Non-Invasive Detection of Landmines, Unexploded Ordnances and Improvised Explosive Devices Using Bespoke Unmanned Aerial Vehicles

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***Abstract*—In this study, a small-scale customised drone was developed to automate the procedures of cleaning explosive devices. It was instrumented with innovative intelligent automated techniques and magnetometer sensor technologies. Its performance was assessed in field t ests. T he r esults, obtained in the open-air minefields a nd t he b enchmark assessments, verify the viability of the technologies, methods, and approaches employed in this research for the efficient d etection o f legacy landmines and IDE/UXO.**

***Index Terms*—Landmine detection, airborne demining, Aerial-supported detection of landmines, UAV-supported detection of landmines, Magnetometer.**

I. INTRODUCTION

All around the world, there are approximately 100 million buried landmines [1] due to the low-cost manufacturing [2] and simplicity of deployment across wide regions. More than 1,000 deminers have lost their lives or suffered injuries while performing demining operations between 1999 and 2012 [3]. 61 states worldwide are severely impacted [4] by the slow demining process [5]; these include, but are not limited to, Croatia ([6]), Bosnia and Herzegovina, Serbia, Afghanistan, Montenegro, Libya, Syria, Iraq, and most recently, the war-torn regions of the west of Ukraine and Azerbaijan. By the end of 2005, Bosnia and Herzegovina declared that there was a possibility that over 4% of their territory was contaminated with landmines [7]. In 1997, two years after the war ended, 23% of Croatian territory was thought to be mine-suspected [7]. 10.413 people in Colombia, one of the nations most affected by landmines worldwide, lost their lives to landmines between 1990 and 2013 [8]. Over 35,000 amputees in Cambodia have been impacted by a landmine explosion [3]. The average number of people killed or maimed annually is 26,000 [9] and 80% of this figure is children [4]. Ten mines are placed for every mine removed, despite recent efforts to reduce their use [10]. The precise locations of legacy landmines that have been buried are unknown, and landmines can shift slightly depending on the features of the land and the time they were buried. Using conventional methods to remove millions of landmines/IDE/UXO would take more than a century [11] with potential risks and high costs [12], which will have a long-term, significant impact on these nations in a variety of ways. Their presence continuously puts communities in danger, obstructs economic growth, and makes it difficult for infrastructure, agriculture, and resettlement to have safe access to land [13]. The development of a landmine/UXO/IDE detection system that is quick, safe, and economical is urgent. Land-based vehicles face a number of challenges, including accurate navigation over rough terrain despite being supported by various mechanisms like wheeled, legged, and dragged robots [14]. Furthermore, it takes a while to scan larger terrain with those slow, heavy vehicles. Autonomous drones have recently been deployed to accomplish a diverse range of missions (e.g. logistics [15], smart cities [16], agriculture [17]), due to their efficient and effective use. Drones can expedite surveying and provide better access to challenging terrain with tough and hard-to-reach topography and thick vegetation [18], [19], [20]. Unmanned Aerial Vehicles (UAVs) suited to covering a large area for the purpose of easing labour-intensive mine clearance have been used in numerous studies with different detection approaches [21]. Thanks to cyber-physical systems (CPSs) and enhanced Artificial Intelligence (AI) techniques, recent years have seen an increase in the intelligence of the ”everyday things” in our environments considering Internet of Everything (IoE) [22], [23] enabling them to make decisions with an increasing degree of autonomy and little to no help from humans, leading to the development of advanced robotics systems.

The effectiveness of drones equipped with magnetometers in detecting buried metallic explosives was demonstrated in various studies [24], [25]. In this work, a bespoke, low-cost, small footprint, easy-to-use, and autonomous robotic drone (Fig. 2) – integrated with magnetometer sensor modalities (Fig. 1), the so-called MagnoUAS, was developed to detect landmines/IDE/UXO locations rapidly and safely. Low mass, small size, and lightweight UAS with low energy consumption is capable of inspecting fields at low altitudes through pre-programmed routes with extreme height precision and terrain following mode for revealing the probable landmine/UXO/IDE spots.

