Detecting Pedestrian Flows on a Mobile Ad Hoc Network and Issues with Trends and Feasible Applications

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Abstract-Due to the rapid development of mobile and ad hoc communication technology, research on extracting social contexts including the movement and density of pedestrians has also emerged in recent years. This study explores methods to extract pedestrian flows in a distributive manner from Bluetooth detection logs. Bluetooth devices are widely installed in mobile equipment such as laptops, tablet PCs, cell phones and PDAs, which pedestrians carry with them in daily life. The results of experiments have revealed that detection logs implicitly record traces of surrounding pedestrian flows, which might provide possibilities to analyze and distinguish pedestrian flow patterns in various situations. Moreover, the paper discusses the data management system on a serverless ad hoc network, including methods for interpolating detections in order to pick up missing devices and configurating a range query designated to gather data within the geographical range. While examining problems to be faced with technological changes, several possible scenarios are also presented for feasible applications.

Keywords-distributed database; Bluetooth; social context; mobile devices; ad hoc network.

I. INTRODUCTION

This study is an extension of a previous paper [1] dealing with the methods and issues in extracting pedestrian flows in a distributive manner by examining the detectable signals from mobile devices.

With the increase of urban population and the expansion of social activities, we cannot avoid sharing the same public spaces with other people when traveling or in day-to-day life. On many occasions, it will be one of the major concerns for people whether the area is crowded or less-crowded, and sometimes it is necessary to know what is actually going on in such places, including the changing flow of pedestrians. Many location-based services have appeared on the market, thanks to the enhancement of computational ability and wireless communication technology in mobile devices. These include Bluetooth, WiFi and GPS technology. These advancements have paved the way to methods for detecting pedestrian flows or social contexts using high performance mobile devices [2], [3].

Our research employs methods to extract the density and flows of pedestrians from Bluetooth detection logs, while considering the data management scheme on a mobile ad hoc network [4]. This ad hoc network can be generated from connections between mobile devices to work as a distributed database, which can manage and update the detection log data, or modify the log data by accessing geometrically adjacent devices to check for missing detections. The policy of this work is to avoid initial preparations, such as installing a large number of expensive immovable sensors and high performance computational equipment in physical space, in order to minimize cost, time and effort. In this research, we focus on extracting pedestrian flows in physical world, while the specific services to utilize the detection results are left for future work.

We attempt to grasp social contexts such as changes of pedestrian flows and density by detecting the surrounding electronic equipment. Recent hand-held electronic equipment such as cell phones, smart phones, PDAs and laptops contain wireless devices such as WiFi and Bluetooth, which pedestrians carry with them in their daily lives. If these devices surrounding the user are detected and logged continuously, it may be possible to detect not only the density of crowd, but also the changes of pedestrian movements.

We have conducted a preliminary investigation to examine the statistics of detectable types of terminal (mobile phone, PC, etc.) at various locations [5]. Comparing two wireless technologies, WiFi and Bluetooth, WiFi was detected from many types of electronic equipment either carried by pedestrians or fixed in the environment. Therefore, it seems difficult to discriminate the type of equipment by WiFi, and in particular whether they are carried by the pedestrians or not. On the other hand, most of the detected Bluetooth radios were from mobile devices. In this paper, we focus on Bluetooth devices installed in equipment to be carried by users in order to examine the flows and movements of pedestrians.

Related research and comparable studies are reviewed in Section II. Section III explains our method of extracting pedestrian flows using Bluetooth detection logs. Based on the results of experiments, the density and movements of pedestrians are examined in different situations by the analysis of detection patterns in Section IV. Section V discusses the distributive and autonomous data management scheme, and the interpolation of missing detections. Section VI describes issues arising from technological changes and then suggests possible applications of the proposed method in related fields. Section VII reviews the research with conclusion.

