Tackling Localization in RoboCup Soccer

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Abstract

This paper surveys the research and development work in the localization domain of the RoboCup Soccer. As the trend of modifying the RoboCup field environment and game restrictions/requirements is going on from the last several years in providing less information every passing year, various techniques have been proposed by researchers for increasing the self-localization performance. The major problem occurs when the robot is lost/kidnapped and result in local minima. In order to tackle this issue, we will discuss various localization techniques. Some of them involve Monte Carlo while other takes particle-filter into account. State of the art techniques also uses deep reinforcement learning for localization. This paper discusses the most innovative and efficient localization techniques.

Introduction

RoboCup, an international robotics competition is held every year for promoting AI research and robotics. This competition has various simulation and robot variant leagues like RoboCup Soccer, RoboCup Junior, RoboCup Rescue,RoboCup@Work, RoboCup@Home and RoboCup Logistics Leagues. This paper describes the localization approaches used in RoboCup Soccer - Standard Platform League (SPL), formerly known as Four-Legged League (FLL). In SPL, autonomous robots play soccer and make the decisions either individually or collaboratively by communicating with their teammates in challenging scenarios, thus aiming to achieve real-world solutions for difficult problems. Initial experiments were performed on AIBO (Artificial Intelligent Robot), designed by Sony until 2008 and more recent experiments are done on NAO robot, developed by Aldebran Robotics. Localization is an important criterion for reliable and efficient navigation of robots. Every year, some modifications are done in the SPL requirements and the environment by making the competition more real, dynamic and challenging by decreasing or removing artificial colored landmarks, making the soccer field bigger, or introducing non-unique landmarks. All these modifications make the competition more challenging because the robot has to deal with the uncertainty in the unknown environment and symmetry at the center of the field (real soccer) which can cause the errors in both location and orientation of the robot.

Researchers are coming up with different localization techniques, like Monte Carlo Localization (MCL) variants or Multiple Hypothesis Localization (MHL) extensions, to deal with these difficulties every year. This paper describes the localization techniques such as:

- Fuzzy-Markov self-localization filter for robustly and efficiently detected field features,
- Standard Monte Carlo Self-Localization using odometry and horizontal bearings to landmarks for self-localization,
- Sequential Importance Sampling (SIS)/Resampling with Multiple Hypothesis Tracking (MHT) for observing non-unique landmarks,
- Psychologically inspired Room Awareness Module with Color Histogram for spontaneous Reorientation,
- Multi-robot Localization by merging different robot's visual perceptions for increasing localization performance and general planning model.

Related Work

Field Features as Landmarks

In RoboCup-2006, color-coded objects are used for detecting objects, but the more natural and real landmarks are field lines. Pérez and Barberá 2006 detected these field features depending on the field line intersections, i.e. corners, because corners can be labeled and tracked easily, in real time.

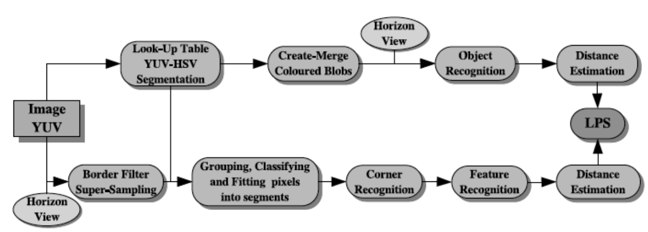

Figure 1: Vision System Flowchart

The Perception or vision system used for feature detection goes through several stages as described in the figure 1.

It takes YUV image as an input and outputs Local Perceptual Space (LPS), a feature-set in relation to robot-centric coordinates. After taking only the horizontal plane of the image to save computation time, Pérez and Barberá used Sobel as a border extraction filter. This image is then sub-sampled to the horizon line, followed by converting YUV image to HSV image using precomputed Look-Up Table. The next step is to filter out non-field line transactions and group the labeled transactions (using Recursive Iterative End Point Fit Algorithm) into different segments. Corners are detected using the intersections of these different segments which are then grouped together into labeled field features. The last step for the pose estimation of the robot is to compute the distance between its LPS and the detected field features and modeling the perception by fuzzy-Markov localization.

