Sensors on IoT Systems for Urban Disaster Management

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The occurrence of disasters has the potential to impede the progress of sustainable urban development. For instance, it has the potential to result in significant human casualties and substantial economic repercussions. Sustainable cities, as outlined in the United Nations Sustainable Development Goal 12, prioritize the objective of disaster risk reduction. According to the Gesi Smarter 2030, the Internet of Things (IoT) assumes a pivotal role in the context of smart cities, particularly in domains including smart grids, smart waste management, and smart transportation. IoT has emerged as a crucial facilitator for the management of disasters, contributing to the development of cities that are both resilient and sustainable.

sensors Internet of Things urban disaster management flood earthquake landslide

1. Introduction

Cities serve as the primary hubs for economic activities, social interactions, cultural expressions, and overall human existence [1]. It is anticipated that by the year 2050, approximately 86% of affluent nations will have undergone urbanization, while around 64% of developing nations will have experienced the same phenomenon [2][3]. At present, the global urban population stands at approximately 4.27 billion individuals, constituting approximately 55% of the total global population [1][4]. It is anticipated that almost 70% of the global population will undergo urbanization and relocate to urban areas by the year 2050 [4]. This significant shift will probably result in a corresponding expansion of the world's metropolitan regions, encompassing an estimated additional land area of 1.2 million square kilometers [4].

Cities often have larger population densities, making them more vulnerable to many sorts of disasters. As a result, cities have major impacts as a result of these disasters [5]. Disasters possess the capacity to cause harm to human lives and give rise to unfavorable economic and environmental outcomes [6][7]. From 2001 to 2020, there was an annual occurrence of big and medium-sized disasters ranging from 350 to 500 [8]. Furthermore, it is important to acknowledge that a greater population density results in a heightened demand for rescue services, therefore requiring more sophisticated strategies for catastrophe management and the deployment of disaster relief efforts [9]. The lack of effective communication between public rescue and safety groups, rescue teams, first responders, and persons who are trapped worsens the situation [10]. Furthermore, it is important to acknowledge that disasters possess the capacity to inflict substantial harm against essential infrastructure systems, encompassing, but not limited to, electrical grids, water distribution networks, transportation networks, and communication systems [5]. Disasters have the capacity to disrupt economic activities and yield significant economic losses. Between the years

2008 and 2018, an extensive examination indicates that a cumulative count of 3751 occurrences of natural catastrophes took place, including a diverse range of phenomena, including earthquakes, floods, and tsunamis. The occurrence of these catastrophic catastrophes led to a significant economic downturn, resulting in a total financial loss of $1.658 billion [9]. Urban disasters have the potential to yield substantial environmental ramifications, encompassing the release of pollutants and the handling of waste disposal. In light of the considerable repercussions that catastrophes have on urban environments, leading to enormous losses, it is crucial to improve the management of urban disasters. The achievement of the United Nations Sustainable Development Goal (UNSDG) 12 entails the need to diminish the probability of catastrophic events and enhance the overall resilience of urban regions to withstand and recuperate from such occurrences by the year 2030 [11].

The concept of disaster management entails the systematic coordination and administration of various endeavors during all phases of a disaster, including but not limited to mitigation, relief, response, and recovery [9]. The primary objectives of disaster management encompass the initiation of timely alerts, the acquisition of real-time data, the precise assessment of damages, the prompt identification of evacuation pathways, and the efficient administration of emergency provisions [9]. The conventional methods of disaster management are becoming outdated due to their inability to effectively gather data from various sources in real-time and process and evaluate vast quantities of catastrophe-related information in real-time [9].

IoT enables the collection and analysis of real-time data, presenting opportunities for addressing catastrophe management in urban areas [11][12]. IoT can be described as a framework that facilitates inter-device communication via the Internet [9]. The promise of technology to facilitate complex decision support systems is evident through its ability to deliver services in a more accurate, organized, and intelligent manner [12]. IoT has significantly enhanced the capacity for analyzing catastrophe risks, namely in the areas of floods and earthquakes. This advancement has facilitated the development of more effective disaster response plans and risk management policies [11]. Numerous instances exist wherein the IoT is employed for the purpose of regular surveillance of natural occurrences, transmission of alert alerts, and provision of timely information to disaster management authorities [11].

