FIELD REPORT

Supporting Wilderness Search and Rescue using a Camera-Equipped Mini UAV

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Wilderness Search and Rescue (WiSAR) entails searching over large regions in often rugged remote areas. Because of the large regions and potentially limited mobility of ground searchers, WiSAR is an ideal application for using small (human-packable) unmanned aerial vehicles (UAVs) to provide aerial imagery of the search region. This paper presents a brief analysis of the WiSAR problem with emphasis on practical aspects of visual-based aerial search. As part of this analysis, we present and analyze a generalized contour search algorithm, and relate this search to existing coverage searches. Extending beyond laboratory analysis, lessons from field trials with search and rescue personnel indicated the immediate need to improve two aspects of UAV-enabled search: How video information is presented to searchers and how UAV technology is integrated into existing WiSAR teams. In response to the first need, three computer vision algorithms for improving video display presentation are compared; results indicate that constructing temporally localized image mosaics is more useful than stabilizing video imagery. In response to the second need, a goal-directed task analysis of the WiSAR domain was conducted and combined with field observations to identify operational paradigms and field tactics for coordinating the UAV operator, the payload operator, the mission manager, and ground searchers. © 2008 Wiley Periodicals, Inc.

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1. INTRODUCTION

Wilderness search and rescue (WiSAR) operations include finding and providing assistance to humans who are lost or injured in mountains, deserts, lakes, rivers, or other remote settings. WiSAR is a challenging task that requires individuals with specialized training. These searches, which consume thousands of man-hours and hundreds of thousands of dollars per year in Utah alone (Utah County, 2007), are often very slow because of the large distances and challenging terrain that must be searched. Moreover, the search timeliness is critical; for every hour that passes, the search radius must increase by approximately 3 km,[1] and the probability of finding and successfully aiding the victim decreases.

The goal of this work is to develop a camera-equipped mini unmanned aerial vehicle (UAV)[2] that can be used by WiSAR personnel to improve both the probability that missing persons will be found and the speed with which they are found. We begin by presenting a brief analysis of the WiSAR problem with an emphasis on practical aspects of search. A key contribution of this analysis is the generalized contour search, which includes the spiral and "lawnmower" search as special cases. Extending this analysis with lessons from a series of field tests, two important areas were identified that need to be addressed before a UAV can be deployed in practical searches; improved presentation of video information and integration into the WiSAR process. The remainder of the paper addresses these two needs. Throughout the paper, we rely on observations from search trials, input from volunteers and subject matter experts from Utah County Search and Rescue, and experiments with human participants.

2. RELATED LITERATURE AND PREVIOUS WORK

There is a great deal of current research dealing with the human factors of semi-autonomous UAVs (HFUAV, 2004; Cooke, Pringle, Pederson & Connor, 2006). Toward applying human factors analysis to UAV-assisted WiSAR, this paper uses results from a goal-directed task analysis (Endsley, Bolte & Jones, 2003). Cognitive work analysis is a complementary analysis approach that yields different types of information (Vicenti, 1999; Cummings, 2003); a cognitive work analysis was also conducted for this application, and the results from this analysis are available in a technical report (Goodrich et al., 2007b).

A key human-factors consideration when using UAVs in WiSAR is the number of humans required to operate the vehicle. Typically, a UAV engaged in a search task requires either two operators or a single operator to fill two roles: A pilot, who "flies" the UAV, and a sensor operator, who interprets the imagery and other sensors (Tao, Tharp, Zhang & Tai, 1999). Lessons from ground robots suggest that it is sometimes useful to include a third person to monitor the behavior of the pilot and sensor operators, to protect these operators, and to facilitate greater situation awareness (Burke & Murphy, 2004; Casper & Murphy, 2003; and Drury, Scholtz & Yanco, 2003). Important work has analyzed how many unmanned platforms a single human can manage (Olsen Jr. & Wood, 2004; Hancock, Mouloua, Gilson, Szalma & Oron-Gilad, 2006; Cummings, 2003). Although there is no certain conclusion coming from this work, it is apparent that the span of human control is limited so that, for example, it would be difficult to monitor information-rich video streams from multiple UAVs at once, though it is possible to coordinate multiple UAVs a la air traffic control (Miller, Funk, Dorneich & Whitlow, 2002; Mitchell & Cummings, 2005). Although an important issue, using multiple UAVs to perform a WiSAR task is beyond the scope of this paper.

We explore how autonomous information acquisition and enhanced information presentation can potentially simplify the pilot and sensor operator roles. The goal is to support fielded missions in the spirit of Murphy's work (Burke & Murphy, 2004; Casper & Murphy, 2003), but to focus on different hardware and operator interface designs in an effort to complement and extend existing designs. Higher levels of autonomy, which can help reduce the number of humans required to perform a task, include path-generation and path-following algorithms, and lower levels include attitude and altitude stabilization (Quigley, Goodrich & Beard, 2004).

In the WiSAR domain, literature related to aerial search is particularly relevant (Koopman, 1980; Bourgault, Furukawa & Durrant-Whyte, 2003). Recent work includes the evaluation of three heuristic algorithms for searching an environment characterized by

[1]This assumes a nominal 3 km/h walking pace for the average missing person.

[2]Mini UAVs have wingspans in the 2–8 ft range. Unless otherwise stated, this paper uses the term "UAV" to mean mini-UAV.

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a probabilistic description of the person's likely location (Hansen, McLain & Goodrich, 2007). Additional literature includes operator interface work for both UAVs and traditional aviation displays (Calhoun, Draper, Abernathy, Patzek & Delgado, 2003; Prinzel, Glaab, Kramer & Arthur, 2004; Alexander & Wickens, 2005; Drury, Richer, Rackliffe & Goodrich, 2006; Wickens, Olmos, Chud & Davenport, 1995). The exact type of interaction between a human and onboard autonomy varies widely across UAV platforms. At one extreme, the Predator UAV, operated by the United States Air Force, essentially recreates a traditional cockpit inside a ground-based control station, complete with stick-and-rudder controls. At the other extreme are architectures employed by research UAVs that follow specific, preprogrammed flight paths for such applications as the precise collection of atmospheric composition data (Goetzendorf-Grabowski, Frydrychewicz, Goraj & Suchodolski, 2006). The interactions represented by these two extremes typify the extreme points of several adjustable autonomy scales (Sheridan & Verplank, 1978; Kaber & Endsley, 2004; Parasuraman, Sheridan & Wickens 2000). The presented work uses altitude, attitude, and direction control algorithms, as well as the ability to autonomously travel to a series of waypoints. Thus, this work is between the extremes of teleoperation and supervisory control.

The presented work is limited to fixed-wing UAVs. Rotocraft UAVs provide the ability to hover and perform vertical take-off and landing—features that have made them attractive in many search domains (Whalley et al., 2003; Murphy, Stover, Pratt & Griffin, 2006). State of the art fixed-wing UAVs allow longer flight times for a given UAV mass, largely because fixed-wing UAVs are more efficient. Many fixed-wing UAVs compensate for the inability to hover by using a gimballed camera that allows them to focus on a fixed point on the ground even as the UAV circles. This paper employs a fixed-wing UAV because it is light, affordable, and can stay aloft for a long enough period of time to cover reasonable search distances.

3. PRACTICAL ASPECTS OF VISUAL-BASED AERIAL SEARCH: FRAMING AND ANALYSIS

This section begins by describing the UAV platform and autonomy used in field trials. We then frame the visual-based aerial search problem using a Bayesian perspective and identify the two obligations of effective search: coverage and detection. Constraints on detectability translate into practical constraints on the height above ground at which the UAV flies. Considerations of coverage lead to a generalized contour search, which includes spiral and lawnmower search patterns as special cases. Lessons from field trials are presented that indicate that two capabilities were not identified in the analysis: (a) the need to effectively present video information, and (b) the need to coordinate the UAV with ground searchers.

3.1. The Platform

The experimental UAVs used in this work are small and light, with most having wingspans of approximately 42–50 in. and flying weights of approximately 2 lbs (see Figure 1(a)). The airframes are derived from flying wing designs and are propelled by standard electric motors powered by lithium batteries. It was concluded from preliminary discussions with Utah County Search and Rescue that at least 90 min of flight time was required for a reasonable search, so the BYU MAGICC lab created a custom airframe capable of staying aloft for up to 120 min while supporting an avionics sensor suite, a gimballed camera, and an autopilot.

