Research on disaster information dissemination based on social sensor networks

Shanshan Wan, Zhuo Chen, Cheng Lyu, Ruofan Li, Yuntao Yue and Ying Liu

Abstract
Sudden disaster events are usually unpredictable and uncontrollable, and how to achieve efficient and accurate disaster information dissemination is an important topic for society security. At present, social sensor networks which integrate human mobile sensors and traditional physical sensors are widely used in dealing with emergencies. Previous studies mainly focused on the impact of human mobility patterns on social sensor networks. In this article, based on the inherent autonomy property of human individuals, we propose a social sensor information dissemination model, which mainly focuses on the impact of the individual characteristics, social characteristics, and group information dissemination mode on social sensor networks. Specifically, the human sensor model is first constructed based on the inherent social and psychological attributes of human autonomy. Then, various information dissemination models such as one-to-one, one-to-many, and peer-to-peer are proposed by considering different transmission media and human interaction preferences. We simulate the environment of information dissemination in disaster events based on the NetLogo platform. Evaluation matrix is applied to test the performance of social sensor information dissemination model, such as event dissemination coverage, event delivery time, and event delivery rate. With the comparisons to epidemic model, social sensor information dissemination model shows excellent performance in improving the efficiency and accuracy of information transmission in disaster events.

Keywords
Social sensor networks, disaster event, autonomy, human mobile sensors, information dissemination

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Introduction
With the development of advanced technologies such as 5G and artificial intelligence (AI), Internet of things (IoT) connects every smart device more closely to constitute a smart society, where sensing technology plays an important fundamental core role. In current sensor networks, static sensors are usually connected to physical infrastructure and physical devices, while dynamic sensors are carried by and move with mobile bodies such as humans and vehicles in society, forming a unique social sensor network.

In order to deal with sudden disasters, the current society is actively creating an intelligent disaster management model. The application of large number of smart devices and the widespread use of big data have provided the necessary conditions for the formation of social sensor networks (SSNs). The implementation of disaster response to sudden disaster events on
the basis of SSNs can greatly improve the information coverage and the efficiency of dissemination of emergencies, thereby the appearance of SSNs is promising on reducing the damage and impact of disaster events. SSNs are very different from the traditional sensor networks, because as the most important element in SSNs, human can continuously perceive and understand society through their personal or social activity behaviors. And human can integrate, disseminate, and feedback this information through social interaction actively, which naturally achieves the purpose of timely perception of the environment and quick information propagation in emergencies.

At first, limited by the development of communication devices and communication technologies, human individual perceived and disseminated information only on a small scale. With the emergence of technologies such as the Internet and 5G, a large number of interactive platforms have emerged, which makes it possible that everyone can be a center source of information dissemination. Thus, it has contributed to the wide sharing and two-way flow of information among users. Hence, users can not only quickly release perceived information, but also directly participate in the process of integration and dissemination of perceived information in social environment. As a social sensor, human beings have the characteristics of autonomy and mobility that traditional sensors do not have, which ensures the ability of social network sensors to simulate information transmission in the real world, and achieve higher information coverage and faster information delivery rate at a lower cost. Currently, many SSNs based on human intelligences are used in various fields such as politics, economy, culture, climate, and transportation.

In SSNs, human autonomy-based mobile sensors can be coupled with traditional static sensors, and human mobility patterns lead to different interaction patterns between mobile and static sensors. Human Mobility Model focuses on collecting real-world movement data and filtering the data, and then modeling the environment and people’s behavioral decisions. The study of human mobility models is a fundamental problem in many disciplines such as networks, urban transportation planning, crowd management, and disaster management. Among the common mobility models, one is the temporal characteristic model of human behavior, which is a study of the dwell time (duration) of a single activity and the interval between two consecutive activities, as well as other time-related patterns that humans exhibit when performing certain activities. The other is the study of the spatial characteristic of human behavior, which focuses on the distribution of geographical locations where humans perform certain activities, frequency of visits, and so on. This article focuses on the spatial characteristics of the human mobility model based on the significant regularity characteristics of individual human mobility during sudden catastrophic events. The Individual Mobility (IM) human model of Song et al. is applied to this social sensor network, which proposes the characteristics of a human mobility model based on two social mechanisms: exploration and preference reward.

More importantly, how to build a reasonable and accurate information dissemination model is a key research topic in social sensing networks and it is also crucial for effective response to emergencies. B Mahmood et al. defined information proximity contact dissemination and distant social dissemination as two main characteristics of strong and weak relationships to assess their communication performance. The work described above targets to optimize the deployment of sensors. The main difference between these efforts is the calculation of the desired location of the sensors; in this article, SSNs with mobility are used to achieve optimal configurations in an extended sensing environment. In this article, we propose a social sensor information dissemination model (SSIDM). In which, we study the disaster responses made by human individuals in unexpected events by considering the characteristics of human individuals, human social groups, and the behavioral attributes of human autonomies. And some information dissemination models are proposed, which include one-to-one, one-to-many, and peer-to-peer. Experiments are designed to compare the proposed model with traditional information dissemination models, and the performance of SSIDM is evaluated based on indicators such as information dissemination coverage and information delivery time.

The rest of this article is organized as follows. Section “Related work” presents the related work on sensor networks, human mobility models, and information propagation models. Section “Simulating social networks of sensors” describes the application of human mobility models and information dissemination models to SSNs. Section “Experiments and analysis” introduces the designed simulation experiments using NetLogo and discusses the experimental results. Section “Conclusion and future work” gives the conclusions and introduces the future work.

