A UAV-based Algorithm to Assist Ground SAR Teams in Finding Lost Persons Living with Dementia

Dalia Hanna
Department of Computer Sicence
Ryerson University
Toronto, Canada
dhanna@ryerson.ca

Alexander Ferworn
Department of Computer Science
Ryerson Universit
Toronto, Canada
aferworn@ryerson.ca

***Abstract*— Unmanned Aerial Vehicles (UAV) are now used in many applications. Our focus in this paper is on their use in public safety, specifically in search and rescue (SAR) operations involving lost persons living with dementia (LPLWD). When it comes to saving lives, there are many human factors associated with UAV operations that impact the performance of expert human SAR that could be improved through forms of automation. These include tasks associated with piloting and search/flight management during SAR operations with the assistance of analysis performed on data from similar incidents in the past. A LPLWD may not be interested in assisting in their own rescue as they may not know they are lost. As such, it has been observed that they tend to keep walking until they are faced with an obstacle that bars their further progress. Knowing this behavior allows us to make predictions. Our approach in developing a people finding algorithm is to identify higher probability locations where an LPLWD might be found through informed, behavior-based analysis of the given terrain. We develop an algorithm to fly a UAV to the vicinity of these higher probability locations. We have validated our algorithm through field testing. In this paper, we present the results from both our data collection and the field tests. In addition, validation tests are presented and compared.**

Keywords*— *uav, dementia, search, rescue, human, robot, probability, area

I. Introduction

Finding a missing person requires that search and rescue (SAR) teams identify the last known location of a person in order to determine the probability of the lost person being in a potential area based on an understanding of their behaviour. This also allows SAR teams to estimate the lost person's survivability. Once an estimate is made of the potential search area a search plan can be formulated. In this paper we focus on the behaviour of lost persons living with dementia (LPLWD). One way to calculate the probability of area is by using potential risk/occupancy estimation which depends on the analysis of the terrain as well as emergency factors which could be gleaned from historical data [1]. By calculating terrain factor inputs like first 'staying' which refers to whether the area is often visited by people or not, second 'hazard' which calculates the hazard's characteristic in the area in relation to the natural elements like the terrain and finally 'transit' it expresses, potential risk/occupancy maps can be calculated and Euclidean distances can be established.

This work is partially funded by The Ontario Government, Ryerson University and AGE-WELL NCE Inc.

Markov models are used to predict an event, outcome or a process based on known past information or data collected in the past [2]. The models are composed of states, transition patterns between states, and the production of outputs (distinct or continuous). There are several applications for Markov models; they could be used in prediction or estimation, identifying patterns and learning statistics of sequential data [3]. Hidden Markov Models (HMMs) and Bayesian Networks are examples of these models. The HMM tool is widely used in modeling time-series data and is a type of Bayesian Network. The term "hidden" comes from its defining characteristics: first, it assumes that the observation of the variable Y_t at a certain time t was generated by some process S which is hidden from the observer. Second, it assumes that this hidden process satisfies the Markov model which recognizes that the state at an observation time encapsulates all the details about the process that will be predicted in the future of all other incidents [3]. A Bayesian network is a graphical representation of a specific factorization of a combined distribution. To elaborate, given the value S_{t-1} the current status S_t is independent of all the states prior to $t-1$ [3]. Bayesian Network diagrams represent the conditional independence relations for HMMs. Lin in [4] utilized a Bayesian network framework that accounted for the UAV operator's uncertainty which represented actual human behaviour. Data collected about this behaviour enabled the generation of a distribution map. This map then can allow SAR teams to allocate or extend the search area dynamically.

The Kalman Filter is a set of mathematical prediction equations that implement a predictor-corrector type estimator that is considered optimal as it minimizes the estimated error covariance [5]. Therefore, it is used as an optimal estimator for a sizable class of problems using a few conceptual tools [5]. This filter is a representation of normal or Gaussian distribution and historically was used to predict a specific event based on previous knowledge that provides a probability of occurrence. "Bayes" Rule follows the concept of conditional probability offering a way to specify the probability density of the random variable given a random variable [5]. The Local Hill Climbing (LHC) anomaly detection algorithm was used in [6] to determine an optimal path by planning for UAV flight paths without identifying an end point. Applying a fixed search area and assuming that there is a static object moving with only one search resource, the researchers calculated the probability distribution which is the priority search area. The search area is then divided into equal cells; a visited cell is updated using the