II. RELATED WORK

The development of mobile equipment and ad hoc communication has led to several attempts to analyze social context. O' Neill et al. [6] and Nicolai et al. [7] examined the correlation between Bluetooth detections and pedestrian movement by deploying stationary Bluetooth sensors in the environment and analyzing the logs. Eagle et al. [8] have shown methods to analyze social patterns of users' daily activities. These studies show that scanning for Bluetooth (or other wireless devices) and analyzing detection logs give us the possibility to extract the flow of pedestrians or discover relationships in the community. However, not every Bluetooth device can be guaranteed to be detected depending upon the performance of the device and its physical environment. Thus, their methods may not be able to cope when too much incoming data is generated in crowded environments.

To cope with such problems, Kim et al. [9] examined the detection pattern of Bluetooth device logs, and employed a clustering algorithm and Gaussian blur to remove noise caused by inquiry fault of undetected Bluetooth devices. They inferred the transition time of events from multiple device detections. However, inquiry faults for devices cannot be detected individually. As there are many complicated situations in the physical world, this method may not be enough to cope with all situations. Weppner et al. [10] estimated crowd density through collaboration with multiple devices to improve the accuracy of detections. Users carried multiple devices for Bluetooth scanning, which might be awkward or inconvenient.

Other related work includes Bulut et al. [11], which exploits friendship-based features of a mobile social network to perform efficient routing. Friendship is defined from the traces of surrounding personal wireless devices, and the closeness relationship is analyzed from frequency and duration of the connectivity between devices. Our work aims to extract users' activities and the situation occurring around them, while Bulut examines the social relationship between a user and the surrounding pedestrians.

Our research is designed to extract social context by scanning Bluetooth devices in the surrounding environment, with consideration given to the user's location and the communication range of Bluetooth devices. The method is proposed to work autonomously and distributively with the users' devices on an ad hoc network, avoiding such troubles as installing fixed sensors or carrying multiple devices. It also enables to deal with inquiry faults by performing computation collaboratively with nearby devices.



Figure 1. Detections for different places and situations

III. DETECTION OF PEDESTRIAN FLOWS

A. Concept of our Research

Our objective is to extract social contexts such as changes of pedestrian flows or the crowdedness of pedestrians from the traces of detected devices carried with them in their daily activities. These devices include cell phone, smart phone, PDA, portable games, tablet PC and laptop equipped with wireless devices such as WiFi and Bluetooth. In fact, the detection pattern differs depending upon the situations of the surrounding pedestrians (Figure 1). Thus, by analyzing the detection patterns, it might be possible to infer the social contexts or trends and changes of surrounding situations. We avoid extracting the personal information of pedestrians, such as location and name, since recording this kind of information might violate the privacy of pedestrians. Instead, we examine the detection patterns (e.g., numbers and changes of simultaneous or continuous detections) of devices carried by pedestrians surrounding the user.

B. Features of Bluetooth Devices

During the manufacturing process of a Bluetooth device, it is assigned a unique ID in the form of a 48-bit MAC address. This address is called a Bluetooth Device Address (BDA) and is used for communicating with other devices by exchanging BDAs for identification. Thus, BDAs are sent constantly without requiring authentication to build connections with other Bluetooth devices. We target class 2 Bluetooth devices embedded in hand-held mobile equipment as cell phones, laptops, PDAs, etc., having a communication range of approximately 10 meters. The protocol for the Bluetooth inquiry first receives the BDA of surrounding Bluetooth devices, and then requests the names of these devices. A combination of BDAs and timestamps are stored in the log file for each fixed time interval.

Figure 2 shows an example of the pedestrian's Bluetooth Device, which has entered the reachable communication



Figure 2. Detection of pedestrian flows

range of user's device. The user's device continuously inquires for nearby pedestrian devices, and logs the time and BDA of devices which respond. From the log, different types of detection patterns can be verified, such as continuously detected, newly detected, undetected or disappeared, and so on. These are the key to determining the dynamic flow of pedestrians in the physical world.

The model of Bluetooth device can be determined by inspecting the 24-bit prefix of the BDA. In other words, every device which has the same BDA prefix has the same manufacturer, which enables to identify what kind of device it is. For example, a BDA with prefix 0022F3 identifies a cell phone from a certain manufacturer, the device with prefix 001BDC a certain desktop computer, the device with prefix 001D4F a certain laptop computer, and so on. We can identify the device models without retrieving the device name and classify whether the device is cell phone, smart phone, laptop, PDA, iPad, and so on.

