Green Social CPS Based E-Healthcare Systems to Control the Spread of Infectious Diseases

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***Abstract*—Recently, social network based e-healthcare service has emerged as a promising way to control the spread of infectious diseases. However, the large-scale deployment in reality faces a fundamental challenge to reduce the cost where social features of mobile users and the properties of networks should be considered. To tackle the above problem, this paper presents a green social cyber physical system (CPS) based e-Healthcare scheme to control infectious diseases. Firstly, based on the analysis of social features, the high influential users are selected to inoculate immune drugs when an infectious disease is identified. Secondly, we develop an epidemic spreading model with the dynamic equations to analyze the efficiency of immune strategy. With the proposed model, the spread of infectious diseases can be effectively monitored and the spreading range of the infectious can be predicted. In addition, simulation experiments prove that the proposal can be more efficient to prevent infectious diseases from being spread than conventional methods.**

***Index Terms*—E-healthcare, social networks, infectious spreading, immune strategy.**

I. Introduction

Infectious disease is an acute disease which can rapidly spread among human beings within a short period, such as Ebola and severe acute respiratory syndromes (SARS). In 2016, nearly 7,000,000 Chinese were infected with these highly contagious diseases, while more than 18,000 infected patients lost lives [1]. The infectious disease can easily spread by many ways, such as through air, water, and contact. For example, when the infected patients cough and sneeze around non-infected people, the probability that the non-infected people are infected is very high. The outbreaks of these infectious diseases make a great loss. Thus, the spread of infectious diseases should be efficiently monitored, controlled, and prevented with proper approaches. Especially, the early detection of abnormal healthy events is the key to efficiently prevent infectious disease from being spread.

However, the traditional approaches mainly depend on the manual labor and bring a large cost. To overcome the above public health crisis, a promising wearable and social cyber physical system (CPS) based e-healthcare technology has been proposed to continuously detect user's real-time health parameters including the temperature, heart rate, blood pressure, and electrocardiogram (ECG), etc, which are distributed through multiple mobile devices. In the such social CPS based e-healthcare system, the health data are collected by a server in the medical centre to analyze the abnormal phenomena and provide supporting information for diagnosis [2]- [11]. Through the analysis of the health data, the medical centre can observe user's health condition. If the health condition of people in an area shows the symptom, the medical centre can conduct immune strategies to prevent the spread of this infectious disease. For example, users can be informed by e-healthcare system to inoculate immune drugs such as vaccines.

Due to the rapid growth of social networks and the popularity of mobile devices in CPS, social CPS based e-healthcare system can offer various applications to mine users' heath data based on their social interactions [12]. For example, Wechat friend discovery program (WFDP) can find users in a given area and its speech recognition can be helpful to detect if some people cough or sneeze. Although, social CPS based e-healthcare system can provide a novel paradigm to control the spread of infectious diseases, how to construct an efficient e-healthcare system based on social features and the properties of CPS becomes a new challenge.

Therefore, in this paper, we propose an immune strategy with social CPS to conrol infectious disease spreading for e-healthcare system. Firstly, the system is divided into social CPS platform and e-healthcare platform. The e-healthcare platform will analyze the health data of mobile users. Once an infectious disease is identified by the mobile devices in CPS, the medical centre can collect social data to select mobile users with the high influential to inoculate immune drugs. Secondly, the dynamic equations are constructed based on the epidemic spreading model to analyze the efficiency of the proposed immune strategy. With the proposed model, the infections spreading can be effectively monitored, where the spreading range of the infectious can be predicted with a high immune efficiency. Simulation experiments show that the proposal is more efficient to prevent infectious diseases from being spread than conventional strategies.

The rest of this paper is organized as follows. Related works are given in Section II. System model is described in Section III. The immune strategy is introduced in section IV. The dynamic model is constructed in section V. Section VI conducts simulations and the conclusion is given in Section VII.

