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Use of coded infrared light for mobile robot localization

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Abstract

This paper presents mobile robot localization using coded infrared light as artificial landmark. Different from RFID, coded infrared light has highly deterministic characteristics. It is implemented with IR LEDs and phototransistors. By putting several IR LEDs on the ceiling, the floor is divided into several sectors and each sector is set to have a unique identification. Coded infrared light tells which sector the robot is in, but the size of the uncertainty is still too large if the sector size is large, which usually occurs. Dead-reckoning provides the estimated robot configuration, but the error becomes accumulated as the robot travels. This paper presents an algorithm that combines both the encoder and the coded infrared light information so that the size of the uncertainty becomes smaller. It also introduces a framework that can be used with other types of artificial landmarks. The characteristics of the developed coded infrared light and the proposed algorithm are verified from experiments.

Keywords: Localization; Infrared light; Mobile robot

1. Introduction

The number of potential applications for autonomous mobile robots in indoor/outdoor environments is increasing, ranging from maintenance and repair of mechanical machinery, to clean up operations for accidents involving hazardous chemicals and materials, to interchanging atomic fuel in nuclear power plants, to search and rescue operations in burning buildings or hostage situations.

Unlike manipulator robotics in many manufacturing applications, mobile robotics requires a global understanding of the environment and the ability to dynamically plan in it. There are some fundamental issues that must be addressed to achieve autonomous mobile robot navigation. First, a path planner is needed to select a route for the robot to follow. Second, since unavoidable odometer errors render it impossible for any mobile robot to precisely follow a planned trajectory, localization techniques are needed to precisely determine the robot's position and orientation.

Commonly, dead-reckoning (open-loop estimation) is used for intermediate estimation of position during path execution. Dead-reckoning is often used when wheel encoders are available for drive wheel position measurement. However, due to errors in kinematic model parameters, wheel slip, or an uneven surface, poor position estimates may occur. A great deal of work has been done in mobile robot localization using range sensors, vision cameras, natural/artificial landmarks, indoor GPS, etc., in order to reduce the errors from dead reckoning.

Recently, new types of sensors, networks and devices are becoming popular in a new domain called a ubiquitous environment. RFID is one of those and is getting attention in material distribution, inventories, etc. Several researches on mobile robot localization using RFID and wireless LAN have been done. Other types of artificial or natural landmarks have been widely used, especially in the vision society.

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Kantor and Singh [1] provided methods of localization using multiple RF beacons that provide the ability to measure the range only. This method enables an accurate estimation of robot location by using Markovian probability grids and the known beacon locations. Similarly, Privantha et al. [2] dealt with an RF wireless network based system for locating and tracking users inside buildings. It uses multiple receiver locations' signal information to triangulate the user's coordinates by using both empirically determined and theoretically computed signal strength information. Bahl and Padmanabhan [3] developed an inexpensive location support system which is indoor, mobile, location-dependent application by using RF signal and ultrasonic pulse from beacons spread throughout a building. They estimate distances to the different beacons using the difference in RF and ultrasonic signal propagation times, and therefore infer the space they are currently in. Maeda et al. [4] proposed a three-dimensional position and orientation tracking system that combines infrared markers with a head-mounted stereo camera to detect the user's position, and an orientation sensor to measure the orientation of the user's head. They also used extended Kalman filter to reduce the error of multiple sensors. A localization method using ultrasonic and infrared signals at the same time is investigated by Ghidary et al. [5], and a method of personal positioning with self-contained sensors and a wearable camera is presented in Kourogi and Kurata [6]. Tenmoku et al. [7] described a system that measures the orientation of a user's viewpoint by an inertial sensor and the user's position by using positioning infrastructures in environments and pedometers. The system receives ID from RFID tags or IrDA markers to specify the user's position. To avoid problems like power supply or undesirable visual effect, Nakazato et al. [8] introduced a new localization method based on using an IR camera and introduced invisible markers consisting of translucent retro-reflectors.

