A Data-Driven System for Probabilistic Lost Person Location Prediction

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***Abstract*— Today, when a report of a lost person occurs, both the Search And Rescue (SAR) team and Lost Person (LP) have limited access to assistive technologies, leaving manual or ad-hoc search planning as an all too common solution. Geospatial data exists, however, that when coupled with appropriate models and algorithms can enable decision support systems to help predict the location of lost persons and provide guidance for optimal search execution given the available search resources. The environments and context for application of these technologies, however, introduce several key complexities. The data required for accurate analysis and prediction (e.g., elevation, land cover, exclusion zones, known markers) can be large and the exact subset needed for any particular incident may not be known until the lost person event occurs. The algorithms required to generate location probability distributions are compute intensive in comparison to the limited compute resources available on the devices located closest to the incident or carried by a search team. That search team is by design, distributed, conducting operations with multiple independent operators, often in areas with limited, degraded access to network infrastructure. This paper describes the design, algorithms, models, and evaluation of software entitled LandSAR that employs geospatial datasets and tooling in a distributed context to address these challenges and enable such capabilities at the network edge.**

Keywords-search and rescue; geospatial algorithms; team awareness kit; geospatial data.

I. INTRODUCTION

Time and situational awareness are crucial to search and rescue efforts. While there is a plethora of geospatial data to assist and guide action in response to LP incidents, the ability to gather, process, disseminate, and leverage this information is one more challenge at a time of significant risk and stress. Weather, sustenance requirements and injuries all impose a time clock on the search teams. Today's practices are laden with manual elements and thus can only operate at human speed, accuracy and scale, and further require expert knowledge of terrain, personnel and other factors. The work described in this paper presents a machine-speed and machine-scale solution to these issues, with the goal of saving lives, and reducing the duration and thus cost of searches. The LandSAR technology provides a tool that presents probabilities of lost person locations over time, and based on this information, presents search teams with search recommendations given their available assets. Figure 1 depicts this tool executing within an Android-based team Situational Awareness (SA) tool.

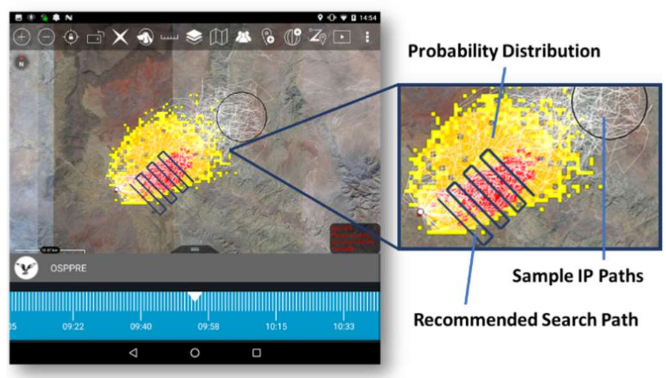

Figure 1. LandSAR UI showing probability distribution, sample paths used by underlying calculations, and recommended search path.

To understand the LandSAR concept of operations, let us consider an event that leads to a lost person who must be located and recovered. LandSAR operators use the LandSAR client software resident on their mobile device, or in a web browser, to record the event and last known position of the LP along with several other parameters, including selection of a model representing the class of LP (e.g., a hiker, someone with dementia), that can help guide the search process. The LandSAR models further capture awareness of destination goals, the most likely selection among multiple such points, and the subsequent choice the LP must make to determine a route to that objective. As an example, a model and its parameters might indicate that the LP has one of several known locations that they may try to get to if lost, and that there may be an area that they will likely avoid if they encounter it (e.g., due to recent flooding that area is no longer easily traversable). The LP will have to make a

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quick rough estimate of the difficulty of such a path based on the information at hand. That information centers on elevation and major features such as water bodies and rivers. Paths which reduce the total elevation deltas and traverse the most amenable land cover types are favored by the LP and thus are also favored by the model. Of course, the LP will not follow the planned route exactly. While keeping with the general trend of the path, the LP will make the final determination based on local factors. For example, the LP will favor open fields over wooded areas to increase visibility. The model will similarly estimate LP paths by using land cover data to make the final determination for each considered path. LandSAR uses these models and accompanying algorithms to develop a time parameterized probability distribution which is sent to the search team, as seen in Figure 1. They can then drag within the interface forward and backward in time to estimate where the LP was, is, or will be. A user can then request that LandSAR calculate an optimal search rectangle and representative search path, providing the system with information about the available assets (searchers on foot, helicopters, or small unmanned aerial systems). LandSAR will generate a recommended search path and disseminate this to the client devices for inspection and execution.

