Self-localization Method Using Two Landmarks and Dead Reckoning for Autonomous Mobile Soccer Robots

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Abstract. We propose a new method of self-localization using two landmarks and dead reckoning for a soccer robot equipped with an omnidirectional camera as a local vision sensor. This method requires low computational cost. Thanks to rapid process, the system can afford to run multiple localization process in parallel resulting robust and accurate localization. An experimental result in the field of Robocup Middle-size league indicates that the approach is reliable.

1 Introduction

Many problems are left unsolved to develop an autonomous mobile robot working in a dynamically changing environment. Especially, self-localization is the most fundamental problem. Many solutions developed so far are classified into two categories, i.e., relative method and absolute method. Relative method estimates pose of the robot by the integration of incremental motion using information obtained by intrinsic on-board sensors. A typical technique of relative localization is dead reckoning[1]. This method cannot be used for long-distance navigation because it suffers from errors caused by various disturbances. The localization error grows over time. Absolute method calculates the absolute pose of the robot using various landmarks. The localization error is suppressed when measurements is available. One problem in this method is that movement of small distances cannot be calculated because of rather lower resolution of sensed data as compared with resolution of motion. Another problem is that the robot cannot always observe sufficient number of landmarks due to occlusion.

Both approaches have drawbacks. To cope with the drawbacks, absolute method and relative method are often combined[4][10][12][13][14]: Kalman filter[2][3][7][8] and Monte Carlo Localization (MCL)[6][9][11][15] are often intro-

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duced. Kalman filtering, MCL and other localization methods are comparatively reviewed in [16].

In self-localization in the soccer field of RoboCup Middle-size league, the goals and the corner posts can be used as landmarks. The mutual geometrical relationship among these landmarks is known. These field features are mainly distinguishable by their color. If three landmarks are recognized by vision sensor, the pose of the robot can be obtained by triangulation based on the measured direction of them with respect to the robot frame[5]. However, robots often fail to simultaneously recognize three different landmarks during the soccer game: landmarks are easily occluded by opponent robots and teammate robots which are always moving around and are rushing to the ball.

We developed a new self-localization method for a mobile robot and applied it to the soccer robot in RoboCup Middle-size league. Initial samples of the pose of the robot are distributed on a circumference of a circle determined by measured direction of two landmarks. Then the correct pose is determined through iterative evaluation steps. This method requires low computational cost. This enables multi-process of localization running simultaneously. In addition to this, reinitialization of samples is performed when samples become highly improbable. Thus robustness and accuracy of localization is guaranteed.

This paper is structured as follows. Principle of our localization method is explained in Sect. 2. In Sect. 3, we explain techniques for satisfying constraints of real-time response. Sect. 4 describes our soccer robot and an experimental result is included in Sect. 5.

2 Principle of Localization

Throughout this section, we assume that observed landmarks are recognized correctly and that their position in the soccer field is precisely known. When a robot detects two landmarks and measures angles of their directions with respect to a robot centered coordinate system, the robot is positioned at somewhere on a circle which passes these two landmarks while satisfying that the angle at the circumference is the measured angle (Fig. 1). Orientation of the robot is determined as a function of its position on the arc and measured direction of the landmarks. To uniquely determine position and orientation of the robot, dead reckoning of the successive motion of the robot is used as followings. Discretizing position on the arc, we obtain a set of candidates of pose of the robot $P(t) = \{p_i(t)|i = 1 \dots N\}$. N is at most 360 in our current implementation. Successively the robot moves for a short period Δt, and then detects plural landmarks and measures angles of direction. Pose displacement of the robot for this short period is also obtained using odometry with measured rotation of wheels. Adding this displacement to each candidate of the pose, we obtain a set of renewed candidates $P(t + \Delta t)$.

