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Computation of Infection Risk via Confidential Locational Entries: A Precedent Approach for Contact Tracing With Privacy Protection

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ABSTRACT To effectively mitigate the COVID-19 pandemic, various methods have been proposed to control the infection risk using mobile phone technologies. In this respect, short-range Bluetooth in mobile phones has been mostly used to detect contacts with other devices that approach within a certain range for a specific duration and to notify residents regarding potential contact with infected patients. However, the technology can only detect direct contacts and neglects various modalities of infection, which might have contributed to the pandemic worldwide. In this article, we proposed an approach that evaluates the infection risk for residents, using the locational information of their mobile phones and confidential information of infected patients. The article first outlines the proposed method, the Computation of Infection Risks via Confidential Locational Entries method. Moreover, a comparative evaluation is qualitatively and quantitatively performed against the Bluetooth method. Results highlight the advantages of the proposed method and suggest that it could work in a complementary manner with the Bluetooth method toward effective mitigation of infection risks, while protecting privacy.

INDEX TERMS Contact tracing, privacy protection, mobile phones, location, infection risks.

I. INTRODUCTION

As a countermeasure against the pandemic caused by a new coronavirus disease in 2020, contact tracing applications have been introduced in many countries. Among them, contact tracing using Bluetooth has been considered promising [1]. It uses short-range Bluetooth between mobile phones to exchange anonymized device IDs without personal information, which enables the detection of close contacts with other devices without knowing the identity of the owners. When a device owner is identified as infected, devices with a history of prior contact with that device are notified of the intersection with the infected patient. Using this technology that directly detects potential contact with infected patients, public health authorities can effectively alert residents regarding their risk of infection while protecting their privacy.

Although the Bluetooth method can accurately detect the proximity of two devices within a certain range for a specific duration, it cannot detect indirect contact. For example, it cannot detect *contagious infection* [2], which occurs when people touch the same doorknob at different times. Another example is the infection among people working in the same area but without direct contact, which could possibly get the infection through ventilated air that brings airborne droplets along the path of the ventilation [3].

Meanwhile, from the lessons of the Swine flu pandemic in 2009, we investigated the application of mobile location information for risk management of infectious diseases and published a conceptual note for the control of infection risks, in late 2019 [4]. In the proposed approach, named Computation of Infection Risks via

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Confidential Locational Entries (CIRCLE method) afterward, histories of location data of infected patients collected by public health authorities are provided to mobile phone owners under a nondisclosure agreement. Then, the owners of mobile phones requested their mobile phone carriers, which have their location information, to calculate their risk of infection based on the provided location information of the infected patient. Results are sent back to the owners and they are asked to consult with public health authorities if the contact risk is considered high. The CIRCLE method protects the privacy of the infected patients, as well as the information of mobile phone owners from government agencies, while realizing efficient warning of potential infections to residents, including indirect contacts.

This article aims to materialize the proposed CIRCLE method and provide a comparative study with the popularized Bluetooth method to establish an effective technology to combat infectious agents with the use of mobile phones. The rest of the article is organized as follows: First, Section II outlines related research on the use of mobile phones for crisis management of infectious diseases. The proposed CIRCLE method is presented in Section III, and evaluation is provided in Section IV with the comparison against the Bluetooth method. A discussion is made in Section V, and the paper concludes in Section VI.

II. RELATED WORKS

Several studies have been conducted since early 2010 on the use of mobile phone location information to address problems related to infectious diseases [5]–[9]. This field was pioneered by an attempt to model the spread of infection during the cholera outbreak in Haiti in late 2010 [10]–[13]. Previous studies used the coarse-grained location information, known as Call Detail Records (CDRs), which constitute the log of calling by mobile phones. Although the data provide the rough location of the devices from which people made calls, the data carry only partial information for epidemiological analysis, because the location information is not linked to demographic data of the owners. In developing countries, most of the phones are prepaid and do not have such demographic data due to the absence of contracts [8]. Such a statistical analysis of people's movement history plays a central role during the new coronavirus pandemic in 2020. In Japan, various statistics on population density have been used to monitor the effects of social distancing policies, such as NTT Docomos Mobile Space Statistics [14], Yahoo's congestion radar [15], and Zenrin Datacom Inc.'s congestion statistics [16]. These spatial data have been used to analyze the population in more detail, using demographic data such as the age of the owners.

The above-noted approaches are used for the statistical analysis of people's location information, in the light of spatial epidemiology, but not the tracing of individuals for privacy concerns. However, in some Asian countries, location information of mobile phone owners is used to trace infected individuals, for containment operations. Such a radial approach was first reported in an article summarizing the Middle East respiratory syndrome (MERS) epidemic, which occurred in South Korea in 2015 [17]. Since then, there are few articles that mention the use of mobile phone data for tracing of individuals prior to the COVID-19 pandemic, probably because the use of such data by governments may violate the privacy of residents [18]. However, due to the outbreak of the pandemic in 2020, some Asian countries have adopted positioning technologies for crisis management of infectious disease. For example, in Taiwan, people subjected to home quarantine are reportedly being tracked using mobile phone location information [19]. In Hong Kong, foreign travelers are required to wear a Global Positioning System (GPS) band for a certain period of time [20].

In Western countries, however, government agencies are trying to avoid the use of location information of individuals due to privacy concerns. Consequently, they developed mobile phone applications that notify infection risks to residents without violating their privacy. Following some pioneering works [21]–[23] in this regard, Singapore's TraceTogether was released as the first practical case in March 2020, which uses Bluetooth to detect contacts with infected patients [24]. After this attempt, various countries have developed and released related applications, for digital contact tracing, which amounted up to 120 applications [25], across the world. For example, the National Health Service of the United Kingdom released NHS COVID-19 [26], Germany released Corona-Warn-App [27], and France released Tous AntiCovid [28], some of which used the Bluetooth API [29].

However, these applications have also led to privacy concerns, and the download of the applications has remained sluggish. Because Bluetooth technology can effectively detect contacts only when people have activated applications on their mobile phones, challenges still exist before the applications fully perform as expected. For example, even in Singapore, where the largest percentage of people has downloaded the application, 45% of the population had downloaded TraceTogether by October 20, 2020, the estimated percentage is still far below for the contact tracing to be functional [30].

