Improved Search Paths for Camera-Equipped UAVs in Wilderness Search and Rescue

Michael Pelosi
Department of Mathematics and Computer Science
East Central University
Ada, Oklahoma, USA
mpelosi@ecok.edu

Michael Scott Brown
ITEC Software Engineering
University of Maryland
University College
Adelphi, MD, USA
michael.brown@umuc.edu

***Abstract*—The goal of the performed research was to investigate potentially improved UAV Wilderness Search and Rescue [](WiSAR) search leg paths that attempt to maximize the weighted [](by terrain area) cumulative sum of Probability of Detections [](PODs) over segments of intervening terrain on consecutive search legs. Maximized POD values, as a consequence, increase the overall probability of success of a search. It is possible the application of the derived techniques can be extended and improved to include searching areas of interest for high value targets [](HVTs), searches for signs of improvised explosive devices [](IEDs), searches for activity in urbanized areas [](during, for example, MOUT), and for other types of generalized searches, such as search and rescue in combat areas [](CSAR), drug interdictions, and preventing border crossings.**

Keywords—UAV, WiSAR, A*, route-planning, probability of detection, high-value target, search theory, CSAR, MOUT, SRTM.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have been adopted by military and civilian organizations for use in many applications [1](Ermis, Hasircioglu, & Topcuoglu, 2008). Advances in guidance technologies enable many UAVs to execute missions independently of direct operator control [2](Feron, How, Schouwenaars, & Valenti, 2005). Some of these missions involve flight reconnaissance and search operations, and a route can be planned in advance of the mission using geographically referenced waypoint coordinates that include latitude, longitude, and true altitude . The UAV can then fly the assigned route independently in an automated fashion. Prolific recent research has endeavored to find more efficient and effective route planning methods for UAVs [3](Arévalo, de la Cruz, Pajares, & Ruz, 2007). More efficient routes have been demonstrated as being planned by using Mixed Integer Linear Programming (MILP) [4](Arévalo, de la Cruz, Pajares, & Ruz, 2006), the A* algorithm [5](Barber, Goodrich, Griffiths, & Quigley, 2005, p. 3), Evolutionary Algorithms [6](Andres-Toro, Besada-Portas, de la Cruz, Lopez-Orozco, & Torre-Cubillo, 2008; Nikolos, Tsourveloudis, & Valavanis, 2003), and several other techniques (such as in Heinze & Karim [7](2005)).

Efficient route planning normally involves finding a specific solution that aspires to achieve a certain goal, such as having the UAV avoid radar detection over the course of the route [8](Bulseco, 2005), finding the shortest route in terms of time traveled [9](Krishna, Mohan, Sawhney, & Srinathan, 2008), or conserving the maximum amount of fuel by taking advantage of prevailing winds [10](Nachmani, 2007). The subject of the research description that follows is one of planning more ideal routes in the use of camera-equipped UAVs for Wilderness Search and Rescue (WiSAR). WiSAR in itself is a complicated problem typically requiring thousands of hours of search over large and complex terrains [11](Adams et al., 2007).

By following search routes where a camera-equipped UAV is continuously in better positions and orientations to observe the respective terrain being searched, the Probability of Detection (POD) of the search object can be increased [12](Cooper & Goodrich, 2008, p. 5). As a consequence this increases Probability of Success (POS) in finding objects lost in wilderness terrain in accordance with Equation 1 [13](Cooper et al., 2003, p. 28) (where POC is equal to the Probability of Containment in a terrain area delimited by boundaries). The explicit goal of an intelligent search is to maximize POS, sometimes subject to a time constraint [14](Cooper et al., 2003, p. 28, 31).

$$POS = POC * POD \tag{1}$$

The described modified UAV flight routes are in contrast to standard linear "parallel sweep" and "spiral" search routes normally used for WiSAR. Standard linear sweep and spiral routes do not take into account variegated, non-uniform terrain and as a result, a UAV camera will not necessarily or intentionally often be in a more advantageous location and orientation to detect and recognize a search object along its flight path. Parallel sweep search routes were considered exclusively in the performed research as opposed to spiral or other route types, as these are most commonly used in the case of uniform probability containment areas [15](Ousingsawat, 2006) that were evaluated in the study. Spiral routes are commonly used in the case of point datums, where a search object is known or believed to have been lost in the vicinity of a specific location or position [16](Frost & Stone, 2001, p. 4-13 to 4-16). There are also other types of datums, such as line and generalized datums, see Frost [17](1996), pages 3-1 to 3-11 for more information.

978-1-5386-2726-6/17/$31.00

II. CURRENT WISAR PRACTICE

A common practice in WiSAR involving camera-equipped UAVs would be to route visually searching UAVs over parallel sweep search routes inside the search area boundaries (this area is often referred to as an "area of containment"). A typical parallel sweep search route is illustrated in Figure 1 [18](Frost, 1996).

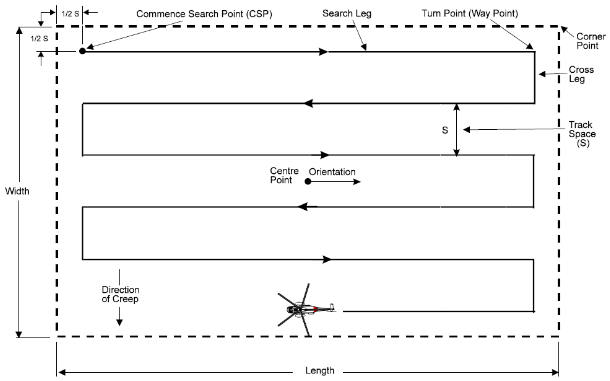

Fig. 1. Illustration of a typical parallel sweep search route plan [](Frost, 1996, p. 5-7).

