Localization using Relative Mapping Technique for Mobile Soccer Robots

Tushar Agrawal, Deepak Gopinath

***Abstract*—Localization is an important topic in the field of mobile robotics. It is the process of estimating the position and orientation of a mobile robot. Several probabilistic techniques are available for this purpose, some of which use a compass sensor to directly determine current orientation. This sensor is highly susceptible to magnetic interference. Here, we propose an association based approach which solely relies on camera images to localize in a pre-defined environment. We use the Monte Carlo Localization for position based filtering. Further, we present a relative landmark mapping technique and white points based filtering used to obtain the final pose of the robot after incorporating its orientation. To check the accuracy of the proposed methodology, it was tested on a large number of real-world test cases. The technique resulted in a high success rate and accurately estimated the position and orientation of the mobile robot in the field. It is currently being employed for localizing humanoid robot, AcYut, in humanoid robot soccer games.**

***Index Terms*—Computer vision, localization, mobile robots.**

I. Introduction

An important requirement of mobile robots is the awareness of their position and orientation in their environment at all instants of time. Here, we demonstrate localization in a pre-defined environment, a scaled down soccer field, consisting of fixed colored markers and white field lines. The updated pose is essential for optimal path planning towards a position of interest. The path may contain obstacles which are to be avoided during navigation. The continuous pose updates help in maintaining and correcting the trajectory to reach the goal. The pose estimation requires constant data updates regarding distances to the landmarks and other features on the field. Various approaches exist which need sensors like laser scanners, omni-directional camera to estimate distances to the desired markers. However, such sensors are expensive and difficult to incorporate into several designs such as humanoid robots. We use a single view camera to gather visual data which can be used for purposes apart from localization. In order to determine the current orientation of the robot, magnetic compass sensors maybe employed. However, we avoid the usage of such sensors as they suffer from erroneous data due to magnetic interference from neighboring electro-magnetic elements of the robot. Hence, we propose an association based approach in addition to the well-known Monte Carlo Localization technique. This eliminates the need of acquiring the absolute orientation of the robot beforehand. This method is based on the intuitive human technique of localization wherein the landmark elements in the scene are mapped onto a model of the environment from memory. A relative map consisting of observed landmarks is created and superimposed on a model of the field. Error is calculated based on proximity of actual landmarks from observed landmarks. The pose with the least error in superimposition is adjudged to be the best-fit pose. Furthermore, we propose a white field line based filtering algorithm to resolve any ties that may occur.

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II. Related Work

Monte Carlo Localization is a highly robust technique to continuously update the position of a mobile robot in a generic environment and it has been widely used. The concept was introduced by Dellaert, F et al. [1], who used it to localize a mobile robot in an indoor environment. As far as localization of soccer robots is concerned, Hannes Schulz et al. [4], H. Strasdat et al. [3] and A. Bais et al. [2] have proposed two different approaches which are soccer field line structure based. The former ([4]) uses skeletonization and other morphological techniques while the other two ([2],[3]) use a Hough transform based method.

III. The Setup

The algorithms discussed in the paper are limited to localization solutions in a controlled, pre-defined environment, in our case, a soccer field.

The field has the following characteristics:

1) Green baize field which represents the area covered by the soccer field.
2) White field line pattern, similar to soccer fields.
3) A goal having two vertical posts with a connecting horizontal post. Goal posts in one half are colored yellow and blue in the other.
4) Special landmark poles are used in the field. These consist of horizontal striped pattern colored Yellow-Blue-Yellow (YBY) in one and Blue-Yellow-Blue (BYB) in the other. The poles are placed midway from the two goals-just outside the field boundary.

