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Review:

User Participatory Sensing for Disaster Detection and Mitigation

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Rapid growth in communication bandwidth has enabled novel uses of mobile wireless technologies in areas such as smartphone-based user participatory sensing for disaster detection and mitigation. In this manuscript, we discuss novel approaches to resolve fundamental problems that currently hamper the effective utilization of user participatory sensing in this critical application domain. Our approaches to address major challenges related to energy efficiency, collaboration, privacy, ease of deployment, and robustness of communication can be integrated with external systems in a complementary manner to overcome the limitations of current disaster detection and mitigation systems that rely on expensive stationary devices.

Keywords: participatory sensing, mobile sensing, citizen science

1. Introduction

Owing to rapid growth in communication bandwidth and other resources, citizen science or crowd science is now considered to be a powerful tool to gather and analyze scientific data. In particular, the rapid penetration of smartphones, which have a rich set of sensors, enables the retrieval of real-time environmental data and the mobility of humans. These sensor data can be used in ordinary situations; however, such data can also play a critical role in disaster monitoring [1]. An understanding of the situation and a fine-grained analysis of the data can be achieved only by user participatory sensing because conventional, expensive sensors cannot be deployed with sufficient density. Some scholars also discuss "human sensors," "citizens as sensors," or "human-in-the-loop sensing" [2], thus proposing different roles that humans can play in sensing disasters. However, many challenges must be addressed to effectively utilize user participatory sensing in such disaster situations.

When people use smartphones and participatory sensing to cope with disasters, smartphones will be transformed from passive information access devices into active generators of continuous streams of sensor data. By going beyond intermittent spurts of GPS coordinates and call detail records, smartphone sensors will generate big data that are an order of magnitude bigger than current smartphone big data. Hence, if the unprecedented bigness of smartphone data is not handled, the usefulness of participatory sensing in disasters is limited. First, we must make the data easier to handle by applying algorithmic and statistical approaches such as aggregation, indexing, filtering, compression, data mining, and machine learning. Second, contextual information plays an important role in the utilization of these approaches, and the accurate determination of the locations of smartphones is often very useful. In addition, combining different data sources such as accelerometer measurements, mobility traces, proximity data, social media, and crowdsourcing can add depth to data and convert the data into useful information to mitigate disasters. We must also address privacy issues in the presence of an increasing magnitude of data, which are processed, integrated, and communicated continuously in significantly different situations, i.e., daily life and disaster emergency.

Our goal in the CREST project – "Establishing the most advanced disaster reduction management system by fusion of real-time disaster simulation and big data assimilation" (hereafter referred to simply as the CREST project) – is to tackle these issues. We study the detection mechanism of the events occurring in a disaster – such as the location of a fire, the detailed seismic intensity information, and the mobility and density of the victims – by utilizing smartphone big data. Then, the collected data must be delivered and analyzed at the server to mitigate the disaster. Thus, we must study robust and effective communication means to deliver data and to disseminate the appropriate evacuation message based on the analysis of the sensed data by user participatory sensing and conventional expensive sensors. Social media platforms such as Twitter contain precious semantic data, and hence, methods to monitor or "sense" a disaster from social media also constitute an important research area. In the following sections, we introduce related work. The future research direction of the CREST project is also discussed.

2. Collecting Big Data by User Participatory Sensing

This section introduces NaviComf [3], our pioneering research on participatory sensing, as a basis of the on-

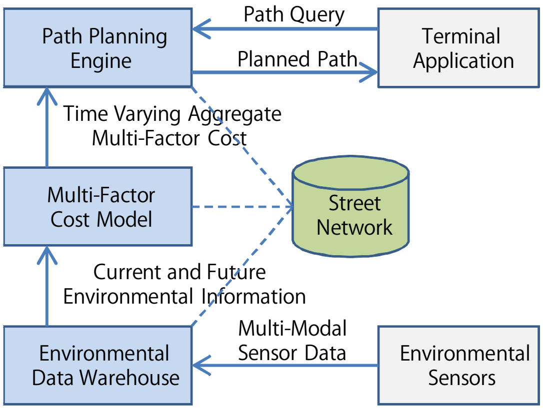

Fig. 1. Concise architecture diagram of NaviComf.

