Autonomous Navigation: Achievements in Complex Environments

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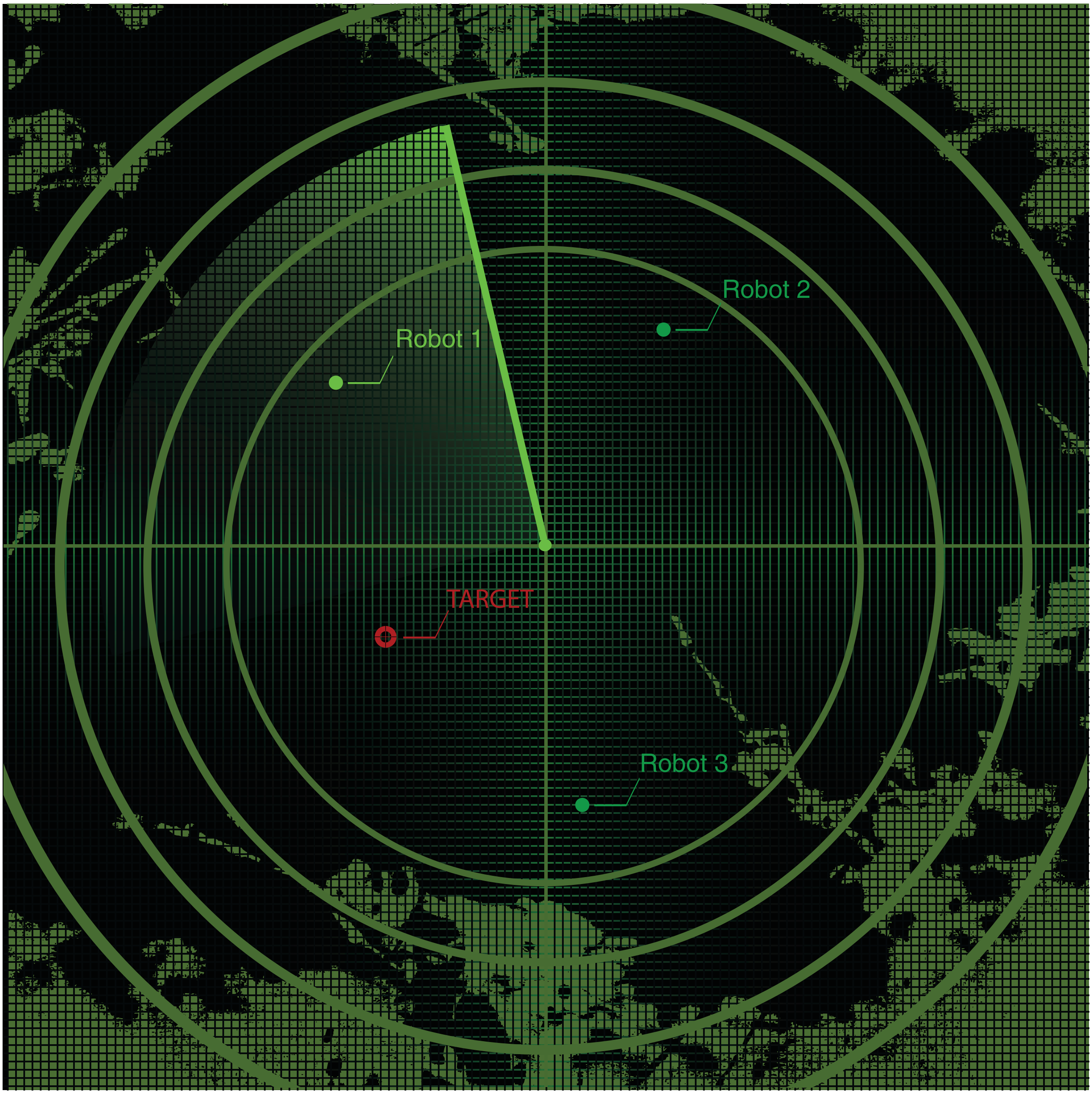

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During the past decade, challenging applications for autonomous robots have been identified in the areas of servicing crowded, built-up areas; mining; search and rescue operations; underwater exploration; and airborne surveillance. Autonomous navigation arguably remains the key enabling issue behind any realistic commercial success in these areas. Consequently, autonomous robotic research has focused on large-scale and long-term navigation algorithms, sensing technologies, robust sensor data interpretation, and map building.