Related work

This section presents the current research related to node deployment for sensor social networks, mobile sensor mobility models, and information dissemination models of mobile sensors.
SSNs deployment

The deployment of sensor nodes is a fundamental problem of SSNs, which refers to the use of appropriate optimization methods to place sensor nodes in a designated monitoring area to meet some specific target requirements. A number of studies have been conducted by domestic and foreign researchers about the node deployment problem of sensor networks.

A Howard et al.\textsuperscript{12} proposed an incremental self-deployment algorithm for mobile sensor networks. In the deployment process of this algorithm, only one node is deployed at a time, and the deployed node needs to make full use of the information of all deployed nodes to determine its best target location, and finally such deployment can obtain the maximum network coverage. The incremental deployment algorithm is more suitable for the situation where the environment of the monitoring area is unknown, and it requires less nodes. However, each node needs to be equipped with ranging and positioning modules, and the cost for this kind of deployment is relatively higher. Zou and Chakrabarty\textsuperscript{13} applied the virtual force theory to the deployment process of sensor networks and proposed a node deployment algorithm for homogeneous nodes. Some other researchers have proposed algorithms based on grid partitioning, for example, S Dhillon et al.\textsuperscript{14} proposed a deterministic sensor node deployment algorithm to achieve target point coverage based on square grid scanning. The algorithm divides the target detection area into multiple grids, and selects the optimal location grid of nodes from them until all target points are covered. This kind of algorithm achieves the maximum coverage of a given target area using the least nodes with the help of tangent, overlap and other related geometric knowledge, and so on. However, the effectiveness of such network deployment is highly susceptible to the size of the divided grid. Inspired by random sampling theory and optimal algorithms, Du et al.\textsuperscript{15} proposed a coverage optimization algorithm for heterogeneous wireless sensor networks. The algorithm transforms the coverage problem for a two-dimensional plane into a coverage problem for a one-dimensional straight line by sampling the detection area in a straight line. The coverage of the target plane can also be achieved optimally when multiple sampled straight lines reach the optimal coverage with the minimum node movement distance.

In the previous sensor deployment work, the main difference between these efforts is the calculation of the desired location of the sensors, and the SSNs for mobility employed in this article achieves an optimal configuration in an expanded sensing environment. Since the effect of sensor network deployment largely depends on the mobility of mobile sensors, we consider the combination of traditional mobile sensor networks and mobile sensor networks, and integrate the information of urban population living density into the sensor deployment.

Human mobility model

Recently, the application of a large amount of geographic data has facilitated the study of human mobility models. Brockmann et al.\textsuperscript{16} studied human spatial mobility behavior using circulation data in US dollars. The authors used a continuous-time random wandering model with a wide tail of displacement and waiting time distributions to describe human mobility patterns. MC González et al.\textsuperscript{17} analyzed mobile phone communication data and pointed out that the displacement and movement radius of human movement is a power-law distribution with an exponential tail. In addition, they found that there is a stable radius of gyration for individual movement, so they described human travel behavior as a Lévy flight model. The stochastic travel model is considered to be the best stochastic process models to describe human spatial movement which includes the continuous-time travel and Lévy flight models. Most of the time, the stochastic travel model is used to describe disease transmission as a stochastic process rather than to describe the spatial movement of individuals.

However, human spatial movement behavior is not completely random, and human movement sometimes exhibits regularity and periodicity due to specific individual, social, or physiological reasons. Neither of the above two models has well addressed these two mechanisms of human spatial movement behavior, that is, the exploration mechanism and the preference return mechanism. These two mechanisms are used to explain the scale-free properties in human spatial movement behavior, and they emphasize that humans exhibit important tendencies in their spatial mobility behavior, that is, a tendency to return to locations they visit with high frequency, for example, home and workplace.

At the same time, human behavior shows some exploratory and humans tend to visit places they have not visited before. Song et al.\textsuperscript{10} and Lu et al.\textsuperscript{18} proposed entropy theory to investigate the predictability of human spatial mobility behavior. They found that human spatial mobility behavior is highly dependent on historical behavior and it shows 93% predictability. Several researchers have considered the influence of the living environment of mobile individuals on mobility. Kang et al.\textsuperscript{19} studied the patterns of intra-city population spatial mobility behavior from the perspective of urban morphology and confirmed that human intra-city spatial mobility behavior obeys an exponential distribution and the exponent varies with the geographic
location and shape of different cities. For example, populations living in large cities typically move greater spatial distances every day. To consider the constraints of geographic space on human spatial mobility behavior, such as city boundaries, traffic patterns, and activity locations, various spatial networks have been used to model human spatial mobility behavior during disease transmission. Han et al. proposed a human spatial mobility model based on hierarchical transportation networks. In a hierarchical transportation network, population individuals need to move from one village to another town, and there is no direct transportation road between the two places, they usually move to the nearest central city through the transportation network first, and then move to the destination town via other central cities through the transportation network.

