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Estimation of Relative Self-Localization Based On Natural Landmark and an Improved SURF

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***Abstract*—**It is important for an autonomous mobile robot to know where it is in any time in an indoor environment. In this paper, we design a relative self-localization algorithm. The algorithm compare the interest point in two images and compute the relative displacement and orientation to determent the posture. Firstly, we use the SURF algorithm to extract the interest points of the ceiling. Second, in order to reduce amount of calculation, a replacement SURF is used to extract orientation and description of the interest points. At last, according to the transformation of the interest points in two images, the relative self-localization of the mobile robot will be estimated greatly.

***Keywords*—**Relative Self-Localization Posture, SURF, Natural Landmark, Interest Point.

I. Introduction

THE indoor self-localization for mobile robots is a mandatory task in accomplishing full autonomy during navigation. Various solutions in the robotics community have been developed in order to solve the self-localization problem. The solutions can be categorized into two groups: relative localization (dead-reckoning) and absolute localization [5].

In absolute localization, the location of a robot can be determined by detecting and recognizing the landmarks in the environment. The location is estimated from the known coordinates of landmarks, based on the ranging and/or bearing measurements between the robot and the landmarks. Absolute localization methods are based on exteroceptive sensors information. These methods yield a stable locating error but are more complex and costly in terms of computation time. The most important, it is very difficult if using natural landmark.

Relative localization is applied in most wheeled mobile robots and odometry (or dead reckoning) is commonly used to calculate the robot positions from a starting reference point, because of its ease of use, efficient data output and low cost. The landmarks do not need to design artificial landmark.

With the development of science and technology, visual positioning method plays an important role in the self-localization of autonomous service mobile robots working in indoor environments, as in [8]. Visual image data has the potential to disambiguate objects for localization, as it provides high resolution, and additional information such as color, texture, and shape [4]. Generally, the knowledge existing in indoor environments can be used to determine the position and orientation of a mobile robot via visual positioning approaches, as in [8]. Indeed, the selected visual features have apparent influence on the performance of the positioning approach.

In an indoor environment, the floor is usually assumed to be planar. The ceiling is parallel with the floor. In our research, a camera is mounted on the top of a mobile robot working on the floor. Its orientation is upright and directs to the ceiling. The design of the robot is shown in Fig. 1.

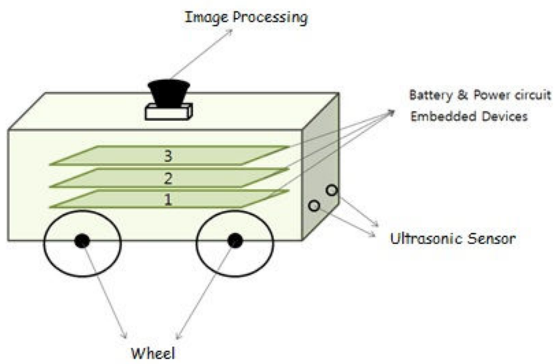

Fig. 1 Autonomous robot system the robot contain a camera, a DSP board for image processing, and two battery (one for DSP board, one for robot)

This paper is organized as follows. In Section II, we introduce an overview of our relative localization algorithm, and the reason that using the replacement algorithm. In Section III, we describe processing of the SURF and the replacement algorithm. In Section IV, we describe the relative self-localization algorithm detail. We present the experimental setup and results in Section V and the conclusion in Section VI.

II. The Constitution of the Algorithm

Generally, feature-based methods are often very efficient, providing that some features can be found. According to the information of the features, the position of the robot can be determined. In this section, we describe our relative localization system, which is shown in Fig. 2. A series of interest point I (feature point) is extracted using image processing. These interest points have three coordinate: a global coordinate, two relative coordinate in two images (before and after moving). The relative self-localization is calculated using changes of coordinate of interest point.