The Bluetooth method has its disadvantages. Before the applications to be functional, the population must install the same application even though expected performance cannot be achieved unless the owners reach a certain threshold that allows the effective exchange of contact information. To address this problem, Apple and Google jointly announced that they would release a platform in April 2020, which enables the exchange of contact information among their smartphones, providing necessary protection of owners' privacy [29]. Once the platform is established, which realizes a significant improvement in terms of device coverage, contact tracing applications can use the same method for contact tracing using both iOS and Android mobile operating systems. However, as long as the mechanism is operated on an opt-in basis, the limitation remains because the algorithm is effective only when the device coverage exceeds

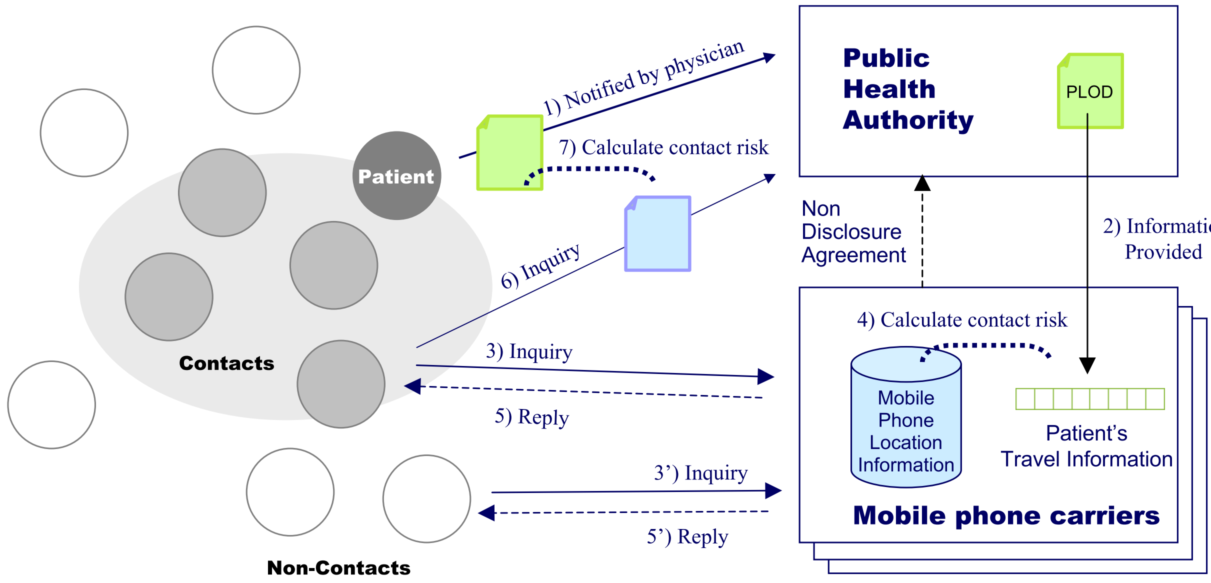

FIGURE 1. Overview of the proposed approach.

a critical value. Authorities are suggesting to provide incentives, such as priority services for diagnostic testing and treatment, to owners who opted in [31]. Additionally, the approach leaves the mainstay technology against pandemic at the discretion of the multinational technology giants although it is fundamental to national security. Undoubtedly, there must be alternative technologies that complement the limited method. In the following sections, to show the data characteristics, the Bluetooth method is used as a comparison target, which is the most widespread method among the digital contact tracing methods proposed.

III. CIRCLE METHOD

A. OVERVIEW OF THE PROPOSAL

In the event of an outbreak of highly contagious infectious diseases, such as tuberculosis, measles, novel influenza, as well as new coronavirus infections, public health authorities need to identify contacts and contain the agents. To this end, public health authorities publish press releases to alert residents who may have potential contacts to inform and provide them with necessary information including the area of residence and history of exposure to the public. However, ordinary residents are not interested in such information. Besides, detailed information of the patient, such as addresses and travel routes, may infringe privacy. Additionally, public health authorities cannot possibly release the details that interest the residents and, as a result, cannot effectively alert the potential contacts and the information is mostly limited to visits to large commercial facilities and public transportation.

In response to this problem, the authors proposed a method for effective risk notification using mobile phone location information to protect the privacy of both patients and mobile phone owners [4], as shown in Figure 1. First, when a patient is confirmed as positive for infectious disease, the consulted physician reports to the public health authority and the authority collects detailed information of the patient. The collected information comprises extremely sensitive personal information, such as the patient's name, address, medical history, and risk factors. Second, the public health authority provides only the patient's mobility information to mobile phone carriers and mobile application operators that hold location information, under a nondisclosure agreement for the protection of personal information. Third, owners of mobile phones inform their mobile phone carriers or mobile application operators regarding their possible contact with the infected patient. Fourth, based on the customer's inquiry, the mobile phone carrier or the mobile application operator calculates the possibility of contact with the patient using the location information of the customer against the patient movement information. Fifth, the mobile phone carrier or the mobile application operator then replies to the customer with the calculated possibility of contact. Customers may also ask the carriers and operators, in advance, to notify them when they have a possible contact. The two notifications include appropriate guidance, such as encouraging customers to consult with public health authorities. Sixth, customers may voluntarily consult the authority. Lastly, the authority calculates the risk of infection using the information of the contacted residents and the patient's information held in advance. If the resident is suspected of being infected, the authorities now take necessary measures, such as testing.

By following these steps, the risk of infection can be informed to the public without disclosing the patient's information. Additionally, this avoids mobile phone carriers from giving customer information to government agencies, thereby protecting the privacy and communication confidentiality of their customers. All the calculations are performed under appropriate permissions, and the confidential data held by the carriers will never be used against the residents' free will.

TABLE 1. Location information that can be used to calculate the infection risk.

Location data source	Geographical coverage	Spatial resolution	Time resolution
Mobile phone base stations	All over Japan	Low (km)	Carrier-dependent, At least every handover
GPS	Outdoors	High (from cm to m)	Application-dependent
Wi-Fi base stations	Urban area	Middle (from m to km)	Application-dependent

B. LOCATION INFORMATION OF MOBILE PHONES

There are multiple sources of location information related to mobile phones [32], as summarized in Table 1. The most general information among them is the in-cell information based on a base station to which a device connects. This method uses a server history called Home Location Register (HLR) in 3G networks and Home Subscriber Server (HSS) in LTE [33]. The coverage area of a base station varies regionally depending on the population distribution and topography of a setup location, ranging from 1 km to 20 or 30 km in diameter. Note that devices are not always connected to the nearest base station. Therefore, in-cell information is supposed to be at a coarse level of granularity. In LTE, Observed Time Difference of Arrival (OTDOA) and Enhanced-Cell ID (E-CID) are being introduced to provide location information [34], which is reported to be available with an accuracy of less than 50 m [35], but it does not cover all devices.