The remainder of this paper is organized as follows: Section II describes related work. The LandSAR system design and its subcomponents are described in Section III. Section IV details the challenges and solutions in geospatial data acquisition and fusion to address the LandSAR information requirements. Section V describes the probability distribution generation and search recommendation algorithms and the models that support them. Section VI describes evaluation of performance and exercise-based evaluation of efficacy. Finally, in Section VII, we conclude and discuss ongoing and future work extending, enhancing, and augmenting the LandSAR capabilities.

II. RELATED WORK

Search Theory [1][2], a mathematical approach to the search for objects, dates back to World War II and the search for German U-boats. Work in the application of this theory to search and rescue [3], and in particular land-based search, provided the basis on which LandSAR realizes optimal search recommendations.

Other systems exist to predict locations of lost persons and provide search recommendations. SAROPS [4] is a US Coast Guard tool that produces probability distributions using a particle filter for the location of the search object and that recommends search allocations to maximize the increase in probability of detection with the assets available. SAROPS applies these techniques to the sea domain, as opposed to the land-based domain employed in LandSAR.

The Android Team Awareness Kit (ATAK) [5], described in more detail in Section III, is a platform in which the LandSAR capabilities are exposed (in addition to a web-based version). ATAK provides a plug-in interface that allows for easy extension. Other ATAK plug-ins [6] have been developed that project movement to predict potential locations of an entity, but require non-trivial terrain pre-processing and don't provide search recommendations. LandSAR requires only lightweight processing of input datasets before they can be used, and can perform this processing at runtime, is focused more on LP models than determining concealed routes to be used, and recommends optimal search paths based on the determined probability distributions.

III. THE LANDSAR SYSTEM

LandSAR, as seen in Figure 2, is a distributed system where the core computation executes on the server, and the results can be disseminated to a team of users. In this section, we briefly describe these technologies and then provide an overall system view of the LandSAR software.

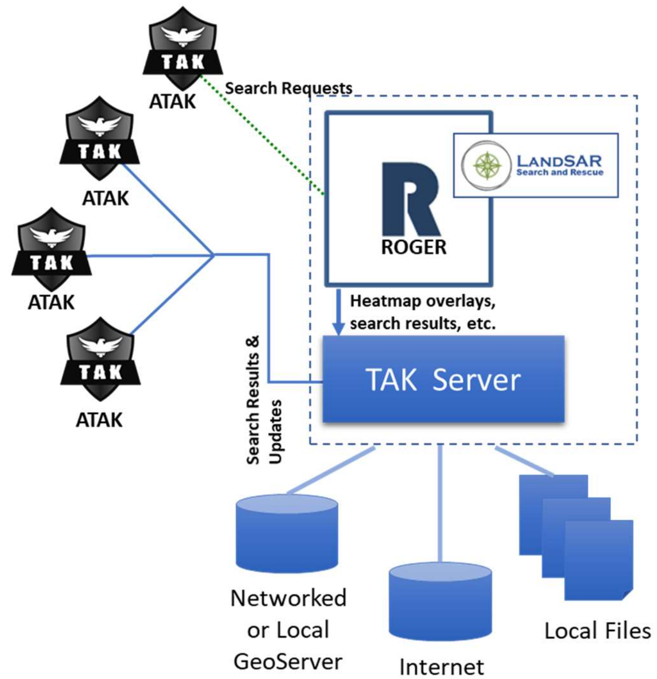

Figure 2. LandSAR Systems View.