The standard aircraft sensor suite includes three-axis rate gyroscopes, three-axis accelerometers, static and differential barometric pressure sensors, a global positioning system module, and a video camera on a gimballed mount. The UAV uses a 900 MHz radio transceiver for data communication and an analog 2.4 GHz transmitter for video downlink. The autopilot is built on a small microprocessor, and is described in Beard et al. 2005. We adopt the hierarchal control system, described in Beard et al., 2005, in order to reduce the risks associated with automony while still taking advantage of autonomy's benefits. The UAVs are equipped with autopilot algorithms that stabilize the aircraft's roll and pitch angles, attitude stabilization, altitude controller, and ability to fly to a waypoint.

3.2. A Bayesian Framing: Coverage and Detection

Search is the process of removing uncertainty regarding the probable location of a missing person. Uncertainty is removed by identifying such things as the point last seen (PLS) and the direction of travel, by finding signs that a missing person has

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(a) The 5' UAV. (b) Complete Camera Frame (c) Close-up of Portion Containing the missing person

Figure 1. Aerial photograph taken of a mock missing person to show the maximal sweep width of the UAV with a standard NTSC video camera.

recently been in an area, or by "covering" an area without finding a sign. Let s denote a cell state in a discretized version of the earth's surface in an area of interest, and let S denote the set of all such states. The search outcome assigns each state to one of the following sets: a sign of the missing person, no sign (nominal), or unexplored. Formally, the classification process, c, is a partitioning of the state space, $c: S \mapsto \{\text{sign}, \text{nominal}, \text{unexplored}\}$. Although denoted simply as sign, a sign includes labeling information such as a color, time stamp, etc. The classification map, m^c, is the set of classified states: $m^c = \{c(s): s \in S\}$.

The classification map is constructed by taking environmental observations, o, and using these observations to construct m^c. The map is a representation of the entire search region, but observations are localized to what is visible by the UAV camera, which is controlled by the pose of the UAV and its camera. We represent this pose using the state variable x_t. Although automated target recognition technologies exist, this analysis is limited to observations made by a human from the UAV's video stream. Such observations can include different types of information at different resolution levels:

- Location: "over there," "something interesting a few frames ago," "by the trail," GPS location (from triangulation), etc.
- Label: color, object name, brightness, "something unusual," etc.

We can represent the relationship between the classification map at time t, a series of observations, $\mathbf{o}_{t:1} = o_t, o_{t-1}, \ldots, o_1$, and the UAV/camera pose, $\mathbf{x}_{t:1} = x_t, x_{t-1}, \ldots, x_1$, as $p(m_t^c | \mathbf{o}_{t:1}; \mathbf{x}_{t:1})$. Given that UAVs operate outdoors and are equipped with a sensor suite, we can assume that GPS coordinates and pose information are available. In practice, this is not entirely perfect, but it is good enough for this analysis.

The objective of UAV-enabled search is to accumulate observations in order to make the posterior estimate of the classification map as accurate as possible. In terms of creating the posterior classification map given the observations, this problem is known as "mapping with known poses," as described in Thrun, Burgard & Fox, 2005. When one uses Bayes law and makes standard independence assumptions (Thrun et al., 2005; Bourgault et al., 2003; Koopman 1980), the posterior probability becomes

$$p(m_t^c | \mathbf{o}_{t:1}; \mathbf{x}_{t:1}) \propto p(o_t | m_t^c; x_t) p(m_t^c | \mathbf{o}_{t-1:1}; \mathbf{x}_{t:1}). \qquad (1)$$

Therefore, the posterior probability of the classification map given the observations is proportional to the product of the likelihood of making the observation given the map and the probability of a predicted map given previous observations and poses.

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The likelihood[3] represents the probability that a sign will be detected if it is present, and the predicted map represents the probability that we will cover the correct area of the world. Thus, the Bayesian framing of the problem allows us to identify the two key elements of effective search: detection and coverage.

There is a tension between these two objectives. This is illustrated by observing, for example, that it is possible to cover ground completely but so quickly that no signs are actually detected by people watching the video. Conversely, it is possible to ensure that almost every sign sensed by the camera is always detected but move so slowly that coverage takes an unacceptable amount of time. Finding a workable tradeoff between coverage and detection requires careful analysis and field practice to discover ways to minimize the expected amount of time required to find the missing person.

The remainder of this section presents results that relate to finding a workable tradeoff. Practically speaking, detection constrains the UAV's pose so that observations accurately reflect the presence or absence of signs. The next subsection sets a practical ceiling on the height above ground to ensure an acceptable likelihood of correct detection. Practically speaking again, coverage implies that x_t should be chosen to maximize the benefit to the posterior probability. Generalized contour search is an approach to performing efficient search that includes two important search tactics as special cases.

3.3. Detection: Practical Constraints on Height Above Ground

The previous subsection identified the detection probability, $p(o_t|m_t^c)$, as a key factor in the search effectiveness. This subsection translates this probability into a practical constraint on how high the UAV can fly. The UAVs for this work use NTSC[4] video cameras that capture approximately 200,000 pixels. Figure 1(b) shows a missing person in a video frame captured by a microvideo camera on a UAV. The image was digitized at 640×480 resolution and the missing person is 40 pixels tall.

The portion of the image containing the missing person is magnified and shown in Figure 1(c). As illustrated, the human form is on the border of recognition; the color of the clothing is primarily what allows the form to be recognized, and if fewer pixels are devoted to the missing person or the clothing color is less detectable, recognition can become extremely difficult. If Figure 1(c) is taken as the fewest pixels possible that enable recognition of a human form, the minimal resolution of the image must be 5 cm per pixel. This means that each image can cover an area no wider than 32 m wide$\times$24 m tall.

We can translate information from this image into a practical constraint for the particular camera and UAV used in the field trials. Given the camera's field of view, the constraint on detecting a human shape implies that the UAV should fly no higher than 60 m above the ground. Flying lower is unsafe, given wind currents. If the requirement to detect a human form is abandoned, then flying higher is possible, but the UAV must still be low enough to detect unusual colors from clothing, man-made objects, etc. Flight tests suggest that colors of human-sized objects are difficult to perceive if the UAV flies higher than 100 m. Thus, the operational maximum height above ground for this work is between 60 m and 100 m.

We can translate the probable size of objects into design guidelines for other UAVs and other cameras. Observe that the practical height above ground from the previous paragraph is insufficient for detecting small signs of the missing person, such as discarded food wrappers. This limitation can be overcome, to some extent, by using a camera with a narrower field of view. Indeed, for a fixed pixel resolution on the ground, the allowable height above ground grows as $1/\tan(\theta/2)$, where θ is the camera's field of view. However, using a narrower field of view means that (a) less context is available for interpreting the sign, (b) the number of frames containing a sign is smaller for a given UAV ground speed, (c) camera jitter is amplified, and (d) the spacing between search paths must be smaller, which means that the search will proceed more slowly. Fortunately, the possibility of building temporally localized image mosaics helps address the first three deficiencies as described in Section 4.

3.4. Generalized Contour Searches

Optimally covering an area implies two objectives: completeness and efficiency (Koopman, 1980). Com-

[3]The likelihood represents the observation process and varies from application to application; examples of specific likelihoods are given in (Koopman, 1980; Bourgault et al., 2003).
[4]NTSC is an analog television standard adopted by the National Television System Committee.

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pleteness means that the search algorithm eventually covers the entire search area. Efficiency means that the algorithm quickly obtains an image containing a sign of the missing person's location; efficiency reflects the utility of finding signs quickly because the probability of rescue decreases over time. The most efficient complete search is one that obeys the operational principle that states "information about the classification map accumulates most quickly when the camera is aimed at the area where new signs are most likely to be found."

The key enabling technology that allows us to use this operational principle in practice is the ability to aim a gimballed camera at a target point on the ground while orbiting that point. Fortunately, there are a number of references that discuss how to make a UAV orbit a point (Nelson, Barber, McLain & Beard, 2006). The UAV in this paper uses a simple orbiting routine built from the Hopf bifurcation vector field (Madsen & McCraken, 1976; Quigley, Barber, Griffiths & Goodrich, 2006). By intelligently creating a queue of target points, it is possible to have the camera progressively follow almost any possible ground path (except those where terrain increases faster than the UAV can climb). An effective search is obtained by creating a queue of target points that follow the contours of the likely location of the missing person or relevant signs.