C. Trends for Detectabe Types of Bluetooth Devices

Here we discuss some points about the detectability of Bluetooth devices arising from a preliminary investigation examining the detectable types of terminal.

Bluetooth devices can only be detected when the Bluetooth function is turned on with Discovery mode enabled (a configuration option to enable the surrounding terminals to discover the user's terminal). Fortunately, many mobile phones were detected easily, probably because several models with Bluetooth functions were sold in Discovery mode as a default setup. Moreover, it seems that there are several cases in which inexperienced mobile phone users unintentionally accept the mobile phone application's request to turn on the Bluetooth device without knowing what it is. For example, a chat application for Softbank mobile phones has been popular for several years in Japan [12] allowing users to communicate with other users within

Table I CHARACTERISTICS OF PEDESTRIAN FLOW BY SITUATIONS

		User		Surrounding ppl		Sharing Space
		Stay	Move	Stay	Move	
Town		\triangle	0	\triangle	0	\triangle or \times
Conference room		0	×	0	×	0
Cafeteria		0	×	0	0	\bigcirc or \times
Train	Moving	×	0	×	0	0
	Stopping	0	×	0	0	\bigcirc or \times
notations: (())many: ((\triangle) some	e: (×)few	Inone		

the Bluetooth device detection range. This application asks users to enable the Bluetooth function, but does not ask them to disable it when no longer needed. Another example is users who purchase cell phone and then try to use all the functions of the phone while reading the instruction manual, inadvertently turning on the Bluetooth function on without paying attention. In either case, the result is that many users walk around town with their mobile phone's Bluetooth device turned on and discoverable, enabling the

We have chosen Bluetooth devices as our detection target in order to extract the flows and movements of pedestrians, because most Bluetooth devices are installed in equipment to be carried by users. The method we have proposed can be performed using only the mobile device carried by the user, without installing additional equipment such as mounting fixed sensors or video cameras in the environment.

method described here for detecting those devices.

IV. VERIFICATION OF DETECTION PATTERNS

The authors have done several investigations to observe surrounding Bluetooth devices in various situations, such as: (i) normal daily routine for commuting to and working at a university, (ii) special events such as conferences and school festivals, and (iii) other off-campus activities such as tourism, shopping, public festivals and new year celebrations. To collect data, we used a HP iPAQ 112 Classic Handheld PDA set to record BDA with a timeout interval of 6 seconds and a 30-second inquiry signal cycle.

Table I shows Bluetooth detection logs in different situations, and their characteristics for specific movements of the user and the surrounding people. Four different cases have been examined in this paper, namely strolling in town, traveling by train, attending a conference, and taking lunch at a cafeteria.

The results of examination of detection logs are summarized in Figure 3. The upper half of Figure 3 shows the detection pattern of Bluetooth devices, with the time-line expressed on the horizontal axis and the device ID assigned in chronological order of the incoming BDA on the vertical axis. The mobile phones are shown in red, and PCs and devices other than mobile phones in green, and unidentified devices in blue. The lower half of Figure 3 shows the number of detected devices, with the time-line expressed on the horizontal axis and the quantity of BDA on the vertical axis.



Figure 3. Detection pattern of BDA (upper), detected number of BDA (lower)

(a) Strolling in Town: Figure 3(a) shows the changes of multiple detection logs encountered while strolling in town. The number of BDAs is not constant as the number of passers-by is always changing. Even if the pedestrians are walking in the same direction, their devices disappeared occasionally probably because their directions coincided only for a while or their walking speed was different. On the other hand, the same BDA was continuously identified in some places while the examiner was lingering in a store.

(b) Transporting by Train: Figure 3(b) shows the detection in a train during rush hour. From the log, we can identify characteristics such as: (i) devices were continuously detected from passengers in the same carriage; (ii) many incoming and outgoing devices were detected when changing trains; and (iii) a large number of people got on/off the train at major stations. The passenger's devices can be constantly detected while the train is moving. However, due to the limited size and shape of the carriage, the detection has been low even in rush hour. This observation shows that it is necessary to identify the situation from detection patterns by integrating the analysis from different points of view, as it cannot be inferred merely by the quantity of devices.