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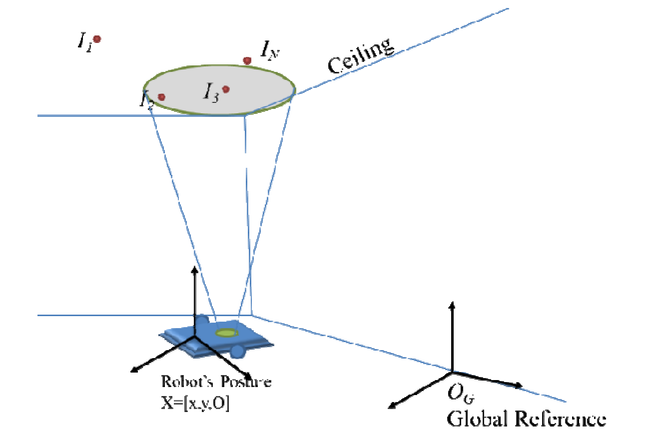

Fig. 2 Vision self-localization system the global coordinate origin O_G, the robot's current posture X_e, the interest point I_i

At 2002, Lowe presented SIFT (Scale Invariant Feature Transform) [1] for extracting distinctive invariant features from images. The features can be invariant to image scale and rotation. Then SIFT [1] was widely used in image mosaic, recognition, retrieval and etc. At 2004, Ke and Sukthankar used PCA (Principal Components Analysis) to normalize gradient patch instead of histograms for interest point's orientation [3], [6]. They showed that PCA-based local descriptors were also distinctive and robust to image deformations, as in [6]. But the methods of extracting robust features were still very slow. At 2006, Bay and Tuytelaars proposed SURF (Speeded Up Robust Features) which used integral images for image convolutions and used Fast-Hessian matrix to detect interest point [2], [6]. Their experiments turned out that it was faster and it works well.

Normally, the SURF is the fastest one with good performance as the same as the SIFT. The SURF algorithm mainly contains two parts: interest points extract, orientation and descriptor of the interest points extract. In the part of interest point extracting, the SURF use integral image and box filter to replace Gaussian filter and DoG (Difference of Gaussian) in the SIFT. Due to the use of integral images, the SURF filters the stack using a box filter approximation of second-order Gaussian partial derivatives, since integral images allow the computation of rectangular box filters in near constant time, as in [6]. In our research, we use this part of the SURF completely.

However, in the part of orientation and descriptor of the interest points extracting, the SURF scan the neighborhood region for interest point twice. After first scan and calculation, the orientation of the interest point is extracted. The second scan, according to orientation of the interest point, the descriptor is extracted. In indoor environments, the ceiling is parallel with the floor. Additionally, during the moving of the robot, the images just need translation and rotation. The image is not scaled and illumination is not changed. In low-speed devices, such as DSP board, the twice scans and calculation increased the amount of computation. So, the SURF is seemed to be complex and waste time.

