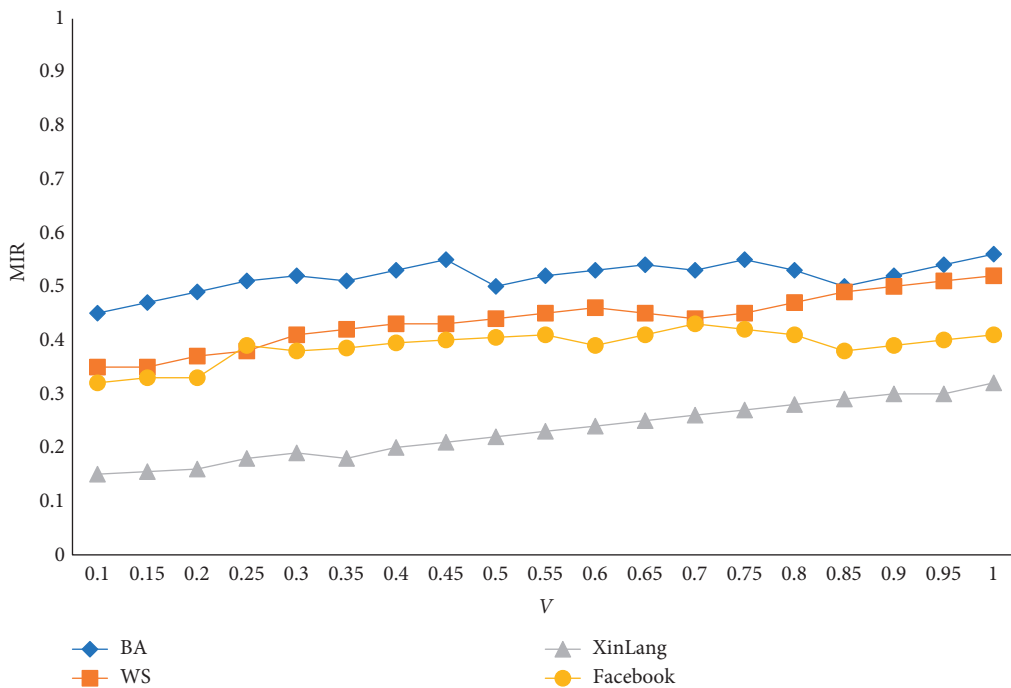


FIGURE 13: Maximum ratio of four network environments.

5. Conclusion

For the propagation of degraded images on the network, we choose the SIR model as the most representative propagation model. By improving the model, we define the state transition probability function between different nodes, set

various parameters of the environment, and consider various influencing factors. By comparing four different network environments, we carry out simulation experiments. It is found that the proportion of propagation nodes in the simulated BA and WS networks of the SIR model is small and the propagation process is relatively smooth. Secondly,

it is found that the information transmission speed in Facebook is faster than that in Sina and the information coverage is wider, but the information cannot cover the whole network. In addition, the subjective attitude and information value of users have a significant impact on information dissemination, which accords with the dissemination law of degraded images in actual social networks.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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