



Luis Ernesto Ynoquio Herrera

**Mobile Robot Simultaneous Localization and Mapping
Using DP-SLAM with a Single Laser Range Finder**

DISSERTAÇÃO DE MESTRADO

Dissertation presented to the Postgraduate Program in Mechanical Engineering of the Departamento de Engenharia Mecânica, PUC-Rio, as partial fulfillment of the requirements for the degree of Mestre em Engenharia Mecânica.

Advisor: Prof. Marco Antonio Meggiolaro

Rio de Janeiro

April 2011



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Rio de Janeiro, 7 de abril de 2011

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Bibliographic data

Ynoquio Herrera, Luis Ernesto

Mobile Robot Simultaneous Localization and Mapping using DP-SLAM with a single Laser Range Finder / Luis Ernesto Ynoquio Herrera; advisor: Marco Antonio Meggiolaro. – 2011.

167 f.: il. (color.) ; 30 cm

Dissertação (mestrado) – Pontifícia Universidade Católica do Rio de Janeiro, Departamento de Engenharia Mecânica, 2011.

Inclui bibliografia.

1. Engenharia Mecânica – Teses. 2. Robótica móvel. 3. Filtros bayesianos. 4. Alinhamento de varreduras laser. 5. Mapeamento e localização simultânea. 6. Medidor laser de varredura. I. Meggiolaro, Marco Antonio. II. Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Engenharia Mecânica. III. Título.

CDD: 621

Thanks to

My advisor Marco Antonio Meggiolaro, for friendship, patience, help and support that motivated me to perform this work.

PUC-Rio for the opportunity and the great academic environment.

CNPQ for the financial support, without which it would not have been possible to do this work.

My parents, Eumenia and Gilber, and my siblings, who however distant, always support me.

My friend Juan Gerardo Castillo Alva, who facilitated the opportunity to come to Brasil and for his wise counsel, thanks.

Abstract

Luis Ernesto, Ynoquio Herrera; Meggiolaro, Marco Antonio (Orientador).
Mobile Robot Simultaneous Localization and Mapping Using DP-SLAM with a Single Laser Range Finder Rio de Janeiro 2011, 167p.
M.Sc. Dissertation – Mechanical Engineering Department, Pontifícia Universidade Católica do Rio de Janeiro.

Simultaneous Localization and Mapping (SLAM) is one of the most widely researched areas of Robotics. It addresses the mobile robot problem of generating a map without prior knowledge of the environment, while keeping track of its position. Although technology offers increasingly accurate position sensors, even small measurement errors can accumulate and compromise the localization accuracy. This becomes evident when programming a robot to return to its original position after traveling a long distance, based only on its sensor readings. Thus, to improve SLAM's performance it is necessary to represent its formulation using probability theory. The Extended Kalman Filter SLAM (EKF-SLAM) is a basic solution and, despite its shortcomings, it is by far the most popular technique. Fast SLAM, on the other hand, solves some limitations of the EKF-SLAM using an instance of the Rao-Blackwellized particle filter. Another successful solution is to use the DP-SLAM approach, which uses a grid representation and a hierarchical algorithm to build accurate 2D maps. All SLAM solutions require two types of sensor information: odometry and range measurement. Laser Range Finders (LRF) are popular range measurement sensors and, because of their accuracy, are well suited for odometry error correction. Furthermore, the odometer may even be eliminated from the system if multiple consecutive LRF scans are matched. This work presents a detailed implementation of these three SLAM solutions, focused on structured indoor environments. The implementation is able to map 2D environments, as well as 3D environments with planar terrain, such as in a typical indoor application. The 2D application is able to automatically generate a stochastic grid map. On the other hand, the 3D problem uses a point cloud representation of the map, instead of a 3D grid, to reduce the SLAM computational effort. The considered mobile robot only uses a single LRF, without any odometry information. A Genetic Algorithm is presented to optimize the matching of LRF scans taken at different instants. Such matching is able not only to map the environment but also localize the robot, without the need for odometers or other sensors. A simulation program is implemented in Matlab® to generate virtual LRF readings of a mobile robot in a 3D environment. Both simulated readings and experimental data from the literature are independently used to validate the proposed methodology, automatically generating 3D maps using just a single LRF.

Key Words

Mobile Robots, Bayesian Filter, Scan Matching, Simultaneous Localization and Mapping, Laser Range Finder.

Resumo

Luis Ernesto, Ynoquio Herrera; Meggiolaro, Marco Antonio (Orientador). **Mapeamento e Localização Simultânea de Robôs Móveis usando DP-SLAM e um Único Medidor Laser por Varredura** Rio de Janeiro 2011, 167p. Dissertação de Mestrado – Departamento de Engenharia Mecânica, Pontifícia Universidade Católica do Rio de Janeiro.