Straight line search leg paths (at an assumed uniform altitude for aerial vehicles) are ideal for a maritime environment where the environment is consistently flat, homogenous, and relatively free of obstructions [19](O'Conner, 2004, p. 9). However, for inland searches visually intervening terrain and other obstacles play a large role in search success and will adversely impact POD, due to the fact that these surface inconsistencies can block visual lines of sight, and cause observation at awkward oblique angles [19](O'Conner, 2004, p. 4).

According to search theory, a visual POD of the search object can be calculated using an inverse cube function model. This model relies on the lateral (or direct) range in "sweep widths" from the searcher to the search object to derive a POD, as shown in Figure 2 [20](Frost, 2000). Effective sweep width (measured on the abscissa in Figure 2) is a measure of the effectiveness with which a particular sensor can detect a particular object under specific environmental conditions [21](Cooper et al., 2003).

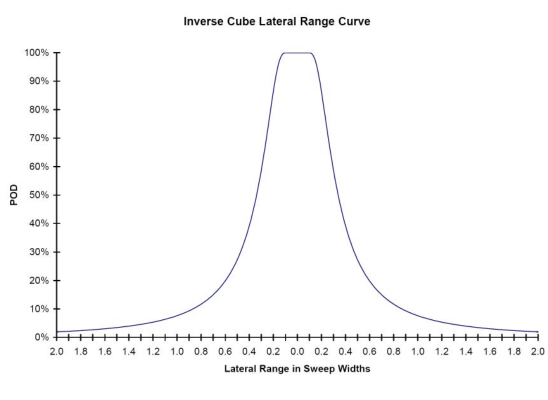

Fig. 2. The inverse cube lateral range curve function [](Frost, 2000, p. 55).

As a result, the lesser the distance of the observer to the search object at the time of a potential glimpse, the higher the corresponding POD. If at any time along a parallel sweep search leg, intervening terrain or other visual obstacles block a potential line-of-sight between the searcher and the search object, the POD at that time will be reduced much closer to zero. Therefore, in order to maximize the cumulative sum of PODs at various search locations over the length of consecutive search legs, an improved UAV camera path should attempt to reduce distance to the terrain being observed and also attempt to ameliorate the potential of intervening terrain and other objects to block lines-of-sight to the terrain under observation.

The hypothesis of the performed research was that resulting improved paths will not be straight lines, but paths that attempt to follow the various topographic hills, valleys, and folds of a terrain surface (and similarly elaborated on for helicopter contour search patterns on page 5-6 of the National Search and Rescue Committee's [22](2000) National Search and Rescue Supplement; this prospect is also hinted at in Adams et al. [23](2007)), as well as ones that avoid blockages of lines-of-sight to potentially observable areas. The path changes would be in order to more maximally exploit the usefulness of the UAV's camera detection abilities at all times. This approach resulted in a higher probability of search success for the same expenditure of search effort as the straight line technique (an extreme example of a contour search pattern is shown in Figure 3 as an intuitive example of optimizing a path to a specific contour). The problem of the research was to identify if the research hypothesis is true or false. Results are clearly measurable as positive changes in search POS values.

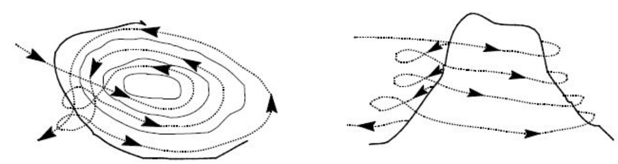

Fig. 3. An extreme example of a contour search pattern.

Source: The National Search and Rescue Supplement [24](2000), p. 5-7.

III. RESEARCH GOALS

The goal of the performed research was to investigate potentially improved UAV WiSAR search leg paths that attemptted to maximize the weighted (by terrain area) cumulative sum of PODs over segments of intervening terrain on consecutive search legs. Maximized POD values, as a consequence, increase the overall probability of success of a search as previously stipulated in Equation 1.

A comparison of search leg path techniques was implemented using a stochastic Monte Carlo simulation environment (similar to the work of Ayani & Kamrani [25](2007)) specifically created for the purpose of this research. The first technique investigated consisted of standard straight-line search leg paths at true and terrain-following altitudes. The second technique consisted of the previously described contour-aware search leg paths that take into consideration terrain elevations and visual obstacles. If one or more variations of the second technique resulted in an improved summation of calculated weighted POD over the terrain, and therefore a higher resulting POS, for the same overall UAV search effort (which can also be considered flight time if traveling at uniform speeds), it was be concluded that this technique can be an attractive alternative to straight-line search leg paths for UAVs involved in WiSAR. Findings can be conclusively demonstrated by repeated and statistically significant higher overall search success rates using the Monte Carlo simulation of searches in the described simulation environment.

Further, improved POS values can be proven analytically using search theory rather than simulation. If it can be shown that summation of PODs multiplied by terrain area segments over a total area of containment is increased over an alternative, POS will also increase in this situation [26](Cooper, 2004, p. 3). However, it should also be mentioned simulation is a better approach to investigating and maximizing the benefit of alternative search methods, since it is difficult or impossible to estimate the effects of changes in various path techniques using analytic equations [27](Frost, 2001) .

