Autonomous Indoor Mobile Robot Navigation by detecting Fluorescent Tubes

Fabien LAUNAY   Akihisa OHYA   Shin'ichi YUTA

Intelligent Robot Laboratory, University of Tsukuba
1-1-1 Tennoudai, Tsukuba, Ibaraki 305-8573 JAPAN
{launay,ohya,yuta}@roboken.esys.tsukuba.ac.jp

Abstract

This paper proposes an indoor navigation system for an autonomous mobile robot including the teaching of its environment. The self-localization of the vehicle is done by detecting the position and orientation of fluorescent tubes located above it's desired path thanks to a camera pointing to the ceiling.

A map of the lights based on odometry data is built in advance by the robot guided by an operator. Then a graphic user interface is used to define the trajectory the robot must follow with respect to the lights. While the robot is moving, the position and orientation of the lights it detects are compared to the map values, which enables the vehicle to cancel odometry errors.

1 Introduction

When a wheel type mobile robot navigates on a two dimensional plane, it can use sensors to know its relative localization by summing elementary displacements provided by incremental encoders mounted on its wheels. The main default of this method known as odometry is that its estimation error tends to increase unboundedly[1]. For long distance navigation, odometry and other dead reckoning solutions may be supported by an absolute localization technique providing position information with a low frequency.

Absolute localization in indoor navigation using landmarks located on the ground or on the walls is sometimes difficult to implement since different objects can obstruct them. Therefore a navigation system based on ceiling landmark recognition can be thought as an alternative to this issue.

The navigation system we developed consists in two steps. In the first step, the vehicle is provided with a map of the ceiling lights. Building such a map by hand quickly becomes a heavy task as its size grows. Instead, the robot is guided manually under each light and builds the map automatically. The second step consists in defining a navigation path for the vehicle and enabling its position and orientation correction whenever it detects a light recorded previously in the map.

Since the map built by the robot is based on odometry whose estimation error grows unboundedly, the position and orientation of the lights in the map do not correspond to the reality. However, if the trajectory to be followed by the vehicle during the navigation process is defined appropriately above this distorted map, it will be possible for the robot to move along any desired trajectory in the real world. A GUI has been developed in order to facilitate this map-based path definition process.

We equipped a mobile robot with a camera pointing to the ceiling. During the navigation process, when a light is detected, the robot calculates the position and the orientation of this landmark in its own reference and thanks to a map of the lights built in advance, it can estimate its absolute position and orientation with respect to its map.

We define the *pose* of an object as its position and orientation with respect to a given referential.

2 Related work

The idea of using lights as landmarks for indoor navigation is not new. Hashino[2] developed a fluorescent light sensor in order to detect the inclination angle between an unmanned vehicle and a fluorescent lamp attached to the ceiling. The objective was to carry out the main part of the process by hardware logic circuit.

Instead of lights, openings in the ceiling for aerations have also been used as landmarks to track. Oota *et al.*[3] based this tracking on edge detection, whereas Fukuda[4] developed a more complex system using fuzzy template matching. Hashiba *et al.*[5] used the development images of the ceiling to propose a motion planning method. More recently, Amat *et al.*[6] presented a vision based navigation system using several fluorescent light tubes located in captured images whose absolute *pose* estimation accuracy is better than a GPS system.

One advantage of the system proposed here is its low memory and processing speed requirements that make its implementation possible on a robot with limited image-processing hardware. Moreover, our navigation system includes a landmarks map construction process entirely based on the robot's odometry data. The development of a GUI enables the connection between the lights map produced during the teaching process, and the autonomous robot navigation, which results in a complete navigation system. This is the main difference with the previous works which either assume the knowledge of the ceiling landmarks' exact pose thanks to CAD data of building maps, or require the absolute vehicle pose to be entered manually and periodically during the landmarks map construction so as to cancel odometry errors.

a b c

Figure 1: Target environment consisting of lights of different shapes in corridors exposed to luminosity variations due to sunning.

