Data Agent-Based Volumetric Progress Monitoring over Mobile Ad-Hoc Network in Disaster Management

Pranjal Tiwari, K. K. Pattanaik(✉), and Garima Nain

Department of Information Technology, ABV-IIITM, Gwalior, India
kkpatnaik@iiitm.ac.in

Abstract. Post disaster rescue operations are usually undertaken in a severely constrained communication environment, often leading to difficulties in coordination among various machineries. This work proposes an autonomous data agent-based automation of post disaster progress monitoring of volumetric activities over Mobile Ad-hoc NETwork (MANET) by leveraging WiFi Direct communication functionalities. This approach enables efficient and reliable communication among rescue teams, facilitating coordination and information exchange in challenging post disaster scenarios. The proposed work enables a Light Detection and Ranging (LIDAR)-based volumetric analysis with minimal computing overhead. A mobile application for Android 11 demonstrated the practical applicability of the proposed system.

Keywords: Post disaster management · Data Agent · LIDAR · WiFi Direct and Legacy WiFi · Wireless sensor network

1 Introduction

Disasters like earthquakes and landslides can severely impact the availability and reliability of communication networks [1,2]. This, inturn, hinders emergency response efforts and problematizes coordination among disaster management authorities in post disaster management and rescuing [3]. Post-disaster management in a region with massive volumetric shifting involves various activities such as pothole filling and clearing displaced soil or debris [4,5]. Figure 1 shows the various post disaster phases and among them the current work focuses on the debris removal and clearance. The progress of the work is measured in terms of volumetric analysis.

In the absence of communication, the in-activity volumetric progress monitoring and reporting requires manual efforts, wherein the supervisor must physically traverse each affected region to collect and document information on the ongoing volumetric activities and developments [3,6]. The traditional reporting

This work is supported by the Science and Engineering Research Board (SERB) under the Grant MTR/2021/000354.

A. Verma et al. (Eds.): ANTIC 2023, CCIS 2091, pp. 228–244, 2024.
https://doi.org/10.1007/978-3-031-64064-3_17

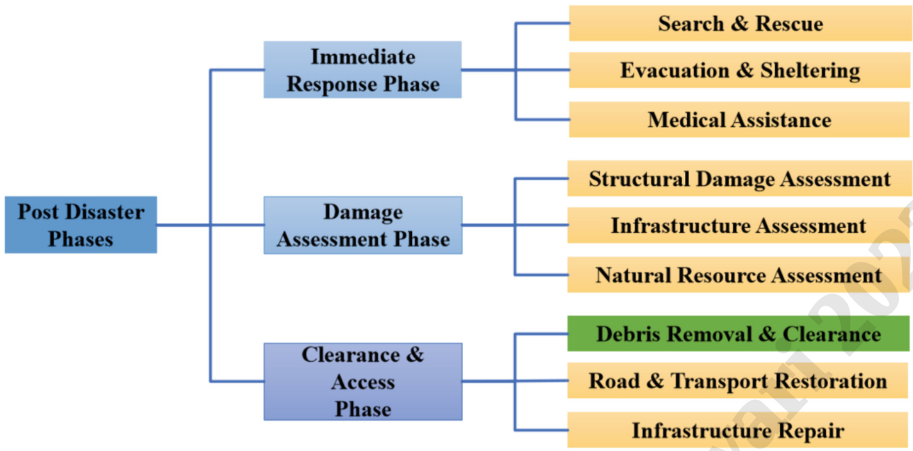

Fig. 1. Post Disaster Phases

approach to these activities is time-consuming, labor-intensive, and prone to delays and inaccuracies.

Wherein, accomplishing post disaster rescue operations requires efficient coordination and real-time information exchange between rescuers and the supervision authority to maximize the effectiveness of relief efforts [2,5,7]. It has become a worldwide challenge for rescuers to automate the process of reporting the progress to central authorities or supervisors at the rescue site.

Therefore, this work aims to provide an autonomous framework to monitor and report the progress of post disaster volumetric activities such as debris removal and clearance under the availability of minimal resources (like smartphones) with rescuers.

In this context, technology has played a pivotal role in managing post disaster rescue operations, and one promising approach is using data agents [8–10]. These data agents work specifically to perform a particular activity autonomously. They can be designed to capture the volumetric progress of the digging activity at different regions in post disaster management scenarios. This work explores the concept of a Finite State Automaton (FSA)-based Autonomous Data Agent (ADA) over WiFi Direct-enabled Mobile Ad-hoc NETworks (MANET) [11,12] to reduce the physical efforts of the supervisor in post disaster rescue operations. The volumetric progress of debris removal and clearance is performed through the topography scanned by Light Detection and Ranging (LIDAR) [13,17] scanners available on smartphones nowadays. LIDAR technology provides the accurate 3D point cloud of a scanned region.

The key contributions of this work are:

– Developed an FSA-based ADA for the automated volumetric progress analysis in post disaster management.

