Thesis Project

Autonomous 3D Map Building for Urban Settings with Range Data

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1 Introduction

The main objective of this thesis is to contribute to the state of the art in 3D outdoor navigation by developing an accurate exploration strategy using a 3D range sensing as the main sensor for terrain perception. Specifically, we work in pedestrian urban areas for a robotic guidance and surveillance application. So far, most of the mobile robot navigation approaches for indoor and outdoor environments assume that the robot lives in a plane [17, 23, 68], but in urban settings, uneven characteristic of the terrain can be found such as ramps or stairs. Also, unpredictable elements in the environment further difficult the navigation task. To alleviate the localization problem and to help the robot take appropriate navigation decisions, we are interested in building maps for our robots, and to do it as autonomously as possible. In this context, our robot must be able to build a locally detailed and globally consistent map, the robot must be able to perform traversability analysis for exploration decisions to cover the desired area with a trade between execution time and coverage, furthermore must be able to determine it position with 6 degrees-of-freedom (DOF) within this map. This task is known in the robotics literature as Autonomous Simultaneous Localization and Mapping. Recent contributions add the word 'planning' to the problem to account for the autonomous aspect in exploration (SPLAM) [36]. Once the map is built some post-processing might be necessary to obtain a complete digital compact volumetric model, merging information to reduce the memory space of the map without compromising details and consistency.

The proprioceptive modalities that can be used for mapping vary from ultrasonics devices, typically used for indoor mapping [14, 44], to 2D and 3D range data used for indoor and outdoor mapping, respectively [17, 23, 28, 68, 67, 82], to vision which is a cheaper sensing technique with the ability to use appearance information during data association [33, 45, 46, 47], but using camera in outdoors has troubles such as illumination issues. In our work we will concentrate in the use of 3D range sensing as the primary source of information for mapping, a technique better suited for unstructured outdoor mobile robot urban mapping [57], because it offers much and more detailed information than 2D maps. The disadvantages of 3D sensing technologies are its slower acquisition rate and the significant increase in data that needs to be processed, calling for a compact and robust representation of the map.

Multiple 3D scans are necessary to build a map with enough environment information. To create a correct and consistent map, the scans must have a common reference coordinate system. The process of aligning scans is called registration, and can be done for every two consecutive scans. This method is prone to error accumulation from local data alignment leading to an inconsistent global map, making the map useless for navigation. Moreover, the robot sensors uncertainty. We will contribute with novel range registration mechanisms and their use for SLAM. As for SLAM backbone, we consider the probabilistic alignment of 3D point clouds employing a delayed-state Extended Information Filter (EIF) algorithm. The resulting relative poses from consecutive registration of the point clouds are used as constraints and fed, to this algorithm to produce the overall map of the robot trajectory.

Aside from localization and mapping we must devise exploration strategy to be used. The main question in exploration is *given what you know about the world, where should you move to gain as much new information as possible.* The main idea on exploration is to pursue low traversable cost and whilst avoiding obstacles. The next point to acquire new information is thus predicted with a cost function that trades of the robot's traveling cost through a path and the information gain from the new location. One alternative we will study to perform exploration are Partially Observable Markov Processes (POMDP's). They address non-deterministic action outcomes and can cope with uncertainty in perception for non fully observable states. States being in our case the robot poses and the map. We need to analyze whether it is appropriate to use POMDP's with limited horizons state spaces. Since limited horizons in POMDP's can

become computationally intractable we will study the use of sums of small horizons to produce a computationally tractable exploration algorithm.
This proposal is organized as follows. In section 2 we state the outdoor navigation problem and identify the challenges that is has. In Section 3, the specific goals of the thesis are presented. Section 4 contains a literature survey. The section is divided in four parts. First the state of the art in scan matching is given, considering its application to mobile robotics. Later, a small account on the relevant state of the art on SLAM is given, next the state of the art on navigation mainly using range data is presented introducing to some exploration strategies, and finally map models are presented. Section 5 contains a description of our current scan matching implementation, which serves as a starting point for our investigation, including submitted and accepted papers contibutions to relevant conferences. Section 7 contains the work plan and calendar.

2 Problem definition

The problem of autonomous navigation arises when a robot needs to know its environment without human intervention by using its sensors to observe and represent the world, and subsequently, using the acquired information in the execution of a mission. In general the autonomous navigation problem for mobile robots comprises three tasks which should be performed simultaneously: mapping, localization and exploration. Autonomous navigation algorithms must negotiate between the individual objectives for each task, which are respectively, to maximize the accuracy of the map, to minimize the robot's position uncertainty, and to maximize the environment coverage while minimizing the travelling cost.
Specifically, the elements we have identified to solve the aforementioned three task are:

- **Perception.** The robot must be able to interpret the environment where it is standing. In our application we use a 3D range scan laser and a scan matching technique to perceive the environment.
- **Representation.** The robot must be able to represent the world in a rich and low weight representation, perhaps multilevel multiresolution maps, octrees maps or planes based maps will be provided.
- **6DOF SLAM.** The robot needs to keep memory of it's surroundings while at the same time its position should be encoded using the full 6DOF of 3D pose knowing it's current position in the explored environment.
- **Exploration.** A cost function that trades of the robot's traveling cost through a path and the information gain given for the predicted possible new information, must be determined. Moreover, the robot must be able to decide how to move in the represented environment (action selection).
- **Navigation.** The nonholonomic constraints of the robot must be studied to determine its action space. This and the perceived and represented environment will help us to determine safe regions to walk through for exploration decisions (traversability analysis). Moreover, the robot should be able to avoid obstacles while traveling to the next position following the path planner's trajectory and to modify this trajectory if necessary to reach the goal (obstacle avoidance).

Several authors have proposed a variety of solutions for the 2D [20, 43, 46, 47, 78, 82] and 3D [68] indoor autonomous navigation problem. In most of these cases it is assumed that the robot lives in a plane. Some authors take these assumptions to the outdoor navigation problem [23, 35].

Outdoors navigation in urban settings is more complex than indoor's because of the existence of unstructured information such as trees or shrubs. Also uneven characteristic of the terrain can be found (like ramps, stairs, or holes in the floor) leading to the need for devising new methods.

3 Objectives

The proposed solution should reach the following milestones:

- **Detailed and low weight environment representation**

  Using a 3D laser range scanner as the main sensor, we will be able to obtain rich and detailed features, helping to obtain a semantic division of the map, and a low weight environment representation which helps to obtain a good registration.

  We seek to explore different detailed and low weight environment representations for exploration such as planes, multilevel and multi-resolution maps.

- **Achieve on-line and accurate data association during pairwise range data registration.**

  Nowadays in the context of pairwise scan alignments low computational cost correspondence search is possible by means of kd-tree structures and sampling strategies but which produce non optimal data association with a significant number of false matches between points. The most important factor that produces wrong point correspondences during range registration is the noisy nature of the range sensor data. For this reason proper sampling, proper environment representation, proper filtering and a novel geometric feature correspondence hypothesis are needed, such as point to line or point to plane matching. Moreover we will use a semantic division of the map which will help both to increment convergence speed and accuracy.

- **Real-time SLAM.**

  We must choose the correct SLAM technique for a real-time application to get a consistent global map. We will use the computed relative pose measurements from consecutive 3D point clouds, as constraints in a six degrees-of-freedom (DOF) delayed-state information-form SLAM algorithm that is currently under development [26, 27, 75].

- **Exploration techniques for 3D range data**.

  One possibility we seek to study is to develop an exploration technique for 3D map building perhaps by means of a Partially Observable Markov Decision Process formalization, using a finite-horizon.