Random walks are a very useful tool for modeling IM, and in our work, human mobility models have been found to help better analyze the effects of mobility in SSNs. However, the analysis of human movement through the series of human mobility models described above is not random, so it is possible to improve the performance of SSNs protocols directly through the predictability of the models. Although some of the above models have some complete representations of human movement, they lack generality and are too complex for mathematical reasoning. Considering the characteristics of sudden disaster events, we apply the exploration and preference return mechanism-based human mobility model to specific SSNs. Such human mobility model defines the scale-free characteristics of human spatial mobility behavior and is able to accurately describe most of the characteristics of human movements through realistic simulation and experiments.

**Mobile sensor information dissemination model**

The process of information propagation is very similar to the propagation of infectious disease. Hence, it is feasible to study the propagation model of mobile sensors in disaster events referring to the contagion dynamics model. Existing propagation models, such as susceptible infected (SI), susceptible infected susceptible (SIS), and susceptible infected removed (SIR), simplify the real situation to some extent and cannot meet the research needs under the quick development of social networks. Therefore, researchers have further divided the stages of information dissemination based on the analysis of individual attributes according to the specific research field and established many new information dissemination models, such as susceptible exposed infectious recovered (SEIR) and susceptible contacted infected removed (SCIR).

PP Shu et al. constructed a group emergent model with scale-free characteristics of group emergent information dissemination network model based on the fact that the information dissemination behavior among group members is actually influenced by both meritocratic and stochastic action mechanisms. Considering the characteristics of propagation networks, D-Q Ding and X-H Ding proposed an inoculation immunization strategy for virus propagation in a cluster network based on real-time information construction. PV Mieghem et al. studied the immune strategy of the delay propagation dynamic model with multiple populations. The control of the propagation network topology aims to indirectly affect the propagation behavior by changing the connection relationship between nodes. As well, the direct removal of some key nodes or important connected edges are two of the most direct control strategies. Since Gross et al. introduced the concept of adaptive networks, a large number of studies have focused on the dynamic coupling between the network structure and the propagation process. For example, M Taylor et al. proposed a threshold-based broken-edge reconnection mechanism. B Wu et al. proposed a mechanism that edges can be randomly activated and deleted. G-H Zhu et al. proposed a broken-edge reconnection mechanism including various edge connection types. Compared with the broken-edge reconnection mechanism, the application of adjusting the connected-edge weights is more general. For example, W Wang et al. studied the weight control problem based on the SIS propagation model.

This article mainly focuses on the information dissemination pattern of SSNs in disaster events. Therefore, we first define the contact dissemination of offline crowds during emergencies based on the infectious disease model. Then, we define the online information dissemination in social networks considering the characteristics of human autonomous agents, which focuses on the propagation of information, the feedback characteristics of agents, and the environment. A variety of information dissemination modes are proposed which can more accurately simulate the information dissemination patterns under disaster events, so as to greatly speed up the information dissemination time and provide sufficient help for disaster rescue.

**Simulating social networks of sensors**

In this article, we study the SSNs model under disaster events. First, the environmental simulation of sudden disaster events is designed to complete the deployment of traditional sensors and mobile sensors. Then, we give the human mobility model based on IM. Finally, the information dissemination based on human mobility model in SSNs is defined in detail, and a real information dissemination scene of sudden disaster events in the city is restored to evaluate the proposed model.
Sensor deployment model

SSNs are constantly interacting through the social activities of individuals, hence, SSNs can provide users with more social and business opportunities. The dense nature of human interaction in SSNs can be used to disseminate information about disaster events, allowing social media to quickly sense and disseminate information during emergencies. The network provides a flexible system for emergency response. At the same time, building a better data forwarding and routing protocol is a primary concern after a disaster event. However, due to the mobility of humans, the topology of SSNs changes dramatically over time dynamics, and it is difficult to maintain fixed communication links. A number of mobile network models have been proposed to simulate mobile networks, but the existing models do not take into account the multiple properties of human autonomy. As social sensor mobile individuals carry in real environments, the way movers in SSNs potentially reflect the characteristics of human mobility. In today’s urban environment, the individual characteristics, social characteristics, and group information dissemination patterns of self-organized users are also extremely important for network performance. Based on these knowledge, we construct the SSIDM.

To simulate the environment of disaster event, we consider the situation of both mobile and static sensors. Static sensors are installed in urban infrastructures, such as street lights and buildings. Dynamic sensor refers to intelligent devices with communication function carried by people, such as mobile phones and note-books. Both static and dynamic sensors together form social networks.

First, a square grid with side length \( l \) is used to represent the area, and then the grid is divided into a square patch per unit area, in which two types of sensors are deployed. In which, static sensors are uniformly distributed in the environment and mobile sensors are deployed according to the urban population density model proposed by Clark.\(^{37} \) The population density functions are shown in equation (1)

\[
D_{(x)} = D_0 e^{-\gamma x}
\]

where \( x \) denotes the distance of the sensor from the city center, \( D_{(x)} \) is the population density, and \( D_0 \) is the scale factor. When \( x = 0 \), it refers to the population density in the city center. According to the population density model, we complete the coverage simulation of sensors related to urban population. In this study, the environment of metropolis is used as a background for disaster events, so the population density of Beijing, \( D_{(x)} = 1300 \) persons/km\(^2\), is referred here.\(^{38} \)

