Estimation of Relative Self-Localization for Indoor Mobile Robot and Its Error Analysis

Xing Xiong[1] and Byung-Jae Choi[2]

Ph.D and Prof
[1]GaleWing@gmail.com and [2]bjchoi@daegu.ac.kr

Abstract

The self-localization for a mobile robot is very important at indoor environments. In this paper, we propose a relative self-localization estimation algorithm based on relative locations and orientation changes of image features. We also analyze errors caused by a variety of factors to estimate the relative self-localization of a mobile robot and discuss a few techniques to remove them. The proposed relative self-localization algorithm is based on the facts that the global orientation and location of image features are not altered by changing of images. We show that the proposed algorithm is valuable through some simulation examples.

Keywords: *Mobile Robot, Self-localization, Image Feature, SLAM, SURF, SIFT*

1. Introduction

With the development of science and technology, mobile robots have been employed for a wide area of industrial applications including factory automation, medical assistance, and rehabilitation for the provision of new forms of services. The robots' self-localization recognition is becoming crucial. It has seemed as a good idea for GPS solving this problem. However the use of GPS is limited or is not feasible in indoor environments. Therefore the mobile robots require other methods for their self-localization.

As mentioned in [1], various solutions for the estimation of self-localization have been proposed in the field of robotics. They can be classified into two groups: relative (dead-reckoning) and absolute localization. Although the relative localization will cause unbounded accumulation of errors, its ease of use and low cost are considered noteworthy. In practice, common indoor environments do not have large spaces. Therefore, few mistakes could be avoided. Or in [1], some objects or landmarks whose absolute coordinates known are used for correcting self-localization of mobile robots. For reference, the objects or landmarks' coordinates could be known or obtained by SLAM (Simultaneous Localization and Mapping).

As shown in many researches [2], visual images have provided a lot of valuable information such as color, texture, and shape of objects. The information has the potential to help the robot to estimate its self-localization. In general, the data of indoor environments can be used to determine the position and orientation of a mobile robot through visual self-localization algorithms. For example, in [3-6], vision-based algorithms are used to estimate robot self-localization. In these papers, a few image-matching algorithms are referred. The image-matching algorithms play an important role for self-localization estimation. Some characteristics of SIFT (Scale Invariant Feature Transform), PCA (Principal Components Analysis)-SIFT and SURF (Speeded Up Robust Features) were compared in [7]. In this paper we propose a new algorithm to reduce computing time and complexity. The SURF is here employed for the extraction of interest points and an improved algorithm which was proposed in [8] is employed for interest points' orientation and descriptors' extraction. In this paper a relative self-localization algorithm is proposed to estimate a location of the robot and it is based on the changing of the location and orientation of image features. In practice, because of matching mistakes of interest points and pixels offset, the calculated self-localization contains errors and it needs to be corrected.

This paper is organized as follows: The relative self-localization method is in detail introduced in Section 2. Then, some errors caused by mistake matching interest points are discussed and corrected in Section 3. For verifying the effectiveness of the method, some simulation results are shown in Section 4. Finally, the concluding remarks are presented in Section5.

2. Relative Self-localization Method

According to the general theories mentioned in [1], the self-localization process based on landmark is composed of the following five stages in monocular vision: ① Image Acquisition from Current Robot Pose, ② Image Segmentation and Feature/Landmark Extraction, ③ Model Rendering, ④ Matching 2D Image and 3D-model Feature, and ⑤ Robot Pose Computation. In this paper, we propose a new algorithm based on interest points as nature landmarks for calculating self-localization. The self-localization process is composed of the following five stages: ① Interest Points Extracted, ② Interest points' Orientation and Descriptor Extracted, ③ Matching Interest Points, ④ Relative Localization Estimation and ⑤ Error Correction.

The relative localization system is described as shown in Figure 1. A series of interest points I_i (i = 1, 2, 3…N. N is the number of interest points) are extracted using SURF [7] for their efficiency. The interest points are not changed with time, image scale, blur and illumination. These interest points are considered nature landmark. For example, in Figure 2, the two images are captured on the ceiling before and after robot moving. The interest points (the circles) are extracted. From the two images in Figure 2, although the Figure 2(b) is an image after robot moving and is blurred, the most interest points have the same location in two images.

