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CrowdBIG: Crowd-Based System for Information Gathering from the Earthquake Environment

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Abstract

Natural disasters have always threatened the lives of humans and other creatures. One of the significant challenges for quickly responding to an earthquake is the need for precise and comprehensive information. Given that part of the environmental infrastructure is destroyed, quickly acquiring the required information is a serious challenge. Due to the ubiquity of smartphones, which have sensing, processing, and communication capabilities, this paper proposes CrowdBIG, a crowdsourcing-based architecture for information acquisition from the disaster environment. CrowdBIG architecture consists of four layers: sensing, fog, cloud, and application. Given that the reliability of crowdsourcing systems is dependent on the quality of user data, detecting malicious users as well as scoring and selecting useful users are of great importance. The CrowdBIG system is equipped with a reputation management component, which contains two sub-components: malicious user detection and user scoring. To evaluate the CrowdBIG system, first, we validate the information acquisition and dissemination workflow of the system using a scenario-based method. We then simulate the disaster environment through several well-known scenarios. The results show that CrowdBIG can detect malicious users appropriately. The CrowdBIG system can also score non-malicious users reasonably based on their usefulness and information completeness rates. The simulation results reveal that the reliability of the CrowdBIG system is 92%. Finally, the usability evaluation survey shows that more than 80% of the participants rated the usability of the proposed information-gathering tool as good or excellent.

Keywords Disaster management, Earthquake, Mobile crowdsourcing/crowdsensing, Information gathering, Reputation management, Malicious user detection

1. Introduction

Every year, natural disasters such as earthquakes, floods, hurricanes, volcanic eruptions, and tsunamis occur in different parts of the world. These tragic disasters can cause irreparable damage and loss of lives. These events may also affect the lives of people in the neighborhood of the disaster environment (Mirbabaie et al., 2016; Wang and Ye, 2018). After such catastrophic disasters, crisis management organizations or volunteer teams rush to the aid of the victims (Maryam et al. 2016).

Disaster management consists of four phases: prevention, preparation, response, and recovery (Haworth and Bruce, 2015). In disaster management, especially in the response phase, rescue and relief teams should quickly plan and take appropriate decisions and actions. For good crisis management and appropriate decision-making, disaster management organizations require accurate environmental information (Hafil et al., 2017; Heinzelman and Waters, 2010; Kucuk et al., 2020). Gathering accurate information from the disaster environment is one of the most important challenges in disaster management because significant parts of the data collection infrastructure are destroyed during the disaster. In fact, carrying out rescue operations right after an earthquake requires diverse up-to-date and real environmental information, much of which cannot be obtained from our previous knowledge of the area. For example, urban routes such as streets and alleys change due to debris falls. Also, other required information, such as the location of the injured, must be obtained (Sinha et al., 2019).

Today, mobile phones with various sensors, such as cameras and GPS, are smart computing devices (Hu et al., 2013). Smartphones allow users to produce useful information in addition to exploiting information (Poblet et al., 2018). Due to the ubiquity of smartphones among people, leveraging mobile crowdsensing/crowdsourcing techniques can play an important role in the timely collection of information from the disaster environment (Hu et al., 2013; Vahdat-Nejad et al., 2019). In mobile crowdsourcing, the required information is extracted from the environment with the participation of people (Hu et al., 2013). The extracted information can be aggregated and stored on a cloud server (Vahdat-Nejad and Asef, 2018). Related organizations use this information to make decisions and perform actions according to the latest conditions of the disaster environment (Xu et al., 2018).

Previously, crowdsourcing has been limitedly used for disaster management. For example, Albuquerque et al. (De Albuquerque et al., 2015) proposed a system to collect disaster information by analyzing user comments on Twitter and Facebook (Dong et al., 2021; Kabir et al., 2020). Besides, the relief request system was presented based on sending an image by the users located in the disaster environment (Radianti et al. 2014). The main limitation of the previous research is that it is impossible to comprehensively gather the information requirements from comments published and images taken by people. To respond better, organizations urgently need comprehensive, up-to-date, and reliable information regarding the disaster area. Accordingly, this paper addresses the following research gaps:

1) Designing a system via crowdsourcing for gathering comprehensive information from the disaster area.
2) Providing reliable information by being able to detect malicious users.

In this paper, we adopt the essential information needed from an earthquake disaster environment from our initial paper (Vahdat-Nejad et al., 2021). Then we propose CrowdBIG (Crowd-Based Information Gathering) system, which leverages mobile crowdsourcing for information acquisition from the earthquake environment. The proposed system has four layers, including sensing, fog, cloud, and application. As the most important challenge of crowdsourcing systems is the detection of malicious users (Bhattacharjee et al. 2017; Mrazovic and Matskin 2015), CrowdBIG is equipped with a reputation management component, which includes two sub-components: malicious user detection and user scoring. The reputation management component uses dynamic parameters to identify malicious users and rank non-malicious participants. We use three simulation scenarios to assess the malicious user detection and scoring mechanisms. The evaluation results validate that the proposed system can appropriately detect malicious users and score non-malicious users. We also used a fourth simulation scenario to demonstrate the reliability of the CrowdBIG system. Finally, a usability survey reveals a satisfying usability degree of our proposed information gathering tool.

The rest of the paper is organized as follows: Section 2 introduces the proposed information requirements categories regarding an earthquake area. Section 3 reviews the research background and related work. Section 4 describes the proposed CrowdBIG system, and section 5 describes the reputation management mechanism. Section 6 includes simulation and evaluation, and finally, the conclusion is provided in section 7.