ROGER [7][8] is a framework for building modular network middleware by composing plug-ins. The LandSAR capabilities are realized through ROGER plug-ins that model the movement of lost persons over time and provide optimal search recommendations. These plug-ins embody the logic of the search algorithms and work alongside another set of plug-ins that ingest inputs for these algorithms from client devices and local or remote data stores, and a 3rd set of plug-ins that expose the LandSAR outputs to a situational awareness platform called the Team Awareness Kit (TAK). TAK provides a suite of mobile mapping and SA applications employed by over 100,000 US users from numerous local, state, federal, and military agencies. ATAK, the Android-based primary TAK client, supports mobile teams and the wide variety of operating environments and roles that mobile scenarios demand. A server component, called TAK Server, acts as a publish-subscribe middleware connecting ATAK (and other) devices. As shown in Figure 2, client devices communicate with TAK Server for normal SA operations, and can send lost person notifications and search requests directly to ROGER (the box labeled R in the figure) for processing. Generated probability distribution and search recommendation map overlays are distributed to TAK Server as Keyhole Markup language Zipped (KMZ) files to be distributed to all members of the search party, and rendered on ATAK.

The LandSAR client-server model is augmented by the use of a peer-to-peer information management capability called BANDIT [9]. BANDIT processes geospatial situational awareness messages like TAK Server, but does so in a decentralized manner using a light-weight quality of service aware broker on each node in a set of devices. Through the use of mesh networks and the BANDIT technology, LandSAR operations can extend beyond direct line of sight ranges and can handle partitioned group operation (e.g., a subset of searchers out of range of the server or other users).

IV. Geospatial Data Acquisition and Dissemination

LandSAR requires a number of data inputs in order to generate high quality probability distributions and search recommendations. Some of these inputs may be prepositioned on the server for targeted use cases, while others are required at the time of an lost person event. Several of the key inputs are depicted in Figure 3. On the client side, the last known position

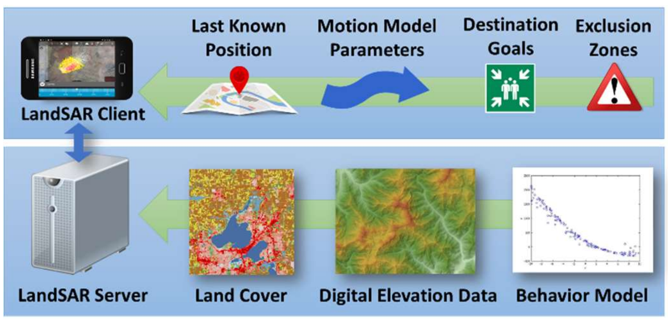

Figure 3. LandSAR Input Data.

is used to center a search. Motion model parameters describe properties of a lost person's movement that may be context specific. For example, a hiker lost in a national park may only move during the day time. Destination goals describe locations known to the LP that they may be more likely to move towards. Exclusion zones are those places an LP is more likely to avoid, and fall into two categories: those known in advance, and those that may be discovered during an event. On the server side the datasets become larger. Land cover data describes the type of terrain (e.g., deciduous forest, grasslands) and is used to help calculate the Speed Of Advance (SOA) – how fast someone may move across that terrain. Digital elevation data is similarly used to determine a realistic SOA and to guide path selection (e.g., an LP may favor flatter terrain over mountainous). Behavior models are used to guide estimation of how an LP will act and make decisions while lost (these models are discussed in detail in Section V.A). These inputs present challenges in terms of both data hygiene, and data acquisition, dissemination, and storage at the tactical edge.

The accuracy and precision of the LandSAR algorithms is a direct function of the quality of the data inputs. Many elevation data sources, for example, contain voids – spaces for which no sensor data was present in the dataset. These voids are often filled with marker values (e.g., some extreme minimum or maximum) and can impact path prediction. An extreme positive value used as a void-filler, for example, might lead the algorithms to believe extreme elevations are present in a path when in fact none exist. Smoothing operations, or dataset fusions to fill such gaps are thus useful. In testing and evaluation, LandSAR thus often uses the Shuttle Radar Topography Mission (SRTM) [12] Version 2 elevation data, which has been post-processed by the National Geospatial-Intelligence Agency. Among other improvements, this post-processing removed single pixel errors and defined coastlines. SRTM data for the United States is accurate to within 1 arc-second, or 30 meters.