SLAM (Mapeamento e Localização Simultânea) é uma das áreas mais pesquisadas na Robótica móvel. Trata-se do problema, num robô móvel, de construir um mapa sem conhecimento prévio do ambiente e ao mesmo tempo manter a sua localização nele. Embora a tecnologia ofereça sensores cada vez mais precisos, pequenos erros na medição são acumulados comprometendo a precisão na localização, sendo estes evidentes quando o robô retorna a uma posição inicial depois de percorrer um longo caminho. Assim, para melhoria do desempenho do SLAM é necessário representar a sua formulação usando teoria das probabilidades. O SLAM com Filtro Extendido de Kalman (EKF-SLAM) é uma solução básica, e apesar de suas limitações é a técnica mais popular. O Fast SLAM, por outro lado, resolve algumas limitações do EKF-SLAM usando uma instância do filtro de partículas conhecida como *Rao-Blackwellized*. Outra solução bem sucedida é o DP-SLAM, o qual usa uma representação do mapa em forma de grade de ocupação, com um algoritmo hierárquico que constrói mapas 2D bastante precisos. Todos estes algoritmos usam informação de dois tipos de sensores: odômetros e sensores de distância. O Laser Range Finder (LRF) é um medidor laser de distância por varredura, e pela sua precisão é bastante usado na correção do erro em odômetros. Este trabalho apresenta uma detalhada implementação destas três soluções para o SLAM, focalizado em ambientes fechados e estruturados. Apresenta-se a construção de mapas 2D e 3D em terrenos planos tais como em aplicações típicas de ambientes fechados. A representação dos mapas 2D é feita na forma de grade de ocupação. Por outro lado, a representação dos mapas 3D é feita na forma de nuvem de pontos ao invés de grade, para reduzir o custo computacional. É considerado um robô móvel equipado com apenas um LRF, sem nenhuma informação de odometria. O alinhamento entre varreduras laser é otimizado fazendo o uso de Algoritmos Genéticos. Assim, podem-se construir mapas e ao mesmo tempo localizar o robô sem necessidade de odômetros ou outros sensores. Um simulador em Matlab® é implementado para a geração de varreduras virtuais de um LRF em um ambiente 3D (virtual). A metodologia proposta é validada com os dados simulados, assim como com dados experimentais obtidos da literatura, demonstrando a possibilidade de construção de mapas 3D com apenas um sensor LRF.

Palavras-Chave

Robótica Móvel, Filtros Bayesianos, Alinhamento de Varreduras Laser, Mapeamento e Localização Simultânea, Medidor Laser de Varredura.

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List of Variables

A_t : State transition matrix

B_t : Matrix that translates control input into a predicted change in state

d : Measured data

f : Function that represents the motion model in EKF-SLAM

h : Function that represents the perception model in EKF-SLAM

h_j^i : Function that represents the perception model for the particle i

H_j^i : The Jacobian of h_j^i at L_j

H_t : The Jacobian of h at $\bar{\lambda}_t$

Jf_{u_t} : The Jacobian of f at u_t

K_t : Kalman gain

L : Set of landmarks with known exact location

$L_{n,t}^i$: Position of landmark n , related with particle i , at time t

$L_{t1} L_{t2} \dots L_{tn}$: n -th landmark estimated at time t

L_q : New observed landmark

η : Normalizer

p : Vector of the parameters to estimate (in DE)

p_c : Probability of crossover

p_m : Probability of mutation

P_t : Covariance of the process noise

P_r : Reference robot position

P_n : New robot position

Q : Covariance matrix for the sensor noise in EKF-SLAM

R_0, R_1, \dots, R_t : Robot position at time t

R_x, R_y, R_θ : Robot position in two-dimensional planar coordinates

$R^{i,t}$: Robot path, related with particle i , until time t

S_{new} : New scan

S_{ref} : Reference scan

t_x : Translation in x

t_y : Translation in y

U : Uncertainty of the control u_t in EKF-SLAM

u_t : Control at time t

w_t^i : Weight of particle i at time t

x_t^i : Particle i at time t

Z_0, Z_1, Z_t : Map estimated at time t

x_i : Distance that the laser ray travels through the square i

x_t : State variable at time t

z_t : Sensor measurement at time t

$z_{j,t}$: The j^{th} landmark sensor observation in z_t

$\Delta x, \Delta y, \Delta \theta$: Displacements that are referenced to the current robot position

λ_t : Gaussian mean at time t

$\lambda_{n,t}^i$: Mean related with the landmark position $L_{n,t}^i$

ρ_i : Opacity of the square i

Σ_t : Gaussian covariance at time t

$\bar{\Sigma}_t, \bar{\lambda}_t$: Predicted covariance and mean at time t

$\Sigma_{n,t}^i$: Covariance related with the landmark position $L_{n,t}^i$

ϕ : Rotation in z

Φ_t : Set of particles at time t

List of Abbreviations

SLAM : Simultaneous Localization and Mapping

LRF : Laser Range Finder

GPS: Global Positioning System

KF : Kalman Filter

PF : Particle Filter

EKF-SLAM : Extended Kalma Filter SLAM

FastSLAM : Fast SLAM

DP-SLAM : Distributed Particle SLAM

ICP : Iterative Closest Point

IDC : Iterative Dual Correspondence

ICL : Iterative Closest Line

HAYAI : The Highspeed and Yet Accurate Indoor/outdoor-tracking

NDT : Normal Distributed Transform

GA : Genetic Algorithm

GP : Genetic Programming

DE : Differential Evolution

LSLAM : Low SLAM

HSLAM: High SLAM

Stdv : Standard Deviation