Hough-transform based map stitching after localization uncertainty

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Abstract

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Chapter 1

Introduction

The Simulatenous Localization And Mapping (SLAM) method employed by the AJORF (Amsterdam-Oxford Joint Rescue Forces team ¡¡cite team description paper¿¿ is not robust against sensor failures, which occur for example when the laser scanner is severly tilted.

In this report, we propose a novel method which splits a map when the localization uncertainty exceeds a certain threshold. The different pieces of the map are then stitched together using a Hough transform based map stitching method.

Chapter 2

Background

2.1 USAR Sim

* The Urban search and rescue challenge

2.2 SLAM

One of the goals of the USAR challenge was to create a useable map of the environment.

The problem an agent faces when it needs to find it's way in an unknown environment is called SLAM, for Simulatenous Localization and Mapping. The agent has no map of the environment, and also no way of knowing it's exact location. It needs to infer the map and it's position on the map from the information it gathers from it's sensors throughout time.

Thus, SLAM is a chicken-and-egg problem: without a map it is hard to estimate the agent's position, and without the agent's position it's hard to estimate the map!

In this section we will first examine how the robot keeps track of the state of the world, and then how the SLAM problem can be solved with Extended Kalman Filters.

2.2.1 State

The state of the world as it is known to the agent is denoted x. The value of this set of variables may change over time, as the agent collects sensor data from the environment. The state at time t is denoted x_t.

Many variables may be included in the state variable x. For the purpose of this work, we will assume that it contains at least the agent's *pose and a* map of the environment.

In most SLAM approaches, two types of sensor data is collected: *environmental measurement data and* control data. Environmental measurement data collects information about the environment, while control data collects information about the robot within the environment. Environmental measurement data is denoted z (at a specific point in time z_t). Examples of environmental sensors available to an agent are laser scanners, sonars and video cameras. Control data and GPS signals. Control data sensors collect information intrinsic to the agent: it's velocity and position. Examples of control sensors are odometry sensors, inertia sensors and global positioning systems.

For the purpose of this paper we are mainly interested in the online SLAM problem, in contrast to the full SLAM problem. Online SLAM seeks to estimate the current pose x_t and map m:

$$p(x_t, m | z_{1:t}, u_{1:t}) \tag{2.1}$$

In contrast, the full SLAM problem estimates all poses x and map m:

$$p(x_{1:t}, m | z_{1:t}, u_{1:t}) \tag{2.2}$$

In practice, the difference is that the full SLAM problem reconsiders the location of all previous poses in estimating the map, while online SLAM treats these as given. The full SLAM problem is computationally much more expensive. Thus for time sensitive applications, such as real time robot control, usually only online SLAM is performed.

2.2.2 Gaussian state representation

It is often convenient to represent the belief of the current state as a multivariate Gaussian. A Gaussian is defined by its mean μ and covariance Σ:

$$p(x) = \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\} \tag{2.3}$$

Gaussian state representations have the advantage of being easily understood and straightforwardly manipulated. This comes with a cost: a Gaussian is unimodal – there is only one maximum (the mean) possible. This makes Gaussian representations ill suited when there are many different hypothesis distributed across a map.

In UsarCommander, the state is represented by a 3-dimensional vector: (x, y, θ), and the acc

2.2.3 Scanmatching

2.2.4 ManifoldSLAM

2.2.5 2D slam in 3D environment

Only a slice of the world is returned - so we need to make sure we are horizontal. Otherwise, the scanner returns wrong readings.

UNCERTAINTY MEASURE BY ARNOUD: To see if the reduced correlation distance also improves the robustness of the scan matcher the uncertainty measures returned by the algorithms were analyzed. This uncertainty measure is the full 3-by-3 covariance matrix of the Gaussian distribution over the displacement estimate and does not lend itself well for charting in its original form. Therefore we took the on-diagonal elements that describe the independent uncertainty in x and y direction and combined these into a Euclidean distance measure. The trace of the covariance matrix acquired with Q-WSM is in most cases (94average uncertainty of the incremental version.

2.3 Map stitching

Magda's work on Hough-based map stitching

Chapter 3

Method

3.1 Map Stitching

Map stitching prior work, magda etc

3.2 SLAM confidence measure

The confidence measure based on the determinant of the covariance matrix of the pose uncertainty. The hypothesis is that if this measure is larger, then the confidence is lower (the uncertainty is bigger).

The determinant of the covariance matrix is used as metric:

is the sample variance-covariance matrix for observations of a multivariate vector of p elements. The determinant of D, in this case, is sometimes called the generalized variance. (http://www.itl.nist.gov/div898/handbook/pmc/section5/pmc532.htm)

3.3 Inertial sensor data

Gives the rotations on three axis, enables you to detect

3.4 Prior work on confidence measures

cite bayu and max: Good examples of single confi- dence values that can be derived from a covariance matrix are the determinant det() or the trace trace(). The relations lend themselves very well for use in path-planning and search algorithms. In addition, heuristic algorithms can take advantage of the uncertainty information stored on the links. (P61)

(paper not found): L. Carlone, M. Kaouk Ng, J. Du, B. Bona, and M. Indri, Reverse KLD-Sampling for measuring uncertainty in Rao-Blackwellized Particle Filters SLAM, in Proc. of the 2009 IEEE/RSJ Int. Conf. on Intelligent RObots and Systems, Workshop on Performance Evaluation and Benchmarking for Next Intelligent Robots and Systems, 2009.

Carlone et al. use a particle filter based representation of their belief.

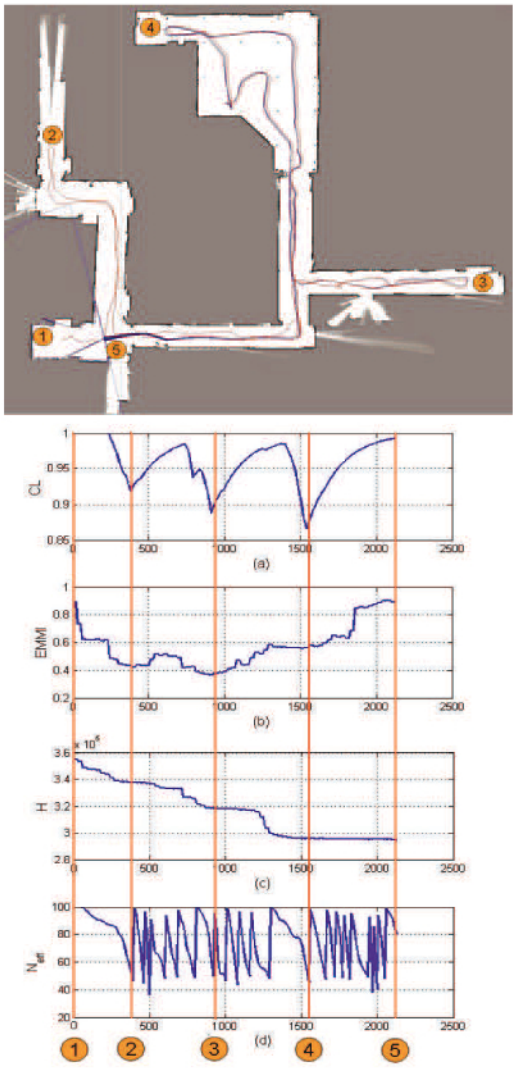

Fig. 4: Time-history of the different uncertainty estimators obtained in real experiment performed in Politecnico di Torino (100 particles): (a) CL, (b) *EMMI*, (c) Map Entropy *H* and (d) The effective sample size *Neff*.

Figure 3.1: