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Robot Self-Localization in Dynamic Environments

Carlos Miguel Correia da Costa

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Supervisor: Armando Jorge Miranda de Sousa (Ph.D.)

Second Supervisor: Germano Manuel Correia dos Santos Veiga (Ph.D.)

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Approved in oral examination by the committee:

Chair: Doctor Name of the President
External Examiner: Doctor Name of the Examiner
Supervisor: Doctor Name of the Supervisor

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Abstract

Mobile robot platforms capable of operating safely and accurately in dynamic environments can have a multitude of applications, ranging from simple delivery tasks to advanced assembly operations. These abilities rely heavily on a robust navigation stack, which requires a stable and accurate localization system.

This dissertation describes an efficient, modular, extensible and easy to configure 3/6 Degrees of Freedom (DoF) localization system, capable of operating on a wide range of mobile robot platforms and environments. It is able to reliably estimate the global position using feature matching and is capable of achieving high accuracy pose tracking using point cloud registration algorithms. It can use several point cloud sensing devices (such as LIght Detection And Ranging (LIDAR) or RGB-D cameras) and requires no artificial landmarks. Moreover, it can update the localization map at runtime and dynamically adjust its operation rate based on the predicted robot velocity in order to use the minimum amount of hardware resources. It also offers a detailed analysis of each pose estimation, providing information about the percentage of registered inliers, the root mean square error of the inliers, the angular distribution of the inliers and outliers, the pose corrections that were performed in relation to the expected position and in case of initial pose estimation it also gives the distribution of the acceptable initial poses, which can be very valuable information for a navigation supervisor when the robot is in ambiguous areas that are very similar in different parts of the known environment.

The ROS implementation was tested in several dynamic indoor environments using two mobile robot platforms equipped with LIDARs and RGB-D cameras. Overall tests using sensor data from simulation and retrieved from the robot platforms performed in a high end laptop with an Intel Core i7 3630QM processor, 16GB DDR3 of memory and NVIDIA GTX680M graphics card, demonstrated high accuracy in complex dynamic environments, with less than 1 cm in translation error and less than 1 degree in rotation error. Execution times ranged from 5 to 30 milliseconds in a 3 DoF setup and from 50 to 150 milliseconds in a full dynamic 6 DoF configuration.

The sub centimeter accuracy achieved by the proposed localization system along with the dynamic map update capability and the need of no artificial landmarks will allow the fast deployment of mobile robot platforms capable of operating safely and accurately in cluttered environments. Moreover, the resilience to dynamic objects will grant the possibility to use robots as coworkers, helping humans perform their work more efficiently and thus reducing the overall production costs.

Resumo

Plataformas móveis robóticas capazes de operar com precisão e de forma segura em ambientes dinâmicos têm um alargado espetro de aplicações, desde simples entregas de objetos até operações complexas de montagem. Para atingir estes requisitos de operação é necessário um sistema de navegação robusto, que por sua vez requer um módulo de localização preciso e estável.

Esta dissertação descreve um sistema de localização para 3/6 graus de liberdade (DoF), que é eficiente, modular, extensível e fácil de configurar, capaz de operar num alargado conjunto de plataformas móveis e ambientes. É capaz de estimar a posição inicial de um robô usando métodos de associação de características geométricas e consegue seguir a sua pose com alta precisão através de algoritmos de registo de nuvens de pontos. A sua implementação consegue tirar partido de vários sensores laser e câmaras RGB-D e não necessita de marcadores artificiais ou modificação do ambiente. Possui ainda a capacidade de atualizar o mapa incrementalmente e ajustar a sua frequência de funcionamento de acordo com a velocidade do robô de forma a usar o mínimo de recursos computacionais possível. Para facilitar a avaliação da qualidade da localização para operações críticas, cada estimativa da pose do robô é acompanhada com a análise do registo da nuvem de pontos, contendo informação acerca da percentagem de pontos corretamente registados, a raiz quadrada do erro quadrático médio, a distribuição angular dos pontos classificados como pertencentes e não pertencentes ao mapa de referência, as correções aplicadas à estimativa da pose e no caso de ser efetuada localização global também é disponibilizada a distribuição das poses iniciais aceitáveis, o que pode ser informação bastante útil para um supervisor de navegação quando o robô está em posições ambíguas do ambiente nas quais existe geometria semelhante em sítios diferentes do mapa.

A implementação em ROS foi testada em vários ambientes dinâmicos recorrendo a duas plataformas móveis equipadas com LIDARs e câmaras RGB-D. Os resultados obtidos usando dados de simulação e recolhidos das plataformas robóticas realizados num portátil com CPU Intel Core i7 3630QM, 16GB DDR3 de memória e placa gráfica NVIDIA GTX680M demonstraram que o sistema consegue fazer a estimativa da pose do robô com um erro de translação inferior a 1 centímetro e um erro de rotação abaixo de 1 grau. Os tempos de execução oscilaram entre 5 e 30 milissegundos para uma configuração 3 DoF e entre 50 e 150 milissegundos para 6 DoF.