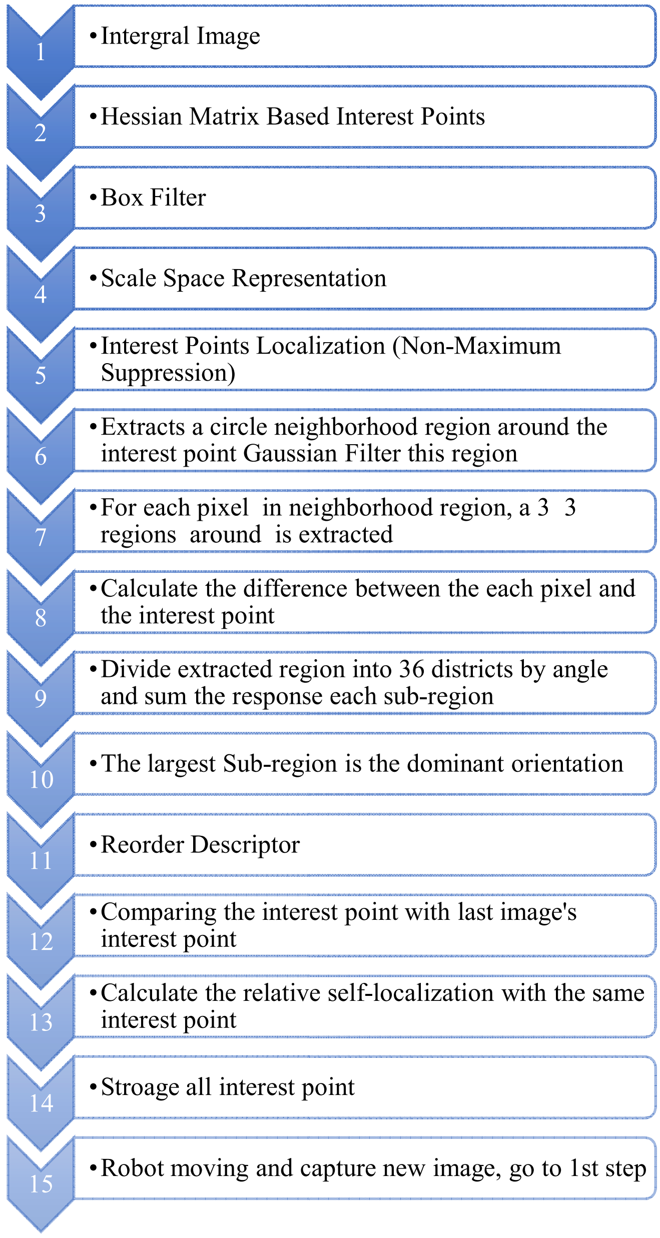

Fig. 3 Flow chart of the algorithm it contain 15 step

Then, a simple replacement algorithm [7] is proposed for orientation and descriptor of the interest point. In our research, we use a replacement method to obtain the orientation and descriptor. The replacement method only scan neighborhood region of interest points once.

In short, the relative self-localization algorithm contains three parts. First, the interest points of the ceiling are extracted using the SURF. Second, the orientation and descriptor of the interest points are extracted using improved SURF. At last, the relative self-localization algorithm is proposed. The overall algorithm for relative self-localization is presented in the flowchart in Fig. 3. In next two sections, we will description the process for the algorithm.

III. The SURF and the Replacement Algorithm

In this section, we describe the execution of the SURF and the replacement algorithm.

A. Interest Point Extraction

The SURF [2] uses integral image for fast implementation of box type convolution filters. The entry of an integral image $I_{\sum}(x)$ at location $X=(x,y)$ represents the sum of all pixels in the input image *I* of a rectangular region formed by the point x and origin, $I_{\sum}(x)=\sum_{i=0}^{i\le x}\sum_{j=0}^{i\le y} I(x,y)$. With calculated $I_{\sum}$, it only takes four additions to calculate the sum of the intensities over any upright, rectangular area, independent of its size. The SURF [2] uses a very basic Hessian Matrix approximation. This lends SURF to the use of integral images, which reduces the computation time drastically.

The interest point extraction contain: Integral image, Hessian Matrix Based Interest Points, Box Filter, Scale Space Representation, and Non-Maximum Suppression. The flow chart is shown in Fig. 3.

B. Orientation and Descriptor Extraction

As discussed in Section II, a replacement algorithm [7] is proposed.

The replacement algorithm contains 6 parts, which is shown in Fig. 3 from step 6th to step 11th. The detailed process is shown in [7]. It only scan the neighborhood of the extracted interest points once comparisons with the SURF.

IV. Design of the Self-Localization Algorithm

This section describes the relative self-localization algorithm and provides an error analysis. For relative self-localization, the robot uses the posture of interest points, its last posture, and the geometric relationship between the last and current postures. Fig. 4 shows the method. There are two images that have the same interest points. As shown in the Fig. 4, there are two rectangles representing the two images. The center of the image represents the localization of the robot: one for the last posture and the other for the current one.

Assume that there are *N* ($N \geq 2$) same interest points in two images. Let P_{si} and P_{ei} be the *i*-th interest point, where $i=1,\ldots,N$. If *i* is the same, then P_{si} and P_{ei} represent the same interest point in the original image and the current one, respectively.

A new coordinate system C_s about the interest point is created. The x-axis of the coordinate system is the relative orientation of the interest point. The global orientation of the interest point does not change in a short period of time.

Let $X_e=(x_e,y_e,\theta_e)$ be the final global posture (current image) of the robot, where θ_e represents the current orientation of the robot. Then a new coordinate system is created. Here the x-axis of the coordinate system is the global orientation of the robot. As the relative posture of the interest point $P_{ei}=(x_{pei},y_{pei},\theta_{pei})$ in the current image (current image), the coordinate of P_{ei} in the new coordinate system is

$$(x_{pe}',y_{pe}')=\left(x_{pei}-\frac{width}{2},\frac{height}{2}-y_{pei}\right) \tag{1}$$

where *width* and *height* represent the width and height of the image.

