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LORA-DRIVEN ALGORITHMS FOR ACCURATE RETURN-TO-HOME (RTH) PREDICTION IN UNMANNED AERIAL VEHICLES

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ABSTRACT: Unmanned aerial vehicles (UAVs) are prone to crashes due to user inexperience, technical issues, or adverse weather conditions. Most commercial UAVs have a real-time monitoring feature, where important UAV parameters can be monitored. However, low-cost, non-ready-to-fly UAVs often lack these capabilities, making assessing their condition challenging or taking preventive measures when faults occur. This paper presents a novel return-to-home (RTH) prediction algorithm for UAVs, which is triggered when a fault is detected in the UAV. The key contribution of this study is the innovative application of LoRa data in the design of the prediction algorithm, which sets it apart from existing reviews and research that have not explored this approach. The data from the LoRa wireless communication network will be utilized in this algorithm, which consists of three critical parameters: the speed of the UAV (V), the flight range (R), and the battery level (T). Specifically, the algorithm utilizes LoRa's received signal strength indicator (RSSI) data to estimate the flight range and is designed for use within a 1 km flight radius. It provides actionable recommendations to UAV pilots to return the UAV to its home position or to land immediately, which can be accessed through a mobile application. This approach enhances safety by reducing the risk of UAV crashes and ensuring timely interventions.

ABSTRAK: Kenderaan udara tanpa pemandu (UAV) terdedah kepada kemalangan kerana faktor seperti pengguna kurang berpengalaman, isu teknikal atau keadaan cuaca buruk. Kebanyakan UAV komersial yang terdapat di pasaran didatangi dengan ciri pemantauan masa sebenar, di mana parameter penting UAV boleh dipantau. Walau bagaimanapun, UAV berkos rendah dan tidak sedia terbang sering kekurangan keupayaan ini, menjadikannya mencabar dalam menilai keadaan atau mengambil langkah pencegahan apabila berlaku kerosakan. Kajian ini mengkaji algoritma baharu ramalan pulang ke pangkalan (RTH) untuk UAV, tercetus apabila kerosakan dikesan dalam UAV. Sumbangan utama kajian ini adalah aplikasi inovatif data LoRa dalam reka bentuk algoritma ramalan, membezakannya daripada kajian terdahulu yang belum menggunakan LoRa dalam konteks ini. Data dari rangkaian komunikasi tanpa wayar LoRa digunakan dalam algoritma ini, iaitu terdiri daripada tiga parameter penting: kelajuan UAV (V), penerbangan (R), dan paras bateri (T). Secara khusus, algoritma menggunakan data penunjuk kekuatan isyarat (RSSI) yang diterima LoRa bagi menganggarkan julat penerbangan dan direka bentuk bagi kegunaan radius penerbangan 1 km. Kajian ini memberi cadangan tindakan yang boleh diambil oleh juruterbang UAV, sama ada bagi mengembalikan UAV ke kedudukan asal atau mendarat serta-merta, yang boleh diakses melalui aplikasi mudah alih. Pendekatan ini meningkatkan keselamatan dengan mengurangkan risiko kemalangan UAV dan memastikan campur tangan pengguna tepat pada masanya.

KEYWORDS: *Unmanned Aerial Vehicle, Wireless Communication, Predictive Algorithms, Flight Time, Signal Strength*

1. INTRODUCTION

Drones, also known as unmanned aerial vehicles (UAVs), have undergone remarkable advancements over the past fifteen years [1,2,3]. While initially limited to military applications, UAVs are now widely available for civilian use. Their growing popularity stems from affordability and versatility, enabling their use across various applications. Typically, a UAV is equipped with a global positioning system (GPS) and operates via a radio channel transmitter and receiver. One of the most appealing aspects of UAVs is their adaptability, as users can customize them by incorporating additional hardware and implementing specific algorithms to meet their needs.