- An algorithm has been designed to determine the volumetric analysis using the 3D point cloud from the LIDAR sensor.
- A mobile application is developed on Android 11 smartphones enabled with the LIDAR sensor and WiFi Direct technology to demonstrate the practical applicability of the proposed automated progress supervision in post disaster scenarios.

2 Related Works

Supervising the progress of the post disaster debris removal and clearance is achieved manually in the absence of the communication system [7]. It requires the supervisor to monitor these activities by moving through different regions and keeping a record of progress in each region, which is tedious. Although satellite communication exists, those devices have limitations like high cost, heavy, bulky, difficult to operate, and high battery consumption. It has become a worldwide challenge for rescuers to automate the process of reporting the progress to central authorities at the rescue site. Kamruzzaman et al. [2] presented the benefits of wireless communication technology and IoT sensors in post disaster management. A MANET is the best fit to tackle this communication gap. It takes advantage of the rescuers available at the rescue site carrying a smartphone device with the minimal required resources. For instance, [1], and Rawat et al. [3] proposed using WiFi Direct in the disaster management application over an Android platform. This work indicates the transmission efficiency and accuracy of the WiFi Direct, an infrastructure-less MANET [11,12], over other communication modes. Thus, WiFi Direct [1,14] has been adopted as an efficient communication mode in this work.

In addition, the literature includes LIDAR-based Volumetric Measurements for applications such as salt stockpile inventory management [13], wherein the LIDAR-generated 3D point cloud data is used to determine the volumetric calculation of an object or elevated surface. Zieba-Kulawik et al. [15] monitored the urban forests using a LIDAR sensor. Some researchers, such as [16], created a fusion of the 3D LIDAR and color camera to provide a colorful 3D real-world scene representation. The calibration of the camera and LIDAR sensor is important in autonomous driving, topographical scanning, object detection, etc. This work utilizes the LIDAR [13,17] sensor for depth analysis, i.e., the volume of the debris removed and cleared. Each rescue site is divided into different regions, wherein each region has a Group Owner (GO) or Co-supervisor, and all other devices in that group are Group Clients (GCs). The GCs capture a region with the smartphone LIDAR sensor and forward it to the GO or Co-supervisor. A co-supervisor collects data and calculates the progress by merging the data of different GCs in a particular region and communicates with another Co-supervisor of different regions through the Legacy WiFi access point.

Dube et al. [14] and Necsulescu et al. [11] proposes a routing algorithm based on the neighboring node's signal strength. This is an on-demand routing algorithm that uses signal strength and location stability to find the most stable path from the source to the sink node. After peer-to-peer communication, routing is the major concern for MANETs. In implementing this routing algorithm, two routing tables are maintained; the first is the Signal Stability (SS) Table, and the other is the routing table. These tables help in finding the most stable neighbor of a node for further transmission.

Autonomous data agents (ADAs) [8,9] have been used in Wireless Sensor Networks (WSNs) [18] for data analysis, such as the monitoring of tunnel disasters autonomously without human intervention. This work is based on the interpersonal interaction behavior of ADA to bridge the gap between technology and humans. This proposed setup is capable of perceiving its environment and raising alerts during disasters in the tunnel. This intends to use ADAs deployed over MANETs, which can play a critical role in post disaster rescue operations for automated real-time data sharing and analysis, even without traditional communication infrastructure. The use of ADAs over Android devices enabled with the LIDAR sensor and WiFi Direct technology reduces the need for remote data collection and reliance on human supervision of remote sites.

The literature suggests that, individually, different researchers have done several types of research on WiFi Direct-based MANETs, ADAs, and LIDAR technology. However, designing an ADA over MANET to capture the volumetric progress of the digging activity through a 3D point cloud LIDAR input at different regions is yet to be achieved.

3 Autonomous Data Agent for Volumetric Progress Monitoring

An Autonomous Data Agent (ADA) is an intelligent software agent designed to perform data processing, analysis, and management tasks autonomously without human intervention. ADAs can work independently or collaboratively with other agents to perform complex tasks, challenging for human operators to complete manually with higher efficiency and reliability. They can process gigantic amounts of data, operate continuously in real-time data analysis, and adapt to new environments, addressing suitability to applications requiring timely and accurate data insights. This section proposes the functionalities of an ADA for volumetric progress detection.

3.1 Finite State Automaton (FSA)

Finite State Automaton (FSA) [19] is a machine with certain rules following the transition from one state to another to recognize patterns based on predefined conditions and transitions. It can be represented using five symbols: Q, σ, δ, Q_0, F, where these represent a set of states, a set of input symbols, the transition function, initial state, and a set of represents final states, respectively.