Then, the orientation and descriptors of interest points are extracted by an improved SURF algorithm [8] for fast calculation. The interest points are matched by Euclidean distance function. The less Euclidean distance, the more a similarity of two interest points. The matching results are shown in Figure 4.

These interest points all have three coordinates (x, y) and three directions Θ: a global coordinate (I_{Gi}), two relative coordinates (I_{1i} and I_{2i}) in two images (before and after moving). The relative self-localization is calculated by using transition of coordinates of the interest points. The center (mark as * in Figure 2) of image after robot moving represents the current location of the robot. The center of image before robot moving represents the last location of the robot. In fact, relative self-localization is the distance between the centers of two images. The current location of robot is transformed from dash coordinate system to solid coordinate system twice in Figure 3.

For example, the I_2 can be considered as a landmark in Figure 1 because the interest point I_2 is contained in two images. In practice, the global orientation and coordinate of I_2 are not changed by images. The current location of the robot is the center of current image. Its coordinate is transformed from current coordinate system (I_{22}) through I_2, to global coordinate I_{G2}, then to the last relative coordinate I_{12} by the following equation [1].

$$\begin{bmatrix} \hat{y} \\ \hat{x} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} y \\ x \end{bmatrix} \quad [1]$$

where (x, y) and $(\hat{x}, \hat{y})$ represent the coordinate of robot before and after coordinate system transformation in two images, respectively. The Θ represents the relative angle of coordinate system transformation in two images.

Therefore, for every interest point, the relative self-localization of mobile robot could be estimated through the transformation of two coordinate systems.

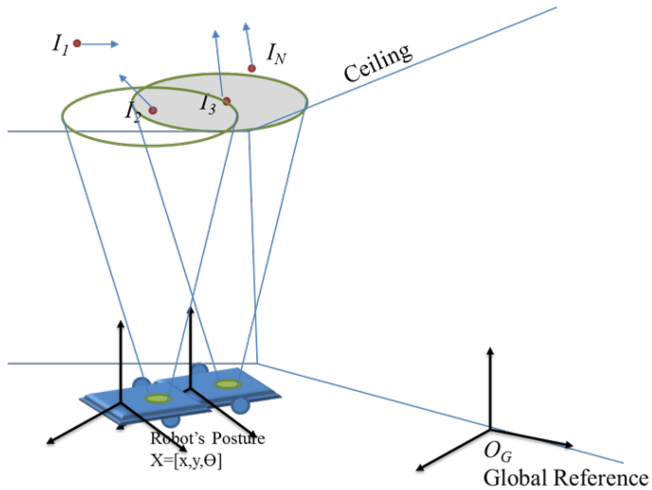
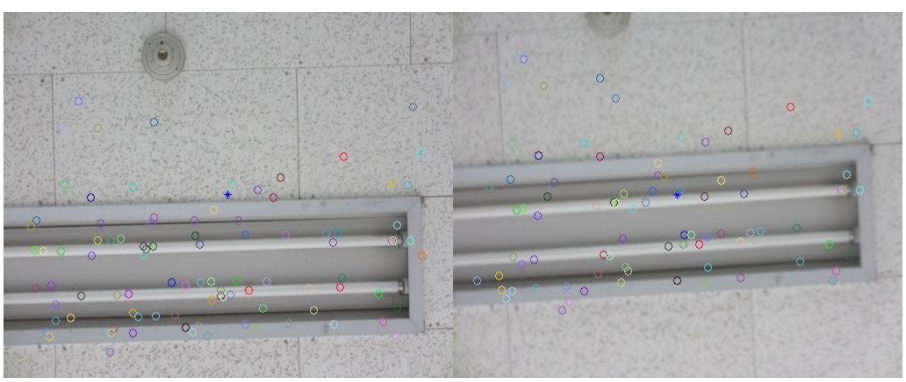