II. Related Work

Recently, the e-healthcare system has drawn an increasing attentions from both the industry and academia. *Zhou et* *al.* [13] presented a secure and privacy-preserving scheme for medical image analysis with cloud assisted e-healthcare systems, which is based on an efficient privacy-preserving fully homomorphic data aggregation. *Lee et al*. [14] introduced a framework of medical-grade wireless local area network for healthcare facilities. The proposal can prioritize medical applications according to their medical urgency. *Huang et al*. [15] designed a healthcare system to collect medical data from wireless body-area networks. With the send-receive model to realize key distribution, the medical data can be securely transmitted into wireless networks. *Lomotey et al.* [16] studied how to ensure efficient synchronization to keep patients' electronic health record in unreliable mobile networks with mobile cloud computing. Although these works focus on the e-healthcare, most of them don't consider the applications of e-healthcare to control and mitigate the spread of infectious diseases.

In addition, social networks have been extensively studied. *Zhang et al*. [17] presented a novel human-to-human infection analysis approach. With social network data and health data collected by social network and e-healthcare cloud, the privacy-preserving data can be transferred. *Li et al*. [18] presented a novel information diffusion model in social networks, where the nodes are treated as intelligent and rational agents. The corresponding payoffs can be calculated to provide different choices to make strategic decisions. *Gao et al*. [19] designed a novel diffusion prediction model based on the information-dependent embedding, where the users in the observed diffusion process are mapped into a latent embedding space. *Wang et al.* [20] used the social relationships and physical coupling among mobile users to select important user as a helper to cache contents. The recommendation system with caching placement was designed to maximize the offloading probability. Although these works have studied some applications of social networks, the studies on social networks and e-healthcare to prevent the spread of infectious diseases are still insufficient.

Therefore, this paper comprehensively studies the features of the e-healthcare and social networks, and then proposes an immune strategy by utilizing the social networks and e-healthcare system to efficiently control and prevent the spreads of infectious diseases.

III. System Model

Consider an e-healthcare system with the following three components, which are shown in Fig. 1.

Mobile users. The set of mobile social users in the network is denoted as $\mathcal{I} = \{1, 2, \cdots, i, \cdots, I\}$. There exist social relationships among mobile users, such as relatives, classmates, and workmates, etc. Let $w_{i,j}$ denote whether mobile user i and mobile user j have social relationships such as friends. If $w_{i,j} = 1$, mobile user i and mobile user j are friend. Otherwise, $w_{i,j} = 0$. Then we can denote a friend matrix

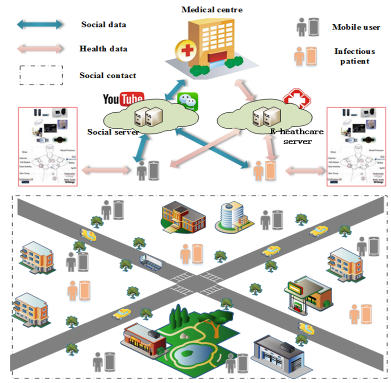

Fig. 1. E-healthcare system.

by

$$W = \begin{bmatrix} w_{1,1} \; w_{1,2}, \cdots, w_{1,I} \\ w_{2,1} \; w_{2,2}, \cdots, w_{2,I} \\ \vdots, \quad \vdots, \quad \ddots \quad \vdots, \\ w_{I,1} \; w_{I,2}, \cdots, w_{I,I} \end{bmatrix}, \tag{1}$$

Here the friend matrix is a symmetric matrix, which is

$$w_{i,j} = w_{j,i} \tag{2}$$

In the network, a mobile user often has contact with her/his friends to construct the interactions and communications. In order to identify the contact frequency between any two mobile users, the contact information of these two mobile users during an interval time T is recorded, which includes the times of contact and the duration of each contact. Let $K_{i,j}$ denote the times of contact between mobile user i and mobile user j. $t_{i,j,k}$ is used to denote the duration of the k^{th} contact. Thus, we can get

$$T \geq \sum_{k=1}^{K_{i,j}} t_{i,j,k}. \tag{3}$$

Let $\bar{K_i}$ denote the average times of contact between mobile user i and others, which can be obtained by

$$\bar{K_i} = \frac{\sum_{j=1, j\neq i}^{I} K_{i,j}}{I-1}. \tag{4}$$

Then, the normalized contact frequency between mobile user i and another mobile user can be calculated by

$$TF_i = \frac{\bar{K_i}}{\max\{\bar{K_j} | j \in \mathcal{I}\}}. \tag{5}$$

The average duration of contact between mobile user i and another user is $\bar{t_i}$, which can be obtained by

$$\bar{t_i} = \frac{\sum_{j=1, j\neq i}^{I} \sum_{k=1}^{K_{i,j}} t_{i,j,k}}{I-1}. \tag{6}$$