Figure 2 represents a FSA with five states and seven transitions where $Q = \{Q_0, Q_1, Q_2, Q_3, Q_4\}, \sigma = \{a, b, c, d, x, y\}$, and Q_2 represents the final state of this automaton. The state transition function δ is given below:

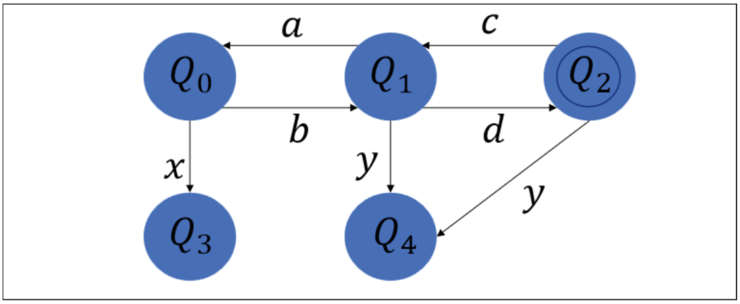

Fig. 2. Finite State Automaton

$$\delta = \begin{cases} \delta_1(Q_0, b, Q_1), Q_i = Q_0, b \in \sigma \\ \delta_2(Q_0, x, Q_3), Q_i = Q_0, x \in \sigma \\ \delta_3(Q_1, d, Q_2), Q_i = Q_1, d \in \sigma \\ \delta_4(Q_1, y, Q_4), Q_i = Q_1, y \in \sigma \\ \delta_5(Q_1, a, Q_0), Q_i = Q_1, a \in \sigma \\ \delta_5(Q_2, c, Q_1), Q_i = Q_2, c \in \sigma \\ \delta_5(Q_2, y, Q_4), Q_i = Q_2, y \in \sigma \end{cases} \tag{1}$$

FSA plays a significant role in defining a data agent with finite capabilities or functionalities. The transition function in FSA is equivalent to the triggering events in an ADA, where the data agent switches its states on the occurrence of a certain event. The states of FSA represent the state of the data agent, and the transitions are equivalent to the actions taken against any event.

3.2 FSA-Based ADA

The proposed ADA in this work is based on the FSA to enact an intelligent software agent that performs tasks related to data acquisition, processing, analysis, filtering, classification, and management autonomously through predefined states and events. The FSA acts as a control system that governs the behavior of the ADA based on its internal state and external stimuli.

The deployment of the ADA on the Android platform is done to achieve the volumetric progress of different regions. Different states of this proposed data agent are Capture, Target Identification, Store on Device, Area Comparison, Calibrate Targets, Volumetric Analysis, Calculate Progress, and Update Variables. At each step, an action is performed by getting the input from the previous state and generating the output as input for the next state. The following are the states of the proposed data agent:

- **Capture:** The rescuers carry an Android device with minimal resources and capture the region with the LIDAR sensor deployed in each region. The output of this state is the LIDAR and camera fused 3D Point Cloud. The device

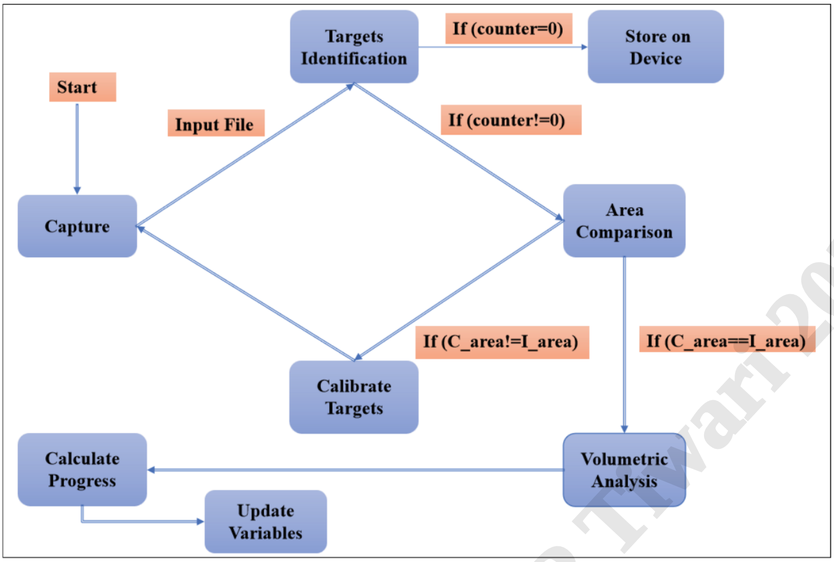

Fig. 3. Design of FSA-based ADA

operator only captures the region of interest with the help of physical targets while capturing the region, and the generated output works as an input to the next state.

- **Target Identification:** This step identifies the region of interest to ensure the accuracy of the volumetric progress of a particular region. This step defines the boundary for the region such the device bearer selects the region of interest.
- **Store on Device:** The relative volumetric calculation requires the reference point to compare the progress at different time instances. The condition "if(counter==0)" corresponds to the availability of reference point cloud data of a particular region.
- **Area Comparison:** The condition "if(counter!=0)" holds *True* for the already available (stored) reference data at the device. The captured area (C_area) is compared with the reference area (I_area) and generates a boolean result for the next step.
- **Calibrate Targets:** If the captured area (C_area) is not the same as the reference area (I_area), i.e., the output of the above state gives the *False* output, it represents the inaccurate target capturing. Hereafter, the user recaptures the region by calibrating physical targets to ensure the accuracy of the overall outcome.
- **Volumetric Analysis:** Once the area comparison (C_area=I_area) event is correct, this stage proceeds to calculate the volume of the excavated site and quantify it. A volumetric analysis algorithm is proposed in this work and tested against the 3D point cloud data.