The architecture of IoT primarily has three layers, namely the perception layer (sometimes referred to as the sensor layer), the network layer, and the application layer [13]. In the realm of IoT devices, sensors play a pivotal role in the collection and aggregation of data [14]. Sensors have the capability to be deployed in diverse environments, including riverbeds and soil. The sensors have the capability to gather and transmit data in real-time on a continuous and automated basis. Sensors are vital link between the physical and digital realms, assuming a pivotal function within the IoT framework. Subsequently, the data would be conveyed to the application layers for the purpose of data analysis and support applications, utilizing diverse communication technologies and protocols. Then, the data would be transmitted to application layers for data analysis and handle applications through various communication technologies and protocols, facilitated by gateways in the network layer [13].

2. IoT Systems in the Pre-Disaster Stage

2.1. Sensors

Sensors used in the pre-disaster stage mainly collect environmental data. Accelerometers are usually used to detect earthquakes [15][16]. Except for accelerometers, more sensors are used to detect landslides, such as inertial sensors, bar extensometers, and borehole inclinometers. More publications focus on flood monitoring. Floods may occur more frequently in cities. One reason is that urban drainage systems often become saturated due to prolonged and intense rainfall [17]. Regarding flood monitoring systems, scholars use more sensors, such as rain gauges [17][18], water level sensors [17][19][20][21][22][23][24], water pressure sensors [18][22][24], cameras [18][25][26], soil moisture sensors [19], weather sensors [19], drones with drones [19], water presence sensors [21][27], temperature sensors [27], and a triaxial accelerometer [27]. The sensors are usually powered by solar batteries [18][27].

2.1.1. Earthquake

We commonly use accelerometers to detect earthquakes. Accelerometers include triaxial accelerometers and dual-axis accelerometers. Regarding triaxial accelerometers, it can choose the accelerometer ADXL362 [16] for low-power use, while it can choose the accelerometer EPSON M−A351AU [16] and the accelerometer LSM9DSO [28] for high-precision use. Regarding dual-axis accelerometers, it can choose the accelerometer ADXL203, which is low-power and high-precision [29]. Also, it can choose triaxial accelerometers, such as L1S3DSH sensors (manufactured by STMicroelectronics) and EpiSensors [30]. The L1S3DSH sensor is ultra-low-power and high-performance [30]. The accelerometers are placed on the object being detected (e.g., buildings or bridges). The single computer boards include Raspberry [15], CC2420 DBK [29], and Sparrow v4 [28]. The microprocessors include the ATmega128L [29], ATmega128RFA1 [28], and ARM processor [30]. Sensors should be equipped with antennas to enable data transmission over long distances [16]. The sensors should be energy-saving [16]. Regarding batteries, it choose d-cell batteries [16] and CR2032-3V lithium-ion batteries [28]. The sensors should sleep when they do not need to collect data [16].

2.1.2. Landslides

People detect landslides with more sensors, such as inertial sensors [31], accelerometers [31], bar extensometers [32][33], borehole inclinometers [32], rainfall sensors (e.g., rain gauge [34]), and displacement meters [34]. The models of inertial sensors include the IMU6050 [31]. The models of accelerometers include LIS3331LDH [31]. The models of microprocessors include the ESP32 [31][35]. The models of single computer boards include the Waspmote PRO board [31]. Usually, the sensors can store data locally on SD cards [31]. Batteries [31][32][33] and solar [32] are the major power sources.

2.1.3. Floods

People develop flood detection systems based on more considerations such as rainfall [17][18][19][36][37][38][39], water level [17][20][21][23][24][37][38][40][41][42][43], water pressure [18][21][22][24][27][44], soil moisture [19], solar radiation [19], vapor pressure [19], relative humidity [19], humidity [19], temperature [19][36][37][45], air pressure [19][37], wind speed [19][36], wind gust [19], wind direction [19], tilt [19], lighting [19], lighting average distance [19], the flow velocity [19][37]. Moreover, Ragnoli et al. [27] also used GSM to detect locations in their flood monitoring systems.