- **Development and construction of a novel 3D range scanner**

  We will build a light weight and fast 3D range scan laser capable to work on-line in robot applications such as autonomous navigation. This scanner will supersede in computation time, and range resolution the current scanner also developed in our group [25].

The resulting algorithms will be evaluated both in simulation, following the approach proposed by [35] using Gazebo and with simulations standards currently under development at IRI bases on ODE an open source physics simulator [65, 72, 30], and experimentally with a robotic platform from the Institut de Robótica i Informática Industrial (IRI) with the sensor that will be developed for the purpose of this thesis.
This thesis is part of the URUS (Ubiquitous Robotics in Urban Settings) [62] project at IRI, funded by the EU, and coordinated by Alberto Sanfeliu, and PAU (Perception and Action Under

Uncertainty) a CICYT project coordinated by Juan Andrade-Cetto. Our contribution in URUS will be in the form of new robust mapping and exploration algorithms for outdoor mobile robots in pedestrian areas, using laser range data and stochastic state estimation tools.

4 State of the art

The present section is organized as follows: In Subsection 4.1 we identify the key issues for registering data based on the Iterative Closest Point (ICP) algorithm. In subsection 4.2 we overview the most popular existing solution for the SLAM problem and the current work on SLAM using range data. In subsection 4.3 we succinctly deal with the navigation and exploration techniques. Subsection 4.4 covers the various data structures that con be used to encode our maps. Finally, in subsection 4.5 we discuss the main conclusions of the literature survey and sketch our foreseen contributions to extend the state of the art.

4.1 Scan matching or range data registration

Scan matching algorithms are often used in mobile robotics to correct the relative motion of a vehicle between two consecutive configurations, by maximizing the overlap between the range measurements obtained at each configuration. The most popular scan matching methods [61] are based on the ICP from Besl and Mckey [5] which is borrowed from the computer vision community. The objective of this algorithm is to compute the relative motion between two data sets partially overlapped. The algorithm iteratively minimizes the matching using Mean Square Error (MSE) and proceeds as follows: first, for each point in one data set, the closest point in the second one is found (correspondence step), then the motion that minimizes the MSE between the correspondences is computed (registration step), finally the data shape is updated (update step).

In the registration proposed by Besl and Mckey a point-to-point metric is used to measure the “closeness” of data, they also suggest an accelerated version of the algorithm that uses a linear approximation and a parabolic interpolation with the last three minimization vectors if they are well aligned, which means they have been moving in an approximately constant direction. The use of sampling or tree-based-search to speed up the algorithm are mentioned as future refinements to reduce the computational cost. Chen and Medioni [9] proposed a point-to-plane error metric, which makes the algorithm less susceptible to local minima than the metric proposed by Besl and Mckey. The idea in [9] is, that given a so called control point in the first surface, one must compute the distance to the nearest tangent plane in the second cloud. Blais [8] suggests a point-to-projection solution computing the sum of the distances between the two range views in the direction of the rays. This approach has also been called “reverse calibration”. This approach makes registration very fast because it does not involve any search step to find the correspondences. However, one of its disadvantages is that the resulting registration is not as accurate as the one given in the point-to-point and point-to-plane metrics [61]. Turk and Levoy [74] proposed a point-to-triangle correspondence using meshes which they call zippered meshes finding the nearest position on a mesh to each vertex of another mesh. They find the rigid transformation that minimizes a weighted least-squared distance between correspondences with a value in the range from 0 to 1, called confidence. For the case of structured light scanners, they measure the confidence of a point on a mesh to be the angle between the mesh normal and the sensor viewing angle. The confidence is a measure of how certain they are of a given range point’s position, which helps to eliminate possible wrong matches. On the other hand, Yamany et al. [80] used genetic algorithms maximizing an objective function, where the genes are formed by concatenating six binary coded parameters, representing the three angles of rotation and the 3DOF for translations. More recently, a new error metric which explores the compensation between rotation and translation was proposed by Minguez et al. [40, 41] for the 2D space, Biota et al. [6, 7] extended this metric to the 3D space. They used a point-to-projection minimization using triangles as the projection surface, and perform the Nearest Neighbor (NN) correspondences in the space of the new metric. They did not tackle the computational complexity of the algorithm, so it is understood they use brute force search to do the matching.

The ICP bottleneck in time execution is the search for point matches. One strategy to reduce the computational complexity is to use a tree-based search techniques [55]. Nütcher et al. [49] use a library called Approximate Nearest Neigborh (ANN), developed by Arya and Mount [2], that uses a balanced kd-tree or box decomposition tree (bd-trees). Also Nütcher et al. [49] showed that kd-trees are faster than bd-trees for the NN problem. Simon et al. [64] used a kd-tree but using a caching points technique, where in the first iteration n neighbors for all the points in the reference cloud are found from the model query and they are cached. It is assumed that after updating the reference cloud, the cached points for each point in the updated cloud should be neighbors. Benjemaa [4] used a double z-buffer structure which provides an explicit space partitioning. Yamany et al. [80] said that the time spent on matching can be significantly reduced by applying a grid closest point (GCP) technique. The GCP is another sampling scheme which consists of superimposing a fine 3D grid on the space such that the two clouds lie inside the grid, dividing the space on cells, each cell with an index of its closest point in the model set. Greenspan and Godin [19] presented a new solution for the matching step which they called Spherical Triangle Constraint. Like Simon et al. [64], they store correspondences at each iteration so that these are available at the next iteration. The Spherical Constraint is applied to determine whether or not the nearest neighbor falls within the neighborhood of each point estimate, and if so, the Triangle Constraint and the Ordering Theorem, are applied to the neighborhood to quickly identify the correspondence. The Ordering Theorem orders a set of points by increasing distance to some point. They show that after aprox. 20 iterations, their method is more efficient than kd-trees in computational complexity and time execution. More recently Akca and Gruen [1] used a box structure [10] which partitions the search space into boxes, where for a given surface element, the correspondence is searched only in the box containing this element and in the adjacent boxes, the correspondence is searched in the boxing structure during the first few iterations, and in the meantime its evolution is tracked across the iterations. In the end, the searching process is carried out only in an adaptive local neighborhood according to the previous position and change of correspondence. One of the main advantages of the box structure is that it has a faster and easier access mechanism than the tree-based search methods.

Another common strategy to accelerate the matching process is to reduce the number of points. Sampling the data reduces the match execution time by a constant factor, but retains linear asymptotic computational complexity. Coarse-to-fine strategies haven been used by Zhang [84] and Turk and Levoy. They start using a less detailed description of the data and as the algorithm approaches the solution, the resolution is hierarchically increased. The techniques used for sampling data vary. Turk and Levoy [74] and Blais [8] used uniform sampling. Masuda et al. [39] used instead, random sampling for each iteration. Moreover, Nütcher et al. [51] and Gutmann [20] used a technique best suited to the nature of data for laser range finders called reduction filter, which has been shown to work well on real time applications.

However, sampled methods are very sensitive to data content, i.e. noise level, occlusion areas, complexity of the range data, etc. If many points come from outliers due to sensor errors, this may produce too many wrong correspondences, and may cause the solution to converge on a local minimum leading to a poor final overlap, or in the worst case, to divergence. We shall remember that the original algorithm from Besl and Mckay considers data sets without outliers. Several approaches to dismiss possible outliers have been proposed using rejection strategies.