Localization error of each renewed pose is evaluated by difference of direction angle to the landmarks: comparison is made between computed direction to each landmark from the renewed pose and actually measured direction by the robot (Fig. 2). Error value is accumulated over time by equations:

$$AngleError(t + \Delta t) = \sum_{k=1}^{m} a_k(t + \Delta t) + \sum_{k=1}^{n} d_k(t + \Delta t) \quad (1)$$

$$m = {}_nC_2, \quad n \mid number\ of\ observed\ landmarks.$$

$$Error(t + \Delta t) = AngleError(t + \Delta t) + Error(t) \quad (2)$$

In these equations, $a_k(t)$ is an absolute value of difference between measured observation angle of two landmarks from the robot and computed one, $d_k(t)$ is an absolute value of difference between measured direction angle and computed one for each landmark respectively.

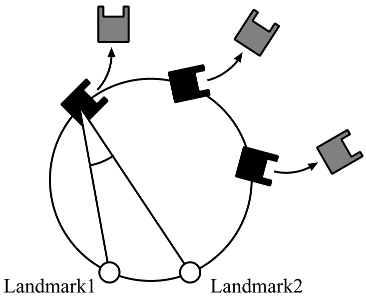

Fig. 1. Initial and renewed candidates of robot pose

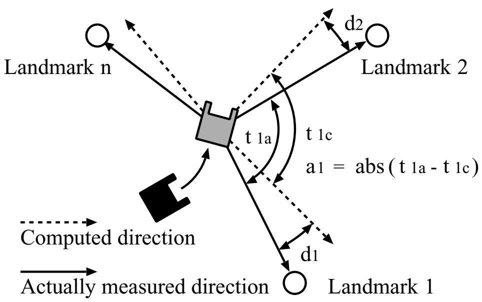

Fig. 2. Localization error of each renewed pose

$Error(0)$ is cleared to be 0 at the beginning of the localization process. Then evaluation of all the candidate for the pose of the robot is repeated based on visual measurement of the landmarks and odometry in every short period Δt. Error value obtained by Eq. 2 increases gradually. Increase of accumulated error value is slow for those candidates which are closely located near the correct pose, while increase is rapid for those which are far from the correct pose. Finally correct pose is determined uniquely as the one having the smallest error accumulation.

In the initial step, the robot needs to detect two landmarks to make a circle corresponding to the candidates of the pose of the robot. On the other hand, in subsequent evaluation step, a robot should just discover one landmark at least. If plural landmarks are observed by the robot, observation of landmarks effectively functions to evaluate errors, resulting earlier determination of the unique pose of the robot.

3 Localization Process

Localization is formalized as a selection process of the best one in a set of candidates based on the error evaluation over time. Error evaluation is performed for every candidates in every short time period Δt. Generally number of candidates in an initial set is large, outliers should be eliminated as soon as possible to reduce the number of candidates to be evaluated. We have developed several methods to satisfy constraints of real-time response of the soccer robot.

3.1 Early Elimination of Inadequate Candidates for Pose

As the robot moves, accumulated error increases rapidly for these candidates located far from the correct pose. So we introduce threshold values for the accumulated error, the error in observation angle of two landmarks, and the error in observation direction to each landmark. As soon as an error exceeds the corresponding threshold value, the candidate is immediately removed from the set of pose thus reducing computational cost (Fig. 3).