When the distribution of signs is stationary, unimodal, and symmetric, continuously following contours of the missing person distribution is optimal, meaning that the path is complete and maximally efficient. Although these assumptions are very strict, the analysis of missing person behavior suggests that in the absence of significant terrain features, the distribution of where a missing person is located is a probability density that peaks at the PLS and appears to monotonically decrease as one moves away from the PLS (Setenicka, 1980; Syrotuck, 2000). One reason for this distribution is an element of randomized movement that is produced by the psychology of being lost (Hill, 1998), and the fact that some missing persons stop moving after a period of time. Moreover, signs regarding where the missing person has been, such as discarded clothing, will probably not move so it may be possible to assume that these clues are stationary.

Under these conditions, the optimal (complete and maximally efficient) search is a spiral that begins at the center of the distribution and spirals outward. This pattern creates a continuous path that follows the contours of the distribution of signs. As the camera follows this pattern, it gathers observations from the region with the highest probability of containing an unobserved sign. Previous work (Quigley, Goodrich, Griffiths, Eldredge & Beard, 2005) presented a series of equations that guide the camera footprint in an appropriate spiral,

$$r \leftarrow r + \frac{\alpha\beta}{r} \quad \theta \leftarrow \theta + \frac{\alpha}{\beta\theta}, \tag{2}$$

where (r, θ) is the camera target point in polar coordinates relative to the center of the search area, (x_0, y_0). The parameters α and β make it possible to vary the space between the computed target points (the search speed) and the space between the spiral arms to compensate for camera footprint, and thus follow adjacent contours.

We can formally encode the practice of creating a continuous path that follows the contours of a probability distribution, and then use the resulting algorithm to follow the contours of other distributions or the contours of a terrain map. The resulting algorithm yields a complete and efficient search for two important distributions. For a unimodal and symmetric distribution the algorithm approximates the optimal spiral, and for a uniform distribution over a rectangular area the algorithm gives the optimal lawnmower search. The formal algorithm is as follows:

1. Initialize search parameters.
   (a) Specify a starting point for the search and an initial direction of travel.
   (b) Specify the maximum path length before switching to a new contour. This allows the algorithm to stay within a specified search area.
   (c) Specify a desired height above ground.
   (d) Specify whether the UAV will ascend or descend contours.

2. Sample points around the current end of the path and close to the specified direction of travel. Select the neighbor with surface height approximately equal to the starting point. Repeat until the length of the resulting discrete path is within a tolerance of the path length, or until a point on the path is within a tolerance of the beginning point (which oc-

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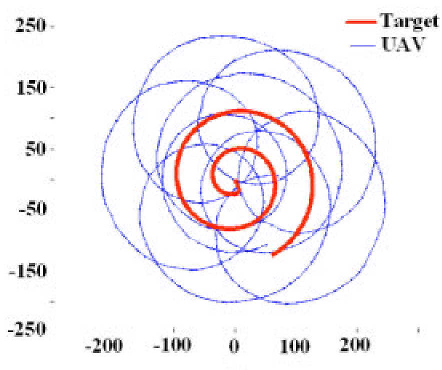

(a) UAV and Camera Path

(b) Search Coverage

Figure 2. (a) An example of a spiral search flown in calm wind conditions by a UAV. The motion of the search point is shown by the heavy (red) line. The generated UAV flightpath is shown as the thin (blue) line. The x and y axis units are meters from launch point. Variants of this algorithm have been flown in over ten flight tests. (b) Pixel density as a function of location for a search pattern consisting of concentric circles. The pixel density is projected onto a map of the flight area.

curs when the target points follow a circuit to the start point).

3. Interpolate the discrete points (we currently use bicubic interpolation) and resample this path at uniform distances. Compute a center of the UAV orbit for the first point on the path. As the UAV orbits this point, command new orbit centers and camera focal points that follow the path.
4. When the camera reaches the last point on the path, compute a new path by ascending or descending the surface.
   (a) Compute the distance from the terminating point by projecting the distance from the camera to the ground, computing the size of the camera footprint, and choosing a new starting point that yields a new camera footprint that slightly overlaps the previous footprint.
   (b) Use Step 2 to compute a new contour using the new starting point.
   (c) If the maximum distance between the previous contour path and the newly computed contour path leaves a gap between the camera footprints for the two paths, move the starting point of the new contour path closer to the ending point of the previous contour path and repeat.
   (d) Change the direction of travel and repeat Step 2.
5. Repeat until the entire region is searched, or until the UAV's batteries need to be recharged.

For a unimodal distribution, a complete search can be obtained by specifying an infinite maximum path length. The resulting path flies concentric circuits over the surface. For a unimodal, symmetric distribution, the resulting circuits are concentric circles that follow the contours of the distributions. To illustrate that such paths are usable in practice, Figure 2(a) shows the optimal spiral path (unimodal symmetric distribution) in calm wind conditions.

If the distribution is uniform across a rectangular area and if the direction of travel is parallel to the side of the rectangle, the contour search yields the optimal lawnmower search pattern. This is important since it implies that the algorithm yields behavior that is optimal in two known cases.

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Several practical limitations affect the usefulness of the contour search. The first limitation arises when the UAV's altitude must change to maintain a consistent height above ground. Since the camera footprint is a projection onto uneven terrain from a possibly oblique angle, not every area is covered with equal pixel density. This issue is aggravated by managing the height above ground, which can cause the camera to pitch up when the UAV climbs, and then pitch down when the UAV descends. This effect is illustrated in Figure 2(b), which displays the number of pixels per area as intensities on a map from a flight test; higher intensity represents a higher pixel density.[5] Note the poor coverage in the middle caused by only a brief dwell time at the point last seen. Also, note that regions near the border of the search are covered at different pixel densities; this is caused by both the UAV pitching and rolling to maintain a consistent height above the ground and the way the UAV switches from one circular contour to another.

Recall that the lawnmower and spiral searches emerged from the generalized contour search when the UAV followed contours of a uniform and a symmetric unimodal probability distribution, respectively. It is also possible to use the generalized contour algorithm to follow contours of the terrain. Indeed, for very steep hills or rugged terrain, following terrain contours may be more efficient than trying to follow the contours of a probability distribution.

Searching in very steep terrain can be done by aiming the camera out the side of the UAV while the UAV follows a contour of the terrain. This causes the camera footprint to obliquely cover a swath along the side of a hill. Figure 3 shows the series of camera aim points selected using the algorithm. It should be noted that to increase the amount of time that the camera dwells on a particular point, it may be necessary to have the UAV orbit waypoints along the contour path while the camera persistently records video along the path of aim points. This causes the camera to cyclically approach and recede from the aim point, meaning that resolution changes over time. Currently, this algorithm has been used only in simulation, but future plans include testing it in the field.

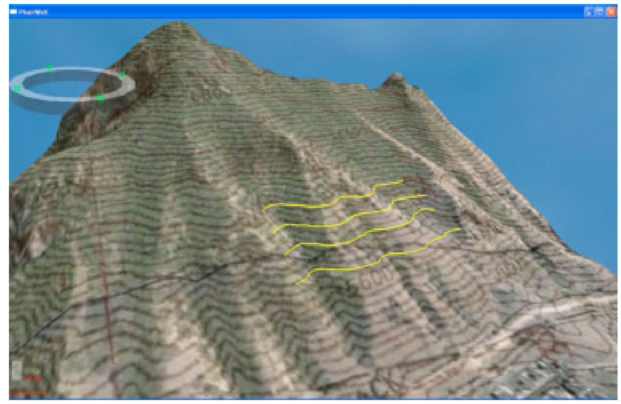

Figure 3. Four contour paths obtained from data from a terrain database. The planned paths are shown as bright lines. For reference, a known contour map is wrapped onto the terrain map.