3 Lights' map building

In order to cancel odometry errors whenever a light is detected, the robot needs to know in advance the *pose* in a given referential of the lights under which it is supposed to navigate.

Since we are aiming at long distance autonomous indoor navigation, the size of the landmarks map is unbounded. Building such a map manually becomes a heavy task for the operator and we believe that an autonomous mobile robot can cope with this issue.

During the learning process, the vehicle equipped with a camera pointing to the ceiling is guided manually under each light and adds landmark information to the map whenever a new light appears above its path. This human assisted map building is the first step of our research concerning landmarks map building. We want to change it to a fully autonomous map building system. As the image-processing involved during the learning process is identical to the one used during the navigation, we will present the feature extraction method in sections 5 and 6.

Once the teaching phase is completed, the robot holds a map of the lights that can be used later for the autonomous navigation process.

4 Dealing with a robot-made map

4.1 Odometry error's influence on the map

Asking the robot to build a map implies dealing with odometry errors that will occur during the learning process itself. As the robot will be guided under new lights, because of the accumulation of odometry errors, the *pose* of the landmarks recorded in the map will become more and more different from the values corresponding to the real world.

Several maps of the environment represented in Fig.1 are given in Fig.2. The odometry data recorded by the robot during the learning process has also been represented for one of the maps.

The same robot was used for all the maps shown in Fig.2, and special care was taken to set the initial robot *pose* identical for each experiment. The difference appearing between each of these maps has therefore little to do with the initial robot orientation, but is rather illustrating the problem of the random odometry error drift.

4.2 Usage of the map

Only one map is needed by the robot to correct its *pose* during the navigation process. Whenever the robot detects a light learnt previously, it corrects its absolute *pose*[1] by using the landmark's information recorded in the map. Since the map contents don't correspond to the values of the real world, the trajectory of the robot has to be specified according to the *pose* of the lights in the map, and not according to

[1]By the term *absolute pose*, we mean the absolute *pose* of the vehicle with respect to the referential of its map, which differs from the absolute *pose* of the robot in the real world.

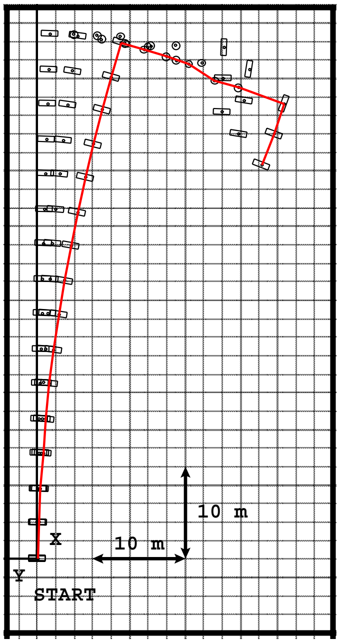

Figure 2: Several maps of the environment represented Fig.1 built by the same robot. Rectangles and circles represent lights of different shapes.

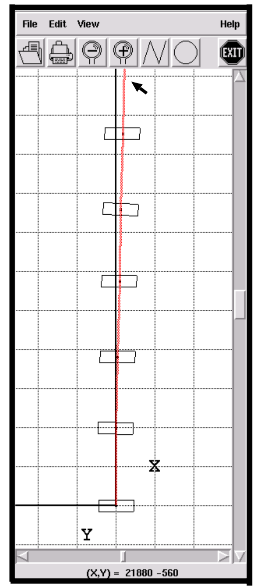

Figure 3: Screenshot of the GUI interface used to specify a path to the robot using one of the maps represented in Fig.2. This trajectory corresponds to a straight line in the middle of the corridor shown in Fig.1.a. Rectangles represent the fluorescent lights learnt during the teaching process.

the trajectory we want the robot to follow in its real environment.

