Calibration and Validation of Earth-Observing Sensors Using Deployable Surface-Based Sensor Networks

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***Abstract*—Satellite-based instruments are now routinely used to map the surface of the globe or monitor weather conditions. However, these orbital measurements of ground-based quantities are heavily influenced by external factors, such as air moisture content or surface emissivity. Detailed atmospheric models are created to compensate for these factors, but the satellite system must still be tested over a wide variety of surface conditions to validate the instrumentation and correction model. Validation and correction are particularly important for arctic environments, as the unique surface properties of packed snow and ice are poorly modeled by any other terrain type. Currently, this process is human intensive, requiring the coordinated collection of surface measurements over a number of years. A decentralized, autonomous sensor network is proposed which allows the collection of ground-based environmental measurements at a location and resolution that is optimal for the specific on-orbit sensor under investigation. A prototype sensor network has been constructed and fielded on a glacier in Alaska, illustrating the ability of such systems to properly collect and log sensor measurements, even in harsh arctic environments.**

***Index Terms*—Arctic environments, autonomous robots, mobile sensor networks, remote sensing, satellite sensor validation.**

I. Introduction

NASA's Earth Observing System (EOS) provides a potential wealth of information regarding the state of the environment through a variety of on-orbit sensing capabilities. NASA's Ice, Cloud, and land Elevation (ICESat) satellite [1] is mapping the earth's surface using a Geoscience Laser Altimeter System (GLAS), while Landsat is capturing high resolution imagery. Several climate-oriented instruments on-board the Terra [2] gather such information as the Land Surface Temperature (LST) and pollution levels. Despite the fact that satellite data is the only practical means of collecting dense sensor readings over entire continents, there has been hesitation on the part of the climate modeling community to make use of this data, citing concerns over accuracy and the lack of thorough validation [3]. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, from which LST is derived, has been independently validated at only a handful of sites [4], [5], partly due to the manpower required to perform such sensor validations.

The problem of acquiring validation data is particularly acute in arctic regions. The harsh environment makes routine human expeditions to collect *in situ* sensor measurements an expensive and dangerous proposition. At the same time, the unique surface properties of packed snow and ice are poorly modeled by other surface types. Values derived from calibration sites for almost any place on Earth may introduce systematic biases if applied to measurements over glacial regions [6]. Instead of relying on human-led campaigns, a mobile robotic sensor network is proposed which greatly mitigates the human resource requirements associated with performing satellite validation tasks.

Section II describes several existing techniques used for satellite validation experiments, while Section III extrapolates from these experiments the base requirements needed by a robotic sensor network for satellite validation tasks. Section IV describes the implementation of a prototype sensor web, detailing how each requirement has been fulfilled. The prototype sensor network was then fielded on a glacier in Alaska, the details of which appear in Section V. Finally, conclusions drawn from these experiments are presented in Section VI.

II. Limitations of Current Calibration and Validation Techniques

Orbital measurements of ground-based quantities are heavily influenced by external factors, such as air moisture content or surface emissivity [1]. Detailed atmospheric models are created to compensate for these factors, but the satellite system must still be validated to ensure the accuracy of the instrumentation and correction model [3], [6]. For proper on-orbit sensor validation, calibration sites should be selected to cover the expected range of global ground surface properties. Further, data should be collected at a variety of scales, similar in size to the single pixel area of the data product under consideration [2]. Calibrating over areas that closely represent the measurement areas of interest enhance the accuracy of the model. These measurements can take the form of airborne sensing, automatic weather stations (AWS), or human-led field expeditions, with each method carrying its own drawback.

Airborne sensing, particularly laser altimetry for validating digital elevation models (DEMs), has been found to be extremely useful when the sensor suite available includes commercial scanning laser equipment, multiple GPS receivers,

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and high-end inertia navigation systems [7]. Aerial measurement campaigns enable scientists to collect data on areas that would be otherwise unreachable for ground-based experiments or are simply too vast to cover accurately. Typically, however, performing these runs requires safe flight conditions (wind speed, temperature, visibility) as well as sufficient funding and resources to maximize the number of possible experiments that take place within a short period of time.

AWS networks are popular tools for *in situ* measurements as well. These instruments remain fixed in a single location and are usually equipped with several weather-oriented sensors, such as pyranometers. These devices enable the collection of albedo data allowing inference of elevation change. Given the immobility of these devices, the accuracy of measurements taken becomes a function of sampling and estimation capacity relative to the entire network. Each AWS unit spans a limited radius of coverage and scientists must consider other units in the network, relying more heavily on extrapolation methods to obtain a breadth of coverage in an area. For example, the AWS system in Greenland and Antarctica average one station per 100,000 km^2. Short of accessing measurements taken by the network, any data collected from one unit can only represent a single point on a map, useful only as a heuristic to indicate what changes may be taking place [8].