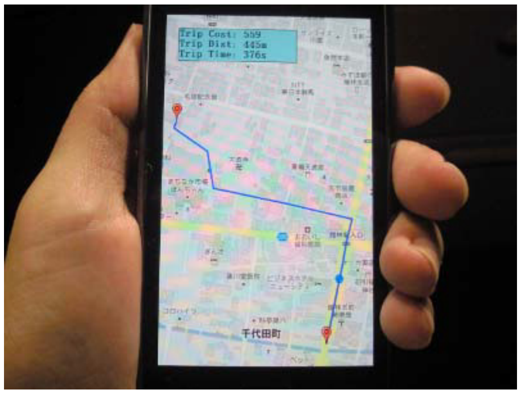

Fig. 2. A map view with planned path displayed on a client smartphone.

going CREST project. The research aims to collect fine-grained environmental information about a city as big data from various sensors including smartphones.

NaviComf developed an integrated framework that constructs pedestrian navigation systems for comfortable movement in varying environments by using multi-modal sensing technologies. We aim to use NaviComf to systematically provide solutions to three key problems: (1) how to build the environmental data warehouse (EDW) that functions as an infrastructure providing comprehensive and predictive environmental information, (2) how to integrate heterogeneous environmental information from multi-modal sensors into an aggregate value that facilitates further processing, and (3) how to determine the optimal path plans in environments that vary continuously.

A concise architecture diagram of NaviComf is shown in **Fig. 1**. Raw multi-modal sensor data are provided as input to fact tables of the EDW where the multidimensional data model and data prediction method are applied. The dimensional information of space and time is extracted and aggregated into dimension tables. The EDW contains predictive functions; therefore, it can provide historical, current, and future environmental information.

The walkable space for pedestrians is modeled as a street network. The intersections are treated as nodes, and the walkable street segments between intersections are treated as edges. Sensor data is associated with the corresponding street edges by applying map matching.

In order to integrate the multi-modal sensor data consistently and flexibly, a novel multi-factor cost (MFC) model is proposed. The aggregate cost rates for edges are calculated by applying the MFC model. The cost value of an edge accessed by the path planning (PP) engine is the product of the aggregate cost rate and the travel time for that edge.

Based on the earlier two solutions, the optimal PP problem is solved in a time-dependent network by applying a dynamic programming method. The PP engine receives path queries that are submitted by pedestrians in real time. We have developed a prototype client application running on an Android smartphone. A map view is displayed on the smartphone, and the pedestrian can specify her origin and destination by touching the screen. Then, the planned path calculated on a server is displayed in the map view to guide the pedestrian toward her destination. A map view with a planned path is shown in **Fig. 2**.

The performance of NaviComf is evaluated near a railway station in the city of Tatebayashi, Japan; the sensor systems are deployed with a range of approximately 600×600 m^2. There are two independent sensor systems: a wireless sensor network (WSN) to gather temperature and humidity information, and a distributed camera system to detect the traffic flows of pedestrians [4]. A prototype system has been implemented with the data. The prototype system is evaluated; the results show that NaviComf can efficiently navigate pedestrians through more comfortable paths than the traditional navigation method.

3. User Participatory Sensing in Disaster Situations

Participatory sensing can be useful in disaster situations if we determine practical solutions to fundamental challenges such as energy efficiency in sensing and communication, effective design of social media environments, privacy, inference of accurate location information, and robustness of communication in extreme environments. We discuss our proposed approaches to tackle these challenges and related proposals by other researchers.

3.1. Understanding Human Relationships by Using Smartphone Sensors

Several studies aimed to determine the social relationship among people by using special devices and technologies such as infrared [5], RFID [6], and Social Network Services [7, 8] to capture meetings among different persons. A recent trend in this field is the usage of a smartphone [9–11]. Many people keep their smartphones in close proximity almost all the time; hence, we can capture human density and relationships by determining the number of smartphones in a certain area and their physical proximity to each other. Several methods for interac-

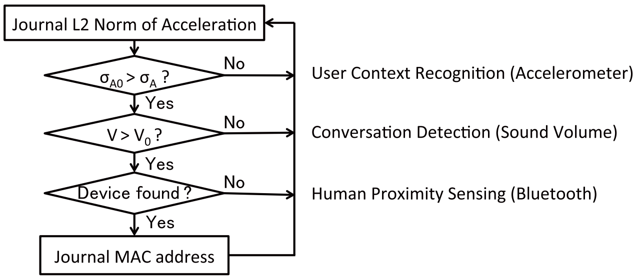

Fig. 3. Flowchart of proposed sensing method.

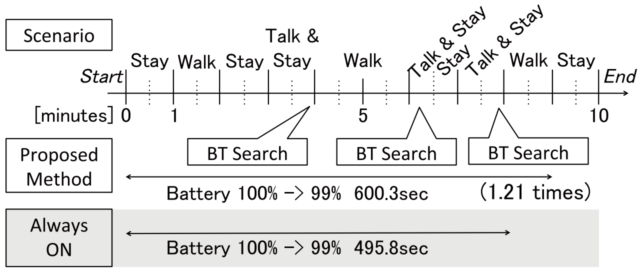

Fig. 4. Scenario and result of evaluation of energy consumption.