IV. Application

Pre-planned UAV flight paths using waypoints are becoming widely used in many applications, such as military targeting [28](Morales, 2003), radar counter-measures [29](Larson, Mears, & Pachter, 2005), search and rescue [30](Hedrick, Nguyen, & Ryan, 2005), aerial mapping [31](Luotsinen, 2004), and reconnaissance missions [32](Glinton, Okamoto, Owens, Scerri, & Sycara, 2007). Since the numbers of UAVs in usage are rapidly increasing, and are likely to continue increasing [33](Cocaud, 2006), research related to UAV flight paths is likely to be both useful and relevant in the future. The costs of fielding UAVs for many tasks is lower than that for manned vehicles, and has the added benefit of not putting a human pilot at risk [34](Beveridge, Richards, & Whitley, 2005). Therefore, demonstration of a technique for improved WiSAR search paths is likely to further reduce costs in an area where the vast majority of human searchers are volunteers [35](Cooper et al., 2003, p. 15), improve search efficiency, and be utilized in practice in the field with an increasing adoption. Obviously in the case of WiSAR, it will also save additional human lives by reducing successful search times and increasing successful search rates.

V. A Brief Review of the Literature

There is a tremendous amount of recent literature related to route planning for UAVs using various goals and techniques. Arévalo et al. [36](2006, 2007, 2008) developed methods that were used as a foundation for the performed research. Andres-Toro, Besada-Portas, de la Cruz, Lopez-Orozco, & Torre-Cubillo [37](2008) explicitly build upon the work of Arévalo et al. [38](2008) and developed an evolutionary path planner for UAVs in realistic environments. Ermis et al. [39](2008) developed on the notion of 3-D path planning for the navigation of unmanned vehicles by using evolutionary algorithms. Rubin & Vincent [40](2004) proffered a framework and analysis for cooperative search using UAV swarms. Implementation and flight test results of MILP-based UAV guidance is the subject of the Feron et al. [41](2005) paper. Ayani & Kamrani [42](2007) suggested a simulation-aided path planning method for UAVs. Their method uses Sequential Monte Carlo simulation. Path planning for UAVs for searches and other goals has also been demonstrated in the literature using Genetic Algorithms [43](Lamont & Russell, 2005), Dynamic Programming [44](Fernandez, Flint, & Kelton, 2008), Bayesian Updating [45](McCadden, 2008), Reactive Tabu Search [46](Bailey, Carlton, Moore, & Ryan, 1998), Evolving Cooperative Control [47](Barlow, Oh, & Smith, 2008), and additional methods not mentioned.

UAVs have also recently come under examination by researchers involved in WiSAR for use in improved searches. Adams et al. [48](2007) outlines task analysis and lessons from field trials of camera-equipped mini UAVs for wilderness search support. Hedrick et al. [49](2005) addressed hybrid control of UAV-assisted search and rescue. In an effort to reduce human workloads, Cooper & Goodrich [50](2008) investigated combining UAV and sensor operator roles in UAV-enabled visual search. Also, Barber et al. [51](2005) surveyed the problem of real-world searching with fixed-wing mini-UAVs. Further, Beard, Eldredge, Goodrich, Griffiths, & Quigley [52](2005) specifically targeted the issues and opportunities related to target acquisition, localization, and surveillance using a fixed-wing mini-UAV with a gimbal-mounted camera. However, to date there has been no known research relating UAV automated route planning to improving WiSAR comprehensive searches with the specific goal of improving camera position in relation to probability of detection for search objects.

There is a wide-reaching and robust base of research involving both UAV path planning and camera-assisted UAV searches for WiSAR. Many of the available facts, approaches, and methodologies have been drawn upon in attaining the aspirations of the performed research. The performed research combines documented aspects of UAV path planning with practical aspects of UAV WiSAR, and attempts to incrementally improve the efficiency of lost object searches over real-world terrain.

VI. Research Methodology

The route-planning approach followed for the performed research was be similar to that described by Arévalo et al. [53](including papers published in 2006, 2007, and 2008 ; and the no date webpage listed in the references section) in their papers on radar detection avoidance for UAVs. This approach utilizes the A* algorithm for route planning. However, instead of incorporating probability of radar detection into the cost function of the A* algorithm to find an improved path, utility of the relative UAV camera position and orientation were used in the cost function to induce the UAV to fly through improved camera positions and orientations. Improved camera positions and orientations are defined as those positions and orientations which increase overall POD over intervening terrain area on search leg routes.

The Arévalo et al. approach to the radar detection avoidance problem uses 3D path optimization in Euclidean space (see Figure 4 for a sample graphical solution). Path variables include the UAV's state, and include position, speed, and orientation. Path constraints are derived from a simple model of the UAV flight characteristics, including minimum turning radius, minimum and maximum flight speed, and maximum climb rate. The A* algorithm evaluation function uses cumulative distance from the path origin and a weighted value of the probability of radar detection as a movement cost, and Euclidean distance to the target as the heuristic value. The radar model produces a probability of detection based on a radar cross section value of the UAV. Euclidean 3D space is divided into an array of cells (with axes of x, y, and z as depicted in Figure 4), and a movement path is calculated through a series of cells. Cells can also be classified as obstacles, in which case movement though the cell is blocked. Possible movement between cells during path calculation is limited by the UAV flight characteristic model and variables. Radar detection risk in each cell is calculated during A* inter-cell movement evaluation, and the relative value is added (using a weighting factor) to the cumulative cost to reach that respective cell. As a result, the UAV movement is guided to cells with relatively lower radar detection risk, while at the same time satisfying flying characteristic constraints, and also attempting a least-distance traveled path.