2. Information requirements

Different kinds of information elements are necessary for a better response to earthquake disasters (Hafil et al., 2017). Hence, examining and categorizing the information needs of the earthquake disaster is of great importance. In this

paper, we adopt the classification of the required information elements from our previous work (Vahdat-Nejad et al., 2021), as illustrated in Fig. 1. Four categories of disaster information are required in an information acquisition system, as follows:

- **Victim**: The first category includes information about corpses, survivors, the injured, and the missing, as well as domestic and wildlife animals that need help. These people and creatures are referred to as victims. The information includes the type, number, and physical condition of the victims. Rescue organizations can leverage this information to dispatch and organize their forces more effectively.
- **Facility and livelihood**: This category includes information required for basic facilities such as water, electricity, and gas as well as information related to the necessary livelihood assistance such as tent, food, and drinkable water. This category is one of the most essential information and should be prioritized (Ozisik and Kerle 2004).
- **Security and health**: This category includes information regarding health and security. Health information includes the medications required by patients, medical equipment required by physicians, access to medical centers, doctors, and ambulances, and the prevalence of diseases. Security information includes gas leaks, fires, the safety of the individuals' properties, as well as the safety status of the region in terms of theft, extortion, food poisoning, contamination, and waste disposal.
- **Map and Access**: After an earthquake, the environmental conditions are physically changed, and some regions may not be accessible. For example, bridges and passages may be destroyed, and cracks may be created in the ground. Therefore, previous maps of the disaster environment are no longer valid. In this case, preparing a new map of the disaster environment according to the new situation is vital. Hence, this category includes information related to the situation of the streets, passages, as well as severely damaged places. This information is needed for generating new maps.

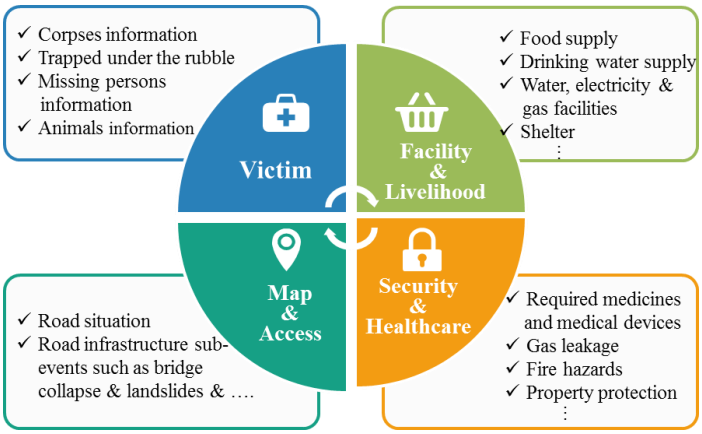

Fig. 1 Categories of the required information

3. Related work

The most essential step in disaster management is to gather accurate, comprehensive, up-to-date, and reliable information in the shortest possible time. Reviewing the research literature generally reveals three approaches for gathering disaster information: social networks, crowdsourcing, and collaborative mapping activities. Sometimes, a combination of these three approaches has been introduced (Santos Rocha et al., 2016).

Previously, the idea of using social networks to gather information from the disaster environment has been presented. This approach has been the subject of many studies. In the social networks approach to information acquisition, users' tweets have been used to identify locations that need emergency assistance (Phengsuwan et al., 2021; Wang and Ye, 2018). Besides, to detect the occurrence of a new disaster, tweets are used based on keywords, the number of words, and their context (Sakaki et al. 2012). Twitter has also been used to trigger tsunami warnings (Carley et al., 2016). Furthermore, a social network platform has been proposed (Middleton et al. 2013) in which geographic information collected from the disaster is matched with tweets to create a map of the disaster environment. Similarly, a mapping system for flooded regions has been presented in which the updated maps are generated using social network data (Ogie et al., 2019). In order to quickly identify the affected areas, social network comments have been used to create a damage map (Ahadzadeh and Malek, 2021). Finally, a hybrid paradigm has been proposed to combine Twitter data with crowdsensing information in an earthquake emergency scenario (Avvenuti et al., 2017). However, the use of social networks as rich sources of information is challenging (Ravi Shankar et al., 2019). In fact, this approach is not an ultimate solution for gathering comprehensive information and has significant accuracy and

reliability issues. It leaves users free to comment, often receiving useless and irrelevant information. The lack of access to the users' accurate geographical location is another limitation of the social networks approach.

In the context of the crowdsourcing information-gathering approach, an IoT framework for disaster management has been presented that applies a crowdsensing clustering algorithm to collect up-to-date information on the status of damage to buildings (Kucuk et al., 2020). To assess the extent of earthquake damage, they gathered images to identify, classify and prioritize the affected regions (Barrington et al., 2011). There is also a smartphone-based platform that includes two components, one for the general public and the other for the authorities. On this platform, users can take photos or videos of the accident and send their data to nearby users and rescue teams (Hafil et al., 2017). In addition, a crowdsourcing-based platform has been presented (Ravi Shankar et al., 2019) that tries to accurately estimate the location of photos and videos on social networks by combining information obtained from social networks and crowdsensing. To monitor the level of damage to buildings, a crowdsensing system has been provided in which, after an earthquake, users participate by uploading photos of buildings into the database (Zhao et al., 2019). To detect road safety issues by high amounts and various types of traffic data, including images, videos, and annotations, a mobile crowdsensing architecture has been proposed (Benbrahim and Benhaddou 2021). To acquire information about the buildings damages for accurately dispatching rescue teams, a post-disaster framework has been presented (Kucuk et al., 2020).

The collaborative mapping activities approach has been used to collect specific information and display it as special maps. In collaborative mapping activities, people work together on a map and update the streets, roads, buildings, and routes in affected regions. These updated maps are finally shared with the relevant organizations. OpenStreetMap and Wikimapia are the most important projects in this field (Santos Rocha et al., 2016). In some cases, collaborative mapping has been able to address specific needs in data collection. However, due to the lack of comprehensive information, using this approach in a sensitive field such as disaster management does not completely yield the needed results.