A alta precisão disponibilizada pelo sistema de localização proposto em conjunto com a sua capacidade para atualizar o mapa incrementalmente e de não necessitar marcadores artificiais, irá permitir o desenvolvimento de plataformas robóticas móveis capazes de operar em ambientes não estruturados. Por outro lado, a sua robustez em relação a objetos dinâmicos abre a possibilidade dos robôs colaborarem com humanos para melhorar a produtividade global de uma dada tarefa e assim reduzir os custos de produção.

Acknowledgments

I would like to express my gratitude to my supervisors and the INESC team, for their helpful contributions. Their experience and expertise significantly improved the quality of this dissertation.

I am also very grateful for the knowledge and experiences that I gather from my friends, teachers and colleagues over the years and for the brilliant work developed by the ROS and PCL community.

And of course, to my family, for their continuous support.

Carlos Miguel Correia da Costa

"Perfection is achieved, not when there is nothing more to add,
but when there is nothing left to take away."

Antoine de Saint-Exupéry

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Abbreviations

CAD Computer Aided Design.
CARLoS Cooperative Autonomous Robot for Large Open Spaces.

GLONASS GLObalnaya NAvigatsionnaya Sputnikovaya Sistema.
GNSS Global Navigation Satellite System.
GPS Global Positioning System.

LIDAR LIght Detection And Ranging.

MCL Monte Carlo Localization.

RADAR RAdio Detection And Ranging.

SLAM Simultaneous Localization And Navigation.
SONAR SOund Navigation And Ranging.

ToF Time of Flight.

Chapter 1

Introduction

This chapter provides an overview about the motivations and objectives of this dissertation along with its practical applications.

1.1 Context

Humanity has sought a reliable method of navigation ever since it started to explore the world. It began with simple landmark reference points for local travels, then perfected celestial navigation for global journeys, and when it finally conquered space, it deployed a global system for high accuracy localization. Autonomous robots face the same problem, because in order to be able to navigate with precision, they first need to know their location.

Over the years, several localization methods have been proposed and refined, according to the navigation environment and the accuracy requirements. Some are meant for high precision local navigation, while others provide an approximate global position.

A robot capable of operating safely and accurately in a dynamic environment can have innumerous applications, ranging from simple delivery tasks to advanced assembly. Besides improving productivity by performing repetitive tasks with precision and speed, robots can also act as coworkers, helping humans perform their jobs more efficiently and thus, reducing the overall production costs.

1.2 Project

Cooperative Autonomous Robot for Large Open Spaces (CARLoS)[1] is a European research project that aims to develop an autonomous robot capable of performing repetitive tasks alongside human co-workers in dynamic environments. The robot will operate in shipyards and is intended to perform fit-out operations, such as stud welding and projection mapping of Computer Aided Design

[1] http://carlosproject.eu/

(CAD) drawings. Stud welding is a repetitive task that provides structural support for other components, such as heat insulation layers or electrical systems. Projection mapping of CAD drawings or other important information will help human co-workers assemble components faster, because it will mark the exact position in which they must be installed.

1.3 Motivation and objectives

With the increase of competitiveness in the current globalized trading markets, companies are trying to reduce production costs and improve the productivity of their assets. Robots can help achieve these goals by performing the simple and repetitive jobs while giving humans more free time to perform the complex and creative tasks.

Mobile platforms equipped with robotic arms provide a flexible way to automate a wide range of tasks that must be performed over large areas. However, before performing the intended operations they first need to know where they are and how they can reach the desired location. Moreover, given their limited computational resources and energy storages, they require efficient, reliable and accurate control systems capable to operate in real time.

1.4 Contributions

This dissertation introduces an efficient, modular and extensible 3/6 DoF localization system for mobile robot platforms capable of operating accurately and reliably in dynamic environments. It is a multi-level registration pipeline that uses geometric features to estimate the initial position of a robot platform and point cloud registration algorithms to track its pose. The tracking subsystem can have two different configurations. One tuned for maximum efficiency used for the normal operation of the mobile platform and another for unlikely situations that may require more robust registration algorithms / configurations. It also supports incremental map update and can adjust its operation rate based on the estimated robot velocity. For critical operations, it provides a detailed analysis of the tracking quality and when initial pose estimation is required it gives the distribution of the acceptable poses, which can be very valuable information if there are several areas in the known map with very similar geometry.

1.5 Dissertation outline

The remaining of this dissertation is split over 6 chapters. Chapter 2 provides an overview of the main localization methods available for mobile robot platforms. Chapter 3 introduces the frameworks used to build the localization system that is detailed in chapter 5. Chapter 4 describes the theoretical foundations and algorithms that were used to process and analyze point clouds. Chapter 6 evaluates the results achieved with the localization system in several testing environments. Finally, chapter 7 presents the conclusions of this dissertation and suggestions for future work.

Chapter 2

Localization methods

Self-localization is critical to any autonomous robot that must navigate the environment and requires the calculation of a 3/6 DoF pose in a given world coordinate system.

Over the years, several approaches were developed according to the precision requirements and the environment in which the robot is designed to operate. Some require support systems to calculate the position, while others are completely autonomous, allowing the robot to localize itself without any outside dependencies. Also, some systems have limited range while others can only be effective in open spaces. Moreover, several of these methods were designed to cope with errors in the localization sensors and tolerate temporary malfunctions.

The following sections will introduce some of the most used self-localization systems that can be employed in the estimation of a robot's pose.

