

The construction of a hospital disease tracking and control system with a disease infection probability model

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Abstract With relatively short latency and rapid propagation, viral diseases could be transmitted through the air to medical personnel or the public during the incubation period. To reduce the possibilities of spread, this research creates an infection probability model based on the settling velocity and concentration distribution of infectious droplets. Then, radio frequency identification (RFID) technology is employed to track the travel history (time, date and place) of the infected patients. A tree structure algorithm and an infection probability model are applied to trace the transmission routes, discover the correlations between carriers and suspected cases, and finally calculate the infection probability on the basis of time interval. In case of an epidemic outbreak or once an infected case is confirmed, the disease tracking and control system could be initiated by accessing RFID logs to plot the carriers' time of onset and to trace possible routes of transmission via tree diagrams. The disease tracking and control system developed in this research can assist hospitals in assessing the risk of infection among medical personnel, as well as in prompt implementation of infection prevention and control measures, in order to reduce hospital acquired infections and provide a safe health care setting.

Keywords Disease tracking and control system · Radio frequency identification (RFID) · Influenza A · Tree structure algorithm

Introduction

Due to a massive outbreak of severe acute respiratory syndrome (SARS) in Asia, the World Health Organization (WHO) announced in April 2003 that SARS was caused by a new variant of coronavirus, officially named the “SARS-Cov” (Peris-Lopez et al. 2011). After the SARS epidemic, human cases of a new influenza A (H1N1) were initially reported in Mexico in 2009. Infection with influenza A (H1N1) virus is defined as acute febrile respiratory illness with laboratory-confirmed positive results (Viviani et al. 2011). Since the 2009 outbreak of the flu influenza in North America, suspected H1N1 cases have continually been reported in other continents. Though the H1N1 epidemic may not lead to worse consequences than SARS (Lau et al. 2009), in view of the fact that infectious diseases spread rapidly in densely polluted areas, proper quarantine and other preventive measures should be taken immediately to curb the spread of the influenza virus. To detect potential routes of disease transmission, the hospital can use radio frequency identification (RFID) technology to develop a tracking and control system that monitors the infected patients. Based on the dynamic records of patients and medical personnel inside the hospital, data analysis (Chien et al. 2007; Hsu and Chien 2007) and a tree structure algorithm can be applied to reconstruct the transmission routes, and then calculate the infection probability by modes of transmission. The disease control personnel can notify the hospital's disease reporting system to have the identification data of the suspected case entered into the tracking and control system. Then the control personnel can determine probability variables based on the spread of infection, while accessing the RFID data stored in the tracking and control system to know people's whereabouts and movements. The infection probability of all people going in and out the hospital could thus be

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calculated in no time to find out who might have been infected and proceed with proper treatment. After identifying exposure sources and suspected cases, infection control personnel will be able to enforce isolation or quarantine and sanitize all affected areas in hope to stop the virus infection from spreading.

Literature review

Tree diagram

Minimum Spanning Tree algorithms, widely applied in complex network design, have also been adopted to minimize risk in solving NP-hard problems (Chen et al. 2009). Integrating tree diagrams with network nodes, a composite neighborhood structure was proposed, using a dynamic programming algorithm for fast and efficient proximity search on large graphs (Ahuja et al. 2003). Besides, spanning tree and genetic algorithms were combined to optimize the system and tackle regional network problems (Gen et al. 2005). Capacitated Minimum Spanning Tree and fuzzy logic rules were also applied to develop a rapid approximate inference algorithm that, with uncertain cost and demand parameters, keeps each node from exceeding gross demand restrictions in order to achieve cost minimization (Öncan 2007). Decision tree algorithms likewise search in the format of a branching diagram that supports classification, linear regression and association analysis. An optimal decision tree represents an effective search strategy that performs only a minimum number of node queries and thus involves the least search time. Dynamic programming is often adopted to help reduce the time complexity of the algorithm (Cicalese et al. 2011). In supervised classification training, for instance, decision graphs have been found to significantly enhance the efficiency of classification models constructed for wireless network planning (Nielsen et al. 2009). In clinical and epidemiological analysis, tree diagrams have also been used to formulate classification rules that help clinical practitioners to distinguish between clusters of signs and symptoms and quickly reach a diagnosis (Marshall 2001). The literature review above shows that tree diagrams have been widely applied in research on search path optimization and data classification, and can clearly demonstrate association rules and hierarchical structures of data. Therefore, this research adopted a tree diagram algorithm to find connections between virus carriers and the infected patients inside the hospital.