In disaster simulation, the more important factors are the source point and transmission end point of information. We set two kinds of special markers in the environment: disaster event points and sink points. Disaster event points mean the sudden events that need to be detected, such as earthquakes and gas leaks. Sink points refer to the spots where the critical event information needs to be delivered, for example, fire station and public security bureau. At the same time, if an event can be detected, it must be within the fixed radius \( r \) of the sensor, that is, the sensor can detect the occurrence of the sudden event when the event lies within \( r \) of the moving sensor and the fixed sensor. For static sensors, \( r \) refers to the coverage radius of a certain physical range. For mobile sensors, \( r \) refers to the user range within which information can be reached in human virtual social networks, such as friends, circles of friends or the objects people can get connected through @ operation. Therefore, in the simulated urban environment, the number of static sensors that can cover the simulated urban environment, \( C_s \), can be calculated as follows

\[
C_s = \frac{(l + r)^2}{r^2}
\]

The number of mobile sensors required, \( C_m \), can be calculated by the following equation

\[
C_m = \frac{D_{(s)} S}{s} - C_s
\]

where \( S \) is the area of the entire urban environment and \( s \) is the area per unit. The sinks and disaster points are deployed randomly at a distance \( d \) from the center of the city, and the distance between them is always fixed at 2\( d \). Thus, \( d \) should be at the radius of a circle centered on the city, and in total, about 80% of urban residents move within the circle of deployed receivers and disaster points. Since the event points and sinks are all over the two ends and edges of the simulated environment, the deployment takes into account the scope of most area of cities, and the possible information dissemination area of emergencies spans most scenes of the simulation environment.

Human mobility model

In this article, the IM human mobility model is applied, which defines a human mobility model consists of human-carried sensors. One of the key factors to evaluate the human mobility model is the distance an individual moves within a fixed time interval, which is called the jump length and expressed by \( \Delta r \). Another factor is the time spent by individuals at the same spot, which is called waiting time and expressed by \( \Delta t \). As well, D Brockmann et al.\(^{16} \) and MC González et al.\(^{17} \) stated that the distributions of the jump length \( \Delta r \) and the waiting time \( \Delta t \) of human trajectories are truncated power-law distributions, and the probability
distribution density functions $P(\Delta r)$ and $P(\Delta t)$ of jump length and waiting time are given as equations (4) and (5)

$$P(\Delta r) = (\Delta r + \Delta r_0)^{-1-\alpha} \exp\left(-\frac{\Delta r}{X_1}\right)$$  \hspace{1cm} (4)  

$$P(\Delta t) = (\Delta t)^{-1+\beta} \exp\left(-\frac{\Delta r}{X_2}\right)$$  \hspace{1cm} (5)  

where $\Delta r_0$ is the minimum jump distance. $X_1$ and $X_2$ are defined as the exponential cutoff of the function. The power-law distributions property in $P(\Delta r)$ and $P(\Delta t)$ proves that humans follow a random wandering model in their daily activities. Two common mechanisms are introduced in IM model which are, namely, exploration and preference reward. The random walk model assumes that the next movement step of human is completely independent of the previously visited location. But in real life, the tendency of human beings to explore new spots decreases with the passage of time. In other words, the longer we observe a person’s trajectory, the more difficult it is to find places they have not yet visited near their home/workplace. Considering such an exploration model, the probability of human visiting a new spot is defined as follows

$$P_{\text{new}} = \rho S^{-\gamma}$$  \hspace{1cm} (6)  

where $S$ is the number of locations people have visited. At the same time, in the random walk model, the probability of human visiting a place is random and uniform in space, but in real life, human beings obviously tend to return to the places they often visited before, such as their home or workplace. This forms a complementary access probability with the previous exploration mechanism

$$P_{\text{ret}} = 1 - \rho S^{-\gamma}$$  \hspace{1cm} (7)  

In this case, $P(i)$, the probability of choosing to visit location $i$, is proportional to the number of times people have visited that location before; hence, it is defined as the following equation

$$P_i = f_i$$  \hspace{1cm} (8)  

Information dissemination model

Information dissemination is the focus of social network research, and it is also an important part of the SSIDM proposed in this article. After a disaster occurs, human beings are transformed into carriers that can spontaneously spread information, and complete the wide dissemination of disaster information through social relationship networks. Finally, the social sensor network is able to realize the rapid coverage of information among populations, help the sink point get information in time, and the relevant timely decision-makers can make timely decisions on disaster events.

In the process of information dissemination, due to the differences of individuals and the different influence of individuals on groups in social relations, each person has different reactions, processing ability, and response methods for handling information on emergencies, which leads to significant differences in the effects of information dissemination and diffusion. For different groups, they have their own social networks and social forms, and also show a relatively fixed way of information transmission. We extract and define the two most common communication modes in information communication, which are specifically expressed as follows

$$RT = <\text{CP}, \text{NCP}>$$  \hspace{1cm} (9)  

where RT indicates the mode of information dissemination during emergencies. CP indicates face-to-face contact dissemination, which is the most common and primitive way of dissemination after an emergency. NCP indicates the way information is disseminated on the Internet, such as WeChat and Weibo. Nowadays, the NCP mode of information dissemination under emergencies greatly affects the efficiency of dissemination of events, which is particularly evident in large cities.

Contact transmission. The distance of contact-based information transmission is very limited, but it is a very direct and flexible form of information dissemination. Contact-based information transmission can be explained as face-to-face transmission, which is the primary and prevalent method of transmission in sensor networks. Contact-based information propagation models fall into three main categories: infectious disease dynamics model, computer virus propagation model, and rumor propagation model.