2.1 Proprioceptive methods

Proprioceptive methods rely on internal information that the robot possesses about its own systems operation and movement in order to update the current pose estimation. As a result, they allow the robot to operate without an external support system.

Since these methods don't correct their estimations based on environment observations, they are bound to have significant cumulative errors. As such, in order to maintain an accurate estimation of a robot's pose, they are usually combined with exteroceptive systems.

2.1.1 Odometry

Odometry estimates the current pose by integrating the velocity of the robot over time. This velocity is usually calculated by measuring the number of rotations of the wheels (using optical encoders like the ones shown in figure 2.1). This method can provide a viable approximated location, as can be seen in [RKZ13].

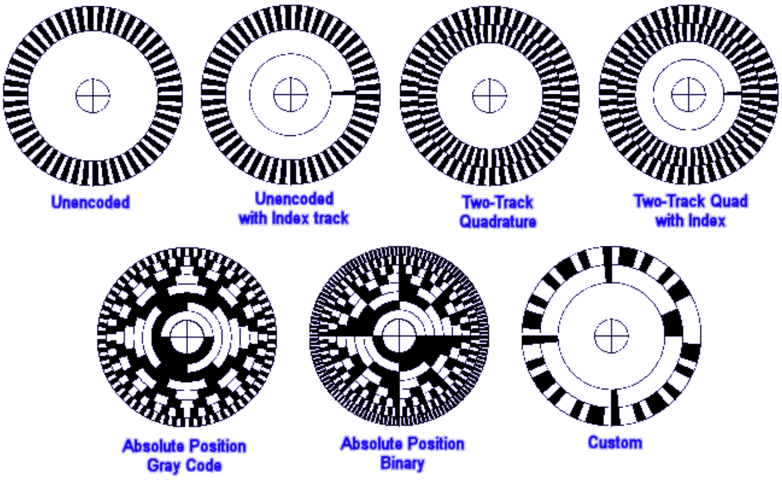

Figure 2.1: Different types of optical encoders used to measure distances[1]

2.1.2 Dead reckoning

Dead reckoning is an extension of the odometry method, in which the acceleration and angular velocity are used to improve the localization estimations.

Other sensors, such as accelerometers and gyroscopes, can also be used to improve the position estimation [Ibr10] and provide the robot orientation.

2.2 Exteroceptive methods

Exteroceptive methods use a range of sensors to analyze the environment and retrieve the necessary information to perform localization.

2.2.1 Time of Flight methods

Time of Flight (ToF) or Time of Arrival (ToA) methods can be used to calculate distances based on the amount of time that a given wave takes from the moment it is created to the moment it is received. This allows the construction of a 3D representation of the world that can be used in conjunction with geometric methods to estimate the pose of a robot.

Since these systems rely on active interaction with the environment, they can be used without being affected by lighting interferences. Nevertheless, they should take in consideration the conditions in which the waves propagate and also the geometry of the environment, because it can affect the path that the waves take, and as a result, can lead to the decrease of precision in the measurements.

[1] http://www.mindspring.com/~tom2000/Delphi/Codewheel.html

Light waves Light waves generated with lasers can estimate distances with high accuracy. Systems like LIDAR take advantage of this fact and can be used to calculate a very detailed 3D point cloud of the environment (like the one showed in figure 2.2).

Given the high velocity in which light propagates, these methods allow the mapping of the environment with low latency, which can be a critical requirement in robots that must react very fast to changes in their surroundings, such as autonomous cars [MCB10].

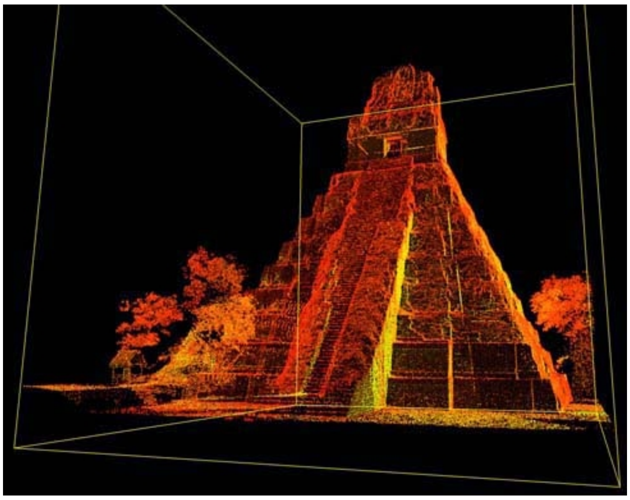

Figure 2.2: LIDAR scan[2]

Radio waves Similar to LIDAR, radio waves can be used to calculate distances using the ToF technique. Systems like RAdio Detection And Ranging (RADAR) provide an effective way to calculate the distance, altitude, direction and speed of objects that can be used as landmarks in navigation.

Like any electromagnetic wave localization method, it must take in consideration ambient interferences and even jamming, in order to validate the obtained measures. Moreover, some types of materials with a given geometric configuration might be invisible to RADAR, and as such, critical localization systems might have to employ some additional techniques to ensure the correct mapping of the robot surroundings.

Since RADAR has a less focused beam than LIDAR, it can have considerable less accuracy, as can be seen in figure 2.3. Nevertheless, it can be an effective method to avoid obstacles [WY07].