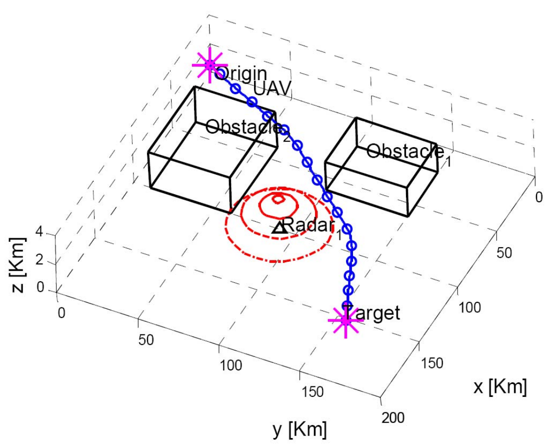

Fig. 4. Arévalo et al. [](2007) graphical solution for trajectory generation to avoid radar detection.

The performed research is similar to that described by Arévalo et al. in that a nearly identical model of 3D Euclidean space is used, UAV flight characteristics and constraints are included in the model, an optimized path is computed using the A* algorithm, cumulative distance is used as the movement cost, and Euclidean distance to a search leg end-point destination is used as the heuristic value. Where the approach differs is in the weighted additional cost added to the cumulative movement cost evaluation. Instead of using an additional weighted cost based on the risk of radar detection, the weighted additional cost is based on the comparative value of the UAV's camera position and orientation for terrain observation purposes. Favorable values incur lower costs. Also, the simulation environment that created will, similarly to the Arévalo et al. work, utilize terrain surface grid-squares with sample elevation data based on publicly available information.

Figure 5 illustrates the geometry and various distance measurements related to a UAV-mounted camera viewpoint. Point "O" is the location of the UAV. Point "A" is the location on the earth's surface the UAV is above. The absolute altitude of the UAV above the terrain (also known as "height-above-ground" (HAG) altitude [](Frost, 1996, p. 4-9) is exhibited by length "h". The angular height of the camera field-of-view is shown by angle "α". The angular width of the camera field-of-view is shown by angle "β". The height and width of the terrain surface visible in the field-of-view is indicated by lengths "a" and "b" respectively. The distance from the camera to the terrain visible at the base of the camera viewport is shown by length "s".

Figure 5 is included for the reason that it was used as a basis for the programmatic implementation of camera traversal modeling in the simulation environment. As the UAV moves forward, the rectangular camera "footprint" formed by width "b" and height "a" also moves forward to contain new terrain areas that may be at various slopes and orientations relative to the orientation of the camera viewport. If the UAV flight path rotates on the x, y, or z axis (or axes), the location, shape and size of the rectangle formed will change and cover new terrain areas. This is the geometric mathematical model approach that was used for camera movement. The research has endeavored to fully understand all the implications, both quantitative and qualitative, of camera viewport movement. The model is able to be manipulated while considering all potential implications of various movements on camera effectiveness.

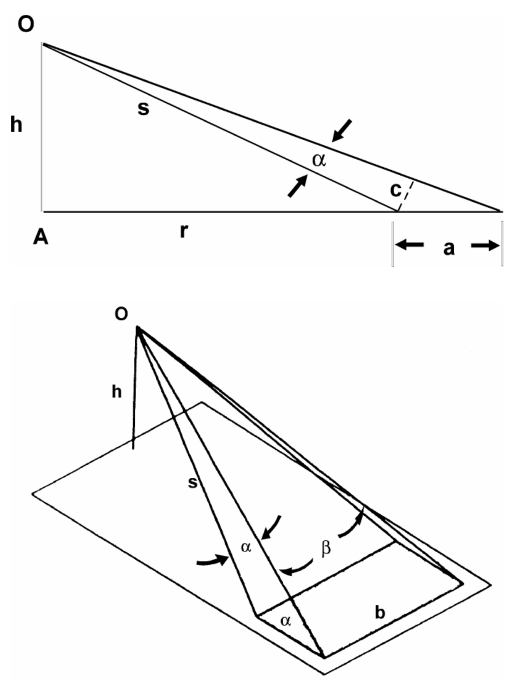

Fig. 5. UAV camera viewport geometry.

A metric was devised to calculate prospective utility of camera position and orientation. This metric takes into account POD of sections of the terrain area under observation, and total viewable terrain area.

The search problem formulation for purposes of simulation consisted of the following :

1. A uniform search object probability density distribution in the search area of containment.

2. An inverse cube visual detection function model.

3. The search object is passive [](one-sided search) and non-moving.

4. Searching does not guarantee detection.

The simulation environment terrain model consists of grid-squares divided at one hundred meter intervals. Terrain elevation data is matched to each grid-square vertice. Satellite photo orthoimagery is then superimposed on terrain areas and a map grid-square database is encoded with ground terrain type and vertically protruding terrain coverage. Path movement cells have a length and width of one hundred meters above the terrain surface, however the height of each cell is adjustable to allow consideration of various maximum UAV flight characteristic climb and descent rates.

In sum, the resulting performed search paths primarily attempt to minimize distances from the camera to the terrain visible in the camera viewport and maximize the width and height of the terrain visible in the viewport at all times. Resulting improvement are then able to be discerned through the simulation.