Bayesian update. After a path has been generated, they calculated the longitude and latitude to feed the UAV flight controller. They proposed a Bayesian update to prevent the fluctuation between two high-probability cells. A new value is given once the cell is visited. This behaviour decreases the probability substantially but accounts for the fact that the searchers may have missed the subject of the search. If the algorithm is caught in a spiral, it will revisit the cell with the highest remaining probability [6][7]. Lin in [4] proposed a Bayesian model to help in mapping lost-person behaviours by utilizing publicly available terrain feature data. This approach provides an opportunity to incorporate human behavior data collected in the form of posterior distributions, which are used to build a first-order Markov transition matrix for generating a temporal, posterior predictive probability distribution map [6] [4]. In [4] Lin explained that the Bayes formula provides a broader framework to incorporate additional elements like weather conditions that may affect the lost person's behaviour. Local Hill Climbing (LHC) cannot be applied directly as the path created remains with one node until it has covered the node entirely before moving on to another [6]. To address this problem, researchers used the global warming similarity map where the ocean surface symbolizes all the zero-valued nodes while the islands denote the probability nodes. Multiple paths are generated and the probability accumulated for these paths are recalculated; this technique allows the LHC algorithm to break out of one node before fully covering that node and move to another [6]. Further, the authors in [6] provided two methods to break a tie when it happens. A tie is when the value is equal in two nodes. The following example in [6] was performed to determine the best path that supports the UAV's onboard video camera to cover as much of the probability distribution area as possible. For a starting point, an ending point and specified flight time, they assumed that the UAV will always maintain the at the same height of 60m above ground (through Height-Above-Ground automation) and travel at the constant speed of 12m/s. They used 24m x 24m as the effective camera view size. The experiment showed that the algorithm could generate good paths with high efficiency or estimated efficiency that approximate the optimal solution within reasonable computation time [6]. Later, the same researcher modified the model to incorporate publicly available geographic information. Based on prior knowledge of how missing person will transition from one terrain features to another, a Bayesian model was applied and human behavior data in wilderness incorporated into the model to generate posterior beliefs [8]. "Following a first-order Markov process, the posterior beliefs can be used to build a temporal state transition matrix that allows the generation of the posterior predictive probability distribution map for any given time interval." [8, pp.321]. They evaluated the model using the Bayesian $\chi 2$ test of goodness-of-fit for multiple p- values and the results were promising. The limitation is that this method is applicable to only certain terrains and the recommendation is to incorporate additional factors such as intended destination and trail following behaviour.

Petri nets are mathematical and graphical modeling tools that could be applied in many systems [9]. Also, they are considered a discrete-time stochastic dynamic multi-agent system used to describe concurrent activities [9][10][11]. Petri nets could be used as visual aids to describe a system and the tokens incorporated into these nets used to simulate the concurrent and dynamic events of the system; therefore, they are a useful tool to provide an assessment of multi-agent systems [9]. The three components of the Petri net are the places which may represent input and output data or activities, with transitions in between representing computation steps. The tokens then represent a condition [10] or the resources available associated with places.

The authors in [12] developed a human-robot interaction modeling (HRI) tool that is based on operators interacting with UAVs. They analyzed the complete task, cognitive work, and Petri net models to build a representational framework of a three-person team operating a UAV. The successful framework depended on the communication between the team and their expertise. Using Petri net diagrams, [12] described the framework as it relates to the primary duties of the UAV operators--the pilot, the mission specialist and the flight director. They concluded that besides the automation which is effectively could be achieved using Petri nets; the same tool could be used to capture the communications among the team which is a critical component for understanding HRI. Ideally, HRI requires a high-level of situational awareness with a low cognitive load. Situational awareness is the amount of understanding of the environment achieved through the robot [13]. In addition to modeling interactivities among SAR teams, Petri nets could be used for software architectures. Based on multi UASs' behaviour and environmental conditions, they could be used to simulate its control structure. Through simulation and utilizing Petri nets provided a visual tuning control structure for a UAS [14].

Locomotion models are used to estimate walking targets in virtual environments [15]. The human locomotion model is generated by collecting data which then forms a predicted path that can be compared with actual observations. This means that the path generated by the model would be the expected path, given the known start and intended end positions. These models could be used in detecting wandering person as, in these cases, the initial planning search point can usually be determined and the point the person was last seen is also listed in incident reports and collected in databases such as the International Search and Rescue Incident Database (ISRID). Examples of these locomotion models are the Walking and Turning Speed Model, the Optimal Criteria Model, the Position and Orientation Model, and the Graph Model [15]. Zank et al in [15] performed experiments based on the previously cited four models and concluded that the cost optimization model (model 2) provided the best solutions due to the efficiency in calculation times. This confirms that while we could build algorithms and models, we need to consider the efficiency of running the algorithms besides their accuracy in order to present the outcome desired within a reasonable time, as the speed of execution is usually what defines an efficient algorithm [16].

Outdoor environments require various capabilities in robotic systems [17]. These capabilities vary from decision-making, autonomy, reliability, power management and dealing with communication challenges [17]. Therefore, it is important to do field testing under realistic and stimulating scenarios with varied terrains, vegetation, water sources and dense forests naming only a few challenges difficult or impossible to simulate.

Unmanned aerial systems are used for various hobby, commercial and military purposes. For example, the sensing and monitoring of wildfires is a modest use of UAVs capabilities, while SAR missions are considered highly complex tasks [18]. The variable nature of SAR-related missions provides a challenge in mission planning. Using aerial robots, the researchers in [18] proposed a software and hardware framework for the autonomous execution of urban SAR missions. SAR operations are unpredictable and depend on many complex variables like the weather, the environment and the rescue teams. Decision making as well as subject matter expertise are vital to the success of each operation. In crisis management, human behaviour forms an essential aspect in responding to the crisis [19]. Therefore, training in this area plays a significant role in preparing the crisis manager to manage the cognitive and emotional skills that affect the decision making in these critical situations [19]. Reacting with environmental conditions would be built on the operator's attitude, previous experiences and beliefs [19] [12].