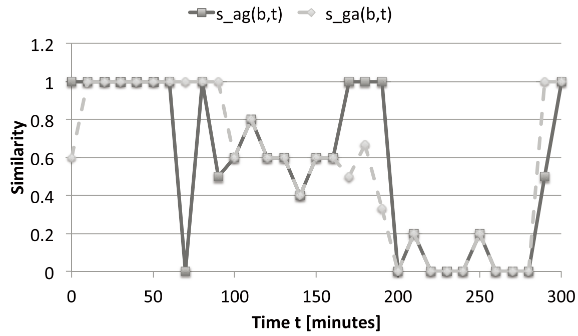

Fig. 5. Partial Bluetooth similarity between A and G.

tion between the directories of two or more smartphones are already available, e.g., usage of a camera, NFC, ultrasound, and Bluetooth. Therefore, by utilizing these methods to report the existence of a smartphone and measure the distance between smartphones, we can determine the entire smartphone picture that represents human relationships.

3.1.1. Proposed Method

One of our ongoing studies aims to record the daily interactions of a person by utilizing the Bluetooth in a smartphone as a sensor [12]. Although Bluetooth is superior to other direct-communication methods owing to its usable identifier (MAC address) and appropriate communication range (10 m), the energy consumption continues to be a challenge. We developed a method that improves the energy consumption of Bluetooth beaconing by leveraging 3-axial accelerometers present on smartphones. Further, this method uses the similarity of acceleration and sets of Bluetooth MAC addresses to improve the robustness of finding social links that tend to fail due to collision.

The detailed method to find other smartphones while considering energy consumption is illustrated in **Fig. 3**. First, based on the method proposed by Ravi et al. [13], the proposed method determines whether a user is "staying" or not by using an accelerometer. Second, the method determines whether a user is "talking" or not by using a microphone. The method does not utilize speech recognition; it utilizes only the volume of sound. Finally, the method senses proximity by using the Bluetooth inquiry mode, which is typically used to search for unpaired devices. The phone collects the MAC addresses of nearby phones in a certain number of seconds.

The proposed method predicts a social link in a robust manner that is tolerant to failures in Bluetooth inquiry. In the following equation, $s_{ij}(B,t)$ is the strength of the social link between the person i and the person j from time t to $t+T$, where B_{it} and B_{jt} represent sets of collected MAC addresses. Even when a smartphone cannot be found by the Bluetooth directory the equation indicates the proximity of two smartphones.

$$s_{ij}(B,t) = \begin{cases} 1 & \text{(Found)} \\ \dfrac{B_{it} \cap B_{jt}}{B_{it} \cup B_{jt}} & \text{(Not found)} \end{cases}$$

Figure 4 illustrates the result of a preliminary evaluation of the energy consumption using Galaxy Nexus with Android 4.0.1. We compared the proposed method with the baseline method that has Bluetooth always on. In the university campus, a subject moved in accordance with the scenario represented in **Fig. 4**.

With the baseline method, the battery consumption reduced from 100% to 99% in 495.8 seconds. However, with the proposed method, the battery consumption reduced from 100% to 99% in 600.3 seconds. Therefore, the battery life of the proposed method was 1.21 times longer than that of the baseline method, which continuously collected proximity in this scenario.

3.1.2. Experiments

We conducted indoor and outdoor experiments with seven and four subjects, respectively. First, we analyzed the strength of the social link obtained from Bluetooth. **Figure 5** shows the partial result for participants A and G. From $t = 160$ minutes to 190 minutes, participant G found A; however, A did not find G. We found 525 one-way social links during the indoor experiment, and 13.3% of these links are exact social links owing to the robustness of the proposed method.

In the CREST project, we will extend the method that determines human existence and relationship to enable its applicability in evacuation and rescue situations.

3.2. Social Media and Citizen Collaboration

People use social media tools to respond to natural disasters such as earthquakes, floods, and hurricanes. Social media are often used as means to collect (or "sense") critical information by organizing and coordinating volunteers. This form of crowdsourcing enables swift sharing of disaster information although it has certain limitations in terms of data quality and ease of collaboration and coordination [14]. Olteanu et al. have analyzed tweets from various recent crises and shown their substantial variability across crises [15]. We can utilize social big data in a more informed manner as we deepen our understanding about the types of information that crowds generate in various crisis situations.