(c) Attending a Conference: Figure 3(c) shows that many BDAs were detected continuously in the same room. As most of the participants were staying in the room during the conference, the number of BDAs was almost constant (14 to 18 devices), except during the coffee break. As the room was wide enough to hold many people, the quantity

of detections remained high.

(d) Taking lunch at a Cafeteria: Figure 3(d) shows that many devices have been detected during lunch time, as customers enter, take lunch and leave the cafeteria one after another. Some devices are detected continuously with long duration, and others are divided into several times with short duration, because two types of situation are mixed together: people sitting and eating lunch, and people walking around to look for seats or friends.

These results show that pedestrian flow can be inferred by analyzing the detection logs as follows:

- The number of logged BDA detections: crowdedness of people (requiring reference to the scale of space)
- **Time length of BDA detection:** people staying in same space or duration of the event
- Appearance/Disappearance in BDA detection: people staying, entering, leaving, or passing by

The detection logs show that there are several undetected devices even among those staying in the same space. Therefore, a method to interpolate the missing detections is also explored in the following sections.

V. CONSTRUCTION OF THE AD HOC NETWORK

Another issue of concern is the management of the log of pedestrian flow obtained from each mobile device. It is not efficient to collect and manage the entire data sent from mobile devices on a server. In this section, we describe a peer-to-peer (P2P) mechanism necessary to manage data and



Figure 4. Delaunay network and Voronoi diagram



Figure 5. Selection of nodes to connect

perform computation between mobile devices cooperatively, and provide a method to perform location-based range queries for retrieving the data managed on mobile devices.

A. Scheme for Distributive Data Management

To build this mechanism we propose an ad hoc network between the mobile devices to manage the data and communicate with other devices. In this network, each device builds connections directly with other devices without communicating to a base station. In generating connections, it is important to employ an efficient scheme to choose mobile devices to connect with, considering their location and limited communicable distance. Note that not all surrounding pedestrians with mobile devices are viable for generating connections on the ad hoc network. Some of their devices might be cell phones or other devices with limited or no computational capability.

We propose a peer-to-peer Delaunay network, which is a geometry-based network whose topology is defined by the geometric adjacency of mobile devices (see Figure 4) [13], [14]. These devices are connected in a geometrical structure called a Delaunay Diagram, which is well-known in computational geometry. It has the following features: (i) each device connects to nearby devices based on geographical distance, (ii) the degree of connection for each device is low (approximately six), (iii) the network can deal with join/leave of a device only affecting the surrounding devices to reconstruct and update the connection, and (iv) the data on distant devices is retrievable through multi-hop communication.

A P2P Delaunay Network lets us construct an environment in which the mobile devices are connected to each other autonomously and distributively. It is not necessary to prepare a server in order to maintain the system or manage pedestrian flow data on it. Moreover, it also provides possibilities to perform collaborative computation or processing to work with set of mobile devices nearby. Delaunay Networks are effective for accessing data in geometrically adjacent devices, which can expose missing detections by comparing the detection logs of nearby devices. In this paper, we refer to the geographical location of each mobile device as a node.

A Voronoi Diagram is the dual of Delaunay Diagram and is generally used to determine the governing regions for each node. Let $V = \{v_1, v_2, \ldots, v_n\}$ be a set of nodes distributed in a plane. The Voronoi diagram for V is a partition of the plane into n Voronoi regions, each region associated with each point v_i of V. For example, the shaded region in Figure 4 is a Voronoi region of a node with a man in the center. Each node v_i has its own Voronoi region, and the entire n Voronoi regions cover the entire plane, of which any particular point is managed by one of the nodes of V. The edges of the Voronoi Diagram are generated by connecting the perpendicular lines stretched out from the midpoint of the edges of the Delaunay Diagram. In this work, we use a Voronoi Diagram to determine the nodes to which point or range queries are sent for access to distant nodes.