One project did make use of sparse, stationary weather stations for estimating MODIS error measurements [3], but only readings taken at night were considered. During this validation exercise, it was assumed that the Earth's surface was a uniform temperature over large areas, allowing a single point measurement to be representative of the whole region. However, this is only valid for nighttime measurements, and only vegetated regions were included in the study.

Finally, human-led field campaigns provide the highest resolution for these types of weather measurement data. GPS and Ground Penetrating Radar (GPR) surveys are useful calibration techniques for validation of remote sensing equipment such as GLAS [6]. These surveys require constantly manned equipment with integrated sensing, and carefully planned navigation paths. Though the coverage area is considerable for *in situ* trials (100 km^2), the duration of these field experiments is potentially more strenuous on the scientists performing the tests.

An example of this methodology has been used to validate the LST recorded by MODIS on-board the Terra satellite [5]. A 1 km^2 region of a large rice field in Spain was selected as the validation site. The rice field offered a large, flat area that was uniformly covered in vegetation. Hand-held temperature sensors were stationed at several points within the test site. During the satellite overpass event, GPS-registered temperature readings were collected and logged several times a minute as the sensor was moved over a 100 m traverse. Due to the satellite orbit, only a handful of overpass events occur within the validation site during each repeat cycle. Further, as the satellite repeat cycle is 183 days long, only one such cycle occurs each year within the growing season, during which the site has uniform vegetation coverage. During the three year period over which these experiments were performed, only 11 validation events of MODIS were recorded.

III. Sensor Network Requirements

Most of the calibration and validation procedures described in the preceding section are human intensive. The use of appropriate robotic technology could be used to mitigate the expense of human-based data collection, particularly in the hazardous terrain of arctic environments.

For such a solution to be viable, the network must meet certain goals. First, the network must be fault-tolerant. When deployed in unknown, natural environments, unforeseen events could disable specific robotic nodes. A failure of a single node should be handled gracefully, with other nodes taking over critical positions in the network topology. Because a large number of nodes will be required for the network, and because of the environmental threat to the health of a node, each agent must be relatively inexpensive. Secondly, the network must be reconfigurable. The deployed location, inter-agent spacing, and scientific instrumentation package must all be easily modified in order for a single network to be used for different satellite instrumentation or different data product resolutions from a single satellite sensor. Next, each robotic node must be able to navigate to its goal position autonomously. The number of nodes and size of the deployment area preclude teleoperation as a viable control strategy. As such, each agent must be able to assess the environment for potential hazards, and replan paths to the goal that avoid hazardous areas. Finally, each agent must be able to properly stamp each sensor reading with the acquisition location. Since the agent position can never be known exactly, beyond just accuracy, an estimate of the current positional error is needed.

IV. Prototype Sensor Network

A set of prototype rovers were designed to fulfill the identified network requirements. The mechanical design emphasized high mobility, low cost construction. A snowmobile chassis was selected as the base for the SnoMote prototype robotic mobile sensor. The chassis, based on an *RC* snowmobile chassis, was heavily modified to incorporate a dual-track design. The main reason tracks are used for snow traversal is a matter of weight distribution. Similar to cross-country skis or snow shoes, the large area of a snowmobile track is able to distribute the vehicle weight, allowing it to "float" on the surface of the snow. The original front suspension mechanism was replaced by a passive double-wishbone system, increasing the ski-base over 30%. The overall increase in the platform width drastically increased the platform's stability and roll characteristics. The modified platform has been equipped with an embedded processor and microcontroller for controlling the on-board systems, a high-torque drive and steering system for negotiating the snow-covered terrain, and a wireless communication system for relaying sensor data and rover state information back to an observation computer. To simulate the science objectives of the mobile sensor, a weather-oriented sensor suite was added to the rover. The instrument suite includes sensors to measure temperature, barometric pressure, and relative humidity. Ultimately the science package can be configured for the specific sensing and validation task to

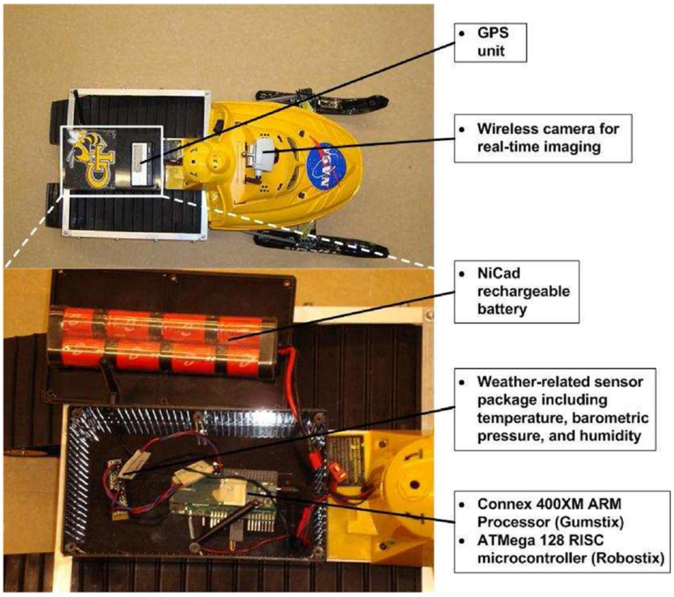

Fig. 1. A diagram of the electronics and sensors on-board an early revision of the rover.

be performed. Fig. 1 shows a diagram of the internal and external robot components.

A. Fault Tolerance

To achieve fault-tolerant operation, a distributed algorithm was used to allocate tasks to the different agents [9], [10]. After the desired sensor locations have been established, the agents conduct an auction to award each sensor location to a specific robot. So-called market-based algorithms work like regular auctions where two roles are played dynamically by robots: auctioneers and bidders. The auctioneer is the agent in charge of announcing the tasks and selecting the best bid from bidders. In our case the bid is a quantity that reflects how much it will cost the robot to go to a certain waypoint, such as the euclidean distance or the traversability index [11]. Market-based algorithms are independent from the number of robots, and have no single point of failure. Therefore, if one robot fails, tasks will be allocated to the remaining robots automatically.

B. Autonomous Navigation

In each robot, a path planning algorithm, an obstacle avoidance routine, a slope assessment algorithm, and a task execution unit have all been integrated into a single behavior-based architecture [10]. Navigation is implemented using the DAMN architecture [12] to combine the competing outputs of each behavior module. The DAMN architecture was designed to combine different behaviors for mobile robots in unknown and dynamic environments. Within the DAMN architecture, each behavior votes for a set of possible actuator values satisfying its objectives. Then, an arbiter combines those votes and generates actions which reflect the behavior objectives and priorities.

The path planning unit allows the system to integrate map-based information in the navigation scheme. The algorithm is based on a heuristic estimator to find the optimal solution faster than a general search algorithm. A Pure Pursuit algorithm [13] is then applied to follow the path generated by the planner. The Pure Pursuit algorithm geometrically determines the curvature that will drive the vehicle to a chosen path point defined as one lookahead distance from the current position of the robot.

As small-scale surface variations cannot be determined from existing map sources, the threat of roll-over is a major concern. To minimize the likelihood of roll-over, a fuzzy logic slope assessment scheme has been developed to keep the rover on level terrain [14]. The behavior makes use of a slope estimation technique using only a single camera [15]. The control scheme is able to easily capture inherently nonlinear heuristic knowledge, providing a flexible, easily extendable architecture for designing navigational control laws [16].

C. Localization

The need for low-cost units pushes the localization methods away from centimeter accuracy GPS and military-grade IMU sensors, and towards consumer-grade sensing technologies. In particular, vision is an attractive option. By tracking the motion of visual features within the image, the motion of the camera can be computed. Recent advances in computer vision algorithms have shown that camera-based localization can be solved tractably [17], [18], and a camera is already included on the platform for hazard detection.

The use of vision for localization purposes revolves mainly around multi-view geometry methods and the related simultaneous localization and mapping (SLAM) methods. Vision-based SLAM attempts to solve this problem in a probabilistic framework [19], [20]. The system attempts to maximize the joint probability of the robot pose, x_t, and a map of 3-D landmarks, m, given the entire set of robot control inputs, $\mathbf{u}_{0:t}$, and observations, $\mathbf{z}_{0:t}$.

$$\arg\max_{x_t,m}\left(p(x_t, m \mid \mathbf{z}_{0:t}, \mathbf{u}_{0:t})\right) \tag{1}$$