RFID applications

Radio frequency identification (RFID) technology, which uses radio waves to identify and track people or objects

(Najera et al. 2011), can be encapsulated or implanted into products to withstand harsh environments. With penetrating signals, RFID can detect position and distance. Scholars (Akpınar and Kaptan 2010) found that RFID tags can serve as portable databases that allow easy and quick access to information. RFID technology is the best choice for automation systems. Already ranked among the most important technologies in the global industries of the future, RFID finds a wide range of applications in diverse industries, such as the high-tech industry, localization (Zhou and Shi 2009), information service industry (Tian et al. 2002), manufacturing sectors (Zhang et al. 2012; Qu et al. 2012), retail sectors, healthcare and logistics. Most RFID applications are involved in storage management and the manufacturing process (Tzeng et al. 2008; Brewer et al. 1999; Huang et al. 2008).

With the increasing emphasis on patient security and medical quality in healthcare, RFID technology has also been broadly implemented in healthcare facilities, such as medical equipment monitoring or real-time locating systems, anti-theft devices, identity tags for patients and medical personnel, drug anti-counterfeiting mechanisms (Wertheimer and Norris 2009). Most of these RFID applications are used for tracking and identity recognition to ensure that patients receive needed medical care and to support disease control (Kumar et al. 2009). Meanwhile, through visual images and RFID tags attached to predefined objects, healthcare personnel could also deliver home care services to dementia patients and have a better understanding of the patients' behavior (Wherton and Monk 2008). Besides, RFID could help to deal with events involving great complexity, such as monitoring and tracking patients' body temperatures, so much so that, in case of emergency, medical personnel could make professional judgement decisions immediately based on collected data (Yao et al. 2011). RFID can also be applied to medical inventory management. Without incurring any extra costs, RFID technology is capable of providing continuous review of inventory, which has been proven superior to the periodic review of barcode technology (Çakıcı et al. 2011). In medication management, RFID has been used to enhance inpatient medication safety through a wireless network system for automated tracking of prescription drugs (Ohashi et al. 2010). With continuous, real-time information regarding the clinical situations and patients' location, hospital pharmacy personnel could differentiate batch number, dosage, and usage of drugs to reduce dispensing errors, while nurses could correctly identify patients, administer medication on time, and keep track of drug delivery routes (Peris-Lopez et al. 2011).

Disease transmission routes

Infectious disease transmission may occur either by direct or indirect contact. Direct transmission results from having

physical contact with an infected individual, such as that person's mouth, nose, and skin, or infectious droplets of saliva and mucus from coughs and sneezes. Coughing and sneezing are symptoms of respiratory infection, such as the SARS and influenza A (H1N1). Both SARS and influenza A (H1N1) are caused by newly discovered respiratory tract viruses. The SARS virus, according to WHO's announcement in April 2003, is a novel coronavirus SARS-Cov, which is a single-stranded RNA virus (Lau and Peiris 2005; Feng and Gao 2007). The pathogen of influenza A (H1N1) is swine influenza virus (SIV). SIV, classified into the Orthomyxoviridae family, is a negative strand RNA virus (Leahy et al. 1997). These pandemic-prone diseases, mainly spread by infectious droplets or droplet nuclei, can be contracted by inhaling small-particle aerosols (Tang et al. 2006; Buchbinder et al. 2011).

In general, droplets sprayed during talking, coughing, or sneezing will remain suspended in the air for a brief time only (Chao et al. 2009). These airborne droplets come in different sizes. Whereas small droplets evaporate and disperse in the air quickly, large droplets are subject to influences of such external factors as the size of a space, wind speed, airflow, temperature and humidity change. As large droplets evaporate and gravitationally settle, they would attach to different surfaces and materials (Redrow et al. 2011). Aerosols refer to small solid and liquid particles suspended in the air. For spherical particles of unit density, falling from a place 3 m above the ground, the settling time is 10 s for particles with a diameter of 100 μm ; 4 min for 20 μm ; 17 min for 10 μm ; 62 min for 5 μm ; while those with a diameter less than 3 μm do not settle (Tellier 2006). Current research on RFID applications in the medical field rarely explores the potential for RFID in conjunction with infection probability. Therefore, based on the information collected with RFID tags, this study analyzed the sequence of movements performed by carries and suspected cases, calculated infection probabilities, and used tree diagram principles to reconstruct disease transmission routes. The results would provide healthcare personnel

with information that helps them to quickly locate suspected cases and implement effective isolation measures.

Methods

RFID motion detection

The disease tracking and control system consists of three RFID detection devices: tags, readers and antennas, as shown in Fig. 1, all of which serve to assist with infection control. Their functions are briefly described below:

Active tags

Worn by patients and healthcare workers, the tag comes with a built-in battery that allows the tag to automatically send signals to an RFID reader within communication range. The advantage of deploying active RFID tags is that they could track mobile users and objects in real-time.

