

ROBOCUP SS17

submitted
PRACTICAL COURSE

B.Sc. Tianming Qiu

born 30.03.1993
resident in:
Felsennelkenanger 15
80937, Munich
Tel.: +49 17643387325

Institute for
COGNITIVE SYSTEMS
Technical University of Munich

Prof. Dr. Gordon Cheng

Supervisor: Mohsen Kaboli
Start: 24.04.2017
Delivery: 24.07.2017

Abstract

RoboCup is a competition for soccer robot held annually, which aims at promoting researches on robot and artificial intelligence. We work on the RoboCup Standard Platform League (SPL) by using humanoid robot NAO, based on the code framework from University of Bremen's team BHuman.

Self-localization is a very important task for NAO during the game. The action decisions, ball tracking and different team cooperation strategies are dependent on the precise location on the standard soccer field. Self-localization is also related computer vision and statistical signal processing. These topics are the foundations of autonomous robot. So this semester I focus on figuring it out, how does NAO localize itself on the soccer field by cameras and how could it be improved.

The current method in BHuman framework has been continuously developed, verified and implemented for several years and it has been considered as state-of-the-art method which is already very robust and compact. The main idea is to apply particle filter to estimate robot pose. But there are still some issues that when robot is walking, some shake noises from camera will cause deviations in visual odometry.

Contents

1	Introduction	5
1.1	Motivation	6
1.2	Overview and goals	6
1.3	My Contributions	6
2	Role: Denfeder State machine	9
2.1	The current method	10
2.1.1	Visual odometry procedure	10
2.1.2	Current problem	10
3	Self-Localization	11
3.1	General Framework: Particle Filter	11
3.2	Unscented Kalman Filter	13
4	Improvement of Visual Odometry	15
4.1	The current method	16
4.1.1	Visual odometry procedure	16
4.1.2	Current problem	17
	List of Figures	21
	Bibliography	23

Chapter 1

Introduction

RoboCup, namely “**Robot Soccer World Cup**”, is an annual international robotics competition which was founded in 1997. The aim of this game is to promote robotics and AI research in a public appealing way. In 2016, it was held in Leipzig with more than 35,000 participants and teams from over 45 countries and regions. There are mainly four major categories in the whole RoboCup, namely *RoboCup Soccer*, *RoboCup Home*, *RoboCup Rescue*, *RoboCup Industrial*. The original and still largest focus is the *RoboCup Soccer*, in which teams of fully autonomous robots from different teams compete with each other. The teams are typically supported by a technical university or a research institute and carry strong academic and industrial backgrounds.

From the summer semester 2016, practical course “Humanoid RoboCup” was first offered at the Institute for Cognitive Systems. Each team consists of 3-4 master students with three NAO robots from Aldebaran Robotics as in Figure 1.1.



Figure 1.1: NAO robots

1.1 Motivation

The courses in artificial intelligence like machine learning, computer vision, pattern recognition are given as fundamental knowledge for the students in “Kernbereich” of Automation and robotics . After learning these theoretical knowledge, a practical course like “Humanoid RoboCup” is a perfect choice for students to know how these knowledge are applied in real scenarios. The given robots, namely NAOs, are cute from its out-looking and powerful with its computing ability. Based on this platform, the students can choose their own tasks according to their different background knowledge.

Apart from technical knowledge, team-working, time-organization are also beneficial for the students involved in this course as they will work in small groups and decide when to work and how to work by groups.

1.2 Overview and goals

The course in winter semester of 2016/2017 is offered for the second time. It is divided into two phases, namely the lecture phase and practical phase.

In the lecture phase, about four lectures will be given as the introduction to different fields, such as control, vision, planning, or machine learning. In the second phase, the student will form individual teams for a soccer competition with NAOs, like yellow team or blue team. All the students in each team will do the basic setting up tasks together and then each student will choose his or her own task according to the on-hand knowledge. In this period, the student can come to the lecturers who given introductions in different field for more detailed help.

The goal of this semester is to establish the code framework and play a real robot game with each other. The code framework is developed based on the B-Human CodeRelease as in [1]. As the student from last semester only complete the match in simulation environments, more emphasis on real Robots were spent on testing and implementing designed algorithms.