An alternative is GPS information, which has an accuracy of 10 m and can be used for contact assessment with higher accuracy. Nevertheless, not all devices are equipped with GPS, and it is not always activated even if a device is equipped with GPS. Additionally, logs may be stored in the mobile phone application in some cases and in the platform of the OS in other cases. Therefore, data availability is limited compared to in-cell information.

Additionally, connection logs to Wi-Fi base stations might be available for use in urban areas [14]. Indoor facilities, such as stores and subway stations, are equipped with Wi-Fi base stations that are provided by mobile phone carriers. Using the connection history or Wi-Fi signal strength of these stations, the location of the mobile phones can be estimated, sometimes in high-resolution. It is assumed that there is a reasonable chance of contact between devices connected to the same base station simultaneously, although it might be difficult to achieve a spatial resolution in the order of meters, even with this method. Again, data availability is limited because this method can only be used when devices are connected to public Wi-Fi.

As described above, the location information of mobile phones includes different types with different characteristics: information with high coverage but low accuracy and information with high accuracy but with limited availability. When calculating the possibility of contact using the location information, there is a possibility of false detection of a significant number of contacts if the location information with low accuracy is used. Additionally, a substantial amount of calculation time might be required to identify mobile phones that may have contacts with mobile phones of infected persons, considering the considerable amount of location information for millions of devices that mobile phone carriers' control. Particularly, to evaluate the possibility of contact with high accuracy, the computational cost is expected to increase in proportion to the length of time, temporal resolution and geographic resolution used, number of mobile phones, and number of infected patients for the assessment. Therefore, to show the advantages of the method compared with the high-accuracy Bluetooth method, it is necessary to develop a method for calculating the possibility of contact, combining location information with high coverage and with high accuracy while reducing the total computational cost.

C. CALCULATING THE POSSIBILITY OF CONTACT AND RISK OF INFECTION USING LOCATION INFORMATION

To address the issues in the previous section, the CIRCLE method proposes a multistage process, as presented in Figure 2. In the primary filter, approximate calculations are performed to exclude devices that are considered extremely low risk from subsequent calculations. In the secondary filter, high-precision calculations are performed and the devices with little contact potential (considered as low risk) are excluded. In the tertiary filter, the evaluation of infection risks is performed by public health authorities, with detailed data of patients and devices, to extract only the close contacts. In this section, each filtering process is outlined.

The **primary filter** focuses on the most basic location information obtained from the mobile phone carrier's network, which is the history of mobile phone in-cell information. To evaluate the possibility of contact, we generate the mobile phone's geocoded data and the in-cell information of each device is compressed into a two-dimensional array on a predefined duration. Information on the movement of infected patients will also be provided by geocoding the names of places and stores they visited, which is collected through active epidemiological surveys by public health authorities [36]. To facilitate the subsequent comparison operations, the dimensions might be compressed by converting the two-dimensional information to one-dimensional information of the virtual cell IDs. By employing the data structure, the approximation of the possibility of contact is simplified to comparative operation between the cell ID arrays. If the cell IDs do not match at any time, the possibility of contact is considered to be extremely low, which is category D in Table 2 and the device is excluded from subsequent calculations. If the agent of infection is more contagious, which allows indirect contact infection or aerosol infection, the conditions for comparison could be relaxed.

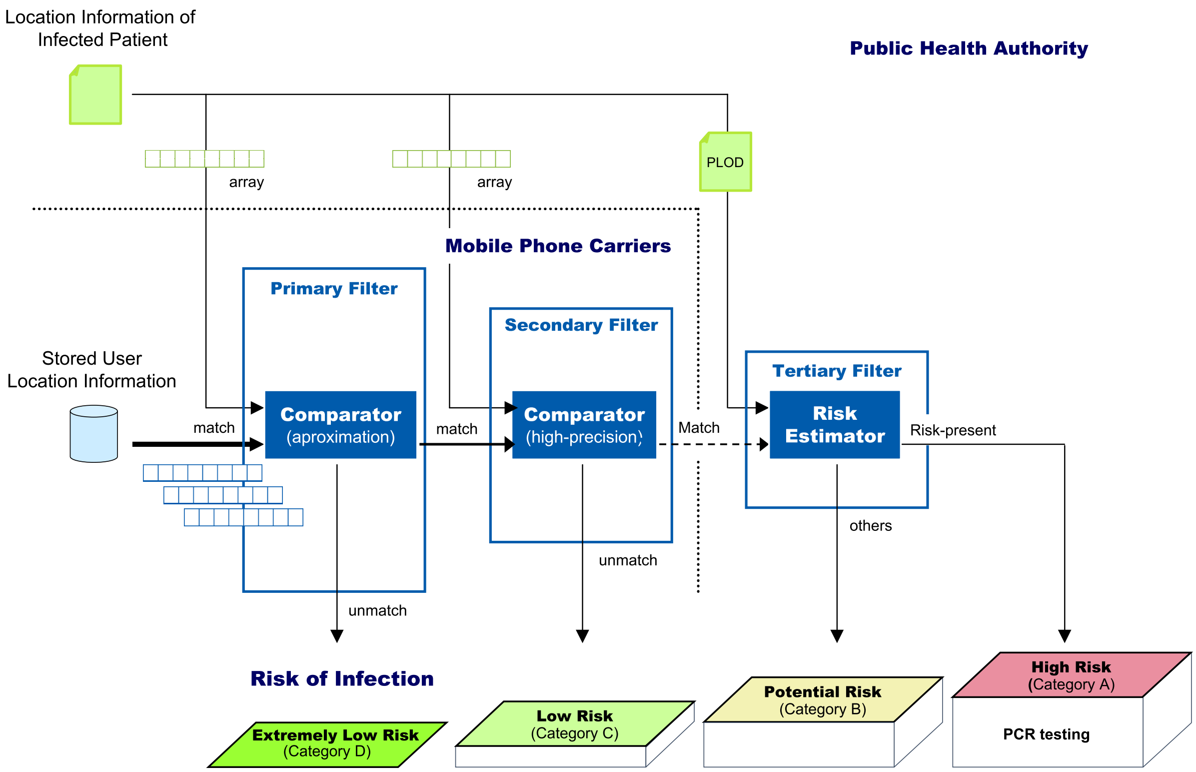

FIGURE 2. Overview of contact risk assessment using mobile location information.

TABLE 2. Infection risk categories.

