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IoT-Based Disaster Detection and Response in Urban Areas

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Abstract

Every year, both natural and human-caused disasters lead to damage to infrastructure, financial costs, distress, injuries, and fatalities. Regrettably, climate change is enhancing the destructive capabilities of natural disasters. In this scenario, disaster detection and response systems based on the Internet of Things (IoT) have been suggested to manage disasters and emergencies more effectively by enhancing detection and Search and Rescue (SAR) operations during disaster response. Consequently, IoT devices are employed to gather data, which aids in identifying risks post-disaster and locating injured individuals. Nonetheless, relying solely on an IoT-based detection and response system may not be entirely adequate for emergency response in smart cities, as connectivity issues with IoT devices may arise due to damage in communication infrastructure or network overloads. Therefore, a new architecture is proposed for an intelligent disaster detection and response system tailored for smart cities. It outlines the key components of our proposed intelligent system and highlights the significant challenges that must be addressed in order to implement it successfully.

Keywords: Sensors, Smart cities, Monitoring, Computer architecture, Data collection, Climate change, Meteorology.

1 | Introduction

Natural disasters are unexpected events that concern world-wide nations. Every year, extreme weather conditions, hurricanes, earthquake, droughts, floods, and heatwave cause considerable damages, monetary costs, mass evacuations, distresses, injuries and deaths. For instance, the tsunami that hit Japan in March 2011, destroyed more than 120,000 buildings, occasioned an estimated financial damage of about $199 billion dollars, and caused 15,894 deaths [1]. In Canada, the Fort McMurray wildfire forced over 88,000 people to leave their town, caused an estimated C$3.6 billion of insurance costs, destroyed about 10% of all structures in the town, and provoked chaos with people leaving their home with whatever they could take [2]. Unfortunately, the frequency and intensity of natural disasters are increasing due to climate change [3], [4].

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When a natural disaster happens, Search and Rescue (SAR) missions must take place immediately, in order to maximize the chance of rescuing survivors. Indeed, the first 72 h after the occurrence of a natural disaster is critical for rescuing survivors [5]. While an impromptu response must occur after the occurrence of a disaster, the performance of a SAR mission may be diminished by the lack of suitable situational awareness and communication capabilities. Furthermore, the immediate response can threaten first responders' lives if not properly planned, coordinated and executed. Traditionally, SAR missions are performed by well-trained government teams, which follow a well-defined and established international protocol. Accordingly, a command post is placed in a safe area, which is responsible for centralizing the information and coordinating SAR teams. The teams, in turn, are divided between scouts and rescuers.

Scout teams are responsible for searching the impacted area and reporting trapped victims, live or dead, to the command post. Rescuer teams rely on information available at the command post for recovering the trapped victims. The communication between teams and the command post is often performed by internationally-defined annotation marks and VHF/UHF radio systems [6]. In recent years, Internet-of-Things (IoT) has also been proposed to improve situational awareness for disaster response. The use of a large number of already deployed physical objects, accessed through the Internet, can supply command posts with more precise situational information. The improved situational awareness would them help to monitor the affected area and predict the occurrence of new disasters. However, IoT does not cope with the need for reliable and secure communication during SAR missions. Moreover, IoT devices might become inaccessible during disasters, as network infrastructures get clogged.

In this paper, it is proposed a novel architecture for smart disaster prediction, discovery, and response system for smart cities. The proposed architecture relies on the following five main building blocks: 1) smart sensing for data acquisition, 2) smart processing for knowledge discovery and disaster detection and prediction, 3) smart response to support timely, coordinately and effective SAR missions, 4) wireless ad hoc networking of everything for data exchange among entities in the proposed smart system, and 5) privacy and security for empowering a reliable and secure system, which will ensure data integrity, privacy and users' anonymity.

The main contributions of this paper are threefold: a review of the state-of-the-art of solutions for disaster discovery and response; the design of an innovative smart system for disaster prediction, discovery and response for smart cities; a thorough discussion of the fundamental challenges that must be tackled in order to enable our envisioned smart system.

The remaining of this paper is organized as follows. Section 2 presents our proposed smart system for disaster prediction, detection, and response for smart cities. Finally, Section 3 presents the conclusion and future work.

2 | The Proposed Smart System

This section proposes a smart system for disaster prediction, detection, and response tailored for smart cities. The envisioned system, illustrated in *Fig. 1*, relies on five main building blocks, briefly outlined below:

I. The smart sensing component will handle the challenges and enable people-centric and IoT-centric opportunistic and participatory sensing for data collection related to disaster and emergency events.