1.3 My Contributions

Based on the problems found on real robots, the first task is to fix all these fundamental problems to make the robots be able to play a real game against another team.

The fundamental problems are discussed in detail in Chapter ??, which includes:

- Joint Calibration
- Camera and color Calibration
- Coding and Debugging in simulation

- Coding and Debugging on real robots

The insufficient calibration leads to some problems. To fix the problem of “bad” joint calibration, teammate Benno proposed a method called *moving towards a target*. To get a better localization, teammate Ahmed proposed a method for better self-localization. For the details of these proposals one can refer to their reports.

Based on these proposals for fixing calibration problems, the behavior improvement is the main work of me and also the emphasis of this report. More concretely, the following new behaviors are proposed and implemented both in simulation and on real robots:

- Defender: dynamic defense area
- Striker: dynamic kicking direction

These new behaviors are discussed in detail in Chapter 4.

Chapter 2

Role: Denfeder State machine

This chapter introduces concrete method used in current framework for NAO, the mobile roboter lacialization.

2.1 The current method

2.1.1 Visual odometry procedure

ave been finished.

So we could get the corresponding goal post coordinate in the ideal camera frame. Since we know the geometrical value of NAO's body construction, we can transform the coordinates into the robot frame, which is shown in the figure Based on this, we could get the related distance between robot and the goal post in robot frame. At the same time, the precise location of goal post in the global field is also known. So we could calculate the robot pose from this above information.

2.1.2 Current problem

In the process of transforming the coordinate from camera frame into robot frame, the current method only use a constant transform. However

Chapter 3

Self-Localization

This chapter introduces the concrete method used in the current framework for NAO, the mobile roboter lacialization. RoboCup self-localization is a problem that NAO robot could determine its pose, which includes both position and angular, relative to the given map of the standard soccer field. Almost all the tasks for each robot player require knowledge of its pose on the field. We call this problem as rather a self-localization than a SLAM(Simultaneous localization and mapping) problem, one important reason is the map of the environment has been provided as prior knowledges. Self-localization could be treated as a problem of coordinate transformation. Map of the field or environment is described as the global coordinate system, which does not rely on robot's pose. The robot pose will be finally transformed into the global frame and represented as a global coordiante[2]. In our project the NAO pose is only changes in a plane, the z element is always remains as zero since the robot always stands firmly on the ground. So the pose could be written as $(x, y, \theta)^T$.

However, the pose of robot could not be aquired directly, instead it could be inferred from the sensor data, which here come from camera. The sensor could not be hundred percentage accurate, it alway contains noise, especially image processing by using camera. So we have to find a proper method to calculate the pose from imperfect sensor data, which will be introduced in this chapter.

3.1 General Framework: Particle Filter

For self-localization, B-Human uses a particle filter based on the Monte Carlo method [3] as it is a proven approach to provide accurate results in such an environment [4]. The reason for selecting particle filter in this self-localization problem is that in the RoboCup soccer match the robot will from time to time fall down, and then it will not get the correct knowledge of its position. The problem is that the robot might believe it knows where it is while it does not. This is called kidnapped robot problem [2]. So the particle filter will be adopted to solve this kidnapped robot problem and it does not demand initial position of robot.