Pérez and Barberá compared their technique with the colored landmark techniques on AIBO and found out that the uncertainty in positions introduced by their technique is lesser than the uncertainty obtained in the RoboCup SPL. The most important task in this novel localization technique is to circumvent the false positives, produced by some obstacles, leading to erroneous localization.

Landmarks Odometry and Horizontal Bearings

With the change in RoboCup rules in 2007 and removal of two artificial landmarks, previous methods of localization become ineffective. Jűngel and Risler 2007 proposed bearing-only localization approach using odometry to generate templates for Monte Carlo Localization. This method takes observations at different times and knowledge of robot's motion as inputs and outputs the robot pose or MCL template.

Jűngel and Risler introduced two methods for stationary robot's localization, first uses simple geometry while the other uses angular constraints. With simple geometry, a possible robot position is obtained by the intersection point of three landmark bearings circle. However, many erroneous positions are detected with this method. Therefore, angular constraints approach is used to check the likelihood of the robot position. The similarity between the angles of the robot with the landmarks helps in identifying the correct location of a stationary robot. While with the robot in motion, this method considers odometry to measure the movement of the robot. The last observed robot position is calculated by using the current robot position, displacement and landmark positions. The robot's pose is determined by calculating the maximum value of the function or by applying the Gradient Descent.

This method gives a large number of particles in comparison to landmarks, so a normalization is done to get fewer particles for generating MCL template. The main advantage of this approach is that current pose estimation is not affected by the past localization errors.

Non-Unique Landmarks

The tendency of extracting information from the observations or artificial landmarks started decreasing in RoboCup competition every year. Therefore, the researchers have to take into consideration multiple hypotheses for localization. Thus, the new techniques are more probabilistic than optimal due to the scarcity of information. Őzkucur and Akin 2011 proposed the probabilistic model (SIS/Resampling) with multiple hypotheses for self-localization.

In the standard model with unique landmarks, the current pose depends on the previous robot pose and control/odometry data. However, in proposed Switching Observation Model, the current pose depends on the current discrete labels and the current labels depend on the previous labels, hence utilizing the information from observations in the consecutive steps. Unfortunately, this approach is not scalable on observations because of the exponential growth. In order to tackle the problem of high complexity, MHT with pruning is used to eliminate the low weight Gaussian components. SIS/Resampling Approximation is similar to MHT with Pruning, as in sampling step new hypotheses are created and in resampling step bad hypotheses are removed.

The complexity of this model with non-unique landmarks is similar to the complexity of other localization techniques with unique landmarks, although a high complexity is required to reach the same adaptive level as unique point localization technique. Őzkucur and Akin experimented on the 2009 NAO robot setting naïvely (without additional information), and also with external information. Results show that in naïve approach, particles converge to a false position in case of lost robots as opposed to informative approach. Therefore, a supervised training with known labels will result in large localization accuracy.

Room Awareness Module for Orientation

All the three approaches discussed above focus on the localization not considering the orientation symmetry which is also a key requirement in the self-localization accuracy. Bader and Vincze 2013 introduces a new approach which gives orientation's confidence values for correct self-localization to the Behavior Controller (BC). Thus, controlling the robot to prevent it from falling into wrong positions. This approach depends on the scientifically inspired geometric impressions and integrated awareness of room.For breaking the rotational symmetry around the robot, Non-Static features (for example, ball and other robots) are used directly and Static features (for example, field lines and goals) are mapped with the background environment using Self Localization and Mapping method.

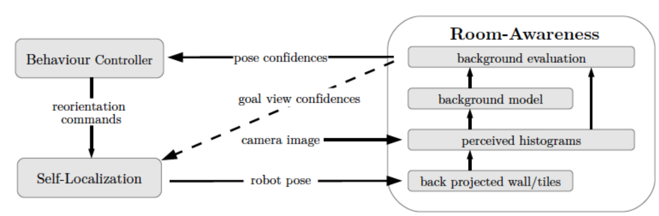

Figure 2: Room Awareness Module

The room-awareness modules such as projected environment, perceived color histograms, background model and background evaluation help in estimating confidence values of pose and orientation. BC takes these confidence values and outputs the reorientation commands to particle-filter for self-localization as depicted in figure 2. The reorientation commands consist of flip pose, purge reflection and reset orientation. Different Color Histograms are modeled with a virtual background cylindrical wall to differentiate between the symmetric rotations. After perceiving color-based histograms, the background model is trained using moving average update strategy to discard the unstable areas. The current viewing direction is then calculated based on the background model using particle-filter on the three most significant histograms obtained by Sum of Squared Differences.