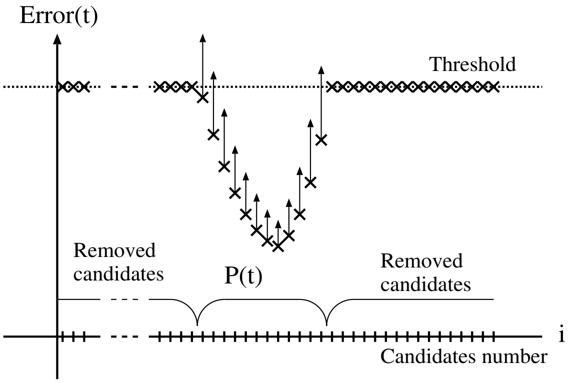

Fig. 3. Accumulation of errors

3.2 Selection of Two Landmarks among Available Landmarks

There are eight landmarks available in the soccer field: four corner poles and four goal posts. Two adequate landmarks must be selected whenever more than three are observed by an omni-directional camera of the robot to make the initial set of candidates of the pose of the robot $P(0)$. This selection is made in real time based on a table prepared in off-line as followings. An initial set of possible pose $P(0)$ is composed of points obtained by discretization of a circle: the circle is defined by two landmarks and observation angle of them by a robot. Maximum number of elements is 360 in our current implementation. Those located out of the field are eliminated at the beginning. Therefore, those two landmarks which generates least number of initial pose in the field are selected. Considering the symmetry of the field and location of landmarks, there are eleven possible pair of two landmarks. Given an observation angle of landmarks from the robot, number of discretized points on the circle within the field is enumerated for each pair. Using 180 discretized observation angles from 1 degree to 180 degrees, a table is structured containing number of possible candidates for eleven pairs of landmarks. Using this table, selection of two landmarks is made in real-time.

3.3 Control of Localization Processes

As described so far, the localization process is composed of generation of pose candidate and successive selection of unique pose by traveling with dead reckoning. Due to various errors, the pose of the robot may not be determined uniquely even if the robot continues traveling. Further extension of travel distance causes increase of accumulated error in dead reckoning. This would result erroneous pose even if the pose should be determined uniquely. In such case, the localization process should be aborted and a new process should be initiated. In the current implementation, the running process is aborted if the number of eliminated candidate exceeds a threshold value and the minimal error exceeds a threshold value.

On the contrary, once the pose is uniquely determined in the course of traveling, a new localization process is initiated at the point while the former process is continued. In this way the robot maintains multi-process of localization running simultaneously (Fig. 4). We compute a weighted sum of poses obtained in each process as a best estimate of the pose of the robot. Reciprocal of accumulated error obtained in Eq. 2 for each pose is used as a weight value. Number of processes cannot grow limitlessly due to the real-time constraint of the soccer robot. In addition, a lifetime is defined for a localization process, since an accumulated error of the dead reckoning increases over time. In the current implementation, number of the processes is limited to three.

4 Robot System

Our soccer playing robot is shown in Fig. 5. The robot is driven by two powered wheels and is equipped with an omni-directional vision system. Two additional free wheels with rotary encoders are installed to the robot for odometry with least slippage.

An omni-directional camera is mounted on the top of the robot enabling panoramic view around it (Fig. 6). The camera is composed of a CCD camera with a hyperboloidal omni-directional mirror. Obtained image frame is processed by an electronics board (IP5005, Hitachi).

5 Experiment

An experiment has been made in a half of Robocup soccer field composed of a goal and a corner pole on the green carpet (Fig. 7). Two goal posts (A and B) on both side of a goal and a corner pole (C) are used as landmarks. Performance of the proposed method is compared with conventional two methods.

A field player robot is initially placed at point a. Then it is manually pushed to follow a given reference test trajectory $a-b-c-d-e-f-g-h-a$ composed