Rejection based on thresholds for the maximum tolerable distance between paired points were implemented by Turk and Levoy, the threshold is set as twice the maximum tolerable space between range point meshes; and is adaptively changed when building the points in the mesh. Rejection that uses a statistical method based on the distribution of point distances were used by Zhang [84], and Pulli [59], who used two thresholds for the maximum allowed distance between paired points, one of them dynamic. Masuda et al. also reject pair matches whose point-to-point distances are larger than some multiple of the standard deviation of distances. Pulli as well as Turk and Levoy use not only statistical reasoning, but also topological information to discard matches. They removed matches that occur on mesh boundaries, and Zhang and Pulli used the angle between the normals of the paired points as a constraint to keep matches. Chetverikov et al. [11] presented a robustified extension of the ICP applicable to overlaps under 50%, robust to erroneous and incomplete measurements. The algorithm is based on the consistent use of the Least Trimmed Square [60], a method that sorts the squared errors (residuals) increasing order and minimizing the sum of a certain number of smaller values which helps on rejecting outliers. When using laser range data Nütcher et al. use a median filter to remove the Gaussian noise for each scan row.

Another issue on the ICP is the rate of convergence of the minimization step. To accelerate such convergence and to reduce overshoot, some authors propose minor changes to the original extrapolation proposal of Besl and McKay. For instance, Rusinkiewicz and Levoy [61] used the update based on linear zero crossing of the line instead of the extremum of the parabola when quadratic extrapolation is attempted and the parabola opens downwards, and multiply the amount of extrapolation by a dampening factor, arbitrarily set to 0.5 in their implementation. Even when this occasionally reduces the benefit of extrapolation, it also increases stability and eliminates many problems with overshoot. Simon et al. [64] said that while Besl and McKay calculate a single acceleration scale factor for both translation and rotation, they decouple the acceleration of translation and rotation achieving better results.

Recently within the mapping community Nütcher et al. [52] presented a semantic division of the space in ceiling, floor and walls using forest of kd-trees with the semantic information which improves matching and speeds up the convergence time by 30% compared to simple approximate data association [49] . Pfaff et al. [56, 73] presents a semantic division using traversability analysis, using it during the correspondences and minimization steps. The main reason for using this semantic division is the extension of elevation maps as data to register. Semantic labeling surely helps range registration in environments with underpasses and ramps, such as the one we will encounter.

4.2 6DOF SLAM

A globally consistent representation of a robot's environment is crucial for basic robot tasks such as localization and navigation. Many mobile robotic systems gather information about their local environment using laser range data. These local representations have to be matched to build a global map. Iterative procedures of local pairwise matching algorithms leads to inconsistencies due to errors in laser scans and the matching procedures itself. To avoid these problems, global matching algorithms are needed, taking correspondences between all scans into account.

Mapping with 3D laser range finders has been addressed in many ways. A non-probabilistic approach is proposed in [50], where the alignment of two scans is done mainly by improvements to the basic ICP algorithm proposed in [5]. Current common methods for merging all scans are based on probabilistic information. Probabilistic methods allow for a straightforward way to distribute errors when closing a loop. That is, when revisiting a location after a long traverse. One possibility for 3D probabilistic SLAM in outdoor environments is to employ a delayed-state framework with an Extended Kalman Filter (EKF) [12].

However, using an Extended Information Filter (EIF) within the delayed-sate paradigm has better scalability properties compared to the EKF [15]. A delayed-sate EIF generates exact sparse information matrices and, during open loop traverse, the information matrix becomes tri-block diagonal as consecutive robot poses are added to the state. At loop closure, the matrix structure is only modified sparsely, setting information links between non-consecutive robot poses. Thus, one advantage of the delayed-state information-form for SLAM is that predictions and updates take constant time, assuming an efficient or approximate way for state recovery is used to evaluate Jacobians.

The approximations performed by linearizations, together with covariance and state recovery and data association are issues of concern in the use of EIF filters for SLAM. Our group has proposed an alternative to reduce the overconfidence effects of linearizations by closing only the most informative loops, decreasing the total number of loop closure links, maintaining the sparsity of the information matrix [26]. The technique not only defers filter inconsistency but also has better scalability properties. As for state recovery in information form, efficient techniques for exact recovery of covariance and state estimates are proposed in [24, 29]. In a recently submitted contribution from our group it is shown that during open loop traverse exact state recovery can be performed in constant time, and that we can perform efficient data association in $\mathcal{O}(log\ n)$ for the delayed-state EIF framework [27].

4.3 Exploration

Mobile robot navigation in planar worlds is a well studied problem with many publications on the subject, however robot navigation for a 3D is difficult to attain. For navigation and exploration several kind of sensors have been used (sonar, monocular-vision, stereo-vison, laser range finders). In this work we concentrate in the use of laser range finders for full 3D spaces.

A fully autonomous exploration robot has to map a new environment as efficient as possible and acquire as much information of the environment by optimally deciding future viewpoints. The robot has to plan these positions to efficiently generate a complete environment model and plan a sequence of actions to drive to them. The next best viewpoint (NVB) [3] could be for instance the pose which produces the largest information gain while at the same time the robot short path to it is free of obstacles. González-Baños and Latombe [16] conclude that traditional NBV algorithms are not suitable for mobile robotics. According to González-Baños and Latombe [17] two major issues come with the NVB computation in mobile robotics. One is to achieve safe navigation despite an incomplete knowledge of the environment and sensor limitations (e.g., in range and incidence), the other is the need to ensure sufficient overlap between each new local model and the current map, in order to allow registration of successive views under positioning uncertainties inherent to mobile robots. To ensure this they defined a safe region (in a 2D representation), defined as the largest region that is guaranteed to be free of obstacles given the sensor readings (and its limitations) made so far. They use the union of the local safe regions acquired to compute the NBV.

Several solutions for the NBV exist for the 2D and 3D navigation problem. In [16] a 3D map is built using 2D navigation decisions, and in [17] candidate poses are sampled in the visibility range of frontiers to an unknown area. A solution for an indoor 3D environment is given by Surmann et al. [68], in which the viewpoints are computed with an approximation of the *art gallery problem* (i.e., given a map of a building, where should guards be placed to watch for the whole building [53]) and derives an on-line greedy version based on the algorithm of González-Baños et al. [18]. As in [16], the art gallery is modeled by a horizontal plane (i.e. a 2D map) through the 3D scene. The approach is extended by considering several horizontal planes at different heights to model the whole 3D environment. Surmann et al. randomly generate candidate positions in the interior of the map, they compute for all candidate positions the visible part of the map using the Hough transform to find lines which are transformed into polygons, where the edges are either labeled as seen or unseen. Finally they approximate the set cover problem finding a minimal subset of the candidate positions from which the entire polygon is visible. In [13] they solve the problem using a greedy algorithm where they provide an efficient approximation for the set cover problem.

In a more recent work for 3D navigation, Joho et al. [28] define candidate viewpoints in the patches that lie on the frontier between obstacle-free and unexplored areas similar to Triebel et al. [73], using Yamauchi's heuristic (the frontier approach) [82]. Joho as well as Triebel, considered a patch as, explored if it has eight neighbors and its uncertainty is below a threshold, and unexplored if it has at one to seven explored neighbors. They use a sampling strategy using a 3D ray-casting technique to determine close candidate viewpoints, emitting virtual beams from the frontier patches instead of tracking emitted beams from the sensor at every reachable position and then, selecting admissible sensor locations along those beams. With this approach they reduce the number of needed ray-casting operations. They apply another view point sampling constraint clustering the frontier patches by the neighboring relation, and prevent patches from very small frontier clusters to generate candidate viewpoints. Then they evaluate the set observed viewpoints computing the utility of a candidate viewpoint using the expected information gain and the travel costs, penalizing paths along poorly traversable patches. To evaluate the information gain of a viewpoint candidate, they perform a ray-cast similar to [66], determining the intersection points of the cell boundaries and the 3D ray projected into the 2D grid. Because of the use of a range 3D sensor they cannot drive directly to the next view point, performing several 3D scans along the way and, after each scan, replaning the path to the selected view point if necessary. The proposed solution is a one step look a head strategy.