For example, if the mobile robot's task is to navigate right below a straight corridor's lights, the robot won't be requested to follow a straight line along the middle of the corridor. Instead of this simple motion command, the robot will have to trace every segment which connects the projection on the ground of the center of two successive lights. This is illustrated in Fig.3 where a zoom of the trajectory specified to the robot appears in dotted line.

A GUI has been developed in Tcl/Tk in order to specify easily different types of trajectories with respect to the map learnt by the robot. This GUI can also be used on-line in order to follow the evolution of the robot in real time on the landmarks map during the learning and navigation processes.

5 Fluorescent tube detection

5.1 Fluorescent tube model

It is natural to think of fluorescent tube as a natural landmark for a vision-based process aimed at improving the localization of a mobile robot in an indoor environment. Indeed, problems such as dirt, shadows, light reflection on the ground, or obstruction of the landmarks usually do not appear in this case.

One advantage of fluorescent tubes compared to other possible landmarks located on the ceiling is that once they are switched on, their recognition in an image can be performed with a very simple image-processing algorithm since they are the only bright elements that are permanently found in such a place.

If a 256 grey levels image containing a fluorescent tube is binarized with an appropriate threshold $0 \leq T \leq 255$, the only element that remains after this operation is a rectangular shape. Fig.4.a shows a typical camera image of the ceiling of a corridor containing a fluorescent light. The axis of the camera is perpendicular to the ceiling. Shown in (b) is the binarized image of (a). If we suppose that the distance between the camera and the ceiling remains constant and that no more than one light at a time can be seen by the camera located on the top of the robot, a fluorescent tube can be modeled by a given area S_0 in a thresholded image of the ceiling.

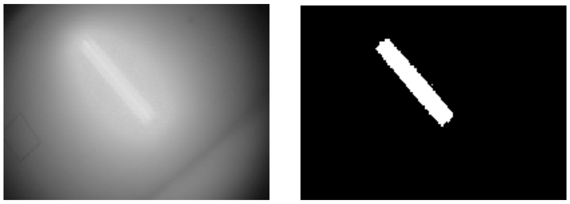

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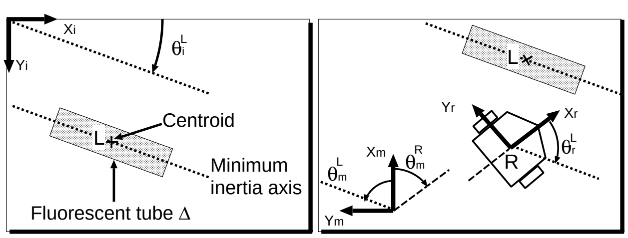
Figure 4: (a) Sample image of a fluorescent light, (b) binarized image.

5.2 Fluorescent light detection process

Using odometry, the robot is able to know when it gets close to a light recorded in its map by comparing in a close loop its actual estimated position to the different locations of the lights in the map. Once it gets close to one of them, it starts taking images of the ceiling and binarizing them with the threshold T used to memorize the corresponding light during the learning process.

This step is repeated until the number N of pixels brighter than T becomes close to S_0. When it happens to be true and when the binarized shape does not touch any border of the image, the detection algorithm is stopped and further image-processing is done as explained in the next section.

In order to discard too bright images, the detection algorithm increases automatically the threshold. Moreover, because the intensity of the light emitted by fluorescent tubes changes with a frequency corresponding to the cycle of electric power, the threshold has to be decreased automatically if $N \leq S_0$, so that the robot has a chance to detect the light located above it even if this one appears darker than usual.



a b

Figure 5: (a) Moment-based features of a fluorescent tube, (b) definition of the robot local reference.

a b c d

Figure 6: (a) Fluorescent light located on the border of the image. (a),(b) original and binarized images before distortion correction, (c),(d) after distortion correction.