2. Coded infrared light

RFID has either 64bit or 96bits of information so that the number of possible identifications is almost infinite. It is reported that RFID is being studied as an artificial landmark for mobile robot localization. However, due to the characteristics of the radio frequency signal, the signal strength and the distribution of the signal are highly stochastic (for example, positive/negative false readings), so that relying on the RFID reading only may even make the localization result even worse.

Coded infrared light is simply a set of an infrared LED and a phototransistor. The light is modulated at 38KHz, so that a phototransistor with a filter can get the light with less interference with fluorescent light and sunlight. Depending on the pulse train of the light, each LED can emit a unique ID. However, only one LED should be turned on at each time to avoid collision with lights from other LEDs. The following figure (Fig. 1) shows the concepts of the coded infrared light. Three IR LEDs are installed on the ceiling and each delivers a unique ID. The robot moves on the floor with a receiver.

The floor is divided into six different sectors as shown in Fig. 2. A supervisory controller coordinates the firing of the emitters, so that there are two sectors (sectors 4 and 5 in Fig. 2) where the robot receives two different identifications not at the same time, but sequentially, which are differentiated from the other three sectors (sectors 1,2 and 3 in Fig. 2) where only one identification is received. The last sector (sector 6

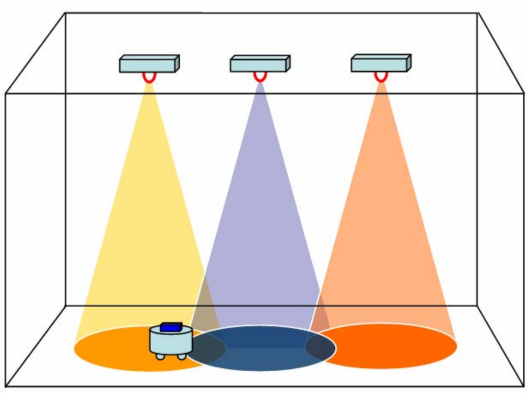

Fig. 1. Three coded infrared lights and a mobile robot.

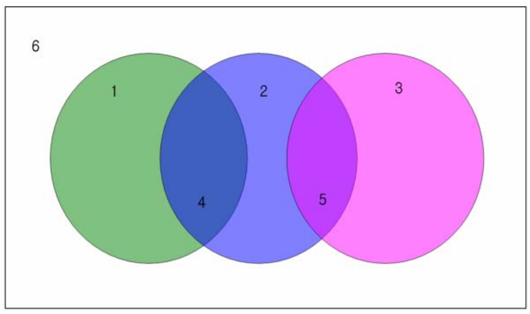

Fig. 2. Sectors based on identification.

in Fig. 2) is where the robot receives no identification.

3. Dead reckoning with coded infrared light

It is well known that the size of the uncertainty in robot location grows larger as the robot travels in Siegwart and Nourbakhsh [9] and Thrun et al.10]. The error should be reset before it becomes too large. For a differential drive mobile robot, the robot configuration can be estimated starting from a known configuration by integrating the movement.

The configuration vector, p is defined as

$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \tag{1}$$

If right and left wheels travel $\triangle s_r$ and $\triangle s_l$ respectively, then the new configuration is represented as

$$p' = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = f(x, y, \theta, \triangle s_r, \triangle s_l) = p + \begin{bmatrix} \triangle s \cos\left(\theta + \triangle\theta/2\right) \\ \triangle s \sin\left(\theta + \triangle\theta/2\right) \\ \triangle\theta \end{bmatrix} \tag{2}$$

where $\triangle s = \dfrac{\triangle s_r + \triangle s_l}{2}$ and $\triangle\theta = \dfrac{\triangle s_r - \triangle s_l}{b}$