The major advantage of this approach for localization is the explicit use of probability distributions to describe the current state. The positional uncertainty can be extracted at any time by simply marginalizing out the appropriate variables from the current solution. A commonly used method of solving for the SLAM probability distribution is to employ a Rao-Blackwellized particle filter (PF) to estimate the robot pose [21], also known as FastSLAM. The PF samples many pose "particles" from the pose distribution, and assumes each pose particle is the true robot pose. Since the error in the robot pose is now assumed to be zero, the landmark distribution estimates become decoupled, allowing the independent estimate of the visual landmarks. The standard FastSLAM factorization is shown in (2). The decoupling of the robot pose from the landmark locations allow systems with large databases of landmarks ($>$10000) to be calculated in real-time. Although the FastSLAM system was not originally derived for use with vision, vision-based implementations have recently been presented [22], [23].

$$p(x_t, m \mid \mathbf{z}_{0:t}, \mathbf{u}_{0:t}) = p(x_t \mid \mathbf{z}_{0:t}, \mathbf{u}_{0:t}) \cdot \prod_{i=1}^{M} p(m_i \mid \mathbf{x}_{0:t}, \mathbf{z}_{0:t}) \tag{2}$$

where M is the current number of landmarks in map m.

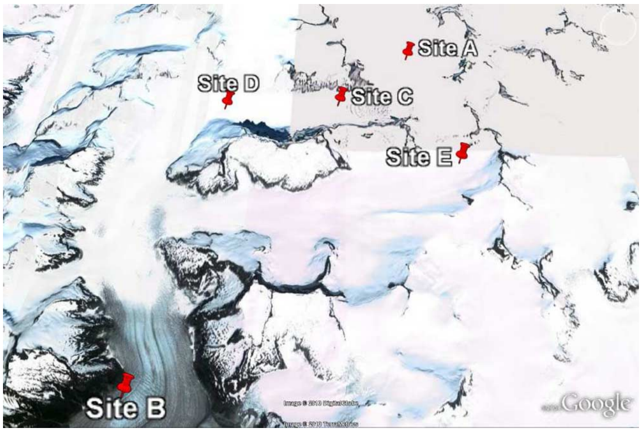

Fig. 2. A map of the relative position of each test site on Mendenhall Glacier.

However, these methods require strong visual features, or distinctive areas in the image. As distinctive areas are rare in the all-white images of snow-covered glaciers, methods for enhancing and extracting subtle features are first applied [24].

V. Results

Mendenhall Glacier is part of the Juneau Ice Field, the fifth largest glacier system in North America. As part of the Tongass National Forest, the Mendenhall Glacier is visited by almost half a million people annually. In addition, the Mendenhall Glacier is the subject of ongoing scientific research by the SEAMonster Project [25]. Due to the continued interest in Mendenhall by the public and scientists alike, it was selected as the subject for the SnoMote rover deployment.

Several test sites were selected across Mendenhall Glacier in order to test the system in a variety of glacial terrains. Sites A and C are located at the top of the northern branch. These areas are completely covered with soft snow and are largely flat for several kilometers in any direction. The areas are ultimately surrounded by distant mountain peaks, with an “ice fall” visible near Site C. Site B is located in the upper plateau of the terminus. Here the underlying ice is exposed and the terrain is characterized by small, rolling hills several meters in height. Some crevasses are present in this area, and melt water pools in some of the small valleys. Site D is located at the lower edge of the northern branch, near a bend in the glacier. Again, the site is completely snow covered, but is much closer to the mountains. Due to the proximity of the Mendenhall Tower peaks and the bend in the path, the terrain exhibited large-scale undulations. Finally, Site E is located at the top of the southern branch, with terrain similar to that of Site A. Fig. 2 shows the location of each test site on the glacier.

During a satellite validation event, each rover would be required to perform a traverse of the validation site. Based on human-conducted validation experiments, these traverses are expected to be on the order of 100 m. Though, the actual traverse distance could be dependent on the terrain as well as the on-orbit sensor in question. During these traverses, the sensor data must be logged, and tagged with both the acquisition time and position. To test the rover’s ability to localize itself, thus