While highly accurate data is useful for high quality results, such data also implies large storage requirements and retrieval costs. Each SRTM file, for example, is 25.9 MB once unzipped, and represents 1° latitude by 1° longitude. The 968 such files across six regions of the contiguous United States (CONUS), are, therefore, just over 25 GB in size. All available SRTM data was also obtained in Digital Terrain Elevation Data (DTED) format from the U.S. Army Geospatial Center, consisting of 13,986 files totaling 322.9 GB. For search operations in CONUS, land cover data is obtained from the National Land Cover Database (NLCD), available from the Multi-Resolution Land Characteristics (MRLC) consortium. The CONUS NLCD data is 1.1 GB when compressed in a zip file, and 18.3 GB uncompressed. Visual Navigation (VISNAV) [10] land cover data covers the globe, excluding CONUS and Alaska, and is 17,437 files totaling 288.5 GB. Importantly, the NLCD data and the VISNAV data have the same resolution as SRTM data, allowing for a consistent discretization of the area of interest.

The LandSAR data acquisition design was tailored specifically to address the challenges posed by large datasets representing the areas relevant to a mission, while accounting for the constrained networks, and limited resources of devices at the edge traditional network connectivity. LandSAR allows users to specify an Area of Interest (AOI) within which the LP is likely to be located. Determination of the appropriate area is based on the space an LP could cover within the time period of interest (e.g., a few days). LandSAR also provides support for obtaining elevation and land cover data from a mission/deployment-scoped dataset on a GeoServer [13], an open-source Java-based software server that allows access to geospatial data using open standards. A GeoServer can be co-resident with the LandSAR gateway, or, for deployments with sufficient network connectivity, hosted remotely. LandSAR also has a capability to load data directly from local disk to avoid the need for additional data servers. In cases where high bandwidth Internet connectivity is available, LandSAR can also access data directly from public sources, on-demand as needed, without any preloading.

While LandSAR currently relies heavily on elevation data and land cover data, the algorithms and models can be further tailored to specific scenarios with more data (e.g., weather). Additionally, LandSAR has support for a trails-based motion model, which requires machine-ingestible trail data.

The more data available to LandSAR, the more accurate and precise the results can be. Getting access to additional data feeds where the search teams operate and network connectivity is often limitedcan be challenging; however, work is currently underway to be able to ingest and employ data that is already available at the network edge. LandSAR is positioned within the TAK software suite so that it can consume situational awareness data already flowing through TAK Server, allowing for knowledge of team locations, structures, landmarks, routes, etc.,

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to help refine probability distributions and search results. For example, we are currently exploring probabilistically generated exclusion zones and LP destination goals, based on existing team reported locations, speed and heading data.

Beyond data acquisition and processing, data dissemination presents numerous challenges in the constrained networks in which search and rescue often occurs. The aforementioned BANDIT capability is able to shape the data that flows through each node to meet the constraints of the network. LandSAR enhanced this capability to deal directly with the data formats of concern in SAR operations, such as KMZs which describe place marks, images, polygons, etc. that can be overlaid on a map. Format specific KML compression techniques are being employed by LandSAR. This is accomplished by compressing the points in each line segment described in the KML. Each one of these lists is run through the Microsoft Bing point compression algorithm [11], which generates a single compressed string representing the entire list of points. Each of these strings is then stored in a JSON array and then further compressed using a simple GZip compression. In early test results, a 2MB KML file is initially reduced to 140 KB and after final processing including the GZip step, to 30 KB.

The size of the data dissemination is only one component of addressing effective dissemination in search and rescue contexts. Radio compatibility is another concern. A search team's effectiveness is in part a function of its size, and thus allowing for ad hoc team augmentation is desirable in some scenarios. The team members added in this fashion, however, may not have devices with compatible radios. LandSAR is thus using a QR code transmission mechanism that allows sharing search recommendations using only the camera and screen of mobile devices. QR codes are ubiquitous for visually transferring small amounts of data without a network connection, but their bandwidth is limited, especially by the displays and cameras of mobile phones. The BANDIT technology provides a streaming QR code capability that can be thought of as a flip book of QR codes. This went a long way to mitigate bandwidth limitations by allowing data to be transferred through multiple QR codes, but even this has limits, as it requires the sender and receiver to be physically still, and in close proximity for extended time periods. To achieve even greater bandwidth LandSAR is being extended with the use of color in QR codes. Using color allows more data to be stored in each pixel, thereby increasing their bandwidth and shortening data transfer time. As an example, using 16 colors in a QR code, instead of the normal 2 (black/white), would allow a four-fold increase in bandwidth, essentially quartering the time required to send the same amount of data. It is not without difficulty, though, as introducing color increases the computation complexity of encoding / decoding the data, and it introduces another source of possible errors which must be dealt with, especially in a mobile setting where local lighting conditions can vary.