II. METHODOLOGY

We planned to use a small single-board computer (SBC) on MagnoUAS to process the internal management of its parts as well as the sensor components. Arduino and Raspberry Pi are both suitable to our design and development objectives. In this application, the Arduino board was selected to execute simple sensing operations from the sensors wher e i) it is cheaper than the Raspberry Pi, which helps us to accomplish one of our objectives – a bespoke drone as less expensive as possible and ii) it needs less current than Raspberry Pi does, which is important for us regarding the battery-constrained MagnoUAS for the extention of flight time. This section consists of two subsections (Sections II-A, II-B), i) design and development of the drone – MagnoUAS – with sensor technologies (Fig. 2), and ii) development of the tablet/smartphone application to manage MagnoUAS and process data streaming from MagnoUAS to locate landmines/IDE/UXO.

A. Integration of MagnoUAS With Sensors

The incorporation of the internal software and hardware components with the sensors into the bespoke UAS is explained in this section. Fluxgate magnetometer sensors were used to detect MF generated by the metallic parts of landmines, UXO or IDE. Magnetometer sensors should be integrated with MagnoUAS appropriately concerning the magnetic interferences relating to onboard electronics as elaborated in [26], [27], [28] even though the small electronics of MagnoUAS help reduce the interferences significantly. The magnetometers were integrated below a lightweight drone to minimise magnetic interferences, specifically, caused by MagnoUAS. The properties of the magnetometer sensors shown in Fig. 1 are presented in Table I. Two fluxgate sensors – magnetometers – are connected to Arduino using the serial port via the Modbus multiple connections. One of the magnetometers is placed on MagnoUAS to collect MF data via the Z direction and the other is placed to collect via the X direction. The sampling rate was adjusted to 10 Hz in order to reduce the noise.

$$\begin{aligned} MF(uT) = (Maggy_{rawdata} * Sensitivity)/1000; \\ where\ Sensitivity = 13nT/LSB; \\ -800uT < Maggy_{rawdata} < +800uT; \\ 1000\ converts\ nT\ unit\ to\ uT\ (micro-Tesla); \end{aligned} \tag{1}$$

$$\begin{aligned} MF_{XYZ} = sqrt(MF_X^2 + MF_Y^2 + MF_Z^2); \\ where\ MF\ is\ the\ magnetic\ field\ with\ respect\ to\ axis. \end{aligned} \tag{2}$$

TABLE I: Properties of Fluxgate sensor — HWT3100-485.

Sr.No.	Features	Properties
1	Output	MF and heading angle
2	MF range	-800uT—+800uT
3	Heading angle range	-180—-+180
4	Sensitivity	13nT/LSB
5	Return rate	can be adjusted between 0.2-100Hz
6	Components	Built-in sensor chips: 2*Sen-XY-f(pn13104) and 1*Sen-Z-f(pn13101) geomagnetic module; 1*Mag12C(pn13156) control chip
7	Resolution	16 bits for each axis
8	Voltage	5V—36V
9	Current	<10mA
10	Volume	83mm*25mm*25mm
11	Data interface	485 serial port (the specific level depends on the selection, the baud rate
12	Casing	Waterproof and vibration-resistance aluminium casing

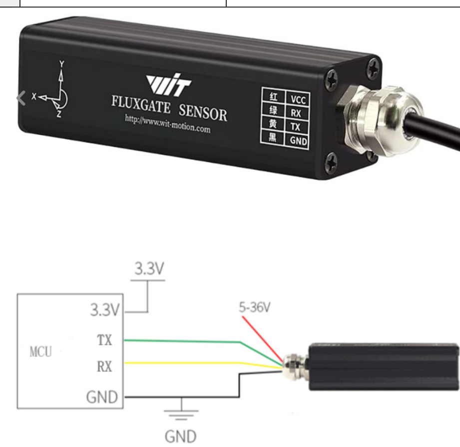

Fig. 1: Fluxgate sensor with three-axis MF output. Model: HWT3100-485.