While the automation of the search process is important, human input is an integral part of the design and development of related frameworks or algorithms. Operating UAV in the event of searching for a lost person requires more than automation; it requires creative thinking and understanding of the lost person behaviour. Data from previous incidents could provide input in the areas of social intelligence and creative thinking. Social intelligence is defined as being able to recognize the surrounding social contexts, understand others' concerns, efficiently deal with situational challenges and building successful relationships that lead to social interactions [19].

II. METHODOLOGYAND DISCUSSION

Several field tests were conducted to confirm the required steps to design an algorithm, including identifying input, output and efficacy. In addition, the communications between the SAR team personnel was captured. In this paper, we provide the results from two of our latest field experiments. The first was for testing and design of the algorithm and the second was for verification of the conceptual approach to searching. All field experiments were set up with an initial planning point (IPP); this point resembles the point where a person was last seen by a bystander or a family member or could be the last known point that the person resided in as used in an actual search mission. An expected “Find Location” was also planned which is the location in which the person is predicted to be found. This approach was informed through the analysis of 3273 incident reports involving lost persons with dementia from ISRID records. We were able to conduct prediction analysis to identify the probability of finding a lost person alive. The method, process and results were published in [20]. From this data analysis, it is concluded that it is common for a LPLWD to keep walking until they are faced with an obstacle. These could be structure such as a building or tower, a stream or river or even thick under bush, trees or similar obstructions. In addition, LPLWD tend to follow a road or a pathway without intentionally turning left or right.

Our field test locations were selected for their flat terrain which combine the characteristics of temperate and dry conditions. Various teams were involved in this experimentation supporting the research team. These were police officers who were part of SAR teams, professional SAR pilots and SAR experts. This live exercise-based simulation was used to mitigate the reality that it impossible to conduct these experiments on actual LPLWD, for ethical, and legal reasons. The methodology used, as explained in the paper, is based on conducting a real search by applying scenarios from the ISRID with preplanned IPP and find locations. Two major tests are listed below, one to collect data and do pretesting and the other to verify the design of the algorithm. Some of the most important factors that contributes in predicting the survivability of the missing person learned from the data are age, terrain and the number of hours since being declared lost.

A. *Field Experiment to Pre-Test and Collect Data (EXP1)*

Three field tests were conducted using drones based on three scenarios obtained from the ISRID. The research team consisted of a number of groups including the researchers tasked as observers: a flight manager who was an experienced SAR manager who had considerable experience working with the regional police; an experienced UAV pilot; and a test subject from the research team to act as a LPLWD surrogate. The flight manager confirmed that once the police receive a lost person alert they deploy SAR teams to start the search process. In all experiments, only the pilot and flight manager are responsible for searching with the UAV. For this reason, in our experiment, communication is set to be between two not among a team of three SAR members as described in [12]. Table 1 provides the modified detailed tasks performed by the pilot and the flight manager. All of the responsibilities of the mission director listed in [12] are shifted to the flight manager and three of the mission manager responsibilities in [12] were shifted to the pilot. Those tasks are maintaining the drone, operating the camera and capturing the video feed and still photos.

TABLE I. PROPOSED TASKS PERFORMED BY THE PILOT AND THE FLIGHT MANAGER

Pilot	Flight Manager (FM)
• Line of sight operator • Preflight rehearsal and equipment check • Operation of miniature UAV via handheld remote • Provide confirmation communication to FM • Maintain overall vehicle safety • Operate camera on-board • Capture video feed and still photos	• Prior subject matter expertise and training • Preflight rehearsal and equipment check • Search-and-Rescue SME • Maintain overall situational awareness • Flight plan coordinator • Establish safe area of operations for civilian protection • Provide relevant warning communications to pilot

The following steps were employed for all the three experiments:

- The researchers provide instructions to the LPLWD surrogate (the test subject) who traverses the search area based on a preplanned track.
- The flight manager (FM), who is a SAR expert, provides instruction to the pilot (UAV operator) stating the scenario and the possible find locations. The FM identifies these locations and hotspots (the spots in which the lost person maybe found) based on the bahaviour profile of an LPLWD. Beside his experience, the FM uses the behaviours listed in [21]. This handbook is used by almost all SAR teams in North America.
- GPS tracks of test subject, GPX files from search attempts and MP4 videos were recorded and analyzed. Also, the altitude, coordinates of IPP and find locations, battery life, time, distance, speed and number of track points were all captured.
- Communication among the SAR team (the pilot and FM) was documented.
- Four Scenarios were planned.
- The outcome from these experiment was analyzed and based on the data collected, an algorithm was designed and then used at the final verification field test.
- IPP and Find Locations were planned.
- The wanderer was equipped with the GPS tracker and contact was maintained by cell phone.
- The drone was operated by a professional and certified drone pilot flying a Durham Region Police SkyRanger R70 manufactured by Aeryon Labs.