V. Algorithms and Models

A. *Modeling the Lost Person's Location*

In typical lost person events, the search team decision makers have too many unknown variables, limiting their confidence of where to search. LandSAR attempts to help the decision maker by modeling possible outcomes of where the LP could be over time using different combinations of these variables in conjunction with land cover, elevation and other data to estimate how fast and in what direction the LP might travel.

The system generates a path based on several interrelated models and the available elevation and land cover data, beginning from an initial distribution of potential starting points. It will repeat this procedure many times to produce a sufficiently representative collection of possible paths for the LP. Given this set of paths, LandSAR can provide an estimate of where the LP will be at any time in the future. The simulation ultimately generates a heat map that visually depicts the probability distribution of the LP at any given point in time. An example of this output is shown in Figure 4. On the heat map, red equates to 50% probability that the LP is in these rasters. If you combine red and orange, then 90% of the generated LP paths are in these rasters. If you combine yellow on top of orange and red, then you have all possible outcomes of where the LP was predicted to be according to the simulation.

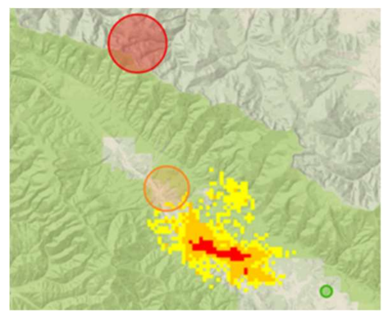

Figure 4. LandSAR generated probability distribution heatmap.

LandSAR uses three model types to probabilistically estimate the location of the LP: a model of where the person starts, a motion model capturing decision processes and ultimately impacting the paths they could traverse, and a model of how fast they traverse those paths. These are described in detail in turn below.

1) Modeling an LP's Starting Point and Intial Movement

To understand where an LP may be at a future point in time, it is critical to understand where they may have been at some point in the past. An exact time and location may not always be known, and thus the starting point model often has incomplete information. There may, therefore, be a distribution of possible starting locations based on the last received information from the LP. LandSAR allows the user to represent these initial distributions via a uniform circle, uniform polygon or several other methods.

Figure 4 shows the likely location distribution from a lost person moving towards one of several potential rendezvous points (one shown as a green circle) and avoiding a known exclusion zone (red) and discovered exclusion zone (orange).

2) Motion Models

LandSAR motion models estimate what an LP is likely to do by integrating assumptions about the thought processes of the LP with information about the area in which they are isolated. A LandSAR user chooses a motion model to best fit the circumstances of the LP. The motion model is used to produce a probability distribution for the location of the LP over time. The approximation for this distribution is a set of sample paths. There is a tradeoff between the number of sample paths (and thus the quality of the results) and computational cost. The more sample paths available to represent the distribution, the better the approximation. The computational cost scales linearly in the number of sample paths. There is, of course, significant uncertainty in that process and, consequently, a Monte Carlo technique is applied to determine the probability distribution of where the LP could be over time.

TABLE I. EXAMPLE LANDSAR MODELS.

Model	Description
Stationary	The LP is assumed to be injured
Lost Hiker With Destination	The LP knows where they are and where they must go. They move in the terrain that best affords success in reaching their goal.
Trails-Based	The LP will move until they reach a trail and then follow it in one direction until found.
Easiest Short-Term Path	The person does not know where they are nor do they have an idea of where help may be, and will take the easiest short-term path

LandSAR supports a number of motions models, examples of which are listed in TABLE I.

3) Speed of Advance

The generated sample paths will describe where an LP may go, but not when they will be there. Their speed of advance along each path is needed to account for the temporal dimension. That speed will be a function of the steepness of the path, the type of land cover, the physical fitness of the LP and other aspects. The Speed of Advance (SOA) model includes all of these factors. After LandSAR determines an initial route that only takes into account water features and elevation variation, it will then utilize other costs to determine minor variations from this route. As LandSAR forms a feasible route, it moves through land cover which has the lowest cost available to choose from. A user may choose to change the default costs to account for assumed choices the LP would make. In the case of an LP moving through woods, for example, the user may assume he/she would choose to move through less densely wooded areas to provide better visibility and thus the user would change the values of deciduous, evergreen and mixed forests to be less likely to be considered. The adjustment factor for slope is a modified version of the formula for walking speed adjustment based on slope, also known as Tobler's Hiking Function [14]. The SOA models take into account facts such as a gentle downslope increases speed of advance, while a steep downslope decreases it.