UAVs can be categorized into two main types: fixed-wing and multirotor [4]. Fixed-wing UAVs feature a pair of wings that passively generate lift as the UAV moves through the air at a specific angle, while multirotors rely on the speed and direction of their motors for movement. Multirotors typically have motors, propellers, and electronic speed controllers (ESCs). Multirotors have lower flight speeds, shorter ranges, and reduced flight durations than fixed-wing UAVs due to the substantial power required to generate lift and remain airborne [5]. Some of the well-known UAVs include the Parrot Disco (fixed-wing), DJI Phantom 4 (multirotor), and DJI Matrice (multirotor). However, UAVs, particularly multirotors, are susceptible to crashes, potentially causing unwanted casualties. These incidents can arise from factors such as communication interference, battery issues, extreme weather conditions, and failures in mechanical or electrical components.

Several fault detection and diagnosis systems have been developed to monitor the condition of UAVs, based on vibration, acoustic, and current parameters, to address these challenges. Al-Haddad et al. [6] proposed a UAV unbalanced fault classification approach by analyzing the frequency-domain vibration signals. An ADXL335 accelerometer was applied to acquire the vibration data on the quadcopter in the indoor laboratory environment. Pourpanah et al. [7] analyzed the vibration characteristics to differentiate between healthy and faulty propellers (normal, 5%, 10%, or 15% damaged) of a quadcopter, where four accelerometers are mounted at the bottom of each motor. In the study conducted by Altinors et al. [8], they proposed a method for detecting faults in drone motors using acoustic data. They employed machine learning techniques and achieved an accuracy of over 99% in detecting motor failures. Lee et al. [9] proposed a method for diagnosing faults in hexacopter motors using an IR sensor to compute angular speed and measure current at the ESC input. Next, Iannace et al. [10] utilized the noise generated by the drone to develop a classification model based on neural networks to identify broken propeller blades. However, the previously mentioned studies do not address countermeasures for faults occurring during drone operations. While most research on return-to-home (RTH) prediction focuses on UAV navigation or path planning [11-14], there is a limited exploration of the predictive aspect of determining whether a drone can successfully return to its home position. Additionally, no studies have proposed RTH prediction based on LoRa wireless communication data.

This study introduces a novel RTH prediction algorithm for UAVs based on LoRa wireless communication data. When a fault is detected during flight, the algorithm evaluates whether the UAV can safely return to its home position or must be landed immediately. While this feature is available in most commercial UAVs, it remains absent in certain drones, particularly non-ready-to-fly models. The research contributions are as follows:

i) Novel RTH prediction algorithm based on LoRa communication data

ii) Enhanced UAV safety, especially for custom-built drones

The remainder of the paper is organized as follows: Section 2 presents the LoRa wireless communication system and data collection. Next, Section 3 discusses the proposed RTH prediction algorithm, which consists of three parameters: flight range, battery level, and UAV speed. Finally, Section 4 concludes the study.

2. LORA WIRELESS COMMUNICATION

LoRa is one of the low-power wide-area network (LPWAN) technologies from the LoRa Alliance. It attracts considerable attention because it can efficiently trade communication ranges with big data rates, thus allowing IoT applications at an urban scale [15]. LoRa-based communication networks have been implemented in several applications such as precision agriculture [16], traffic monitoring [17], rescue operations [18], and military [19]. LoRa is based on the chirp spread spectrum modulation, and its spreading factor and coding rate parameters can be adjusted to achieve the desired communication network [20]. Depending on the operational region, LoRa mainly operates in the unlicensed ISM bands at 433, 868, or 915 MHz. In Malaysia, 915 MHz is a permitted free band for LoRa applications according to the Malaysian Communications and Multimedia Commission (MCMC). In this research, the Cytron LoRa radio frequency modulation (RFM) shields were utilized as a transmitter and receiver equipped with 2 dBi antennas, as shown in Figure 1. The Cytron LoRa Shield stacks directly onto an Arduino UNO and communicates via SPI, enabling the Arduino to send and receive data through the LoRa transceiver. It generally supports point-to-point (P2P) communication, while LoRaWAN requires additional configuration and infrastructure. The transmit power of both LoRa shields was set at 23 dBm, and a 915 MHz frequency band was utilized in this research. The technical specifications of the Cytron LoRa shield are listed in Table 1.