1) First Scenario (EXP1)

This scenario involved a male test subject with moderate dementia who was attending a place of worship with their family. He went to a restroom around noon and did not return. The wanderer was found less than one kilometer from the building. In our experiment, an open green area outside the city was selected. The IPP was in an empty parking lot near a closed building. The planned end point was set to be at 0.88 km with the river identified as a hot spot north. Fig. 1 provides the track of the UAV flight Scenario 1 (EXP1) - The orange arrows and teal track is attempt # 1, the green arrows with the purple track is attempt # 2 and the blue arrows and yellow track is attempt # 3--when the test subject was found. In this case study, there were three flight interruption due to dying UAV batteries which required the three flights to find the test subject. Table 2 lists all the data collected based on the notes taken and recorded videos capturing the conversations between the pilot and flight manager. Also, it lists the flight details including, start and end times, battery life, altitude, coordinates, speed, furthest point travelled, total distance, the IPP type, coordinates and the number of track points captured during the flight.

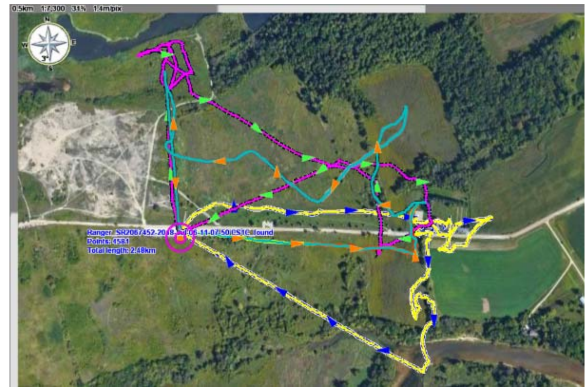

Fig. 1. The track of the drone flight for scenario 1 (EXP1)

2) Second Scenario (EXP1)

The second scenario involved a male living with mild to moderate dementia who left home by driving his car which was later found in a parking lot. The common steps were followed in the experiment and the same data was collected and listed in Table 3. Fig. 2 represents the complete flight track. It took two attempts to locate the missing test subject. The green arrows and purple track is attempt # 1 and the blue arrows and yellow track is attempt # 2. The test subject was found with a Total Search Time = 44 (Flight time) + 3 (battery change) = 45 min. Average altitude to clear visibility on screen = 63.5 m.

3) Third Scenario (EXP1)

The third scenario simulated a missing person with moderate dementia. The person went out and drove his care; later the SAR team found the car stuck on a rural road leading to an old family farm. The terrain was flat with a walking trail. In the original reported scenario, the person was found deceased. Table 3 lists the same data collected for the above two scenarios. Fig. 3 represents the complete flight track. It took two attempts to locate the missing test subject. The blue arrows and yellow track is the attempt # 1. It is noted that the more the pilot is familiar with the search process, the faster the lost person is located.

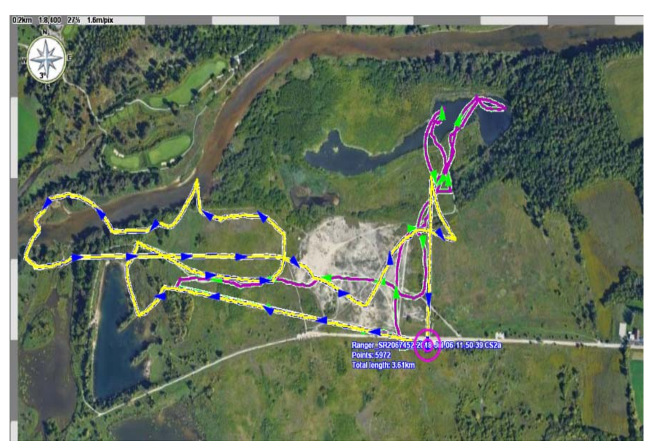

Fig. 2. The track of the drone flight for scenario 2 (EXP1)

Fig. 3. The track of the drone flight for scenario 3 (EXP1)

TABLE II. DATA FROM THE FISRT SCENARIO (EXP1)

Attempt #	1	2	3
Start Flight Time (min)	10:27	10:49	11:07
End Flight Time (min)	10:45	11:03	11:23
Total Flight Time	18	14	16
Distance of Flight (km)	2.59	2.67	2.48
Avg. Speed (km/h)	17.5	17	17
Average Altitude (m) – (ASL)	70 - (350)	70 - (350)	65
Status	Battery low - Back to IPP	Subject not found. FM: go back to IPP. Pilot: change batteries	Test subject found at 11:20 near river
Time took to change battery (min)	3	4	NA
IPP Type	Building	Previous location of search when battery was low (river)	Parking lot near straight road leading to a building
Coordinate at IPP	N 43.30344 W 80.49914	N 43.50903 W 80.28177	N 43.50969 W 80.49914
Coordinate of End Point (before flying back to base)	N 43.50903 W 80.47333	N 43.50961 W 80.47179	N 43.50650 W 80.47210
Number of Track Points	5333	4115	4580

The first column indicates the attempt number. The test subject was found after the third attempt with a Total Search Time = 48 (Flight time) + 7 (battery change) = 55 min. Average altitude to clear visibility on screen = 70 m. The IPP for the first attempt was a building, for the second attempt it was the Previous location of search when battery was low and the last one was same as the first attempt.