A second known limitation of the generalized contour algorithm is that it is incomplete when the missing person is moving because the camera and the missing person may inadvertently evade one another. To illustrate this, let V_{cam} denote the groundspeed of the camera's footprint.[6] Let V_{MP} denote the speed of the missing person. Monte Carlo simulations depicted in Figure 4 show how sensing rates for the spiral search drop as the ratio of UAV speed to missing person speed approaches one.[7]

Since Figure 4 uses the ratio of missing person speed to UAV speed, the patterns can be interpreted for many time scales and many possible speeds of the missing person. Data was gathered assuming that the camera covered the ground at a nominal speed of 3 m per simulation time step. Thus, if the time scale is assumed to be one simulation time step

[5] The UAV is flying 70 m above the ground at 13 m/s with a camera angle of 40° by 30°. It started with a radius of 50 m and then flew out in increments of 25 m to a maximum radius of 250 m.

[6] Since the speed with which the camera traverses the ground is determined by the ground speed, not the UAV's airspeed, wind can strongly affect the camera traversal speed.

[7] These results were obtained by setting the UAV's altitude and the camera's field of view to provide a camera footprint of 32 m $\times$ 24 m. We assumed a perfect observer, that is, if a sign was within the field of view then it was observed. Thus, the x-axis represents the ratio of $V_{\mathrm{MP}}^{\max}$ to V_{cam}. This figure is generated using a spiral search strategy given the following conditions: (a) The missing person's initial location is normally distributed with a standard deviation of 100 m around the point last seen. (b) The missing person moves at a velocity selected from the interval $[-V_{\mathrm{MP}}^{\max}, V_{\mathrm{MP}}^{\max}]$ driven by a random walk with reflecting boundaries at the edge of the interval, and with travel directions driven by an unreflected random walk.

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Figure 4. Detection rates as a function of the ratio of missing person speed to camera speed for a fixed search period.

Figure 5. A "dummy" in a field test.

per second, then the V_{cam}=3 m/s, and if the time scale is two simulation time steps per second then V_{cam}=6 m/s. For these two time scales, a ratio of 1.0 indicates that the missing person is moving at the same rate as the camera footprint. As a point of calibration, a speed of 3 m/s (or 6.7 mph) is a steady jog, and a speed of 6 m/s is a very fast sprint.

Suppose that we are interested in the detection rate, assuming that the missing person will not move faster than 3 m/s. If the unit of time is given as one simulation time step per second, 5000 simulation time steps corresponds to approximately 83 min of flying. Additionally, V_{cam}=3 m/s, which means that we should look at a ratio of 1.0 in Figure 4 to determine that the UAV has only about a 25% probability of obtaining imagery containing the missing person when the missing person is moving at approximately the same rate.

Again, suppose that we are interested in the detection rate, assuming that the missing person will not move faster than 3 m/s, but assume that the unit of time is given as two simulation steps per second. This means that the simulation covers approximately 42 min of flying time. Additionally, V_{cam} =6 m/s so we should use a ratio of 2.0 in Figure 4 to conclude that the UAV has only about a 40% probability of obtaining imagery containing the missing person, given that the missing person is moving twice as slowly as the camera.

The conclusion from this analysis is that although the generalized contour search eventually covers a specified search area, it is incomplete in terms of always "seeing" a moving missing person. Indeed, this is true for all searches, though redundant searches and searches by multiple UAVs/ground searchers can mitigate the problem (Setnicka, 1980; and Bourgult et al. 2003).

The third known problem with the generalized contour search is that many distributions or areas of terrain have multiple modes. Planning an optimal search path to such problems is known as the orienteering problem, which is known to be very computationally complex (Fischetti, Gonzalez & Toth, 1998). Although future work should address this problem, we presently require the incident commander to create a plan based on his or her experience given a multimodal search space.

3.5. Lessons from Field Trials

Although the previous analysis is important for identifying practical limits on height above ground and efficient patterns of search, it is essential to conduct field studies to identify critical things not identified in the analysis. A typical field trial involves placing a dummy in the wilderness along with realistic clues (see Figure 5). A scenario, obtained from

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prior missing person case studies, is presented to the group. The incident leader then constructs a search plan and the UAV is used to execute this search plan insofar as possible. A series of field search trials was conducted with search and rescue personnel in 2006 and 2007 using the technology described in the previous subsections.

Following the series of field trials, we surveyed participants to identify things that were essential for effective search. From these surveys, a strong consensus[8] emerged on two needs that must be met for practical field deployment: improved video presentation consisting of stabilized video and image enhancement, and improved integration of the UAV into the WiSAR process. Sections 4 and 5 address these needs, respectively.

4. IMPROVING VISUAL DETECTION

Lessons from field trials strongly indicate that improving video presentation is necessary for UAV-assisted WiSAR. Because the UAV is so small, the UAV video is plagued with limited spatial and temporal fields of view, distractive jittery motions, disorienting rotations, noisy images, and distorted images. As a result, it is very difficult to maximize the probability of correct detections without incurring a high false alarm rate.

Video should be presented such that the probability of correct detection is maximized and the probability of a false alarm is minimized. Given the nature of this classification task, detection theory indicates that it is very difficult to perfectly accomplish both objectives (Sheridan, 1992); there is an inherent tradeoff. It is tempting to conclude that, because the cost associated with missed detections is the potential loss of a human life, then a high number of false alarms can be tolerated. Two observations temper this conclusion. First, a high false alarm rate will negatively influence practical usage of the UAV technology. Second, false alarms trigger additional effort to acquire and analyze information. This effort may involve sending search teams to a location or requiring the UAV to gather additional information regarding a particular location. The cost of these responses is the loss of information that could have been accrued if these resources were employed in other search regions.

Improving video presentation includes many factors. At a minimum, improved presentation includes calibrating the camera, deinterlacing the image, and correcting for camera distortion. We refer to video that has been modified in these ways as "nominal video." This section describes three potential video presentation improvements followed by a study comparing the three improvements to the nominal video feed. The computer vision algorithms used to produce these improvements find feature correspondences in real time and then use these correspondences to determine frame-to-frame alignment. The algorithm details can be found in Gerhardt, 2007.

4.1. Brief Description of the Presentation Views

In order to improve the presentation and support the analysis of UAV-acquired video, four separate but related presentations were derived: nominal video, the stable view, the temporally localized (TL)-mosaic view, and the stable-mosaic view. Each view presents one or more blended images in a viewframe. The viewframe is delineated by a black bounding rectangle. Figure 6 shows two different views within the viewframe: (a) represents nominal video and stabilized imagery; stabilized imagery allows the image to drift within the viewframe so that image features remain in approximately the same viewframe location. (b) represents a mosaic;[9] the difference between the two views is how the viewframe scrolls as imagery moves. Note that the four presentations do not use terrain information to blend or display images, but instead assume a flat earth model.

The first and simplest presentation view is nominal video. The rectangle bounding the video remains constant within the viewframe in the traditional manner of displaying video.

The second presentation attempts to improve nominal video by making image features more stable. The resulting stable view displays images using a smoothed view path independent of any mosaic. Roughly speaking, over time the location and

[8] Survey participants included people with search and rescue experience, students and faculty. Seven participants were surveyed. As shown in the accompanying technical report (Goodrich et al. 2007b), statistically significant results are obtainable from the survey, but since most participants were not search and rescue experts the statistical analysis is not included in this paper.

[9] A mosaic is a composite image consisting of several other images "stitched" together.

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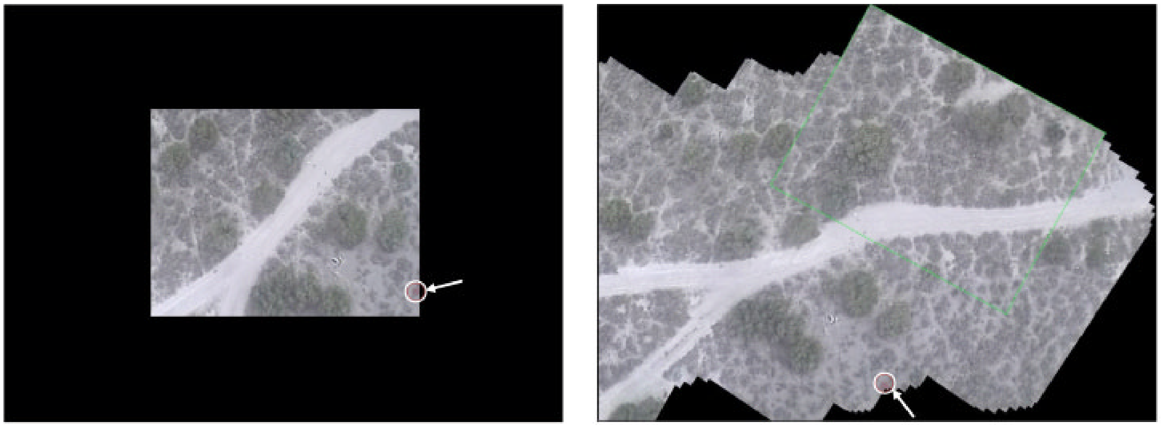

(a) Nominal video presentation. (b) Mosaic video presentation.