Dead-reckoning results can give only a very rough estimate of the actual position. We assume that the errors of the individually driven wheels are independent, and the variances of the errors of the left and right wheels are proportional to the absolute value of the traveled distances as the following equation,

$$\sum_{\triangle} = covar(\triangle s_r, \triangle s_l) = \begin{bmatrix} k_r\left|\triangle s_r\right| & 0 \\ 0 & k_l\left|\triangle s_l\right| \end{bmatrix} \tag{3}$$

then, the covariance matrix is represented as

$$\sum_{p'} = \nabla_p f \cdot \sum_p \nabla_p f^T + \nabla_{\triangle} f \cdot \sum_{\triangle} \nabla_{\triangle} f^T \tag{4}$$

where $\nabla_p f = \begin{bmatrix} 1 & 0 & -\Delta s \sin\left(\theta + \triangle\theta/2\right) \\ 0 & 1 & \Delta s \cos\left(\theta + \triangle\theta/2\right) \\ 0 & 0 & 1 \end{bmatrix}$ and

$$\nabla_{\Delta} f = \begin{bmatrix} f_1 & f_2 \\ f_3 & f_4 \\ f_5 & f_6 \end{bmatrix}$$

$$f_1 = \frac{1}{2}\cos\left(\theta + \triangle\theta/2\right) - \frac{\Delta s}{2b}\sin\left(\theta + \triangle\theta/2\right),$$

$$f_2 = \frac{1}{2}\cos\left(\theta + \triangle\theta/2\right) + \frac{\Delta s}{2b}\sin\left(\theta + \triangle\theta/2\right),$$

$$f_3 = \frac{1}{2}\sin\left(\theta + \triangle\theta/2\right) + \frac{\Delta s}{2b}\cos\left(\theta + \triangle\theta/2\right),$$

$$f_4 = \frac{1}{2}\sin\left(\theta + \triangle\theta/2\right) - \frac{\Delta s}{2b}\cos\left(\theta + \triangle\theta/2\right),$$

$$f_5 = \frac{1}{b}, \quad f_6 = -\frac{1}{b}$$

In this paper, the coded infrared light information is being used to reduce the uncertainty size. Fig. 3 shows a simple example. The size of the uncertainty becomes smaller if the coded infrared light information tells the robot is inside the circle where the robot receives the infrared light (Fig. 3). Even if the robot does not move into the neighbor sector, but stays in a sector while getting the same coded infrared light, the uncertainty size does not diverge because it is trimmed continuously.

Mathematically, this trimming is represented as the following equation. For simplicity, if we assume one-dimension, the configuration is estimated from,

$$\mu = \int_{-\infty}^{\infty} x f(x) dx \tag{5}$$

If the Coded Infrared Light tells the robot belongs to a region of $x_1 \le x \le x_2$, then, Eq. (5) becomes

$$\mu^* = \int_{x_1}^{x_2} x f(x) dx \tag{6}$$

However, the reduced covariance resulting from the trimming process is geometrically an arbitrary shape, and the dimension of the robot configuration is 3 (x, y, θ). Therefore, the robot configuration is estimated discretely as follows.

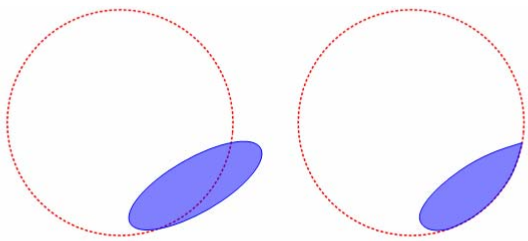

Fig. 3. Uncertainty of the robot location with dead-reckoning.

Characteristics of the motors used for driving the mobile base are estimated from experiments. One of the important features is the variance of errors as used in (3). For one candidate of the robot configuration, the total number of $(2n-1)$ equally spaced points is sampled for each motor as (7) and (8).

$$\triangle s_r + \varepsilon_r[i] \tag{7}$$

$$\triangle s_l + \varepsilon_l[j] \tag{8}$$

where $i, j = 1, \cdots, 2n-1$. $\varepsilon_r[i]$ and $\varepsilon_l[j]$ are the perturbation errors following the Gaussian distribution of the right and left motors, respectively. Also, the corresponding probability density function is represented as $p_r[i]$ and $p_l[j]$. With the index (i, j) is equal to n, the probability density is the largest, and when the index is either 1 or $2n-1$, it is the smallest.