B. Network Construction

In the present investigation, we apply a method proposed previously [13] to generate a P2P Delaunay Network with mobile devices. We assume that each mobile device only has the location information of other devices, but not the knowledge of how the other devices are connected. Thus, each mobile device must choose the appropriate mobile devices to connect to, using their locations to generate a P2P Delaunay Network.

To build connections of a P2P Delaunay Network under such conditions, each node draws an inscribed circle with two other nodes on a plane, with the Delaunay Network property that no other nodes shall be enclosed within the circle. Figure 5 shows an example of v_0 determining the nodes to generate connections to on a plane. Inscribed circles





Figure 7. Geometric-based routing method for range query

Figure 6. Interpolation of BDA data (BDA1)

are generated connecting three nodes each, namely (v_0, v_i, v_j) { $0 \le i \le 17, 0 \le j \le 17, i \ne j$ }, which any of these circles has no nodes in the internal. The nodes $(v_2, v_8, v_9, v_{10}, v_{17})$ are assigned as the neighbors of v_0 to generate connections with. If the rest of the nodes $(v_1 - v_{17})$ perform the same processes, a Delaunay Diagram can be generated. The detailed algorithm for generating and maintaining connections are discussed in the previous work [13]. Delaunay Network can be used not only to generate or maintain connections with adjacent nodes on a plane, but also to perform collaborative computation with adjacent nodes as described in the following section.

C. Interpolation of Missing Detection

We have described methods to extract and manage the Bluetooth detection logs on an ad hoc network. However, there are false-negative cases in which some devices within the communication range may not be detected. That is, too much BDA data arrives at once in a crowded place, and the device cannot handle it all within the limited time interval while scanning for the surrounding Bluetooth devices.

To deal with such problems, we consider methods to check the detection logs of adjacent nodes on Delaunay network, and interpolate the BDA data which is definitely within the communication range of Bluetooth device. Initially, each node sends a copy of its own detection logs to adjacent nodes, and receives their copy of detection logs. Then, it extracts the BDA data which is not detected from its device, but detected from other adjacent nodes' devices. These BDA data will be the target data to perform interpolation, and the location of these adjacent nodes will be the criterion to determine whether or not to perform interpolation.

We validate only the BDA data owned by more than three adjacent nodes to perform interpolation. That is, a polygon is drawn using the location of adjacent nodes with the target BDA data as vertices. If the location of its own node is within the polygon, then the target BDA will be interpolated. We have chosen a polygonal shape to determine the interpolation because it is obvious that the entire polygonal region is covered from the communication range of the Bluetooth device. The purpose of this interpolation method is to deal with missing detection, and the deformation of communication range caused by walls, buildings, and other obstacles is beyond our focus.

Figure 6 shows the interpolation process using the same Delaunay Network as Figure 4. Node v_0 has five adjacent neighbor nodes, namely v_2 , v_8 , v_9 , v_{10} , v_{17} , and has the copy of their BDA detection logs. Among the BDA on detection logs, BDA1 is the only one that v_0 does not have, but more than three adjacent nodes (v_2 , v_8 , v_{10} , v_{17}) do have it. Using these nodes as vertices, a polygon is drawn starting from the upper node in clockwise direction. Finally, BDA1 can be determined to be included in v_0 's detection data, as it is allocated within the polygon area.

D. Location-based Range Query

When users would like to know the pedestrian flows or the situation of a physical area, they designate a particular location or range and ask what is going on in that location. Therefore, the location should be used as a key for searching and gathering data on the ad hoc network.

In order to send a query or data to a destination, each node v_i generates a Voronoi diagram using v_i and the neighbor nodes of v_i . Here, we define global Voronoi diagram as a Voronoi diagram drawn with all the nodes on a plane, and local Voronoi diagram as a Voronoi diagram drawn only with a given local node and its neighbor nodes. Using its local Voronoi diagram, each node v_i selects the neighbor node to send the query, and performs multihop communication between nodes. The shape and locational data of the query range is sent together along with the query.