Crowdsourced disaster information is often linked to location information and can be visualized on a map. For example, volunteers monitored wildfires in Santa Barbara by showing text reports, photos, and videos on a digital map [16]. Crowds can generate such maps much before authoritative information becomes available; this important benefit can outweigh the cost of error-prone crowdsourcing data. Further, in addition to grassroots organizations, governmental agencies have started taking advantage of crowdsourcing. For example, the Federal Emergency Management Agency (FEMA) in the U.S. recently introduced a crowdsourcing feature in their mobile application [17].

Smartphones are often used as social and participatory platforms to collect disaster-relevant information. Further, several experimental projects explore the uses of ubiquitous sensors in smartphones to infer critical information such as tremors, infrastructural damages, and fires in earthquakes.

The accelerometers of smartphones can be used to measure and communicate the strengths of tremors quickly and inexpensively with significantly higher spatial resolution than professionally managed high-quality sensors such as K-NET in Japan. Existing research by Naito et al. has shown that smartphone accelerometers are particularly effective in monitoring tremors with seismic intensity greater than two on the seven-level Japanese seismic scale [18]. A high spatial resolution in the monitoring of strong tremors in buildings can be extremely useful in analyzing the cumulative impact of tremors on buildings and in designing safer physical structures. The Community Sense and Response (CSR) system utilizes accelerometers in smartphones and dedicated devices to monitor tremors at a low cost and to infer complex spatial patterns of tremors based on a machine learning mechanism [19]. The Citizen Seismology Project senses Twitter messages and web traffic on a popular earthquake website to detect earthquakes quickly [20, 21].

Fires, which can be triggered by earthquakes, often cause significant damage to inhabitants. Early detection of the locations of fires is extremely important to predict the spread of the fires and to formulate appropriate evacuation plans in time. However, very few projects explore smartphone-based fire detection. Some recent high-end smartphones such as Samsung Galaxy S4 are equipped with temperature and humidity sensors that can be useful in detecting high temperature and low humidity as well as the temporal variances of these parameters in the proximity of the fires. In a recent project, Amjad utilizes such high-end smartphones to build FireDetector; FireDetector infers the occurrences of fires in indoor environments by using Naive Bayes Classifier with the data from the temperature, humidity, pressure, and light sensors of smartphones [22]. However, one of the limitations of this approach is the dependency of classification results on environmental factors such as weather conditions and regional climates. Thus, a classifier that is trained in one region may not work in other regions. This situation can be problematic if the cost of training is high.

3.3. Privacy Preservation

3.3.1. Importance of Privacy Preservation

In case of concerns about privacy preservation in user participatory sensing, people are discouraged from joining any participatory sensing applications. Further, if the privacy preservation mechanism cannot be easily understood by users, they will be discouraged. Although conventional encryption schemes may be considered powerful, they cannot be easily understood by the general public. In addition, even if the data are encrypted, they must be decrypted for analysis. Thus, an intrinsic risk is associated with conventional encryption systems.

However, in many applications, users are not required to send the "exact" data; instead, they need to send only obfuscated or randomized data, depending on the objective. For example, if we would like to know the average weight of the women in a certain group, each user is not required to send her exact weight; instead, she could send her "obfuscated" weight by adding some noise, such as up to ± 5 kg, to her true weight. If the noise level is moderate and the number of samples is large, the average of the sum of the obfuscated weights should be approximately equal to the actual average weight. This technique is called data perturbation. Data perturbation is not performed at a server or cloud; it is performed within the mobile device, and hence, it will not violate the privacy of the users. The relative simplicity of this mechanism will also give them peace of mind. In the following subsection, among various perturbation techniques, we introduce Negative Survey [23] and some of its extensions.

3.3.2. Negative Survey

The basic principle of the Negative Survey can be easily understood from the following example:

Let us suppose that an election for the post of the governor has five candidates: A, B, C, D, and E. The media would like to conduct an exit poll; however, many people tend to have a feeling of distrust and may not wish to honestly declare whom they voted for.

However, if we modify the question and ask, "With equal probability, tell us which candidate you did not vote for," the feeling of distrust would dramatically decrease.

Let us suppose that the support percentage for each candidate is as shown in **Table 1**. The supporters of candidate A, who received 60% of the votes, respond with either B,

Table 1. Negative survey for exit poll.