6 Estimation of the absolute position

The detection algorithm has been designed so that the *pose* of the fluorescent tube is calculated only if the whole shape of the tube appears in the captured image. Therefore it is possible to calculate the location of the tube's centroid L in the image as well as the orientation of its least moment of inertia axis θ_i^L using the moment-based features of the binarized shape Δ represented in Fig.5.a.

$$\begin{cases} X_i^L &= \frac{1}{N}\sum_{(x,y)\in\Delta} x \\ Y_i^L &= \frac{1}{N}\sum_{(x,y)\in\Delta} y \\ \theta_i^L &= \frac{1}{2}\arctan\left\{\frac{2\mu_{1,1}}{\mu_{2,0}-\mu_{0,2}}\right\} \end{cases}$$

Where $\mu_{p,q} = \sum_{(x,y)\in\Delta}(x - X_i^L)^p(y - Y_i^L)^q$ stands for the (p,q) order central moments of the shape Δ (N has been defined in the previous section). In the case of non-rectangular fluorescent lights, the orientation of the binarized shape is ignored.

The above operations are evaluated on the image after its distortion has been corrected. Indeed, image distortion becomes a major issue whenever a light detected by the robot is not located in the center of the image. In this case, the error on the shape orientation can reach 5 degrees. Fig.6 shows an image taken by the robot when it is not exactly below the light and when its Y_r axis defined in Fig5.b was parallel to the light's main axis. The binarized shapes, before and after distortion correction are also given.

By converting the previous values into the robot's local reference $(X_r^L, Y_r^L, \theta_r^L)$ [2] defined in Fig.5.b and using the *pose* of the light in the the map $(X_m^L, Y_m^L, \theta_m^L)$, it is possible to determine the absolute *pose* of the vehicle in the map referential $(X_m^R, Y_m^R, \theta_m^R)$. Once the

[2]The relation between $(X_i^L, Y_i^L, \theta_i^L)$ and (X_r, Y_r, θ_r^L) is not given explicitly here. It involves the *pose* of the camera with respect to the robot's local referential, the distance between the camera and the ceiling as well as the flattening rate of the image.

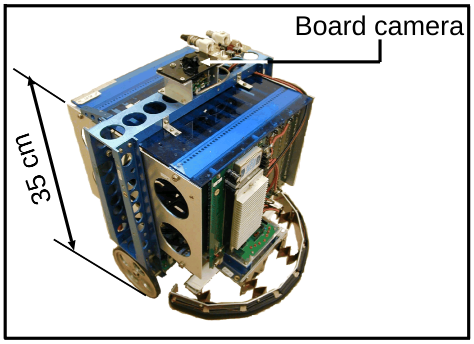


Figure 7: The YAMABICO robot with its top board camera.

absolute *pose* is obtained, it can be fused with the estimation of the robot's relative *pose* provided by odometry at the moment when the image was taken.

Since the calculation of the vehicle's absolute *pose* estimation from an image is time consuming, retroactive data fusion with odometry data is necessary[7]. This function is achieved thanks to an algorithm developed previously in our laboratory[8].

7 Implementation and experiment

We implemented this system on the YAMABICO robot[9] developed in our laboratory and shown in Fig.7. The sensors used by the robot to estimate its *pose* are optical encoders mounted on the wheels and a board CCD black and white camera facing the ceiling. The navigation program and the absolute *pose* estimation program based on fluorescent lights are implemented as independent modules. It is therefore possible to run simultaneously other *pose* estimation programs based on different landmarks and using different sensors without any modification of the existing vision-based module.

The validity of the proposed navigation system has been shown by making experiments in the corridor shown in Fig.1 at different times of the day. The robot was first guided under each light in order to build the landmarks map. Then it used the map and a path defined above it to navigate in the middle of the corridor until a goal point. The maximum speed of the robot was 35 cm/s and total distance on one way was about 50 meters. On the robot's path 24 fluorescent tubes of different shapes were present, separated by a distance varying from 2.2 meters to 4.5 meters.

