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Sensory Fusion for Planetary Surface Robotic Navigation, Rendezvous, and Manipulation Operations

Terry Huntsberger, Yang Cheng, Eric T. Baumgartner, Matthew Robinson, Paul S. Schenker
Jet Propulsion Laboratory, California Institute of Technology
4800 Oak Grove Drive, Pasadena, CA 91109
(Terry.Huntsberger, Yang.Cheng, Eric.T.Baumgartner, Matthew.Robinson, Paul.S.Schenker)@jpl.nasa.gov

Abstract

The upcoming missions to Mars planned by NASA/JPL in 2009 and 2013 are more ambitious than any previously flown. Included in these missions are extended multi-kilometer traverses, and autonomous rover rendezvous with science targets and man-made structures such as landers. This paper reports some of the ongoing work at JPL in the areas of autonomous sensory fusion of both raw and derived inputs for better localization during long traverses, precision rendezvous operations with both labeled (man-made) and unlabeled (natural) targets, and precision manipulation of targets. We also present the results of some experimental studies done in laboratory and external environments.

1. Introduction

The sensor suites on the JPL technology prototype rovers such as SRR (Sample Return Rover) and FIDO (Field Integrated Design and Operations) shown in Figure 1 span a wide range of spectral bands, stereo baselines, and fields of view. Traditionally, these sensor suites have been used in isolation for such tasks as planetary surface traversal. For example, although distant obstacle information is known from the narrow FOV navigation camera (NavCam) suite on SRR or FIDO, it is not explicitly used at this time for augmentation of the wide FOV hazard camera (HazCam) information for localization. Such augmentation coupled with internal state sensors such as gyros/accelerometers and sun-sensors can greatly improve the localization of the rovers and enable precision autonomous operations. Due to the long round-trip time delay for communication with Mars during a mission (up to 45 minutes), teleoperation is not a control option in such cases.

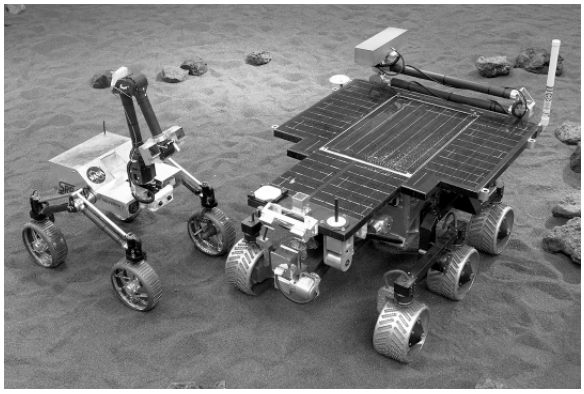

Figure 1. JPL technology prototype rovers: left -Sample Return Rover (SRR); right – Field Integrated Design and Operations (FIDO).

During the past six years, members of the Planetary Robotics Laboratory (http://prl.jpl.nasa.gov) at JPL in Pasadena, CA have been developing and field testing a suite of algorithms that run onboard rovers to address performance issues with respect to rover localization and manipulation capabilities [16, 28]. In this paper, we report on some of the ongoing work at JPL in the areas of autonomous sensory fusion of both raw and derived inputs for better localization during long traverses, precision rendezvous operations with both labeled (man-made) and unlabeled (natural) targets, and precision manipulation of targets.

Section 2 describes an improved rover localization technique for autonomous long-range navigation. Section 3 describes the suite of algorithms for long-range rendezvous operations. Section 4 presents the multi-step algorithm for precision rendezvous with natural targets. Section 5 describes the HIPS algorithm for precision manipulation. This is followed by an experimental studies section, and finally a summary section including current directions.

2. Fusion of Range Map and Internal State

This section describes the development of a state estimation approach for surface rovers that derives the pose transformation between two range maps of the terrain, and then fuses this information with wheel odometry, inertial measurement sensors, and a sun

sensor to generate accurate estimates of the rover's position and attitude.