VII. Barriers and Issues

The primary task of the completed by the research was the creation of a simulation environment to test the various existing and performed search methods. It should be noted that in general practice, UAV camera footage is buffered or otherwise recorded and available at a ground station [54](Adams et al., 2007). This footage is available to sundry viewers at their convenience and leisure, and can be reviewed at various speeds or frame-by-frame. Hence, many of the negative effects of fast or sweeping camera movement by the UAV search path is greatly reduced in comparison to the benefit gained by well-planned systematic movement, even considering relatively fast and sharp movements.

Several foundational issues were addressed during the course of the research, with viable solutions, alternatives, and explanations offered for each as a result. Some are addressed or introduced as follows:

1. Camera operation during cross-leg traverses [](see Figure 1). It was be assumed the UAV camera is not operational during cross-leg traverses to simplify the search simulation. The camera was only considered to be operational during actual search legs. The effect of this turned out to be immaterial, as not only is the camera at a perpendicular angle to the search area, but search leg turn points will be outside the respective area of containment. This is to ensure thorough coverage of the search leg area by the camera at both the start and end of each search leg. Since camera angles tend to look forward and down from the UAV, this is an important consideration.

2. Establishing credible sweep width (W) values for various sensors (cameras), at various distances, under various environmental conditions, and of various search objects. The International Aeronautical and Maritime Search and Rescue Manual specifically categorizes and documents many of these measured or otherwise established values, and offers approaches for their calculation if not known. Listed values can be confidently and reliably used as conservative benchmarks in comparative simulations.

POD at various distance ranges can be calculated from published sweep widths according to the Equation 2 [](Frost, 2000) , where W is the effective sweep width and x is the distance in lateral sweep widths:

$$\mathbf{POD} = 1 - e^{-\frac{W^2}{4\pi x^2}} \quad (2)$$

Figure 6 illustrates some published effective sweep width examples.

		Visibility (km(NM))				
Search Object	**Height (m(ft))**	**6 (3)**	**9 (5)**	**19 (10)**	**28 (15)**	**37 (20)**
Person	150 (500)	0.7 (0.4)	0.7 (0.4)	0.9 (0.5)	0.9 (0.5)	0.9 (0.5)
	300 (1000)	0.7 (0.4)	0.7 (0.4)	0.9 (0.5)	0.9 (0.5)	0.9 (0.5)
	450 (1500)	--	--	--	--	--
	600 (2000)	--	--	--	--	--
Vehicle	150 (500)	1.7 (0.9)	2.4 (1.3)	2.4 (1.3)	2.4 (1.3)	2.4 (1.3)
	300 (1000)	1.9 (1.0)	2.6 (1.4)	2.6 (1.4)	2.8 (1.5)	2.8 (1.5)
	450 (1500)	1.9 (1.0)	2.6 (1.4)	3.1 (1.7)	3.1 (1.7)	3.1 (1.7)
	600 (2000)	1.9 (1.0)	2.8 (1.5)	3.7 (2.0)	3.7 (2.0)	3.7 (2.0)
Aircraft less than 5700 kg	150 (500)	1.9 (1.0)	2.6 (1.4)	2.6 (1.4)	2.6 (1.4)	2.6 (1.4)
	300 (1000)	1.9 (1.0)	2.8 (1.5)	2.8 (1.5)	3.0 (1.6)	3.0 (1.6)
	450 (1500)	1.9 (1.0)	2.8 (1.5)	3.3 (1.8)	3.3 (1.8)	3.3 (1.8)
	600 (2000)	1.9 (1.0)	3.0 (1.6)	3.7 (2.0)	3.7 (2.0)	3.7 (2.0)
Aircraft over 5700 kg	150 (500)	2.2 (1.2)	3.7 (2.0)	4.1 (2.2)	4.1 (2.2)	4.1 (2.2)
	300 (1000)	3.3 (1.8)	5.0 (2.7)	5.6 (3.0)	5.6 (3.0)	5.6 (3.0)
	450 (1500)	3.7 (2.0)	5.2 (2.8)	5.9 (3.2)	5.9 (3.2)	5.9 (3.2)
	600 (2000)	4.1 (2.2)	5.2 (2.9)	6.5 (3.5)	6.5 (3.5)	6.5 (3.5)

Table N-9 - Sweep widths for visual land search (km (NM)).

Search Object	**15-60% Vegetation or Hilly**	**60-85% Vegetation or Mountainous**	**Over 85% Vegetation**
Person	0.5	0.3	0.1
Vehicle	0.7	0.4	0.1
Aircraft less than 5700 kg	0.7	0.4	0.1
Aircraft over 5700 kg	0.8	0.4	0.1

Table N-10 - Correction factors - vegetation and high terrain.

Search Object	**Terrain**	**Recommended Altitudes**
Person, light aircraft	Moderate Terrain	60-150 m (200-500 ft)
Large aircraft	Moderate Terrain	120-300 m (400-1000 ft)
Person, one-person raft, light aircraft	Water or Flat Terrain	60-150 m (200-500 ft)
Medium-sized liferaft and aircraft	Water or Flat Terrain	300-900 m (1000-3000 ft)
Pyrotechnical signal at night	Night	450-900 m (1500-3000 ft)
Medium-sized aircraft	Mountainous Terrain	150-300 m (500-1000 ft)

Table N-11 - Recommended altitudes according to nature of search object and terrain.

IAMSAR_TablesN9-10-11.p65 - DCC (1 Sept 2000)

Fig. 6. IAMSAR Manual, Volume II, sample recommend sweep width values and terrain correction factors for aircraft searching over land with parallel sweeps.