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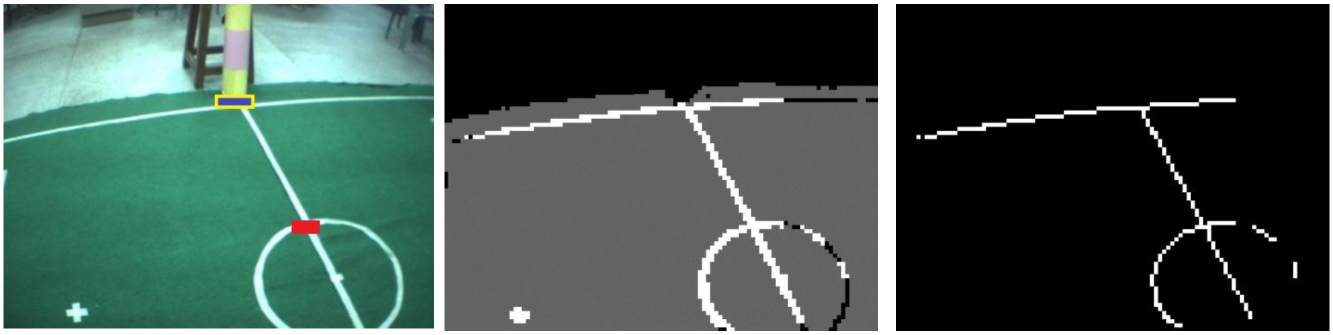


(a) (b) (c)

Fig. 1. Step wise pre-processing: (a) Camera image with landmarks detected. (b) Green and white segmented image. (c) Skeletonized image.

IV. Pre-processing

A. Segmentation

The landmarks in the field are all defined uniquely by their color or combination of colors and hence the first step in finding the landmarks is color segmentation which is done using pre-calibrated ranges for every color. The YCrCb color space is currently used for image segmentation but the same may even be obtained using RGB segmentation. The segmentation is done for significant colors including yellow, blue, green and white and further processed for landmark detection.

B. Landmark Detection

The important landmarks used for localization algorithms are landmark poles (both YBY, BYB poles), goal posts (yellow and blue) and line intersections. In order to extract field line information, we need thin lines with the width of one pixel.

The method of finding landmarks efficiently is as explained:

1) Goal posts - Groups of connected yellow pixels with green pixel below it are identified. It is checked if the same post continues upwards up to a predefined number of pixels. Algorithm is repeated for adjoining columns in the image. Two such posts are searched for in the image.

2) Landmark Poles - For YBY pole, groups of connected yellow pixels with green pixel below it are identified. It is checked if the column continues to a yellow-blue and further a blue-yellow boundary. The algorithm is repeated for adjoining columns. Similarly, BYB pole is searched in the image.

3) Line Intersections (X's and T's) - Firstly, segmentation of white pixels surrounded by green is carried out. The Hilditch algorithm is applied to skeletonize the line to a single pixel width. Pixels (nodes) with a degree (number of surrounding white pixels) of 4 (for X's) and 3 (for T's) are marked.

V. Localization of the robot

A. Monte Carlo Localization

The Monte Carlo localization is a very popular technique used to determine the position of a robot given a map of its environment. The particle filter uses Bayes theorem to determine a set of high probability hypothetical configurations of the robot, which in turn is updated at every sensor update. The configuration of the robot is stored as a 3-tuple (x, y, θ) which consists of both its position in a 2D field and orientation.

The field consists of a grid of equidistantly placed particles p. The grid size is proportional to the size of the real-world playing field. These particles represent the probable positions where robot may be found. The belief that a point p is the position of the robot is recursively updated taking into account the movement of the robot in the past. This belief is further strengthened by the application of observation model, which uses observed data at the current time.

In the observation model, the likelihood that a point, represented by particle p, is the current location of the robot is computed by comparing the expected distance and the observed (measured) distance from every landmark observed.

$$P_p \propto \prod_{\forall i \in L} \exp\left(\frac{\left| s_{ie} - s_{io} \right|}{2\sigma_i^2} \right) \tag{1}$$

where s_{ie} and s_{io} are the expected and observed distance to the landmark i and σ_i^2 is the variance of the distances between particles and landmark i.

B. Relative Landmark Mapping Technique

To account for the orientation of the robot without a compass sensor, on the current high probability particles obtained, a relative mapping technique is applied. The relative field as seen by the robot is superimposed over the actual field. For every particle in consideration, the robot is placed at several angles (resolution is subject to requirements, a 1^{o} resolution was used in the implementation), and the probabilities are further filtered based on the error calculation.

For all particles obtained from the Monte-Carlo Localization process having a probability value greater than a threshold (which depends on the probability function in the MCL technique, we use 0.99 as the threshold), a relative map is constructed. This map consists of all observed landmarks at observed distances and angles from the robot's perspective.