RFID readers

An RFID reader is set up on each floor in the hospital to receive tag signals. With 433 MHz operating frequency, the reader has a read range of up to 100 m. After receiving RFID tag signals, the reader sends the signals to the RFID controller in a wired or wireless mode, where the information will be stored in the system database.

Antennas

An RFID antenna is installed at the entrances and exits of each floor in the hospital, such as entrances to stairs and elevators. With 123 KHz operating frequency and a reading distance up to 3.5 m, the antenna could enable/disable the RFID tags within communication range, or update the

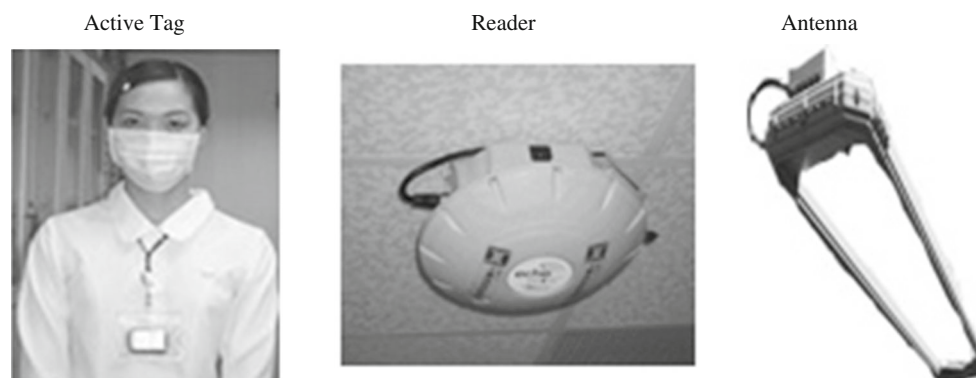


Fig. 1 Equipments of RFID

data in the tags. When a healthcare worker passes by an antenna, it will enter a specific message into his/her RFID tag, such as the entrance/exit code. Then message in the RFID tag will be picked up by the reader on each floor, and then transmitted to the system database, as shown in Fig. 2. Because RFID antennas allow the tracking and alert system to verify the history of locations any RFID tag has visited, it is easy to trace the path travelled by the infected.

Infection probability model

The U.S. Centers for Disease Control (CDC) declared that the H1N1 virus is primarily transmitted through infectious droplets that pass among people in close contact. H1N1 could spread rapidly in crowds or practically anywhere infected people traveled. This study therefore focuses on droplet transmission—the predominant route of transmission of infectious respiratory diseases like H1N1. RFID access control technology is adopted to track the spread of communicable diseases in the hospital. The tracking data collected by RFID devices are in turn analyzed using tree diagrams to search possible routes of transmission. Eventually, infec-

tion probabilities are calculated according to the infection probability model.