TABLE III. DATA FROM THE SECOND AND THIRD SCENARIOS (EXP1)

	Scenario 2		**Scenario 3**
Attempt #	1	2	1
Start Flight Time (min)	11:50	12:15	12:58
End Flight Time (min)	12:12	12:37	1:22
Total Flight Time	22	22	24
Distance of Flight (km)	3.61	4.76	2.59
Avg. Speed (km/h)	17.5	17	17.5
Average Altitude (m)	63	64	63
Status	Battery low - Back to IPP	Test subject found , return to IPP	Test subject found, return to IPP
Time took to change battery (min)	3	NA	NA
IPP Type	Parking lot near straight road leading to a building	Previous location of search when battery was low (river)	Field Laneway
Coordinate at IPP	N 43.50969 W 80.49914	N 43.51102 W 80.48814	N 43.30 325 W 80.283633
Coordinate of End Point (before flying back to base)	N 43.51102 W 80.48814	N 43.51325 W 80.47887	N 43.50886 W 80.47694
Number of Track Points	5972	6360	6689

From Table 2 and Table 3 we could conclude that the more experienced the pilot wit the search the less attempts to find the missing person illustrated in Fig. 4.

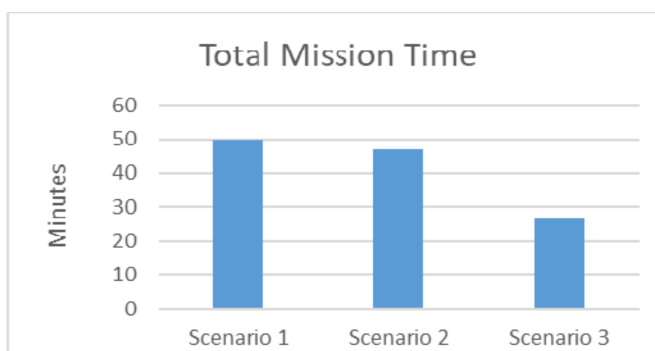

Fig. 4. Total mission time taken to find th emissing person.

B. *Verification Field Test (EXP2):*

This experiment was designed to verify the proposed algorithm and used the roles and responsibilities for both the pilot and flight manager (FM) listed in Table 1. The field experiment was planned with a Durham Region Police Services (SAR team) who operated the drone and secured a suitable flight area. In addition, a team from our industrial partner, LocateMotion, participated and provided their proprietary wearable technology providing GPS and communications tracking services that the test subject used. The steps followed to prepare for the experiment are listed below:

- A complete plan of the field test was generated based on the outcome from the previous field tests. The plan listed the duties of the pilot and the FM.
- Three scenarios were planned but only two were attempted as the third location was very close to the IPP as the search area was limited to 2 km. As such, the third scenario was abandoned.
- The researchers provided the FM with the proposed algorithm and then the FM provided the pilot with instructions based on the algorithm.
- The test subject was supplied with the wearable tracking device and their track was recorded by the support team from an industrial partner, LocateMotion.
- The altitude, coordinates of IPP and find locations, battery life, time, distance, speed and number of track points were all captured.
- The theoretical verification of probability of area is based on calculating the probability of area by using potential risk/occupancy estimation which depends on analysis of the terrain as well as emergency factors which could be obtained from historical data [21] the modified factors are listed in Table 4. This is created based on assumptions listed in [1]. By calculating terrain factors a modified risk/occupancy map could be calculated.
- The UAV employed was a SKYRANGER R60 owned by the Durham Region Police Services which is very similar to the R70. Additional recording of the event was provided by a DGI UAV operated by a volunteer from the Global Medic organization.

The proposed initial algorithm is:

1. Identify coordinates (waypoints) of the closest hot spot to IPP within the 0.5 km radius. Save coordinates.
2. Fly straight to the first hot spot, if test subject not found, return straight to IPP
3. Identify the 2nd hot spot within the 0.5 km radius
   a. If there is another hotspot, save coordinates, fly straight to the 2nd hotspot, if the test subject is found then, report to FM and stay there until rescuers arrive. Fly back to IPP.
   b. If not found, return straight to IPP and go to 4.
4. Identify coordinates of the closest hot spot (3rd) to IPP between 0.5 and 1 km radius.
   a. If test subject found. Save coordinates.
5. Fly straight to the identified hot spot, if no test subject is found, return straight to IPP
6. Identify the 4th hot spot within the 1 km radius
   a. If there is another hotspot, save coordinates, fly straight to the 5th hotspot, if the test subject is found then, report to FM and stay there until rescuers arrive. Fly back to IPP.
   b. If nothing is found, return straight to IPP

1) *First Scenario (EXP2)*

The first scenario is based on a case on an incident involving an 85 years old male living on a farm. A caregiver reported to the police that the subject was not in the house. The pilot identified the three hot spots as per Table 4. Fig. 5 illustrates the two flight attempts. The recorded winds were 25 and 21 km/h with an average altitude of 65 m. The purple arrows and green track the blue arrows and yellow track is for attempt # 2. The test subject found in a total of 32 min. + 13 min battery change time with a total time of 45 min.