The process of information propagation in SSNs has similar patterns to the process of infectious disease diffusion in a population. In order to solve the problem of disaster information propagation in SSNs, the infectious disease model is applied in this study. Considering
that the individual nodes of social sensors will only present two states: event unknowns and event knowns at the time of an unexpected event; therefore, we use the classical susceptible infected model, that is, \(^{22}\) SI model for contact-based information propagation in SSNs. The diagram of SI model is shown in Figure 1.

In Figure 1, \(U\) denotes the human’s unknown state for the event, \(K\) denotes the known state for the event, and \(U\) will be transmitted as \(K\) under a propagation rate of \(\beta\). \(\beta\) is influenced by the attributes of human population, that is, different human populations show different propagation probabilities.

Finally, with the passage of time, more and more unknown people are transformed into the known ones of the event. The differential equation of the propagation dynamics of the model is shown as follows

\[
\begin{aligned}
\frac{dU(t)}{dt} & = -\beta U(t)K(t) \\
\frac{dK(t)}{dt} & = \beta U(t)K(t) \\
\end{aligned} 
\]

(10)

The ratios of unknowns and knowns at moment \(t\) are denoted as \(U(t)\) and \(K(t)\), respectively, \(U(t) + K(t) = 1\).

**Social network dissemination.** Based on the virtuality, extensibility, and non-regionality of network, disaster information can spread across the social network without physical region limitation and it can quickly spread throughout the whole social network. Considering the characteristics of social networks, we give the definition of information dissemination mode, NCP, which includes different ways

\[
\text{NCP} = \{\text{oto, otm, ota, otp}\} 
\]

In equation (11), \(\text{oto}\) refers to one-to-one information dissemination mode, which means that people \(U_a\) select one person \(U_b\) as the object to transmit information. Usually, \(U_b\) usually has the closest social relationship with \(U_a\). The communication media is phone or SMS mostly. \(\text{otm}\) represents the one-to-many information dissemination in the social network, and the representative social media is the circle of friends of WeChat. This kind of communication mode covers more social areas of \(U_a\). \(\text{ota}\) means the one-to-many information dissemination in social network. Its objects are all netizens who use the corresponding social media, and each person has the possibility of receiving information. The transmission media are usually Microblog and Ins. Although this mode is the most extensive way of information dissemination, the relationship between the objects and the event knower is not so close; hence, the feedback is not very high due to uncertain trust and attention. \(\text{otp}\) represents the online point-to-point information dissemination mode, that is, the people who receive emergencies directly disseminate the information to the corresponding security institutions. The target object of this dissemination may not be very accurate, but the effect of dissemination is usually significant. It can greatly reduce the time for information to reach the best receiving point.

However, the dissemination of information in social networks is a multi-agent collaborative process, which has the characteristics of small world and power-law distribution. Network information dissemination is not a simple one-way linear process, which is complex and dynamic. In order to better simulate the spread of disaster information in social networks, it is necessary to analyze the individual characteristics in social networks. Generally speaking, the evolution process of information interaction is affected by individual characteristics, such as education level, social status, and interpersonal relationship. In this article, some individual characteristics most related to information dissemination in social networks under emergencies are extracted and defined as IC. The specific characteristics of IC are defined as follows

\[
\text{IC} = <W, V, Fo, ER, Co, Int> 
\]

(12)

The elements in IC are explained here:

1. \(W\) and \(V\) represent the individual attributes and social attributes of human, respectively

\[
W = \{W_1, W_2, W_3, \ldots, W_x\} 
\]

(13)

\[
V = \{V_1, V_2, V_3, \ldots, V_y\} 
\]

(14)

where \(W\) denotes the \(x\) kind of individual attributes of people based on their age, for example, adolescents, youth, middle-aged, and elderly. \(V\) denotes the social attributes of human based on their career, which consists of students, workers, unemployed, retired, professional safety officers, and so on. In this study, these two kinds of attributes of individuals are mainly considered and analyzed to achieve the different information dissemination characteristics of agents in social networks.

2. \(Fo\) refers to the influence of individuals. According to the basic theory of communication, the phenomenon of obeying authority exists in the information communication network, that is, the greater the influence of the
node, the greater the breadth of information communication. The value of influence is proportional to the propagation probability of the node, so the influence is defined as follows

\[ Fo = \sqrt{ \frac{d}{d_{\text{max}}} } \]  

(15)

where \( d \) is the propagation probability of the node, and \( d_{\text{max}} \) is the maximum value of the propagation probability of the node. The range of values is the continuous interval \([0,1]\).

3. \( ER \) denotes the event relevance. Individuals’ reactions to unexpected events vary greatly, with individuals involved in their own relevance showing a strong desire to exchange and disseminate information, and conversely showing indifference and generally not actively expressing their opinions. Define event relevance as follows

\[ ER = \text{Norm}(\gamma \cdot f(D_i, D_s)) \]  

(16)

where \( D_i \) denotes the distance from the individual to the event location, and \( D_s \) denotes the distance from the individual to the receiving point. \( \gamma \) is the correlation of interest between individuals and disaster event, and its value is in the continuous interval \([0,1]\). \( ER \) is set between \([0,1]\) by the normalization function norm.