Sound waves Other localization approach that can be used to map under water environments relies in the acoustic analysis of the reflections of sounds in the surrounding objects.

Like the previous methods, SOund Navigation And Ranging (SONAR) can actively scan the environment to calculate the locations of the objects using a ToF technique (as can be seen in

[2] http://blogs.scientificamerican.com/cocktail-party-physics/2012/03/12/l-is-for-lidar/

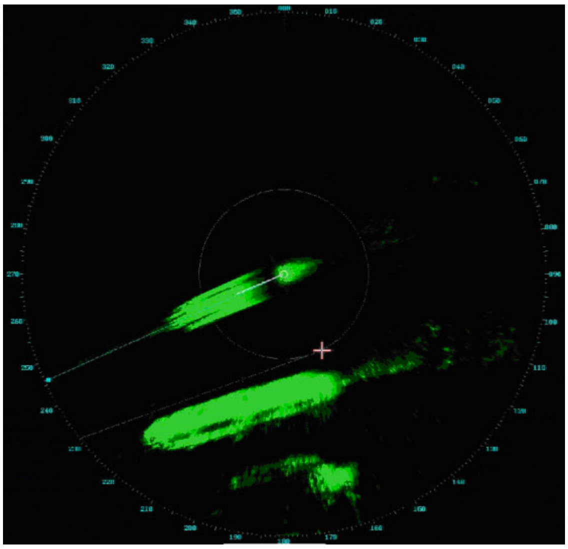

Figure 2.3: RADAR scan of two ships[3]

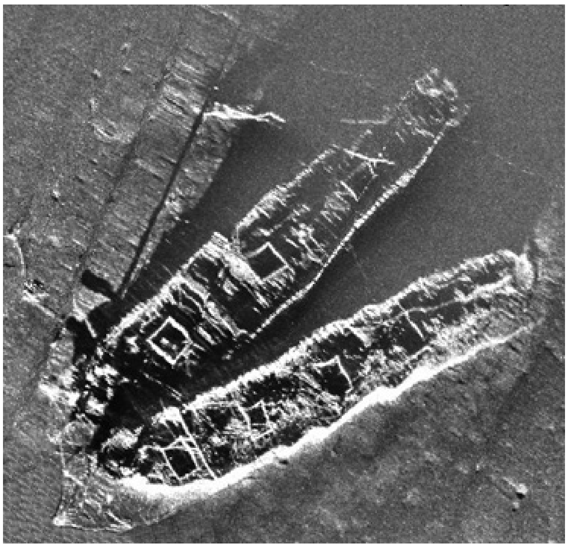

Figure 2.4: SONAR scan of two ships[4]

figure 2.4). Although this method is usually applied to underwater mapping, it can also be used in other sound propagation environments, such as air [GWG13].

2.2.2 Trilateration methods

Trilateration is a geometric technique that can be employed in the calculation of absolute or relative positions using distances from known points.

For 3D localization, it usually involves the intersection of 4 or more spheres, in which their radius is the distance to known positions.

Global Navigation Satellite System (GNSS) Global Navigation Satellite System (GNSS) such as the Global Positioning System (GPS) or GLObalnaya NAvigatsionnaya Sputnikovaya Sistema (GLONASS), allow 3D positioning in the planet Earth using a trilateration method [DKU$^+$07].

In these systems, a constellation of satellites broadcasts a radio signal with information about its position along with the time of the message dispatch. Using this data and knowing the speed of the radio waves, the distances to the satellites can be computed.

With at least 3 satellites distances, the 3D position can be calculated, since the Earth can be used as the 4^{th} sphere (figure 2.5 shows a visual representation of the trilateration technique used in a global localization system).

Given that the correct measurement of the distances to the satellites relies in the accurate computation of the elapsed time between the message dispatch and its reception, it is critical that both the satellites and the receiver have synchronized clocks. This is achieved by using high precision atomic clocks in the satellites and a clock reset technique in the receiver. This reset methods rely on the fact that 3 satellite distances will only have a valid location if the clock of the

[3] http://www.sintef.no/Projectweb/STSOps/News/Operational-Aspects-on-Decision-making-in-STS-Lighteri
[4] http://stellwagen.noaa.gov/maritime/palmercrary.html

receiver is synchronized. With this knowledge, the receiver can compute the necessary corrections to reset its internal clock to match the satellites time.