Our group has also contributed with one step look ahead exploration strategies for monocular SLAM [76, 77]. In this case, a limited set of actions is evaluated with respect to information gain. The computation of overall map and pose entropy reduction is readily available from EKF-SLAM covariances. In that work some heuristics had to be made to have the system explore instead of choosing homeostatic actions. For instance, the area to be explored had to be initially populated with virtual largely uncertain features uniformly distributed. Other authors that follow the same strategy of virtual environment population include Martinez-Cantín [37, 38]. Sim [63] suggests that maximizing the expected information gain for one step look ahead in monocular SLAM leads to ill-conditioned filter updates. The reason is that monocular observations produce only partial revisions to the state and the state covariance. He suggested instead the use of an-a-optimal information metric.

All these exploration strategies are greedy in the sense they choose only the one step look ahead optimal actions. Other greedy approaches include [20, 78, 82], but in contrast to the aforementioned approaches they only seek to reduce either map or robot pose uncertainty but not both.

Another strategy that only reduces robot uncertainty is that of Stachniss et al. [67]. They present an active loop-closing approach for SLAM using raw laser range scans for the FastSLAM algorithm to compute a grid map. Closing a loop means actively consider the utility of reentering previous visited areas to reduce the uncertainty. This work is later improved in [66], where instead of using a heuristic to re-traverse loops, they present an approach entirely decision-theoretic, based on the expected uncertainty reduction in the posterior about the trajectory of the robot as well as in the posterior of the possible maps.

There has been little work on performing multistep destination selection, primarily due the fact that computing even a standard minimum distance is NP-hard. Although there has been work in solving continuous POMDP's [58, 71], the difficulty in scaling these algorithms to actual SLAM implementations makes them ineffective in addressing the exploration problem. Kollar and Roy [31] address the exploration problem using reinforcement learning exploiting the fact that it has successfully solved large sequential decision-making problems in both fully observable and partially observable domains. Martinez-Cantin [37] presents a direct policy solution that use an any-time probabilistic active learning algorithm to predict what policies are likely to result in higher expected returns, balancing the goals of exploration and explotaition in policy search.

4.4 Map models

In mobile robotics, map representation is crucial for real-time navigation, one way to represent 2D maps for navigation is with occupancy grids, also know as evidence grids. Occupancy grids are a spatial representation developed in the mid-eighties by Elfes and Moravec [44], in wich occupancy is a binary variable, either the cell is occupied or it is free. To accomodate for occupancy likelihood the space can be represented as a Cartesian grid where each cell holds a certainty value that a particular patch of space is occupied. Initially, each of these cell values is set to an estimated prior probability of occupancy and this probability is modidfied as evidences are aggregated to the map. Occupancy maps have been built using sonar sensors [44, 81], laser range finders [70], or fusing sonar sensors and laser rage finders [82] and stereo vision [33, 46, 48]. Also occupancy grid maps may accommodate certain types of dynamics in the environment, by decaying occupancy over time [83] used in this way to detect dynamic obstacles. The occupancy grid maps enjoy the reputation of being extremely robust and easy to implement, which has contributed to its popularity. They are arguably one of the most successful environment representation in mobile robotics [32]. Occupancy maps have been used to evaluate traversability in indoor environments [14, 82] and have recently started to build grid-based traversability maps for aoutdoor settings [75]. A disadvantage of occupancy grid map is that they usually only take into account the occupancy probability of a grid cell implicitly assuming an even environment with only positive obstacles. This assumption is an issue of concern for outdoor environments because of the existence of ramps and abyss.

For three-dimesional spaces, Montmerlo and Thrun [42] present a multi resolution approach for the outdoor terrain modeling problem using Bayesian reasoning. Using a Bayes filter they estimate the state of terrain segments considering the ranges at which that terrain is observed. They develop a pyramid of terrain models, in which each terrain model captures the occupancy from measurement data acquired at different ranges. Also, for three-dimensional spaces we can find other versions of occupancy grids [45]. Gutmmann et al. [21] present an application of this representation, using a grid which stores the height values of planar surfaces for humanoid robot. However memory requirements for such maps in outdoor environments are heavy. This would prevent the robot from exploring an environment larger than a few hundred square meters. In order to avoid the complexity of full three-dimensional maps such as 3D occupancy grids, a popular way for representing outdoors environments or on not-flat surfaces are elevation maps [22]. They are a grid-based structures, where each cell stores the height of the surface from the corresponding place in the environment. However, this representation is disadvantageous because vertical or overhanging objects cannot be appropriately represented. In addition, such objects could lead to registration errors when two elevation maps have to be matched. Pfaff and Burgard [56] presented an extension of elevation maps that allows to deal with vertical and overhanging objects, compared with some elevation maps techniques [22, 34] their contribution lies in classifying when the environment points correspond with such objects or not, which is important when a robot is deployed in an urban environment. Although this representation is able to handle vertical or hanging objects, it lacks the ability to represent multiple levels. Triebel et al. [73] presents an approach which can be regarded as a major extension to elevation maps based on the work of [56]. This representation is able to deal with multiple levels and is called Muti-Level Surface (MLS). These maps offer the opportunity to model environments with more than one traversable level using a two-dimensional grid structure with a Gaussian distribution that reflects the uncertainty of the measured height of an object's surface, as well as a depth value which helps to represent vertical structures. The depth is the length of a vertical interval starting at the height mean and pointing downwards. If necessary, it is able to store multiple depth values which helps to deal with vertical and multilevel structures. Lamond et al. [35] used the MLS maps to perform traversability analysis, using this representation to describe flat objects, such as street, ground, etc., and non-flat objects such as buildings in the same framework. Joho et al. [28] also use MLS maps for traversability but enriched information about the environment is used. In addition to the parametric height they take into account the slope and the roughness of the terrain. Also to determine the traversability value they fit a plane into its local 8-patch neighborhood minimizing the distance of the plane to the elevation values of the neighboring patches. Joho's approach also is able to deal with abyss which are usually ignored in 2D representations.

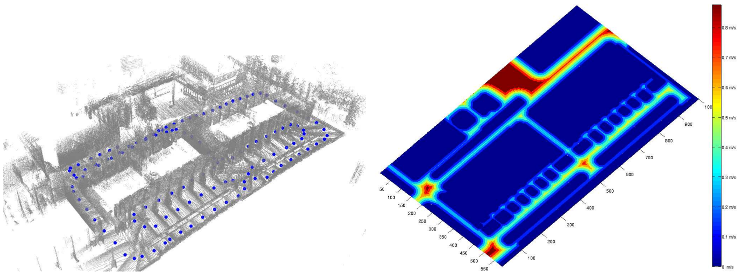
4.5 Conclusions

Considering the presented literature, in the ICP algorithm there are several metrics to compute the minimization (point-to point, point-to-plane, etc.) every one with advantages and disadvantages. When solving the minimization, translation is relatively easy to find but rotation takes more iterations to properly converge. Some authors have proposed weighted metrics to compensate the trade between rotation and translation which seems to work well improving the final local registration which could be very advantageous. Computing first order uncertainty propagation of these and other metrics is still an open problem that will be tackled for this thesis. The correspondence search is the most expensive step in the ICP, but it has been proved that using tree based structures, such as kd-trees, reduces effectively computational load. Data association is a key issue, when the number of outliers is large, many wrong correspondences are unavoidable, and would produce convergence on a local minimum leading to a poor final overlap, or in the worst case, to diverge. We shall remember that the original ICP algorithm considers data sets without outliers, which is not our case. Different metrics and filtering heuristics have been proposed proving to have an important improvement in the final clouds alignment, but there is still work in outlier removal and data associations. Specially for our application, we must be able do exploit topological information such as planar surfaces and trees during data association.

Current state of the art SLAM techniques has shown the possiblity to implement on-line algorithms for SLAM.

Although there has been work in solving continuous POMDP's the difficult in scaling these algorithms makes them ineffective in addressing the autonomous navigation problem. Recently some works on reinforcement learning policies have been introduced to solve continuous spaces states. It has been proved that reinforcement learning can cope with large scale problems. Now a days navigation state of the art considers greedy cases. Specifically for 3D range data exploration, despite they are able to evaluate the next best view point, they lack a previous theoretical planning strategy to reach the goal while obtaining the necessaries range data sets to get a consistent map global, instead they use a heuristic technique and a replaning strategy to reach the goal is applied if necessary. We foresee to study theoretical exploration using finite-horizon strategies.

Traditional 2D autonomous navigation is a very known problem were almost every approach assume the robot lives in a plane and there only exist positive obstacles using traditional grid representation. Also some indoor as well some outdoor 3D navigation strategies do this assumption. However, a complete 3D outdoor navigation task for mobile robotics ought to avoid this assumption and must consider uneven features such as roughness, slopes, stairs, etc.. Multi-level surfaces maps are a viable environment representation for 3D navigation, on disadvantage they



(a) Final map of the experimental site computed with our approach. (b) Computed traversability map.

Figure 1: 6D range based SLAM results.

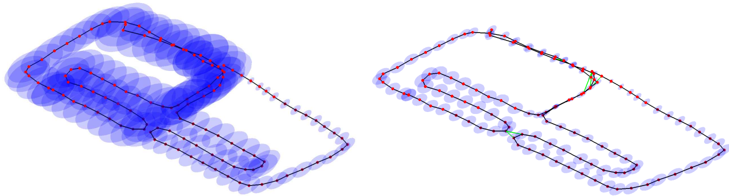
lack a multi-robot frame work to use them, since the way they are build depend only on the robot acquiring it. Another 3D map model is 3D occupancy grid but it may prevent the robot from exploring an environment larger than a few hundred square meters. In the other hand, derived traversability 3D maps lack of maximum speed information for the patches. Finally both kind of maps lack from a multi-resolution frame work, which could be a good strategy to reduce the states spaces in autonomous navigation.

5 Achievements

Considering the task of mapping pedestrian urban areas for a robotic guidance and surveillance application we present a technical report [69] where we solve this task using a variant of the ICP algorithm proposed in [5] for scan matching. In the minimization step we use the metric proposed by Biota et al. [7] taking advantage of the compensation between translation and rotation they mention. To reduce computational cost in the original ICP during matching, the original data is sampled and correspondences are searched with the Approximate Nearest Neighbor library. Finally we propose a hierarchical new correspondence search strategy, using a point-to-plane strategy at the highest level and a point-to-point metric at finer levels. At the highest level the fitting error between a plane and its n adjacent points describing the plane is computed, using it to decide the correspondence search metric. Two different three-dimensional laser rage finders are used. The first was mounted in the SmarTer car robot from ETHZ and the second one, built at IRI, is mounted on our robot Helena, a Pionner mobile robot.

In [75], accepted for presentation at the IEE/RSS International Conference on on Intelligent Robots and Systems (IROS) 2009, we present an approach to the problem of 3D map building in urban settings for service robots, using three-dimensional laser range scans as the main input sensor. Our system is based on the probabilistic alignment of 3D point clouds employing a delayed-state information-form SLAM algorithm, for which we can add observations of relative robot displacement efficiently. These observations come from the alignment of dense range data point clouds computed with a variant of the iterative closest point algorithm, Figs. 1 to 3. The data sets were acquired with our custom built 3D range scanner integrated into a mobile robot platform. Our mapping results are compared to a GIS-based CAD model of the experimental site. The results show that our approach to 3D mapping performs with sufficient accuracy to derive traversability maps Fig. 1(b), that allow our service robots navigate and accomplish their assigned tasks on a urban pedestrian area.

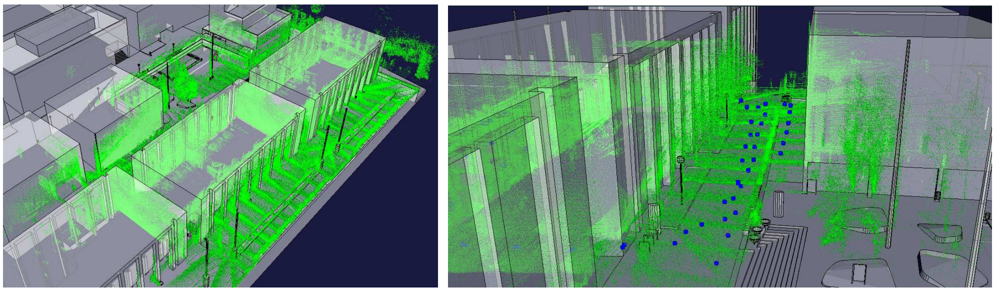
A second paper will be presented at IROS 2009 [54], in which the obtained 3D map was used for outdoor camera network calibration, Fig. (4). In this case, the point cloud is segmented,



(a) State estimate before loop closure.

(b) Estimated trajectory after loop closure.

Figure 2: 6D range based SLAM results.



(a) Top view of the 3D map.

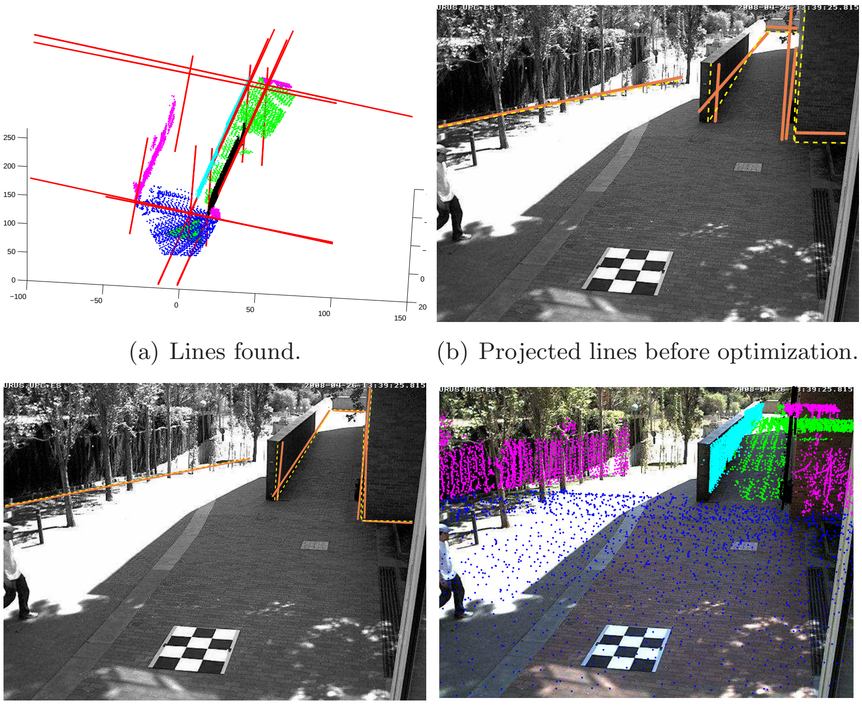
(b) A section of the map. The blue points indicate the estimated robot positions.

Figure 3: Projection of the 3D point cloud on a 3D georeferenced CAD model.

and the segmented intersections reprojected on the camera images. An optimization step is used to align the projected 3D features to the image features both intrinsic and extrinsic camera calibration parameters.