The configuration for a candidate is estimated simply from (2) for all $i, j = 1, \cdots, 2n-1$. Therefore, $(2n-1)\times(2n-1)$ new configurations ($x[i][j]$, $y[i][j]$, $\theta[i][j]$) are calculated with the probability of $p[i][j] = p_r[i] \times p_l[j]$ for each configuration. In order to limit the computational load, $n = 10$ is used for real-time estimation. All $p[i][j]$ are sorted so that only the top 100 highest probability candidates are selected at each sampling. Therefore, $19 \times 19 \times 100 = 36100$ calculations of x, y, θ are performed at each sampling. One important parameter is $r[i][j]$, the flag variable which tells the position $(x[i][j], y[i][j])$ belongs to the sector or not: if $r[i][j] = 1$ then, the position is inside the sector. Otherwise, $r[i][j] = 0$. Finally, the updated configuration for each candidate is calculated as in the following equations.

$$x_e = \frac{\sum_{i,j} x[i][j] \times p[i][j] \times r[i][j]}{\sum_{i,j} p[i][j] \times r[i][j]} \tag{9}$$

$$y_e = \frac{\sum_{i,j} y[i][j] \times p[i][j] \times r[i][j]}{\sum_{i,j} p[i][j] \times r[i][j]} \tag{10}$$

$$\theta_e = \frac{\sum_{i,j} \theta[i][j] \times p[i][j] \times r[i][j]}{\sum_{i,j} p[i][j] \times r[i][j]} \tag{11}$$

Eq. (6) is for continuous one dimensional distribution and (9)-(11) are for irregular shaped (and not continuous) discrete variables.

Information is also available at the instant when the robot moves into another sector (crosses the border between two sectors). We can tell the robot is on an arc at the instant of the identification change. Therefore, the uncertainty size shrinks abruptly.

A more important feature of using coded infrared light is the so called back-propagation. In Fig. 4, the uncertainty grows from P1 to P2 as the robot moves (T12). Another movement (T23) makes the uncertainty grow from P2 to P3. Let us assume the robot gets ID#2 after completing T23 movement. The instantaneous transition from ID#1 to ID#2, which tells the robot crossed the red line, is not considered for explaining the back-propagation. Getting ID#2 means the robot is deterministically in Sector #2 and the uncertainty P3 shrinks to P3*. P3 does not represent the uncertainty any more but P3* does. Therefore, the previous step's uncertainty P2 is not correct. From the inverse transition I32, we can find P2*, a subset of P2 which would give P3* only. Especially, it helps in reducing the uncertainty of the previous steps in which the uncertainty ellipsoid belongs to a sector (no part of the ellipsoid can be trimmed out from the IRID information), and the IRID information is not effective at all.

By repeating this back-propagation whenever available, the uncertainly region becomes much smaller than simply being trimmed. Mathematically, back-propagation is getting the covariance matrix, $\sum_p$ from the following equation:

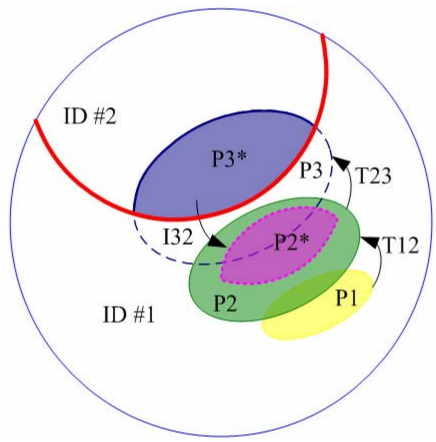

Fig. 4. Back-propagation.