4. \( Co \) means conformity. Conformity refers to the characteristics that when individuals are influenced by the group, they will doubt and change their views, judgments and behaviors, and change in the direction consistent with the majority of the group. Subordination is related to individual education, knowledge, experience, and other factors. People with little conformity tend to have their own opinions and are less influenced by the views of others, and vice versa. Here, conformity is defined as follows

\[ Co = f(V, W) \]  

(17)

Obviously, conformity is related to people’s individual attributes and social attributes. The value range of conformity index is a continuous interval \([0,1]\).

5. \( Int \) represents the intimacy. In interpersonal activities, intimacy refers to the fact that two individuals have continuous and frequent interactions over a considerable period of time. Intimacy affects people’s cognitive activities. In general, the closer the relationship between individuals, the more willing they are to accept the opinions of others, and conversely the more likely they are to be skeptical of others’ views. \( Int \) is defined as follows

\[ Int = f(\text{Con\_fre}, \text{Con\_time}, \text{Count\_circle}) \]  

(18)

\( \text{Con\_fre}, \text{Con\_time}, \) and \( \text{Count\_circle} \) indicate the frequency of contacts that individuals present in the social network, the duration of contacts, and the number of their common circle of friends. The range of \( Int \) is also the continuous interval \([0,1]\).

In view of the spontaneous interaction characteristics of agents, in social networks, an information dissemination network diagram is constructed, in which, individuals are nodes and the interconnection between nodes are taken as edges. At the beginning, the network scale is small. With the passage of time, the network scale gradually expands, and finally forms a continuous and stable information dissemination network, which we call dynamic diffusion network.

When a disaster event occurs, the mobile sensor (human witness) which is close to the place of the event or the physical sensor will first perceive the event information and become the initial node of the information dissemination network. Next, the event information is spread through SSNs. Information dissemination is carried out in four modes defined in NCP, and individuals follow the characteristics defined by IC. With the progress of propagation activities, nodes with unknown information change into known information state and join the dynamic diffusion network. The growth of the number of nodes in dynamic diffusion network is consistent with the growth of the number of individuals with known information state. In the process of information dissemination, the spread of early information is fast, and the number of people who know the event increases exponentially. In the middle stage, the number of individuals who are interested in information and do not know information gradually decreases, and the growth rate slows down. The individuals with unknown information left in the later stage are usually not interested in the information. The growth rate of the number of known information nodes is very slow, and finally stops growing. At this time, the dynamic diffusion network converges and the network structure tends to be stable.

After we complete the deployment of the SSNs, the selection of the human mobility model, and the definition of the information dissemination model, it is possible to accurately describe the realistic environment for the dissemination of disaster information about disaster events in the event of an emergency.
Experiments and analysis

Due to the unpredictability and non-repeatability of emergencies, reasonable modeling and simulation of emergencies is an effective means to study the performance of SSNs under emergencies. Human individuals reflect the characteristics of diversity, and the social sensor network composed of individuals is also a complex social system. In this study, we use agent-based modeling and simulation method and apply NetLogo platform to verify the proposed SSIDM.39

The NetLogo platform consists of two elements, the world and the agent. The world is the main view interface of the platform, which is made up of patches. The agent consists of turtles, patches, links, and observers. Turtles are the independent individuals that move through the world and are assigned various properties. Patches form the network of the world. Chains are abstract connections without entities at two endpoints and are often used to represent logical relationships between two turtles; observers are users who observe the world, input instructions and control the behavior of other subjects, but never achieving the goal of controlling the operation of the world, that is, the world operates spontaneously without external intervention.

NetLogo is a multi-agent complex network modeling environment that makes it relatively easy to construct models of mobile agents moving and interacting in a certain space, where modelers can issue commands to hundreds of independent agents. In this environment, it is possible to represent several spatial distributions of static sensors, for example, exponential and normal distributions, as well as to model random walking of different types of mobile sensors, for example, Lévy walk, continuous-time random walk (CTRW), and Cauchy flight.

Simulation interface design

After the occurrence of sudden disasters, human agents in SSNs are transformed into social sensors. They change their state through mutual information transmission. We use NetLogo to simulate this propagation process.

The ultimate objectives of this simulation modeling are (1) to accurately simulate the information dissemination process of disaster events through the deployment of static and mobile agents in SSNs and (2) to evaluate the efficiency and accuracy of the proposed model for information dissemination during the event of emergencies by observing the performance of the model in the metrics of information dissemination coverage, information delivery time, and information delivery rate.

Figure 2 shows the visualization interface diagram of the initial NetLogo simulation system for a simple emergency. The red cross represents the location of the event, and the yellow flag represents the ultimate sink of information dissemination. Purple dots represent the static sensors evenly distributed according to urban area, and green dots represent the initial human sensors in unknown information state distributed according to urban population density. The process of sensor affected by disaster information is represented by the changes in node color. After the disaster event is detected by the physical sensor, the purple points will be converted to red. Similarly, with the progress of information dissemination, more and more green points will be converted to red. Red dots represent the static sensors that detect events and human sensors which are known to disaster events. The environment state diagram when the event information propagation stops is shown in Figure 3.

In the specific environment design, first, the size of the simulated environment is matched with the actual size of the city. The side length of the square lattice is set to $l = 100$. The sensor radius is set to match the real-world sensor action range, and the sensor action radius is set to 10 m, which is equivalent to $r = 0.1$ in the simulated environment. Since person/km$^2$ is selected as the density unit of the sensor, we define the unit area in the simulated environment as a square of 10 m × 10 m.