The most successful robot navigation algorithms to-date have been derived from a probabilistic perspective, which takes into account vehicle motion, terrain uncertainty, and sensor noise [1]. During the past decade, an explosion of interest in the estimation of an autonomous robot's location state and that of its surroundings, known as simultaneous localization and map building (SLAM), is evident. The goal of an autonomous vehicle performing SLAM is to build a map (consisting of environmental features) incrementally by using the uncertain information extracted from its sensors, while simultaneously using that map to localize itself with respect to a reference coordinate frame [2]. New algorithms that represent uncertain information based on particle filters and Gaussian mixture models, as well as the more classical Kalman filter–based techniques, are advancing the progress of a robot's long-term navigation abilities. This has been significantly aided by recently affordable sensor technologies, including GPS and inertial measurement units (IMUs) as well as fast and reliable laser range finders.

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To demonstrate the state of the art in autonomous navigation, this article focuses on outdoor research work within complex, semi-structured environments with an array of vehicles, using RADAR and laser range finders. Two classes of sensors that we use to get information are proprioceptive sensors and exteroceptive sensors. Proprioceptive sensors make measurements of the internal state of the vehicle (e.g., its speed, relative displacement, etc.) by using motor encoders or on-board accelerometers, IMUs, etc. These sensors do not interact with the world beyond the autonomous guided vehicle (AGV) at all.

Exteroceptive sensors make measurements of the external state surrounding the vehicle (e.g., distances to obstacles). These sensors interact with the world beyond the AGV by transmitting laser light or receiving images beyond the vehicle. Even GPS is an exteroceptive device, as it is needed to communicate with satellites to infer the state of the vehicle.

Autonomous navigation is completely dependent on

- the successful extraction of useful information from exteroceptive sensors
- the correct association of that information from different vehicle positions
- algorithms that can fuse this information with proprioceptive sensor data estimates.

In this article, we summarize our research that addresses these issues.

The Key Role of Sensing: A Proprioceptive Sensor Interpretation

Reliable localization ability is essential for an autonomous vehicle to perform any function. For ground vehicles operating outdoors, the localization task becomes much more difficult, because wheel encoder measurements are unable to take into account wheel slippage or uneven terrain. In urban or forest environments where high buildings or tall trees exist, GPS sensors also fail easily. A robust localization method therefore needs to be found. In this article, the term "pose" means both position and the heading of the vehicle. The pose of a vehicle traveling on a two-dimensional (2D) plane would be given by the coordinates (x,y,θ). The word "position" usually only implies the coordinates (x, y).

IMUs are non-jammable and self-contained and can provide pose estimation in three-dimension (3D) because of a triad of orthogonal accelerometers (translatory rate sensors) as well as gyroscopes (angular rate sensors). Low-cost IMUs, such as the Inertial Sciences D-MARS IMU used in this work and shown in Figure 1(a), are increasingly being made commercially available, and their use in automotive applications has increased in the past decade. Since rate information must be integrated with respect to time to produce velocity, position, and attitude, the small errors in the rate measurements will cause accumulated unbounded errors in the integrated measurements. This is demonstrated in Figure 1(b), where the dashed red curve represents the true path of a vehicle executing a 1.1-km path within the Nanyang Technological University (NTU) Singapore campus. The dark blue trajectory represents the estimated path after integration of the IMU data. The path estimated by the integration of the raw IMU data quickly diverges from the true path because of the time integration of biases and noise. Hence, IMUs are usually combined with external sensors and aiding algorithms to produce an inertial navigation system (INS) to improve the effective vehicle pose information.

INSs that bound the errors of IMUs exist in the literature. Barshan et al. modeled the biases and drifts of inertial sensors as exponential growth parameters and augmented the estimated robot state (typically its 2D pose) to include these parameters [3]. In [4], a method was presented for combining odometer and inertial information to provide an estimate of the six degrees of freedom of a rough terrain rover. A limita-