2.1. Range Map Registration & Motion Estimation

Significant errors may occur in rover localization when executing obstacle avoidance maneuvers during a long traverse. In such cases, 3D registration of successive range maps can be used to estimate rover motion. Previous work in this area includes maximum likelihood estimation of motion coupled with a Kalman filter update of rover position [20, 21]. A recent method using probabilistic map matching based on a maximum likelihood map similarity estimator was developed by Olson [23, and references therein] for rover localization. His studies, which only included translations in the environment, indicated that sub-pixel accuracy within a discretized pose space was achievable. The only concern raised was that of scaling for pose determination from a totally unknown state, which usually wouldn't be an issue due to other sensors onboard the rover.

We use a range map registration technique that blends Zhang's Iterative Point Matching (IPM) [38] and the surface interpolation of Besl and McKay's Iterative Closest Point (ICP) [6] algorithms to compute a 3D rotation and translation which aligns one set of data points (S_1) with another (S_2). Initially, the data points in S_1 are transformed according to estimated rover motion taken from the commanded movement. Next, the algorithm constructs a k-dimensional (or k-D) tree for the points in S_2, then alternates between two phases: closest-point computation, and estimation of the transformation between corresponding points. The k-D tree enables efficient determination of the closest point in the data set [26]. Previous studies using this technique have shown that the rover's change in heading and lateral position can be accurately estimated, while the estimates of the rover's change in forward position are not as accurate [13, 15, 18].

2.2. Extended Kalman Filter

The rover localization approach is based on the work presented in Baumgartner and Skaar [2] and Yoder et al. [37] that describes a time-independent EKF formulation for the determination of the rover's state estimates. The problem of integrating inertial measurement units (IMU) on mobile robots for improved rover state estimation, sometimes called the simultaneous localization and mapping or SLAM process, is the topic of research at a number of labs, including but not limited to Dissanayake, *et al.* [8], Vaganay, *et al.* [33], Goel, *et al.* [11], Chung, *et al.* [7], Julier and Uhlmann [17], and Roumeliotis and Bekey [27]. The IMU modeling approach presented in this paper closely matches the techniques described by Goel, et al. [11] and Chung, et al. [7].

For the IMU sensor, the attitude of the vehicle is described by the roll, pitch, and the yaw (heading) angles where the yaw angle (ψ) is defined in relation to true North, and the roll and pitch angles are specified relative to the local gravity vector about the rover's local X and Y coordinate frame axis, respectively. The roll and pitch angles of the rover are determined by the 3-axis accelerometer and the heading of the vehicle during motion is determined using the yaw gyroscope rate sensor. When the rover is stationary, the IMU rate sensor bias terms are estimated via a linear Kalman filter. When the rover begins its motion, the rate sensor bias estimator is deactivated and the most recent rate sensor bias term is then used to integrate the yaw rate sensor measurements in real-time to determine the heading of the vehicle throughout the rover's traverse. Finally, the absolute heading of the vehicle is determined via a sun sensor which is then utilized to initialize the rover's heading prior to the next planning cycle for the rover's operations. A more detailed discussion of this technique can be found in papers by Hoffman, et al. [13] and Baumgartner, et al. [2-4].

3. Multi-feature Fusion

Precision navigation from relatively great distances (~125-200 meters) to rendezvous points such as a lander for operations during the upcoming 2013 Mars Sample Return (MSR) mission, as well as from shorter distances to science targets prior to instrument placement on the upcoming 2009 Mars Science Laboratory (MSL) mission, is key to a successful completion of the science objectives. The main differences between the lander and the science target rendezvous operations are the types of targets (man-made vs. natural), and the relative localization of the targets (possible unknown vs. selected from imagery). We have developed a multi-feature fusion algorithm suitable for long-range rendezvous operations that integrates the outputs of horizontal line and wavelet-based visual area-of-interest operators [9]. The wavelet operators fuse horizontal, vertical, and diagonal texture characteristics at multiple scales for detection of a man-made target such as a lander and rendezvous with the same from distances greater than 125 meters. This technique is coupled with 3D visual terminal guidance algorithms that extract and utilize cooperative features of the lander to accurately, iteratively estimate structure range-and-pose estimates, and then steer the rover to the rendezvous position.