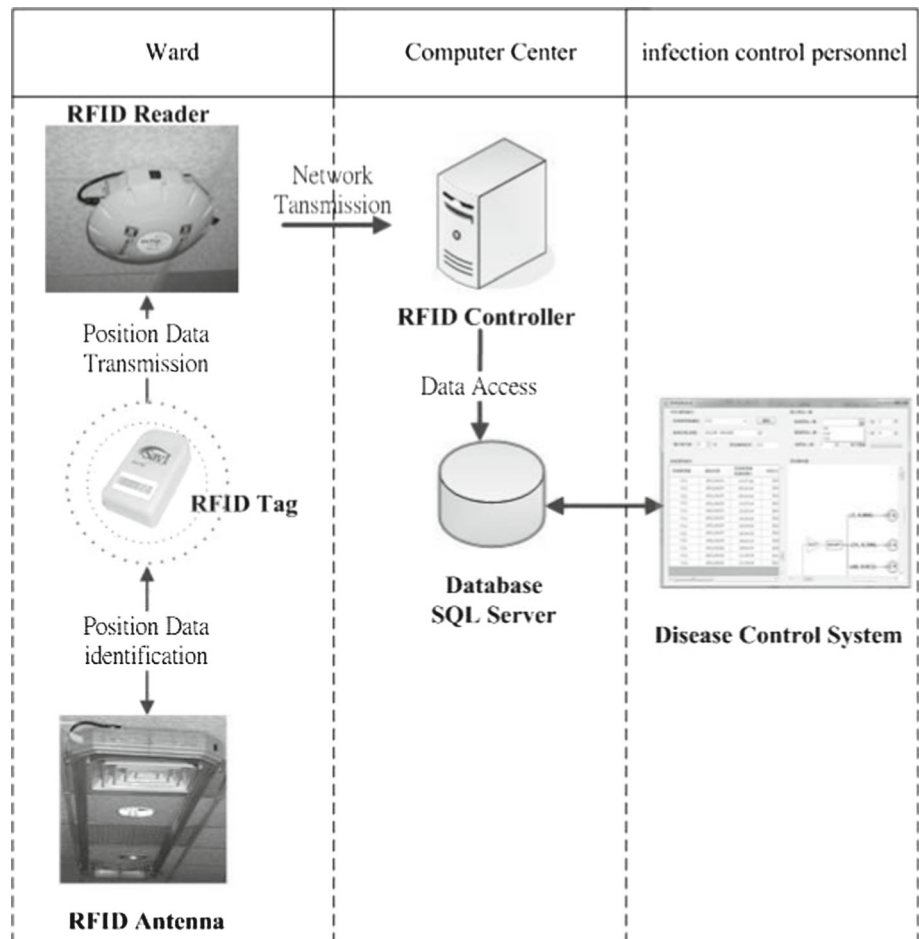
Infection probability hypotheses

In general, droplet particles released during talking, coughing, and sneezing would briefly stay suspended in the air, resulting in higher indoor airborne pathogen concentration. If droplets carrying biologically active viruses are inhaled, virus particles might enter host cells and cause infection. This phenomenon is called droplet infection. This study puts forward three hypotheses on the probability of droplet infection:

Hypothesis 1 When the time $t = 0$ min, the pathogen concentration in droplets sneezed by carriers is the highest, so the infection probability is 1.

Hypothesis 2 Droplet concentration is closely connected with disease infection probability (Lin et al. 2012). For instance, because the immune system is impaired in SARS patients, it provides an excellent venue for SARS virus replication. Therefore, virus concentration in their sputum and spray droplets is higher, and the virus lives longer, and is

Fig. 2 RFID motion detection



extremely contagious (Peng 2012). Based on the above studies, we assume that infection probability is directly proportional to droplet concentration.

Hypothesis 3 Droplet size is one of the major factors affecting disease transmission (Chao et al. 2009). Droplets emitted from the mouth and nose range from 1 to 2,000 μm in diameter, 95 % of which fall within the 2–100 μm range, and most commonly 4–8 μm (Duguid 1946). Studies show that, for a 3 m fall, the settling time for spherical particles 5 μm in diameter is 62 min. Particles with a diameter less than 3 μm do not settle (Tellier 2006). Therefore, regardless of air conditioning air flow and human activities, it can be assumed that only 5 % particles with a diameter less than 3 μm will remain suspended in the air. Therefore, at the 62nd min, the infection probability can be set at 0.05 according to Hypothesis 2.

Infection probability

Flu viruses are often transmitted by airborne droplets. The longer droplets coughed or sneezed by infected individuals stay in the air, the higher the virus concentration in the air, and the greater the infection probability. The infection probability model developed in this study, therefore, builds and expands on a recent research by Gao et al. (2009) on droplet residence time. In the research, indoor particle concentration is shown to rise in a few seconds as a result of particle dispersion in sudden expansion flows. As the concentration changes with time and airflow fluctuation, particles in air will gradually decline. The indoor air concentration calculation model that expresses the relation between time and droplet particle concentration is shown in formula (1) (Gao et al. 2009):

$$C_t = C_0 \exp[-(\alpha + \kappa) \cdot \Delta t] \tag{1}$$

where

- C_0 initial indoor particle concentration (g/m³)
- α airflow fluctuation rate (h⁻¹)
- κ deposition-caused particle loss rate coefficient (h⁻¹)
- Δt time interval (s)

Since α and κ are both constants, they can be expressed by another constant symbol C_1 here instead.

Let $\Psi = \alpha + \kappa$ (2)

Then formula (1) can be rewritten as:

$$C_t = C_0 \exp - (\Psi \Delta t) \tag{3}$$

Based on Hypothesis 2 of infection probability, i.e. that droplet particle concentration is proportional to infection, the infection probability can be derived as follows:

$$P = \lambda C_t \tag{4}$$

where $\lambda = \text{constant}$.

Integrate formula (3) into formula (4). Formula (3) can be rewritten as:

$$P = \lambda C_0 \exp - (\Psi \Delta t) \tag{5}$$

Since v and C_0 are both constants, they can be expressed by another constant symbol ω instead. Therefore, vC_0 can be converted to ω .