$$\sum_{p} = \left(\nabla_{p} f\right)^{-1} \left(\sum_{p'} - \nabla_{\Delta} f \cdot \sum_{\Delta} \cdot \nabla_{\Delta} f^{T}\right) \left(\nabla_{p} f^{T}\right)^{-1} \tag{12}$$

Similar to the uncertainty estimation, the back propagation is implemented discretely. It can be done very simply by adding one more variable for each configuration. The variable represents the parent of the configuration. If a configuration becomes invalid because it does not belong to a sector, then its parent configuration also becomes invalid. So, the parent configuration will be updated from (9)-(11) but with only valid samples.

All three ways of utilizing the coded infrared light information (simple trimming, the instantaneous change of the ID and the back-propagation) are used in order to continuously make the uncertainty region smaller.

4. Experiment

The most important feature of the coded infrared light is its highly deterministic characteristic of receiving the identification (unique infrared light pulses) depending on where the receiver is located. A supervisory controller is used with several LEDs which controls the firing sequence for anti-collision and for modulation of the light.

Four IR emitters are used with unique IDs so the workspace is divided into 14 sectors. The robot refollowing figure (Fig. 5) shows the sector with its unique identification represented by color. The IR emitters are installed at 2m high from the floor. Each emitter covers a region with approximately 0.8m in radius. Even though the area is not perfectly circular, the location of the corresponding sector to each of the identifications is deterministically known. Therefore, it is possible to decide the region in which the robot is represented in global coordinates.

As shown in Fig. 6, a mobile robot with the receiver is used for experiments. The robot controller gets both the encoder and the coded infrared light information while it is moving. The configuration of the robot is estimated in real time.

Experimental results are shown in the following figures, which clearly show the benefits of combining the identification information with dead-reckoning. Fig. 7 shows the robot configurations from the encoder information (dead-reckoning) only and those from the proposed method which combines the encoder and IRID information. The values for the error constants are experimentally established by performing and analyzing representative movements of the robot as in Martinelli et al. [11]. The robot started on an arc where the robot began getting the coded infrared lightinformation (yellow). As the robot moves while getting the same coded infrared light, the uncertainty grows but not as rapidly as the case without using the coded infrared light information. Then, the robot gets a different coded infrared light (pink) so

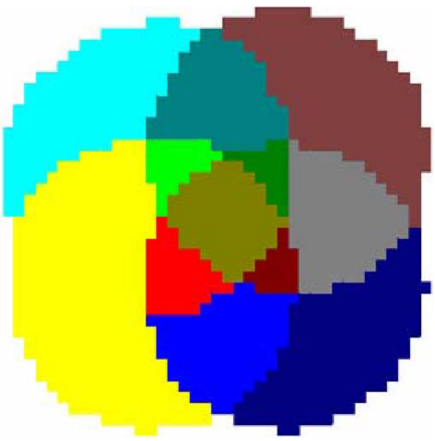

Fig. 5. Measured sector with four coded infrared lights.

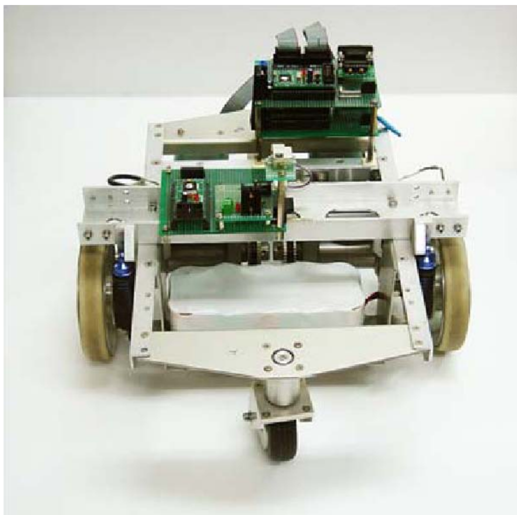

Fig. 6. Mobile robot with coded infrared light receiver.