Figure 1. Vision based Self-Localization. (O_G, X, and I_i are the Global Coordinate Origin, the Robot's Current Posture, and the Interest Point, Respectively). The Arrow of the Interest Points Represents its Global Direction



(a) (b)

Figure 2. Interest Points Extraction. The Circles Represent Interest Points. (a) Is the Image which is Captured before Robot Moving on the Ceiling. (b) Is the Image which is Captured after Robot Moving on the Ceiling

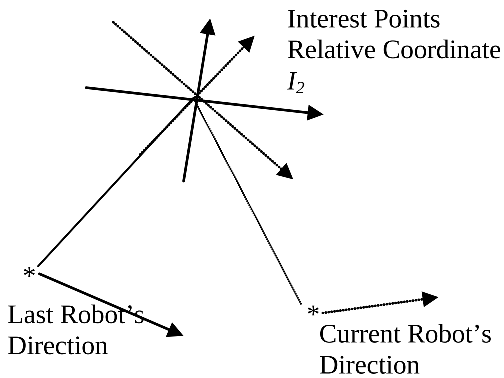
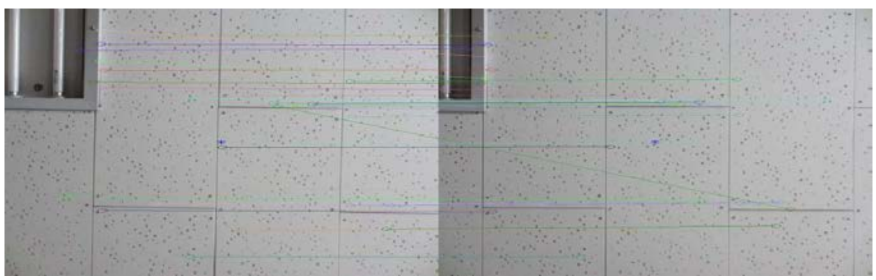


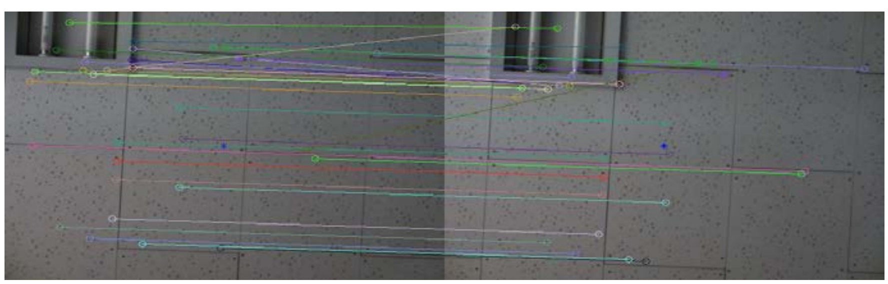
Figure 3. Relative Self-Localization Estimation

3. Error Analysis and its Correction

In practice, some errors are taken place caused by inaccurate matching between two images. Illumination change and interest points drifting also can cause errors. For example, there are inaccurate matching between images and interest points' drift in Figure 4. Although the interest points' drifts are not obvious in Figure 4, they will greatly affect for self-localization estimation.



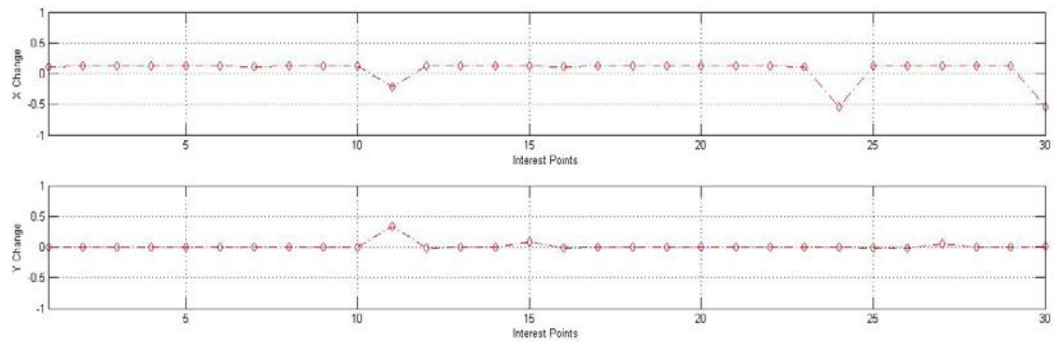
(a)