The relative map is superimposed at the respective particle's position on the actual field at angle θ_j varying from 0^o to 360^o at a desired step.

For every particle p, the best-fit angle θ_p is the angle with the least error d_p in superimposition of relative map on the field. The error $err(p, \theta_j)$ is quantitatively measured as the sum of squared differences between the superimposed landmark position and the actual landmark position for angle θ_j.

$$err(p, \theta_j) = \sum_{\forall i \in L} \left[(x_{io} - x_{ia})^2 + (y_{io} - y_{ia})^2 \right] \quad (2)$$

where (x_{io}, y_{io}) are the observed and (x_{ia}, y_{ia}) are the actual coordinates of landmark i.

$$d_p = \min_{for\,all\,j} \{ err(p, \theta_j) \} \quad (3)$$

and θ_p is the corresponding θ_j.

The best-fit pose (x_p, y_p, θ_p) is determined by choosing the particle with the least d_p. In case this pose is not unique, we proceed to resolve the ties using filter based on the white field lines.

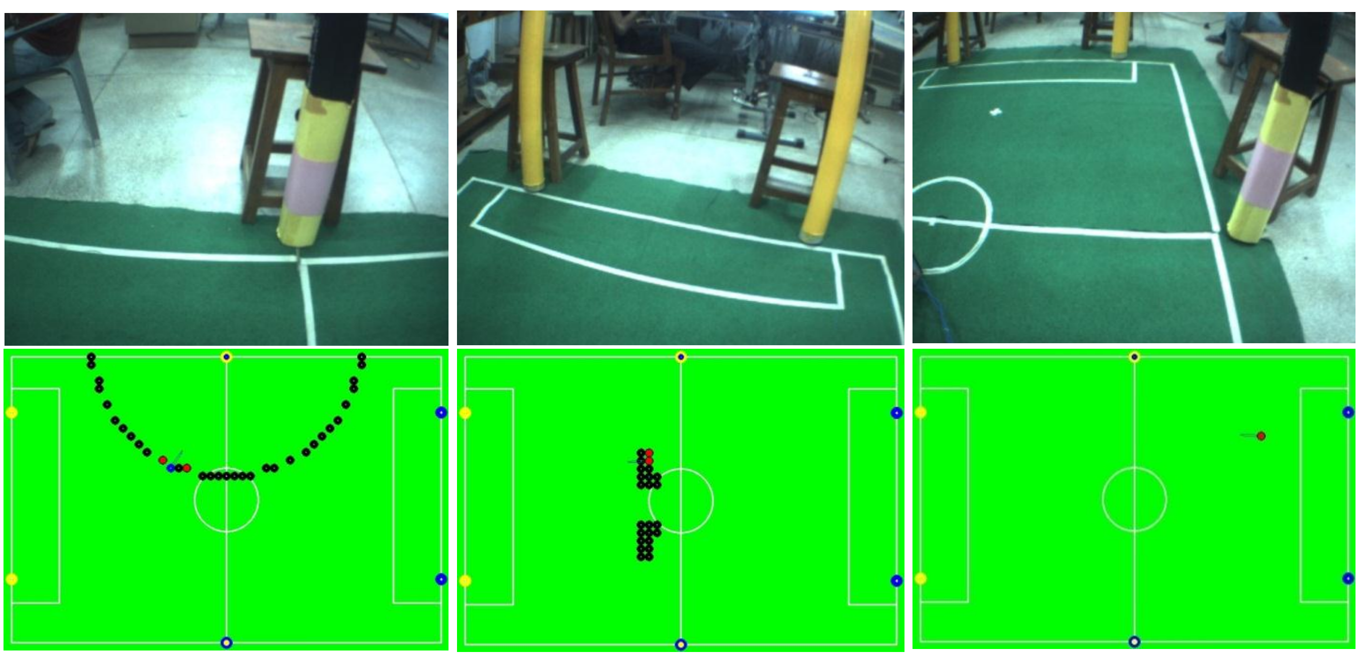
$$d = \min_{for\,all\,p} \{ d_p \} \quad (4)$$

and every such particle p is added to set T, the set of all tied particles.