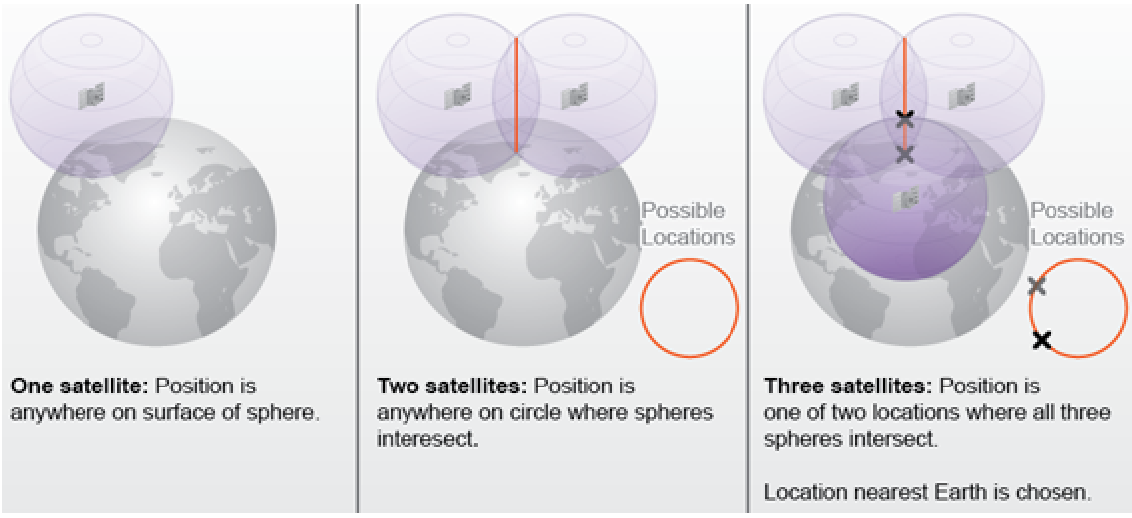

Figure 2.5: Trilateration technique in a global localization system[5]

Differential Global Positioning System (DGPS) The accuracy of the GPS position can be increased with the help of local broadcast stations. These stations are fixed and provide information about the corrections that can be made to the satellite signals in order to improve the localization precision.

These corrections are useful to mitigate some of the ambient interference that the satellite signals face. These interferences can range from simple signal reflection in the environment landscape to the more complex interactions with the atmosphere, which can change the speed and path of the radio signals.

The computation of the corrections [KKOO07] is based on the fact that these stations are fixed, and as such, they can compare the location given by the satellite signals with their known location. With this position differential, the appropriate corrections can be calculated and broadcasted to the GPS receivers.

Assisted Global Positioning System (AGPS) Assisted Global Positioning System (AGPS) systems are a common method used to speed up the Time To First Fix (TTFF) of a GPS receiver. They usually rely on the cellphone network to provide location estimation and signal corrections [R.48]. This information can greatly reduce the TTFF when there are few satellites visible or their signal is very weak and only temporary available.

Signal strength geolocation methods Signal strength geolocation [CK02], also known as fingerprinting localization [BOG+10], is an approximate method that can be used to calculate relative positions.

[5] https://www.e-education.psu.edu/geog160/node/1923

It relies on the analysis of the signal attenuation from a given access point (like a Wi-Fi router or cellphone tower), to estimate distances. With enough access points (usually 4), an approximate position can be computed.

This type of distance estimation can be useful for indoor navigation, but requires a propagation model of the signal and the environment. If these models aren't accurate, then the localization precision of these methods will be very low.

Although this method is less accurate than the more recent global localization systems (such as GPS), it can be used without human made infrastructures, and as such, is a viable solution in case of temporary disruption of the GPS signal.

2.2.3 Celestial navigation

Celestial navigation [YXL11] relies on the observation of stars, planets or other reference objects, to calculate the latitude and longitude.

The calculation of the position on the surface of the Earth using celestial navigation is similar to trilateration, but in this case, angles are used instead of distances. These angles (delta), are measured between the Earth horizon and the center of the celestial object.

Having the delta, and knowing the relative position of the Earth to the reference object, along with the Greenwich hour time, it is possible to calculate a circle of position (as shown in figure 2.6).

Having at least 3 circles of position, the latitude and longitude can be computed.

Although this method is less accurate than the more recent global localization systems (such as GPS), it can be used without human made infrastructures, and as such, is a viable solution in case of temporary disruption of the GPS signal.

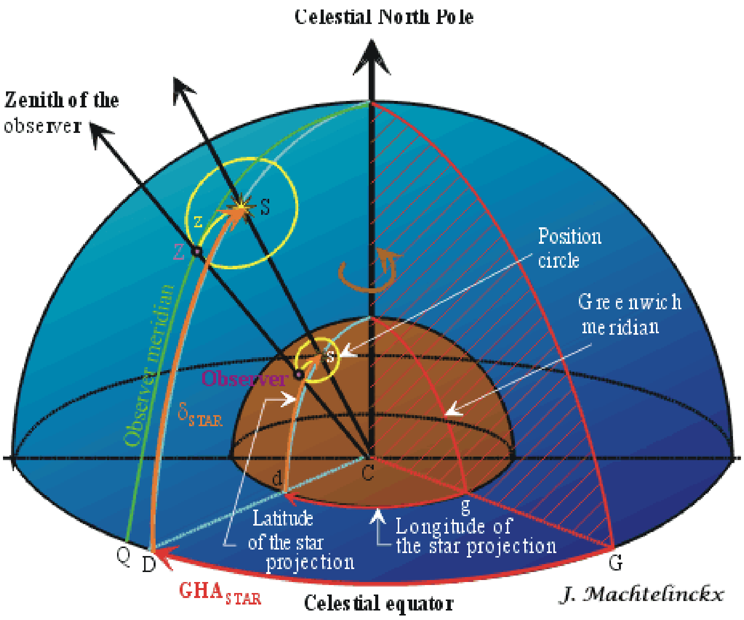

Figure 2.6: Circle of position in celestial navigation[6]

[6] http://onboardintelligence.com/CelestialNav/Celnav2.aspx

2.2.4 Landmark methods

Landmark methods [LKP06] can be used to perform relative localization, and are very useful to reduce the required information for navigation.

In these methods a database of markers / environment geometry is stored along with its location, and when the robot recognizes one of these markers, it corrects its proprioceptive methods measures.

It is a simplification of the method that will be presented in the next section, and it is useful for environments that have unique geometry in key positions of the navigation map.

2.2.5 Point cloud methods

Point cloud localization methods can be used to perform relative localization by finding the best point cloud match between the environment and the know map (figure 2.7 shows its application to small objects). These methods require a 2D or 3D representation of the environment and tend to be used in conjunction with proprioceptive methods (to have an estimation of movement), and also with probabilistic methods (when the point cloud acquisition location is not known).

One of the most used algorithms for 3D point cloud matching is the Iterative Closest Point (ICP) [BM92, Jez08, Zha94, BTP13, CSSK02, DZA+13, ZL11]. It is an iterative algorithm that finds the translation and rotation transformations that minimizes the distances of the corresponding points on both clouds.

There are several variants that optimize different parts of the algorithm [RL01].

The main steps for each iteration of ICP algorithm are presented below.

1. Selection of points in one or both point clouds (source and reference clouds)
2. Matching / pairing source points to reference points
3. Weighting the corresponding pairs
4. Rejecting low quality matches (outliers)
5. Assigning an error metric based on the point pairs
    (a) Usually mean square error based on points distance

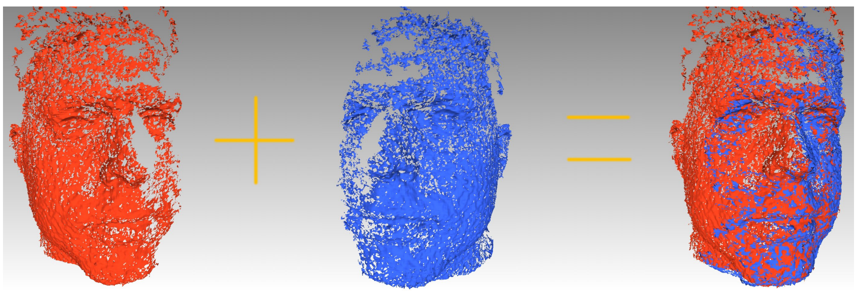

Figure 2.7: ICP point cloud matching[7]

[7] http://dynface4d.isr.uc.pt/database.php

2.2.6 Probabilistic methods

Probabilistic methods aim to reduce the impact of sensor accumulated errors or even temporary malfunctions by using Bayesian estimations and Markov processes.

Monte Carlo Localization (MCL) Monte Carlo Localization (MCL) (also known as particle filter), is a global localization algorithm that estimates the position and orientation of a robot by analyzing and adjusting the distribution and weights of state particles on a given environment [BOG+10, AMGC02, BGFM10, Che03, FBDT99, SS09].

It starts by randomly distributing the state particles on the map, and over time it changes their position and weight according to new sensor readings. The probable location of the robot will be in the area of the map that has the largest cluster of state particles. The figures below show the evolution of the state particles distribution during the robot movement in the environment, and illustrates how the new sensor readings changed the particles clusters [8].