According to the openness of crowdsourcing systems (Mrazovic and Matskin 2015), information collected from the disaster environment might be obtained by regular people; hence collected information is error-prone (Mirbabaie et al. 2016). Therefore, user reputation management is one of the most important challenges of the system. To address this issue in general domains (other than disaster areas), several research studies have been performed. For example,

a scoring model based on user experiences and personal characteristics has been proposed (Kaleem et al., 2015). A recruitment model based on the genetic algorithm was also presented that tries to choose the most suitable people in the system by examining the three parameters of area of interest, device features, and user information (Azzam et al. 2016). Also, a reputation management model has been presented that scores users based on completed tasks and evaluators' credibility to select appropriate users for crowdsourcing operations (Allahbakhsh et al. 2012). There also exists a community-aware crowdsourcing approach that uses users' reputations to select the most appropriate contributors and reward the users according to these contributions (Ren et al., 2015).

Each of the above approaches has made great efforts to improve the collection of information from the disaster environment. Amongst them, crowdsourcing revolutionized information gathering from the disaster environment. In our previous work (Vahdat-Nejad et al., 2021), we stated the importance of using mobile crowdsensing to collect information from the earthquake environment. According to the significant changes in environmental conditions after disasters, we need comprehensive, up-to-date, and reliable information in order to respond to the disaster in the shortest possible time. However, most related crowdsourcing studies have used only images and videos. Comprehensively understanding disaster information from photos and videos is often difficult and impossible. To solve this issue, we categorize the required information into four categories. We extend our previous work and propose a crowdsourcing system that comprehensively gathers all the required information. To ensure reliability, we propose a reputation management component to detect malicious users and eliminate outlier data received from them. In summary, the proposed system is able to collect comprehensive, up-to-date, and reliable information.

4. Proposed architecture

The proposed Crowd-Based Information Gathering (CrowdBIG) system is designed using the multi-layer architecture, as illustrated in Fig. 2. The proposed architecture includes four layers: Sensing, fog, cloud, and application. Each layer contains one or more components that provide a specific service. In continue, these layers are elaborated.

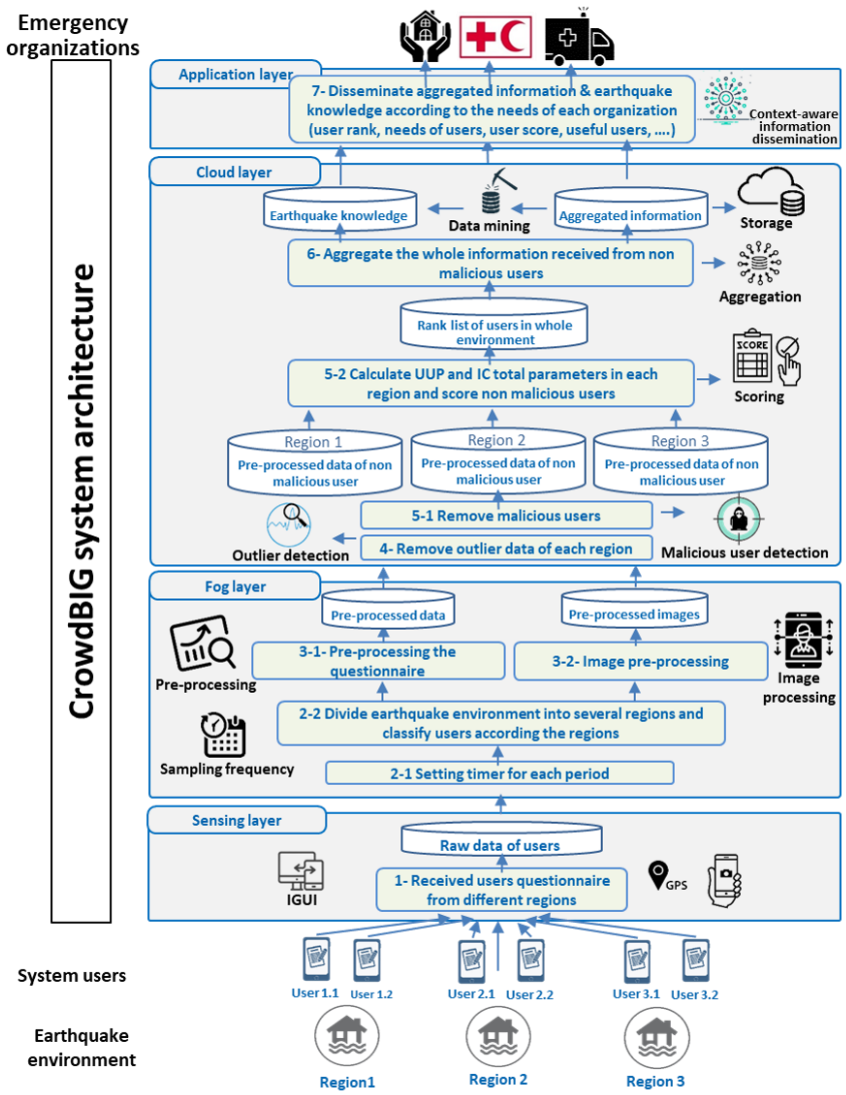

Fig. 2 The proposed architecture of CrowdBIG

4.1 Sensing layer

This layer is responsible for collecting different types of information required from the disaster environment. The sensing layer includes the information gathering user interface (IGUI), GPS, and camera.

4.1.1 Information gathering user interface

The Information gathering user interface (IGUI) is the main part of the sensing layer. IGUI implements a comprehensive questionnaire with twenty pre-determined four-choice queries. This questionnaire addresses the four categories of the required information (Section 2) that cannot be directly measured by the sensors. People participate in information gathering by answering the four-choice questions and choosing one of the four options, including

excellent, good, attention-required, and critical. Received answers are then stored and sent to the higher layer to be used for local analysis purposes. At the end of the questionnaire, a section is provided to receive unstructured information (including comments and images) from participants. Users can easily send the information by selecting the relevant category. These comments can be processed by experts, and the implicit information is manually extracted. Collected comments and four-choice responses can be a rich source for the data mining component.