Candi-dates	Actual percentage of votes	Voting percentage by Negative Survey				
		A	B	C	D	E
A	60%	0%	6%	3%	1%	0%
B	24%	15%	0%	3%	1%	0%
C	12%	15%	6%	0%	1%	0%
D	4%	15%	6%	3%	0%	0%
E	0%	15%	6%	3%	1%	0%

C, D, or E with equal probability, i.e., 15%. By performing another similar calculation, we determine that 10% of the respondents provide A as a response to this Negative Survey.

Next, we must determine a method to reconstruct the actual voting percentage for each candidate. This voting percentage can be reconstructed by the following simple equation:

The actual voting percentage for a candidate $= 100\% -$ (#of candidates $- 1) \times$ the voting percentage for this candidate by the Negative Survey.

In our previous study, we extended this Negative Survey to multiple dimensions and to the special case with only two categories in a dimension [24]. We also extended Negative Survey to the case of continuous data and discussed its application [25]. In the CREST project, we apply Negative Survey and its extension to user participatory sensing for disaster situations and attempt to use smartphones as sensors to complement the existing expensive ones. A typical example is the usage of smartphones as seismometers to complement the existing infrastructure deployed by K-NET [26]. Early and detailed fire detection and detection of people in the event of a disaster are within the scope of our study.

3.3.3. Location Privacy

Location privacy is one of the most sensitive types of privacy, and in user participatory sensing, it must be carefully preserved. Location privacy has been studied intensively in literature, including our proposal of "silent period" [27]. In a "silent period," nodes or smartphones are not allowed to transmit or receive any message during a designated period. Further, each node uses different pseudonyms for each duration of the communication. This technique makes it difficult to trace the trajectory of a specific node.

The degree of location privacy is not yet well defined; hence, we are tackling the challenge and attempting to redefine it [28]. In the CREST project, we will apply this new framework to disaster situations.

3.4. Localization of IoT Devices

In five years, humans will be surrounded by approximately 26 billion connected objects in the Internet of Things [29]. These objects include sensor-enabled appliances such as smart smoke detectors and smart thermostats, as well as sentient houses and buildings that consist of networked embedded devices. IoTs can be extremely useful in collecting environmental information before, during, and after disasters. Further, they can cooperate with personal and wearable devices that citizens carry. For example, IoT devices could help smartphones to detect their context more accurately by providing useful reference data.

Many disaster information systems require accurate location information to monitor or control environments, evacuate citizens, and support urgent decision-making. Therefore, it is critical that systems maintain accurate location information of IoT devices. In this context, we have proposed a mechanism to determine the locations of IoT devices easily and accurately [30].

Smartphones can use IoT devices as location reference points or "location tags" if they can identify nearby IoT devices by using short-range radio, visual recognition, audio detection, etc. Our proposed mechanism considers two types of location tags: T1, the tags that already know their exact location accurately, and T2, the tags that do not know their exact location accurately. In addition, location tags have *onstage* and *offstage* states: the system uses *onstage tags* to compute location information and trains *offstage tags* until they are ready to "go on stage."

Now, we consider a physical space in which onstage *T1/T2 tags* and *offstage T2 tags* coexist. Let L be the location estimate of an *offstage tag*. Our system collects location information from the smartphones that are in proximity to the tag and incrementally computes L as follows:

$$L_{i+1} = \frac{(i \cdot L_i) + S_{i+1}}{i+1}$$

It obtains new location estimate L_{i+1} from smartphone location information S_{i+1} and existing location estimate $L_i (0 \leq i)$. This computational process can be triggered periodically, using the best smartphone location information S_{i+1} in each interval. Further, when multiple smartphones are nearby, S_{i+1} is a weighted sum of their location information. It must be noted that our system currently uses Received Signal Strength Indicator (RSSI) to select the best S_{i+1} within each interval and to assign a weight to each smartphone.

An *offstage tag* is transformed into an *onstage tag* when its error estimation becomes smaller than a threshold value. We estimate the error by using the maximum likelihood estimator of a corresponding covariance matrix. Then, we derive an ellipse that contains the real location of the tag with 95% confidence and use the area of the ellipse as the error estimation of the tag.

We used the NS-2 network simulator[1] to verify the effectiveness of our approach for a setting in which 10 nodes move around in a 500 m $\times$ 500 m two-dimensional space, based on the Random Waypoint Model (**Fig. 6**).