Category	Levels of infection risk	Notes
A	High	It is suspected that he/she was in the same place or in the same vehicle as the infected person judged by public health authorities.
B	Potential	It is deniable that he/she was in the same place or in the same vehicle as the infected person judged by public health authorities.
C	Low	It is deniable that he/she was in the same place or in the same vehicle as the infected person judged by high-precision calculations using base station information
D	Extremely low	It is deniable that he/she was in the same place as the infected person judged by approximation using base station information

The **secondary filter** is used to calculate the possibility of contact with high precision. To this end, we first determine the state of the devices. If the device is connected to consecutive cells in a certain time series, the owner is considered as *moving*. If the device is connected to a specific cell via a single base station for a certain duration, the owner is considered as *staying*. This calculation can be made for all the devices, and the results are used to assess the contact risks between devices: If device A is *moving* and device B is *staying*, the contact risk between the devices is considered low, which is category C in Table 2. Devices that conflict with the patient's state in this way are excluded from subsequent calculations.

A period in which both the mobile phones of the infected patient and another individual stay in the same cell, contact between these devices is possible. However, because a cell may span several kilometers in its diameter, the match of cell IDs does not necessarily mean a contact. In metropolitan areas with high population density, the number of terminals in the same cell can range from several hundreds to several thousands. Accordingly, it is necessary to improve the spatial and temporal resolutions of location information for higher accuracy. In this regard, the access history of Wi-Fi base stations is more accurate than the in-cell information that carriers can use. GPS information might also be used here. For example, iPhones record their GPS information for about a week. Data are kept mostly by mobile phone carriers, mobile platform and GPS application providers, and mobile phone owners would willingly approve the use of their detailed information for the calculation of their

TABLE 3. Estimated speed of transportation.

Means of transportation	Speed	Notes
Walk	4.8 km/h	Speed used in real estate advertising
Bicycle	15 km/h	3 times as much as walk
Bus	10–20 km/h	Rated speeds of route buses
	50–70 km/h	Express bus speed
Car	15–60 km/h	Legal speed of the road
	80–100 km/h	Legal speed on the highway
Train	30 km/h	Nominal speed of urban subways
	30–90 km/h	Nominal speed of JR conventional trains
	50–110 km/h	Nominal speed of JR conventional express
	120–230 km/h	Rated speed of Shinkansen

infection risks. Because of the potential value of the collected data, mobile phone carriers and platform providers would also have incentives for providing the data for calculation, although the detail is left for future work.

For the time period in which both the infected patient and the mobile phone owner are moving across cells, there must be other algorithms. We first approximate the travel speed of each device by dividing the linear distance between cells by the time spent and estimate the type of transportation by referring to Table 3. If a mobile phone owner is assumed to be outside and be on foot or riding a bicycle, the risk of infection is considered *low*, because the owner is not in an enclosed space. Likewise, the risks of device owners who do not match the transport information of the infected patient, which can be collected through interviews by the public health authority, can be considered *low*.

Now, we need to detect the coincidental ride of the infected patient and mobile phone owner on the same public transportation, such as a train and a bus, because an enclosed area may contribute to a higher risk of infection. If it is clear that a customer is in a different vehicle than the infected patient, the possibility of contact is low and classified as category C. If a customer and the infected patient are riding on the same transportation system, it is assumed that a high degree of similarity in the cell IDs will occur for a certain period of time. Therefore, the Jaccard coefficient between arrays of cell IDs can be calculated to determine the similarity between their traces. If they demonstrate a certain level of similarity, the potential risk of infection is categorized as category B.

There can be detection approaches with higher accuracy if the information on public transportation [37] is available, such as GTFS [38], [39], and GIS data [40] (bus stop, station, airport, port). For this purpose, clustering on the trajectories of mobile phone owners that are assumed to be at risk of infection must be performed first. Now, each cluster is considered to be passengers of the same public transportation system, and the information of vehicles is checked against the public transportation database to see if they match the record of the infected patient.

D. RISK ESTIMATION BY PUBLIC HEALTH AUTHORITIES

As a result of the calculations, mobile phone owners with the possibility of contact with the infected patient will be notified for them to consult with public health authorities. However, because the calculations have limited accuracy, notifications are sent to a higher number of owners than the true contacts with infection risks. Therefore, excessive consultations are received by public health authorities from residents, and thus, the automation of further risk assessment would greatly reduce the burden on public health administrators. This process would also greatly streamline the contact tracing process without significantly compromising the privacy of the population.

The **tertiary filter** is designed to automate the estimation of infection risks. Public health officials manually interview the contacted residents for their health status and mobility information to perform the estimation of the infection risk, against the patient information manually collected as well. Authors have been proposing to automate the process through a data structure, named Patients' Locational Open Data (PLOD), which allows the flexible description of infected patients and residents [36].

At first glance, one might think that this movement of infected patients and residents with possible contact can be expressed by a simple set of quantitative information: latitude, longitude, and time. However, unless the data are automatically obtained from GPS or other automated sources, information of the infected patients is mostly given in a more complex, unstructured form [36]. It comprises name of the facility visited and public transportation used, including their specific location in the car sometimes. The time of the visit might be specified, but it may come in ambiguous manner. There are also instances where only the order of visits might be available. Sometimes, the information may include a negation of a visit to a specific location. In some cases, others such as professional drivers are constantly on the move while there are those who have limited contact with other individuals. Some people may have repeated travels on a specific route, for commuting to work for example. As illustrated, the data are a mixture of numerical location information, such as distance and range, and qualitative information, such as places they visited, with ambiguity. These data must be described flexibly in a machine-readable format before they are eventually converted into orthogonal coordinate information. To address the complexity of the task, PLOD has been developed [36].

TABLE 4. Comparison between the CIRCLE method and the Bluetooth method.

	Points of comparison	CIRCLE method	Bluetooth method
Detection	Detection of contact infection	Detectable	Can only be detected if it meets the definition of contact
	Detection of droplet infection	Detectable	Hard to detect
	Detection of aerosol infection	Detectable	Hard to detect
	Coverage	Relatively large (population is mobile phone users)	Relatively small (population is application users)
	Sensitivity (people at high risk of infection undetected)	High (relatively small)	Low (relatively large, the infection between two subjects with large distances or time gaps is undetectable)
	Singularity (overdetection of people at low risk of infection)	Low (relatively large, anyone who was in the same base station area will be detected in the first approximation)	High (relatively small)
Costs	Data storage cost	Relatively high (operators store mobile phone users' location information for the number of days required)	Relatively low (users store the IDs of devices they have been in contact within the last 14 days on their devices)
	Computational costs	Relatively high	Relatively low
	Cost uncertainty	Small (R&D and operational costs)	Large (dissemination cost)
Privacy protection and governance	Privacy protection	Public health authorities do not get mobile location information.	No personal information or location information, such as phone numbers, can be passed on to others.
	Owner of information	Mobile phone location information is owned by the cell phone company. Information on infected people is owned by the government.	Mobile phone location information is owned by the cell phone company. It is not stored in application. Information on infected people is owned by the government.
	Owners of contact detection technology	The government and mobile carriers and other location information providers	Platform providers and governments (public health authorities)

Now, utilizing the PLOD of the patient and residents, it is possible to estimate the risk of infection among them by determining the modalities of infection represented in an appropriate ontology. For example, if the names of the place they visited are known, indirect contact can be detected, which cannot be evaluated by the Bluetooth method. In the case of an infectious disease, such as COVID-19, which can rarely be transmitted to others unless the person coughs, sneezes, or talks [41], the risk of infection can be reduced even if two persons travel in the same car. Even for this case, the extent of contact can be efficiently assessed through knowledge processing. Both of the cases are good examples of the advantages of the CIRCLE method over the Bluetooth method that only detects direct contact among devices.

The three filters would classify the infection risk of residents into four categories (Table 2). Category D indicates "extremely low probability of crossing an infected patient." The group excluded by the primary filter using mobile phone location information falls under this category. Category C indicates "possibly in the same area as the infected patient" and refers to the group for which contact risk was recognized by the primary filter but excluded by the secondary filter with higher precision. Category B indicates "probably in the same place or vehicle as the infected patient" and excluded from further consideration by public health authorities using the tertiary filter. Category A indicates a group estimated by public health authorities in the tertiary filter to be "in a state of probable contact with an infected patient."

IV. EVALUATION

This section evaluates the CIRCLE method in comparison to the Bluetooth method. For this purpose, we used a contact tracing application developed by the Japanese government (COCOA) as a representative of the Bluetooth method [42]. First, we compared the properties of these methods for detecting contact with infected patients. Second, we discussed the cost of implementing such a method. Third, we evaluated them from the perspective of privacy protection and crisis management. Results are summarized in Table 4.

A. DETECTION PERFORMANCE AND CHARACTERISTICS

The CIRCLE method first uses coarse-grained location information to extract residents with the possibility of potential contact with an infected patient. Then, multiple filters are applied to detect the residents with various risks of infection, even the contact between two parties who are distant from each other or cross each other at different times. The tertiary filter provides the detection of contacts in a highly flexible manner, including contact infection, droplet infection, aerosol infection, and even indirect contact infection (Table 5).

TABLE 5. Situation of infection.

Type of infection	Situations	Example
Contact infection	You can get infected by visiting the same place as an infected person, separated by time, and touching a common facility, such as a doorknob or a vending machine.	• "Contact infection through doorknobs? Male office worker in Iwamizawa, Hokkaido" (June 13, 2020, Sankei newspaper)
Droplet infection	The droplets released when an infected person coughs or sneezes adhere to the conjunctiva, nasal mucosa, and oral mucosa of an infected person within a distance of ∼1m.	• "Among 344 clusters involving 1308 cases (out of a total 1836 cases reported) in Guangdong Province and Sichuan Province, most clusters (78%—85%) have occurred in families" [43]
Aerosol infection	Infection of persons in an enclosed space, e.g., in a single room and in the path of ventilation, by floating droplets, although there is no direct contact.	• A case in the call center of Korea Insurance Finance company in March 2020. "Coronavirus threatens to spread in South Korea's capital region. Outbreaks in the hundreds could occur in rapid succession."(March 12, 2020, FNN) • A case in the restaurant in Guangzhou, China on January 24, 2020 [3]

Contact infection is literally an infection caused by contact with a patient. Droplet infection occurs through droplets emitted by an infected patient who coughs or sneezes and when they adhere to the conjunctiva, nasal mucosa, or oral mucosa of a people nearby. Aerosol infections are caused by smaller droplets that are carried by the airflow, which may travel long distances. Indirect contact infection may occur when a person visits the same location visited by an infected patient, separated by time, and touches a common facility, such as a doorknob or a drink vending machine.

The Bluetooth method defines contact as being with an infected patient continuously for more than 15 min within a distance of 1 m [29], [42]. Under this definition, the Bluetooth method can detect contact and droplet infections that have direct contact with the patient but cannot detect indirect contact, droplet, or airborne infections that can be separated by distance or time. Indirect contact infections, such as contact infections through common objects and infections by droplet nuclei in confined spaces, have been reported in COVID-19 [1], [2], and the Bluetooth method can only detect a sole type among possible contact modalities.

Next, we considered the population coverage of the methods. Since the CIRCLE method uses mobile phone location information, it covers all the population possessing the mobile phones. The individual possession of mobile phones in Japan reaches 84.0% [44]. The Bluetooth method targets only the smartphone owners who have downloaded the application. The individual ownership of smartphones in Japan (2018) is 64.7% [44], which will be discounted by the percentage of the corresponding OS versions (the lowest versions of supported OSs are iOS 13.5 and Android 6 [29]) and by the proportion of the owners who activated the application. The Bluetooth method, in principle, can only effectively detect contact if the percentage of residents activating the application exceeds a critical mass. There is a controversy about that threshold, and there are arguments that the approach works to some extent, even if the adoption rate is low [45]. However, low usage rates would certainly limit the effectiveness of the detection. This is a clear disadvantage of the Bluetooth method compared to the CIRCLE method that allows any mobile phone owners to perform the calculation of infection risks.

Based on the observation, we summarized that the CIRCLE method clearly outperforms the Bluetooth method in the detection performance and characteristics. The CIRCLE method extracts various types of contacts. The Bluetooth method, however, is specialized for detecting direct contact among devices within a limited range for a certain duration, for example, 15 min in the case of COCOA. As a result, it cannot detect contacts at high risk of infection through indirect contact or aerosol transmission. Contact cannot be detected also in places where mobile phones are expected to be turned off, such as theaters and examination halls.

The Bluetooth method has a strict definition of contact and is less likely to over detect the devices. In particular, the Bluetooth method may possess a higher specificity than the CIRCLE method. However, false detection is also possible even with the Bluetooth method, most importantly during an excessive commuter rush in urban areas wherein the method would yield false alerts to commuters riding around patients. Particularly in Japan, there are notorious congestions of commuter trains in urban areas. The tertiary filter would also be helpful for public health authorities to regulate the false alerts caused by the Bluetooth method.

B. COSTS OF CONSTRUCTION AND OPERATION

1) STORAGE CAPACITY

Infectious diseases have a certain period of infectiousness before the onset of the disease, right after the recovery of the infected patient. Additionally, there is a lead time for an infected patient to receive a positive diagnosis. Accordingly, it is necessary to have a storage capacity that keeps track of location information and contact history prospectively for a certain period, to retrospectively identify persons with whom the patient had contacted. To put the CIRCLE method into practice, mobile phone carriers (and other location data holders) need to store the location data of the devices for a certain number of days in which an infected patient may infect others.