Let $\omega = \lambda C_0$

Then formula (1) can be rewritten as formula (6):

$$P = \omega \exp(-\Psi \Delta t) \tag{6}$$

According to Hypothesis 1 of infection probability, when $t = 0$, the infection rate is 1:

$$1 = \omega \exp(-\Psi 0)$$

$$\therefore \omega = 1$$

According to Hypothesis 3 of infection probability, when $t=62$, the infection rate is 0.05:

$$0.05 = \exp(-\Psi 62)$$

$$\therefore \Psi = 0.0483$$

Use the symbols ω and C_1 in formula (6), the infection probability between carrier (i) and affected individual (j) can be derived from formula (7) below:

$$P_{ij} = \exp(-0.0483 \cdot \Delta t) \tag{7}$$

Route search algorithm

This study makes a distinction between direct and indirect infection. However, as opposed to the standard focus on direct and indirect contact with infected individuals, the sequence of events at the same site, like the hospital, is underscored here.

Direct infection is defined in this study as cases in which viruses are spread through inhalation of infectious droplets emitted by a carrier who is the initial or primary case in a chain of infection. Indirect infection, on the other hand, refers to secondary cases—i.e. people infected by the primary case—passing on the viruses to other people (tertiary cases and more). When a carrier is discovered, this study proposes using the RFID database to investigate transmission routes, so that all potentially infected personnel could be traced and tracked for effective infection control.

According to World Health Statistics (WHO), the incubation period of most typical flu is usually 2 days, but ranges from 1 to 4 days. Adults who have contracted Influenza A (H1N1) may be contagious from 1 day before the onset to 3–7 days after the symptoms appear. Yet it all depends on how the patient’s antibodies respond to the virus. The stronger the patient’s immune system and the less the exposure to the virus, the longer the incubation period is to be expected. On

the contrary, the weaker the patient’s immune system and the more the exposure to the virus, the shorter the incubation period. Because the incubation period varies from person to person, this study distinguishes between two tracking modes of indirect infection: conservative and loose estimate.

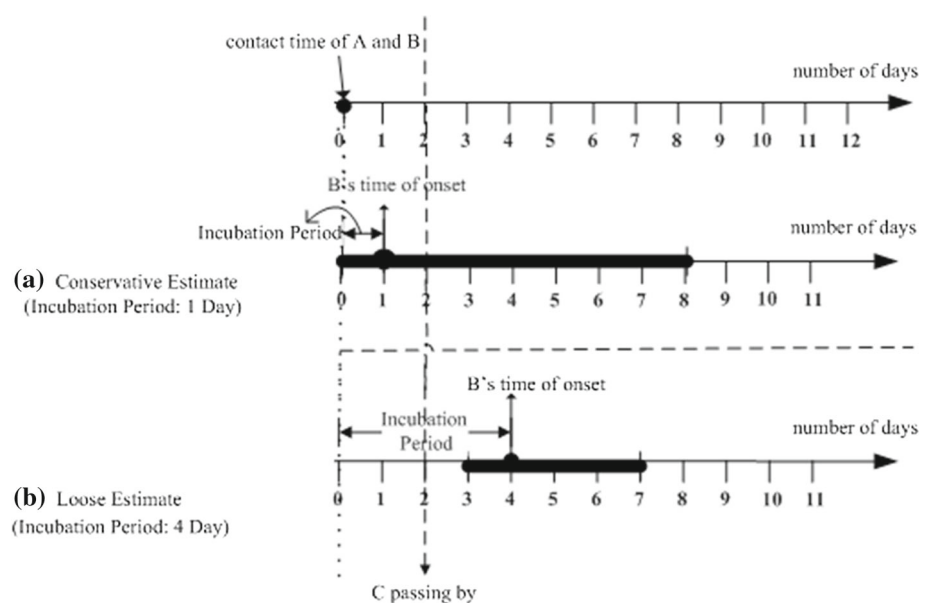
Conservative estimates

The mode of conservative estimate is adopted to achieve tight tracking and infection control. In this mode, when a person comes into contact with an H1N1 virus carrier, the incubation period of this person is estimated to last only 1 day, namely, 1 day before the onset. In Fig. 3, with A as an initial carrier, both A and B pass by the same place on day 0. Then B’s incubation period will be 1 day according to the conservative estimate. B is considered infectious from 1 day before the onset to 7 days following the onset. As shown in Fig. 3a, this means that B can transmit the virus to others from day 0 to day 8. Suppose C and B pass by the same place on day 2, C is likely to be infected.

Loose estimates

According to the loose estimate, after coming into contact with a H1N1 virus carrier, a person will have an incubation period of 4 days, namely, 4 days before the onset of symptoms. In Fig. 3, with A as a carrier, A and B pass by the same place on day 0. Based on the loose estimate, B’s incubation period will last 4 days. B can transmit the virus to others from 1 day before the onset to 3 days following it. Hence in Fig. 3b, he is shown to be infectious from day 3 to day 7. Suppose C passes by the same location B visits on day 2, he will not be infected.