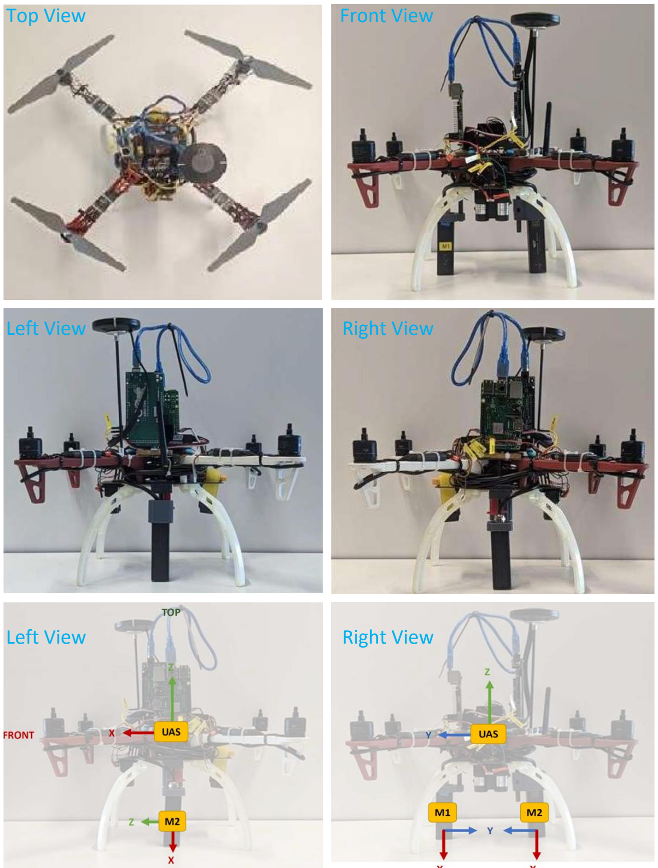

Fig. 2: Outer design of MagnoUAS.

$$\begin{aligned}&Maggy_{heading}(degrees) = atan2(mag_y, mag_x) * (180/pi);\\&where\ mag_x\ and\ mag_y\ are\ the\ magnetic\ field\ strength\\&values\ in\ the\ x\ and\ y\ axes\ respectively;\\&180/pi\ converts\ radians\ to\ degrees;\end{aligned} \tag{3}$$

Each full battery can perform up to 4 min 30 sec at low speed flying (i.e. 1 m/s). An altimeter was incorporated into MagnoUAS to make the flights accurate under 1 meter, enabling reliable terrain-following flight. The "position mode" is the easiest to fly with the centre stick configuration. MagnoUAS uses a distance sensor (i.e. altimeter) for "position hold" below 1 m altitude. In "altitude mode", MagnoUAS will drift with the wind and is sensitive to control input. The "transmitter timer" is set to 4 min and will start to beep to notify "low battery". By integrating wireless communications with antennas using telemetry radios for remote control, WiFi for real-time data transmission using a 5G Netgear Router and a drone flight controller for precise navigation – we can implement a provision of real-time data which opens up many operational advantages as elaborated in next subsection II-B. X, Y and Z component directions of the magnetometers are processed as formulated in Eqs. 1, 2, 3) to result in the total magnetic strength/intensity. A Gaussian low-pass filter as well as a high-frequency pass filter are applied to the acquired signals to suppress the background noise and accomplish a satisfactory signal-to-noise ratio (SNR) (Figs. 8), which help detect small-scale MF caused by the targeted explosives with metallic objects. The autopilot control system of the drone was optimised for flight close to the ground, integrating a radar altimeter into the drone to enable terrain following flight at a distance between 50 cm and 1 m above the ground to maximise the sensor performance.

B. Development of the Application

An intelligent tablet/smartphone application was developed using the Xamarin.Net development platform. The Xamarin platform enable us to create an application which can run on both Android- and iOS-based devices. It was fully integrated with MagnoUAS to i) manage MagnoUAS, ii) process data streaming from MagnoUAS to locate landmines/IDE/UXO, iii) perform detailed survey analysis considering varying MF, and iv) communicate with the landmine/UXO/IDE clearing team for reporting the exact locations of explosives. From a technical standpoint, the application establishes an agreed-upon communication link with MagnoUAS using either a TCP or UDP connection. Preferably, a UDP connection is suggested to be used where each data point read by MagnoUAS needs to be readily displayed on the application without stricter protocols as in a TCP connection. MagnoUAS can be used in an automated manner where planned waypoints can be fed into MagnoUAS using the UgCS system – drone flight planning software. MagnoUAS transmits MF values with related information at each data point on its waypoints to the application. The flight information and MF data are streamed to the application to be processed and monitored in near real-time. The streaming of data was coded using Pyrton. The streaming is communicated through 5G Netgear Router's WiFi connection as mentioned earlier. The application readily processes these values using Eqs. 1, 2, 3 for MF classification and clustering based on the MF threshold chosen by the user and shows landmine/UXO/IDE GPS locations on the local map with abstract information (Figs. 8) as data is streamed from MagnoUAS. The classification of MF values is carried out based on the distribution of the MF values obtained from various landmine/UXO/IDE devices considering the "no MF" values as exemplified in Section III-A. Regarding the clustering, values below the threshold value are ignored and clustering is executed based on these values above the selected threshold. These algorithms are employed to classify the MF values as "very high MF" represented by "red"' colour, "high MF"' represented by "orange" colour, "low MF" represented by "yellow" colour, and "no MF" represented by "green" colour. This is demonstrated in Section III, particularly, in Fig. 8. The use of the application with its functionalities is explained in Section III-B with real-field implementations.