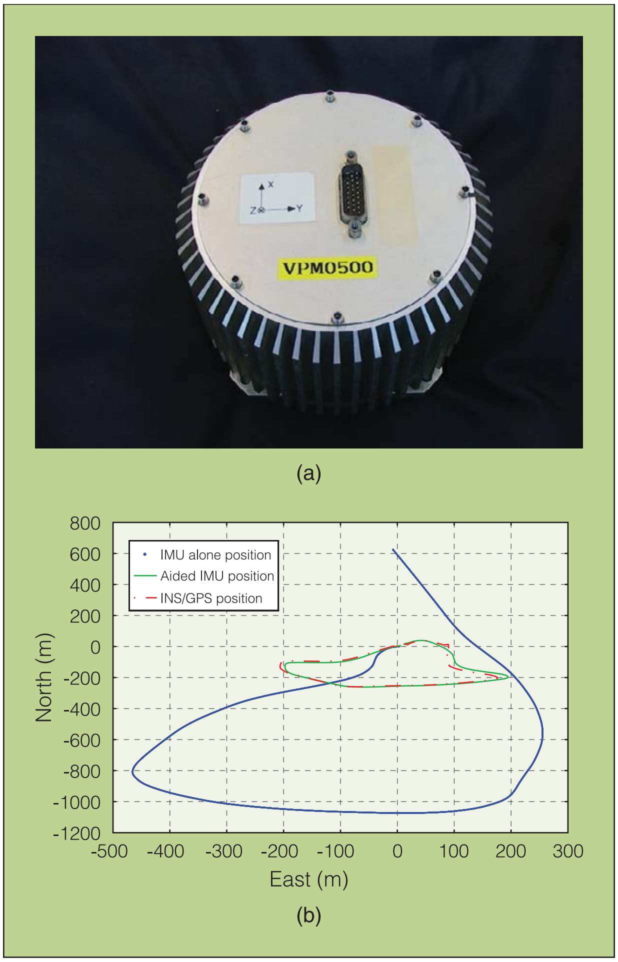

Fig. 1. (a) An Inertial Sciences IMU and (b) raw and aided IMU estimated paths.

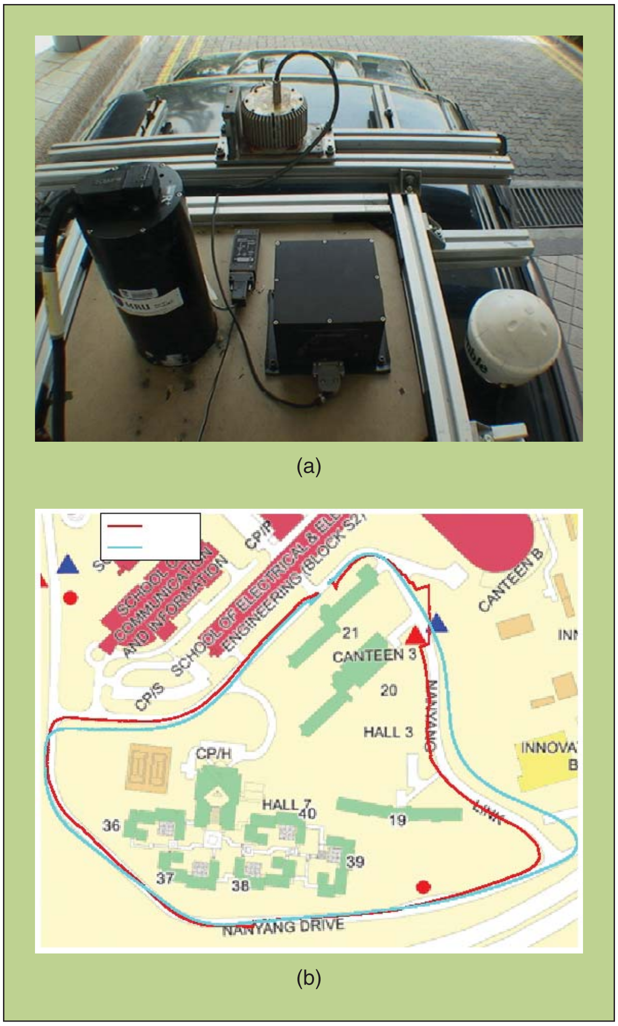

Fig. 2. (a) A suite of IMUs and (b) a complete INS estimated trajectory.

tion of these methods is that the position and attitude are not directly observable and the imposed constraints are often violated.

Therefore, one of the research fields at NTU is multi-aided, inertial-based localization to constrain the outdoor localization problem. The multi-aiding information is from an odometer, a gyroscope, and the known vehicle constraints themselves. Contrary to previous work, a kinematic model is developed to estimate the lateral velocity of the inertial sensor [5]. Figure 2(a) shows a suite of IMUs (for comparison purposes) mounted on the roof of a utility vehicle used in these experiments, and in Figures 1(b) and 2(b) the cyan-colored trajectories show the estimated vehicle path using the aided INS, which is able to significantly reduce the drift in the position of the vehicle, velocity, and attitude estimates, even when the testing vehicle runs in outdoor uneven environments.