The experimental results of one of those experiments are shown in Fig.8 where the bold line corresponds to the odometry data of the robot. The map used by the robot for this experiment and the corresponding path are represented partially in Fig.3. When a light is found, the absolute *pose* of the robot is corrected after a certain delay represented by the distance between the marks '+' and '×' respectively. The table below gives average computing times for the different steps of the image-processing algorithm. All image-processing is done on board by a vision module developed in our laboratory which is equipped with a 20MHz Thomson T805 processor.

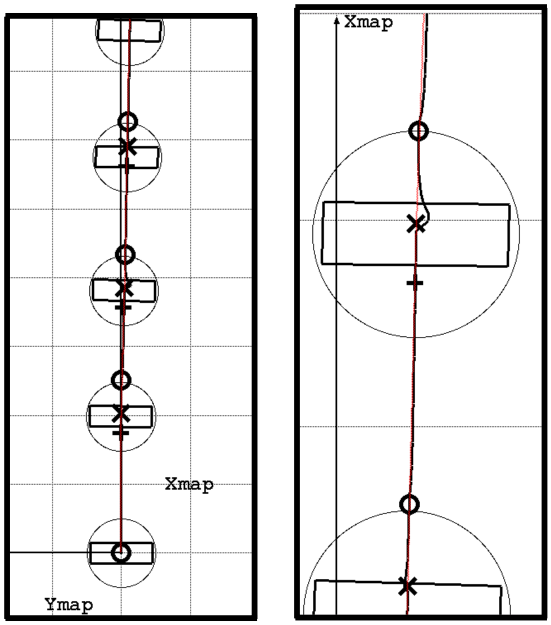
Table 1: Average computing time for the different steps of the image-processing algorithm. The image size is 756×238 pixels.

Capture	0.03 s
Distortion correction, thresholding	1.82 s
Borders scanning	0.19 s
Light position calculation	0.06 s
Light orientation calculation	0.13 s
TOTAL	2.23 s

For better understanding of the navigation process, the robot was asked in this experiment to enter the next segment on its trajectory one meter after passing the light corresponding to the end point of the previous segment. The point when the robot changes its trajectory to enter a new segment is represented by a '∘' in Fig.8.

Because the odometry errors that occur during the building of the map remain small for short distances, the relative angle between two successive segments used to specify the robot's path remains acceptable (in average less than 2 degrees), even when the robot is far from the map's origin. This interesting property could be observed during the experiments where the vehicle slightly moved away from the center line of the corridor when it entered a new segment, which lead to small *pose* correction when the next landmark was detected.

More generally, the robot could cope with lights switched off and variations in the lightening conditions of the corridor since it could adapt automatically the threshold to detect the lights.



a b

Figure 8: Odometry data of the robot correcting its trajectory using the detection of fluorescent lights in a corridor. (a) Zoom on the first lights, (b)zoom on one light. The circular disc corresponds to the light detection area. '+': light detected, '×': *pose* correction, '∘': the robot enters a new segment.

8 Conclusions and future work

In this paper, we presented a complete navigation system that enables a mobile robot to achieve long distance indoor navigation thanks to lights located above its trajectory.

In a first step, the robot builds in advance a map of these landmarks that can be detected easily. Once the map-building process is finished, the trajectory the vehicle has to follow is defined above the previous map thanks to a GUI in order to handle the errors included during the learning procedure. In the second step, the robot looks for the lights it has learnt and fuses its new estimated absolute *pose* with odometry whenever a landmark is detected during the navigation process.

Experiments show that it is possible for the robot to navigate with precision on a long distance without any other position or orientation sensing system than optical encoders and a black and white camera pointing to the ceiling.

The landmarks map building we presented needs at present a human operator to guide the robot during the learning process. We want to convert it to a fully autonomous map building system. Future work will also address how to extend the navigation system to several robots moving along corridors.

Because of the accumulation of odometry errors while the robot is guided for the first time throughout its environment, a light detected several times should not be recorded more than once in the map. Since the *pose* of the light computed by the robot in a global referential will be different whenever the vehicle re-encounters the same landmark during the learning process, further work involving loop trajectories management has to be done to cope with this issue.

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