6 Expected contributions

- **An on-line robust range data registration**
  - To provide a rich environment representation capable of representing accurately the robot's surroundings at low computational cost and with reduced effects from the 3D sensor noise.
  - Use a new hierarchical nearest neighbor search, and filtering strategies to get a better registration.
  - Provide a state of the art data fusion and inference mechanism to refine pose estimates from the registered 3D data with first order uncertainties.
  - Computing first order uncertainty propagation of ICP metrics.
- **Novel exploration techniques using 3D range data.**
  - To develop a compact and consistent environment representation for exploration extracting higher order entities/symbols from the registered raw data maps.
  - To study the advantage of using multi-resolution based maps to reduce the spaces states for exploration.
  - To propose a finite-horizon strategy using for exploration.



(a) Lines found. (b) Projected lines before optimization.

(c) Projected lines after optimizacion. (d) Projected map after optimization.

Figure 4: Camera network calibration with the obtained map.

7 Work plan and calendar

In this section we present the required tasks to develop this Thesis. The work plan is conformed by ordered points to reach progressively the goals which are listed next, later a Gantt diagram is presented in table 1.

0.1 Ph.D Curses first quatrimester, 6 months.

0.2 Ph.D Curses second quatrimester, 6 months.

1.0 State of the art review. In-depth study of range data registration, specially focusing on its implementation for mobile robotics including computational complexity , sampling (environment representation) and minimization strategies, 6 months.

1.1 ICP implementation with low noise data such as an indoor scene to better understand the algorithm, 3 months.

1.3 To propose off-line sampling strategies and correspondences search for the ICP algorithm, focusing on environment representation. Perform experiments with real data and report the proposed solution and results (journal/conference publication), 4 months.

1.2 To build a device 3D laser-range. 4 months.

1.4 To build a new device 3D laser-range. Reduce acquisition time of the sensor, 5 months.

1.5 Computing first order uncertainty propagation, report the proposed solution and results (conference publication), 4 months.

1.6 3D range laser for simulation. To program a 3D ray cast laser to future simulations of the algorithms. By means of an off-line computed 3D points or CAD map and integrate it in the simulator, 3 months.

1.7 A real-time implementation of the ICP algorithm. To propose sampling and accurate strategies of the environment for real-time applications and to implement improvements on the correspondences step of the ICP. Report the proposed solution and results, 4 months.

2.0 State of the art review. In-depth study and understanding of Pose SLAM approaches, mainly focusing on the work dealing with, computational complexity and data association, 4 months.

2.1 Analysis and implementation of a 6 DOF SLAM. 5 months.

3.0 State of the art review. In-depth study of exploration techniques considering indoors and outdoor strategies, mainly focusing on range data, 6 months.

3.1 3D exploration strategies implementation. To implement and simulate existing outdoor exploration for a better problem understanding, 5 months.

3.2 Propose 3D exploration strategies, Formalization of exploration strategies. Evaluation by means of simulation for our proposed autonomous outdoor navigation strategy and report the results, 5 months.

3.3 Real world experiments in the Barcelona Robot Lab experiments area of our proposed outdoor navigation strategy and report the results (journal/conference publication), 4 months.

4.0 Thesis writeup and defense. All technical reports, papers and works done along the research will be integrated in a document describing the state of the art, the evolution and details of the research, its contributions, conclusions and future work, 5 months.

8 Resources

This PhD thesis is being carried out at the Instituto de Robótica e Informática Industrial, CSIC-UPC and is part of the EU URUS Project IST-045062 (Ubiquitous Network Robotics in Urban Settings) [62] founded by the EU, and coordinated by Alberto Sanfeliu and the PAU project (Perception and Action Under Uncertainty), DPI-2008-06022 coordinated, by Juan Andrade-Cetto. Our contribution in URUS will be in the form of new robust mapping algorithm for outdoor autonomous mobile robots in pedestrian areas, using 3D range laser data and 3D exploration using finite-horizon strategies.
To realize the experiments we count with IRI's robot Helena, an Activmedia Pioneer 3AT platform fitted with a 3D range laser built at IRI and other sensors such as GPS and IMU Fig. 5(a). The robot is able to climb up hills with a maximum slope of 35%, and travels at a maximum speed on flat surfaces of 1.2 m/s. The platform has an 8 hour battery autonomy and can carry a load of 20kg. Given the uneven characteristic of the terrain in the experimental site and the large number of ramps, odometry data this robot has proved of little value, so point clouds are annotated with IMU.
The 3D laser system is able to obtain points with pan angular range of 190° and a tilt range about 90°, offering an approximate resolution of 529x144 points, about 76000 points per scan. Also we will build in the context of this thesis a new improved 3D sensor in yaw-scan-top configuration, according with Wulf's classification [79], using a Hokuyo UTM-30LX laser. The differences between the previous range sensor and the new one are indicated in Table (2) . In summary the new 3D sensor will be able to cover 360x270 degrees in tilt and pan, shown in Figs. 5(b) [1] and 6(b).

[1]Thank's to the IRIWorkShop for its contribution in the new 3D laser design.

Year	Task ID	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	2.0	2.1	3.0	3.1	3.2	3.3	4.0
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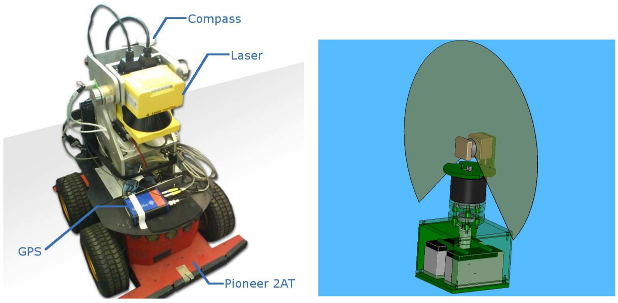
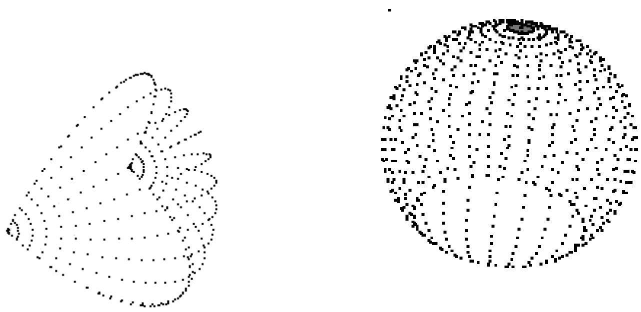
Table 1: Work plan diagram



(a) IRI's mobile robot Helena (b) Improved 3D sensor

Figure 5: Mobile platform and projected Hokuyo 3D laser range finder



(a) Pitch scan, Leuze or Sick lasers. (b) Yaw scan top, Hokuyo laser.

Figure 6: Scan types.

The new 3D range sensor will be installed on a new platform at IRI, a 4 wheel Segway RPM-400 all terrain unit.

To opt for the EU PhD title and reinforce collaboration lints in our projects, a research stay of at least three months is predicted in one of our collaborating partners sites. The stay will be confirmed during next year.

Model	Freq.	Points	Ang. Res.	Ang.	Range (m)	Res (mm)	Weight (Kg.)	Cons. (W)	Sup. (VCD)
UTM-30LX Hokuyo	40 Hz	1081	0.25	270	1	30	0.370	8.4	12
RS4 Leuze	30 Hz	529	0.36	190	5	62	2	7.2	24
LMS 200 Sick	70 Hz	181	1	180	10	80	4.5	20	24

Table 2: Laser technical specifications, table

References

[1] D. Akca and A. Gruen. Fast correspondece search for 3D surface matching. *ISPRS Workshop Laser Scanner*, pages 186–191, September 2005.

[2] S. Arya, D.M. Mount, N.S. Netanyahu, R. Silverman, and A.Y. Wu. An optimal algorithm for approximate nearest neighbor searching fixed dimensions. *Journal of the ACM*, 46(6):891–923, November 1998.