– **Calculate Progress:** Over a period of time, the relative progress determination is obtained after calculating the volume of a region.
– **Update Variables:** This step involves updating the variables on a data packet transmitted over the network. After updating the variables, the final data packet is transmitted to the next GO. This GO or co-supervisor then repeats the same steps from capturing the region, analyzing volume, updating variables, and forwarding it to the next GO until it reaches the Supervisor.

The proposed FSA-based ADA can operate continuously, allowing for real-time data analysis and processing of the sensory data from the rescue site, which is essential for given applications requiring timely and accurate data insights.

4 Volumetric Analysis over LIDAR Enabled Data

This work proposes a volumetric analysis algorithm to calculate the volume from a LIDAR-generated point cloud (in .las file format). This algorithm also generates the relative volumetric progress from the given input at the regional and cumulative regional levels, which has been depicted in Fig. 4. This algorithm consists of five steps given below:

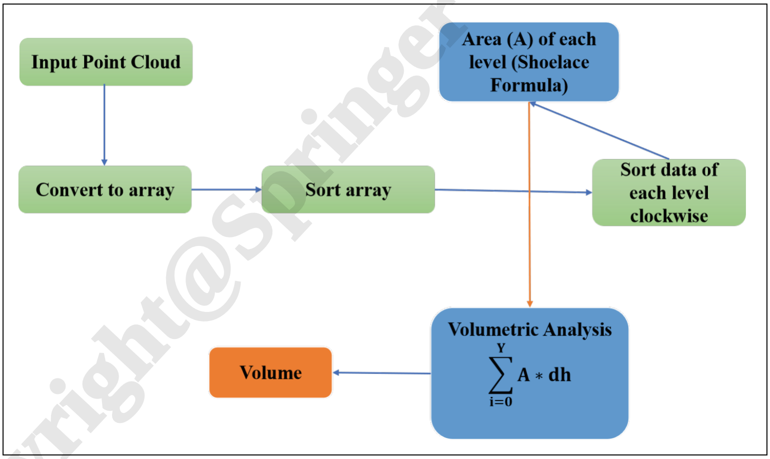

Fig. 4. Volumetric Analysis Algorithm

– **Input Point Cloud:** It is a smartphone-generated LIDAR point cloud that contains numerous points on a 3D cartesian plane. These points can recreate a 3D visualization of the scanned surface or object through the representative point on a 3D plane (point containing its X, Y, & Z coordinates) with additional properties like pixel RGB value, point ID, etc.

- **Convert to Array:** Due to resource limitations and unnecessary attributes, it is not feasible to directly perform any operation on the raw LIDAR sensory data. Therefore, the 3D coordinates (X, Y, and Z) are extracted from Input Point Cloud data and converted into an array.
- **Sort Array:** As the point cloud is a 3D plane, it is assumed that the surface of the data cloud is parallel to the X-Z plane. Therefore, the height of the point cloud increases on the Y axis, wherein the width and length increase on the X and Z axis, respectively. Thus, the 2D array (X-Z plane) is sorted in increasing or decreasing order according to the Y axis for height or depth analysis.
- **Volumetric Analysis:** In the volumetric analysis function, the array is traversed from the low to high level of the Y axis. As the level on the Y axis changes, an area calculation algorithm is called and multiplied with the change in the level. The area of each level is multiplied by the change in height, and by summing up all the volumetric slices from $i = 0$ to $i = y$, the complete volume is calculated.

$$V = \sum_{i=0}^{y} A * dh \tag{2}$$

where V is the generated output volume, and i is the vertical height given below:

$$dh = (y_{i+1} - y_i) \tag{3}$$

where y_i represents the level of point surface at the Y axis for $y_i \geq dh \geq 0$, and dh represents the difference between two consecutive levels at the Y axis for given $y_i \geq 0$.
- **Sort Data Clockwise:** The Shoelace formula is used to determine the area of any polygon, and hence, the array elements are sorted in a clockwise direction on the X-Z plane. This sorting ensures the accurate area calculation at each unit level according to the point cloud density.
- **Area of Each Level(A):** To calculate the overall volume of the point cloud, the area at each level is multiplied by the difference in height of two consecutive levels at the X-Z plane. At each level, a polygon is extracted, and the area is calculated using the Shoelace formula, which can calculate the area of any shape.

Shoelace Formula: This formula, also known as Surveyor's formula, calculates the area of a polygon for the given coordinates of its vertices. Its ease of use and accuracy make it a valuable tool for calculating the area of irregular polygons and other shapes that are difficult to measure using traditional methods. It is based on the concept that the area of a polygon can be computed as the sum of the areas of its triangles. The polygon's vertices must be listed in clockwise or counterclockwise order to use the shoelace formula.