TABLE IV. THE HOTSPOTS WHERE THE MISSING PERSON IS PREDICTED TO BE AT

Type	**Distance from IPP**	**Priority**	**Notes**
Pond	In the middle of the field 100m from IPP	Low	Hard to reach due to fencing
A thick trail of trees at an end of a road. The road starts from the farm house.	600 m from IPP	High	The wanderer will walk straight until she/he gets stuck so it is high probability that the person opened the door and walked straight.
Thick bushes in the middle of the field	450 m from IPP	Medium	The wanderer will have to make a turn to reach it.

Each hotspot will be referred to as (*hs*) point to a total of n number of t in each search area.

2) *Second Scenario (Exp2)*

The scenario in this case is the same case as scenario one but with a different expected find location. It took only one attempt to find the wanderer successfully. Table 4 lists the outcomes of the test and Fig. 6 provides the track of the drone.

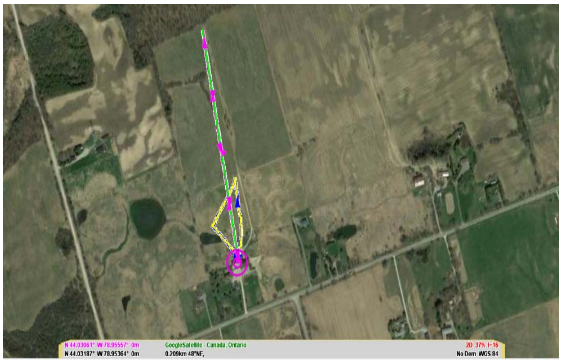

Fig. 5. The track of the drone flight for scenario 1 (EXP2)

Fig. 6. The track of the drone flight for scenario 2 (EXP2)

TABLE V. DATA FROM THE FISRT AND SECOND SCENARIOS (EXP2)

	Scenario 1		Scenario 2
Attempt #	1	2	1
Start Flight Time (min)	11:28	12:00	12:19
End Flight Time (min)	11:47	12:05	12:41
Total Flight Time	18	14	22
Distance of Flight (km)	0.56	1.04	1.12
Avg. Speed (km/h)	16	16	20
Status	Battery low - Back to IPP	Test subject found at 12:03 near thick tree line at the end of the road	Test subject found at 12:28 at thick bushes
Time took to change battery (min)	13	NA	NA
Average Altitude (m)	65	65	75
IPP Type	Parking outside a farm house	Parking outside a farm house	Parking outside a farm house
Coordinate at IPP	N 44.032221 W 78.95587	N 44.032221 W 78.95587	N 44.030299 W 78.998623
Coordinate of End Point (before flying back to base)	N 44.031329 W 78.956373	N 44.031329 W 78.956592	N 44.03049 W 78.956916
Number of Track Points	6151	3091	5483

Table 5 provides the comparison of outcomes from both sets of experiments. For simplicity, we will use EXP1 for the testing set of scenarios in field experiment number one and EXP2 for the verification set of scenarios in the field experiment number two. Below are the results from each test.

TABLE VI. COMPARING TH EOUTCOMES FROM EXP1 AND EXP2

	Testing and Design Test (EXP1)			Verification Test (EXP2)	
Scenario #	**1**	**2**	**3**	**1**	**2**
Outcome	Found	Found	Found	Found	Found
Number of attempts to find the wanderer (#)	3	2	1	2	1
Average Battery life (min.)	16	22	24	16	22
Average altitude to clear visibility on screen (m)	68	64	63	65	75
Time taken to change battery (min.)	7	3	NA	13	NA
Flight time (min.)	48	44	24	22	22
Total mission time (min.)	55	47	24	35	22
Average distance of flight (km)	2.58	4.1	1.77	4.868	3.851
Linear distance between IPP and find location (km)	0.323	0.859	0.2	0.542	0.462
Average number of track points (#)	4676	6166	6689	6151	5483

a) Discussion and Results

- Outcome: Test subject found in all experiments
- Number of attempts to find the wanderer: EXP1: 4 scenarios planned and 3scenarios executed (3, 2 & 1 attempts) to EXP2: (3 Scenarios planned 2 executed with 2 & number if attempt).