The nature of features that can be extracted from visual imagery for goal/target-based navigation has a strong dependence on the finite resolution of the sensors on a mobile platform. In addition, the types of information required for navigation will vary depending on the relative distance of the platform to the target. At longer distances only heading information will be required, but as the rover approaches closer to the target, rough relative pose and orientation and finally precision alignment information is required. We have developed a suite of algorithms that derive distance and heading information from visual images acquired during a three phase approach (shown in Figure 2) to a man-made target, in this case a lander.

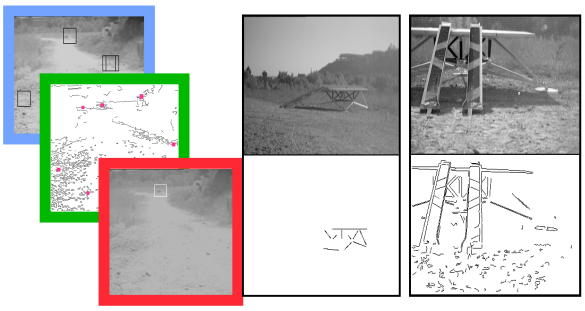

Figure 2. The three phase approach to a lander from 125+ meters away. From left to right: image montage showing from top to bottom - long-range approach with lander candidates from wavelet texture signature, horizontal line detection, and fused result (shown in box); mid-range montage with original image on top and extracted lander deck and truss structure features on bottom; close-range montage with original image on top and extracted ramp and lander features.

For the long distance approach phase, fine details on the target are difficult to distinguish and target signatures oftentimes are masked by the surrounding terrain features. In the majority of cases for planetary rover operations, a distinctive texture measure of the target (lander) can be defined for discrimination. We have previously developed a wavelet-based texture signature operator that has been used successfully for automatic target recognition [9], generation of semi-sparse range maps based on texture analysis [13], and closed loop science instrument deployment [16]. A horizontal line detection algorithm that localizes possible lander candidates based on detection of the lander deck is used to constrain the texture signature extraction to a local window of the wavelet coefficient space for each of the lander candidates. The multi-feature fusion algorithm eliminates the false positives in this process arising from features in the surrounding terrain.

During the mid-range phase of the rendezvous approach, parallel line features are extracted from the lander truss structure. In order to correctly distinguish the truss structure, the lander deck is detected first, which appears as a pair of nearly horizontal parallel lines. Any parallel lines below the deck are considered part of the truss structure. The engineering model of the lander is known and constrains the expected geometry of the truss structure. The average distance between the parallel pairs is used to estimate the distance from the target, and the center of mass of these parallel lines is used to compute the heading direction.

The close-range ramp alignment algorithm includes three major steps: feature extraction, feature match, and pose estimation. Features in this case include six stripes that were deliberately arranged on the ramps leading up to the lander deck so that any two stripes have a unique combination spatially and topologically. This unique configuration greatly reduced uncertainty and computational complexity. A Canny edge detection algorithm is applied, followed by straight-line segment extraction. In order to find the stripes, we first look for the ramps, which are defined by a set of long straight and nearly parallel lines.

With a single detected stripe in the image, a linear affine transformation is constructed based on the four corners. If this match is correct, the transformation is used to find other matches. Because there are relatively few stripes (six on the ramps) an exhaustive search is used to pick up the best match. Once the matches are found, the pose and orientation are estimated by fusing the estimates from the outside corners of all detected stripes. A minimum of four stripes is used for safe navigation.