The normalized duration of contact between mobile user i and another user becomes

$$DF_i = \frac{\bar{t_i}}{\max\{\bar{t_j} | j \in \mathcal{I}\}} \tag{7}$$

E-healthcare server. It has powerful computational and storage capabilities. The e-healthcare server has three functions. Firstly, the e-healthcare server receives health data from users. Secondly, it can train health data from medical institution for analysis to identify the infectious diseases. Thirdly, it will inform object users to get immune drugs for preventing the spread of infectious diseases.

Social CPS server. The social CPS server can extract the contact information of mobile users and analyze the social features of each mobile user. In addition, the social CPS server can also exchange mobile users' information to e-healthcare server for preventing the spread of infectious diseases.

IV. Immune Strategy

This section introduces the immune strategy to prevent the spreads of infectious diseases. Once the medical centre identifies the infectious diseases that has been generated in an area, the medical centre can use the e-healthcare system to inform some mobile users who have high social influence for inoculating immune drugs.

The social server can analyze the social influence degree of any mobile user. The social influence degree of a mobile user shows whether the mobile user has a certain effect on the spread of the infectious diseases. Specifically, the social influence degree of a mobile user has two parts, which are the global social influence degree and the local social influence degree. The global social influence degree means the influence of a mobile user on the whole social network, while the local social influence degree means the influence on a give mobile user. Thus, the social influence degree of mobile user i can be calculated by

$$SID_i = \alpha GSD_i + \beta LSD_i, \tag{8}$$

where GSD_i is the global social influence degree of mobile user i and LSD_i is the local influence degree of mobile user i. α and β are weighted parameters of global social influence degree and local influence degree, respectively.

The global social influence degree reflects the global features of a mobile user, which includes the number of friends owned by this mobile user and the betweenness of this mobile user. If a mobile user who has many friends is infected, these friends also have high probabilities to be infected. Similar to social network analysis, we use the degree to denote the number of friends, which can be obtained by

$$d_i = \sum_{j=1}^{I} w_{i,j}. \tag{9}$$

The normalized degree of a mobile user can be defined by

$$ND_i = \frac{d_i}{\max\{d_j | j \in \mathcal{I}\}}. \tag{10}$$

In addition, some mobile users are key persons to spread the infectious disease, where many shortest paths contain these mobile users. Here we use the concept of betweenness to show this influence. It means that two mobile users who are not adjacent may also influence each other significantly. For a network, the betweenness of a user k is defined as

$$b_i = \sum_{j \in \mathcal{I}} \sum_{k > j \in \mathcal{I}} \frac{\delta_{j,k}(i)}{\delta_{j,k}}, \tag{11}$$

where $\delta_{j,k}(i)$ denotes the number of the shortest paths from mobile user j to mobile user k that passes through mobile user i, and $\delta_{i,j}$ is the number of the shortest paths from mobile user j to mobile user k . The normalized betweenness of a mobile user can be defined by

$$NB_i = \frac{b_i}{\max\{b_j | j \in \mathcal{I}\}} \tag{12}$$

Therefore, the global social influence degree of mobile user i can be obtained by

$$GSD_i = \gamma \cdot ND_i + (1 - \gamma) \cdot NB_i. \tag{13}$$

where γ is the weighted parameter of the degree.

The local social influence degree is related to the contact frequency and the duration of contact between two mobile users. The spreading of infectious disease has positive relation to the contact frequency. Although the degree of a mobile user is small, the mobile user with the high contact frequency has large effect on the spread of infectious disease. Therefore, the local social influence degree of mobile user i is

$$LSD_i = \mu \cdot TF_i + (1 - \mu) DF_i \tag{14}$$

where μ is the weighted parameter of contact frequency.

The mobile users with high social influence degree are the key nodes to spread infectious disease. Thus, if these mobile users are immunized to the infectious disease, the spreading rate will dramatically decrease. Therefore, the medical centre will set a threshold ζ to determine which users should be informed, where we can obtain

$$SID_i \geq \zeta \tag{15}$$

If the social influence degree of a mobile user is larger than the threshold, this mobile user will be informed by the e-healthcare to inoculate immune drugs.