3. The issue of terrain cover. Natural and man-made terrain cover such as trees, woods, forests, jungle, low-grass, high grass, rocks, and buildings, will decrease overall POD values in terrain areas in contrast to similar terrain with little or no vertically protruding terrain cover such as clear areas or areas with roadways. Likely values and effects, and specific POD percentage degradation values for various terrain and terrain cover types, are adequately documented and many are offered in the International Aeronautical and Maritime Search and

Rescue Manual, among others. As mentioned, terrain cover for terrain area grid-cells can be estimated by satellite photos of areas under simulation. As a result, the path simulation model attempts to include the effects of terrain cover on POD values. In certain cases, areas with high terrain cover are better searched by ground teams as opposed to aerial observation to improve search efficiency (National Search and Rescue Committee [](2000) , as some ground areas simply cannot be seen from the air due to the forest density or similar visual obstacle congestion. Aerial search is highly recommended as being very efficient for areas with little or no terrain cover [55](U. S. Army, 2008) .

4. The creation of a theoretically credible and practicable metric to gauge the relative merit of camera position and orientation over terrain in relation to other positions and orientations. As an example of one possible approach, the projection of the viewable area in the camera viewport can be transposed into a rectangular area onto the visible terrain (the rectangular area encompassed by length and width of "a" and "b" as shown in Figure 5). This area can be sub-divided into regions by a factor of one hundred. PODs in various regions could then be calculated based on the distance to the camera from each sub-area region (which could then also be adjusted by a coefficient factor that considers terrain cover, such as trees), and multiplied by the respective terrain area length and width to create a weighted value. Resulting sub-area values could then be summed to create an overall value of terrain area multiplied by adjusted region PODs. This technique was then be further enhanced and changed to include line-of-sight blockages and other qualifications or constraints. There are many possible approaches and Ousingsawat [](2006) also offers some guidance in this regard.

5. The issue of observing the same terrain two or more times along a search leg path. Search theory consistent with Bayes' Rule [56](Bownds et al., 1981) indicates observing the same terrain consecutive times will improve POD for that area as according to Equation 3 (any increase in value also has the characteristic of only a diminishing return on each consecutive pass). Any movement algorithm will have to consider this important fact. It was possible terrain previously observed be flagged and penalized to some extent in regard to further visits and this was implemented in the A* prospective movement cost function using a weighting factor.

$$POD_{cum} = 1-(1-POD_a)(1-POD_b)(1-POD_c)...(1-POD_m) \quad (3)$$

In Equation 3, PODa...m represents the POD values for each search up to m searches (complete passes over the segment).

6. Neighboring search leg path visibility. In certain areas along the search path, the camera may be in an ideal position to observe terrain within in a previous or subsequent search leg terrain boundary area. An approach to maximizing the benefit of this effect, while attempting prevent or mitigate the effects of repeated terrain visits while on neighboring legs, was developed. This involved the flagging of individual terrain areas as having been previously visited in advance.

7. Experimentation with the camera utility cost-weighting factors. Since the performed implementation of the A* involved in this study had as a primary goal the attempt to minimize the distance of the path traveled between search leg start and end points, the additional camera utility cost function received secondary emphasis in relation to a weighting factor. In progression with the empirical results and the exploration of success in relation to various search scenarios, the value of the weighting was experimented with. An attempt to develop a heuristic or analytical approach to determining ideal weighting factors presenting the most likely search success under various conditions was made.

8. Confirming the benefit of, or offering an alternative to, theoretically-optimal Track Space (TS) distances (see Figure 1; also a basis for deviation is indicated in Footnote 7). Search theory posits optimal TS distances in homogenous, idealized terrain. This distance is the search sensor sweep width. However, on terrain that can include areas with higher and lower overall PODs (for example, wooded or heavily forested areas will have much lower PODs than clear terrain for aerial searches), a heuristic or analytical approach can be shown to yield better results than the theoretical TS distance and improve likely values for POS.

9. Evaluating the enhanced effects of gimbaled camera movement and zoom lenses. Many UAV cameras are now equipped with gimbaled mounts and possibly zoom lenses capable of remote control [57](Beard et al., 2005). These features make it possible to improve relative camera field-of-view and corresponding POD values. It was possible to include in the path movement routines a further enhancement for optimizing camera gimbal angles and zoom magnification at various pre-planned locations along the path.

VIII. RESOURCES USED

Elevation data from the Shuttle Radar Topography Mission (SRTM90) was used to construct three-dimensional terrain models of areas likely to be involved in WiSAR. This information is available for download from the U. S. Geological Survey website. SRTM90 data is available in geographically referenced terrain elevation cells nominally spaced at 90-meter intervals. This data is easily interpolated into consistent 100-meter per side grid-squares. The data is available for almost all of the populated world, including U. S. national parks and other remote areas often the subject of WiSAR.

Satellite photo orthoimagery is available and was overlaid upon terrain elevation data grid-square areas in order to determine individual terrain cell's estimated terrain cover values. Several terrain models have been constructed with various typical types of topography and terrain, such as mountains, deserts, forested areas, jungles, and relatively clear or flat areas, in order to run tests under various conditions. The terrain models constructed were used with Monte Carlo simulation of UAV flight paths to derive comparative search successes in relation to randomly placed search objects based on path-sequential POD values. If a random number is less than or equal to the calculated POD while the search object is within the camera field-of-view, the search immediately concludes with success.

IX. Results and Conclusion

The work of Arévalo et al. was duplicated and extended to the field of WiSAR searches. Arévalo et al. devised an approach using the A* algorithm to route UAVs over areas while attempting to avoid radar detection. The performed research uses the same approach, however, it substitutes into the cost function of movement UAV camera positional utility instead of radar detection probability. In the performed modifications, more advantageous camera positions have lower movement costs attached to them.

It has been shown the result of this technique is improved UAV search routes over wilderness terrain to find search objects, which will be in contrast to standard straight line search legs at fixed absolute or true altitudes. Various strategies for search routes [](including standard and modified versions) are compared using simulation and the results documented. Search improvement noted from the simulation results show increased POS from identical search effort.

[1] Adams, J. A., Cooper, J. L., Goodrich, M. A., Humphrey, C., Quigley, M., Buss, B. G., & Morse, B. S. [](2007). Camera-equipped mini UAVs for wilderness search support: Task analysis and lessons from field trials [](BYUHCMI Tech. Rep. 2007-1). Provo, UT: Brigham Young University.

[2] Barlow, G. J., Oh, C. K., & Smith, S. F. [](2008). Evolving cooperative control on sparsely distributed tasks for UAV teams without global communication. In M. Keijzer [](Ed.), Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation [](pp. 177–184). New York: ACM.

[3] Bownds, J., Loveloch, D., McHugh, C., & Wright, A. [](1981). Desert searches: The effectiveness of helicopters. Retrieved October 11, 2008, from http://www .math.arizona.edu/~dsl/casie/helicop.htm

[4] Bulseco, J. D. [](2005). Controlling sideslip angle to reduce the radar exposure of a tactical, rotary winged UAV. Wright-Patterson Air Force Base, OH.: Air Force Institute of Technology.

[5] Cocaud, C. [](2006). Autonomous tasks allocation and path generation of UAVs. Unpublished doctoral dissertation, Ottawa, ON: University of Ottawa.

[6] Cooper, D. C., & Frost, J. R. [](2004). Sweep width estimation for ground search and rescue. Washington, DC: Potomac Management Group.

[7] Cooper, D. C., Frost, J. R., & Robe, R. Q. [](2003). Compatibility of Land SAR procedures with search theory. Washington, DC: U.S. Dept. of Homeland Security.

[8] Cooper, J., & Goodrich, M. A. [](2008). Towards combining UAV and sensor operator roles in UAV-enabled visual search. In Proceedings of the 3rd ACM/IEEE International Conference on Human Robot Interaction [](pp. 351–358). New York: ACM.

[9] De la Cruz, J. M., Besada-Portas, E., Torre-Cubillo, L., Andres-Toro, B., & Lopez-Orozco, J. A. [](2008). Evolutionary path planner for UAVs in realistic environments. In M. Keijzer [](Ed.), Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation [](pp. 1477–1484). New York: ACM.

[10] Flint, M., Fernandez, E., & Kelton, W. D. [](in press). Simulation analysis for UAV search algorithm design using approximate dynamic programming. Military Operations Research.

[11] Frost, J. R. [](in press). Interpreting negative search results. Advanced Rescue Technology.

[12] Frost, J. R. [](1996). The theory of search. Washington, DC: Soza & Company, Ltd.

[13] Frost, J. R. [](2000). An evaluation of some inland search POD experiments. Alexandria VA: IAMSAR Associates.

[14] Frost, J. R. [](2008). SAROPS: Search and Rescue Optimal Planning System. Retrieved October 11, 2008, from http:// www.alidade.net/2005/search5/presentations/ ST05_Frost_SAROPS.ppt

[15] Frost, J. R. [](2001). Review of search theory: advances and applications to search and rescue decision support. Washington, DC: U. S. Department of Transportation.

[16] Hasircioglu, I., Topcuoglu, H. R., & Ermis, M. [](2008). 3-D path planning for the navigation of unmanned aerial vehicles by using evolutionary algorithms. In M. Keijzer [](Ed.), Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation [](pp. 1499–1506). New York: ACM.

[17] Ingeniería de Sistemas y Automática. [](2007). Evaluación de técnicas de inteligencia artificial para toma de decisiones y optimización de estrategias con UAVs [Planification, simulation and control platform for collaborative unmanned air vehicles [](UAVS)]. Universidad Complutense de Madrid. Retrieved October 11, 2008, from http://www.dacya.ucm.es/area-isa/esp/proyects/UAVs/principal.htm

[18] International Aeronautical and Maritime Search and Rescue Manual [](IAMSAR Manual, 1999)published jointly by the International Maritime Organization and the International Civil Aviation Organization.

[19] Kamrani, F., & Ayani, R. [](2007). Using on-line simulation for adaptive path planning of UAVs. In Proceedings of the 11th IEEE international Symposium on Distributed Simulation and Real-Time Applications [](pp. 167–174). Washington, DC: IEEE Computer Society.

[20] Karim, S., & Heinze, C. [](2005). Experiences with the design and implementation of an agent-based autonomous UAV controller. In Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems [](pp. 19–26). Utrecht, the Netherlands: ACM.

[21] Larson, R. A., Pachter, M., & Mears, M. J. [](2005, August). Path planning by unmanned air vehicles for engaging an integrated radar network. Paper presented at the meeting of the AIAA Guidance, Navigation, and Control Conference and Exhibit, San Francisco, California.

[22] Luotsinen, L. J. [](2004). Autonomous environmental mapping in multi-agent UAV systems. Unpublished doctoral dissertation, University of Florida, Orlando.

[23] McCadden, K. K. [](2008). Allocation of UAV search efforts using dynamic programming and Bayesian updating. Monterey, CA: Naval Postgraduate School.