C. White Points Based Filtering

A tie arises when multiple poses are equally possible for the observed set of land-marks i.e. when the robot encounters a single landmark or a pair of undistinguishable landmarks. In such a scenario, the differences in the orientation of the white field lines are used to break the ties.

A random subset of white spots seen by the robot belonging to the field lines W are picked and projected to form a relative map (consisting of set of (x_i, y_i) coordinates of the projected white spots). At each clashing pose in T, this relative map is superimposed at the best fit angle for that pose θ_p on the field and the number of matching white points, m_p, is calculated. A white point is said to match when (x_i, y_i) falls on a white field line in the model of the field. The pose (x_p, y_p, θ_p) with the highest number of matching white points m_{max} is the winner of the tie and hence, the best-fit pose.



(a) (b) (c)

Fig. 2. Experimental results of test cases. (a) Circle of highly probable particles filtered using MCL. The blue particle with oriented as shown is the resultant pose. (b) Final pose along with rejected particles (in black). (c) Unique final pose. (Refer Appendix B for statistical data).

VI. EXPERIMENTAL RESULTS

The localization system was tested on a humanoid robot, AcYut (refer Appendix A), equipped with path planning and behavior systems. We use the 1.8GHz Intel Atom processor which provides a frame-rate of around 20fps with a PointGreyFirefly camera. A grid consisting of 54x36 particles, proportional to the size of the field, is used. We illustrate, in Figure 2, three test cases wherein the robot was placed in three different poses in the soccer field, exposed to different sets of landmarks in each case. In case (a), only an intersection and a unique landmark pole are visible to the robot. Application of distance based Monte Carlo Localization and superimposition of relative map of landmarks at various orientations results in filtering a circle of points around the landmark (shown in black). The 'tie' is now resolved using the white points based filtering method which chooses the correct particle (shown in blue) along with its orientation as shown. However, in case (b), the final pose (in red) is estimated after superimposing the relative map of goal posts which rejects the particles in the lower half of the field. In case (c), the number of landmarks seen is sufficient for the MCL process to pinpoint a unique pose. The upper bound of the error in localization was 10% which arises due to the error accumulated in estimating real-world dimensions using inverse perspective transformation and low grid resolution.

Fig. 3. AcYut, the humanoid robot.

VII. CONCLUSION

In this work, we presented a method of localization of mobile robots in a defined environment using just a single view camera. We first preprocessed the visual data received in order to detect and extract information about the landmarks. We use skeletonization to extract field lines and hence identify the intersection points which are used as markers. Inverse perspective transformation is applied on the image to calculate real world distance to the landmarks. The data collected is used to assign probabilities to every particle using the Monte Carlo Localization technique and subsequently filtered for further processing. A map of landmarks relative to the robot is constructed and superimposed in all angles on a model of the field to find the best fitting set of poses among all the filtered particles. To resolve ties, we also superimpose a random subset of white points observed on the model field and the pose with the most number of hits (matching points) is adjudged the best-fit pose. We demonstrated the results of our localization technique on a humanoid robot by placing it at different poses in a miniature soccer field and also presented a visual representation of the results.

APPENDIX

A. AcYut, the humanoid robot.

AcYut is the name of a series of humanoid robots being developed at the Centre of Robotics and Intelligent Systems, Birla Institute of Technology and Science, Pilani, India. AcYut-1 was India's first indigenously developed humanoid robot. AcYut has won accolades at numerous international events like Robogames, Robocup, International Robot Festival (South Korea) and FIRA. AcYut 4 is equipped with vision, behavior and path planning systems and hence capable of performing autonomous activities such as playing soccer.

B. Statistical data of results shown in Fig. 2.

Measurements are made considering the bottom left corner of the field as origin. Angles are measured in anticlockwise manner. The dimensions of the actual field were 3m x 2m. The field was divided into 54 x 36 grids during computation.

TABLE I
MEASURED AND ESTIMATED VALUES

Fig. No.	Property	Estimated value	Measured value
2(a)	Position	1.11m, 2.22m	1.05m, 2.15m
	Angle	56^o	60^o
2(b)	Position	1.27m, 1.27m	1.25m, 1.20m
	Angle	185^o	190^o
2(c)	Position	2.38m, 1.44m	2.25m, 1.35m
	Angle	177^o	185^o

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