Figure 6. These two images illustrate how the history of a mosaic can increase the positive identification rate. (a) The original view contains a red umbrella, seen in the lower right corner of the view and circled, which is visible in only a couple of frames. (b) The mosaic view contains the same red umbrella, seen in the lower middle of the view and circled, which is visible in over hundreds of frames. Note that the umbrella is extremely difficult to see on a black and white image—color is the key discriminator.

orientation of the image shifts within the viewframe. When a new image is received, features in the new image are compared with features in the previous image. The old image is replaced by the new image, but the new image is presented within the viewframe such that the features between subsequent images are in approximately the same location within the viewframe. The reasoning is that if image features are stable within the viewframe, it is easier for an observer to detect features on the ground. Stabilizing the image hypothetically improves an operator's orientation and balances the removal of content jitter from the original presentation and the presentation jitter of the mosaic view. Unlike many stabilization views, which constrain the viewframe to a subregion of the image, our viewframe is larger than the image (see Figure 6(a)). This larger viewframe is desirable since maximizing the camera footprint increases the search efficiency. A scrolling algorithm that smoothly translates the image allows features to remain relatively stable while still approximately centering the image.

The third presentation attempts to improve nominal video by improving the temporal persistence of image features. The resulting TL-mosaic view builds a local mosaic of recent images (and thus the name "temporally localized mosaic"). In contrast to local mosaics, which seek to construct a unified static image over the entire area, the TL-mosaic constructs a mosaic only over recent video frames. The motivation for this view is to expand both the spatial and temporal viewing windows for the observer by aggregating each frame onto the display canvas. As new images are received, they are added to the collection of previous images within the viewframe by aligning features. This presentation is desirable because features will be stably presented and signs will be persistently displayed in the viewframe. In practice, these image aggregations work well until the images begin to be aggregated onto the canvas outside of the viewing frustum. A simple solution is to translate (or scroll) the viewpoint, when necessary, to follow this image aggregation path and always maintain the current frame within the presentation's viewing frustum. The resulting display expands the effectual viewing frustum and removes video content jitter. However, the viewpoint translations must occur frequently and effectually reintroduce some jitter.

The fourth presentation attempts to retain the benefits of the TL-mosaic and also reduce the jitter caused when the viewing frustrum must shift. The resulting stable-mosaic view combines elements from the TL-mosaic and stable views. The difference

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between the mosaic and stable-mosaic view is the smoothing function that scrolls the mosaic as new images are acquired. Hypothetically, this presentation provides the benefits of both the stabilized view and TL-mosaic view, with a potential cost of providing less imagery in the viewframe at a given time.

4.2. Experiment Description

An evaluation of the different views was performed by 14 naïve and 12 potentially biased volunteer participants. Participant bias was determined based on the participants' familiarity with this work. The naïve participants were recruited from the university student population and compensated $15.00. The biased participants were those affiliated or familiar with this work and were not compensated. One participant reported some color blindness.

Each participant was asked to perform two tasks simultaneously in order to replicate field conditions while maintaining appropriate experimental control. The primary task was to detect and identify prescribed signs in the video display shown on a monitor that was positioned in front of them and to their left. The video was obtained from previous flights where signs (red umbrellas) were distributed in the environment; in the video, these umbrellas appear as blurry red ellipses. During video collection, the UAV was engaged in common search patterns. The secondary task was to detect and identify prescribed objects of interest on a monitor of the same size positioned to the right of the video display. This secondary task was designed to represent an active visual task such as placing waypoints on maps, using maps to localize the imagery, etc.

The video display presented each participant with a controlled random ordering of 16 different short video clips. Each clip lasted about 1.5 min and was presented using one of the four possible views. The participants were asked to detect and identify as many of the signs as possible during each trial. Clip orders were presented in a balanced, randomized order.

The secondary display provided the participant with a controlled random sequence of uniquely colored spots dependant on the corresponding video clip. Each clip corresponded to its own particular randomized spot generation sequence. The set of spots were regenerated every 2–5 s using probabilities that gave the red (target) spot an 82% chance of being displayed each time the spots regenerated.

Any time a participant believed that a sign was visible, he or she was to freeze the frame by mouse-left-clicking anywhere in the video display window. The clicking represented the task of noting an image of interest and localizing the sign. Freezing the frame caused the video display to freeze but did not pause the video. Rather, the video continued to play in the background, which implied that the longer the frame was frozen, the more video content the participant missed. The participant had two options during the freeze-frame state: select the sign by mouse-left-clicking on it, or make no selection and cancel the freeze frame by mouse-right-clicking anywhere within the video display window. If the participant selected a sign, a red ring would briefly highlight the selected area. Any part of the sign (the red umbrella) within the ring counted as a precise hit. When this action was taken, normal presentation continued. A similar control scheme was employed for the secondary task.

After each trial, the participant answered three post-trial questions that were shown on the secondary display. These questions were designed to measure participant preferences and confidence. The hit rates for detecting umbrellas in the primary task, the hit rates for detecting spots in the secondary task, and false-positive rates and types were measured during each trial. Hits were classified as occurring within the current frame, within the mosaic history, and within the viewframe but not within the mosaic.

4.3. Results

Three preliminary observations are in order before comparing the main results. First, there is no statistical difference between the objective results for naïve and biased participants, who had a 73% and 72% probability of detecting the red umbrellas. Thus, the remaining analysis does not distinguish between the two participant types. Second, detection and identification success rates for the secondary display are very high and consistent across all participants and views at about 94%. This suggests that any influence from the additional cognitive load on the results will be expressed mainly in the differences among the red umbrella hit rates within the video display. Third, one particular video clip was an outlier wherein all participants identified all of the umbrellas regardless of the accompanying view. This clip was removed from the analysis.

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Table I. Hit probability comparison among the different presentation views and between the naïve and biased participants, where ω is the least-squares means estimate and $P_D = \frac{e^{\omega}}{1+e^{\omega}}$, i.e., the probability that the sign will be detected given the corresponding presentation view or participant. Also, the improvement over the lowest P_D^{low}, which corresponds to the nominal view, was computed by $\frac{P_D^{\text{view}} - P_D^{\text{low}}}{P_D^{\text{low}}}$.

Presentation	ω	P_D	% Improvement
TL-mosaic	1.6610	84.04%	45.33%
Stable-mosaic	1.5486	82.47%	42.62%
Stable	0.3935	59.71%	3.26%
Nominal	0.3156	57.83%	0.00%

The primary results,[10] shown in Table I, indicate that providing the participant with an increased viewing frustum and stabilized view increases the probability that signs are detected. The TL-mosaic view resulted in the largest increased percentage (45.33%) in hit probability over the original view. Also, there is a strong (43%) improvement from the nonmosaicked to the mosaicked views. The pairwise differences between the two mosaicked views and the two nonmosaicked views are statistically different ($P < 0.01$), but the pairwise differences between the two view sets are not statistically different.

This improvement is largely explained by referring to Figures 6(a) and 6(b). Figure 6(a) demonstrates that the sign (the red umbrella) is visible only for a couple of frames (or 1/15th of a second) in the lower right corner of the nominal view which (would appear very similar to the stable view). However, in the corresponding mosaicked view, as seen in Figure 6(b), this red umbrella is visible for a much longer time, possibly over hundreds of frames, or several seconds, before it moves out of the viewing frustum.

One downside to providing a mosaicked view is the increase in the probability of false positives. A false positive occurs when some object in the image or some image artifact (such as discoloration) causes the observer to think that a red umbrella has been observed. The probability of a false positive is 11% and 18% of total hits for TL-mosaic and stable-mosaic presentations, respectively, and 5.77% and 8.65% for stable and nominal presentations, respectively. If some element of the image is likely to trigger a false positive in the video, then causing this element to persist in a mosaic will increase the chance that the observer will notice the element. Fortunately, experimental results indicate that the probability of correct detection grows much more quickly than the probability of false positive when a mosaic is used.