TABLE 6. **Computational cost of each filter stage (estimation).**

Filter stage	Computational complexity†	Infection rate	0.01 %		0.1 %		1 %	
		# of the infected‡	460		5,100		54,000	
		# of inquiries to mobile phone carriers	10,000	100,000	10,000	100,000	10,000	100,000
Primary filter & Secondary filter	$O(n \times m)$	Time to complete	7 h	70 h	69 h	690 h	720 h	7,200 h
		Parallel degree required to keep computation time within 6 h	2	12	12	115	120	1,200
		# of suspects	3,400	34,000	9,300	93,000	10,000	100,000
Tertiary filter	$O(m)$	# of inquiries to the public health authority	850	8,500	2,300	23,000	2,500	25,000
		Time to respond	3.0 s	4.0 s	3.1 s	13 s	3.1 s	17 s

Note: figures assumed that each comparison takes 10, 100, and 1,000 μs, for primary, secondary, and tertiary filters, respectively.
†: n = number of inquiries, m = number of the infected. ‡: estimated from the statistics of Tokyo, Japan.

The location information of mobile phones has properties suitable for continuous and differential compression, which may allow for efficient reversible compression. Nevertheless, for operators that have a substantial number of customers, substantial storage capacity is required to keep all the location history of the mobile phones for a certain period. Because the data require a high degree of privacy consideration, the cost of data storage would increase accordingly.

The Bluetooth method, however, stores only the special ID of the devices that detect contact with the other party for a certain period in their own memory (in COCOA, this is for the past 14 days). Therefore, the contact information is stored in a distributed manner, on the owner's devices and the cost of data storage is minimized, for it does not require a new storage nor consideration for privacy protection, because the data are anonymized.

2) COMPUTATIONAL RESOURCES

Both the Bluetooth and CIRCLE methods necessitate computational resources. The CIRCLE method evaluates contact possibility and infection risk through calculations whereas the Bluetooth method detects contact directly using radio waves. Consequently, the CIRCLE method requires more computational power than the Bluetooth method. The computational complexity of the CIRCLE method increases with calculation accuracy and the number of devices. To accelerate the computation, multistage filtering is adopted, which combines low-cost approximation and high-cost detailed calculation to achieve high accuracy at an affordable cost.

The computational complexity of each filter, with a rough estimation of their computational cost, is given in Table 6. The complexity of the primary filter is determined by the numbers of devices (n), infected persons (m), and times to check the contact risk (p), which are determined by the time granularity and period to be included in the calculation. In the worst case, e.g., at the peak of infection, the complexity may become $O(n^2)$, wherein the intersection must be calculated between each pair. However, this is unrealistic if $n \gg m$. The secondary filter is considered computationally expensive owing to the increased resolution, particularly the clustering algorithm. However, the computation volume does not explode because the primary filter regulates the number of devices. The tertiary filter can also be computationally expensive. The computational complexity per inquiry is determined by the number of infected persons (m). In any case, the complexity is considered polynomial, and even in the worst case, it is kept at the order of squared nodes.

The right half of Table 6 illustrates the estimated time cost for each filter stage considering the Tokyo metropolitan area as an example. The table assumes different infection rates, which are percentages of the population who are actively infected, excluding recovered patients. The number of infected patients is calculated simply by the multiplication of the population size and infection rate. The number of inquiries to mobile phone carriers is another assumption that gives different scenarios for the CIRCLE method with varying workloads. Under these assumptions, the computational cost for each filter is estimated (see Appendix for more details).

Some figures in Table 6 may appear pessimistic, but they are the worst cases. However, because an excessive number of inquiries to mobile phone carriers may occur in a pandemic, appropriate measures must be taken in advance. First, the overprovisioning of computational resources might be necessary or the allocation of the computational resources must be scalable. Second, pruning of the devices must be performed in advance instead of processing the entire device. Finally, preparing measures to ensure response performance by reducing the accuracy of calculations may be necessary. Indeed, the timing when the infection rate reaches 1% of the population is the beginning of the infection explosion, and the computational cost increases significantly. In such a case, the benefit of contact risk notification is lost; thus, the operation might be temporarily halted. As noted in Appendix, there could be a tipping point between 0.1% and 1% of the infection rate when we should move from the CIRCLE method to strong infection control measures, including lockdowns.

3) COST CHARACTERISTICS

The cost of the CIRCLE method is relatively high, owing to the development and operational costs, with a low degree of uncertainty. The cost majority is due to the storage capacity required to store the location information and the computational resources can be acquired through the cloud, as needed. These costs can be estimated in a deterministic manner from the number of devices and the number of infections that may affect their customers.

However, the cost of the Bluetooth method is uncertain. The computational resources for the development of the applications are mostly predictable. However, the cost required for the popularization of the applications is highly uncertain. There is no guarantee that the performance scales with the budget invested. There is also the risk that the application might cease to function by the drop in the user coverage if confidence in the application is compromised for some reason, such as system problems or privacy violations.

C. PRIVACY PROTECTION AND GOVERNANCE

Privacy has been a central issue in the design of contact tracing technology. In this regard, the CIRCLE method was built to protect the privacy of both infected patients and residents. In Japan, the location information held by mobile phone carriers is classified as private, which cannot be accessed even by government agencies. The location information is never accessed outside the mobile phone carrier, in any form. Although the existence of the storage for non-anonymized location information is a privacy risk, the data is protected physically and legally.

The Bluetooth method does not collect personal and location information, such as the name and phone number of the terminal holder to protect privacy. Therefore, the mobile phones of the owners that come in contact with the infected patient's device are even unknown to the government. Also, the owner of the devices will not be able to identify the infected patient. However, if the number of contacts is small, the mobile phone owners might identify who infected them and the privacy might be compromised. Likewise, the anonymity might be compromised even if the identifier is randomized for the contact tracing, by analyzing the radio waves transmitted by other devices that the owner may carry around. It may also be detrimental for individuals involved in some secret group activity if the mobile phones of the people involved are identified by the government officials.

Regarding governance, the CIRCLE method is operated by the government and mobile phone carriers perform the calculation under a contract with the government. In contrast, the Bluetooth method is virtually operated by Apple and Google, giving them real authority if their APIs of iOS and Android are used. The government is involved in the applications that notify the residents, but it is the multinational platform providers that decide the key policies of the applications, such as the continuation of their service. It is a potential risk for national security and for global efforts against infectious diseases.