[3] J.E. Banta, Y. Zhien, X.Z. Wang, G. Zhang, M.T. Smith, and M.A. Abidi. A best-next-view algorithm for three-dimensional scene reconstruction using range images. In *Intelligent Robots and Computer Vision*, volume 2588, page 418. SPIE, 1995.

[4] R. Benjemaa and F. Schmitt. Fast global registration of 3D sampled surfaces using a multi-z-buffer technique. *Image and Vision Computing*, 17:113–123, 1999.

[5] P.J. Besl and N.D. McKay. A method for registration of 3D shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(2):239–256, February 1992.

[6] L. Biota. Algoritmos de scan matchin basados en métricas para estimar el movimiento de robots que se desplazan en espacios tridimensionales. Technical report, Centro Polit'ecnico Superior de Zaragoza, June 2005.

[7] L. Biota, L. Montesano, J. Minguez, and F. Lamiraux. Toward a metric-based scan matching algorithm for displacement estimation in 3D workspaces. *IEEE International Conference on Robotics and Automation*, pages 4330–4332, May 2006.

[8] G. Blais and M.D. Levine. Registering multiview range data to create 3D computer objects. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(8):820–824, August 1995.

[9] Y. Chen and G. Medioni. Object modeling by registration of multiples ranges images. *IEEE International Conference on Robotics and Automation*, 3:2724–2729, April 1991.

[10] D. Chetverikov. Fast neighborhood search in planar point sets. *Pattern Recognition Letters*, 12(7):409–412, July 1991.

[11] D. Chetverikov, D. Stepanov, and P. Krsek. Robust euclidean alignment of 3D point sets: the trimmed iterative closest point algorithm. *Image and Vision Computing*, 23(3):299–309, 2005.

[12] D.M. Cole and P.M. Newman. Using laser range data for 3D SLAM in outdoor environments. In *IEEE International Conference on Robotics and Automation*, pages 1556–1563, Orlando, May 2006.

[13] T.H. Cormen. *Introduction to Algorithms*. MIT Press, 2001.

[14] A. Elfes. Using occupancy grids for mobile robot perception and navigation. *Computer*, 22(6):46–57, 1989.

[15] R. M. Eustice, H. Singh, and J. J. Leonard. Exactly sparse delayed-state filters for view-based SLAM. *IEEE Transactions on Robotics*, 22(6):1100–1114, December 2006.

[16] H. González-Baños and J.C. Latombe. A randomized art-gallery algorithm for sensor placement. In *Annual Symposium on Computational Geometry*, pages 232–240, New York, 2001. ACM.

[17] H. González-Baños and J.C. Latombe. Navigation strategies for exploring indoor environments. *International Journal of Robotics Research*, 21(10):829–848, 2002.

[18] H. González-Baños, E. Mao, J.C. Latombe, T.M. Murali, and A. Efrat. Planning robot motion strategies for efficient model construction. In *International Symposium Robotics Research*, volume 9, pages 345–352, 2000.

[19] M. Greenspan and G. Godin. A nearest neighbor method for efficient ICP. *International Conference on 3D Digital Imaging and Modeling*, pages 161–168, 2001.

[20] J.S. Gutmann. *Robuste Navigation autonomer mobile Systeme*. PhD thesis, University of Freiburg, Germany, 2000.

[21] J.S. Gutmann, M. Fukuchi, and M. Fujita. A floor and obstacle height map for 3D navigation of a humanoid robot. In *IEEE International Conference on Robotics and Automation*, pages 1066–1071, Barcelona, April 2005.

[22] M. Herbert, C. Caillas, E. Krotkov, IS Kweon, and T. Kanade. Terrain mapping for a roving planetary explorer. In *IEEE International Conference on Robotics and Automation*, pages 997–1002, May 1989.

[23] A. Howard, D.F. Wolf, and G.S. Sukhatme. Towards 3D mapping in large urban environments. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, volume 1, pages 419–424, Sendai, September 2004.

[24] S. Huang, Z. Wang, and G. Dissanayake. Exact state and covariance sub-matrix recovery for submap based sparse EIF SLAM algorithm. In *IEEE International Conference on Robotics and Automation*, pages 1868–1873, Pasadena, May 2008.

[25] M. Morta i Garriga. Disseny i construcció d'un laser 3D per al mapejat d'entorns exteriors. Technical report, Escola Técnica Superior d'Enginyería Industrial de Barcelona, June 2008.

[26] V. Ila, J. Andrade-Cetto, R. Valencia, and A. Sanfeliu. Vision-based loop closing for delayed state robot mapping. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3892–3897, San Diego, November 2007.

[27] V. Ila, J.M. Porta, and J. Andrade-Cetto. Compact maps in Pose SLAM. In *To be presented on IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, October 2009.

[28] D. Joho, C. Stachniss, P. Pfaff, and W. Burgard. Autonomous exploration for 3D map learning. In Karsten Berns and Tobias Luksch, editors, *Autonome Mobile Systems*, pages 22–28, Kaiserslautern, October 2007. Springer.

[29] M. Kaess, A. Ranganathan, and F. Dellaert. iSAM: Incremental smoothing and mapping. *IEEE Transactions on Robotics*, 24(6):1365–1378, December 2008.

[30] A. Kirmse. *Game Programming Gems 4 (Game Programming Gems Series)*. Nelson Education Ltd., March 2004.

[31] T. Kollar and N. Roy. Trajectory optimization using reinforcement learning for map exploration. *The International Journal of Robotics Research*, 27(2):175–196, 2008.

[32] D. Kortenkamp, R.P. Bonasso, and R. Murphy. AI-based mobile robots: Case studies of successful robot systems, 1998.

[33] D.J. Kriegman, E. Triendl, and T.O. Binford. Stereo vision and navigation in buildings for mobile robots. *Transactions on Robotics and Automation*, 5(6):792–803, 1989.

[34] S. Lacroix, A. Mallet, D. Bonnafous, G. Bauzil, S. Fleury, M. Herrb, and R. Chatila. Autonomous rover navigation on unknown terrains: Functions and integration. *International Journal of Robotics Research*, 21(10-11):917–942, 2002.

[35] P. Lamon, C. Stachniss, R. Triebel, P. Pfaff, C. Plagemann, G. Grisetti, S. Kolski, W. urgard, and R. Siegwart. Mapping with an autonomous car. In *IEEE/RSJ IROS Workshop: Safe Navigation in Open and Dynamic Environments*, Beijing, October 2006.

[36] C. Leung, S. Huang, and G. Dissanayake. Active SLAM using model predictive control and attractor based exploration. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5026–5031, Beijing, October 2006.

[37] R. Martinez-Cantin. *Active Map Learning for Robots: Insights into Statistical Consistency*. PhD thesis, University of Zaragoza, Spain, September 2008.

[38] R. Martinez-Cantin, N. de Freitas, A. Doucet, and J. Castellanos. Active policy learning for robot planning and exploration under uncertainty.

[39] T. Masuda, K. Sakaue, and N. Yokoya. Registration and integration of multiple range images for 3D model construction. *International Conference on Pattern Recognition*, 20(1):879–883, 1996.

[40] J. Minguez, F. Lamiraux, and L. Montesano. Metric-based scan matching algorithms for mobile robot displacement estimation. In *IEEE International Conference on Robotics and Automation*.

[41] J. Minguez, L. Montesano, and F. Lamiraux. Metric-based iterative closest point scan matching for sensor displacement estimation. *IEEE Transactions on Robotics*, 22(5):1047–1054, October 2006.

[42] M. Montemerlo and S. Thrun. A multi-resolution pyramid for outdoor robot terrain perception. In *Proceedings of the National Conference on Artificial Intelligence*, pages 464–469. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2004.