The mathematical representation of the shoelace formula is given below:

$$A = \frac{1}{2} \sum_{i=1}^{n} (z_i + z_{i+1})(x_i - x_{i+1}) \tag{4}$$

where A represents the area of a polygon, and the area is in a plane, so z_i and x_i represent the coordinates on the X-Z plane.

5 Signal Strength-Based Energy Efficient Routing (SSEER)

Signal Strength-based Energy Efficient Routing (SSEER) is the dynamic routing algorithm for MANETs that ensures a stable, energy-efficient, proactive, and shortest path. This algorithm considers the device's power consumption to keep track of a device's availability for packet forwarding. Some essential functionalities of this routing algorithm are described below in detail.

5.1 Remaining Link Attempts (RLA)

Power consumption is the primary concern for MANET protocols since the device loses the battery power during the packet transmission. If the device power is exhausted completely, the interrupt occurs in the routing path. Therefore, Remaining Link Attempts (RLA) defines the maximum number of attempts remaining with the available battery power of a device. It is defined as in Eq. (5) follows:

$$RLA = \frac{P_{rem}}{C_{tx}} \tag{5}$$

where P_{rem} is the device's remaining power in milliamperes (mA) and C_{tx} is the power required to transmit a data packet of unit size successfully. The C_{tx} is further calculated as follows:

$$C_{tx}(dB) = a * PL \tag{6}$$

where C_{tx} is in decibels (dB) and PL stands for path loss, which is a measure of the attenuation of radio waves as they propagate through a medium.

Mathematically, the PL can also be denoted as the local average received signal power at the receiver node relative to the transmission power of the transmission node. The calculation of the transmission cost of a link between two devices is derived from the equation of path loss of radio waves in free space. The equation for path loss given in Eq. (7) is retrieved from [20].

$$PL(dB) = PL(d_0) + 10 * n * log_{10}(\frac{d}{d_0}) \tag{7}$$

where, PL is the path loss in dB, $PL(d_0)$ is the path loss at known distance (d_0), and n is the power law relation between a distance and received power.

To calculate the RLA, the C_{tx} is required in mA, and to convert the C_{tx} from dB to mA, the following formula given in Eq. (8) is used:

$$C_{tx}(mA) = 10^{\frac{\left(C_{tx(dB)}-30\right)}{10}} \tag{8}$$

5.2 SSEER Data Packet

The data packet required for the SSEER protocol is shown in Fig. 5. In the given data packet design, each field is described as follows:

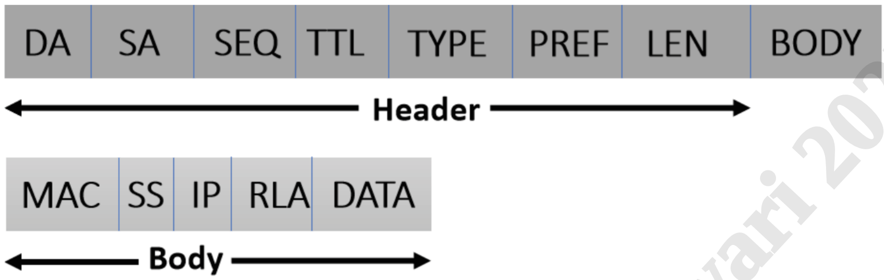

Fig. 5. Data Packet Design

- DA: destination address or the supervisor's address
- SA: source address or address of the devices through which the packet is being transmitted
- SEQ: packet sequence number
- TTL: time to live field, which prevents the redundant or orphan data packet from looping inside the network
- TYPE: determines the type of the message
- LEN: holds the length of the data packet
- CRC: cyclic redundancy check.
- MAC: holds the MAC addresses of the devices in a region, and it is also useful to authenticate the user's devices.
- SS: carries the signal strength table
- IP: holds the IP address of all the devices with respective MAC addresses
- RLA: holds the RLA of all the access points to ensure the stability of the path
- DATA: carries the data to be transmitted

5.3 RLA Table

RLA is an essential factor that allows for keeping track of the status of links between nodes, particularly for portable devices such as smartphones, laptops, and tablets, which rely heavily on battery power. The RLA table records the number of attempts remaining with the available battery. The network routing protocols utilize this information to determine the best path for data transmission between nodes. Additionally, by monitoring the RLAs, the WSN can detect failing or unstable links, and proactive measures can be taken to maintain network connectivity. This improves the overall performance and reliability of the network, ensuring the seamless transmission of data.

5.4 Signal Strength Table

A Signal Strength (SS) table measures and records the strength of signals being transmitted between devices, which helps determine the quality of the connection and ensures that data is transmitted reliably with minimal interference. In a wireless communication network (WiFi, Bluetooth, and cellular networks), signal strength can fluctuate due to various factors, such as distance between devices, obstacles, and interference. A signal strength table visually represents signal strength levels (in dB), allowing users to identify areas with weak signals and optimize network performance. It helps diagnose network issues and make informed decisions regarding the placement and orientation of wireless devices.