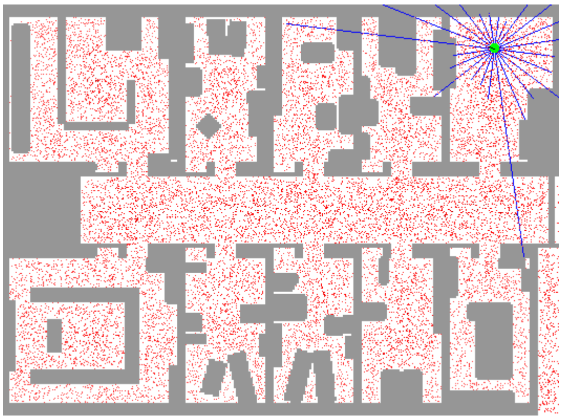

Figure 2.8: MCL particle distribution animation

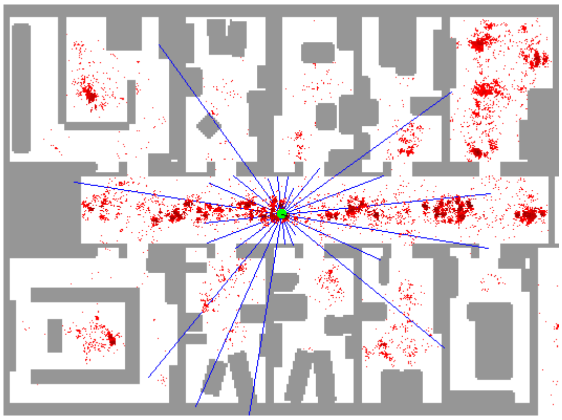

Figure 2.9: MCL redistribution of particles

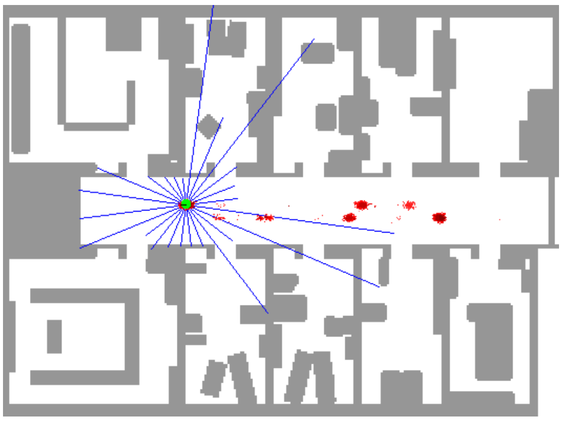

Figure 2.10: MCL position refinement

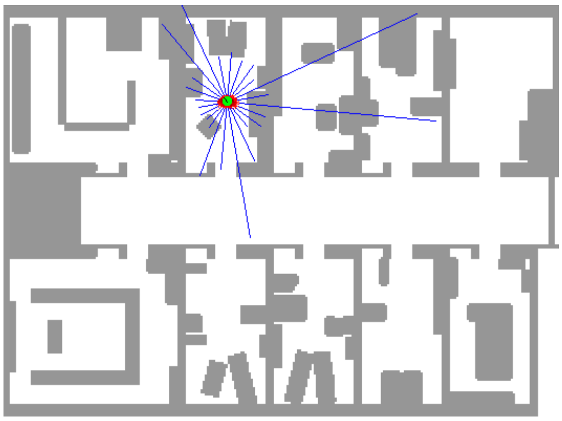

Figure 2.11: MCL position estimation

[8] http://www.cs.washington.edu/robotics/mcl/

Kalman filters Kalman filters [Kal60] are probabilistic algorithms that aim to estimate a given system state even when it is affected by noise or other errors. They perform linear quadratic estimations to achieve optimal results and can be efficiently implemented to be used in real time systems. They are recursive algorithms based on Marcov processes, and as a result, they only need to know the current system state in order to perform measurement corrections.

The Extended Kalman Filter (EKF) [EW99, Rib04, IKP10, LYL11] is a variant of the Kalman filter, designed to handle non-linear systems by performing linear approximations to the state variables. These approximations may lead to divergence in the estimations, and as such, the EKF can't guarantee optimal results.

The Unscented Kalman Filter (UKF) [JU97, WV02] is another variant of the Kalman filter that was designed for highly non-linear systems. It usually achieves better results than EKF due to its unscented transform.

For the particular case of localization, these algorithms start with an initial estimation of the system state, and for each new position (computed from the sensors data), they predict the estimated robot location (according to the Bayes estimation model and the Gaussian distribution of errors), and then update their internal model of the system (mean and covariance) to incorporate the system evolution.

In figure 2.12 can be seen that the UKF estimated position (red) is closer to the real position (blue) than the raw sensor measurements (green).

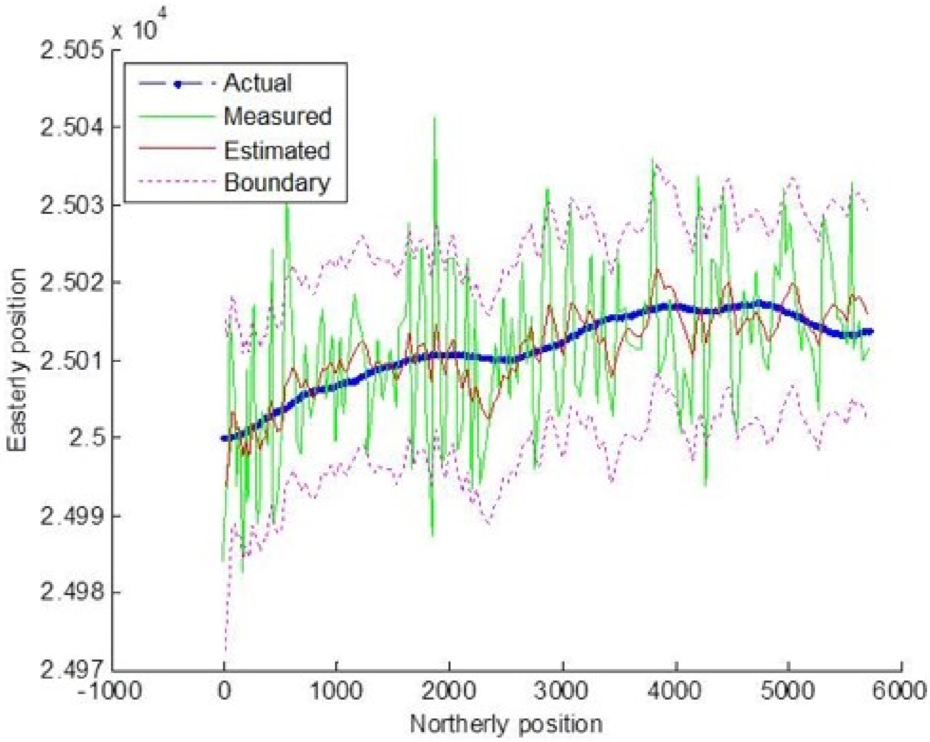

Figure 2.12: Unscented Kalman Filter[9]

[9] http://www.lzcheng.com/courseworks/kalmanfilter

Perfect Match The Perfect Match [LLRM06, PM63] is an efficient self-localization algorithm that is largely used in the Robocup Robotic Soccer Midsize League. Its main goal is to minimize the localization error by carefully analyzing the know map, and selecting the most probable current position using a gradient descent approach. To improve tracking accuracy, the algorithm also uses a stochastic weighted approach.