4.1.2 GPS

In crowdsourcing and disaster management, it is essential to determine the exact location of received images and other collected information. Hence, CrowdBIG uses the GPS of the user's smartphone to record the location tag. Geotagged Information can be used to update the disaster environment maps.

4.1.3 Camera

Images usually contain much information and can be used to recognize disaster events and extract high-level information. The camera of a mobile phone is an important sensor in collecting information from the disaster environment. Disaster response organizations can manually review images and extract the required information. Furthermore, image processing can be used to extract essential information from the disaster environment. However, it is a case-specific process and is out of the scope of this paper.

4.2 Fog layer

This layer refers to the processing hardware near the sensing layer (such as a mobile phone or local gateway). The information collected from IGUI and sensors is provided to this layer. The fog layer consists of sampling frequency management and local analysis.

4.2.1 Sampling frequency management

The information obtained from IGUI and sensors is not static. Such collected information dynamically changes according to spatial and temporal changes. To keep our collected information up-to-date, we need the disaster environment to be sampled regularly. The sampling frequency can be adjusted in two ways: event-based and periodic. In the event-based method, the sampling frequency is adjusted according to the movement of users in the area or the occurrence of new events such as aftershocks. For example, after the user's movement to a new location (e.g., moving

by 500 meters), the system requests them to re-answer the questionnaire. In the periodic sampling method, sampling is performed periodically, and its time interval is adjusted according to the system requirements (e.g., every hour).

4.2.2 Local analysis

The local analysis component is responsible for preprocessing the measured information. This component includes two sub-components: information preprocessing and image processing. The information preprocessing component locally analyzes the answers and comments received from the user. Given that the questionnaire consists of four-choice questions, the four-point Likert scale (1 to 4) (Van Veldhuisen et al. 2017) is used to analyze the received answers locally. Besides, comments are reviewed, and their keywords are extracted using the bag of words model. Hence, the subject of the text is identified and can be sent to the relevant organizations for further processing. Besides, to make it easier to analyze user comments, users are asked to use predefined hashtags (#) depending on the type of their submitted information. Photos submitted by users are processed by the image-processing component. The sharpness or blurriness of a photo is checked. Afterward, the selected photos are sent to other software components to extract useful information. Delegating local processing to the users' smartphones causes a huge amount of processing to be done in a distributed manner. It greatly reduces the overall load of the cloud layer.

4.3 Cloud layer

The information locally analyzed in the fog layer is sent to the cloud layer for aggregation, storage, and final processing. The Cloud layer includes five components: outlier detection, reputation management, aggregation, storage, and data mining.

4.3.1 Outlier detection

Outlier data refers to the unusual data that can have unintended effects on data analysis and may lead to unreal results (Zijlstra et al. 2007). Therefore, identifying and dealing with outlier data is of great importance. In CrowdBIG, most information is gathered through the questionnaire. Hence, the user chooses an option among four available options. The user's response for each question is compared with the mean response of other users for the same question to detect outliers. If the user response significantly differs from the aggregated response, the response will be labeled as outlier data. To detect outliers, we use the non-parametric Tukey's fences method (Zijlstra et al. 2007). In this method, a fence is created with an Inter Quartile Range (IQR) that is equal to the difference between 25% and 75% of a range

(Eq. 1). If Q_1 is the lower quartile and Q_3 is the upper quartile of the range, any data outside the range will be known as outlier data (Eq. 2).

$$Interquartile\ Range\ (IQR) = Q_3 - Q_1 \tag{1}$$

$$[Q_1 - k(Q_3 - Q_1)\,, Q_3 - k(Q_3 - Q_1)] \tag{2}$$

In this method, a fence is created for each positive and negative range so that the farthest option in the other range is identified as the outlier data for the current range.

4.3.2 Reputation management

One of the most important challenges of a crowdsourcing system is its vulnerability to malicious users who degrade the information quality by providing outlier data. To address this challenge, the reputation management component introduces a mechanism for identifying malicious users and scoring non-malicious users. The first mechanism identifies malicious individuals and filters out their poor-quality data. The latter mechanism scores and ranks non-malicious users. It can be utilized in emergency actions. These two mechanisms are explained in the next section.

4.3.3 Aggregation

The information gathered by the sensors and IGUI should be aggregated to infer our required high-level information from the user participants. Given that crowd wisdom is considered a reliable result in crowdsourcing systems, we use the majority decision method to aggregate data (Quoc Viet Hung et al., 2013; Sato, 2004). In this method, users' different responses to a specific question are checked periodically. The majority of participants' answers are selected as the aggregated answer in a particular period. Note that the output of this step can be presented in terms of an information map, which can be used by disaster management organizations.

4.3.4 Storage

One of the advantages of cloud storage is the ability to access information anywhere, anytime, and by any device. In CrowdBIG, the cloud layer, as a massive storage resource, stores aggregated information.

4.3.5 Data mining

Data mining aims to discover knowledge from massive data. Data mining means extracting hidden information or specific patterns and relationships from a large amount of data. By storing and archiving information gathered from the disaster environment in the storage component, this component gradually becomes a rich source for data mining and knowledge extraction. Data mining is a general concept that is defined by specifying its purpose. Therefore, each organization might perform different techniques toward its target to obtain its required information. In summary, as data mining is an organization-specific method, we cannot further elaborate it in this work.

4.4 Application layer

This layer includes applications and services related to the actions of disaster organizations. The application layer also provides a mechanism for sharing information with other applications that are independent of the proposed system. Hence, the context-aware information dissemination component provides up-to-date information and maps for the relevant authorized organizations according to the information derived from the lower layers.