- Average Battery life: EXP1 21 min. and EXP 19 minutes (minimum was 16 and maximum was 24 min).
- Average altitude with clear visibility on screen: EXP1 is 65 m. and EXP2 70 m. Both altitudes provided clear view of the search field and the person.
- Time taken to change battery: EXP1 it took 3 and, 4 min while EXP2 it took 13 min. It depended on the pilot's experience, the 1st set of experiments there was a pilot from the manufacturing drone company, while the 2nd set we had trained police officers. The experience of the pilot is a factor in the time taken to find the lost person.
- Average flight time: in EXP1 it is 38.67 min. and in EXP2 it is 22 min. (In EXP2 the search location was with a radius of 1km while on EXP1 it was 2km)
- Average total mission time (including time to return to IPP and change battery): EXP1 is 42 min and EXP2 is 28.5 min.
- Average distance of flight: EXP1 is 2.82 km and in EXP2 it is 4.36 km
- Linear distance between IPP and find location: in EXP1 minimum 0.2 km and maximum 0.859. EXP2 minimum 0.462 and maximum 0.562

Based on the above outcomes, the steps below provide the planning steps which are considered the input:

- View map on screen; maximum view from an average 70 m altitude is about 0.25 x 0.25 km.
- Divide area into circles: 1 km and 2 km. The UAV flight range is up to 8 km [22], and based on the data analysis, we learned that the test subject may go walking up to 10 km but, would normally be found much closer. However, the researchers learned from the SAR experts that they only fly the UAV while it is in sight which is usually 2km; this is reported as an approved practice by the police force. The area in this case to set to 2 km. The energy constraint in this model is the battery life which is based on the outcomes of the experiments--about 20 minutes on average. The goal is to reach to the test subject by minimizing the flight distance travelled, the time spent and the energy consumed.
- Identify coordinates of the IPP, which is the assumed location where the person was last seen
- Identify coordinates of the Find Location which is the expected location where the test subject will travel to.
- Identify coordinates of the hotspots (*hs*) based on Table 4. Examples are, thick bushes, creeks, thick lines of trees, rivers or any obstacles that could obstruct a person walking (*hs1, hs2* .... *hsn*). (In this experiment (EXP2) there were 3 potential hotspots).
- The equation used to calculate the maximum distance that the UAV could travel on a fully charge battery would be V (with constant speed) and t (the UAV flight time computed in a trip with a fully charged battery), where $dmax = (V * t)$. Thus, the farthest distance the UAV can travel ensuring enough energy in the batteries to have a successful return flight to the take off point R = dmax/2
- Assign priorities to each of hot spots the closer first. The priorities are determined by the risk of being injured or faced with an obstacle. For example, a creek or a river would inflict a high risk of death due to hypothermia. If there are equal risks, the closer hotspot will be visited first. In addition, how the test subject reaches that spot should be considered, from the data most likely the person will continue to follow a road rather than traverse a field.
- Average battery life is 20 minutes, so if the test subject is not found within that time, the pilot will have to head back to IPP to change battery. Also, the drone will automatically head back to based once the battery almost spent.
- Areas searched with no find will be eliminated.

b) The Proposed Algorithm

The algorithm below represents the theoretical processes and outcomes of the algorithm designed to facilitate a UAV to be employed to locate a LPLWD. It provides a framework for the Flight Manager (FM) who informed about a scenario and provides instructions to the Pilot using the following directions:

Fly straight to *hs1*:
  If no LPLWD found and time is >= 20 minutes, return straight to IPP
    Change battery
    Speak with flight manager to identify the coordinates for *hs1* within the 1 km radius:
      If there are no *hotspots* within this radius go to the next *hotspot* within 2 km
      If there is another *hotspot* go to *hs2*
  If LPLWD found, report the find to FM to deploy ground rescue team and return to IPP.
  If no LPLWD found and time is > or = 10 minutes, go to *hs2*
Fly straight to *hs2*:
  If no LPLWD found and time is >= 20 minutes, return straight to IPP
    Change battery
    Speak with flight manager to identify the coordinates for *hs3* within the 1 km radius:
      If there is no *hotspots* within this radius go to the next *hotspot* within 2 km
      If there is another *hotspot* within the 1 km got to *hs3*
  If found, report the find to FM to deploy ground teams and return to IPP.
Fly straight to *hs3*:
  If no LPLWD found and time is > or = 20 minutes, return straight to IPP

Change battery
Speak with flight manager to identify the coordinates for *hs4* within the 1 km radius:
If there are no *hotspots* within this radius go to the next *hotspot* within 2 km
If there is another *hotspot* within the 1 km: Stop and return to IPP.
If LPLWD found, report the find to FM to deploy ground rescue team and return to IPP.

III. CONCLUSION AND FUTURE WORK

The algorithm provided recommendations to the SAR teams engaged in finding a LPLWD. The field tests provided input to the parameters associated with the flights, including the search radius, the expected location of the LPLWD, the average altitude to be able to get a clear view of the lost subject, the time and the battery life. With just a team of two, a flight manager and a pilot, the cost of the search is significantly lower than the average cost for land search which may include, helicopters, a professional SAR teams' time and volunteer's time. By understanding the constraints around flying a UAV, we were able to set the values of the parameters which affected the outcome. In most scenarios used in the field test, the test subject was found in less than an hour and within 2 km. The experience of the flight manager helped in determining when the UAV needed to go back to base to change a battery. It is clear from the above tests that the search using one UAV of similar characteristics to the SkyRanger will be a maximum of 30 minutes based on battery life. If all attempts to find the lost person failed, the IPP moves to the next point. This new point could be one of the high-probability hot spots. Our future work could investigate the use of multiple drones in SAR operations and the cooperation required to achieve a successful search faster.