With the proper configuration, it can achieve a localization accuracy similar to the particle filter, while using about ten times less computations.

An example of the position estimation can be seen in the figures below. Figure 2.13 shows the probable locations when the robot detects a line on the floor, and figure 2.14 illustrates their associated errors (brighter areas indicate smaller error). By using a gradient descent, the most probable location was selected (black circle).

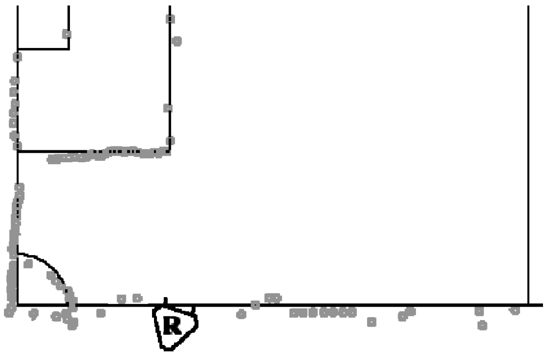

Figure 2.13: Position estimates

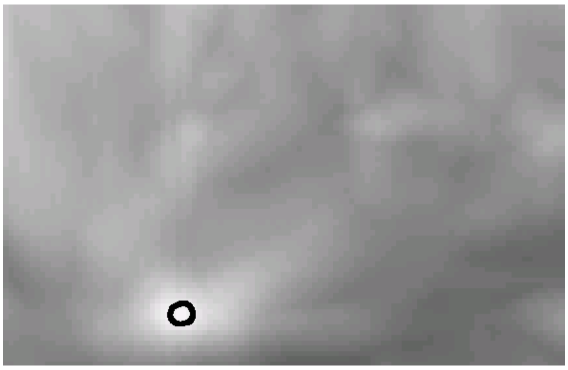

Figure 2.14: Positions associated error

2.2.7 Simultaneous Localization And Mapping (SLAM)

Simultaneous Localization And Mapping (SLAM) [Thr02] is a very effective approach to either explore unknown environments or update a known map. It relies on both proprioceptive and exteroceptive methods to perform localization and mapping. It is also very useful to make the robot navigation more robust in dynamic environments, in which the topology of the world may change considerably over time.

There are numerous approaches to perform SLAM [TGCV12]. Some optimized for exploration and others for map improvement. For the exploration tasks, proprioceptive methods play a critical role, and are usually paired with probabilistic methods, such as Kalman filters, in order to reliably map the environment. For map correction and improvement, several probabilistic methods can be employed according to the precision required. For high accuracy 3D mapping, the ICP algorithm can be used to build accurate point clouds of the environment.

2.3 Summary

This chapter introduced several localization systems that can be used in different types of environments and with different degrees of accuracy. It started with the simple proprioceptive methods and then moved on to the more robust exteroceptive approaches.

Some techniques can be combined to improve the pose estimate or to make the localization more efficient to a particular type of environment.

For outside tasks, a GNSS approach can give accurate localization estimations with very little computation cost. On the other hand, indoor localization requires more advanced techniques in order to infer the current position based on the analysis of the robot surroundings. These techniques usually start with an estimation of the robot movement and then refine it with probabilistic or geometric methods.

Table 2.1 presents an overview of the mentioned localization techniques.

Table 2.1: Overview of self-localization approaches

Method	***Ideal environment***	***Accuracy***	***Operational cost***	***Computational cost***	***Notes***
Odometry	Any	Low	Low	Low	Position estimation is affected by cumulative errors
Dead reckoning	Any	Low	Low	Low	Pose estimation is affected by cumulative errors
LIDAR	Any	High	Medium	High	Needs an auxiliary method to perform global localization
RADAR	Any	Medium	High	High	Needs an auxiliary method to perform global localization
SONAR	Any	Medium	Medium	High	Needs an auxiliary method to perform global localization
GNSS	Outside	Medium	Low	Low	Requires a clear line of sight to at least 3 satellites
Signal strength	Any	Low	Low	Low	Requires an accurate model for the signal attenuation
Celestial	Outside	Low	Low	Low	Requires a clear view of the celestial objects and a nautical almanac
Landmark	Any	Medium	Low	Medium	Requires a database of landmarks
ICP	Indoors	High	Medium	High	Requires a 3D representation of the environment
MCL	Indoors	Medium	Medium	Medium	Inefficient for large areas
Kalman filters	Any	Medium	Low	Low	Useful to improved estimations of other methods
Perfect Match	Any	Medium	Low	Low	Not ideal for large or dynamic environments
SLAM	Indoors	Medium	Medium	High	Adapts well to dynamic environments

Chapter 3

Relevant software technologies

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3.1 FF

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Chapter 4

Point cloud algorithms

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4.1 FF

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Point cloud algorithms

Chapter 5

Localization system

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5.1 FF

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Localization system

Chapter 6

Localization system evaluation

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6.1 FF

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Chapter 7

Conclusions and future work

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7.1 FF

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Appendix A

Appendix 1

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A.1 FF

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Appendix 1

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