Through the translation of the coordinate system from the center to the interest point, the center of the new coordinate system is

$$(-x_{pe}',-y_{pe}')$$

Then the following function is used to rotate the coordinate system:

$$\begin{bmatrix}\hat{y}\\ \hat{x}\end{bmatrix}=\begin{bmatrix}\cos\theta_{pei} & -\sin\theta_{pei}\\ \sin\theta_{pei} & \cos\theta_{pei}\end{bmatrix}\begin{bmatrix}-y_{pe}'\\ -x_{pe}'\end{bmatrix} \tag{2}$$

The orientation of the coordinate system (X-axis) is changed to relative orientation of the interest point in the current image.

Let $P_{si}=(x_{psi},y_{psi},\theta_{psi})$ be the relative orientation of the interest point in start image. The P_{si} and the P_{ei} are the same interest point.

Here the following function is used to inverse the coordinate system:

$$\begin{bmatrix}y_{ps}'\\ x_{ps}'\end{bmatrix}=\begin{bmatrix}\cos(-\theta_{psi}) & -\sin(-\theta_{psi})\\ \sin(-\theta_{psi}) & \cos(-\theta_{psi})\end{bmatrix}\begin{bmatrix}\hat{y}\\ \hat{x}\end{bmatrix} \tag{3}$$

The orientation of the coordinate system (X-axis) is changed to relative orientation of the interest point in the start image (last image). The coordinate (x_{ps}',y_{ps}') is the localization of the robot in the new coordinate system C_s.

Then the coordinate system is translation from interest point to the center point in start image (last localization of the robot). The new coordinate of the robot is

$$(x_{ps}'+x_{psi}-\frac{width}{2},y_{ps}'-y_{psi}+\frac{height}{2})$$

Here (x_{ps}'',y_{ps}'') represent the above coordinate. Let

$X_s = (x_s, y_s, \theta_s)$ be the start global posture (last image) of the robot.

The coordinate is rotated by θ_s angle again.

$$\begin{bmatrix} y_{ps}''' \\ x_{ps}''' \end{bmatrix} = \begin{bmatrix} \cos\theta_s & -\sin\theta_s \\ \sin\theta_s & \cos\theta_s \end{bmatrix} \begin{bmatrix} y_{ps}'' \\ x_{ps}'' \end{bmatrix} \quad (4)$$

Finally, the current global coordinate of the robot is

$$\begin{bmatrix} y_e \\ x_e \end{bmatrix} = \begin{bmatrix} y_{ps}''' \\ x_{ps}''' \end{bmatrix} + \begin{bmatrix} y_s \\ x_s \end{bmatrix} \quad (5)$$