II. The processing component will address the challenges towards efficient and timely knowledge discovery from multimedia mobile big data, in order to detect and predict disasters and estimate their consequences.

III. The smart response component will provide the technological foundations for the prompt, safer and collaborative disaster response.

IV. The mobile wireless ad hoc networking of everything component will supply the need for ubiquitous connectivity and communications demanded for the efficient interaction among the smart sensing, processing, and smart response components, as well as the collaboration between SAR teams.

V. Finally, the privacy and security component will provide the mechanisms to ensure data integrity, data and network security and the anonymity of involved users in all the stages of a disaster prediction and response mission.

The following sections provide a detailed discussion of the components in the proposed smart system for disaster prediction, detection, and response in smart cities.

2.1 | Smart Sensing for Disaster Monitoring

Data collection for disaster prediction and detection is a daunting task. Traditionally, environment-related data is acquired from video cameras, meteorological sensors (e.g., devices to measure precipitation, wind speed, solar radiation, air temperature, humidity, pressure, and evaporation), magnetic sensors, acoustic detectors, passive infrared and radars. Collected data are then used to detect incoming natural disasters (e.g., hurricanes), estimate the destructive power of such events and, more importantly, alert and plan crowd evacuation when needed. In these systems, an emerging approach is the data acquisition from Online Social Networks (OSNs). In this approach, data collection from OSN is explored for real-time situational awareness of ongoing disasters and emergencies [7], that is, to observe how a disaster or emergency is developing and how it is affecting people or a given area.

Data from Twitter, for instance, has been used to predict flu trends [8] and monitor Dengue epidemics [9]. The use of OSN enables real-time disaster monitoring and serves as a channel for issuing warnings, alerts and orientations from police, and other municipalities, to civilians. However, data filtering, information credibility check, data indexing and semantic analysis are examples of the critical challenges that must be addressed when using OSN for disaster monitoring. Our proposed smart sensing component for disaster prediction, detection and response not only include the aforementioned approaches but it proposes the exploration of people-centric (participatory and opportunistic sensing) and IoT-centric sensing. People-centric sensing takes advantage of in-built sensors of users' smartphones [10], [11], such as microphones, video cameras, accelerometer, compass, and gyroscope, to collect sensed data from specific issued queries of variables of interest. A typical work-flow of a people-centric campaign is illustrated in *Fig. 2*. Conversely, IoT-centric sensing takes advantage of the proliferation of IoT devices to collect data of interest. In the following, we provide more details about these considered approaches [12], [13].

2.1.1 | Participatory sensing

This approach consists of sensing campaigns where mobile users are recruited for large-scale monitoring. Citywide monitoring would not be possible with traditional wireless sensor networking technologies. This is due to the challenges for such wide coverage need. In contrast, mobile participatory sensing overcomes the necessity of deploying millions of heterogeneous sensors for citywide-scale monitoring. Accordingly, recruited mobile users use their portable devices (smartphones) to sense variables of interest, while obeying spatial and temporal requirements. After the sensing phase, these devices report collected data to the service provider. Challenges in people-centric participatory sensing include the proposal of incentive mechanisms, user selection based on the requirements of the sensing application, resource management of the users' smart devices and low cost and efficient communication for data delivery.

2.1.2 | Opportunistic sensing

This approach resembles the above mentioned participatory sensing approach in the sense that it also relies on the use of mobile users' smart devices for collecting data on variables of interest. However, opportunistic sensing does not incur in the active participation of the device custodian. Accordingly, the mobile device will autonomously collect data of a given event, when its state meets the applications' requirement (e.g., geographic location) and it has the permission of the custodian to autonomously attend sensing requests. Moreover, additional constraints may take place, for instance, resource utilization and energy level. As soon devices collect data from the variables of interest, they report the collected data to the service provider.

2.1.3 | IoT-centric sensing

This approach consists in the use IoT devices to collect data from variables of interest. An overall architecture, based on the works [13], [14], is illustrated in *Fig. 3*. The proliferation of IoT devices and the advances in machine-to-machine communication and cloud infrastructure have empowered IoT-centric sensing infrastructures and Sensing-as-a-Service (SaaS) systems. Accordingly, data collected from IoT devices are periodically reported, upon the permission of IoT devices' owners, for a sensing service provider. The sensing service provider is then responsible for receiving and processing collected data, and supply the demand of data consumers.