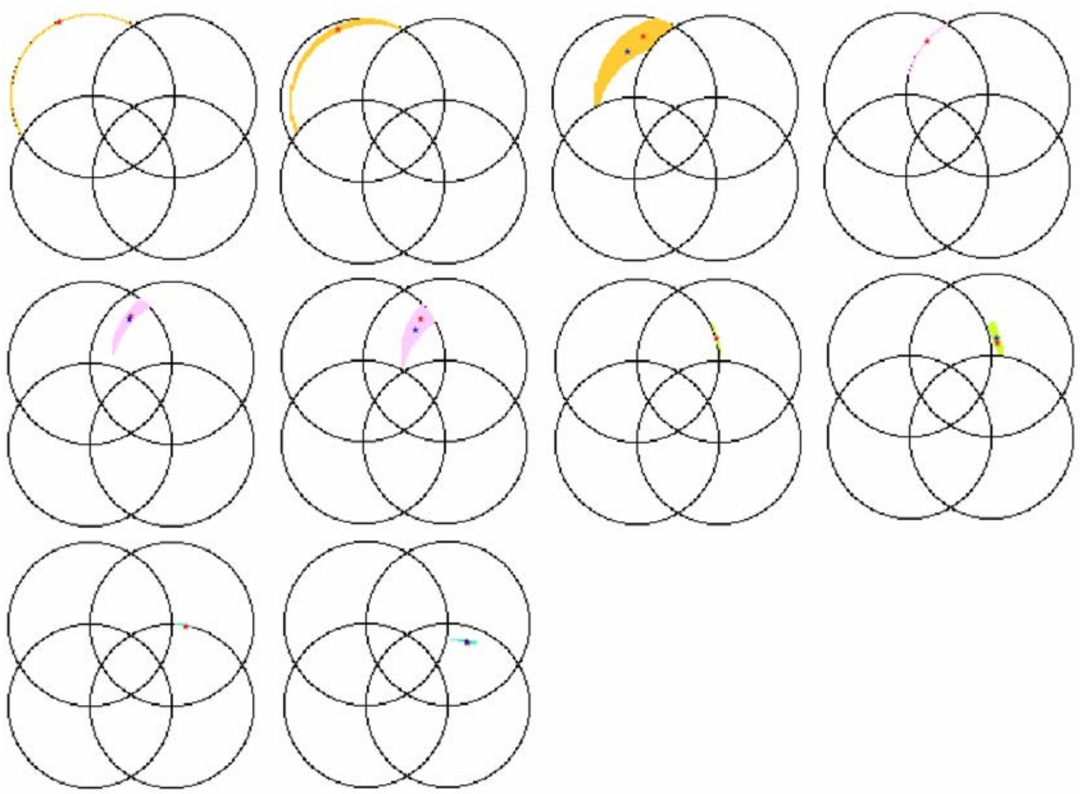

Fig. 7. Uncertainty of the robot configuration according to the robot movement and coded infrared light information.

that the uncertainty resides in the neighbor sector. The uncertainty becomes much smaller whenever it moves into another sector and the ultimate goal is to reset the error. As mentioned in Section III, even if the robot keeps moving in a sector while getting only one coded infrared light, the uncertainty does not diverge but gets even smaller because it is repeatedly trimmed. The red star mark in the uncertainty represents the position of the robot estimated from dead-reckoning. The blue one is the centroid of the uncertainty region, which represents the estimated location of the robot based on the encoder and IRID information.