Table 1. RLA-SS Table

Host	RLA	SS
x		
y		
z		

Table 1 shows the overall RLA-SS attributes required in the SSEER routing. The Host field stores the IP addresses of host devices, RLA stores the RLA value for the available battery of the device, and the SS field stores the respective signal strength of a device for immediate successor.

6 Results and Analysis

6.1 Experimental Setup

Several ADA-installed Android devices (smartphones) are deployed in a rescue site to set up the post disaster rescue environment. To mimic the real-world scenario, the rescue site is divided into several zones or regions, wherein each region contains an adequate number of rescuers having smartphone devices with the minimal required resources and sensors. Rescuers in each region are further separated into two roles: GOs, who also act as co-supervisors, and GCs are other devices in that region. All the GCs connect to their respective GOs, and GOs are responsible for fetching, merging, and calculating the progress from the data of all the GCs inside their region. These GOs then feed the data to a data packet and forward it to the next available GO. As shown in Fig. 6, each region has a co-supervisor (GO), and other devices in that region act as GCs. There exists a supervisor that gathers information from GOs or co-supervisors. This topology follows two modes of communication for data gathering and packet forwarding

1. *In-group Communication:* This communication exists between GCs available in a region and the co-supervisor (GO) of that particular region. Herein,

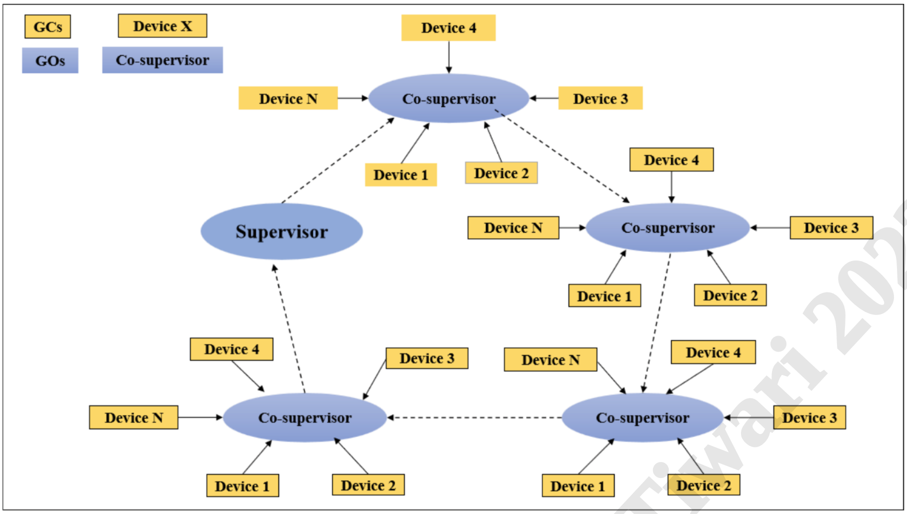

Fig. 6. Device Deployment Topology and Communication

different rescuers (GCs) send their captured data for volumetric analysis to their GO. GCs can communicate with their GOs using WiFi Direct, but communication between GCs in a group is not supported.

2. *Inter-group Communication:* The communication between different GOs comes under this category. Each GO forwards the regional progress to the supervisor. To overcome the technical limitations of WiFi Direct, a Legacy WiFi-based access point is used to achieve Inter-group communication between GOs.

6.2 Simulation Environment

The proposed work covers event monitoring, progress quantification, progress monitoring, and forwarding. An Android application is developed with all the functionalities given above to simulate the proposed work. The graphical user interface of the application is shown in Fig. 7. Apart from the above features, some additional functionalities are given to the users. This application uses two modes of communication to enable smooth packet forwarding throughout the network in a multi-hop manner. The above application supports the following functionalities.

Create Group. The group formation facility is provided by WiFi-Direct technology. The regional Co-supervisor (GO) creates a group and allows devices to connect to the GO, but it does not provide client-to-client and inter-group communication.

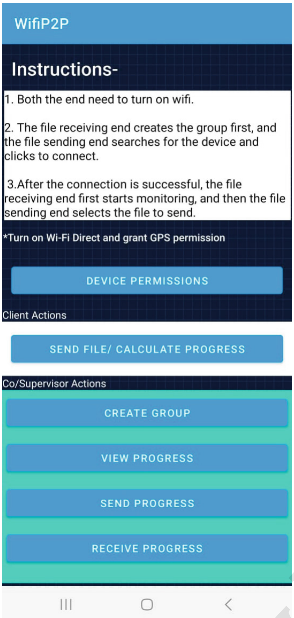

Fig. 7. Developed Android Application GUI

Join Group. Several rescuers are available in a region and can join the group to become a GC. These GCs send their data to the regional Co-supervisor for further processing and calculations.

Upload and Calculate. The regional scanning of digging activity requires the LIDAR-enabled smartphone. After the scanning, a generated point cloud is uploaded to the application for further processing and calculation. This functionality allows the users to calculate the volume and relative progress.