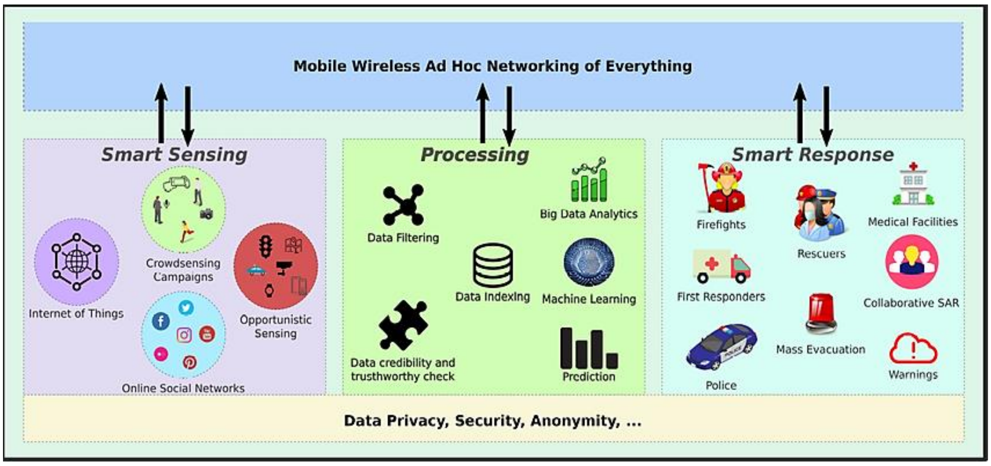

Fig. 1. The proposed smart system for disaster prediction, discovery and response for smart cities.

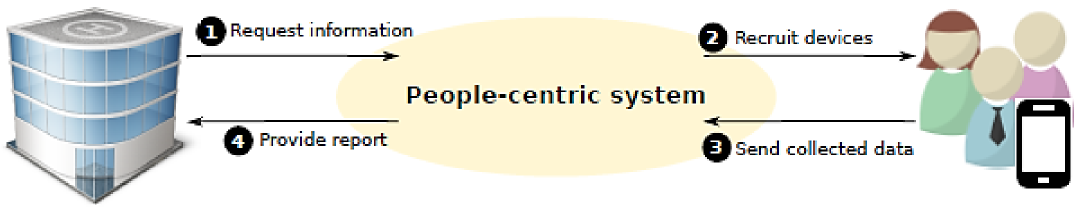

Fig. 2. Generic people-centric sensing architecture.

Fig. 3. Generic IoT-centric sensing architecture.

2.2 | Processing

Multimedia data processing is the next big challenge for empowering our envisioned smart system for disaster prediction, detection, and response for smart cities. The importance of this component goes beyond the disaster detection and prediction. The proper processing of and knowledge extraction from multimedia big data will be used for providing improved information for civilians and SAR teams [6], to assist the preparation of disaster recovery plans [15], and to better assess the socio-spatial impact of disasters [16].

The processing component of the propose smart system must be able of detecting and predicting events of interests, from multimedia noisy unstructured data. As discussed in the previous section, OSNs will represent a primary source of data for disaster detection and prediction. Hence, the processing component of our system will implement web crawlers for the acquisition of streaming data from OSNs. This procedure will also implement indexing mechanism to facilitate further data storage and knowledge discovery processes. Moreover, anonymity and privacy will be implemented to guarantee the use and leak of users' data independently of these data being publicly shared in OSNs.

In addition, statistical tools will be used for data preprocessing. The data pre-processing will consist of data filtering and removal of noisy data, as well as in the summarization of multimedia big data collected from smart sensing in smart cities. This step is fundamental for reducing the large volume of collected data, without diminishing their significance of course, for a further fast and efficient processing of them.

Furthermore, machine learning algorithms will be applied for disaster detection. Supervised learning algorithms will be used to timely detect the occurrence of disasters. To do so, data from pre-disasters and post-disasters, as well as data reported during a disaster occurrence, will be used for training supervised learning algorithms. Moreover, data from weather, traffic, human mobility, popular hashtags and trends in OSN, as well as sentiment analysis, will be used to boost the models and machine learning algorithms aimed to promptly detect disasters. The timely detection of natural events is demanding for efficient evacuation and SAR plans, in order to minimize damages and maximize live rescue victims after disasters.

Finally, disaster prediction will have a fundamental role in the processing component of our proposed smart system. Multimedia big data collected from OSN and sensors in the city will be used for accurately predicting the occurrence of disasters.