In summary, participants overwhelmingly preferred the mosaicked views (92%) and found the mosaicked views to be more orienting (88%) and less straining (73%) than the nonmosaicked views. Importantly, this increased persistence potentially allows the UAV to travel more quickly since the amount of time that a sign must be within the camera's field of view can be small provided that a human has long enough to see the sign.

Many researchers have explored creating image mosaics, including using aerial imagery (Kumar et al., 2001), but few appear to be using mosaics to improve real-time detection. Since such detection is essential for WiSAR, it is necessary to understand how to use spatially and temporally local mosaics to enhance live presentation of video with the goal of supporting an observer watching the video. The experiment results are, to the best of our knowledge, the first to analyze how local image mosaics can improve an observer's ability to detect objects from a video stream.

5. INTEGRATING THE UAV INTO THE WISAR PROCESS

The second need identified in field trials was the lack of an effective process for coordinating among the UAV operator, the incident commander, and ground searchers. It was assumed when preparing for the first field trials that the UAV would fly a complete search path (e.g., spiral or lawnmower pattern), imagery would be recorded, signs would be identified, the signs would be clustered together, and then ground searchers would go to the location of the signs and find the missing person.

The preliminary trials indicated that practice differed from this model in two ways. First, instead of systematically executing a complete but probably inefficient search, the incident commander wanted to execute a probably efficient (but potentially incomplete) heuristic search. Given the desired search path, the UAV operator translated the path into waypoints

[10]These results were obtained via a multiple comparison ANOVA with the Tukey-Kramer adjustment.

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and began flying. Second, the inability to efficiently dispatch ground searchers to a potential sign made it necessary to gather images from many angles and altitudes. Often, this process caused the original search plan to be neglected or abandoned, which meant that the search became incomplete and inefficient.

In order to improve the process and identify effective operational paradigms, it was necessary to better understand how real WiSAR is performed. This section reports results of a human factors analysis of the WiSAR domain. We use these results to identify (a) tasks that must be performed to do UAV-enabled WiSAR, and roles (b) and responsibilities for people performing these tasks. This results in three operational paradigms for organizing the UAV, the incident commander/mission manager,[11] and ground searchers.

5.1. Goal-Directed Task Analysis

A goal-directed task analysis (GDTA) (Endsley et al., 2003) is a formal human-factors process for identifying how complex tasks are performed. GDTAs have been used in other first responder domains (Adams, 2005) military domains (Bolstad, Riley, Jones & Endsley, 2002), screening applications (Segall et al., 2006), etc. The analysis results in a formal description of the goals and tasks required to successfully perform the task with a focus on the information required to support situation awareness. The GDTA can be used to identify how new human-centered technologies can augment existing processes. To encapsulate this, we have performed a GDTA and a partial cognitive work analysis (CWA) (Vicenti, 1999) of the WiSAR domain.

The complete GDTA and CWA are provided in an accompanying technical report (Goodrich et al., 2007b); however, the results of these analyses were employed to identify the central information flow of the process and use this process model to guide our analysis of human-robot WiSAR teams. This summary was previously presented in a workshop paper (Goodrich et al., 2007a), but we significantly extend this paper not only to identify tasks specific to UAV-enabled search but also to include the four qualitatively different types of search used in WiSAR. As shown in Figure 7, the search task involves gathering evidence, utilizing that information to modify the understanding of the search problem, and then directing further efforts at gathering additional evidence.

The information flow for WiSAR personnel begins with the initial details given by the reporting party. Responders immediately consider the urgency of the call based on the potential danger to the missing person and other factors. Combining prior knowledge and experience with information provided by the reporting party, responders develop a model of high probability sources of additional evidence. Potential sources of evidence include both geographic locations surrounding the missing person's point last seen (PLS), as well as information from people familiar with the missing person.

After evaluating initial sources of evidence, the WiSAR team develops and executes a plan for acquiring additional evidence. In the more challenging situations, the plan must allocate human and UAV search resources to efficiently accumulate evidence from different sources. Such allocation is governed by the probability that useful information will be obtained, by the risks involved in gathering the information, and by the capabilities of available resources for acquiring information.

Time and additional evidence result in adjustments to the probability model of possible sources of evidence. Changes in the model lead to changes to the search plan. All evidence changes the expected utility of searching in different areas. Incident command continually evaluates evidence and redirects available resources in order to maximize the value of the search.

Ideally, the search ends when the WiSAR team locates the missing person (the probability distribution moves to a single spike). Work then proceeds to rescue or recovery. However, the process may also end if the search continues long enough that the probability of the missing person actually being within the search area falls below a certain threshold or if dangers or other constraints (i.e., another incident) cause the relative expected value of continuing the search to fall below a threshold (Setnicka, 1980).

5.2. Task Breakdown for UAV-Enabled Search Execution

Using a UAV to support the WiSAR process alters the process identified in the GDTA; some tasks are

[11] The director of the overall search operations is known as the incident commander. In this section, we use the term *mission manager* to indicate that the UAV search team might be directed by someone different from the incident commander, but who reports to the incident commander.

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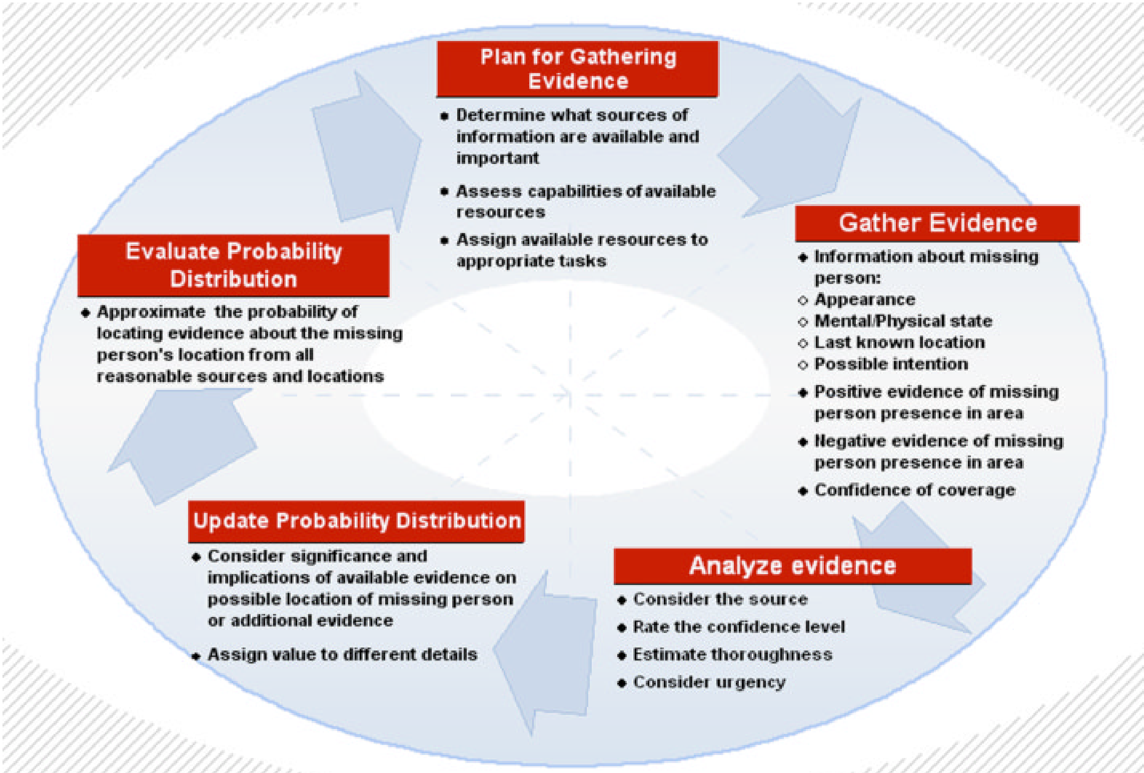

Figure 7. Information flow in the WiSAR domain.

fundamentally changed and other tasks are introduced. We begin by describing what tasks the UAV and its operator(s) must perform in order to follow a plan. As the tasks are presented, we identify various roles that humans must fulfill. Figure 8 provides a UAV-enabled WiSAR task breakdown. This breakdown was obtained by combining the GDTA results, observations from multiple flight tests and search trials, and an activity analysis patterned after the frameworks in Norman, 2005; Parasuraman et al., 2000; and Sheridan & Verplank, 1978.