III. EXPERIMENTAL RESULTS

The functions of the prototype magnetometer-integrated autonomous drone – MagnoUAS – were improved in the lab environments with numerous trial iterations and its viability in realising aforementioned targets was validated in the benchmark test fields with benchmark outputs as explicated in the

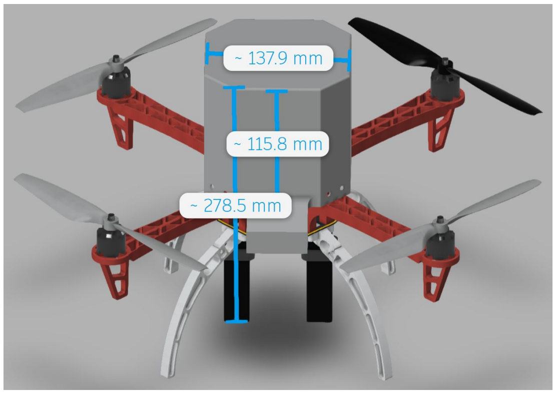

Fig. 3: Shielded Maggy.

following subsections. How to use the tablet application for the streamed data and old survey analysis is explained in [29] with a video.

A. Lab tests with MagnoUAS

In the lab environment, design of sensors and their integration with the drone components were extensively tested to find out i) the ideal component integration that avoids extreme magnetic interferences and ii) ideal configuration that ensures that subsequent sensor trials are reliable with repeatable and valid values under similar conditions. The acquired test data set was used to establish the classification and clustering algorithms ([30]) with respect to the chosen MF threshold value as elaborated in Section II-B.

The results obtained from the earlier trials in the lab environment with 1 m/s, 2 m/s, and 3 m/s flight speeds and 0.5, 1 m, and 2 m altitudes demonstrated that 1 m/s flight speed and 0.5 m altitude outperformed other parameters, namely, 2 m/s, and 3 m/s flight speeds and 1 m, and 2 m altitudes. More specifically, the detection accuracy of MF decreases significantly, primarily, for the explosives with less metallic parts, as the flight/sensor altitude increases and the flight speed increases. The MF values of various landmine/UXO/IDE were measured by MagnoUAS. The change of MF values in the X, Y, and Z axes with the two magnetometers are demonstrated. The MF values of the targeted object can be distinctively noticed when encountered a high MF. MagnoUAS was tested in real benchmark test fields as explained in Section III-B after it passed its tests in the lab environment. To summarise, the test results in the lab environment were instrumented to determine the ideal parameters for MagnoUAS considering its design and configuration.

B. Real field tests with MagnoUAS

The drone was covered with a shield as shown to protect the electronics from bad weather conditions, especially, from rain. In this way, MagnoUAS can function under rainy conditions. It is noteworthy to emphasise that MagnoUAS cannot resist heavy windy conditions due to its lightweight design. MagnoUAS operated with 1 m/s flight speed and 0.5 m altitude. The ability to fly under 1 m altitude and very low speed

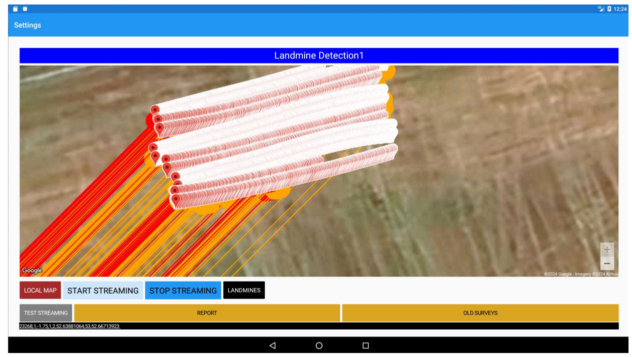

Fig. 4: Autonomous use of MagnoUAS in the UCLan landmine field. All data points.

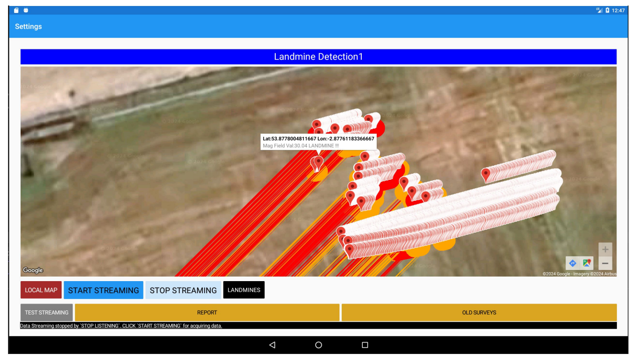

Fig. 5: Landmine locations, until the current scanned point in the route, shown by user during data streaming while MagnoUAS is still in operation.

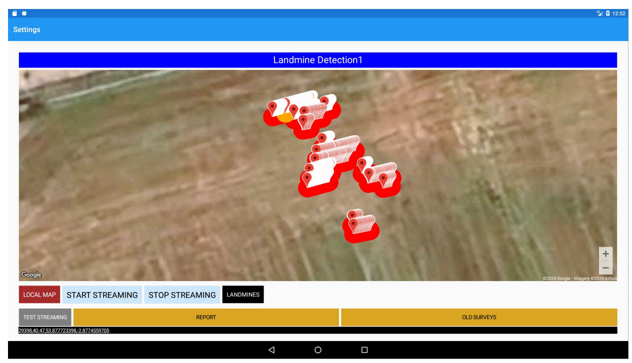

Fig. 6: All landmine locations, with "very high" MF (red), shown by the user.

Fig. 7: Landmine locations, with "very high" (red) and "high" (orange) MF, shown by the user.

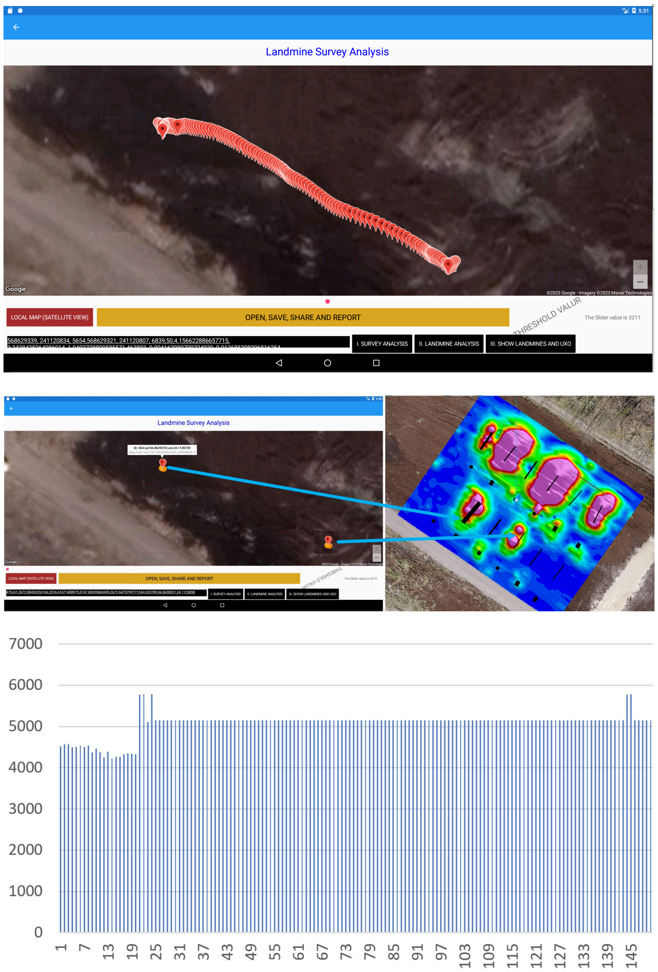

Fig. 8: Latvia field test -III-. Top: all data points; middle: high MF; bottom: MF graph for all data points in the route depicted at the top.

increases the magnetometer sensor performance significantly as explained in Section III-A. MagnoUAS was tested in the UCLan landmine field and the Latvia test field [1]. The results of these tests are explained in the following subsections.