We usually collect rainfall data using rain gauges [17][18], such as double-tipping buckets [17]. Scholars usually measure water level with water level sensors, such as radar level sensors [17][40], ultrasonic sensors [19][24][40][43][45], and force-sensitive resistors [24]. Ultrasonic sensors include MaxBotix MB7066 [45], HC-SR04 [43], and so on. A method to measure water level is to measure water pressure and convert that data into water level [22][39][44].

Cameras are also effective tools for flood detection [18][25][26][38][44][46][47][48]. Regarding the use of cameras, Castro et al. [47] suggested using no infrared cameras, while Castro et al. [47] and Garcia et al. [25] suggested using cameras with water level markers. Regarding water level markers, Castro et al. [47] suggested placing highly visible reflective tapes on surfaces visible to cameras ranging from 0 to 1.5 m. Each tape was spaced out with other tapes, which allowed us to obtain a better approximation of the severity of the water level. This method could improve accuracy because it was not affected by the temperature and humidity of the air or the objects that could absorb wave sounds.

2.1.4. Others

Park and Baek [49] introduced the detection of heatwaves and cold waves. Alhamidi et al. [50] presented an IoT-based tsunami monitoring system. Aljohani and Alenazi [51] introduced a storm detection system. Scholars can use meteorological sensors to detect heatwaves and cold waves by monitoring parameters such as temperature, relative humidity, noise, illumination, ultraviolet, vibration, PM10, PM2.5, wind speed, wind direction, CO, NO_2, SO_2, NH_3, H_2S, and O_3 [49]. Alhamidi, Pakpahan, Simanjuntak and Iop [50] used the ADXL335 accelerometer to read vibrations in the seafloor crust because tsunamis are caused by vibrations and faults in the seafloor crust. They also connected sensors to flare-marking buoys to provide information to the nearest disaster mitigation center. They used the Arduino Uno as a single computer board.

2.2. Communication Technologies and Protocols

People usually transmit the data from sensors to servers through Bluetooth [15], Ethernet [15][19][20], Wi-Fi [15][20][31][32][35][43][47], and cellular communication technology [19][33][35][46][52], Radio Frequency [19], and radio [21]. Cellular communication technologies include GSM [33], GPRS [33][46], and 3G [19]. The communication protocols include Choco protocol [16], UDP [18], IPv6 with LoWPAN [18], IEEE 802.15.4 [18][28][29], Message Queuing Telemetry Transport (MQTT) [19][20][24][35][42][53], concurrent multi-path transfer protocol [26][54], LoRaWAN [27][37][52], TCP/IP Internet protocol [27][55], Hyper Text Transfer Protocol (HTTP) [36], Zigbee [22][28][46], LRWiFi [35], Cat-M1 [35], CoAP [35], XBee [45]. The data is usually transmitted in JSON format [19][27][36]. Regarding data storage, people may use local data storage (e.g., SD memory cards [31]) and cloud storage (e.g., MongoDB [25], Dynamo [20]). Miao and Yuan [34] used the SQL Server 2008 database software.

The connection solutions for earthquakes include Bluetooth [15], Ethernet [15], Wi-Fi [15], Choco protocol [16], IEEE 802.15.4 [28][29], MQTT [53], and Zigbee [28]. Regarding the connectivity solutions for landslides, people can use Wi-

Fi [31][32], cellular communication technology [33][35], MQTT [35], LRWiFi [35], Cat-M1 [35], and CoAP [35]. The connection solutions for floods include UDP [18], IPv6 with LoWPAN [18], IEEE 802.15.4 [18], MQTT [19][20], Ethernet [19][20], cellular communication technology [19][46][52], Wi-Fi [20][43][47], concurrent multi-path transfer protocol [26], LoRaWAN [27][37][52], TCP/IP [27][55], radio [21], HTTP [36], ZigBee [22][46], 6LoWPAN [56], and XBee [19][45]. Concurrent transfer can achieve higher throughput [26][54], accelerate transmission [26][54], reduce packet loss [26][54], and save energy [16]. Choco protocol [16] and 6LoWPAN [56] can save energy. In addition, Luo et al. [57] proposed the “MWAC model” for sensor networks to save power and transmit information over long distances (p. 49).