Fig. 8 shows the number of cells in uncertainty with respect to time. The number of cells is simply regarded as the size of the uncertainty. The robot passed three different sectors. At steps #19, #37, #45, the size abruptly becomes much smaller as the change of the ID is detected and the robot's possible location is on a part of an arc. We can see that the uncertainty does not grow continuously even while in a same sector. It is also clearly shown that the uncertainty is

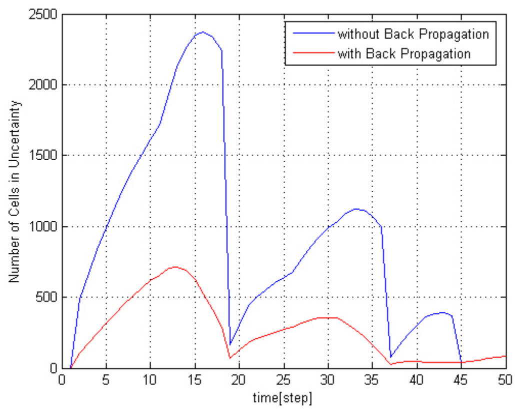

Fig. 8. Uncertainty area change.

much smaller with back-propagation.

Fig. 9 shows the result of dead-reckoning (Encoder), estimated configurations combined with coded infrared light (with and without back propagation) and the actual configuration. The proposed estimation may not provide a continuous path, especially when the robot crosses the border, because it is the

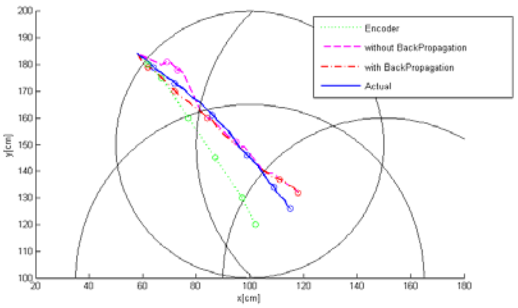

Fig. 9. Comparison of robot configuration.

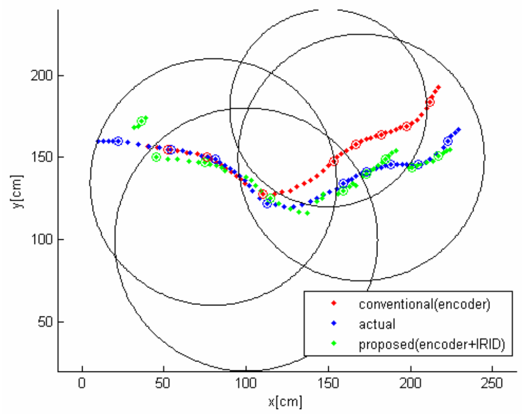

Fig. 10. Estimated configurations (case 1).

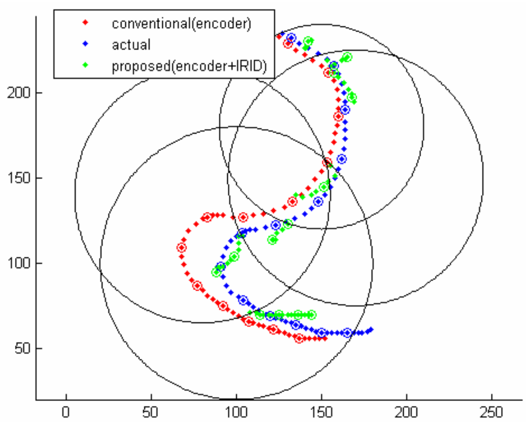

Fig. 11. Estimated configurations (case 2).

centroid of the uncertainty and the uncertainty becomes a part of an arc at that moment.

Figs. 10 and 11 also show the difference of results with and without using the coded infrared light information after the robot has passed several sectors. The difference from the actual path is much smaller with the proposed method. However, by reducing the large amount of error whenever it crosses the border of the sectors, the estimated configuration may not always be continuous, as shown in those two figures.

5. Conclusion

This paper introduces a localization scheme using coded infrared light as an artificial landmark. Coded infrared light is built with infrared emitters and photo transistors. It showed highly deterministic characteristics. Dead-reckoning result is combined with the coded infrared light information in order to reduce the uncertainty of the robot configuration. Three different ways of utilizing the coded infrared light information are introduced. Experimental results show the effectiveness of the proposed method.

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