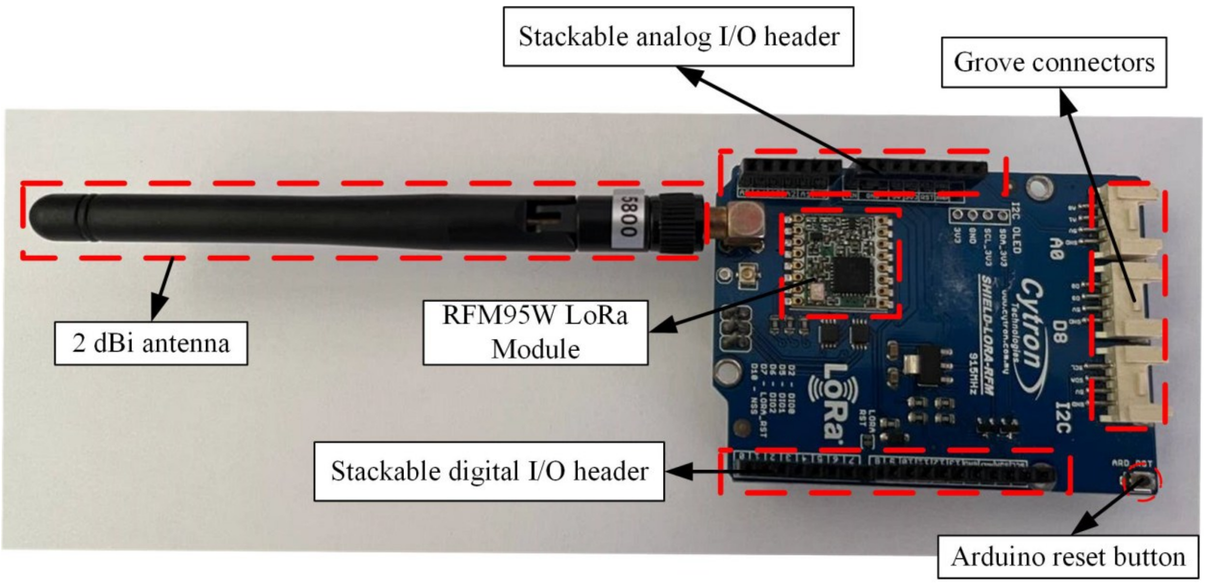
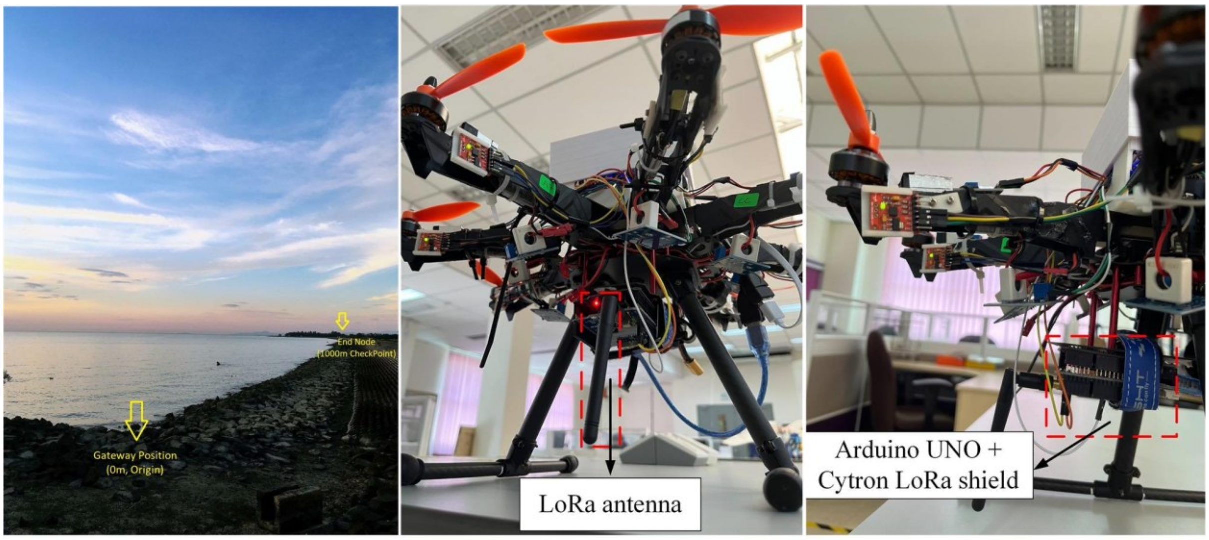


Figure 1. Hardware structure of Cytron LoRa shield

Table 1. Technical specification of Cytron LoRa shield

No.	Specification	Information
1	Dimension	79 mm x 53 mm x 15 mm (without antenna)
2	Weight	30 g
3	Frequency Band	915 MHz
4	High Receiver Sensitivity	Down to -146 dBm
5	Transmit Power	Adjustable up to +14 dBm
6	Antenna	2 dBi antenna

The LoRa data collection was conducted in Ban Pecah, located in Parit Buntar, Perak, Malaysia, as depicted in Figure 2(a). This location was chosen because it can cater to the 1 km direct line-of-sight feature, our maximum communication range set in this research. The 1 km range is selected because, at this range, the user cannot determine most of the UAV's behaviour, even the large ones, through the naked eye. Also, if no FPV is implemented, given small UAVs, it is hard to inspect the UAV's behaviour even at 500 m visually. Although the UAV flying range and LoRa applicability are more than 1 km, only the 1 km range is tested for the sake of the experiment. As shown in Figure 2(b), the LoRa transmitter is installed at the bottom part of the UAV body. In contrast, the LoRa receiver is attached to the personal computer for real-time data recording. Data collection begins at a communication range of 100 m and increments by 100 m with each step, continuing until the final range of 1 km, as summarized in Table 2. The algorithm utilizes LoRa's received signal strength indicator (RSSI), measured in decibels (dBm). Theoretically, the closer the communication range, the higher the RSSI value. The Storm Drone 8 multirotor UAV is adopted in this study, as shown in Figure 2(b).



(a) (b)

Figure 2. (a) LoRa data collection site in Ban Pecah, Perak, Malaysia and (b) Mounting location of Cytron LoRa shield at the UAV

Table 2. LoRa's RSSI recorded at the communication range of up to 1 km across five trials

Communication Range (m)	RSSI (dBm)				
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
100	-66 to -68	-67 to -69	-66 to -68	-66 to -68	-67 to -68
200	-71 to -73	-71 to -72	-70 to -72	-71 to -72	-70 to -72
300	-73 to -76	-73 to -76	-73 to -75	-73 to -76	-74 to -76
400	-81 to -83	-82 to -83	-82 to -84	-82 to -83	-82 to -83
500	-83 to -85	-83 to -85	-83 to -84	-83 to -85	-83 to -85
600	-84 to -86	-84 to -86	-84 to -86	-84 to -86	-84 to -86
700	-87 to -90	-87 to -89	-88 to -90	-87 to -90	-88 to -90
800	-87 to -90	-87 to -90	-87 to -90	-87 to -90	-87 to -90
900	-89 to -92	-90 to -92	-89 to -92	-90 to -92	-90 to -92
1000	-91 to -93	-91 to -93	-91 to -93	-91 to -93	-92 to -93

3. UAV RETURN TO HOME PREDICTION ALGORITHMS

The RTH prediction algorithm is computed to assess whether bringing the UAV back to its initial location is feasible. If the algorithm determines it is not possible, it's recommended that the UAV be landed immediately. The RTH algorithm is only executed when the faulty output is received from the Arduino microcontroller. This algorithm takes into account three parameters: the speed of the UAV (V), the flight range (R), and the battery level (T). These parameters are readily obtainable from most commercial UAVs, but certain UAVs, such as Quadcopter F450 and Hexacopter F550, lack the necessary instruments to determine them.

The maximum flying speed of Storm Drone 8 used is experimentally determined to be 13 m/s. The battery level of the UAV is determined using flight time data recorded from the Arduino microcontroller, which begins at the take-off stage. Thus, based on the flight time data obtained, the battery level of the UAV can be predicted. The flight range is obtained based on LoRa's RSSI data. For instance, if the RSSI obtained is less than -95 dBm, the flight range is determined to be approximately 1 km. The LoRa's RSSI data are recorded in a direct line-of-sight environment, as discussed in Section 2.0.

To acquire flight time data for fault cases, the motor failure conditions were simulated by disconnecting the ESC wires (red and black) from the power supply, as illustrated in Figure 3. During flight time data recording, the UAV hovers at a maximum altitude of 2 m. The verdict on whether the UAV can perform return-to-home is computed by:

$$RTH = T + RT \tag{1}$$

where RTH is the return time, R is the flight range data, V is the flying speed of the UAV, and T is the battery level obtained from the flight time data. The value obtained is then compared with the assumed maximum flight time of the UAV, which in this case is approximately 480 seconds, as listed in Table 3. The maximum flight time is assumed to be 480 seconds by considering the flight time of the minimum partial safe configurations, which is the failure of two motors. Hence, if the flight time is underestimated, the probability of the UAV crashing upon its return home is diminished. Referring to Table 3, the flight tests revealed that the flight time decreased to approximately 490 to 500 seconds, representing a 12.21% reduction compared to the UAV's flight time under a healthy condition. The decrease in the flight time is due to the much higher power required to generate enough thrust force during hovering. Conditions involving the failure of two adjacent motors or more than two motors are not recorded, as the UAV cannot hover and experiences an immediate crash upon takeoff.

Table 3. Flight time recorded at different fault configurations

Trial	Motor 1	Motor 2	Motor 3	Moor 4	Motor 5	Motor 6	Motor 7	Motor 8	Flight Time (Sec)
1	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	565
2	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Faulty	Healthy	550
3	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	Healthy	Healthy	550
4	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	Faulty	Healthy	500
5	Healthy	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	554
6	Faulty	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	552
7	Faulty	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	496
8	Healthy	Faulty	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	492
9	Healthy	Faulty	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	554
10	Healthy	Healthy	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	551
11	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	Faulty	495
12	Healthy	Healthy	Healthy	Faulty	Healthy	Healthy	Healthy	Healthy	551
13	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Healthy	Faulty	550

The proposed RTH prediction algorithm is presented as Algorithm 1 and can be observed in Fig. 4. The algorithm starts by computing the UAV's flying speed and battery level. Then, depending on the performance output (PO) value, the proposed algorithm is triggered. We set the PO threshold to be greater than 5 for the algorithm to activate, which indicates that the UAV is behaving abnormally. Once triggered, the algorithm utilizes the UAV's flight time. The flight range can be determined based on LoRa wireless communication data. Subsequently, the return time and return-to-home (RTH) value are computed according to Eq. [1]. If the RTH value exceeds 480, the UAV can safely return to the home position. However, if the value

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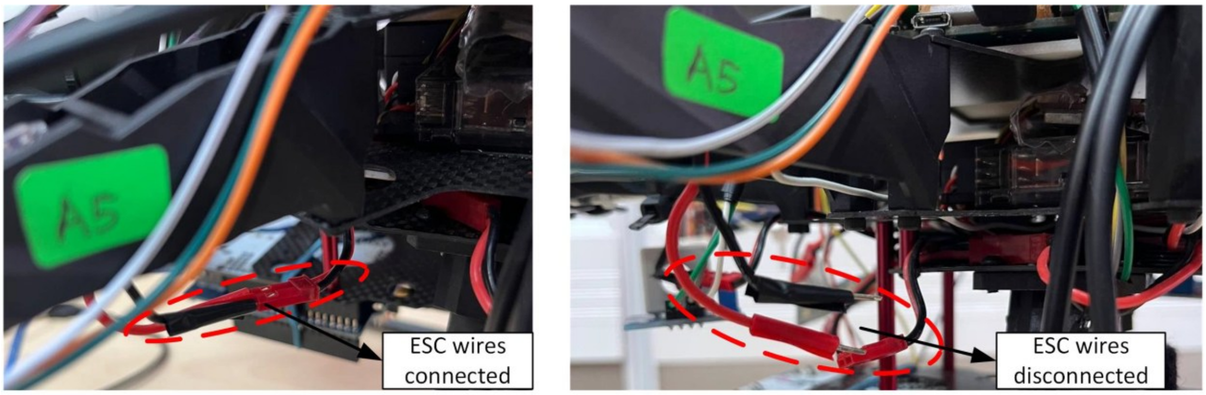
exceeds 480, it indicates insufficient time for the UAV to return home and it must land immediately.



(a) (b)

Figure 3. The UAV motor configurations involved in the experiment: (a) Healthy motor and (b) Condition that represents a faulty motor

ALGORITHM 1 Proposed RTH Prediction Algorithm

FLYING SPEED (*V* = 13 m/s)
BATTERY LEVEL (*T*)
  if (*PO* < 5)
  setMillis(newvalue)
  T = *millis*() / 1000
FLIGHT RANGE (*R*)
  if(*rf 95.lastRssi*() >= −40)
  R = 5
  if(*rf 95.lastRssi*() < −40) and (*rf 95.lastRssi*() >= −45)
  R = 10
  if(*rf 95.lastRssi*() < −45) and (*rf 95.lastRssi*() > −60)
  R = 80
  if(*rf 95.lastRssi*() <= −60) and (*rf 95.lastRssi*() >= −70)
  R = 100
  .
  .
  .
  else if(*rf 95.lastRssi*() < −95)
  R = 1000
RETURN TIME (RT = T/V)
PREDICT RETURN-TO-HOME (RTH = T+RT)
  if(RTH < 480)
  Return to home
  if(RTH > 480)
  Land immediately

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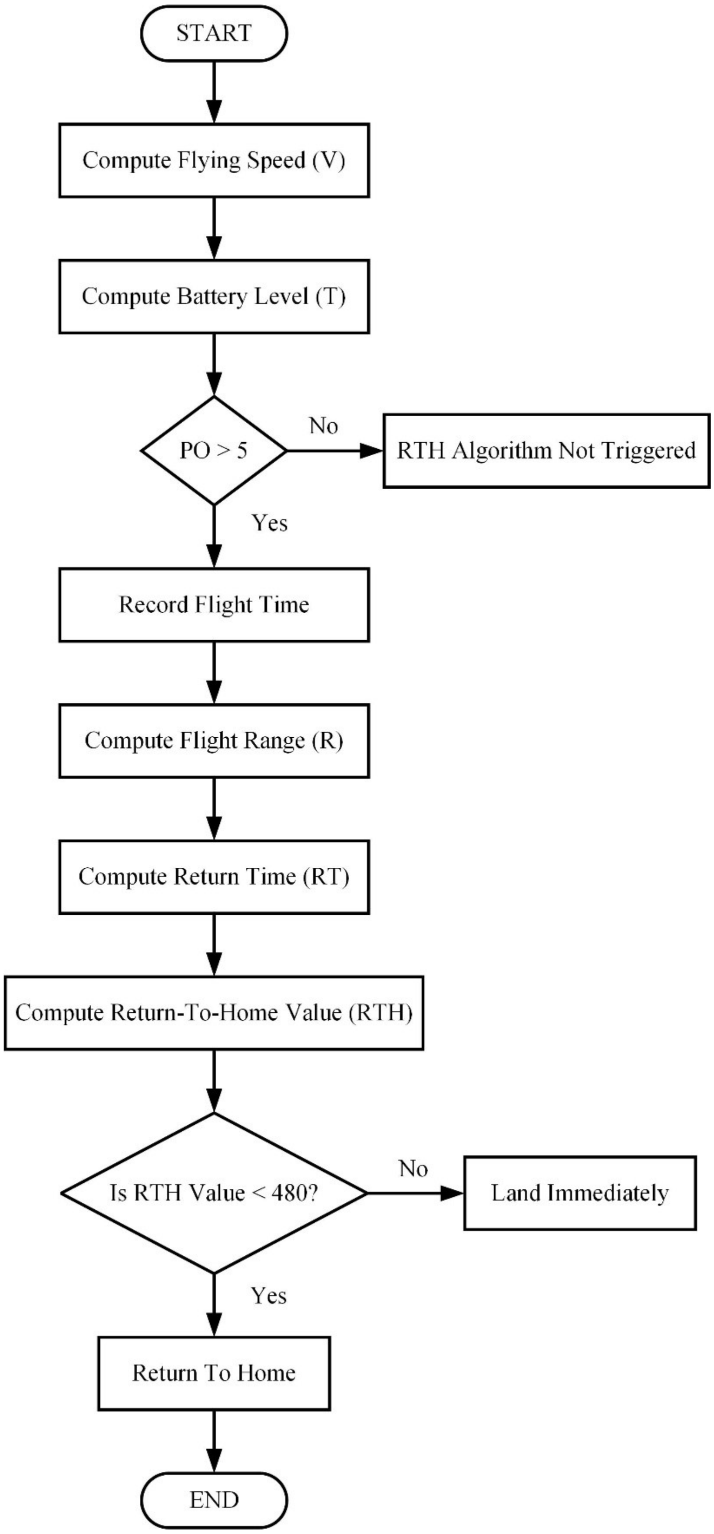

Figure 4. Flowchart of the proposed RTH algorithm

Table 4 shows the latency test for the proposed method conducted again in Ban Pecah, Parit Buntar, Perak, Malaysia. This location was chosen because it can cater to the 1 km direct line-of-sight feature, our maximum communication range set in this research, as discussed in Section 2.0. Based on Table 4, the output of the proposed algorithm can be determined in approximately 1 second within a communication range of up to 300 m, without any delay. Nonetheless, when the communication range exceeds 500 m, delays of up to four seconds are observed. Compared to the work conducted by Fadheli et al. [13], the proposed method does not require a camera or image processing techniques, as the pilot performs the RTH process. Although their approach automates the RTH process, our proposed method focuses on predicting the feasibility of the RTH process.

Table 4. Latency tests conducted in a 1 km direct line-of-sight communication range

Trial	Range [m]	Time Taken for Decision-Making [s]	Delay [s]
1	1	1	0
2	100	1	0
3	200	1	0
4	300	1	0
5	500	1.5	0.5 (max)
6	700	3	2 (max)
7	1000	5	4 (max)

4. CONCLUSION

This study introduced a novel RTH prediction algorithm for UAVs, utilizing LoRa wireless communication data to assess whether a UAV can safely return to its home position or should be landed immediately. By integrating LoRa's RSSI data with parameters such as UAV speed and battery level, the algorithm offers a new method for enhancing UAV safety and operational reliability, specifically targeting UAVs with no RTH feature. The experimental results demonstrated that the failure of two opposite motors can reduce the UAV flight time by up to 60 seconds, where this data will be the benchmark for the proposed algorithm to make a prediction. The findings highlight a new way of incorporating LoRa technology into UAV systems to mitigate crash risks by predicting the UAV's ability to return to the home position. Additionally, the LoRa wireless communication technology demonstrated in this study can be adapted for various applications, including environmental monitoring and communication relay, simultaneously enhancing its versatility. The proposed work is limited to a 1km flight range and direct line-of-sight conditions. Future work may focus on expanding the algorithm's applicability to non-line-of-sight environments and further integrating additional sensor data to enhance predictive accuracy. Additionally, a statistical comparison with algorithms from previous works will be conducted. This contribution marks a significant advancement in enhancing UAV operational safety and adds new knowledge to the domain of fault mitigation by utilizing LoRa data to prevent drone crashes. The proposed approach can also be integrated with the existing UAV fault detection and diagnosis systems available in the literature.

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