2.3. Analysis and Applications of Sensor Data

Since sensors have limited resources, another way to improve the efficiency of data analysis is to combine fog computing and cloud computing [18][58]. To be specific, sensors send the data to the fog periodically [58]. After the fog pre-processes the data, it will be transmitted to the cloud [58]. Therefore, fog computing is mainly responsible for concentrating, distributing, caching, and analyzing the data, detecting abnormalities, analyzing the data on a smaller scale, sending notifications and feedback, and forwarding summarized data to the cloud periodically [18][58]. Fog computing can reduce the latency of the service, respond to any emergency change immediately, and reduce the burden on the cloud [18][58]. Cloud computing is responsible for combining and permanently storing all the data in the system to obtain a general view of the monitored environment [18][58].

Machine learning techniques are commonly used to analyze the data from sensors. Scholars can use machine learning techniques to analyze the data related to different types of disasters, such as earthquakes [15] and floods [22][37][45][58][59][60]. The machine learning techniques used in earthquake detection include convolutional neural networks [15] and recurrent neural networks [15]. They can analyze the data collected by accelerometers. The machine learning techniques used in flood detection include Bayesian Learning [22], Multi-Layer Perceptron Artificial Neural Networks [22], Random Forest [22], J 48 Decision Tree [22], Random Tree [22], Simple Cart Decision Tree [22], and BFTree [22]. They can classify and analyze the water level data. Regarding data classification, it can classify the water level data into stable level (i.e., −20°, 20°), slight increase level (i.e., 20°, 45°), high increase level (i.e., 45°, 90°), slight decrease level (i.e., (−20°, −45°) and high decrease level (i.e., −45°, −90°) [22].

3. IoT Systems in the Post-Disaster Stage

3.1. Sensors

Excepted for environmental data [61][62][63][64][65], the sensors in the post-disaster stage mainly collect human health data [62][64][65][66] and position data [15][61][65][66][67], which can improve the efficiency of search and rescue.

Regarding environmental data, Ochoa and Santos [61] suggested using sensors to collect environmental data in terms of weather, chemicals, and movement. Sahil and Sood [62] placed sensors on the buildings and in-pavements in the disaster-affected areas to collect environmental data, including water level, tilt in structures, temperature of buildings and ambient, smoke detection, obstacles in the path, visibility range, and location of the sensor. Korkalainen et al. [65] suggested using gas sensors to monitor air quality. Usually, multiple agencies participate in rescue operations. Each agency could use the sensors deployed in cities (e.g., weather stations, traffic cameras, wind sensors, precipitation meters, road surface condition sensors, and visibility meters) to collect environmental data [63][64].

The human health data, including the rescuers' health data and the stranded people's health data, Boukerche et al. [66] suggested that command posts should guarantee the safety of first responders through the body-worn sensors in wearable smart devices, such as smart glasses and smart watches. Sahil and Sood [62] developed an IoT system to prioritize the evacuation of panicked, stranded people and provide them with timely medical support. They used the health sensors in stranded people's personal mobile communication devices to collect health data, including heart rate, breath rate, dizziness, sweating, chest pain, trembling, chills, choking, nausea, and the location of the individuals.

3.2. Communication Technologies and Protocols

Normal communication technologies and protocols are also suitable for communication in the post-disaster stage, such as Wi-Fi [15][52][65][68], Bluetooth [68], Internet [68], MQTT [24][52][64][69], LoRa/LoraWAN [64], WPAN [65], 3G/4G [52], and COAP [69]. However, disasters may destroy the infrastructure in the cities [66].

To maintain communication efficiency in the face of a reduced number of communication facilities, scholars should develop resilient communication networks and reduce contention during data communication. Alvarez et al. [70] suggested using the Bluetooth Mesh emergency network to utilize the remaining sensors to mediate device-to-device communication in the post-disaster stage. Regarding energy-constrained IoT sensors, Ai-Turjman [71] suggested using the Cognitive Energy-Efficient Algorithm (CEEA). The CEEA was a topology-independent protocol that can handle randomness in IoT networks. The CEEA determined the path from routing nodes to sensors based on the remaining energy of each node. To be specific, the CEEA would control the remaining energy of neighbors of recent routing nodes each time before sending data from the recent routing nodes. If the energy of one of the neighboring routing nodes was less than half of its initial value, the CEEA might determine a new path to transmit the data. If the residual energy of all neighboring routing nodes are found to be below 50% of the beginning energy, the CEEA uses the same strategy.