In the environment process of NetLogo simulation, the traditional static sensor will check whether there is an event source within its radius at each tick time. Mobile sensors will also detect whether other sensors within their radius release disaster information. If so, they will further spread the information in the form of reproduction and propagation defined in section “Simulating social networks of sensors.” The propagation of information stops until the disaster information...
is transmitted to the receiver by human mobile agent or static agent.

Figure 4 gives the system control interface diagram of the designed environment simulation. The specific meanings of main design components in the simulation environment are shown in Table 1. In Table 1, because the mobile sensor has different individual attributes, social attributes, influence, event relevance, conformity, and intimacy, the sensing radius $r$ of the mobile sensor is different. The sensing radius mentioned in formula (2) is defined as the functional formula composed of the above factors

$$r = f(W, V, Fo, ER, Co, Fa) \quad (19)$$

According to the calculation results of $r$, the sensing radius of mobile sensor is summarized into three types. For example, the category with small sensor radius indicates that the information dissemination ability of individuals is weak, which may happen to the retired elderly people. Their influence and intimacy to other users are not active, and they usually follow one-to-one or one-to-many information communication modes. Therefore, their influence range and population breadth in social networks are relatively limited. Different propagation radius reflects that human individual has different abilities in disaster event dissemination.

**Simulation experiments and discussion**

In this part, we will verify the rationality of the characteristics of SSNs proposed in the SSIDM through experiments. And the experimental results prove that SSIDM model can effectively improve information transmission efficiency in disaster events by analyzing

| Species     | Name                        | Meaning description                             |
|-------------|-----------------------------|-------------------------------------------------|
| World       | environment of emergency    | Purple nodes indicate static sensors            |
|             |                             | Green nodes indicate human mobile sensors       |
| Button      | set up                      | Initialize the world                            |
|             | go-once                     | Run the program once                            |
|             | go                          | Run the program                                 |
|             | reset                       | Initialize all global variables                 |
| Input       | mobile-radius1              | Mobile sensor 1 propagation radius              |
|             | mobile-radius2              | Mobile sensor 2 propagation radius              |
|             | static-radius               | Static sensor propagation radius                |
|             | type-of-walk                | Mobile sensor movement model                   |
|             | routing                     | Mobile sensor propagation model                 |
|             | mobile-sensor-distribution  | Mobile sensor distribution model                |
|             |/static-sensor-distribution  | Static sensor distribution model                |
| Slider      | n-of-mobile-sensors         | Number of human mobile sensors                 |
|             | n-of-static-sensors         | Number of static sensors                       |
| Drafting    | event spreading             | Number of sensors that received the event       |
the performance of the model in terms of indicators such as information dissemination coverage, information delivery time, and information delivery rate.

Sensor deployment experiments. Since static sensors are deployed according to the principle of regional equalization, we mainly discuss the impact of the number of mobile sensors on the dissemination of disaster event information.

Number of mobile sensors. The number of sensors in a sensor network with integrated static and mobile sensors is more critical. The experiments first set the number of static sensors to be constant and vary the number of mobile sensors to test the impact of mobile sensors on performance in information dissemination, and observe when event detection time is rapidly reduced by the principle of mobile sensor deployment. The number of mobile sensors is incremented as a percentage of the number of static sensors. The detection time considered in this step is from the time when the simulated event occurs until the first sensor transmits the event point information to the sink point.

In the sensor network which integrates static sensors and mobile sensors, the number of sensors is key to the performance of the whole network. In the experiment, first, we assume the number of static sensors is fixed, and then change the number of mobile sensors $C_m$ to test the effect of mobile sensors on information dissemination performance. The shortest duration from the occurrence of events to the time that the effective sink receives the disaster information is taken as the principle to decide the optimal deployment of mobile sensors. The number of mobile sensors is achieved by gradually increasing the percentage of mobile sensors relative to static sensors. The experimental results are shown in Figure 4. The $X$-axis is the tick time taken for the disaster event information to reach the sink point, and the $Y$-axis is the sum of the number of static sensors and mobile sensors.

In the experiment, we randomly trigger a disaster point. After the first sensor detects the event point information, we observe that the event point information continues to spread around through the SSNs through the change of the color of the sensor node. With the event point information spreading to sink point, the propagation simulation of disaster events also stops.

We define $T$ to represent the ratio of dynamic sensor to static sensor. $T = C_m/C_s$. It can be visually observed from Figure 5 that the time of event information propagation to sink is also gradually reduced by changing the number of moving sensors. Finally, it can be obtained that the event transmission time in with the increase of mobile agents, event detection time in gradually decreases, but when the number of mobile sensors increases to 60% of the static sensors, the rate of event detection time also becomes flat; however, the overall transmission rate is on the rise.

Different mobile sensor ratios. By changing the proportion of the three types of mobile sensors defined in equation (19), we aim to observe their impact on the propagation performance of disaster events. Three different types of mobile sensors are defined as $ms_1$, $ms_2$, and $ms_3$. The proportions of $ms_1$, $ms_2$, and $ms_3$ are initialized to 20%, 30%, and 50% individually to test the effective propagation time of the event being delivered to sink point. The result is shown in Figure 6(a).
Then, when the proportion of ms1 is 20%, we change the values of \(ms2\) and \(ms3\), respectively, and the sensor proportion which causes the fastest effective propagation time of the event being delivered to sink point is shown in Figure 6(b), that is, \(ms2\) and \(ms3\) are 10% and 70%, respectively.