Figure 7 shows the process of sending a query to a particular range on a plane. First of all, v_0 determines the nodes from its neighbor nodes v_2 , v_8 , v_9 , v_{10} , v_{17} to send the query. Among these nodes, v_2 is the only node selected

to send the query. For this situation, v_3 and v_5 cover the query range and so the query is sent to both of the nodes. This process is performed recursively until the query has reached the destination.

Using this method, we can generate either a point query search, by designating a particular point on a plane, or a range query search which can request data within a designated range. Thus, the global view of the location of nodes is not required to send data to a destination.

VI. ISSUES WITH TRENDS AND APPLICATIONS

A. Considerations for Technological Changes

We have continuously attempted to collect the Bluetooth detection logs in order to observe the changes in various environments for a couple of years. We have also noticed that the technological advancements and changes in consumers' lifestyle have considerably affected the results of detection. In general, it is noticeable that the detection rate by Bluetooth device logs has gradually been reducing even during these past couple of years. In particular, it has become difficult to collect Bluetooth device logs in college environments such as school buses, campus cafeteria or restaurants, lecture rooms, and so on. It can be assumed that students and the younger generations are using smart phones instead of feature phones, and that these smart phones are probably programmed to turn off the Bluetooth connection if not used during a certain amount of time.

We have observed, at the same time, that the detection rate by Bluetooth devices is changing among age groups when we compared the data with those detected in the train, train stations, stores, or while strolling in towns. As these places are likely to be occupied or visited by mixed age groups, including commuters, holiday goers, travelers, children, students, elderly groups, and many others, the changes of Bluetooth detection rate are rather gradual, though not increasing, compared with the detection on campus or while boarding the school bus where the majority of the passengers are young students.

On the other hand, the number of WiFi detections has been increasing rapidly especially in campus environment, probably because several mobile WiFi terminals have appeared on market, or some smart phones are equipped with WiFi connection technology which works as an access point. Therefore, we are also going to collect WiFi logs along with Bluetooth detection logs, and are planning to examine WiFi logs to see whether the device can be classified between static devices that are fixed at a single location, or dynamic devices that move along with people. If both Bluetooth and WiFi log data are detected and examined together, it might be possible to perform more accurate analysis.



Figure 8. Applications to deploy the extracted pedestrian flows

Table II shows the changes in detection logs from the initial experimental stage in 2010 to the most recent data in 2013. The average number of detected logs by minute are calculated for 10 weekday mornings when the user himself is commuting. The results indicate that WiFi detection has been increasing in general even in the train where people with various age groups and different occupations are on board, and that it is more evident with the campus bus in which most of the passengers are students. Therefore, it seems important to detect and analyze using both Bluetooth and WiFi logs in future research.

It is also noted that there may be other reasons to prioritize differently for the detection devices which can be used for the experiment, since the technological advancement as well as lifestyles and cultures are different depending upon particular regions and localities.

B. Possible Applications for Practical Scenarios

It is necessary to consider efficient applications to deploy our method for detecting pedestrian flows. Some of the possible applications are mentioned here as suggestions for further research.

1) Map Visible of Pedestrian Flows: One of the systems to consider for the feasible applications is a map to visualize the flow and situation of pedestrians or the location of congested area as shown in Figure 8 upper left. Pedestrian flows are dynamic and likely to change frequently, therefore it is necessary to gather and process the information as soon as possible. Our method of detecting and analyzing Bluetooth devices may be applicable as it can collect the data seamlessly in real-time, and pass it to the application at the same time. Moreover, it is desirable for users to input time and place so that they can view the past or present location of congested area or pedestrian flows, in order to estimate the future pedestrian flows based on the calculated patterns from the same daily routine of pedestrian activities.