When a portion of a task is automated, the human's responsibility shifts from performing the task to managing the autonomy (Woods et al., 2004). There are four roles that emerge when a UAV is used to support the WiSAR process. The UAV operator is responsible for guiding the UAV to a series of locations that allow the camera to obtain imagery of potential signs. The sensor operator is responsible for directing, for example, a gimballed camera and for scanning and analyzing imagery to detect potential missing person signs. The mission manager is responsible for managing the search progression with an emphasis on processing information, focusing search efforts, and reprioritizing efforts.

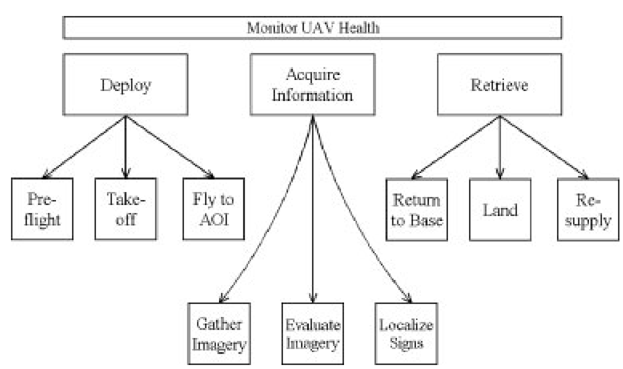

Figure 8. Hierarchical task breakdown of UAV-enabled search.

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New responsibilities for the human include deploying, retrieving, and monitoring the UAV's health. These responsibilities are performed by the human responsible for the UAV operator role. Deploying [12] and retrieving must be performed prior to and subsequent to the aerial visual search, but monitoring the UAV's status and health must be performed in parallel to the visual search.

The purpose of flying the UAV is to acquire information about where the missing person may be located. As illustrated in Figure 8, acquiring information using a UAV requires gathering imagery by flying the UAV and aiming the camera to make it likely that some sign appears in the video (coverage), evaluating the imagery for a possible sign (detection), and then identifying the evidence's location in order to modify search priorities.

5.2.1. Gathering Imagery

Imagery is acquired by planning a path, flying the UAV, and controlling the camera viewpoint to ensure that imagery of the search area is obtained. The speed and path of the camera's footprint over the ground are the key control variables (Koopman, 1980), and the search completeness and efficiency are the key performance measures. The path should maximize the probability of locating a sign in the shortest time. Guiding the UAV and following a search path is incorporated into the UAV operator role.

5.2.2. Analyzing Imagery

Imagery can be scanned either in real-time or offline. Since the purpose of using the UAV in WiSAR is to allow searchers to find the missing person, analyzing imagery for signs is essentially the purpose of flying the UAV. The key performance variable is the probability that a human can detect a sign in an image given a set of image features. Since this probability is strongly influenced by the way information is obtained and presented, the key control variables include how video information is presented, the camera resolution, the UAV's height, and the number of images that contain information from the search area. Managing the camera and analyzing imagery falls into the separate role of the sensor operator.

[12]The UAV is deployed to an area of interest (AVI) that may be some distance from the launch point.

5.2.3. Localizing Signs

Once a sign has been identified in an image, it is necessary to estimate the sign's location so that searchers can reach the sign. Estimating the location is often referred to as "georeferencing" the imagery. In practice, camera footprint localization is performed by projecting the camera angle from the the UAV's pose to a flat earth model (Redding, McLain, Beard & Taylor, 2006). The key control variables are the video and telemetry synchronization, the range of UAV viewing angles of the sign (to support triangulation), and the reliability of the terrain model used in the camera projection model. The key performance variable is the accuracy of the sign's location in the physical environment. Once signs are localized, the person in the mission manager role uses this information to replan using the pattern in Figure 7.

5.3. Coordinating the UAV with Field Personnel

The UAV-enabled WiSAR process indicated the following three roles: UAV operator, sensor operator, and mission manager. Field tests strongly indicate that a fourth role, ground searcher, is needed for a successful search. Ground searchers confirm or deconfirm signs by, for example, inspecting a brightly colored spot to determine if it is a manmade object discarded by the missing person. An operational assumption is that seeing a sign from the ground removes more uncertainty than seeing a sign from the air; in other words, search thoroughness and confidence is very different for aerial and ground resources. Importantly, lessons from other search-related domains (Drury et al., 2003; and Burke & Murphy, 2004) also indicate that multiple roles are required. In both the WiSAR domain and other domains, these roles can theoretically be filled by one or more people with varying levels of authority, often supported by various autonomy algorithms and user interface technologies.

Two factors determine how ground and aerial sources coordinate: the level of search thoroughness and the search strategy. The level of search thoroughness may be represented as a probability of detecting the missing person or a related sign. It is necessary to specify the level of thoroughness since dedicating too much time and effort to one area prevents searchers from searching other areas within the perimeter. A coarse search technique may be pos-

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sible if the missing person can hear, see, or call out to searchers. Similarly, a coarse search may be possible if expected cues are easy to detect, such as knowledge that the missing person is wearing a bright orange raincoat. High thoroughness means higher probability of finding signs, but it also means a greater number of searchers or slower searches. Importantly, repeated searches at a low level of thoroughness can be just as effective as a single search at a high level of search thoroughness (Setnicka, 1980). As this applies to UAV-enabled WiSAR, the UAV can provide a rapid search at a different level of thoroughness than could be performed by (albeit slower) ground searchers.

The GDTA indicated that four qualitatively different types of search strategies[13] are used in WiSAR: hasty, confining, high probability region, and exhaustive (see also Setnicka, 1980). Different search strategies suggest different responsibilities and roles for aerial and ground resources. Prior to discussing these different roles and responsibilities, it is useful to discuss the four types of searches.

A hasty search entails rapidly checking areas and directions that offer the highest probability of detecting the missing person, determining the missing person's direction of travel, or finding some clue regarding the missing person's location. Such searches often use canine and "mantracking" teams to follow the missing person's trail. A constraining search is intended to locate clues that limit the search area. For example, if there is a natural ridge with only a few passages, searchers will inspect the trails through the ridge for signs in order to restrict their search efforts to one side of the ridge. Results from hasty and constraining searches are often used to inform search in high probability regions. The incident commander can estimate the probability of finding the missing person in the various map sections based upon a combination of experience borne of intuition, empirical statistics, consensus, and natural barriers (Setnicka, 1980). The incident commander then deploys the search teams with the appropriate skills to examine the areas of highest probability and to report their findings with an assessment of the thoroughness of the search. An exhaustive search is a systematic coverage of an area using appropriate search patterns. Such a search typically indicates that other (usually more effective) search strategies have failed to yield useful information. If the exhaustive search produces new information, the incident commander may revert to a prioritized search.

[13]Note that we use the phrase "search strategy" to indicate some form of informed method of executing a search. In (Setnicka, 1980), the term "strategy" is restricted "to the process of establishing a probable search area most likely to contain the subject" and the term "tactics" refers to "explicit methods used to deploy search resources into that area." Thus, in the parlance of (Setnicka, 1980), our use of the phrase "search strategy" would more accurately be referred to as "search tactics."

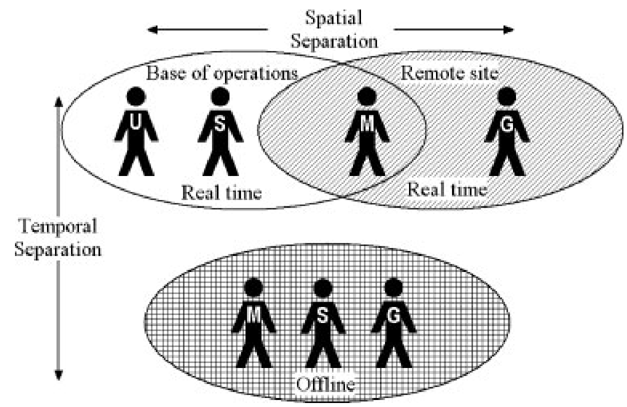

Figure 9. Spatial and temporal relationships between people filling WiSAR roles: U=UAV operator, S=sensor operator, M=mission manager, and G=ground searchers.