[43] L. Montesano, J. Minguez, and L. Montano. Lessons learned in integration for sensor-based robot navigation systems. *International Journal of Advanced Robotic Systems*, 2006.

[44] H. Moravec and A. Elfes. High resolution maps from wide angle sonar. In *IEEE International Conference on Robotics and Automation*, volume 2, March 1985.

[45] H. P. Moravec. Robot spatial perception by stereoscopic vision and 3D evidence grids. Technical report, Carnegie Mellon University, The Robotics Institute, 1996.

[46] D. Murray and C. Jennings. Stereo vision based mapping and navigation for mobile robots. In *IEEE International Conference on Robotics and Automation*, volume 2, April 1997.

[47] D. Murray and J.J. Little. Using real-time stereo vision for mobile robot navigation. *Autonomous Robots*, 8(2):161–171, 2000.

[48] D. Murray and J.J. Little. Interpreting stereo vision for a mobile robot. *Autonomous Robots*, 2001.

[49] A. Nüchter, K. Lingemann, J. Hertzberg, and H. Surmann. 6D SLAM with approximate data association. *International Conference on Advanced Robotics*, pages 242–249, 2005.

[50] A. Nüchter, K. Lingemann, J. Hertzberg, and H. Surmann. 6D SLAM-3D mapping outdoor environments: Research articles. *Journal Field Robot.*, 24(8-9):699–722, August 2007.

[51] A. Nüchter, K. Lingemann, J. Hertzberg, H. Surmann, and S. Thrun. 6D SLAM with an application in autonomous mine mapping. *IEEE International Conference on Robotics and Automation*, 2:1998–2003, May 2004.

[52] A. Nüchter, O. Wulf, K. Lingemann, J. Hertzberg, B. Wagner, and H. Surmann. 3D mapping with semantic knowledge. *Lecture Notes in Computer Science*, 4020:335, 2006.

[53] J. O'Rourke. *Art gallery theorems and algorithms.* Oxford University Press New York, 1987.

[54] A. Ortega, B. Dias, E.H. Teniente, A. Bernardino, J. Gaspar, and J. Andrade-Cetto. Calibrating an outdoor distributed camera network using laser range finder data 3D mapping for urban service robots. In *To be presented on IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, October 2009.

[55] S.Y. Park and M. Subbarao. A fast point-to-tangent plane technique for multi-view registration. *International Conference on 3D Digital Imaging and Modeling*, pages 276–283, October 2003.

[56] P. Pfaff and W. Burgard. An efficient extension of elevation maps for outdoor terrain mapping. In *International Conference on Field and Service Robotics*, volume 165. Springer, 2005.

[57] P. Pfaff, R. Triebel, C. Stachniss, P. Lamon, w.Burgard, and R. Siegwart. Towards mapping of cities. In *IEEE International Conference on Robotics and Automation*.

[58] J.M. Porta, N. Vlassis, M.T.J. Spaan, and P. Poupart. Point-based value iteration for continuous POMDP's. *The Journal of Machine Learning Research*, 7:2329–2367, 2006.

[59] K. Pulli. Multiview registration for large data sets. *International Conference on 3D Digital Imaging and Modeling*, 8:160–168, 1999.

[60] P. J. Rousseeuw. Least median of squares regression. *Journal of the American Statistical Association*, 79(388):871–880, 1984.

[61] S. Rusinkiewicz and M. Levoy. Efficient variants of the icp algorithm. *International Conference on 3D Digital Imaging and Modeling*, pages 145–152, 2001.

[62] A. Sanfeliu and J. Andrade-Cetto. Ubiquitous networking robotics in urban settings. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 14–18, Beijin, October 2006.

[63] R. Sim. Stable exploration for bearings-only SLAM. In *IEEE International Conference on Robotics and Automation*, pages 2422–2427.

[64] D.A. Simon, M. Hebert, and T. Kanade. Real-time 3D pose estimation using a high-speed range sensor. In *IEEE International Conference on Robotics and Automation*, volume 3, pages 2235–2241, May 1994.

[65] Russell Smith. ODE: Open dinamycs engine. *http://http://www.ode.org/*, 2009.

[66] C. Stachniss, G. Grisetti, and W. Burgard. Information gain-based exploration using rao-blackwellized particle filters. In *Robotics: Science and Systems*, pages 65–72, 2005.

[67] C. Stachniss, D. Hahnel, and W. Burgard. Exploration with active loop-closing for fast-SLAM. In *IEEE International Conference on Intelligent Robots and Systems*, volume 2, 2004.

[68] H. Surmann, A. Nüchter, and J. Hertzberg. An autonomous mobile robot with a 3D laser range finder for 3D exploration and digitalization of indoor environments. *Journal Robotics and Autonomous Systems*, 45(3-4):181–198, 2003.

[69] E.H. Teniente and J. Andrade-Cetto. Registration of 3D points clouds for urban robot mapping. Technical Report IRI-TR-08-06, Institut de Robòtica i Informàtica Industrial (CSIC-UPC), September 2008.

[70] S. Thrun. Learning metric-topological maps for indoor mobile robots navigation. *Journal of Artificial Inteligence*, 99(1):21–71, 1998.

[71] S. Thrun. Monte carlo POMDP's. *Advances in Neural Information Processing Systems*, 12:1064–1070, 2000.

[72] V. Tikhanoff, P. Fitzpatrick, F. Nori, L. Natale, G. Metta, and A. Cangelosi. The icub humanoid robot simulator. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, Nice, September 2008.

[73] R. Triebel, P. Pfaff, and W. Burgard. Multi-level surface maps for outdoor terrain mapping and loop closing. In *IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2276–2282, Beijing, October 2006.

[74] G. Turk and M. Levoy. Zippered polygon meshes from range images. *Conference on Computer Graphics and Interactive Techniques*, pages 311–318, July 1994.

[75] R. Valencia, E.H. Teniente, E. Trulls, and J. Andrade-Cetto. 3D mapping for urban service robots. In *To be presented in IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, October 2009.

[76] T. Vidal-Calleja, A.D. Davison, J. Andrade-Cetto, and D.W. Murray. In *IEEE International Conference on Robotics and Automation*, pages 1930–1936, Orlando, May 2006.

[77] T. Vidal-Calleja, A. Sanfeliu, and J. Andrade-Cetto. In *IFAC/EURON Symposium on Intelligent Autonomous Vehicles*, Toulouse, September 2007.

[78] P. Whaite and F.P. Ferrie. Autonomous exploration: driven by uncertainty. *Transactions on Pattern Analysis and Machine Intelligence*, 19(3):193–205, 1997.

[79] O. Wulf and B. Wagner. Fast 3D scanning methods for laser measurement systems. In *International Conference on Control Systems and Computer Science*, volume 1, pages 312–317, Bucharest, 2003.

[80] S.M. Yamany, M.N. Ahmed, and A.A. Farag. A new genetic-based technique for matching 3D curves and surfaces. *International Conference on Pattern Recognition*, 32(10):1827–1820, 1999.

[81] B. Yamauchi. A frontier-based approach for autonomous exploration. In *International Symposium on Computational Intelligence in Robotics and Automation*, pages 146–151. IEEE Computer Society Washington, DC, USA, 1997.

[82] B. Yamauchi. Frontier-based exploration using multiple robots. In *International Conference on Autonomous Agents*, pages 47–53. ACM Press New York, NY, USA, 1998.

[83] B. Yamauchi and P. Langley. Place recognition in dynamic environments. *Journal of Robotic Systems*, 14(2):107–120, 1997.

[84] Z. Zhang. Iterative point matching for registration of free-form curves and surfaces. *International Journal of Computer Vision*, 13:119–152, 1994.