5. Proposed reputation management mechanism

Crowdsourcing systems are open. Openness increases the risk of erroneous and malicious contributions. Besides, as disaster environment information is gathered by regular people, it is often error-prone. Hence, ensuring the quality of provided data is a major challenge in such heterogeneous systems (Mrazovic and Matskin 2015). To this end, it is essential to recognize the accuracy and reliability of the content produced by users. In CrowdBIG, a reputation management component is proposed that includes two sub-components: malicious user detection and scoring. The reputation management component utilizes the user's previous behavior and introduces dynamic parameters for malicious user detection and scoring. This component enables the proposed system to detect malicious users and rank others based on their reputation score. In the following, the two mechanisms of malicious user detection and scoring are elaborated.

5.1 Malicious user detection

Users must register in the proposed system before logging in. In the registration process, a profile is created for each user. This profile stores information about the registered users, such as user ID, user reputation score, and user rating in the system. The disaster environment is divided into multiple regions, and a questionnaire is provided for registered users. Each user response to a specific question is called a data element.

In the proposed mechanism for detecting malicious users, the main parameter is the ratio of outlier data elements sent by a user in the last four (by default) attempts. If the ratio of outlier data elements sent by the user (Malicious Participation Rate) exceeds the predefined threshold, the user is known as a malicious user. The threshold value is set to 0.4 by default; however, this value can be changed if needed. The number of users' contributions in crowdsourcing systems is often high. Besides, in the proposed system, the majority decision approach is used to aggregate data. Hence, a limited number of malicious user contributions cannot significantly impact the result.

The *Malicious Participation Rate (MPR)* parameter of a user according to the last T user participations is calculated as follows (Eq. 3).

$$MPR_i = \frac{\sum_{t=1}^{T} Outlier\ data\ elements_t}{\sum_{t=1}^{T} Total_t} \qquad Where \quad 1 \leq t \leq T \qquad (3)$$

, where $Outlier\ data\ elements_t$ indicates the number of outlier data elements provided in the tth participation and $Total_t$ shows the total number of data elements provided in that participation.

5.2 Scoring mechanism

The proposed scoring mechanism uses dynamic parameters derived from the user's previous participations in the system. The past behavior of the user is important in calculating the user's reputation. The score of the user's past behavior is calculated periodically using two proposed parameters, including User Useful Participation and Information Completeness.

5.2.1 User useful participation (UUP)

The disaster environment in the crowdsourcing system is divided into several regions, and each user sends data about their local region. Users sending information from the regions with low previous participation are more important to the system. Therefore, the parameter *UUP* is proposed to give more credit to such users. To calculate the *UUP* value, for each user participation, the type of participation is firstly determined to be malicious or non-malicious. When the Outlier Rate of the participation is higher than the threshold (by default, 0.4), the participation is labeled malicious. Otherwise, it is non-malicious. According to the total number of non-malicious participations in each specific region, the *UUP* of each user in that region is computed. To this end, it is determined what percentage of non-malicious participations in that region belongs to the user. Formally, to calculate the *UUP* of user i in region r, the number of

non-malicious contributions of the user i in region r is divided by the total number of non-malicious contributions in region r (Eq. 4).

$$UUP(i,r) = \frac{Number\ of\ Non-malicious\ Participations\ of\ User\ i\ in\ Region\ r}{Total\ Non-malicious\ Participations\ of\ Users\ in\ Region\ r} \quad (4)$$

Afterward, the *UUP* of user i in the whole system is calculated by summing the *UUP* of the user in all regions (Eq. 5):

$$UUP(i) = \sum_{r=1}^{R} UUP(i,r) \qquad R = Number\ of\ regions,\ 1 \leq r \leq R \quad (5)$$

5.2.2 Information completeness

This parameter indicates the degree of completeness of user participation in the current period. In each participation, a user can answer twenty optional questions. Users can skip answering a question when they do not know the answer. They can also send a comment or a picture in the report section. Therefore, the user might provide a maximum of 22 data elements in each participation. The *information completeness rate* for the user is calculated as the ratio of the number of provided data elements to the maximum number of data elements in the current period.

Finally, according to the value obtained for the *User Useful Participation (UUP)* and *Information Completeness (IC)* parameters, the initial Reputation Score for each user is calculated as follows (Eq. 6):

$$Reputation\ Score(i) = \frac{UUP(i) + IC_{Total}(i)}{2} \quad (6)$$

After calculating the initial Reputation Score, the user's new Reputation Score will be updated periodically as follows (Eq. 7):

$$Reputation\ Score(i)_{New} = \frac{Reputation\ Score(i)_{Current} + Reputation\ Score(i)_{Old}}{2} \quad (7)$$

, where $Reputation\ Score(i)_{Old}$ represents the previous value of user *Reputation Score* and $Reputation\ Score(i)_{Current}$ represents the *Reputation Score* calculated in the current period.

6. Evaluation

Use case scenario is an important tool in evaluating software architectures (Vahdat-Nejad and Asef 2018). It can indicate how the proposed architecture can appropriately satisfy the desired functionality. After a terrible earthquake, the people in the disaster environment are invited to help in the information-gathering process by installing the application of CrowdBIG. By responding to questions and taking photos of buildings, roads, and events, users can help the disaster management organization acquire various types of the required information. After preprocessing and aggregating data, various up-to-date environmental information and maps are obtained. Accurate, comprehensive, and up-to-date environmental information enables disaster management organizations to make the best decision in the shortest possible time. Fig. 3 illustrates how the proposed architecture satisfies the requirement of information gathering.