ACKNOWLEDGMENT

We would like to thank our partners Durham Region Police Service, Ontario, Canada and LocateMotion who supported (EXP2). We also would like to thank Aeyron Labs and former search and rescue expert from Secours.io who supported (EXP1).

REFERENCES

[1] V. San Juan, M. Santos and J. M. Andújar, "Intelligent UAV Map Generation and Discrete Path Planning for Search and Rescue Operations," *Complexity,* vol. 2018, pp. 1-17, 2018.

[2] "Introduction to Markov Models,"Clemson University. [Online]. Available: http://cecas.clemson.edu/~ahoover/ece854/refs/Ramos-Intro-HMM.pdf [Accessed: 15-Jul-2017].

[3] Z. Ghahramani, "An introduction to hidden Markov models and BayesianNetworks," *International journal of pattern recognition and artificial intelligence*, vol. 15, (*01*), pp. 9-42, 2001.

[4] R. Lin, "UAV Intelligent Path Planning for Wilderness Search and Rescue," M.S. Thesis, Dept. of Comp. Science, Brigham Young Unive., Provo, Utah, 2009. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.1020.4736&rep=rep1&type=pdf

[5] G. Welsh and G. Bishop, "An Introduction to Kalman Filter," [Online]. Dept. of Computer Science, Unive. of North Carolina, Chapel Hill, NC, 2001. Available: http://www.cs.unc.edu/~tracker/media/pdf/SIGGRAPH2001_CoursePack_08.pdf

[6] L. Lin and M. A. Goodrich, "UAV intelligent path planning for wilderness search and rescue." in Intelligent robots and systems, IROS, IEEE, pp. 709-714, 2009

[7] Agcayazi, M. Talha, Eric Cawi, Arsenie Jurgenson, Parham Ghassemi, and Gerald Cook. "ResQuad: Toward a semi-autonomous wilderness search and rescue unmanned aerial system." In *Unmanned Aircraft Systems (ICUAV), 2016 International Conference on*, pp. 898-904. IEEE, 2016.

[8] L. Lin and M. A. Goodrich. A Bayesian approach to modeling lost person behaviors based on terrain features in wilderness search and rescue. In Proceedings of the 18th BRIMS, Sundance, Utah, March. 2010.

[9] T. Murata, "Petri nets: Properties, analysis and applications," *Proceedings of the IEEE,* vol. 77, *(4),* pp. 541-580, 1989

[10] V. Misic, "Capturing The Requirments," in *CP8202: Advanced Software Programming*. Dept. of Computer Science, Ryerson University, Toronto, Canada, 2017.

[11] S. Pujari and S. Mukhopadhyay, "Petri Net: A Tool for Modeling and Analyze Multi-agent Oriented Systems,"*International Journal of Intelligent Systems and Applications,* vol. 4, *(10),* pp. 103, 2012.

[12] R. E. Yagoda and M. D. Coovert, "How to work and play with robots: An approach to modeling human-robot interaction," *Computers in Human Behavior,* vol. 28, *(1),* pp. 60, 2012.

[13] T. Tomic *et al*, "Toward a Fully Autonomous UAV: Research Platform for Indoor and Outdoor Urban Search and Rescue," *IEEE Robotics & Automation Magazine,* vol. 19, *(3),* pp. 46-56, 2012.

[14] D. Xu et al, "A Petri Net Based Software Architecture for UAV Simulation," *Proceedings of the International Conference on Software Engineering Research and Practice*, Las Vegas, Nevada, 2004.

[15] M. Zank, and A. Kunz, "Using locomotion models for estimating walking targets in immersive virtual environments," In *the 2015 International Conference on Cyberworlds (CW)*, pp. 229-236. IEEE, 2015.

[16] T. H. Cormen, Introduction to Algorithms. (3rd ed.) MIT Press. 2009.

[17] S. Lacroix *et al*, "Special issue on Ground robots operating in dynamic, unstructured and large-scale outdoor environments: Editorial," *Journal of Field Robotics,* vol. 32, *(4),* 2015.

[18] D. Hanna, A. Ferworn and A. Abhari. *"Police learning: Examining the use of simulations in police training and the associated learning theories,"* in the 10th Annual International Conference on Education, Research, and Innovation (iCERi), Seville, Spain, 2017.

[19] M. A. Rahim, "A Structural Equations Model of Leaders' Social Intelligence and Creative Performance," *Creativity and Innovation Management,* vol. 23, *(1),* pp. 44-56, 2014.

[20] D. Hanna, R. Husein, R. J. Koester, and A. Ferworn, "Data Analytics to Predict the Survivability of a Lost Person with Dementia Using R," in 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), 17-19 Oct. 2019, pp. 0160-0168, doi: 10.1109/IEMCON.2019.8936163.

[21] Robert J. Koester. 2008. *Lost People Bahviour.* Charlottesville, VA: dbS Productions.

[22] J. Flynt. "11 Best Long Range Drones of 2019." https://3dinsider.com/long-range-drones/ (accessed September 12, 2019).