4. Multi-view, Multi-feature Fusion

For the shorter range science target rendezvous operations, we have developed a technique that fuses the relative rover pose returned from a multi-target tracking algorithm running onboard the rover with the current camera model to update the location of the science target relative to the approaching rover in natural terrain. The previous section described algorithms that exploited the man-made aspects of a lander using a single view fusion of information from derived features. The lack of fiducial marks on natural targets obviates the need for autonomous generation of interest points in the images, coupled with tracking of these points between views for the recovery of 3-D information during the traverse to the science targets. Such techniques have been used previously for updating rover localization information in the absence of a specific goal during traverses [24, 25] and for the approach to and manipulation of science

targets [19]. Both of these previous efforts used short range sensor information derived from the HazCams on the rovers and thus are limited in use to a range of less than 4-5 meters. We have developed a multi-step algorithm based on images from the mast mounted NavCams (range of 20-50 meters) that the scientists use for initial target selection, an example of which is shown in Figure 3.

Figure 3. Sample NavCam panorama used for selection of a science target for instrument placement operations. Labeled target is about 5.9 meters away.

The navigation and tracking portion of the precision rendezvous algorithm consists of an iterative application of multi-feature extraction [10, 14, 29, 31] followed by stereo range determination of the features [20] that have been matched using a fusion of maximum likelihood cross correlation [24, 25] and homographic transformation [12, 36] estimates of position before and after each leg of the traverse. Since obstacle avoidance is active during the approach, it is not guaranteed that the rover will be facing the target after each leg of the traverse. A 13 step algorithm for this process has been developed and tested in the field [16].

5. Hybrid Image Plane Stereo (HIPS)

After navigating to the designated science targets, the primary science objective of the rovers is the robust and reliable acquisition of data using instruments mounted on the end of an instrument arm. The baseline approach for this manipulation task is the localization of the science target with respect to the manipulator arm via the hazard-avoidance stereo cameras located on the rovers. Once the science target has been identified in the image plane of one of the stereo cameras, the 3D range to the target is determined via stereo correlation and triangulation. From this 3D range information, the joint rotations that take the manipulator to the appropriate location in 3D space are determined using the arm's inverse kinematics.

The difficulty associated with this approach is that sources of error tend to accumulate in the stereo system and the manipulator kinematics that ultimately reduce the ability to accurately place the manipulator's end-effector at the desired location. Such error sources include stereo calibration and stereo ranging errors that can yield a range uncertainty of 1.5 cm at 0.75 meters from the stereo pair used on the rover. Errors are also associated with accurate knowledge of the transformation between the stereo reference frame to the base reference frame of the manipulator, as well as kinematic errors such as link length and joint position uncertainties. Finally, degradations and/or changes in the system configuration due to environmental factors such as launch and landing vibrations and thermal expansion will also affect the ability to accurately position a rover-mounted manipulator at a target of interest.

We have developed a precision manipulation technique called HIPS (Hybrid Image Plane Stereo) that fuses the visual feedback from the rover stereo camera pair with manipulator arm joint angles for the robust and reliable positioning of the rover manipulator's end-effector. This technique is an extension of the work by Skaar, et al. [6, 30] which has been come to be known as Camera Space Manipulation (CSM). The HIPS manipulation technique makes use of the basic idea underlying the CSM method - the generation of camera models using visual sensing of the manipulator's end-effector and the use of these camera models to drive the end-effector to a target location without regard to any “real” physical reference frame. The camera models generated accurately reflect the relationship between the position of the end-effector (known via the manipulator's forward kinematics) and image-plane appearance of the end-effector in each of the stereo cameras.

This approach addresses the systematic errors that are present in the baseline technique (separate camera calibration and manipulator kinematics), however, stochastic errors that occur due to finite image-plane cue detection precision, inaccurate knowledge of joint angles, etc. are not necessarily accounted for using the HIPS manipulation technique. Therefore, the manipulator-generated camera models are updated throughout the trajectory that takes the end-effector to the target by identifying the image-plane location of the visual cue on the end-effector and by using this additional information to re-compute the parameters in the camera model.