We also tested the proposed mechanism in an outdoor

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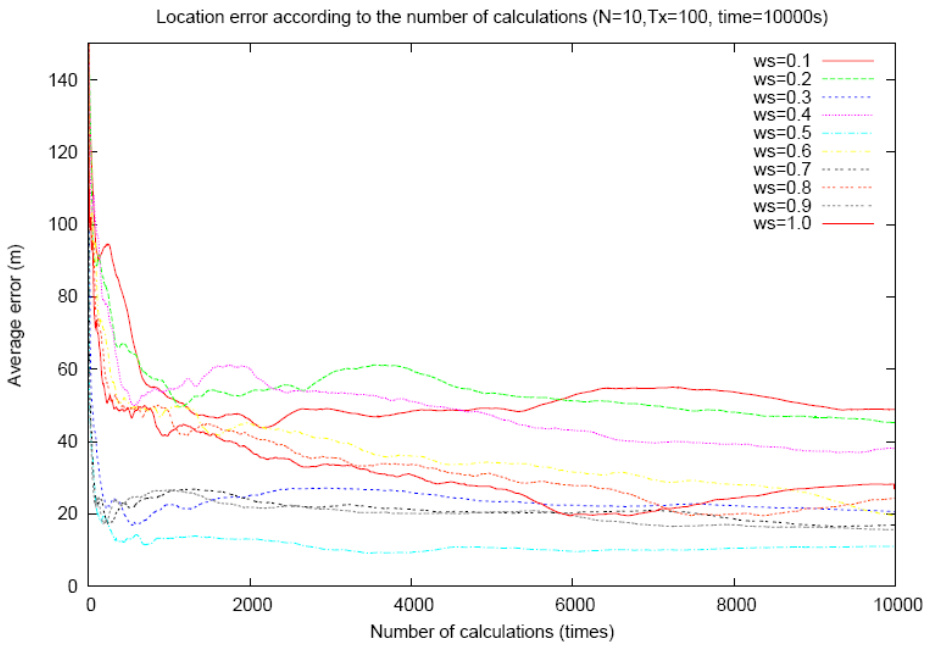
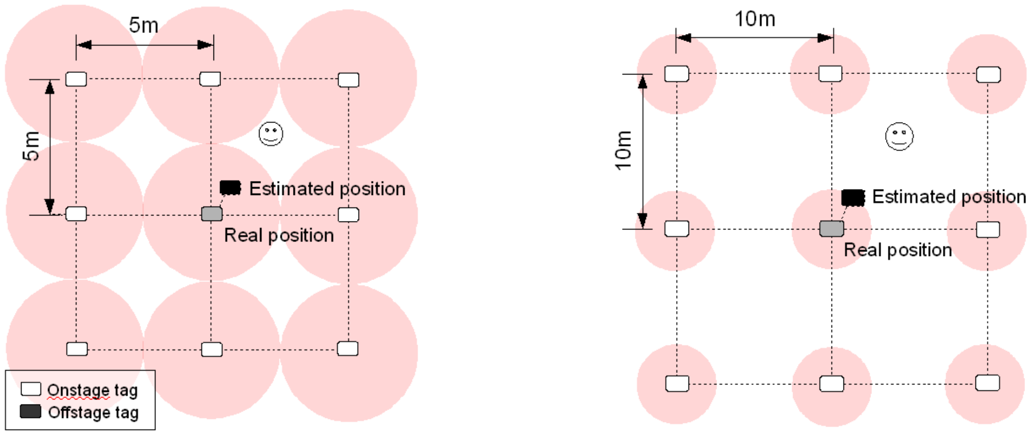


Fig. 6. Simulation result showing average location error for varying window size (i.e., interval between the computation of L_i and L_{i+1}) from 0.1 s to 1.0 s.



(a) 5 m grid configuration

(b) 10 m grid configuration

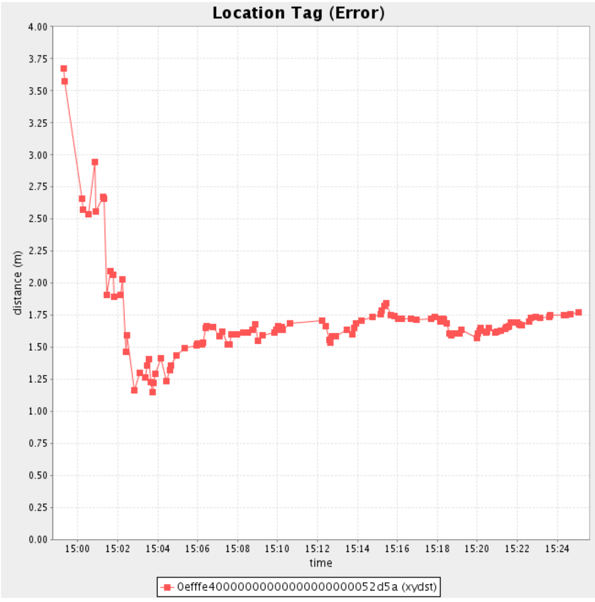
Fig. 7. Placement of location tags in the experiments. Pink circles indicate the 2.5 m range.

athletic ground. We placed nine active RFID-based location tags on the ground using the 5 m and 10 m grid configurations (**Fig. 7**) and measured the accuracy of our system with respect to the location estimation for offstage tags.