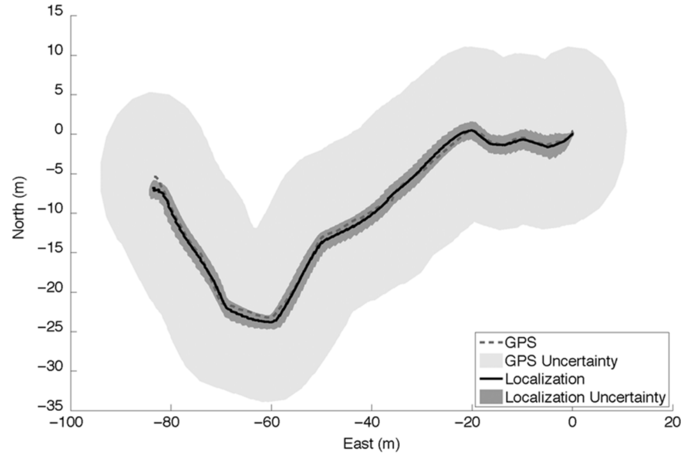

Fig. 3. The localization results using GPS alone and in combination with Visual Odometry at Site E. The calculated uncertainty value has been reduced considerably through the use of vision-based techniques.

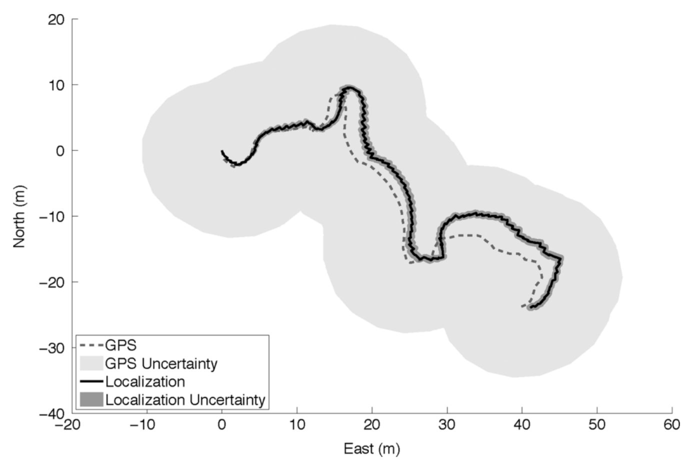

Fig. 4. The localization results using GPS alone and in combination with Visual Odometry at Site B, the most challenging of the test sites due to the large terrain variability.

providing accurate position information, a prototypical data logging traverse was conducted at each test site. During each test traverse, the rover logged the system time, sensor data, raw GPS position, and camera images at a sensor-dependent rate no slower than 1 Hz.

The camera images and robot control values were then used as input to the visual odometry system, and fused with the GPS information. The odometry systems produces a maximally likely position estimate, as well as predicts the current position error covariance based on a linearized system model. Fig. 3 shows a typical example of the localization output recorded at Site E, compared with the recorded GPS values and corresponding GPS error. As seen, the calculated localization variance is significantly smaller than the GPS uncertainty. Fig. 4 shows the localization results at Site B, the most challenging of the test sites due to the large terrain variability. Again, the proposed localization method significantly outperforms GPS alone in terms of measured uncertainty. Fig. 5 presents a summary of the traverse experiments performed, including the GPS coordinates of each site, total distance traveled, and the average 95% confidence uncertainty for the traverse, as calculated by the localization

Site	Reference Location	Date Collected	Distance Traveled	95% Confidence
A	58.56°N, 134.41°W	5/31/2009 10:18	38.4 m	0.59 m
B	58.47°N, 134.54°W	6/04/2009 12:34	194.2 m	1.22 m
C	58.55°N, 134.45°W	6/04/2009 14:35	180.1 m	0.97 m
D	58.55°N, 134.51°W	6/04/2009 15:24	167.0 m	0.86 m
E	58.53°N, 134.39°W	6/04/2009 17:27	100.1 m	1.64 m

Fig. 5. Summary of field trial localization results, listing time and location of each test site, the total distance traveled, and the average positional uncertainty achieved by the proposed localization system.

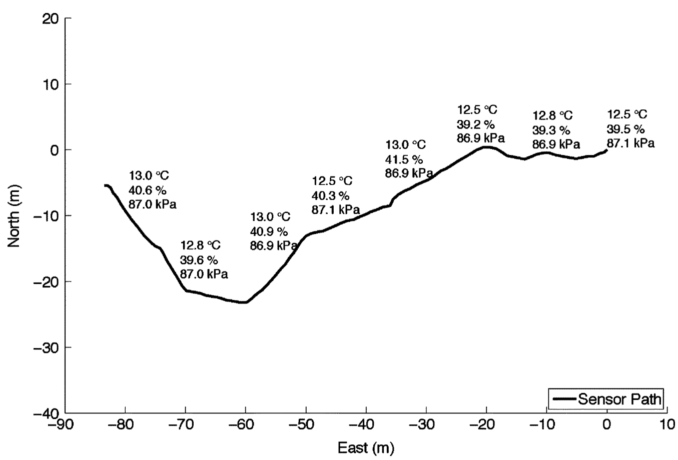

Fig. 6. Weather-related sensor data collected and geolocated during a sensor node placement trial at Site E on Mendenhall Glacier, Alaska. Measurements include temperature, relative humidity, and barometric pressure, with samples displayed at approximately 10 m intervals.

system. As expected, the calculated positional uncertainty generally increases with the total distance traveled, but stays well below the rated 10 m accuracy of the GPS alone.