2.3 | Smart Response

In this smart system, the smart response component will encompass the technological apparatus to aid first responders during SAR missions. Traditionally, SAR missions are performed by specialized teams from the government (e.g., firefighters). These teams act following well-defined and rigid protocols. They use VHF/UHF radio systems for coordination and information exchange. This approach is disadvantageous in the sense that it does not 1) naturally support collaborative missions with the assistance of civilians, 2) ensure efficient communication among teams during post-disaster missions, and 3) guarantee the safety of involved people in SAR missions.

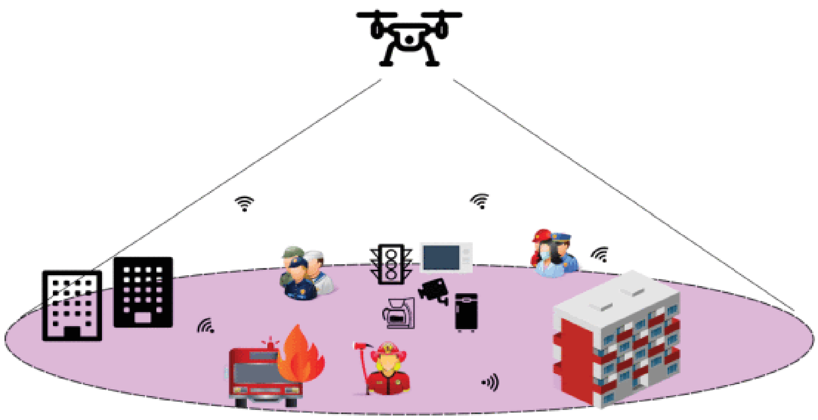

Fig. 4. Mobile wireless ad hoc networking of everything.

The proposal involves using wearable sensors and autonomous devices to enhance monitoring, communication, collaboration, and actuation in SAR missions. First responders, equipped with smart glasses, watches, and other wearable devices, can interact with smart buildings and environments, improving situational awareness, localization, hazard alerts, and victim rescue. These devices will continuously collect data from both the environment and responders, supporting SAR and evacuation planning, collaboration, and future training. Wearables will also enhance safety by monitoring responders' health through biometric sensors, tracking vital signs like temperature, heartbeat, and respiration. This data enables real-time safety assessments, alerts, and support during hazardous situations.

Finally, the smart response is empowered by a mobile wireless ad hoc network (*Fig. 4*). Since disasters can impair communication infrastructure, the proposed city-wide ad hoc network of IoT devices, wearables, vehicular technologies, and remaining sensors will ensure information flow using available infrastructure and mobile drone-based stations when necessary .

Table 1. Sensor specifications and data transmission rates.

Sensor Type	Data Collected	Transmission Rate	Battery Life
Temperature sensor	Temperature variations	1 Hz	1 year
Pressure sensor	Barometric pressure	0.5 Hz	2 years
Biometric sensor	Heart rate, body temperature	2 Hz	6 months
Acoustic sensor	Sound level and frequency	1 Hz	1 year

Table 1 provides an overview of typical sensor specifications used in IoT-based disaster detection. The data transmission rates and battery life indicate each sensor's sustainability and performance under prolonged usage during disaster events.

Eq. (1) is the data aggregation model.

$$D_{agg} = \sum_{i=1}^{n} w_i \times d_i, \tag{1}$$

where

I. D_{agg} represents the aggregated data from multiple sensors.

II. w_i is the weight assigned to each sensor based on reliability and data accuracy.

III. d_i denotes the data value from the i^{th} sensor.

This equation models the aggregation of sensor data for efficient disaster prediction and detection, taking into account the reliability of each sensor to optimize overall accuracy.

Eq. (2) is the network delay prediction model.

$$L = \frac{D}{B} + \sum_{j=1}^{m} t_j, \tag{2}$$

where

I. L is the total latency in data transmission.

II. D represents the data size.

III. B denotes the bandwidth capacity.

IV. t_j accounts for additional delays at each network hop j.

This latency model predicts data transmission delays in a mobile ad hoc network (MANET), ensuring real-time disaster data is transmitted effectively despite potential connectivity issues. These supplementary details offer additional context and quantitative insights, further supporting the system's implementation and performance in real-world scenarios.

3 | Conclusion

This paper proposed a smart system for disaster detection, prediction, and response for smart cities. It designed the main five building blocks of the envisioned system, as well as highlighted the main technologies to be considered in each building block. Finally, the motivation for the interaction between the components of our system was highlighted, as well as how these interactions will happen.

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Author Contributaion

Rashmi Singha: conceptualisation of the study, methodology development, writing of the original draft, data analysis, implementation of load balancing algorithms, and published version of manuscript review.

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Data Availability

The data used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper. These sections should be tailored to reflect the specific details and contributions if necessary.

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