3.3. Analysis and Applications of Sensor Data

People focus on analyzing position data and health data in order to plan evacuation routes [15][62], allocate ambulance vehicles [67], understand the health of trapped individuals [62], and integrate information for rescuers [63][64]. For example, Ehsani et al. [68] can detect COVID-19 cases in a disaster by analyzing people's temperatures with machine learning techniques. Regarding locating people in disasters, Kristalina et al. [72] used the least squares method to improve the generalized geometric triangulation scheme, which allows sensors to track the position of rescuers or victims.

In addition, the combination of fog computing and cloud computing can improve the efficiency of data analysis [62][63][64]. For example, Suri et al. [63] proposed the Sieve, Process, and Forward (SPF) Fog-as-a-Service platform to address the scenario of post-disaster relief. Fog computing is also helpful in reducing the time of search and rescue since it can improve the efficiency of data analysis through pre-processing some data analysis, such as data categorization and data novelty analysis [62][63]. Cloud computing aims to store the data and process deeper data analysis [62][63][64][68]. The fog layer exists in the gateway (e.g., drones and evacuation vehicles) and serves as a bridge between the sensor layer and cloud layer of the Internet of Things [62][63]. The utilization of the fog layer is attributed to its position awareness and close proximity to the sensors [62]. This enables it to perform essential data pre-processing tasks, such as data categorization, novelty analysis, panic health status classification, and alarm creation [62]. Due to the inherent limitations in computing and storage capacities of the fog layer, the cloud layer was employed to store and analyze environmental and health data, as well as the corresponding panic health status data [62]. This facilitated the generation of alerts in the form of compiled medical records [62]. The Cloud layer includes temporal data mining, cloud storage, panic health sensitivity monitoring, evacuation strategy, and evacuation map building [62].

4. Comparison between the IoT Applied in Pre-Disaster and Post-Disaster Stages

We usually use sensors to collect environmental data in the pre-disaster stage. However, scholars should use sensors to collect health data and position data more in the post-disaster stage. The scholars can transmit the data with a number of communication technologies and protocols in the pre-disaster stage. However, disasters may destroy communication infrastructures. Thus, it is important to maintain the efficiency of existing communication infrastructure and use additional mobile communication tools in the post-disaster stage. Machine learning techniques are common data analysis methods both in the pre-disaster stage and the post-disaster stage. With the development of image processing algorithms, scholars used cameras as sensors more. Fog-cloud computing is useful to improve the efficiency of data analysis both in the pre-disaster and post-disaster stages. The data applications aim to provide environmental information and send warnings in the pre-disaster stage. However, they focus more on route planning in the post-disaster stage.

Environmental data should be collected both in the pre-disaster and post-disaster stages since we need to use environmental data to detect disasters in the pre-disaster stage and ensure the safety of the environment in the post-disaster stage. For example, Rahman et al. [24] may use water level data to control the valves to prevent sewerage system overflow and mitigate floods. Since position data is also useful in the post-disaster stage, people can check environmental data and position data in Lwin et al. [73]'s application in the pre-disaster and post-disaster stages. Furthermore, Kim et al. [15] and Konomi et al. [74] provide evacuation route planning in the applications.

5. Conclusions

Disasters have the potential to inflict harm upon human lives and result in significant economic and environmental repercussions, particularly in densely populated urban areas [6][7]. Given the substantial magnitude of losses incurred by urban disasters, it is imperative to enhance the efficacy of urban disaster management. Furthermore, the implementation of effective disaster management strategies is of utmost importance for urban areas to successfully attain the UNSDGs [75]. Sensors play a crucial role in the acquisition of data within IoT devices. They serve as a connection between the physical and digital realms, playing a vital function within the IoT framework. IoT has the potential to offer real-time monitoring, early warning systems, post-disaster response, and rescue support, thereby playing a significant role in the field of urban catastrophe management.

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