Before any of the robotic sensor nodes can perform their data logging traverses, they must first navigate to a desired goal location. However, due to GPS noise, terrain variability, and the dynamics of the rover itself, it is impossible to achieve the desire goal exactly. To assess the autonomous navigation performance of the prototype sensor network, several different three-node sensor configurations were uploaded to the system. The robotic nodes negotiated which node would fulfill each task based on the current network state. Control laws on-board each node then autonomously navigated to its own goal location. Node displacement error is calculated as the difference between the desired goal position based on the GPS position of a fixed location and the final GPS position as reported by each node. During these trials, the average sensor node placement error was 2.84 m. Sensor node orientation was not considered during these tests. Fig. 6 shows the resulting *in situ* sensor data associated with the traverse of one sensor during a node placement trail at Site E.

Finally, the question of data collection frequency should be addressed. During the human-led campaigns to validate MODIS, only 11 satellite overpass events occurred during the three year project. In contrast, the prototype rovers averaged over 1 m/s traversal rate in glacial conditions. This travel rate places 14 overpass events of ICESat within a 4 hour radius of a single base location, potentially allowing far more data gathering opportunities. Although the prototype rovers are not currently capable of such extensive travel, a final rover design should be capable of at least twelve hours of autonomous operation.

VI. Conclusion

A robotic sensor network has been proposed, constructed and tested as a means to minimize the efforts (aerial, AWS, and human) involved in collecting *in situ* ground measurements for sensor validation tasks. *In situ* validation is of particular importance in arctic environments, where data collection campaigns present a serious hazard to persistent human presence. Our prototype network was developed for glacier environments, emphasizing distributed, fault tolerant, low cost sensor nodes, while still enabling significant autonomy. The network was weather-hardened and successfully deployed to glaciers in Alaska, where the three sensor nodes autonomously navigated to desired locations while logging weather-related sensor data. Further, the collected camera images were processed using an arctic-specific visual SLAM implementation to track the robot position within the environment. As expected, the visual localization algorithm resolved many issues that arise when using standard GPS receivers, such as GPS outages and bias shifting as the satellites go in and out of view. The visual odometry system provides more accurate positions than GPS over short deployments, and calculates a situation-dependent error model for the current position estimate. However, as the position error of the visual system tends to increase over time, the visual odometry estimates have been fused with the GPS data to create a bounded, positional estimation system. During trials, the fused position estimate was often able to achieve sub-meter accuracy.

The work has shown how a mobile robotic sensor network can potentially improve data gathering methods for on-orbit sensor validation in several ways. First, the number of accessible validation events, where the satellite-based instrument is directly overhead, is increased significantly by a mobile base. When using fixed weather stations, the number of validation opportunities is limited to, at best, two per cycle, while human campaigns are limited by time, expense, and logistics. In contrast, the proposed mobile rover could reach 14 overpass events of ICESat within a cycle from a single base location. Improvements upon data collection methods are also achieved as our system demonstrates a logging frequency of 10 Hz, efficiently recording weather sensor data points with a corresponding time stamp. Our system combines the automated data logging capabilities of stationary equipment with the mobility of human-led teams. Also, the visual localization algorithm is able to produce position estimates that exceed that capabilities of GPS alone, while simultaneously calculating the current position error. This allows the log file to be tagged with not only the best position estimate, but also the positional uncertainty of all collected science data. Finally, while other robotic systems have been deployed to Greenland and Antarctica in the past, these projects have focused on constructing a single, large robotic unit. This project has demonstrated that autonomous navigation and data collection in glacial environments is feasible using the kinds of low-cost sensing solutions that would be available in a multi-robot deployment.

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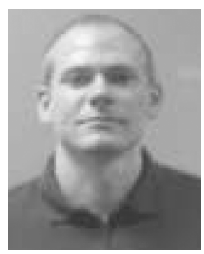

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Dr. Howard received the IEEE Early Career Award in Robotics and Automation in 2005.