6. Experimental Studies

This section reports on a number of experiments that have been run to test the algorithms described in the previous sections. These experiments have been done using the SRR and FIDO technology platforms, shown in Figure 1, in both laboratory and field environments.

SRR is a four-wheel drive, independently four-wheel steered rover platform with a split differential and independently-controlled shoulder (or rocker) joints. FIDO is a six-wheel drive, independently six-wheel steered rover platform with a rocker-bogie suspension system. FIDO has a 4-degrees-of-freedom (DOF) mast that extends to 1.94 m when deployed. The mast-head houses a stereo NavCam (navigation camera) which is a low spatial-resolution (640X480), monochrome, wide field-of-view (45°) stereo imaging (25 cm baseline) system used for traverse planning. In addition to the mast, FIDO has a 4-DOF Instrument Arm with a color microscopic imager mounted on the end-effector. SRR has a 3-DOF manipulator arm that is used for manipulation and doubles as a sensing mast using the same NavCam stereo setup as FIDO. FIDO has a wide field-of-view (112°), narrow baseline (15 cm) stereo camera, the Front HazCam used to provide range data for autonomous hazard avoidance algorithm for obstacle detection during rover traverses, and to choose science targets for in-situ instruments mounted on the Instrument Arm. Both rovers carry a commercial Crossbow three axis accelerometer and gyroscope IMU package The computing platform on both rovers is a PC/104 266Mhz, Pentium-class CPU running under the VxWorks 5.4 real-time operating system.

The first series of experiments was done to test the rover localization algorithms discussed in Section 2. To test the IMU rate sensor bias estimation technique, data was collected from the FIDO's IMU for approximately 10 seconds while the rover remained stationary (usual time taken for stereo image acquisition and processing prior to movement). Nine separate data sets were collected on different days at different times so that the temperature of the IMU varied for each of the data sets. The bias estimator operates on the IMU data at 200 Hz (the same rate as the IMU sampling). Results from two of the nine data sets are shown in Figure 4. In these two data sets, the filter converges rapidly within 0.5 seconds from the start of the run. Also due to the collection of the data sets at different days and times, the rate sensor bias terms converge to different values (approximately -0.02 degrees per second for the first case and 0.01 degrees per second in the second case). Despite the different values for the estimated rate sensor bias terms, the estimate of the yaw angle remained quite stable when compared to the rate sensor integration without bias estimation.

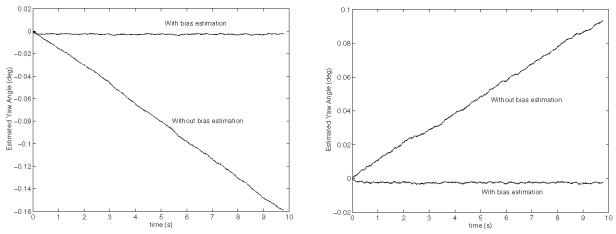

Figure 4. Estimated yaw angle results from two data sets out of nine acquired during different times of day for a stationary FIDO rover. The yaw angle is plotted vs. time in secs over a 10 second time frame for each data set. The horizontal line in each plot is the Kalman corrected yaw angle and the sloped line is the uncorrected yaw angle.

The second study tested the fusion of the motion information derived from matching of range maps between successive views as described in Section 2.1 and the wheel odometry and IMU readings using an extended Kalman filter described in Section 2.2. This study was done indoors and thus the sun sensor was not used as an input. A birds-eye-view of the experimental runs is shown in Figure 5. The results for these runs indicated the mean localization error was decreased by a factor of 4 (mean error of 1.38 m for dead reckoning vs. 0.4 m for Kalman filtered) over a series of 12 meter runs. Further details can be found in Hoffman, et al. [13] and in Baumgartner, et al. [3, 4] for the FIDO rover in field trial situations.