Visualization method of pedestrian flows might also be an important factor for users to understand the situation. The crowded area can be expressed as a circle, and locations

Train, Year 2010						
Date	Time(min.)	Bluetooth	BT per min.	WiFi	WiFi per min.	
Day 1	71	275	3.87	116	1.63	
Day 2	72	182	2.53	207	2.88	
Day 3	81	370	4.57	223	2.75	
Day 4	88	532	6.05	150	1.70	
Day 5	82	399	4.87	170	2.07	
Day 6	70	132	1.88	236	3.37	
Day 7	64	389	6.08	122	1.91	
Day 8	64	344	5.38	77	1.20	
Day 9	77	372	4.83	127	1.65	
Day 10	83	466	5.61	181	2.18	
Avg/Total			4.57/6.70(68%)		2.14/6.70(32%)	

Table II Number of Bluetooth vs WiFi detected in the train and bus

		Train,	Year 2013		
Date	Time(min.)	Bluetooth	BT per min.	WiFi	WiFi per min.
Day 1	50	71	1.42	386	7.72
Day 2	53	297	5.60	208	3.92
Day 3	54	181	3.35	314	5.81
Day 4	53	129	2.43	132	2.49
Day 5	55	107	1.94	318	5.78
Day 6	54	139	2.57	194	3.59
Day 7	57	142	2.49	350	6.14
Day 8	58	108	1.86	425	7.33
Day 9	54	58	1.07	371	6.87
Day 10	57	18	0.32	481	8.44
Avg/Total			2.30/8.12(28%)		5.81/8.12(72%)

with many Bluetooth detections may be filled with dark colors together with numbers expressing the congestion rate. However, the circle may not be enough if there are many sensing devices which cause the creation of multiple overlapping circles or numbers. As an alternative, expressing it with coloring the Voronoi diagrams, instead of circles, might be very helpful in that case. Coloring circles and Voronoi diagrams have both merits of their own. Coloring circles may express the location of sensing devices accurately in vacant areas and Voronoi diagrams may express the detection results from many sensing devices. Therefore, it might be effective to use the advantageous aspects from both methods and choose the preferable ones depending on the situation. The graphical user interface for expressing congestion and frequent changes of pedestrian activities and movements are in our plans for future work.

2) Context-adaptable Pedestrian Navigation System: We have also been working on the context-adaptable pedestrian navigation system shown in the upper right of Figure 8,

Bus, Year 2010						
Date	Time(min.)	Bluetooth	BT per min.	WiFi	WiFi per min.	
Day 1	29	38	1.31	116	4.00	
Day 2	13	58	4.46	37	2.85	
Day 3	13	27	2.08	84	6.46	
Day 4	12	0	0.00	31	2.58	
Day 5	13	28	2.15	87	6.69	
Day 6	13	29	2.23	81	6.23	
Day 7	14	0	0.00	38	2.71	
Day 8	21	125	5.95	85	4.05	
Day 9	18	111	6.17	88	4.89	
Day 10	12	4	0.33	92	7.67	
Avg/Total			2.47/7.28(34%)		4.81/7.28(66%)	

Bus, Year 2013						
Date	Time(min.)	Bluetooth	BT per min.	WiFi	WiFi per min.	
Day 1	13	33	2.54	93	7.15	
Day 2	13	0	0.00	74	5.69	
Day 3	15	3	0.20	100	6.67	
Day 4	15	41	2.73	96	6.40	
Day 5	17	3	0.18	99	5.82	
Day 6	12	0	0.00	103	8.58	
Day 7	16	8	0.05	159	9.94	
Day 8	14	0	0.00	120	3.57	
Day 9	25	0	0.00	134	5.36	
Day 10	15	4	0.27	63	4.20	
Avg/Total			0.64/7.48(9%)		6.83/7.48(91%)	

which is a navigation system to provide users with the preferable route considering the user objectives and conditions of each area, such as with roof (to avoid rain) or no roof, lighted or dark, with stairs or elevators, narrow path or wide road, safe or dangerous facilities, and crowded or less crowded area [15]. Most of these situations are static, except for the crowdedness which changes according to the pedestrian flows.

In relation to this topic, we have previously proposed an algorithm to perform path search considering the user's preference and spatial context. The graph-based approach was employed using metadata to represent logical space built over the real space, and a scoring scheme was applied by partitioning target region into homogeneous cells. Path search was performed by accumulating negative or positive scores to each of the cells according to the user's intention or situation, and the path with the lowest scores to destination was provided. However, not much discussion has been held with the method to detect the situation in space.