1) Real field tests with MagnoUAS at the UCLan Landmine Field: The landmines in the UCLAn landmine field were buried between 15 cm to 50 cm depth. Several off-the-shelf UAV-mounted sensor modalities such as GPR and magnetometer were already tested by the UCLan ASR team successfully. In those tests, the MF map of the UCLan landmine field was constructed. MagnoUAS was deployed in the same landmine field in an autonomous mode with the previously tracked waypoints to conclude if the developed approaches considering all the components of MagnoUAS and their integration with one another were functioning as desired. The MF formation of the landmines with metallic objects is demonstrated through real-time data streaming in the IEEE DataPort [29] with a video using the earlier version of the application. All scanned points are displayed in Fig. 4. The "very high MF" locations, highlighted by red colour, are disclosed in Fig. 6 and "high MF" locations, highlighted by orange colour, are shown in Fig. 7 together with the "very high MF" locations. MagnoUAS was found to be performing satisfactorily in revealing the pre-mapped MF locations. It is noteworthy to emphasise that "very high MF" locations (red) are surrounded by "high MF" (orange), which indicates that MagnoUAS can show the hot/red MF spots inside orange circles when the field is scanned densely. Fig. 5 shows that the user can disclose the previous hot spots while MagnoUAS, with multi-processing ability, is in operation. MagnoUAS accomplished its operational objectives in these field tests in finding landmines.

2) Real field tests with MagnoUAS at the Latvia Field: The size of the Latvia test field is 450x70 meters with permanently installed objects. The MF formation of the field was already obtained using two different sensor modalities, namely, the MagArrow magnetometer and metal detector. MagnoUAS can rapidly scan a large terrain, providing near real-time survey data. However, MagnoUAS flew a few straight lines over known targets as displayed at the top of Fig. 8 due to the battery limit during our flight from the UK to Latvia. The battery does not last very long. Each full battery can function for up to 4 min 30 sec at low-speed flying, which restricts the scanning of larger areas, especially, at the ideal speed of 1 m/s. This testing provided us with data on the system's sensitivity to detect objects with various quantities of metal content, at various depths, in different soil/surface materials. MagnoUAS was successful in detecting objects in this field as presented in the middle of Fig. 8. The histograms of MF values along with those straight lines are shown at the bottom of Fig. 8. The MF locations can be distinctively noticed in those graphs. The real-field tests help us understand the abilities as well as the shortcomings of MagnoUAS in operations to find out the improvement points in its design and functionalities. All the datasets related to this work will be uploaded to the IEEE DataPort [29] for the researchers who would like to perform similar studies, which will lead to new directions in this specific field.

IV. DISCUSSION AND CONCLUSION

This study mainly aims to help in making new fully automated landmine/UXO/IDE detection systems in a time-and-cost-efficient manner. Capable of vertical take-off and landing and flying at very low altitudes with low speed makes easy-to-use rotary drones, if equipped with effective sensor technologies and AI with proper configurations, efficient in humanitarian clearing operations. The near real-time data provided by a UAV-integrated magnetometer system can greatly improve mine clearance operations. In this direction, the methods created in this study address the drawbacks of ground-based operations, such as high operator risk and inefficiency, and provide a quicker, safer, and more economical substitute for conventional landmine/UXO/IDE detection techniques. The developed platform in this work is a small, lightweight drone that can be rapidly deployed by a demining team to scan a

[1] https://www.sphengineering.com/integrated-systems/test-range-for-geophysical-sensors

large area for any magnetic anomalies caused by the presence of metal in landmine/UXO/IDE. It helps accelerate the speed of clearing operations across a large and tough terrain or other hazardous land area, reducing risk, increasing assurance and improving safety for the humanitarian team. More specifically the compact, lightweight, real-time magnetometer aerial surveying system can scan for the presence of ferrous metal, and real-time detection information is displayed on a tablet/smartphone device. The tablet/smartphone application ([29]) overlays detection information on a satellite map image of the survey site. Highly risky terrains can be surveyed by cost-effective MagnoUAS to turn the area into low-risky areas using safer and faster scanning approaches than conventional methods. The risk to human operators can be reduced significantly with MagnoUAS. This research provides the related research community and industry with fundamental design and implementation parameters (e.g. flight speed, flight altitude) in building and using magnetometer-integrated UAS.

In conclusion, while the MagnoUAS study presents a promising advancement in UAV technology for humanitarian applications, for future work, it would be beneficial to explore the implementation of a UAV swarm strategy. Utilizing multiple drones could enhance coverage and efficiency, allowing for simultaneous scanning of larger areas and potentially compensating for individual UAV limitations. Furthermore, optimizing battery performance through improved capacity or better battery management systems as well as low power sensors ([31] could significantly extend mission durations and enhance operational effectiveness.

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