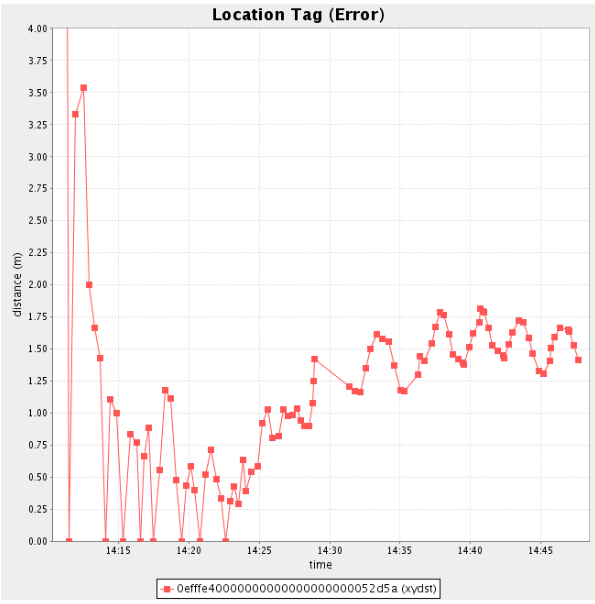
Figure 8 shows the results for a pedestrian walking for (a) 26 minutes in the 5 m grid, and (b) 38 minutes in the 10 m grid. In both cases, the difference between the real and the estimated positions of the *offstage tag* quickly decreases at an early stage and remains less than 2 m thereafter.

Such a localization mechanism provides multiple benefits. First, it can be used to generate georeferenced sensor data from all types of IoT devices, including the devices in indoor spaces and battery-powered or passive devices without GPS modules. Then, we can aggregate the massive georeferenced data to detect points of critical events, such as occurrences of fire or collapse, and possibly guide firefighters quickly to the people in need of rescue, help citizens to evacuate successfully, and assess and predict damages accurately.

Location-tagged IoT devices can provide nearby smartphones with accurate location information. The smartphones can use the received location information to improve their location estimation, which is extremely useful in buildings, underground passages, and urban canyons that lack reliable reception of GNSS signals. Thus, smartphones will be increasingly useful in evacuation and other scenarios in such environments. Further, smartphones can fetch data from nearby stand-alone or disconnected sensors, add corresponding geo-tags to the data, and upload the data to a server. Such delay-tolerant networking mechanisms can provide a robust means of data collection in disaster situations.



(a) 5 m grid configuration



(b) 10 m grid configuration

Fig. 8. Distance between the real and the estimated positions.

3.5. Robust Communication

In a disaster situation, conventional infrastructure-based communication mechanisms such as cellular phone services may be disrupted; however, communication plays a vital role in such a situation. Ad hoc networks and Delay Tolerant Networks are infrastructure-less and must be fully utilized. In the CREST project, we are studying methods to deliver evacuation messages and to gather sensing information to the sink or eventually to the server that analyzes the data collected by user participatory sensing.

3.5.1. Geocast

Geocast, a protocol of ad hoc networks, delivers messages to a designated geographical area. If a simple broadcast protocol is used, nodes will receive a large number of unnecessary messages that are not related to the specific geographical area; further, the bandwidth and other network resources will be wasted. Hence, it is essential to design an effective geocast protocol, especially in disaster situations that require sending evacuation messages, because we cannot waste the battery of nodes or smartphones. In a previous study, we proposed an abiding geocast protocol that can generate a message immediately after a new node joins a designated geographical area [31]. The nodes selected as servers maintain the messages. The servers are adaptively selected based on the density of the nodes, and hence, the protocol achieves high delivery rate without wasting bandwidth.

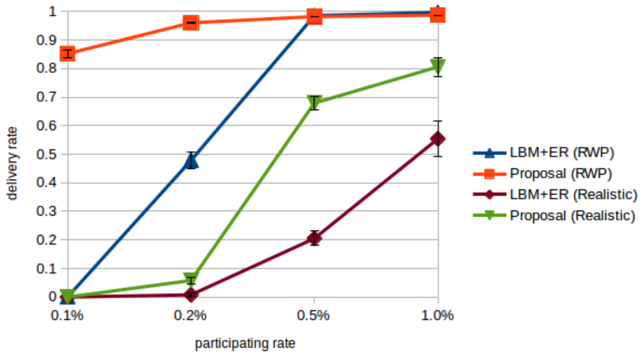


Fig. 9. Performance of Geocast protocols.