and the current orientation of the robot is

$$\theta_e = \theta_s + \theta_{psi} - \theta_{pei} \quad (6)$$

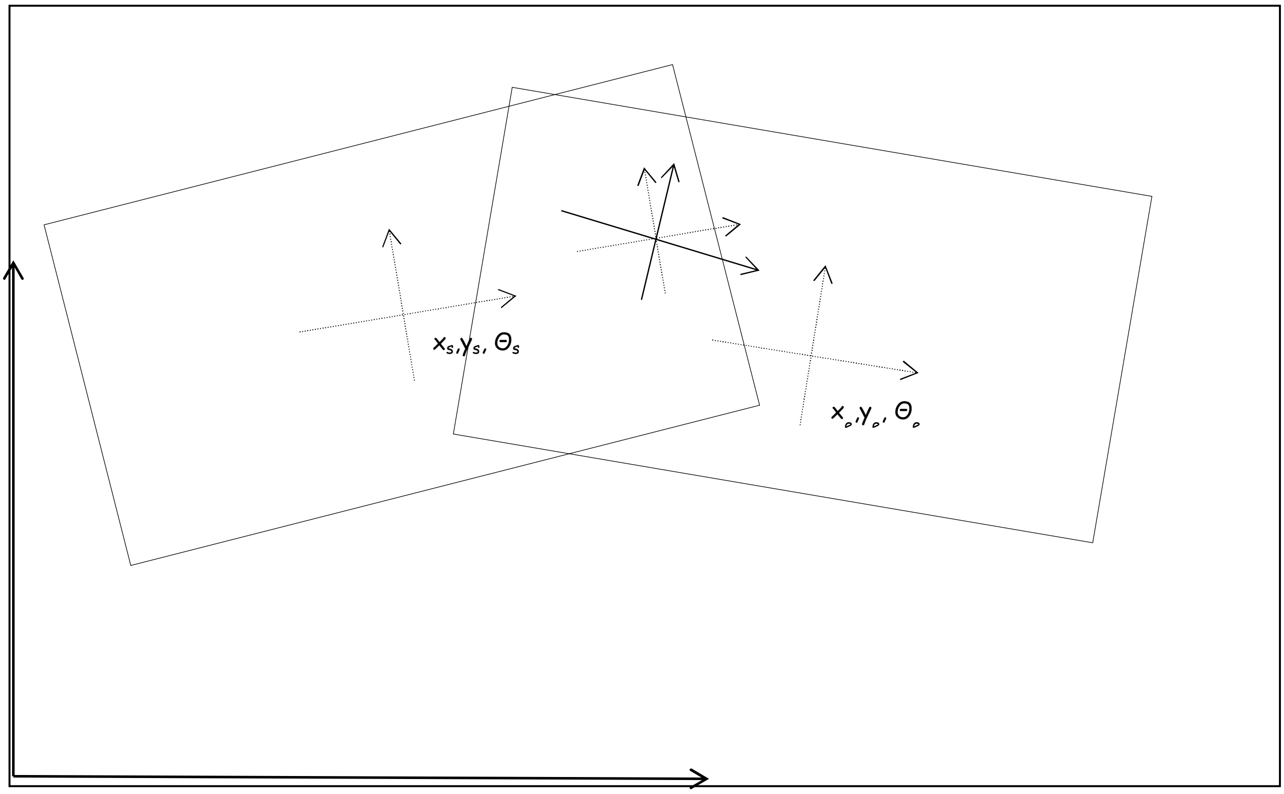

Fig. 4 Self-localization estimation method two image (two rectangles) center points represent the last posture X_s and current posture X_e. Two images contain the same interest point. The relative orientation of the interest point is different

V. Simulation Result

The interest point extraction and orientation and descriptor of the interest point extraction are proven with some novel results [7]. We implemented the proposed algorithms using C in a DSP board (600MHz). When the robot moving slowly, it can process real time.

Currently, the self-localization estimation method is implemented in a personal computer using MATLAB. A simple example is shown in Fig. 5.

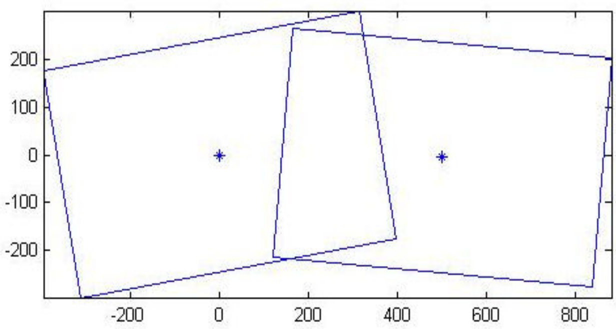

Fig. 5 Self-localization estimation result the last posture is (0, 0, 10º), the relative posture of the interest point in last image is (610, 40, 10º) the relative posture of the interest point in current image is (50, 20, 25º), the current posture is (501.1184, -5.8075, -5º)

In our experiment, the RMS (Root Mean Square) is used to find the error of the posture. Let $e(x, y, \theta)$ be the overall posture error of the current posture. The $e(x, y, \theta)$ is given by

$$e(x, y, \theta) = \sqrt{\frac{1}{N}\sum_{k=1}^{M}\left\|X_{ek} - \overline{X}_e\right\|^2} \tag{7}$$

where $\left\|X_{ek} - \overline{X}_e\right\|^2$ is the Euclidean distance between X_{ek} and $\overline{X}_e$. The $\overline{X}_e$ is the mean of the current posture X_{ek}.

The final localization is:

$$X_e = \overline{X}_e + e(x, y, \theta) \tag{8}$$

VI. Conclusion

We presented a novel relative self-localization for indoor mobile robots in vision localization system. The vision localization system only consists of a single camera. We proposed a replacement algorithm for extracting descriptor and orientation of the interest point, and relative self-localization algorithm. Using proposed method, the global static posture of the robot can be determined accurately and robustly. Simulation and experimental results show the validity and feasibility of the proposed algorithm. We therefore can add various application programs such as path planning and obstacle avoidance program.

In future studies, we plan an expansion to estimate the posture in a DSP board when robot moving. The proposed algorithm can solve the problem the problem of calculating a posture of a robot that move slowly.

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