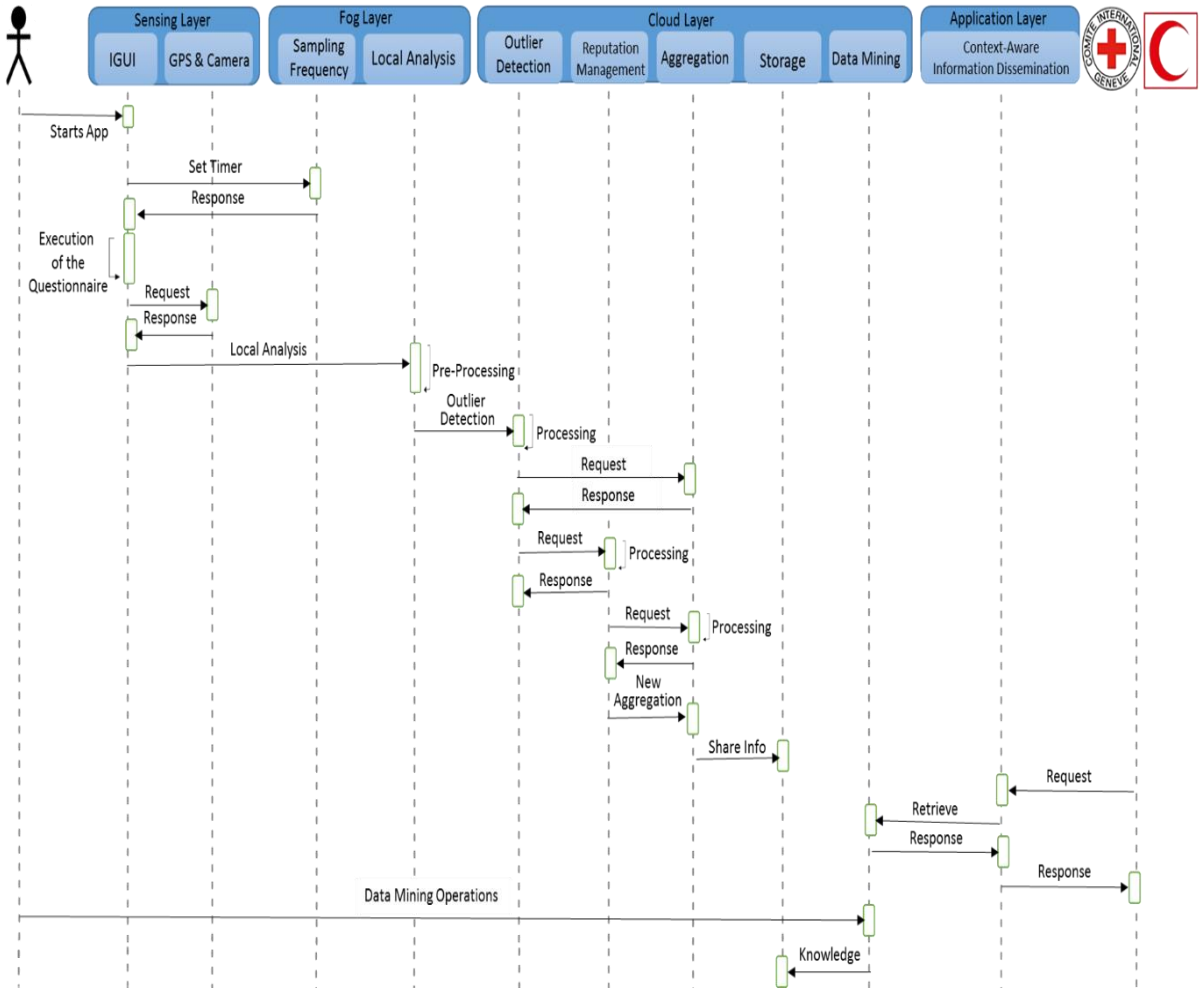

Fig. 3 Sequence diagram of the CrowdBIG architecture

As shown in Fig. 3, the user installs the application and interacts with its interface. Upon the user's request, the period (timer) of information updating is configured. After finishing the questionnaire, the geographical coordinates are labeled. In the next step, the provided data is preprocessed in the local analysis component. Afterward, the data is submitted to the cloud, where various major processes such as outlier detection and aggregation are performed. The reputation management component then removes malicious users and gives scores to other users. The aggregated data is finally stored in the cloud and is used to create comprehensive maps, and is disseminated to the relevant disaster management organizations. A rescue or any legal organization submits its request to the context-aware information dissemination component and can have access to an up-to-date map of the disaster environment. Data mining and knowledge extraction techniques can also be applied to the existing data stored in the cloud.

6.1 Reputation management evaluation

To implement the proposed reputation management mechanism, we need a programming language that can support features like easy-to-write code, easy to troubleshoot, easy to read and understand, and Object-Oriented programming. To this end, we chose the C# language, which has these features. It is worth mentioning that we could also use any other programming language that supports the features above. In the following, two mechanisms of malicious user detection and user scoring are evaluated through scenarios. Then reliability and usability quality attributes are evaluated in the next subsection.

6.1.1 Scenario 1: Selfish users

An important group of malicious users is called selfish users. They respond to questions in a patterned way (Bhattacharjee et al., 2017). Hence, we assume six user types that respond to the questionnaire according to patterns. Table 1 shows the patterns used by each user. It is assumed that each user participates four times. The length of the patterns varies from one to five. The Malicious Participation Rate (MPR) calculated for users indicates that they are all detected as malicious users since their MPR value is greater than the threshold value (0.4). This scenario indicates that the proposed system can identify malicious users who had completed the questionnaire according to a pattern.