Finally, a user can also set a movement schedule for the model of the LP, if for example, the LP is likely to only move during the daylight hours, or in some cases, only at night.

B. Search Optimization

The estimate of location in the future can be used to aid attempts to rendezvous with the LP. Maximizing the probability that the LP is localized uses elements of search theory such as the Koopman random search formula [15]. A probabilistic technique is used to find an appropriate search plan. The appropriate plan will, of course, depend on the capabilities of the search asset. A helicopter can cover more area but a searcher on foot might have better probability of detection. Koopman's random search formula is currently used in most of the search algorithms in LandSAR. A more sophisticated approach using lateral range curves, similar to that employed in the U.S. Coast Guard's search application SAROPS, could be readily implemented. However, the sensors used for land-based search and the environmental conditions affecting their performance have not been successfully modeled to the same level as those used for maritime searches. Consequently, we employ the simpler formula, which takes into account the speed, height above ground, and sweep width for the asset. Obviously, the longer an asset can stay on station and search the area, the higher the probability of detection.

LandSAR provides a search area with an associated Probability Of Success (POS), given the search assets and the time they can search for the LP. To do so, LandSAR generates 1,000 random search boxes and calculates the probability of success for each search box. It will recommend the search box with the highest POS and then make small adjustments (e.g., offset, rotate) to improve it. The POS is defined as $P(\text{success}) = P(\text{containment}) * P(\text{detection})$, where the probability of containment is the likelihood of the search object being contained within the boundaries of some area. It is possible to achieve 100% POC by making the area larger and larger until all possible locations are covered, though data and computation requirements scale as the area considered scales. Probability Of Detection (POD) is the likelihood of detecting an object or recognizing the search object and the POD generally decreases the farther away the asset is from the target. It is assumed that the search object is stationary during the search. As long as the search duration is no more than a few hours or the distribution is no longer changing with time, this is a reasonable approximation consistent with the level of detail elsewhere in the modeling. Searches of longer duration can be broken into shorter time intervals to account for these constraints.

VI. EVALUATION

Our evaluation of LandSAR, like most evaluations, considers both efficacy and performance/resource-cost. Realtime access to isolating events, which happen at unpredictable and stressful times, makes efficacy difficult to measure. Below, we present a small instance-based efficacy evaluation based on use of LandSAR algorithms in exercises and in real LP events where the system was used in parallel to existing manual methods as a way to judge early efficacy without yet completely relying on the system (and potentially putting lives at risk). We next measure the performance of LandSAR to understand how fast it can execute (time is often of the essence in SAR operations) and what device resources it requires for complete and performant operation.

A. Efficacy

Multiple LandSAR evaluations showed the system accurately predicting the location of lost persons in the areas that they were actually found. The number of available lost person incidents during the evaluation were insufficient to provide a true statistical basis, but provided enough evidence of efficacy to warrant subsequent evaluations which will begin in the spring of 2020. Though successfully finding a lost person is the ultimate goal, LandSAR has the secondary effect of reducing the man and flight hours committed to searches. In 2018, the U.S. Air Force Rescue Coordination Center (AFRCC) reported that they responded to 933 SAR mission and the CAP flew 752 missions. Any reduction of time across so large a number of missions has the potential to save lives and to significantly reduce costs for the respective government agencies.

B. *Performance*

We measured runtime performance across multiple devices, looking at how area of interest size and model selection impacted overall execution. Here, we report experiments run on an Intel® Xeon® Dual 4-core laptop with 32GB of RAM.