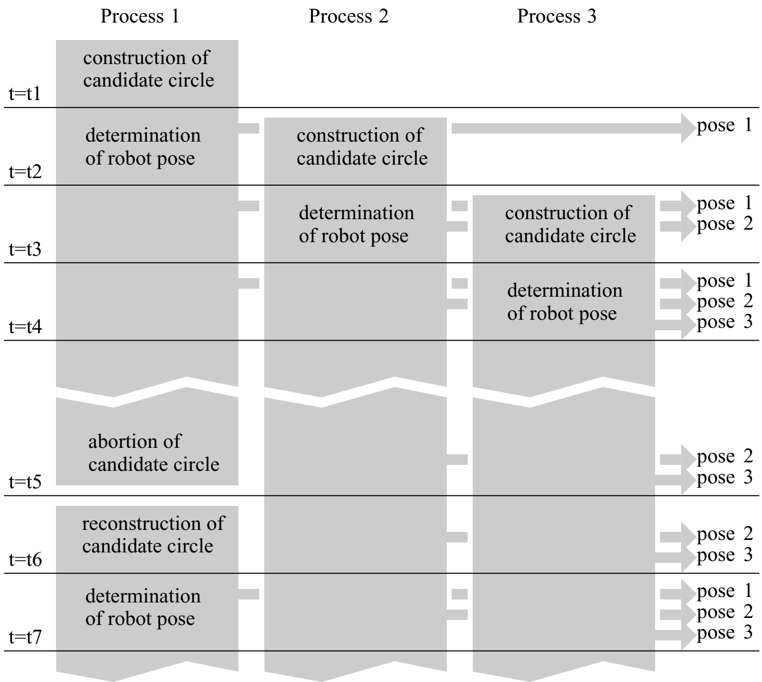

Fig. 4. Multi-process of localization

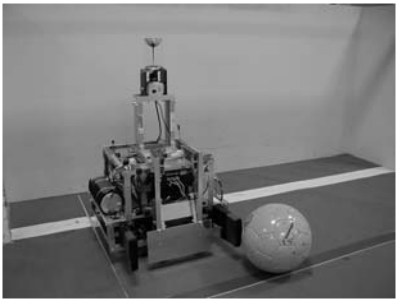

Fig. 5. Our soccer robot for RoboCup Middle-size league

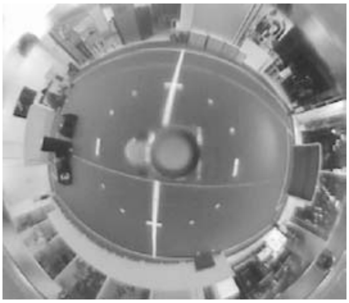

Fig. 6. Panoramic view of omni-directional camera

of straight line segments and rectangular corners. In Fig. 8, we show performance of localization for three different cases: 1) localization by the proposed method with two landmarks(A, B), 2) localization by the conventional triangulation with three landmarks(A, B, C), and 3) localization by conventional dead reckoning.

In the first case, the robot succeeds in localization after traveling for distance of 75 cm, and keep going with good accuracy till the end of the trajectory. In the second case, when all three landmarks are correctly recognized (a–b–c–d, h–a),

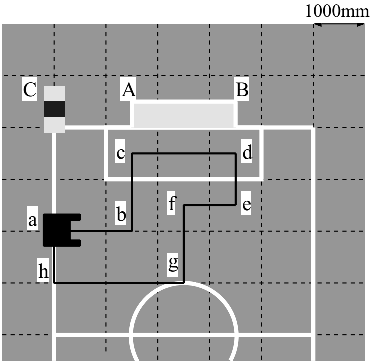

Fig. 7. Experimental setup

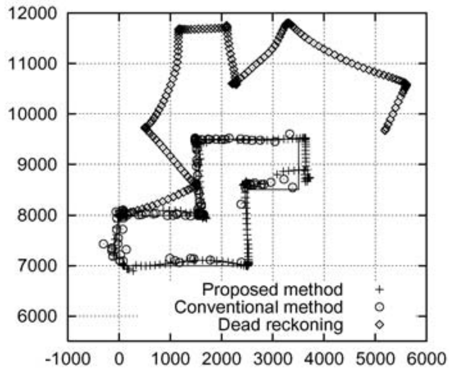

Fig. 8. Experimental result

the robot succeeds in self-localization with good accuracy. On the trajectory $d-e-f-g-h$, the robot often fails to recognize the landmark A and then fails in localization. In the third case, localization by dead reckoning suffers large error. In our proposed method, the amount of movement required to decide the pose of the robot becomes small when three landmarks can be observed, compared with the case of observation of two landmarks.

6 Conclusions

We have presented an self-localization method based on two landmarks and dead reckoning for autonomous mobile soccer robot. The effectiveness of the proposed method was proved by an experiment. The presented method becomes reliable in robot soccer compared with the other technique such as triangulation with three landmarks. Especially the method has a high adaptability for localization of a keeper robot: although the keeper can always observe two goal posts behind, it cannot almost observe other landmarks.

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