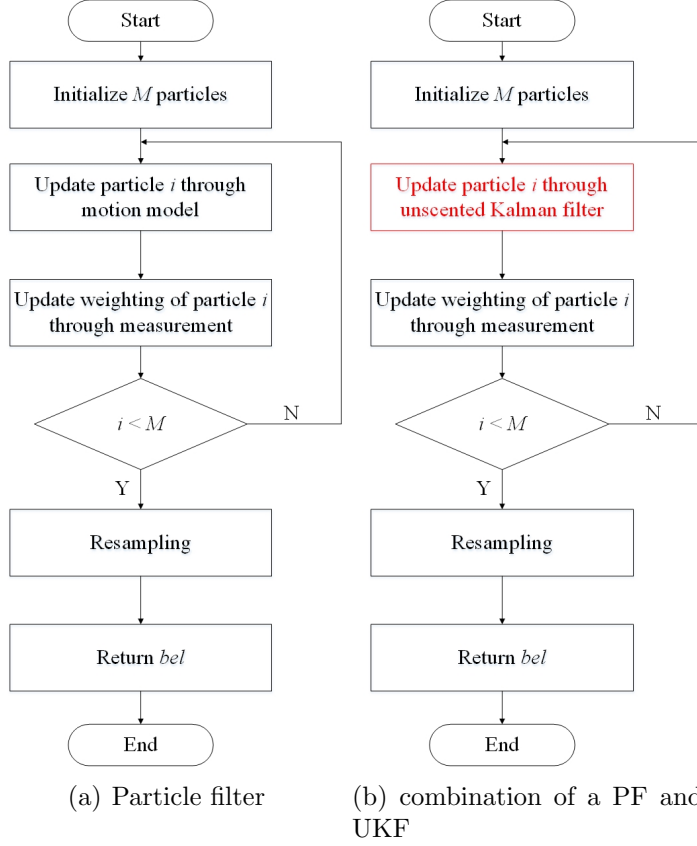


Figure 3.1: Self-localization based on particle filter flowchart

The particle filter is a kind of bayes filter, based on Monte Carlo method. It uses several samples as particles to describe the posterior. In particle filter, the samples of a posterior distribution are called particles are represented as [2]:

$$\mathcal{X}_t := x_t^{[1]}, x_t^{[2]} \dots x_t^{[M]}$$

The posterior of each particle x_t^m (with $1 \leq m \leq M$) is the probalbilty of the state at specigic time t . Usually, M , the number of the particles is very large to get a as perfect as possible approxiamtion, since particle filter is a non-parametrical method to estimate the state updating. However in the RoboCup situation, only 12 to 16 particles are adopted. Because the memory space and computaion speed are both limited on the robot NAO. During the match, it has a high demanding on instantaneity. Here I have not tested or verified the effectiveness of the so small number of samples. But in recent years B-Human team even drop the particles from 16 to 12 [5] and it is proven in practice which shows a great robustness and outstanding performance. Then how does robot NAO apply particle filter to localize itself is shown in the flowchart Figure 3.1(a).

3.2 Unscented Kalman Filter

Since 2012, B-Human framewrok made a big change on self-localization: a combination of a particle filter and an Unscented Kalman filter is used. The former computes a global position estimate; the latter performs local tracking for refining the global estimate [6]. This implementation will improve the local accuracy of particle filter and further results in improvement of localization precision. The change has shown in the Figure 3.1(a).

The idea behind the Unscented Kalman filter is similar to the original Kalman filter. However it is applied for the non-linear motion model and provides priciser result than Extented Kalman filter which uses first order approximation of Talor seires. It generates sigma points and uses the unscented transform to describe the non-linearity. The mean as well as covariance of states will also be modified with measurement and finally be returned.

Chapter 4

Improvement of Visual Odometry

Above the procedure of self-localization was described in general. Both unscented Kalman filter and particle filter will require the pose information which provided by visual odometry part. So the accuracy of pose estimated by visual part will definitely have an obvious influence on the final result.

4.1 The current method

4.1.1 Visual odometry procedure

There are several sensors to acquire information from the environment on NAO: camera, microphone and sonar. From them only the camera is adopted, since the environment of the soccer match will be quite complicated, for example:

- The white border lines and green field are on the same plane.
- The goal posts are perhaps too far away from the robots sometimes.
- There are 6 moving robots on the field, which the opponents are distinguished from our teammates only by colors.
- The ball is small and the detection of a ball requires high precision.

So based on above reasons, the another sensors are not qualified for the requirements. However, the camera is suitable for each specific task and the computer vision skill as well as visual odometry are being perfect so far.