Fig. 3 Estimates of the incubation period



Simulation

Direct infection

The incubation period varies from disease to disease and depending on personal physique. This study uses the H1N1 virus as an example to illustrate the method of transmission route search. The empirical research was conducted in a hospital where 30 medical personnel and patients were asked to wear active tags on them from 2011/9/10 to 2011/9/15. Eighteen antennas were installed in the lobby and at the elevator and stairway entrances on four floors in the hospital. Each subject’s movements in the hospital were recorded by the tracking and control database. This research simulates a situation in which a patient is tested positive for H1N1 infection. When the simulated scenario occurs, the control personnel will activate the tracking and control system right away, and then, based on the RFID records, use the infection probability model to infer potential risks of infection. A carrier of the flu virus is potentially infectious from 1 day before the onset of symptoms to 3–7 days following the onset. As shown in Table 1, carrier C3’s onset occurs on 2011/9/11 and then C3 passes by three RFID access control entry points: ID206, ID110, ID202. Yet because an H1N1 virus carrier is contagious 1 day before the onset, people who pass by ID107 on 2011/9/10 must be taken into consideration as well. In the end, the infection probability can be derived from formula (7) by entering the time interval of each person passing by. For example, in Table 1, C2’s infection probability is $P_{3,2} = \exp(-0.0483 \cdot 14.617) = 0.494$. Diagnostic criteria for infection can be adjusted by healthcare personnel according to the epidemic situation. During the peak of the influenza season, the parameter of infection risk must be lowered to enforce stricter disease controls. When it is not peak

Table 1 Direct infection probability

Infected person C ₃ passing time t ₁	RFID codes	Passing person	Passing time t ₂	Time interval Δt = t ₂ - t ₁ (min)	Infection risk P _{3,i}	Infection probability
2011/9/10 17:18:11	ID107	C2	17:32:48	14.617	0.494	Y
		C8	18:22:47	64.600	0.044	N
2011/9/11 08:10:21	ID206	C5	08:25:11	14.833	0.488	Y
		C1	09:09:47	59.783	0.056	N
		C4	09:13:50	63.483	0.047	N
2011/9/11 15:31:25	ID110	C6	15:57:30	26.083	0.284	Y
		C12	16:06:24	34.983	0.185	N
		C8	16:36:43	65.300	0.043	N
		C7	16:42:17	70.867	0.033	N
2011/9/11 18:39:25	ID202	C6	18:46:28	7.050	0.711	Y
		C10	19:12:17	32.867	0.204	Y
		C1	20:15:32	96.117	0.010	N

season, the parameter of infection risk could be raised to focus on high risk groups, eschewing the need to track a great number of people. In the sample case, the infection risk parameter is set at 0.2. In Table 1, those people with a risk value equal to or greater than 0.2 are marked in boldface in the column “Person Passing by” and with a “Y” in “Infection Possibility”. With these people identified as potential carriers, further investigation could be conducted on patients indirectly infected. However, if the risk value is less than 0.2, the column of “Infection Possibility” will be marked with an “N”, which means it signifies end of search.

According to the carrier tracking and control records in Table 1, after the onset of disease on 2011/9/11, carrier C3 passes by four access control entry points, respectively ID107, ID206, ID110, ID202. The relationship between C3 and other people that pass by the same spots can be represented with a tree diagram, as shown in Fig. 4. The diagram can clearly show the sequence of contacts between carriers and other people to quickly find out the routes of transmission and suspected cases. The symbol “□” stands for each access control entry point, “○” for uninfected people, “⊙” for suspected cases, “→” for the transmission routes, and (T_i, P_i) above each “→” for the time interval (T_i) of contact and infection probability (P_i) between a carrier and an affected individual.

Indirect infection

Conservative estimate Figure 4 shows that at ID206 carrier C3 comes into contact with C5, C1, C4. Among them C5’s infection probability is greater than the standard value of 0.2. C5, therefore, is listed as a suspected case that requires further transmission route search.

According to the conservative estimate, C5 might have onset of symptoms on 2011/9/12. Therefore, by accessing

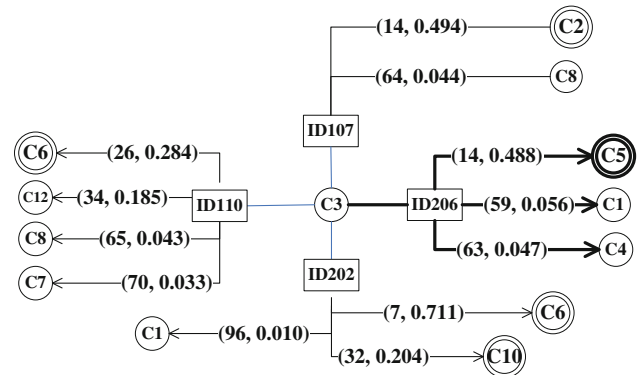


Fig. 4 Correlations of direct infection

all the RFID detection data related to C5’s activities from 2011/9/11 to 2011/9/19, the infection probability of his contacts can be derived from formula (7), which, multiplied by C5’s infection probability of 0.488, is the probability of indirect infection. For example in Table 2, the probability of C13 being infected is $P_{5,13} = P_{3,5} \cdot \exp(-0.0483 \cdot 22.117) = 0.168$. In order to clearly indicate the transmission routes, the infection correlations between C5 and all his contacts are represented in the tree diagram of Fig. 5.

Loose estimates According to the loose estimate, C5 might have onset of symptoms on 2011/9/15. Therefore, by accessing all the RFID detection data related to C5’s activities from 2011/9/14 to 2011/9/18, the infection probability of his contacts can be derived from formula (7), which, multiplied by C5’s infection probability of 0.488, is the probability of indirect infection. For example in Table 2, the probability of C17 being infected is $P_{5,17} = P_{3,5} \cdot \exp(-0.0483 \cdot 3.283) = 0.417$. In order to clearly indicate the transmission routes,

Table 2 Conservative estimates of infection probability

Infected person, C ₅ , Passing time t ₁ (min)	RFID codes	Passing person	Passing time t ₂ (min)	Time interval Δt = t ₂ – t ₁	Infection risk P _{5,i}	Infection probability
2011/9/11 06:06:07	ID107	C13	06:28:14	22.117	0.168	N
		C21	06:45:26	39.317	0.073	N
		C9	07:08:27	62.333	0.024	N
2011/9/12 08:10:30	ID206	C14	08:21:14	10.733	0.291	Y
		C12	08:59:25	48.917	0.046	N
2011/9/12 16:46:11	ID113	C10	16:52:03	5.867	0.368	Y
		C6	17:03:44	17.550	0.209	Y
		C15	17:21:45	35.567	0.088	N

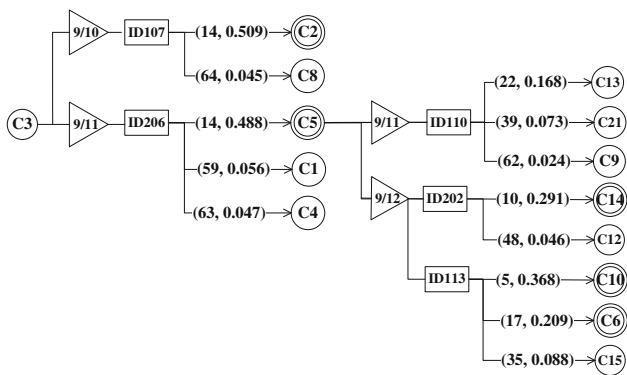


Fig. 5 Conservative estimates of transmission routes

the infection correlations between C5 and all his contacts are represented in the tree diagram of Fig. 6.

Disease tracking and control system

Based on the search method of transmission routes outlined above, this study develops a disease tracking and control system, as shown in Fig. 7. When an epidemic occurs, control personnel could key in parameters in accordance with the disease category, such as carrier, time/date of onset, incubation period, high risk period, risk of infection, etc. The high risk period refers to the time during which an infected patient has the ability to transmit the virus to others. For instance, H1N1 carriers are contagious from 1 day before onset to

Table 3 Loose estimates of infection probability

Infected person passing time t ₁	RFID codes	Passing person	Passing time t ₂	Time interval Δt = t ₂ – t ₁ (min)	Infection risk P _{5,i}	Infection probability
2011/9/14 09:14:02	ID206	C17	09:17:19	3.283	0.417	Y
		C20	09:35:11	21.150	0.176	N
2011/9/15 20:47:18	ID107	C11	20:49:22	2.067	0.442	Y
		C2	21:21:52	34.567	0.092	N
		C6	21:42:41	55.383	0.034	N
		C22	21:49:04	61.767	0.025	N