Experiments are done on a head-only robot and moving robot, with both real robot and simulated environment. The experiment results on a stationary robot with no goal information shows that the real robot failed only 10% of the time as compared to the simulated robot failure of 15%. However, if the robot is moving, then both the experiments results in 0% failure without any goal information. However, some areas still need more exploration like an optimal number of histograms, shape of the wall, etc.

Collaborative Multi-Robot Localization

The localization techniques using the coordination and collaboration of multiple robots outperforms most of the localization methods using independent robots. Erdem and Akin 2014 developed a new probabilistic model for better localization based on the multiple robot's perceptions and reliability in real-time constraints. In RoboCup 2014, there are no unique landmarks which are required for MCL, so players are used as landmarks. The problem with these landmarks-based techniques is that the model is unable to distinguish the player's identity, hence resulting in noisy output.

This new model includes more information about player numbers, orientations, etc. apart from standard message data, to communicate via wireless networks. Erdem and Akin define Circle Method which contains the different type of circles - A, B and C around the robots that gives the robot's position and orientation. Circle A is the claimed player's position, circle B is the claimed teammate's position and circle C is the correct player's position. The reliability depends inversely on the robot's variance in circle A and distance between the robot and perceived teammates position in circle B. After perceiving the positions, the intersected circles A and B are merged and converted into Circle O for increasing the localization accuracy depending on the reliability of multiple robots. After this step, some robots still don't have circled positions, so it occupies and choose the best circle, based on the bounty system using distance, reliability and visibility metrics. After achieving the probabilistic positions, orientations are revised, and the procedure is repeated in an iterative fashion until a certain quality is reached. After the multi-robot coordination, robots are self-localized using MCL. In MCL, Quasi-Gaussian particles are used, and their number depends on the reliability of the circle.

The experiments were done on both NAO robots and on the 2D simulator. With 2D simulator, the accuracy in position is significant and it increases with increase in the number of robots, however, there is not much accuracy achieved in robot's orientation. With NAO robots, localization results are checked by comparing the path followed by the robot with the ideal path and the results are comparable. This model provides a solution to general planning problem in addition to accurate self-localization in real time.

Conclusion & Related Work

Among all the localization techniques described above, multi-robot localization technique gives the best results in the latest competition as some of the previous techniques become pointless with a decrease in the number of unique landmarks every year. The challenge faced in this model is to determine the reliability of the robot and reassignment of a position to the lost/kidnapped solution. Also, the results are less promising with real NAO robots because of noise in location and motion. Although the above-discussed techniques performed well in the past competitions, the self-localization of robots still remains one of the most important areas of research for the coming years.

References

D. Herrero-Pérez; and H. Martínez-Barberá. 2006. Robust and Efficient Field Features Detection for Localization. *RoboCup 2006: Robot Soccer World Cup X, Springer*

Matthias Jűngel; and Max Risler. 2007. Self-localization Using Odometry and Horizontal Bearings to Landmarks. *RoboCup 2007: Robot Soccer World Cup XI, Springer*

N. Ergin Őzkucur; and H. Levent Akn. 2010. Localization with Non-unique Landmark Observations. *RoboCup 2010: Robot Soccer World Cup XIV, Springer*

Markus Bader; and Markus Vincze. 2013. Spontaneous Re-orientation for Self-localization. *RoboCup 2013: Robot Soccer World Cup XVII, Springer*

Ahmet Erdem; and H. Levent Akn. 2014. Multi-robot Localization by Observation Merging. *RoboCup 2014: Robot Soccer World Cup XVIII, Springer*