View Progress. This functionality allows the supervisor and co-supervisors to monitor the work progress of each region and the overall cumulative work progress. A dashboard is provided to give more simple user interaction.

Send Progress. It is the functionality of GO. Inter-group communication is established using this to forward the data packet to the next GO. An access point has been implemented to enable inter-group communication using Legacy WiFi technology.

Receive Progress. This is the functionality provided to the GO at the receiving end, wherein the GO receives the progress data from the previous GO or Co-supervisor. The sender turns on its Hotspot, and the receiving end connects to the sender via Legacy WiFi.

6.3 Accuracy of the Volumetric Analysis

The proposed data agent in Fig. 3 is used to determine the accuracy of the volumetric analysis algorithm over several iterations. This section validates the efficacy of the proposed volumetric analysis algorithm. The theoretical (actual) and LIDAR 3D point cloud-based calculated volumes are demarcated for different shapes. Table 2 shows the actual and calculated volumes of two different shapes, i.e., a cube (with the vertices of dimension 6) and a cylinder (with the radius of 6 and height of 6) using different densities of LIDAR 3D point cloud inputs. The accuracy of the proposed algorithm is also specified by comparing it with the actual volumes.

As shown in Table 2, the accuracy of the proposed algorithm for volumetric analysis is really high, as it closely determines the volume of these two shapes. Additionally, the accuracy increases as the 3D point cloud's density increases from 100 to 10,000 points. This suggests that the accuracy of the volumetric analysis is directly proportional to the density of point cloud input.

A similar observation can be made using the covariance analysis among the accuracy and the density of the point cloud. The covariance measures the extent to which two variables in a dataset vary. Mathematically, the covariance between two variables X and Y can be calculated as:

$$cov(X, Y) = E[(X - E[X])(Y - E[Y])] \tag{9}$$

where $E[X]$ and $E[Y]$ represent the means of X and Y, respectively. A positive covariance indicates that the variables tend to increase or decrease together, while a negative covariance indicates that they tend to move in opposite directions.

The following results have been found from volumetric analysis of the cylindrical shape. The μ_x is the mean of the density of the point cloud input, and the μ_y is the mean of the accuracy of the volumetric analysis.

$$\textbf{Mean } \mu_x = \mathbf{2900}$$

$$\textbf{Mean } \mu_y = \mathbf{99.7935}$$

$$\textbf{Covariance } \sigma_{xy} = \mathbf{556.4073}$$

The above covariance σ_{xy} between the density of the point cloud and the accuracy of volumetric analysis is a high positive value. This shows that the point cloud density is directly proportional to the accuracy and highly correlated. As the density increases, accuracy increases, while sparse points may lead to lower accuracy.

Thus, the choice of the density of the point cloud depends on the availability of the computing resources and the requirement of the application in terms of accuracy. Application scenarios with plenty of computing resources and higher accuracy needs can choose higher density of the point cloud such that the calculated volume approaches the actual volume of the shape.

Table 2. Volumetric analysis using proposed algorithm.

Shape	Density of Point Cloud	Actual Volume	Calculated Volume	Accuracy
Cylinder	100	18.85	18.746	99.50
	500		18.812	99.76
	1000		18.831	99.89
	10000		18.85	100
Cube	100	216	216	100
	500		216	100
	1000		216	100
	10000		216	100

6.4 Performance of the Application Developed

The developed application performs well on smartphones enabled with Android 11 and above. Due to resource limitations, the real-time experiment is done on six devices; each group has three devices. One works as a co-supervisor, and the other two work as GCs and report the volumetric progress to that co-supervisor. The progress of these clients is merged by the respective co-supervisor and then forwarded to the next co-supervisor.

Table 3 shows the performance of the application based on power consumption (P_{con}), CPU utilization (CPU_u), memory requirement (M), sender's speed (S_s), and receiver's speed (R_s). All the results have been averaged for the particular scenario.

Table 3. Performance of the application in terms of power consumption, CPU utilization, memory requirement, sender's speed and receiver's speed

	P_{con}	CPU_u (in %)	M (in Mb)	S_s (in Mbps)	R_s (in Mbps)
GC $\rightarrow$ GO	light	15.76	124.00	4.61	0.1
GO $\leftarrow$ GC	medium-light	20.69	142.33	0.03	13.6
GO1 $\rightarrow$ GO2	medium-light	10.1	146.33	1.53	0
GO2 $\leftarrow$ GO1	medium-light	23.13	220.00	0	1.70

GC $\rightarrow$ GO in Table 3, explains the performance of GC device when it is sending the data to it's GO. GO $\leftarrow$ GC explains the performance of GO device when it is receiving the data from one of it's clients. GO1 $\rightarrow$ GO2 explains the performance of GO1 device when it is sending it's data to the next GO2 and GO2 $\leftarrow$ GO1 explains the performance of GO2 device when it is receiving the data from the previous GO1.

Below are some of the key takeaways from Table 3:

– The WiFi Direct communication is much faster than the Legacy WiFi communication technology.

- WiFi Direct communication enables robust infrastructure-less communication using group formation.
- Comparatively, a resource-efficient device is needed as a co-supervisor because of high CPU and memory consumption.
- The WiFi Direct GO device has a higher receiving speed than the GC sending device because the GO has to receive data from N number of devices.
- Power consumption at each activity is minimal.
- The Listening GO 2 device has higher memory and CPU consumption due to Legacy WiFi communication.

These results demonstrate the smooth functioning of the developed application with multiple smartphone devices. It also shows the feasibility of the proposed volumetric analysis of the debris removal and clearance framework in post disaster scenarios using ADA and MANET technology.

7 Conclusion

This work proposes an integration of available smartphone technologies such as WiFi Direct, Legacy WiFi, and LIDAR sensors to perform the volumetric analysis of digging activity in the post disaster rescue operation. The manual efforts of the human supervisor have been reduced by using the proposed ADA designed to perform volumetric analysis from the point cloud input achieved from the LIDAR sensor. The experimental analysis reveals that the accuracy of the volumetric algorithm depends upon the density of the point cloud input. The developed application allows the quantification of the regional as well as overall relative volumetric progress.

The proposed mechanism can be extended to several domains with numerous functionalities. In the future, different monitoring algorithms for concave problems can be deployed over the same network under limited functionalities.

Acknowledgements. This work is supported by the Science and Engineering Research Board (SERB) under the project entitled "Dynamic Bayesian Network model for behavioral study of autonomous data agents" under the Grant no. MTR/2021/000354.

References

1. Alnashwan, R., Hala M.: Disaster management system over Wifi direct. In: 2nd International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia (2019)
2. Kamruzzaman, M., Sarkar, N.I., Gutierrez, J. Ray, S.K.: A study of IoT-based post-disaster management. In: International Conference on Information Networking (ICOIN), Da Nang, Vietnam, pp. 406–410 (2017)
3. Rawat, P., Haddad, M., Altman, E.: Towards efficient disaster management: 5G and device to device communication. In: 2nd International Conference on Information and Communication Technologies for Disaster Management (ICT-DM), Rennes, France, pp. 79–87 (2015)

4. Ghaffarian, S., Kerle, N.: Towards post-disaster debris identification for precise damage and recovery assessments from UAV and satellite images. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (2019)
5. Berktas, N., Bahar Yetis, K., Oya, Ekin K.: Solution methodologies for debris removal in disaster response. EURO J. Comput. Optim. **4**(3–4), 403–445 (2016)
6. Lorca, A., et al.: A decision-support tool for post-disaster debris operations. Procedia Eng. **107**, 154–167 (2015)
7. Aziz, N.,Kamarulzaman, A.: Managing disaster with wireless sensor networks. In: 13th International Conference on Advanced Communication Technology (2011)
8. Bosser, T.: Autonomous Agents: International Encyclopedia of the Social & Behavioral Sciences. Elsevier (2001)
9. Li, G., et al.: A data agent inspired by interpersonal interaction behaviors for wireless sensor networks. IEEE Internet Things J. **9**, 8397–8411 (2022)
10. Verma, A., Pattanaik, K.K.: Multi-agent communication-based train control system for Indian railways: the behavioural analysis. J. Mod. Transp. **23**, 272–286 (2015)
11. Necsulescu, P., Schilling, N.: Signal strength Based MANET routing protocol: cost calculation and performance evaluation. In: 3rd IFAC Symposium on Telematics Applications, International Federation of Automatic Control, Seoul, Korea (2013)
12. Sharma, H.D., Gupta, A.: A survey on wireless ad hoc networks: 1993–2002. In: IETE Technical Review (2003)
13. "Lidar." Wikipedia. https://en.wikipedia.org/w/index.php?title=Lidar&oldid=1149704019. Accessed 18 October 2023
14. Dube, R., et al.: Signal Stability-Based Adaptive Routing (SSA) for Ad Hoc Mobile Networks. In: IEEE Personal Communications (1997)
15. Zieba-Kulawik, K., Skoczylas, K., Wezyk, P., Teller, J., Mustafa, A., Omrani, H.: Monitoring of urban forests using 3D spatial indices based on LiDAR point clouds and voxel approach. Urban For. Urban Greening **65** (2021)
16. Ding, Y., et al.: 3D LiDAR and color camera data fusion. In: IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (2020)
17. Mahlberg, J.A., et al.: Salt stockpile inventory management using LiDAR volumetric measurements. Remote Sens. **14**(19), 4802 (2022)
18. Lee, J.H., et al.: Wi-Fi direct based mobile ad hoc network. In: 2nd International Conference on Computer and Communication Systems (2017)
19. Fiedrich, F., Burghardt, P.: Agent-based systems for disaster management. Commun. ACM **50**(3), 41–42 (2007)
20. Goldhirsh, J., Wolfhard, J. V.: Handbook of Propagation Effects for Vehicular and Personal Mobile Satellite Systems (1998)