[24] Morales, D. M. [](2005). The effects of target location uncertainty in game theoretic solutions to optimal trajectory formulations. Unpublished doctoral dissertation, Cambridge, MA: Massachusetts Institute of Technology.

[25] Nachmani, G. [](2007). Minimum-energy flight paths for UAVs using mesoscale wind forecasts and approximate dynamic programming. Unpublished doctoral dissertation, Naval Postgraduate School, Monterey, CA.

[26] National Search and Rescue Committee. [](2000). United States national search and rescue supplement to the international aeronautical and maritime search and rescue manual. Washington, DC: NSARC.

[27] Nikolos, Y., Tsourveloudis, N., & Valavanis, K. P. [](2001). Evolutionary algorithm based 3-D path planner for UAV navigation. In Proceedings of the 9th IEEE Mediterranean Conference on Control and Automation. Washington, DC: IEEE Computer Society.

[28] O'Conner, D. [](2004). Controversial topics in inland SAR planning. Needham, MA: Northeast Wilderness Search and Rescue.

[29] Office of Search and Rescue, U. S. Coast Guard [](1996). The theory of search. Washington, DC: Soza & Company, Ltd.

[30] Ousingsawat, J. [](2006, October). UAV path planning for maximum coverage surveillance of area with different priorities. Paper presented at the 20th Conference of Mechanical Engineering Network of Thailand, Nakhon Ratchasima, Thailand.

[31] Pajares, G., Ruz, J. J., Lanillos, P., Guijarro, M., de la Cruz, J. M., & Santos, M. [](2008) Generación de Trayectorias y Toma de Decisiones

para UAVs. Revista Iberoamericana de Automática e Informática Industrial, 5(1), 83–92.

[32] Quigley, M., Barber, B., Griffiths, S., & Goodrich, M. A. [](2005). Towards real-world searching with fixed-wing mini-UAVs. In Proceedings of the 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems. Washington, DC: IEEE Computer Society.

[33] Quigley, M., Goodrich, M. A., Griffiths, S., Eldredge, A., & Beard, R. W. [](2005). Target acquisition, localization, and surveillance using a fixed-wing mini-UAV and gimbaled camera. In Proceedings of the IEEE International Conference on Robotics and Automation. Washington, DC: IEEE Computer Society.

[34] Richards, M. D., Whitley, D., Beveridge, J. R., Mytkowicz, T., Nguyen, D., & Rome, D. [](2005). Evolving cooperative strategies for UAV teams. In H. Beyer [](Ed.) Proceedings of the 2005 Conference on Genetic and Evolutionary Computation [](pp. 1721–1728). New York: ACM.

[35] Russell, M. A., & Lamont, G. B. [](2005). A genetic algorithm for unmanned aerial vehicle routing. In H. Beyer [](Ed.), Proceedings of the 2005 Conference on Genetic and Evolutionary Computation [](pp. 1523–1530). New York: ACM.

[36] Ruz, J. J., Arévalo, O., de la Cruz, J. M., & Pajares, G. [](2006). Using MILP for UAVs trajectory optimization under radar detection risk. In Proceedings of the 11th IEEE International Conference on Emerging Technologies and Factory Automation [](pp. 957–960). Washington, DC: IEEE Computer Society.

[37] Ruz, J. J., Arévalo, O., Pajares, G., & de la Cruz, J. M. [](2007). Decision making among alternative routes for UAVs in dynamic environments. In Proceedings of the 12th IEEE International Conference on Emerging Technologies and Factory Automation [](pp. 997–1004). Washington, DC: IEEE Computer Society.

[38] Ryan, A. D., Nguyen, D. L., & Hedrick, J. K. [](2005, November). Hybrid control for UAV-assisted search and rescue. Paper presented at the ASME International Mechanical Engineering Congress and Exposition, Orlando, FL.

[39] Ryan, J. L., Bailey, T. G., Moore, J. T., & Carlton, W. B. [](1998). Reactive tabu search in unmanned aerial reconnaissance simulations. In D. J. Medeiros, E. F. Watson, J. S. Carson, & M. S. Manivannan [](Eds.), Proceedings of the 30th Conference on Winter Simulation [](pp. 873–880). Washington, DC: IEEE Computer Society.

[40] Sawhney, R., Krishna, K. M., Srinathan, K., & Mohan, M. [](2008). On reduced time fault tolerant paths for multiple UAVs covering a hostile terrain. Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems, 3, 1171–1174.

[41] Scerri, P., Glinton, R., Owens, S., Okamoto, S., & Sycara, K. [](2007). Locating RF emitters with large UAV teams. In Proceedings of the 6th international Joint Conference on Autonomous Agents and Multiagent Systems [](pp. 1–3). New York: ACM.

[42] Schouwenaars, T., Valenti, M., Feron, E., & How, J. P. [](2005). Implementation and flight test results of MILP-based UAV guidance, In Proceedings of the IEEE Aerospace Conference [](pp. 1–13). New York: IEEE.

[43] U.S. Army. [](2006). FMI 3-04.155 Army unmanned aircraft system operations. Field Manual Interim, 4-4. Washington, DC: Author.

[44] Vincent, P. & Rubin, I. [](2004). A framework and analysis for cooperative search using UAV swarms. In Proceedings of the 2004 ACM Symposium on Applied Computing [](pp. 79–86). New York: ACM.

[45] Wikipedia. [](2017). Satisficing. Retrieved September 2, 2016, from http://en.wikipedia.org/wiki/Satisficing