Exteroceptive Sensor Interpretation

Aided INS is able to significantly reduce the localization error of a vehicle. This produces more reliable localization estimates for a longer period of time than odometer or integrated raw IMU data alone. However, the resulting pose errors are still unbounded with respect to time. For autonomous navigation, measurements from beyond the robot are therefore necessary.

Laser Detection and Ranging

Because of their reliability and accuracy, common sensors used in mobile robotics are laser range finders. To use range data successfully in navigation algorithms, it is often useful to achieve complete 360º coverage of the environment surrounding a vehicle, so that extracted information from other robot poses can be successfully fused with new information. Figure 3(a) shows a 3D scanning laser detection and ranging (LADAR) sensor developed at NTU for 3D environmental scanning. The sensor can continuously scan 360º in bearing while simultaneously enabling elevation changes between ±25 degrees. The sensor reliably produces range point clouds to distances of 260 m, as can be seen in Figure 3(b). In the figure, an outdoor courtyard has been scanned, and each white point corresponds to a range point.

Feature-based robot navigation relies on the extraction of reliable and repeatable information from such sensor data. Geometric methods of extracting features from raw, noisy range data often use the Hough Transform and the RANdom SAmpling Consencus (RANSAC) algorithm [6]. These two algorithms are robust in the presence of data outliers. However, it is necessary to define several problem-dependent

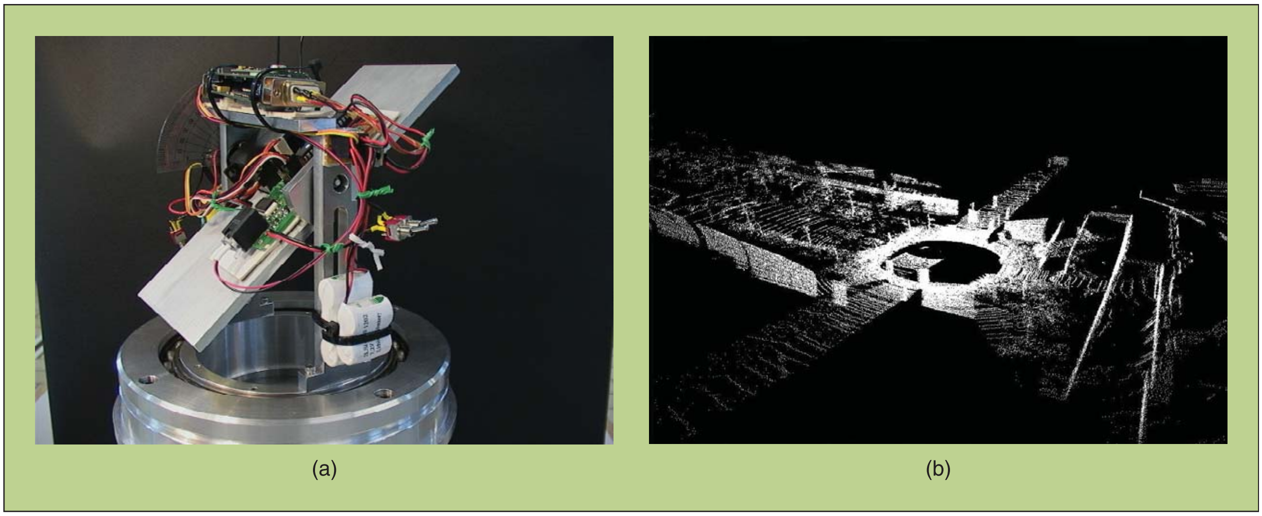

Fig. 3. (a) An in-house developed 3D LADAR for range data acquisition and (b) the resulting point cloud data, recorded within an outdoor courtyard.

thresholds. For example, Figure 4(a) shows the result of applying RANSAC to detect lines and circles in a simple indoor-office–type environment that has four walls and two circular cross-sectioned pillars from a single 2D scan.

Although the algorithm is robust in the sense of data outliers, it produces a randomized result, meaning that each time the algorithm runs, different features can be extracted. Figure 4(a) shows that the four walls are extracted as required but extra features (a line and the larger circle) are falsely detected. We have done a great deal of research at NTU based on local smoothing and feature extraction. We have applied the concept of anisotropic diffusion and scale space theory for the detection of dominant features from noisy range data [7].