V. DISCUSSION

A. SUMMARY IN QUALITATIVE EVALUATION

In epidemiology, diagnostic tests with high specificity are useful for definitive diagnosis even with low sensitivity. However, for screening tests, a method with high sensitivity is desirable, even with low specificity, to minimize false negatives. The CIRCLE method is reasonably sensitive in terms of calculating the possibility of contact and the risk of infection among a large population of mobile phone owners. On the contrary, the Bluetooth method detects devices that only meet the strict definition of contact and works within the population who activated the application. In particular, the Bluetooth method has low sensitivity, and thus, as a screening method, it has relatively unfavorable characteristics.

Because these two methods have different characteristics, a reasonable strategy is to combine both methods to complement their drawbacks. In this regard, the CIRCLE method must serve as a basis, which has high sensitivity but low specificity, and the Bluetooth method would be used as a complement, which has high specificity but low sensitivity, until a certain threshold is reached wherein the Bluetooth method is fully functional.

Aside from COVID-19, there are highly infectious agents that have high public health importance, such as measles, tuberculosis, and new strains of influenza. The mode of transmission of each infectious agent varies from pathogen to pathogen, and the physical distance and time range of contact at risk are not constant. Accordingly, measles and tuberculosis cannot be detected by the Bluetooth method, because they can be transmitted by aerosol even after the patient has left the site. Thus, the CIRCLE method is advantageous, in general, in its ability to address multiple diseases that are of public health importance.

B. QUANTITATIVE EVALUATION OF THE DETECTION PERFORMANCE OF EACH METHOD

The comparative evaluation performed was mainly performed in a qualitative manner; thus, a quantitative comparison is desirable. However, both the CIRCLE and Bluetooth methods are still at developmental stages. Reports indicate that the Bluetooth method is effective in controlling infection management if enough owners are ensured [46]. However, the number of downloads of COCOA in Japan is 18.77 million (14.8%) as of October 23, 2020, which falls far below the desirable level. Even in Singapore, the download rate of TraceTogether is estimated to be 45%, but the evaluation of their performance is still unclear.

Meanwhile, the quantitative performance of the CIRCLE method is estimated as follows: Figure 3 shows the number of terminals possibly in contact with infected patient's mobile phone because of approximation at the first filter. Ten local governments of different population densities have been selected as an example. We used radio station license information in each government to estimate the size of the cell. Two scenarios were used to estimate the volume of the target devices detected: an infected patient who walks for 10 min and an infected patient who travels by train for 5 min. The number of cells passing through in a given time depends on the speed of traffic. When traveling at a higher speed, more cells pass and more terminals are identified to possibly in

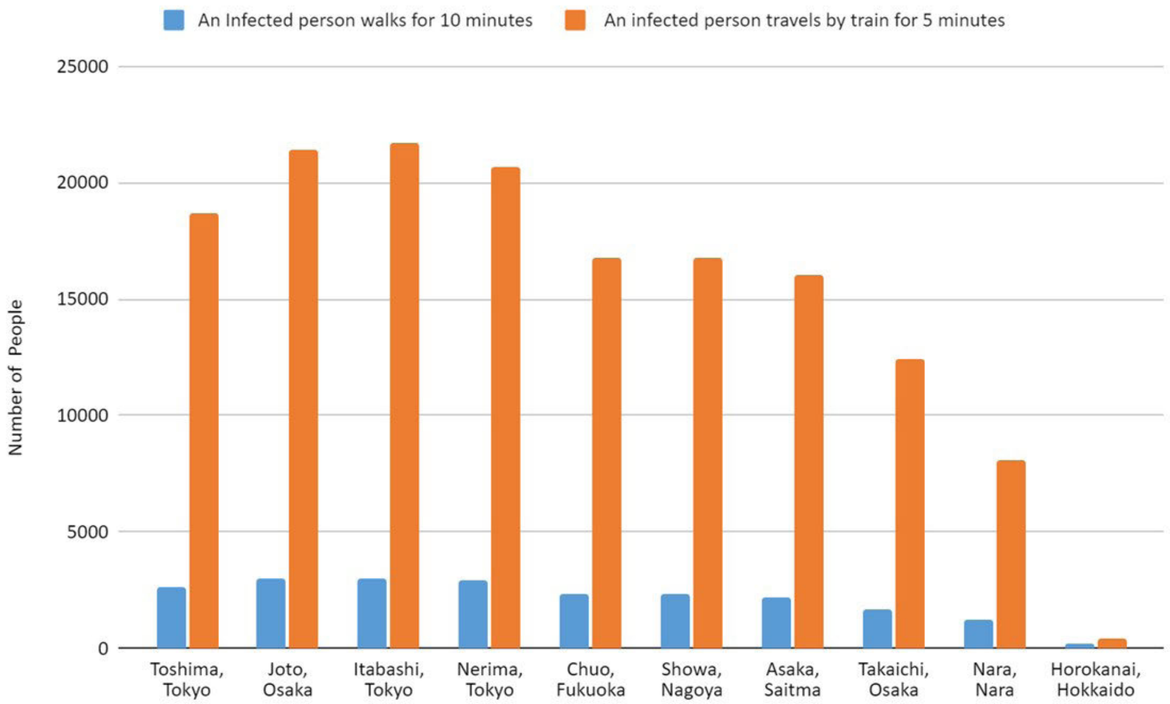

FIGURE 3. **Estimation of the risk of infection by approximate calculation (category A or B or C, not D).**