V. Model Analysis

This section presents a model to analyze the spreads of the infectious disease with the proposed immune strategy.

Let $S_k(t)$ denote of the number of k-degree users who are susceptible at time t. Similarly, let $H_k(t)$ denote the number of k-degree of infectious patients at time t. $R_k(t)$ denotes the number of k-degree mobile users who are recovered. $I_k(t)$ is defined as the number of k-degree mobile users at time t. The fractions of three types of mobile user in $I_k(t)$ is

$$\begin{cases} s_k(t) = \frac{S_k(t)}{I_k(t)} \\ h_k(t) = \frac{H_k(t)}{I_k(t)} \\ r_k(t) = \frac{R_k(t)}{I_k(t)}. \end{cases} \tag{16}$$

Within the time interval $[t + \Delta t]$, the variation of $s_k(t)$ is as follows.

$$s_k(t + \Delta t) = s_k(t)(1 - P(H, k)), \tag{17}$$

$P(H, k)$ denotes the probability that a k-degree susceptible user i is infected by a patient within Δt. Here $k = d_i$.

According to the features of social networks, since mobile users frequently contact their friends, we assume that the patients spread infectious disease only to their friends. The probability that user j is a friend of a user i is $k/(N-1)$. Furthermore, the probability that user j is infected is $\sum\limits_{k'=m}^{I-1} \frac{I}{I-1} P(k') h_{k'}(t)$, where $P(k')$ is the degree distribution. We have

$$P(k') = \frac{I_{k'}}{I}, \tag{18}$$

where $I_{k'}$ is the number of k'-degree users. In addition, the average probability that the susceptible user is successfully infected by an infected patient after they contact becomes

$$P_{in}(t) = \sum_{i=1}^{H(t)} \frac{1}{H(t)} \lambda_i, \tag{19}$$

where λ_i is the spreading rate of mobile user i who is infected, $I(t)$ is the number of infected patients at time t . Indeed, the spreading rate of a mobile user is in proportion to the social influence degree of a mobile user. Namely, it can be known as

$$\lambda_i \propto SID_i. \tag{20}$$

Here, we use the logarithmic function to show the spreading rate of a mobile user, which is

$$\lambda_i = \min\{1, \varphi log(1 + SID_i)\}, \tag{21}$$

where φ is the adjustable parameter. Indeed, arbitrary increasing function can be used to define the spreading rate of a mobile user. Then, the probability $P(H, k)$ that mobile user i is infected within Δt becomes

$$P(H, k) = P_{in}(t) \frac{k}{I-1} \sum_{k'=m}^{I-1} \frac{I}{I-1} P(k') h_{k'}(t) \Delta t. \tag{22}$$

From (17), the differential equations can be obtained by

$$\begin{aligned} &\tfrac{ds_k(t)}{dt} \\ &= -s_k(t) \lim_{\Delta t \to 0} \tfrac{P(G,k)}{\Delta t} \\ &= -s_k(t) \lim_{\Delta t \to 0} \frac{P_{in}(t) \frac{k}{I-1} \sum\limits_{k'=m}^{I-1} \frac{I}{I-1} P(k') h_{k'}(t) \Delta t}{\Delta t} \\ &= -s_k(t) P_{in}(t) \tfrac{k}{I-1} \sum_{k'=m}^{I-1} \tfrac{I}{I-1} P(k') h_{k'}(t). \end{aligned} \tag{23}$$

Similarly, given a small time interval Δt, we can obtain

$$h_k(t + \Delta t) = h_k(t) + s_k(t) P(H, k) - h_k(t) P(R, k), \tag{24}$$

$P(R, k)$ is the probability that a k-degree infected patient recovers within Δt, which can be obtained by

$$P(R, k) = \mu \Delta t, \tag{25}$$

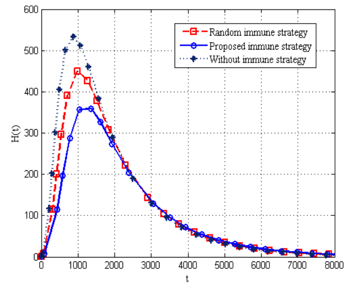

Fig. 2. The comparison of three strategies about the number of infected patients with time .