There two cameras on the NAO's head shown in fig, which can provide large FOV. Several tasks such as image preprocessing, feature detection(including: line perception, penalty mark perception, ball perception) and data association will be performed on the image gathered by each camera. The features on the football field will be described as "X" crossing, "T" crossing and "L" crossing which can be associated to the feature detected in pixel images. The detailed of these tasks will not be mentioned in my part of report, which are introduced by my teammates. My work is that suppose the the feature detection and data association have been finished. Based on feature detection and data association, the corresponding point pairs have been already found. For example the goal post in figure i. whose coordinate in the homogeneous global 3D world could be represented as $(X, Y, 0, 1)^T$. And the corresponding homogeneous coordinate in pixel coordinate can be written as $(x, y, 1)^T$. Since the camera callibration matrix, including both intrinsic and extrinsic calibration parameters, has been acquired through camera calibration before each match. Assuming the camera model as pinhole camera model:

$$x = K \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

So we could get the corresponding goal post coordinate in the ideal camera frame. Since we know the geometrical value of NAO's body construction, we can transform the coordinates into the robot frame, which is shown in the figure Based on this, we could get the related distance between robot and the goal post in robot frame. At the same time, the pricise location of goal post in the global field is also known. So we could calculate the robot pose from this above information.

4.1.2 Current problem

In the process of transforming the coordinate from camera frame into robot frame, the current method only use a constant transform. However

Acknowledgments

First of all, I would like to express my thanks to Prof. Dr. Gordon Cheng and Chair of Cognitive Systems for offering this course and all the hardware support.

I would further like to thank our supervisor Mohsen Kaboli for your patient help and many constructive suggestions. You are always willing to share your experiences and give us significant guide. Your office is always open for us.

Also, I would appreciate the help offered by our teaching assistant Zhiliang Wu, who prepared all the lab stuff for us and wrote detailed tutorial that let me know how to operate NAO step by step. Your careful work make me get start quickly and give me a lot confidence to finish the task.

I am particularly thankful to my team mate: Yao, Fabian, Zhiyi, Jingjie, and Minkai. We discussed a lot and you always give me some useful supports.

List of Figures

1.1	NAO robots	5
3.1	Self-localization based on particle filter flowchart	12

Bibliography

- [1] Thomas Röfer, Tim Laue, Jesse Richter-Klug, Maik Schünemann, Jonas Stiensmeier, Andreas Stolpmann, Alexander Stöwing, and Felix Thielke. B-Human team report and code release 2015, 2015. Only available online: <http://www.b-human.de/downloads/publications/2015/CodeRelease2015.pdf>.
- [2] Sebastian Thrun, Wolfram Burgard, and Dieter Fox. *Probabilistic robotics*. 2005.
- [3] Dieter Fox, Wolfram Burgard, Frank Dellaert, and Sebastian Thrun. Monte carlo localization: Efficient position estimation for mobile robots. *AAAI/IAAI*, 1999(343-349):2-2, 1999.
- [4] Thomas Röfer, Tim Laue, and Dirk Thomas. Particle-filter-based self-localization using landmarks and directed lines. In *Robot Soccer World Cup*, pages 608–615. Springer, 2005.
- [5] Thomas Röfer, Tim Laue, Judith Müller, Armin Burchardt, Erik Damrose, Alexander Fabisch, Fynn Feldpausch, Katharina Gillmann, Colin Graf, Thijs Jeffry de Haas, Alexander Härtl, Daniel Honsel, Philipp Kastner, Tobias Kastner, Benjamin Markowsky, Michael Mester, Jonas Peter, Ole Jan Lars Riemann, Martin Ring, Wiebke Sauerland, André Schreck, Ingo Sieverdingbeck, Felix Wenk, and Jan-Hendrik Worch. B-human team report and code release 2010, 2010. Only available online: http://www.b-human.de/downloads/bhuman10_coderelease.pdf.
- [6] Thomas Röfer, Tim Laue, Judith Müller, Michel Bartsch, Malte Jonas Batram, Arne Böckmann, Nico Lehmann, Florian Maaß, Thomas Münder, Marcel Steinbeck, Andreas Stolpmann, Simon Taddiken, Robin Wieschendorf, and Danny Zitzmann. B-human team report and code release 2012, 2012. Only available online: <http://www.b-human.de/wp-content/uploads/2012/11/CodeRelease2012.pdf>.

License

This work is licensed under the Creative Commons Attribution 3.0 Germany License. To view a copy of this license, visit <http://creativecommons.org> or send a letter to Creative Commons, 171 Second Street, Suite 300, San Francisco, California 94105, USA.