Figure 4(b) shows the results when again extracting lines and circles from the same environment. In this case, simultaneous smoothing in multi-scale space enables the dominant features (the four correct lines and the two correct circular sectioned pillars) to be detected. The advantage of formulating the algorithm under the scale space theory is

- data that is considered by the algorithm to conform to the data model that contains the selected features are smoothed at multiple scales
- whereas all other data remain unsmoothed by the algorithm.

This makes the technique robust to range data noise. Only dominant features are extracted [in the case of Figure 4(b), line intersections at A, B, C, and D] as opposed to false features detected because of noise.

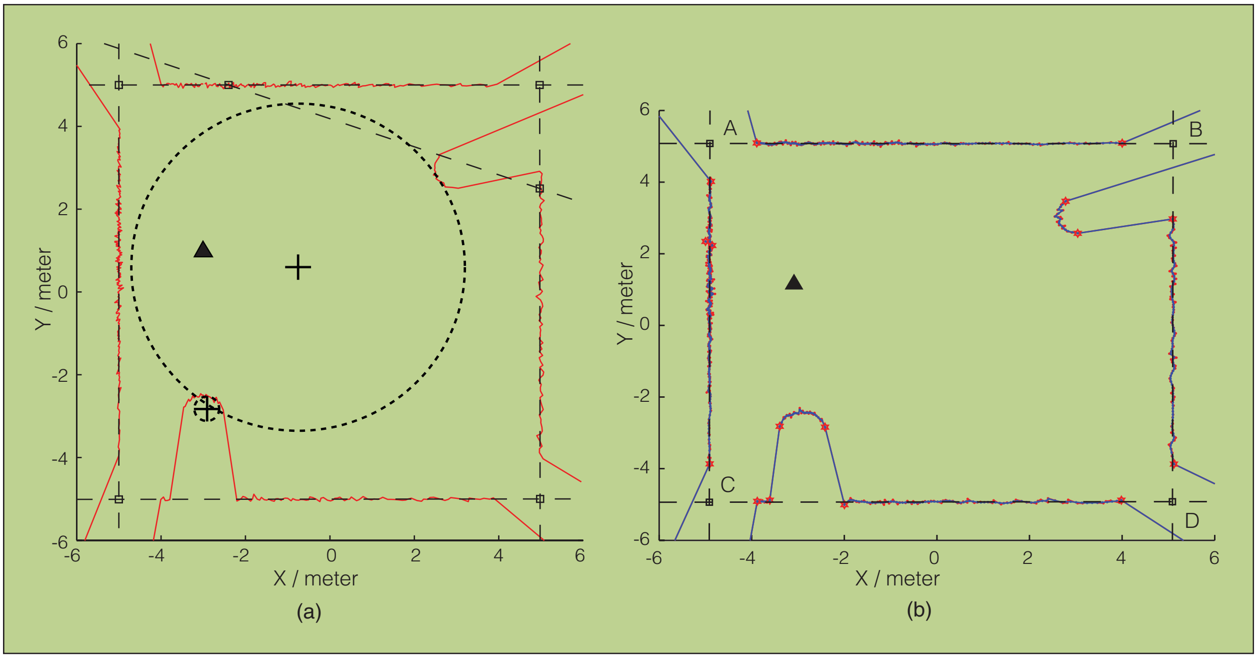

Fig. 4. Feature extraction from range data within an indoor environment. The triangle represents the position of the sensor, squares show extracted line intersections, and crosses (+) show the extracted centers of circles. (a) Applying RANSAC to laser range data, for the detection of lines and circles. (b) Anisotropic smoothing and segmentation in multi-scale space.

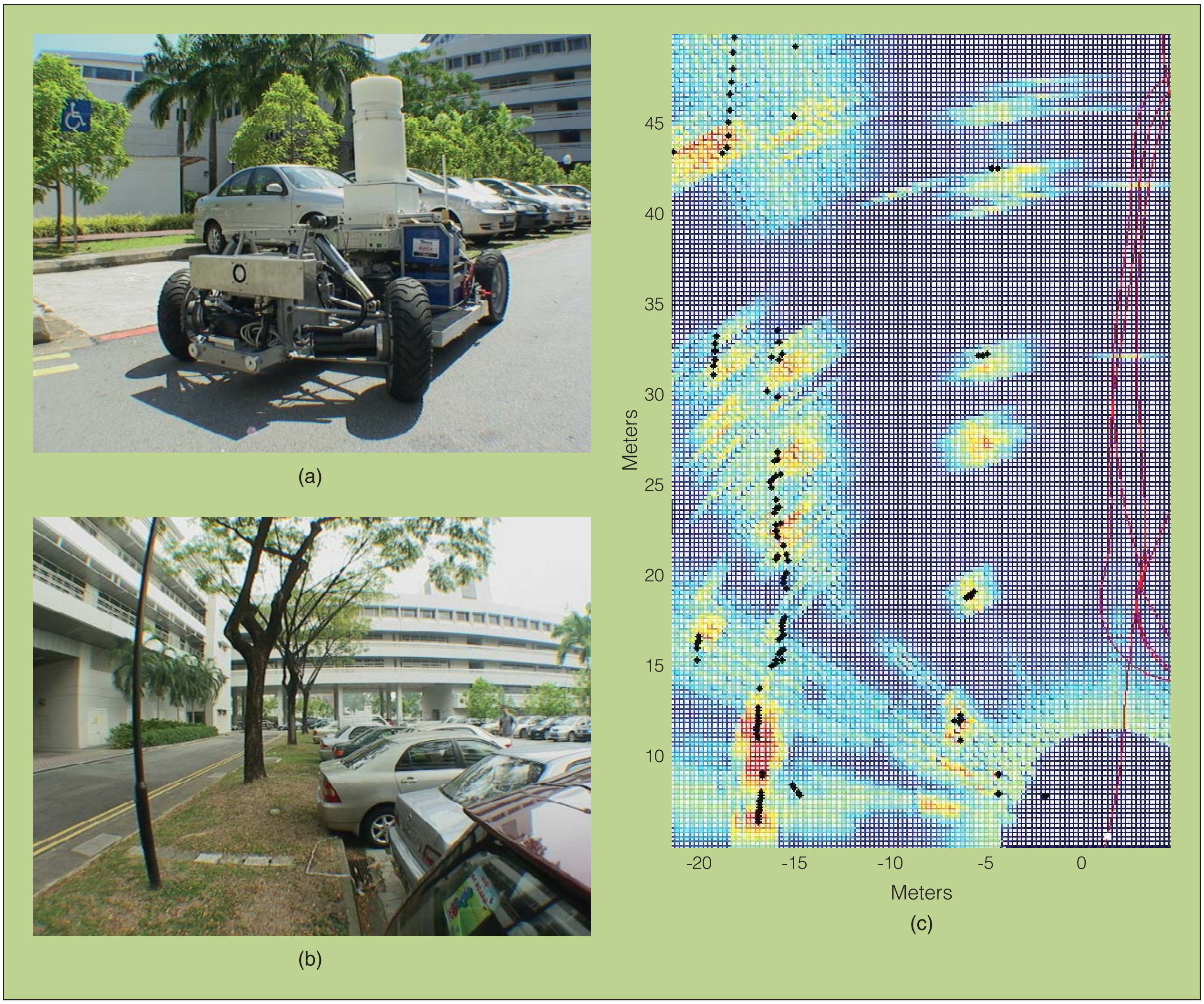

Fig. 5. RADAR mapping on campus. (a) One of NTU's vehicles equipped with the millimiter wave RADAR. (b) A section of a car park environment in which RADAR mapping experiments were carried out. (c) Corresponding occupancy grid map, estimated using the RADAR. The superimposed black dots show laser range data for comparison purposes.

Radio Detection and Ranging

Millimeter-wave RADARs (MMWR) can offer remarkable advantages for autonomous navigation.

- Their performance is less affected by dust, fog, moderate rain or snow, and ambient lighting conditions than other sensors.
- MMRW differs from other range sensors as it can provide complete power returns for many points down range.
- It has a comparatively long range that can enable a vehicle to localize even with sparse features.

Figure 5(a) shows one of NTU's vehicles, equipped with a 77-GHz frequency modulated continuous wave scanning MMWR. A section of the car park environment within which a full 360º RADAR scan is obtained is also shown in Figure 5(b). Note the positions of the two lamp posts and the three trees along the grass verge.