In field trials, coordination among the UAV operator, people watching the video, the mission manager, and ground searchers was often ineffective. This was largely the result of not correctly assigning responsibilities and roles for a specific level of search thoroughness and a specific search strategy. Thus, a necessary step toward effective field practice is to develop a process of coordinating roles.

The remainder of this section identifies operational paradigms for organizing roles; much of this subsection was presented in a workshop paper (Goodrich et al., 2007a), but portions are included and extended herein because they identify key principles and practices for fielded searches. As illustrated in Figure 9, the important distinctions between the three operational paradigms discussed below are in (a) the physical locations of the individuals filling the roles and (b) the temporal sequence in which the roles are fulfilled. We now describe the organization in each paradigm and present principles for deciding when a particular paradigm is appropriate.

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5.3.1. Sequential Operations

- **Organization**. Under the sequential operations paradigm, the UAV is used to gather information independently without coordinating in real-time with the ground searchers. The mission manager works with the sensor and UAV operators to create a plan. The UAV operator then executes the search plan and the resulting video and telemetry information is provided to the mission manager and sensor operator. They evaluate the information with the goal of detecting and localizing signs. If a potentially valid sign is found, a ground support searcher is dispatched to evaluate the sign. Information from ground searchers is then provided to the mission manager and a new plan is created. The paradigm is called "sequential" because the search proceeds in stages: an aerial search followed by a ground search as needed.
- **Principles**. A sequential search is appropriate when there is limited ground mobility or when the probability of identifying missing person locations is uniformly spread across a large area. Such conditions tend to indicate that the UAV will be able to cover more ground at a particular level of thoroughness than what could be achieved with a ground search given the number of people available. Sequential search allows the team to gather data using the UAV, cluster signs, and then dispatch a ground search team to the highest probability locations. Because of the turn-taking nature of this search paradigm, it is most appropriate for exhaustive searches or searches in low probability regions. Generalized contour searches could be appropriately used to support sequential operations.

5.3.2. Remote-Led Operations

- **Organization**. During remote-led operations, the mission manager is physically located with the ground team to perform a hasty ground-based search such as tracking a footprint trail or using a canine team to track a scent trail. The UAV operator flies an orbit that is centered on the ground searchers' location, while the sensor operator controls the camera to gather imagery beyond the ground searchers' field of view. Thus, the UAV effectually extends what can potentially be seen by the ground searchers. This allows the mission manager greater access to potentially relevant information to guide the hasty search.
- **Principles**. Remote-led operations are appropriate when the mission manager has more awareness of search-relevant information at some location in the field than at the base station. This occurs in a hasty search when there is a cluster of signs that allows the mission manager to rapidly update the model of the missing person's location, such as might occur when tracking the individual. The UAV provides supplementary information that broadens the scope of what the mission manager can include in his or her model, and thus increases the field of search without sacrificing search thoroughness. Generalized contour searches are not appropriate for such searches; instead, the UAV operator should fly orbits that center on the location of the ground teams.

5.3.3. Base-Led Operations

- **Organization**. During base-led operations, the mission manager is physically located near the UAV operator control unit. As the sensor operator identifies possible signs in the video, the mission manager adjusts his or her model of the missing person's likely locations and instructs the UAV operator to focus flight time in high probability areas. Ground searchers may track critical points on the UAVs path so that they are close to possible signs, which may be identified by the sensor operator. For example, in a spiral probability contour search, a single ground searcher may be positioned in the center of the search spiral and/or four ground searchers can walk in the four cardinal directions from the spiral center as the UAV spirals out. As another example, in a terrain contour search up the side of a mountain, searchers can be placed near both extremes of the contour line and near the center, and then hike up the mountain as the UAV tracks to higher altitudes. When the UAV records a possible sign, the ground searchers rapidly confirm or

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deconfirm the sign. This paradigm may be appropriate for priority searches where the improved thoroughness of a ground searcher is needed to confirm rapidly signs detected from the UAV.

- **Principles**. Base-led operations are appropriate when the terrain allows ground teams to be sufficiently mobile but when there is insufficient information to perform a hasty search. The ground team can position themselves so that they are within a minimal expected distance when the sensor operator detects a sign. Feedback from the ground allows the mission manager to adapt the search plan rapidly. Generalized contour searches or ad hoc waypoint list could be appropriately used to support base-led operations.

6. CONCLUSIONS AND FUTURE WORK

The WiSAR problem can be framed as one where maps of the likely locations of signs are used to construct a map of the missing person's likely location. The map of signs obtained from the UAV, called the classification map, is combined with other information sources by the incident commander. The classification map provided to the incident commander is a filtered estimate of the likely sign locations given a series of observations; we have restricted observations to visual detections by a human observer from (possibly enhanced) UAV video. The posterior probability of the classification map given all observations is the product of the likelihood that a sign will be correctly detected given the map and the predicted classification map given previous observations. These two elements represent the two obligations of effective search: detection and coverage. In terms of the expected time to find the missing person, there is a tradeoff between detection and coverage. Generally speaking, rapid coverage can reduce the probability of detection and vice versa.

Practically speaking, the requirement for efficient detection translates into a maximum altitude given the minimum sign size and the camera field of view. Similarly, the predicted map translates into a coverage search path that seeks to obtain as much information regarding the environment as quickly as possible. A generalized contour search can provide effective and complete search strategies for stationary signs, but fielded search will require input from a mission manager to produce efficient flight paths.

A series of field tests were performed under various conditions that revealed information regarding effective WiSAR that was not apparent from the a priori analysis. These field tests strongly indicated a need to improve how information was presented and to understand how UAVs can best support the WiSAR process.

Our contribution to the information presentation problem was the development of computer vision algorithms that enhanced the stability and temporal locality of video features. This contribution also included a study comparing nominal, stabilized, and mosaicked video presentations. The comparison metric was the operator's ability to detect objects given a secondary task that distracted visual attention. Surprisingly, no benefit was found by stabilizing the video, probably due to algorithm features that allowed the image presentation to drift within the viewframe. By contrast, temporally localized mosaicked images provided a significant benefit, probably because such mosaics expand the effective spatial and temporal viewing windows of the displayed video, creating more persistence and thus allowing more opportunity for detection.

Our contribution to integrating UAVs into the WiSAR process began with a formal goal-directed task analysis of how WiSAR is currently performed. It was apparent from this analysis that the iterative search planning, search execution, and search replanning cycle was changed by incorporating a UAV. Given the specific goals and information requirements to perform search planning and execution, we created a WiSAR specific breakdown of roles and tasks. We drew on lessons from field tests with search and rescue personnel to identify specific paradigms for organizing the UAV operator, the sensor operator, the ground searchers, and the mission manager across different spatial and temporal locations. Different paradigms have advantages for supporting different search strategies at different levels of thoroughness given constraints on terrain and probability; we have identified some principles to help guide which paradigms should be used in field conditions.

There are several areas of ongoing and future work that have the potential to benefit UAV-enabled WiSAR. Longer searches over wider areas may reveal the need for more user-friendly interfaces. Improved interfaces would be necessary for a single person to fulfill both the UAV operator and sensor operator

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roles. Fulfilling dual roles would also benefit from automated target recognition. Interestingly, the availability of automated target recognition software may lend itself to image enhancement by highlighting areas where signs are detected so that the human can more quickly detect them. Finally, fulfilling dual roles may also be possible if searchers process and evaluate video offline.

Additional hardware and control algorithms may also benefit UAV-enabled WiSAR. Results from preliminary evaluations of a small (flyable) infrared camera suggest that detection at the nominal 60 m height may be possible, but that searches will be most beneficial at night or early in the morning so that the ambient heat of the day does not mask body heat signatures. Other future work includes using high-resolution cameras, using multiple cameras to present an effectively wider field of view, using narrower field-of-view cameras to provide higher resolution, and using color enhancement of likely signs. Using multiple UAVs to perform a coordinated search or to provide a reliable ad hoc communications network also deserves more research to determine how existing solutions apply to the WiSAR problem domain. Importantly, adding more expensive hardware or managing multiple UAVs will likely make it more important to provide user-friendly interfaces plus autonomous support for managing height above ground.

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