Table 1 Scenario 1, Calculation of the MPR parameter for selfish users

Users	User participation		Malicious Participation Rate (MPR)	Type of user	
	Participation number	Exploited pattern		Non-malicious	malicious
User 1	Participation 1	0414	0.43	-	√
	Participation 2	10140			

	Participation 3	40104			
	Participation 4	10014			
User 2	Participation 1	41	0.48	-	√
	Participation 2	1			
	Participation 3	0410			
	Participation 4	4001			
User 3	Participation 1	1114	0.45	-	√
	Participation 2	4110			
	Participation 3	0110			
	Participation 4	1001			
User 4	Participation 1	4004	0.57	-	√
	Participation 2	1004			
	Participation 3	4			
	Participation 4	10411			
User 5	Participation 1	40014	0.53	-	√
	Participation 2	14			
	Participation 3	414			
	Participation 4	001			
User 6	Participation 1	004	0.55	-	√
	Participation 2	14114			
	Participation 3	1401			
	Participation 4	1441			

6.1.2 Scenario 2: Normal distribution users

In this scenario, users are assumed to respond to the questionnaire according to the normal distribution function with the mean of the correct value and various variances (Ren et al., 2015). For this purpose, six user types are simulated whose variances of the normal distribution are 0.25, 0.5, 1, 1.5, 2, and 2.5, respectively. Table 2 shows the *Malicious Participation Rate (MPR)* as well as the Reputation score of these users. As depicted, increasing the variance value leads to the increase in Malicious Participation Rate so that User 5 and User 6, who have a *Malicious Participation Rate* higher than the threshold (0.4), are detected as malicious users. User 4 also has a borderline value that is close to the threshold. Given the low variances of the normal distribution functions for the responses of users 1 to 3, it can be argued that these users have completed fairly accurate answers. Besides, the calculated reputation scores are reasonable as the less the variance, the higher the user's score. In this scenario, the lower variances show that the users are more accurate and reliable.

Table 2 Scenario 2, Calculation of the MPR and score parameters for users

Users	Variance	Malicious Participation Rate (MPR)	Type of user		Reputation score
			Non-malicious	malicious	
User 1	0.25	0.01	√	-	0.99
User 2	0.5	0.04	√	-	0.84
User 3	1	0.22	√	-	0.61
User 4	1.5	0.39	√	-	0.38

User 5	2	0.64	-	√	0.29
User 6	2.5	0.71	-	√	0.18

6.1.3 Scenario 3: Users who participate from less-known regions

In crowdsourcing, users who participate from unknown regions are more important. The purpose of this scenario is to evaluate the scoring mechanism in such situations. It is assumed that the total number of non-malicious participations until the end of the previous period in regions one, two, and three were ten, five, and zero, respectively. In the current period, User 1 has three participations in Region 1; User 2 has three participations in Region 2; User 3 has three participations in Region 3; and, User 4 has one participation in each of these regions (Table 3). To accurately analyze the effect of this parameter, it is assumed that other parameters like *Information Completeness rate* are the same for all users ($e.g.,\ IC_{Total} = 1$).

Table 3 Scenario 3, Calculation of the reputation score for users who send data from different regions

Users	Region 1		Region 2		Region 3		User Useful Participation (UUP)	Reputation score
	Participation	Usefulness rate	Participation	Usefulness rate	Participation	Usefulness rate		
User 1	3	0.21	0	0	0	0	0.21	0.605
User 2	0	0	3	0.33	0	0	0.33	0.665
User 3	0	0	0	0	3	0.75	0.75	0.875
User 4	1	0.07	1	0.11	1	0.25	0.43	0.715

Table 3 shows the values of the *UUP* parameter and the user score. As depicted in Table 3, user 3 has received the highest score, and user 1 has received the lowest score, while all users' total contributions are equal. Since user 3 has sent information from region 3, about which we have no information so far, his/her contribution is much more important than user 1 from region 1, where we have had ten contributions. These results show that the system could compute the score of these users appropriately. In general, in terms of being useful in the disaster environment, user 3 is the best, and user 4, user 2, and user 1 are in the next ranks, respectively.

6.2 Quality attributes evaluation

Reliability and usability are our target quality attributes. In scenario four, the system's reliability is evaluated, and in scenario 5, the usability of the proposed IGUI online tool is evaluated.

6.2.1 Scenario 4: Reliability evaluation

We first assume that there are ten regions in the earthquake environment, and ten users participate in each region. Eight of these users are simulated by the normal distribution, including four users with a variance of 0.25 and four with a variance of 0.5. We assume that the remaining two users are selfish. We also assume that all users answer all the questions in the questionnaire and do not skip any question without an answer ($IC_{Total} = 1$). After simulating users' participation, the system reports an aggregated response for each region. By comparing the aggregated response (system output) with the correct values, the reliability is computed as follows:

$$Reliability = \frac{Number\ of\ Matched\ Items}{Number\ of\ Total\ Items} * 100 \quad (8)$$

Table 4 shows the reliability value in each region. Finally, the reliability value of the system is 92%. For the 8% wrong system output, it should be noted that the proposed system's aggregated values are close to the correct ones and could be used as a good approximation of the information requirements.

Table 4 Scenario 4, Calculation of reliability

Region	Correct values	System output	Matched Items	Unmatched Items	Reliability
Region 1	31223321221331323411	31213321221331323321	18	2	90%
Region 2	12332244123231411123	12332244113231411113	18	2	90%
Region 3	43233121424141333322	43233121424141333312	19	1	95%
Region 4	43331213332224414144	43331213332224314134	18	2	90%
Region 5	23444314144311423212	23444314144311423112	19	1	95%
Region 6	42424214422221411112	42424214422121412112	19	1	95%
Region 7	21133323314112332221	21133313314112331211	17	3	85%
Region 8	34442224122224414134	34442224122224414134	20	0	100%
Region 9	31111324144432242414	31111324144422242314	18	2	90%
Region 10	24132143144314124443	23132143144314114443	18	2	90%
Total Items	200	200	184	16	
Total Reliability			92%		

6.2.2 Scenario 5: Usability evaluation

As described in Section 2, CrowdBIG uses a comprehensive and simple user interface called the IGUI Online Toolkit to collect data from the earthquake environment. In this section, we intend to evaluate the ease of use, the ease of learning, the degree of user satisfaction, and also the usefulness of this online tool for collecting earthquake information. In fact, we aim to evaluate IGUI usability by answering the following two general questions:

1) Ease of learning and using: Is the IGUI online tool easy to learn and use?

2) Usefulness and user satisfaction: Is it useful to use the IGUI online tool for collecting information from the earthquake environment, and does it satisfy the final users of this tool?