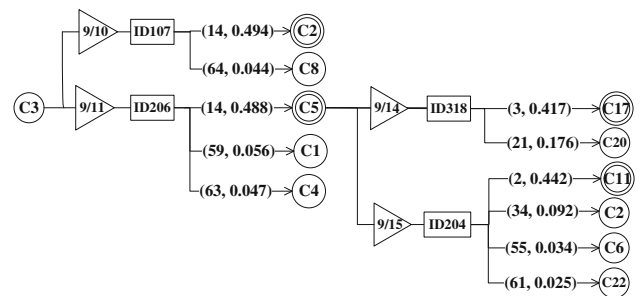


Fig. 6 Loose estimates of transmission routes

3–7 days after symptoms appear. Adopting the mode of either conservative estimate or loose estimate, infection control personnel could key in the corresponding duration of the high risk period. By integrating these parameters into the RFID location records, the tracking and control system could find out those who might have been infected and identify all possible transmission routes, serving as an effective tool in assisting the effort to curb the spread of infection in the hospital. The loose estimates of infection probability are shown in Table 3.

Conclusions

A review of related literature on transmission routes of respiratory diseases shows that droplet transmission is one of the main causes of hospital-acquired infections. This study presents the hypothesis of a direct proportion between

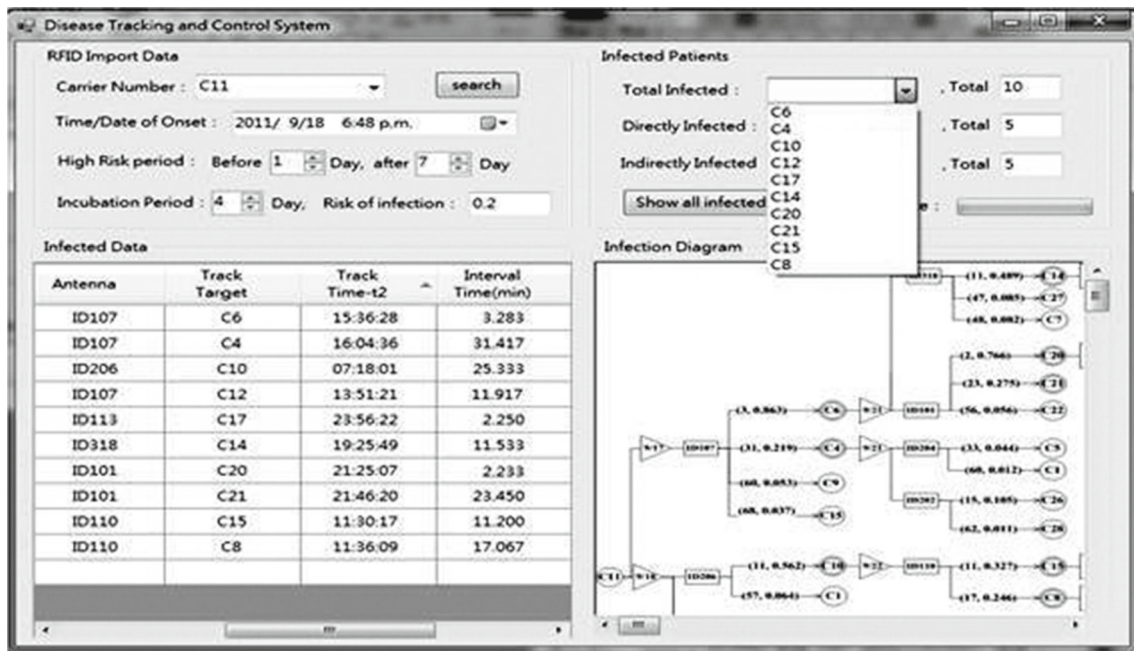


Fig. 7 Interface of the disease tracking and control system

infection probability and droplet concentration based on Gao’s and Lin’s experiments on aerosol transmission and on Peng’s research on virus survival time (Gao et al. 2009; Lin et al. 2012; Peng 2012). In addition, an infection probability model is developed in this study on the basis of Duguid’s and Tellier’s research on the residence time of droplets (Duguid 1946; Tellier 2006). To facilitate the search of disease transmission routes, healthcare personnel, patients and visitors in the hospital should wear RFID tags, so that their location and time data could be recorded. In case of an epidemic outbreak or once an infected case is confirmed, the disease tracking and control system could be initiated by accessing RFID logs to plot the carriers’ time of onset and to trace possible routes of transmission via tree diagrams. With the information, infection control personnel can conduct a prompt search of those who might have been infected, and take immediate protection and quarantine measures to prevent the epidemic from spreading any further. This empirical study is restricted by the resources available at the hospital where the experiment was conducted. Due to the high cost of active tags, only a limited number of subjects were studied. Future research could consider adopting passive tags, which, being of a much lower price, could allow all medical personnel, patients and visitors to be included to build a more comprehensive disease control system.

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