where μ is the recovery rate of a mobile user. Therefore, we can obtain

$$\begin{aligned} &\tfrac{dh_k(t)}{dt} \\ &= \lim_{\Delta t \to 0} \tfrac{s_k(t) P(G,k) - h_k(t) P(R,k)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{s_k(t) P_{in}(t) \frac{k}{N-1} \sum\limits_{k'=m}^{N-1} \frac{N}{N-1} P(k') h_{k'}(t) \Delta t - h_k(t) \mu \Delta t}{\Delta t} \\ &= s_k(t) P_{in}(t) \tfrac{k}{N-1} \sum_{k'=m}^{N-1} \tfrac{N}{N-1} P(k') h_{k'}(t) - h_k(t) \mu. \end{aligned} \tag{26}$$

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In addition, given a short time interval Δt, we can obtain

$$r_k(t + \Delta t) = r_k(t) + h_k(t) P(R, k). \tag{27}$$

Therefore, the following equation can be got by

$$\begin{aligned} &\tfrac{dr_k(t)}{dt} \\ &= \lim_{\Delta t \to 0} \tfrac{h_k(t) P(R,k)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \tfrac{h_k(t) \mu \Delta t}{\Delta t} \\ &= h_k(t) \mu. \end{aligned} \tag{28}$$

Therefore, based on the above equations for the spread of infectious disease with three states of mobile users, we can obtain the number of susceptible mobile users, infected patients, and recovered mobile users at time t by

$$S(t) = \sum_{k=m}^{I-1} P(k) s_k(t) I, \tag{29}$$

$$H(t) = \sum_{k=m}^{I-1} P(k) h_k(t) I, \tag{30}$$

$$R(t) = \sum_{k=m}^{I-1} P(k) r_k(t) I, \tag{31}$$

where m is the minimum degree in the network.

VI. Performance Evaluation

A. Experiment Setup

It is assumed that the unit time of the system is 0.01 hour. The social network is constructed by the real trace from the logs of a mobile social system based on XMPP protocol. Two

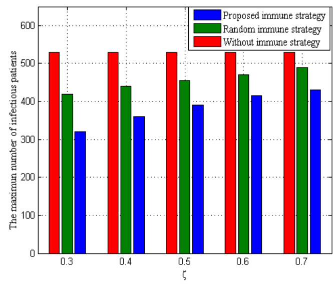

Fig. 3. The comparison of three strategies about the maximum number of infected patients during the spread of infectious disease.

users are friends if they have at least one record in the trace. The number of mobile users is $I = 802$. The threshold ζ is 0.4. Both the weighted parameter of global social influence and the local social influence are 0.5.

B. Numerical Result

Fig. 2 shows the comparison of three strategies about the spread of infected disease. The simulation time is 8000, and the number of infected patients is used to show the comparison results. From Fig. 2, it can be observed that the proposal outperforms other two schemes, where the increasing rate is the lowest initially and the decreasing time is the earliest. In addition, the proposed scheme has the smallest maximum $H(t)$. The reason is that high influential mobile users are immunized in the proposal, which can prevent the spread of infectious disease. However, in the random immune strategy, the immunized mobile users are randomly selected, where some users may have the low social influence degree.

Fig. 3 is the comparison of three strategies about the maximum number of infected patients. The maximum number of infectious patients denotes the largest number of $H(t)$ during the spread of the infected disease. Besides, we use varoius value of threshold ζ to show results, which are changed from 0.3 to 0.7. From Fig. 3, it can be observed that the proposal outperforms other strategies. Firstly, the proposed strategy has the smallest value of the maximum number of infectious patients. The reason is that the most influential mobile users are immunized at the early stage of the spread process, while the immunized mobile users are randomly selected in the random immune strategy.

VII. Conclusion

This paper has designed a novel immune strategy to prevent the spreading of infectious diseases for social CPS based e-healthcare system. Firstly, when an infectious diseases is identified by the e-healthcare system, the medical centre will select multiple mobile users with high influence by the analysis of the social network and inform this mobile user to inoculate. Then, we construct a dynamic model to analyze the spreading of infectious disease with the proposed strategy. The simulation result shows that the proposed immune strategy can efficiently prevent the spreading of infectious diseases. As for the future work, the privacy prevention of mobile users in e-healthcare system will be studied.

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