To answer the above two questions, we used a survey method by adopting the Lund questionnaire (Lund 2001). A modification (Moradi et al. 2022) to this questionnaire measures the user interface usability of software products using four variables called ease of use, ease of learning, the usefulness of the tool, and satisfaction of the final audience. In this questionnaire, the ease of learning and the ease of use variables extract the answer to the first usability question, and the usefulness of the tool and the satisfaction of the final audience variables extract the answer to the second usability question (Moradi et al. 2022). The usability questionnaire, which its various dimensions can be seen in Table 5, evaluates four usability variables based on 11 factors and 11 questions.

Table 5 Usability Evaluation Questionnaire

Usability Dimensions					Satisfaction Ratio
Usability Question	Usability Variable	Usability Factor	Description		Good or Excellent (Option 4 or Option 5)
Easy to Use and Learn	Easy to Learn	Ease of learning	1.	Easy to learn the IGUI online tool	87%
	Easy to Use	Easy to work with proposed tool	2.	Easy to work with the IGUI online tool	85%
		User-friendliness	3.	User-friendliness of the IGUI online tool	78%
		Flexibility	4.	Flexibility of the IGUI online tool for gathering preferred earthquake information	85%
		Consistency & Coordination	5.	Consistency of the IGUI online tool	79%
		Error checking & Fast recovery	6.	User error checking & fast recovery of the IGUI online tool	76%
Audience Satisfaction & Usefulness	Usefulness	Applicability	7.	Applicability of the IGUI online tool for earthquake information gathering	80%
		Requirement coverage	8.	The coverage of the important requirements of earthquake information gathering	82%
		Time-saving	9.	Gathering information with the IGUI online tool saves the audience time	84%
		Effectiveness and Productivity	10.	Utilizing the IGUI online Tool user interface increases the effectiveness and productivity of earthquake information gathering	81%

Audience Satisfaction	Audience satisfaction	11.	Audience satisfaction with the IGUI online tool for gathering earthquake information	89%

We used 100 people in the cities of Mashhad, Birjand, and Torbat-e Jam in Iran by the simple random sampling method without placement. Before starting the experiment, a pre-made 3-minutes tutorial video was sent to the users. Then we sent the IGUI online tool and the usability evaluation questionnaire (presented in Table 5) to the participants. In the questionnaire, the participants were allowed to leave the answer blank or choose an option from the five options, including excellent (score 5), good (score 4), average (score 3), weak (score 2), and very weak (score 1). Finally, we extracted the ratio of people who chose excellent or good to the total number of received answers. The extracted ratio can be seen in the last column of Table 5. This column, known as the Satisfaction Ratio, shows what percentage of participants chose the good or excellent option for each of the 11 evaluated factors. To obtain the minimum satisfaction ratio for a usability variable, we minimized the satisfaction ratio of the whole usability factors associated with that usability variable. The minimum satisfaction ratios of the usability variables are presented in Table 6.

Table 6 shows that 87% of the evaluators were satisfied with the ease of learning, and more than 80% of the participants were satisfied with the ease of working with this tool. In addition, more than 81% of the participants were satisfied with the usefulness, and more than 89% were generally satisfied with the proposed online tool. In general, more than 80% of participants rated the usability of the IGUI tool as good or excellent.

The participant's feedback also reveals that the IGUI online tool can be improved in factors such as user-friendliness, consistency, and coordination of user interfaces, error checking, and fast recovery. Note that we can improve the user-friendliness score by keeping the user interface simple, using better colors, and utilizing more popular user interface elements. We can also improve the score of the consistency and coordination factor by following modern and popular user interface design patterns. The error checking and fast recovery factors can be improved by performing more black-box tests. Such tests identify recurring errors and subsequently provide solutions to eliminate these errors.

Table 6 Aggregated Results of usability evaluation

Usability Question	Usability variable	Minimum satisfaction ratio
Ease to learn and use	Easy to learn the IGUI online tool	87%

	Easy to use the IGUI online tool	80.6%
Satisfaction and usefulness	The usefulness of the IGUI online tool	81.75%
	Users' satisfaction with the IGUI online tool	89%

7. Conclusions

In this research, the information requirements of the earthquake disaster have been identified and classified into four categories: victims, facilities and livelihood, security and health, and maps. To gather these four categories of information from the earthquake disaster environment, CrowdBIG, a crowdsourcing system, has been proposed. The proposed system consists of four layers: sensing, fog, cloud, and application. CrowdBIG collects required data related to earthquake disasters with the participation of users in the disaster environment. The data is then preprocessed, stored, and aggregated, and the resultant information could be used by the relevant disaster management organizations as well as associated applications and services.

Since malicious users can compromise the quality of the collected data, a mechanism has been proposed to identify such users. Besides, a scoring mechanism has been proposed to score and rank all users according to their usefulness and information completeness. To evaluate the two mechanisms of malicious user detection and user scoring, we have used several scenarios. The simulation results have shown that the proposed system is successful in all investigated scenarios. Given that CrowdBIG can collect comprehensive and critical information from the disaster environment, it can truly improve the process of responding to earthquake disasters. While the reliability of the CrowdBIG system is high (92%), more than 80% of the participants rated the usability of our proposed information-gathering tool as good or excellent. Finally, one of the limitations of the proposed system is the total destruction of the cellular network infrastructure that can happen after too severe earthquakes. However, it is anticipated that in the future, satellite-based Internet will be prevalent and will function in even such scenarios.

STATEMENTS AND DECLARATIONS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AUTHORSHIP STATEMENT

Hamid Bahadori: Conceptualization, Methodology, Software, Original Draft Preparation

Hamed Vahdat-Nejad: Supervision, Conceptualization, Methodology- Reviewing and Editing

Hossein Moradi: Supervision, Methodology- Reviewing and Editing

COMPUTER CODE AVAILABILITY

https://github.com/The-J-J/CrowdBIG.git

Open source, 2021, developed in C#

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