The next series of experimental studies field tested the long range rendezvous sequence shown in Figure 2 in the Arroyo Seco at JPL. A representative image from the sequence taken at 25 meters from the lander is shown in

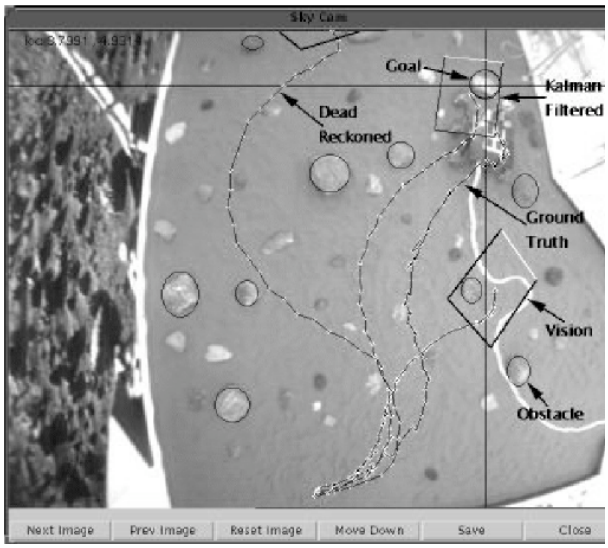

Figure 5. Aerial view of experimental laboratory runs for comparison of dead-reckoned and Kalman-filtered approaches to a designated goal.

Figure 6, where the texture signatures in a localized window about the lander for the first three levels of wavelet decomposition are illustrated. The total fused value for the texture signature window at Level 0 is 0.82, Level 1 is 0.86, Level 2 is 0.94 as compared to the background range of 0.0 to 0.45 in the same sized window. The average error in placement for the rover in

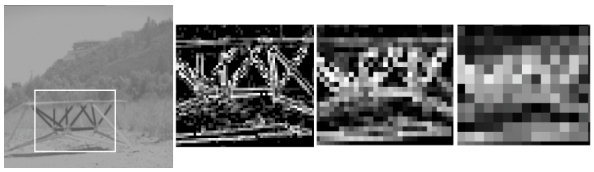

Figure 6. Example of texture signature values for local window in image of lander taken with mast mounted NavCams from 25 meters. From left to right: Original image with lander area boxed, Level 0 texture signature values, Level 1 texture signature values, Level 2 texture signature values. Gray scale is used to give relative values of texture signature, which is the fused value of the horizontal, diagonal, and vertical values for each pixel in the window. The target detail decreases with increasing levels of wavelet decomposition.

relation to the ramps over 15 runs of the entire three phase algorithm was 1.8 cm in the lateral and 2.4 cm in the longitudinal directions, with a average heading error of 2.7º. Representative images of the rover taken at the long, mid and close range offsets to the lander are shown in Figure 7.

Figure 7. Representative images of FIDO rover during long range lander rendezvous sequence in the Arroyo Seco at JPL. From left to right: Range of about 125 meters; range of about 20 meters; rover aligned with ramps at range of 50 cm.

The next series of experimental studies tested the multi-view, multi-feature precision rendezvous with natural targets using FIDO in the Arroyo Seco at JPL. A series of 11 runs was done with a target remotely selected with NavCam images under the WITS (Web Interface for TeleScience) interface that is used for training of the 2003 MER (Mars Exploration Rover) science team. Over the 11 runs, there was an average instrument arm placement error of 7.5cm (1.3%) and RMS of 2.5cm with an average autonomous approach of 5.9 meters. The spread of errors on the science target is shown in Figure 8, where crosses mark the end-effector placement position, and a 1 cm radius circle gives the desired range of accuracy around the nominal target point.