Through the experiments, it can be found that in the social network environment, the higher the proportion of mobile sensors with large propagation radius, the time for disaster event information to spread to the receiver point will be significantly shortened. Therefore, it is very critical to cultivate or set up mobile nodes with strong communication ability to reduce the harm of disaster events.

**Delay time of event information.** In traditional sensor networks, the performance of routing algorithms is usually evaluated by the length of network path or the number of hops in the network. In this experiment, considering the characteristics of social networks composed of static and mobile sensors, we use information transmission delay to evaluate the information dissemination performance of SSIDM. The delay here refers to the time difference between the time when the first sensor detects the event message and the time when the sink receives the information. This experiment takes the average information transmission delay as the standard to evaluate the routing performance of SSNPs. At the same time, the SSIDM is compared with the epidemic protocol (EP) model.\(^{40}\) The method is based on an epidemic algorithm that sends data messages to all network nodes within the communication range of a given node, leading to a scenario where all nodes are guaranteed to receive all data messages generated in the network. This is a program similar to full broadcast. The epidemic approach is widely used for benchmarking other protocols. However, the SSIDM proposed in this article takes the self-organization property into account in the information dissemination of disaster events. The experimental results are shown in Figure 7.

It can be seen from the results that when there are only 80 mobile sensors, the average delay time of information transmission to sink point is very long. With the increase of mobile sensors, both SSIDM and EP model have greatly improved the information transmission time. Moreover, the experimental results verify that the propagation delay of the SSIDM is significantly lower than that of EP, which means that the model with specific interpreting of individual differences and different information dissemination propagation modes of social sensors can transmit information faster.

**Coverage rate of population.** When a disaster event occurs, one purpose of information dissemination is to spread the event information to a larger area and cover more people. Therefore, the range of people covered by the information dissemination is one of the main indicators to measure the performance of SSIDM network. The range of people informed about the event covered by the dissemination of information refers to the proportion of the mobile sensor population that has received the information in the whole environment. Coverage depends heavily on the mobility of the sensors, and as they randomly spread and move, they are able to cover areas that would not otherwise be covered in the environment. Taking the population coverage of known information as the index, this article compares the SSIDM with the EP model, and the results are shown in Figure 8.

From Figure 8, it is clear that the coverage of these two models is rising sharply at 0–20 ticks, and the coverage area gradually tends to be stable after 20 ticks. However, throughout the simulation process, SSIDM
has always shown higher population coverage than EP model, and SSIDM soon reaches 100% population coverage at about 100 ticks. It is mainly due to the NCP communication mode defined in SSIDM, especially the one-to-many and one-to-one information dissemination modes based on individual stable social relations, which ensure that sudden disasters can multiply and spread rapidly in a short time, and cover the crowd in the social network formed by many individuals.

**Delivery rate of disaster information.** Event delivery rate refers to the proportion of event information that can be delivered to the designated sink point within a certain time. Taking the event delivery rate as the index, we study the information dissemination performance of SSIDM network. In the experiment, we deploy multiple disaster event occurrence points and a sink to test the proportion of disaster events received by sink after a certain duration of ticks. Specifically, 30 disaster events are set and the time limit is 50 ticks. Figure 9 shows the comparison of event delivery rate between SSIDM and EP model under different number of mobile sensors.

It can be seen from Figure 9, as the number of mobile agents increases, the event delivery rate of SSIDM and EP models shows an upward trend as a whole. However, due to the randomness of EP model, it also causes unstable performance, such as between 160 and 240 ticks. For the SSIDM, when the number of sensors is about 250, the event delivery rate can reach 100%. At the same time, SSIDM is more stable in event transmission delivery rate.

This article investigates the SSIDM incorporating SSNs in the specific context of disaster events, on the basis of which the characteristics of individual humans and social groups are analyzed and the responses that humans would make in a disaster event are studied. The experimental results show that SSIDM can more accurately simulate the information dissemination patterns under disaster events and greatly accelerate the speed and scope of information dissemination.

**Conclusion and future work**

In this article, we propose a SSNs model based on human agent in the context of sudden disaster events, SSIDM. First, the humans in the social network are simulated as mobile sensors, and the human autonomy model is constructed through the analysis of human individual and social attributes. Then, considering the factors such as human influence, event relevance, conformity, and intimacy, we define four information communication modes in case of sudden disaster events. The simulation experiment is designed using the NetLogo platform to analyze the information dissemination performance of SSIDM under disaster events. The experimental results show that the analysis of individuals and the definition of communication mode in the SSIT proposed in this article are accurate and reasonable. In addition, the experimental results with event coverage, event transmission delay, and event delivery rate as evaluation indicators show that the proposed SSIDM can greatly improve the event transmission efficiency and transmission accuracy in the case of sudden disaster events, and the SSIDM can effectively help people to avoid disasters and help decision-makers make countermeasures quickly.

In the future work, the spatial and quantitative deployment of mobile and static sensors can be considered from the perspective of urban population density and building properties and so on, so as to improve the performance of the whole SSNs. In addition, the form, quantity, and location of sinks are also the focus of SSNs. Finally, for SSNs, it not only needs to consider the participation of human agents, but also should incorporate vehicles and other mobile objects with communication ability into SSNs.
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ORCID iD
Shanshan Wan https://orcid.org/0000-0002-3421-4387

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