3.5.2. Simulation

The effectiveness of the proposed protocol is already shown for the normal condition in which nodes or humans move in a random manner. However, the mobility of humans in a disaster situation is completely different from their mobility in a normal situation. Therefore, the performance of existing geocast protocols must be re-examined under such circumstances to determine a suitable one.

Considering that geocast is used to send evacuation messages, we compared various geocast algorithms in a situation immediately after a major earthquake when public transportation is disrupted and people must return home on foot while avoiding fire [32].

As shown in **Fig. 9**, the performance of the proposed protocol is better than the performance of the conventional protocol, which is a combination of Location-Based Multicast and Epidemic routing [33].

Currently, we are further modifying our proposed algorithms and the introduction of Delay Tolerant Networks, considering that we can control the mobility of certain nodes, especially the ones owned by fire brigades and other volunteers.

4. Discussion and Conclusion

User participatory sensing can be extremely useful in the collection of correct information and its dissemination to the correct people at the correct time, thus helping

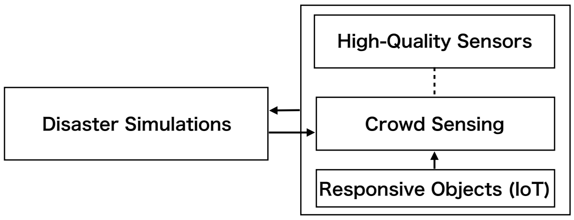


Fig. 10. Framework for the integration of user participatory sensing and existing sensing systems.

people make the correct decisions to mitigate the negative impact of disasters. As we have discussed, the effectiveness of conventional systems in disaster situations is limited and does not address critical issues related to energy efficiency, collaboration, privacy, ease of deployment, and robustness of communication. We are extending and integrating our proposed techniques in view of the technical and practical requirements in the context of the CREST project. This effort should lead to the realization of the environments that can utilize user participatory sensing and professionally managed systems effectively in a complementary manner.

As shown in **Fig. 10**, we can discuss effective models for such integration based on several critical components and their relationships, including crowd sensing, professionally managed high-quality sensors, disaster simulation systems, and IoT as responsive objects. A brief discussion about each component is provided below:

1 **Professionally managed high-quality sensors:** Often, disaster-monitoring infrastructures are of national and/or regional concerns. Infrastructures, such as the Japanese K-NET, are deployed and managed under different budgetary restrictions, which may lead to compromised spatial resolutions of sensors. In the Japanese context, it is particularly important to consider complementary relationships between inexpensive, quick, and dense crowd sensing and reliable infrastructural sensors. Further, people often face scarcity of information in disaster situations, and hence, the provision of additional data through crowd sensing can help reduce false negative problems of failing to issue alarms and warnings.

2 **Disaster simulation systems:** Computer-based simulation systems help us understand the behavior of objects in disaster situations without actually experiencing them in the real world. The connection of simulations to real-world events could effectively narrow down the space for what-if explorations for pertinent decision-making. Then, crowd sensing can play a significant role in making simulations useful in time-critical disaster situations because it provides a way to feed real-world information quickly into simulations, much before authoritative information is made available. Further, microscopic simulations of tremors and fires at the building scale require a fine-grained feed of real-world data; crowd sensing could cater well to this requirement. In addition, simulations could be useful in increasing the smartness of crowd-sensing systems including crowd behaviors and computational processing mechanisms. For example, simulation results could be used to request sensing tasks efficiently by prioritizing data collection based on the most critical goals such as saving lives.

3 **Responsive objects (IoT):** Crowd sensing can be enhanced by populating the world with objects that respond to critical disaster events in ways that can be easily discerned by sensors. For example, smoke detectors emit certain types of loud sounds that can be heard by smartphone microphones; thus, smartphones can help in detecting occurrences of fires without the need for temperature or humidity sensors. Responsive objects include powerful sensor-rich smart Internet of Things as well as RFID-tagged "dumb" objects. Even if objects are relatively "dumb," smartness can be embedded in the software or the context.

This high-level framework is intended to guide the development of the user participatory sensing mechanisms that are cooperative and flexible. We expect that our current results will be extended to create a systemic, yet flexible environment rather than a complex, monolithic system. Thus, our proposed mechanisms could be adapted easily to different disaster situations and different external systems including the systems that will be developed by other groups in the CREST project.

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