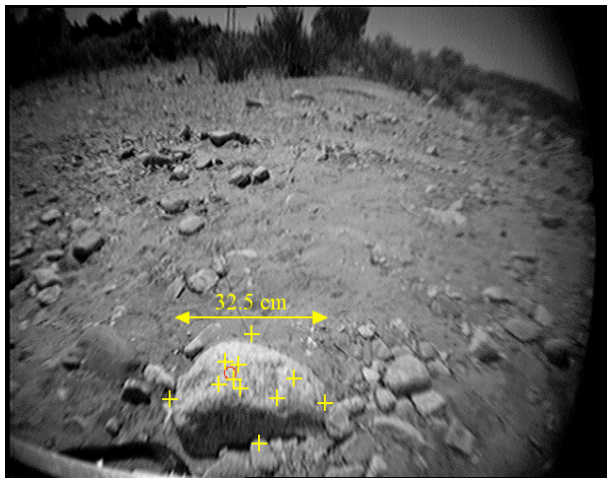

Figure 8. Instrument arm placement results for 11 trials in the Arroyo Seco at JPL. HazCam view of the target taken from 85 cm away. Crosses are arm end-effector positions from all trials, and circle is nominal 1 cm radius area around designated target.

Our final experimental study tested the HIPS algorithm for precision manipulation. The experimental testbed in the Planetary Robotics Lab at JPL is shown on the left in Figure 9, where the target cues are the black/white circular decals on a mockup of a taskboard with a circular grip point. The end-effector cue is the same type of target. On the right side of Figure 9, a graph displays the experimental results. The preplanned cue predictions are shown throughout the workspace as light colored circles, and the preplanned cue samples are shown as dark colored circles. These are used to calibrate the system as described in Section 5. A sample trajectory is shown as a connected path with the predictions and samples shown as small and larger circles respectively. There was an average error of 1.5mm in lateral offset and 1mm in distance for 15 tests.

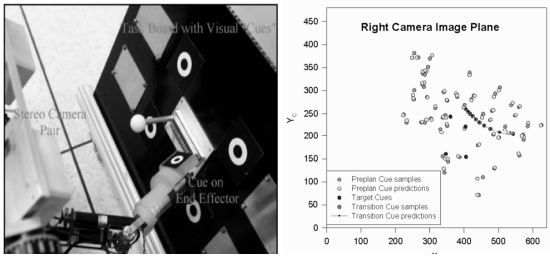

Figure 9. HIPS test setup and results. Left: Task Board with target and end-effector cues; Right: Experimental results plotted in the X/Y image plane.

7. Summary and Conclusions

We have described the development and testing of a number of sensory fusion algorithms for planetary surface robotic operations that would be common to upcoming NASA/JPL missions in 2009 and 2013. These include an extended Kalman filter fusion of range map, wheel encoder, IMU, and sun sensor information for better rover localization during long traverses, fusion of multiple view and multiple feature information for precision rendezvous operations, and fusion of visible and manipulator joint angle information for precision manipulation. Experimental results using the FIDO and SRR technology prototype rovers at JPL were presented for flight-like operational scenarios. The localization results indicated an error of ~3% of the distance traveled for position, and an error ~2-3º in heading [3, 4]. The heading error is greatly dependent on the availability of the sun sensor and time of day [32, 34]. For the long range rendezvous with the lander the average error in placement for the rover in relation to the ramps over 15 runs was 1.8 cm in the lateral and 2.4 cm in the longitudinal directions, with a average heading error of 2.7º. For the short range science target rendezvous, there was an average instrument arm placement error of 7.5cm (1.3%) and RMS of 2.5cm over 11 runs with an average autonomous approach of 5.9 meters. Finally in our HIPS manipulation experiments, there was an average error of 1.5mm in lateral offset and 1mm in distance for 15 tests.

Our current research directions include the integration of the short range science target rendezvous and HIPS algorithms into a system that will reduce the placement error (desired accuracy as specified by the Science Team for the 2009 Mars Science Laboratory mission is 1 cm). This approach combines the accuracy of precision placement found in HIPS with the accuracy of precision rendezvous found in the multi-view, multi-feature navigation algorithm.

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