Figure 5(c) shows a section of the full 360º RADAR scan along with superimposed laser range data (black dots). Within the RADAR data, the red regions correspond to ranges and bearing angles relative to the RADAR located at the origin at which high power returns were recorded. Yellow regions correspond to medium power, and the blue areas are low power (considered to be noise only) returns.

An initial comparison of the RADAR and laser range data reveals that the RADAR suffers from a lower angular resolution, because high power returns become spread out in bearing angle. This can, however, be advantageous as the trees and lamp posts [located in the scan along the vertical line X = –6m (the grass verge)], all give high power returns by the RADAR, but two of them are missed by the laser range finder (the laser was set to record one range sample every 0.5 degrees). Further, this type of RADAR enables the user to define at which received power level an object can be considered detected. Radio waves have the ability to penetrate certain materials. This provides the possibility to detect multiple targets per bearing angle. This property also enables the user to develop algorithms for the optimal extraction of multiple line of sight features and to build occupancy maps that label regions in a robot's environment with the probability of that region being occupied, assuming various noise statistics.

Research at NTU has focused on outdoor RADAR mapping algorithms that use an occupancy grid approach [8], [9]. This work has shown that the occupancy mapping problem is directly coupled with the received signal detection processing that is necessary in such sensors and that the required measurement likelihoods are those commonly encountered in both the target detection and data association decisions. Furthermore, these measurement likelihoods are highly correlated both with the environment and the non-linear target detection algorithm used.

Figure 6(a) shows an aerial view of the car park with its occupancy map in Figure 6(b) as estimated using the MMWR (left) and a laser range finder (right). The maps are the result of the vehicle driving once around the road loop shown in Figure 6(a). It can be seen in the MMWR map that occupancy values beyond many of the targets can be estimated because of the penetrating ability of the radio waves. With the laser range map, no information beyond the sensed targets is available, meaning that the occupancy of these regions remains uncertain. Note that the main structures, the entrance passage and main building walls, in both of the maps are in agreement.

Algorithmic Issues–Data Association

Data association is one of the extremely difficult problems encountered in SLAM. Almost every state estimation algorithm must deal with this problem either by maximum likelihood assignment or maximizing the correlation correspondence between the elements of observations and available map estimates. Uncertainties in vehicle pose, variable feature densities, dynamic objects in the environment, and spurious measurements complicate data association. An efficient data-association scheme must aid feature or track initialization, maintenance, termination, and map management.

Recently, the use of deferred logic data association approaches holds promise in overcoming most of the deficiencies of the data association algorithms proposed for robot navigation applications. However, most such approaches, which are

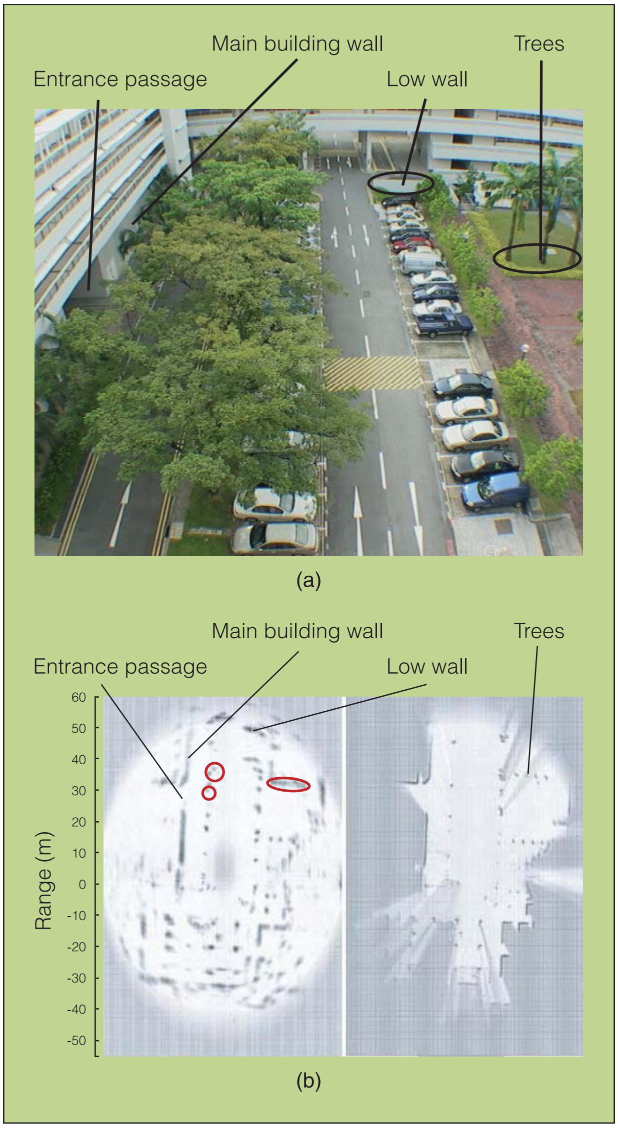

Fig. 6. (a) An aerial view of the car park environment and (b) its estimated probability of occupancy map estimated by the RADAR (left) and the laser range finder (right).