Figure 9. Immobile wireless sensors to detect pedestrian flows

To detect pedestrian flows, we had previously thought to prepare many fixed immobile devices on site, such as stepped-on sensors, wireless sensors, video cameras, etc., as shown in Figure 9. This approach is inefficient, however, as it is expensive, requires a massive number of sensors, takes time and effort to install sensors, and cannot be deployed in all desirable locations. It requires abundant initial preparations to build such systems. Our method to extract pedestrian flows from Bluetooth detection logs may be helpful to solve these problems.

3) Multi-avatar Simulation on Virtual Collaborative Space: We have worked on constructing an autonomous dynamic multi-avatar simulation in a 3D virtual collaborative space (lower part of Figure 8), in which the avatars move according to their behavioral patterns defined beforehand [16]. If the avatar's location and congestion information are mapped to 3D virtual collaborative space, we may be able to perform simulations based on the real world situation. Though our Bluetooth detection method cannot provide the exact number of pedestrians, if we can estimate the number of pedestrians in the real as a ratio to the number of detected pedestrians, we might be able to produce an atmosphere similar to the real world with dynamic pedestrians walking around in the virtual environment. Such simulation is useful in order to understand intuitively the situation occurring at the physical site.

4) Pedestrian Flow Analysis in Airport Environment: Our work might also be a possible extention to Pestana's work which proposes an approach to provide security and safety concerning mobile objects in an airport environment [17]. In the airport environment, there are many gates, restaurants, gift shops, etc., and passengers from various countries congregate in these locations. However, the passengers' behavior patterns might differ depending on their cultural backgrounds. For example, a particular restaurant might be preferred by people from the same or neighboring countries, or some people from the same region or areas might prefer buying many souvenirs at gift shops. Thus, collecting and analyzing the detection logs might contribute to recommending the passengers the preferable shops and restaurants depending on their nationalities, or sometimes suggesting to them uncrowded cafeterias or benches to take a rest.

Moreover, as the departure time of the flight and the departure gates are the same for every day's routine, the analysis of detection logs may clarify the daily routine of pedestrian's behavioral patterns. For example, if United Airlines uses the gate number 15 at 12 pm every day, passengers to the United States may gather at the gate around that time. Most of those passengers might take a lunch at McDonalds fast-food restaurant, even if there are various restaurants other than McDonalds. Such analysis based on the application of our method may contribute to a recommendation system or navigation system, which will provide comfortable, safe, and preferable navigation in the airport.

VII. CONCLUSION AND FUTURE WORK

We have shown possibilities for inferring pedestrian flows by examining the detection patterns of surrounding Bluetooth devices, and proposed methods for generating mobile ad hoc networks and managing the detection data on the network, adhering to our policy to avoid initial preparations to install cameras or sensors on the environment, or manage data on a single server. For deployment in actual environments, energy consumption is an important issue that has to be considered, as the battery for HP iPAQ 112 Classic Handheld PDA used for our experiment lasts for approximately 4 hours. In addition, privacy issues are another concern because such personal data as user name and location should not be exposed to others.

For future work, we plan to perform detailed analysis of Bluetooth device logs, examine the applicability of other sensory data including WiFi, and provide location-based applications using social contexts such as pedestrian flows. We also plan to continue further study on Delaunay networks, explore efficient ways of managing social context data and log files, and evaluate our methods to interpolate missing data caused by inquiry faults.

In addition, from the observations presented in Section VI-A, we have found that Bluetooth devices are becoming harder to detect year by year. Therefore, analysis simply by Bluetooth device detection may not be enough to extract the flow of pedestrians. On the other hand, WiFi is being detected increasingly every year from portable devices, which should be another target to perform analysis on. Moreover, there may be many variations of wireless technologies coming out in the future, and thus, it is important to keep up with new technologies and trends to extend this research in the future.

ACKNOWLEDGMENT

This work was partially supported by MEXT/JSPS KAK-ENHI Grant Number 23650033, and The Telecommunications Advancement Foundation. We would also acknowledge Prof. Yasuyuki Kono of Kwansei Gakuin University, Prof. Satoshi Nakamura of Kyoto University and Dr. Ian Piumarta of Viewpoints Research Institute for their valuable comments and suggestions.

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