TABLE II. EVALUATION GEOGRAPHIC REGIONS

Area Name	Area Description	Center Point (lan/lon)
NM	New Mexico / Arizona border	32.0, -109.1
MA	Massachusetts	42.187279, -73.005823
MI	Michigan	44.017543, -84.252951
NW	Near Coeur d'Alene National Forest, Idaho	47.75, -116.6
RockyMs	Rocky Mountains	44.268656, -109.786399

Five geographical areas, listed in TABLE II, were analyzed. For each area, the center point was used as the single starting point for the LP and bounding boxes of three different sizes were considered:

Large: 107 km east to west by 125 km north to south
Medium: 35.8 km east to west by 36.6 km north to south
Small: 12.0 km east to west by 14.0 km north to south

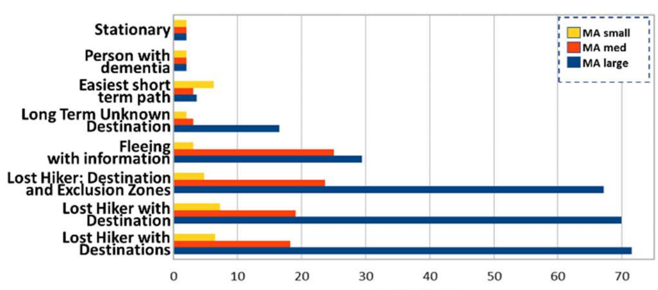

Figure 5. Execution Times for Specific Motion Models.

Figure 5 depicts the overall runtime of the system when operating on the MA small, medium, and large data sets for each of 8 LandSAR models. As can be seen, simple models, such as the stationary model, operate quickly regardless of dataset size. More complex models, such as those that must consider rendezvous points or exclusion zones are more dependent upon the geographic area size (and thus the data size). In the slowest configuration – the large dataset with the most complex model, the runtime is just over 70 seconds, and thus still a very feasible duration for real world contexts.

Figure 6 and Figure 7 look at CPU and heap memory usage respectively, when executing over the MA large dataset. CPU usage, after an initial ramp up, consumes the vast majority of the system's compute resource, indicating multiple concurrent search executions, or slower processors could likely lead to meaningful increases in overall runtime.

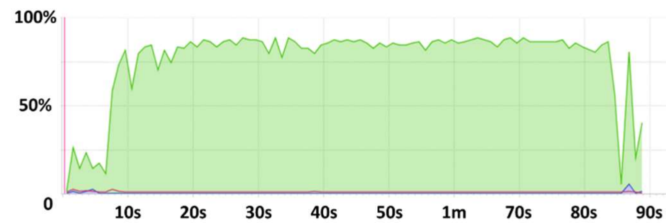

Figure 6. LandSAR CPU Usage on MA Large Dataset.

It can be seen that while the operations employ a non-trivial amount of RAM (peaking around 2GB), it did not come close to consuming the 32GB of available memory on the machine (here we show heap memory; non-heap memory usage was low, approximately 25MB).

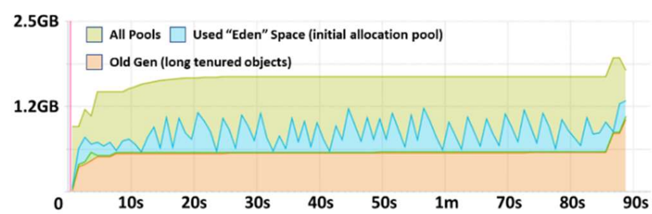

Figure 7. LandSAR Heap Memory Usage for the MA Large Dataset.

VII. Conclusions and Future Work

The LandSAR capabilities described here have shown initial promise in both performance evaluation and in early trials. Embedding of this technology into the TAK platform enables both increased evaluation and increased likelihood that the capabilities will be in the hands of those that need them when and where they are needed. This work is forming a base on which a set of optimized, enhanced, and augmented capabilities are being built. Deployment in real SAR contexts is underway, and work is being undertaken in a number of areas of technical and capability advancement:

- Enhanced accuracy and precision through the ingestion of situational awareness data that is already natively flowing through TAK devices.
- Development of a web-based version to support search command centers and teams without ATAK devices.

- Automated and semi-automated tasking of small unmanned aerial systems (sUAS) based on LandSAR-generated search recommendations.
- Employing streaming color-coded QR codes for increased bandwidth when sharing search information with joint or other forces that may not have compatible radios.
- Extending the LandSAR format-centric compression techniques tailored at reducing size of the KMZ files through the use of point reduction algorithms such as [16] to decimate a curve composed of line segments to a similar curve with fewer points.

This suite of capabilities, combined with the current LandSAR functionality, will result in a SAR- and LP- focused tool that has the potential to dramatically reduce the duration of LP events, and increase the likelihood of successful rescue operations.

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