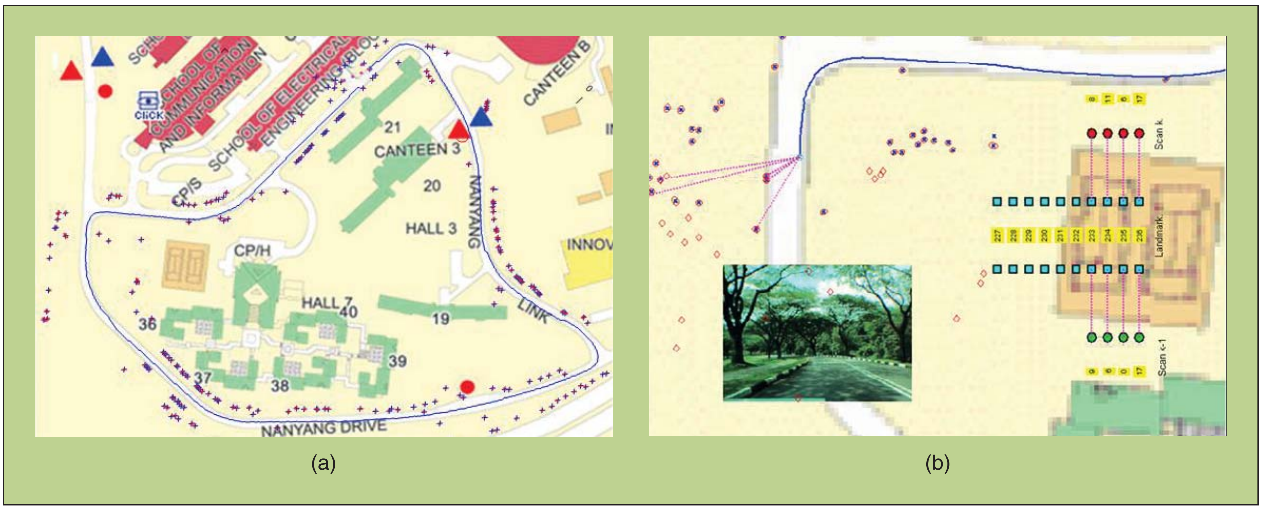

Fig. 7. SLAM using MDA. (a) The estimated vehicle trajectory and point feature map, around a 1.5 km road within the NTU Campus. (b) A zoomed view showing the associated features over 2 time frames, at a particular vehicle location.

often variants of the well known nultiple hypothesis tracker (MHT), are still computationally intensive [10].

At NTU, multiple-frame multi-dimensional data association (MDA) algorithms using a finite sliding window of measurement frames have shown advantages over previous techniques in terms of computational tractability, detecting spurious measurements, and in support of feature initialization and management [11]. The core attribute of such algorithms is the use of several measurement frames to determine the best associations for the current measurement frame. It is established that the MDA is an effective alternative to the theoretically optimal MHT. Compared with single-measurement frame methods, MDA resolves association incompatibilities and ambiguities more effectively and yields consistent maps, as shown in Figure 7. Figure 7(a) shows an entire trajectory (1.1 km in length) and the mapped features (blue dots) within the NTU campus. The current measurement associations at one position are shown in Figure 7(b). MDA enables data association decisions to be reversed across a finite number of measurement frames.

Conclusions

A vehicle capable of performing SLAM using naturally occurring environmental features and being able to navigate for hours or even days in unknown and unstructured environments will be invaluable in several key areas of robotics: autonomous vehicle operation in unstructured terrain, driver assistance systems, mining, surveying, cargo handling, autonomous underwater exploration, aviation applications, autonomous planetary exploration, and military applications. This article has provided a qualitative introduction to some of the key issues in these areas by focusing on sensor data interpretation, information extraction, and data association.

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