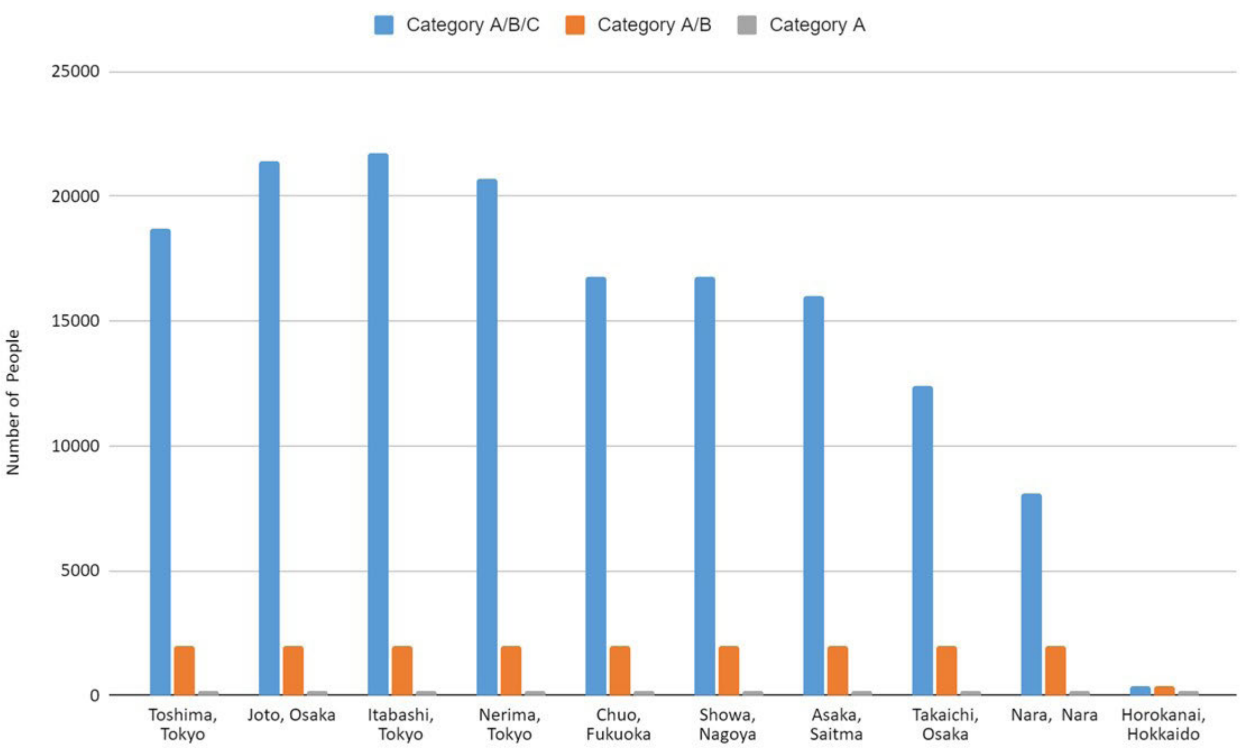

FIGURE 4. **Estimation of the risk of infection by high-precision calculation (in case of an infected person traveling by train for 5 minutes).**

contact with the infected patient. The simple study suggests that devices may be determined to be category C or higher according to the classification shown in Table 2 in the order of thousands in the former situation and tens of thousands in the latter situation.

Now, Figure 4 emulates how the first, second, and tertiary filters perform to regulate the volume of residents detected by the proposed approach, using the 5-min train scenario. It has been suggested that the filters could narrow down to thousands of orders, with high-precision calculations that identify the train on which the infected person boarded, and hundreds of orders through interviews by public health officials to identify the train's vehicles. To improve the efficiency of the filters, more powerful high-precision calculations may contribute to avoid the false alarm effect. Specifically, GPS and Wi-Fi access logs would significantly reduce the false alerts. Particularly, if the GPS data that are held by GPS application providers are available for the calculation, the CIRCLE method might work even without the tertiary filter.

C. PRIVACY CONCERNS

Lastly, privacy protection needs to be considered. In rural areas where the population density is low and the number of mobile phone owners is small, the infected patient might be identified just by being notified of a suspected contact. To avoid this situation, it may be necessary to exclude areas with extremely low populations from the assessment of infection risk, for example. Particularly in the Bluetooth method, there is no entity, other than the device that is actually in contact with the device of the infected patient, that takes such privacy considerations into account. This may be an advantage of the CIRCLE method in some situations.

The CIRCLE method also has the potential to bring together a large number of owners who have been notified that they are at risk, and if the notifications are systematically integrated, the location and movement of infected patients could be calculated. The Bluetooth method also has the potential to disrupt public health authorities and society if infected patients leave their mobile phones in densely populated areas, such as Shinjuku Station. There may be a need to prohibit such activities or to impose penalties for the dissemination of calculated information that may violate the privacy of others.

There are some useful aspects of the privacy information involved in the CIRCLE method. The risk assessment would yield a list of potential contacts, which has a significant value for public health. However, because it is highly private information, the CIRCLE method prohibits the transfer of the data from the mobile phone carriers, to the public health authorities. However, statistics on the number of contacts are not private information, and it might be used to predict the subsequent spread of infection. In urban areas, except in depopulated areas, this statistic is unlikely to damage individual privacy, and it would allow mobile phone carriers to share the data with public health authorities for the benefit of the public.

VI. CONCLUSION

This article technically detailed a method that we proposed in 2019 to mitigate the risk of infection through the calculation of individual infection risks using mobile phone location information [4]. The proposed method has high sensitivity, provides a high level of privacy protection, and does not require the installation of new application software. To avoid false alerts, we elaborated multilevel filters to efficiently extract potential contacts with infection risks. To clarify the advantage, we performed a study comparing the proposed method against the Bluetooth-based contact tracing applications that were developed for COVID-19 responses.

The results show that the Bluetooth method has high specificity, extracting contact between devices at a certain distance and for a certain period of time with high accuracy, but its sensitivity is compromised since it cannot consider modes of infection other than direct contact. In contrast, the CIRCLE method has high sensitivity, uses low-precision location information and can extract all devices that are near the infected patient's device. However, the CIRCLE method has low specificity owing to the low-precision location information and can extract devices that exist in the vicinity of the infected patient's device, depending on the accuracy of the three-step filtering. Additionally, the Bluetooth method requires only the development and distribution of applications, while the CIRCLE method requires investments in infrastructure development for storing location information and calculating the exhaustive possibility of contact and risk of infection.

In addition to the qualitative analysis performed, a quantitative evaluation of the CIRCLE method is essential to demonstrate its usefulness, in the future. Particularly, it would be useful to show the percentage of infected patients who can be selected by both the Bluetooth and CIRCLE methods in the total infected population using statistics on direct and indirect contact among infected patients. It is also essential to evaluate how many candidates are detected for each infected patient at each filtering stage of the CIRCLE method and how many false positives are generated. This is the drawback of this study. However, this evaluation requires detailed trip data and simulators, and thus, we are preparing an evaluation using distinct materials and methods, for the contact risk assessment.

The implementation of the CIRCLE method also requires solutions to several practical challenges. The use of location information held by mobile phone carriers needs to undergo ethical verification, in addition to the development of legislation. In any case, the proposed method is considered a complementary technology that could compensate for the shortcomings of the currently available Bluetooth method. For efficient control of pandemic risks, we envisage that both technologies should be developed simultaneously rather than two separate competing technologies.

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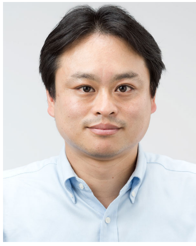

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