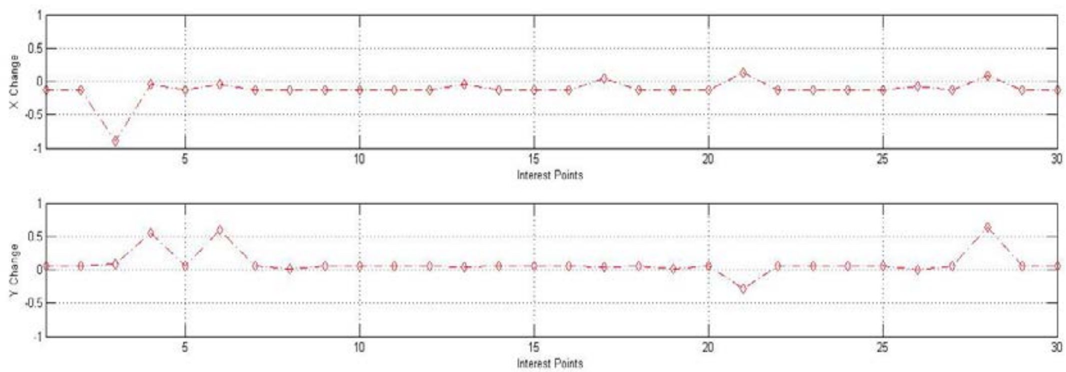
(b)

Figure 4. Image matching Results in the Two Different Sets of Images: The Correct Interest Points are Edge in 30 Top

Figure 5 shows the variations in self-localization using above proposed method for Figure 4. The change in the relative location (x, y) is smooth, and large changes in interest points are cause by inaccurate matching.



(a)



(b)

Figure 5. Relative Displacement changes in Two Different Sets of Images. The Top Figure: *x* changes with Interest Points. The Bottom Figure: *y* Changes with Interest Points

Before all, the relative self-localization calculated by inaccurate matching interest points will be removed. In our experiment, the RMS (Root Mean Square) is used to find the error of the posture. Let $e(x, y)$ be the overall posture error of the current posture. The $e(x, y)$ is given by

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

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

Then a threshold $e_{\min}$ is set to remove inaccurate matching of interest points. The $e_{\min}$ is counted in repeated experiments. If the errors for *x* and *y* of self-localization are both less than $e_{\min}$, then interest points persist:

$$e_{\min} > e(x)\ and\ e_{\min} > e(y) \tag{3}$$

Then the final localization is

$$X_e = \overline{X}_e + e(x, y) \tag{4}$$

The current orientation of the robot is calcuated by remaining interest points

$$\theta_e = \theta_l + \theta_{1i} - \theta_{2i} \tag{5}$$

where θ_e and θ_l represent the current and the last orientation of the robot, respectively. θ_{1i}, and θ_{2i} represent relative directive in two images.

4. Simulation Examples

Some simulations were performed to demonstrate the effectiveness of the proposed algorithm. It is conducted by using a PC hardware configuration with Intel(R) Core(TM) 2, 2.66 GHz, and 4.0 GB RAM and software configuration with Windows 8. In this simulation example we used 12 different images of our laboratory and passageway. Each case is organized by two adjacent images. The two images contain most of the same objects.

Table 1 shows estimated results including errors of the proposed algorithm in 12 different images.

Table 1. Simulation Results of the proposed Algorithm (PA)

						Localization			
Cases	Images	Initial Position		Real Position		Proposed Algorithm			
						Position		Error	
		x	y	x	y	x	y	x	y
1	1-1	5.98	2.18	5.93	2.16	5.9204	2.1689	0.0096	0.0089
	1-2	4.98	2.57	5.15	2.67	5.1603	2.6928	0.0103	0.0228
2	2-1	3.38	2.58	3.48	2.58	3.4938	2.5835	0.0138	0.0035
	2-2	2.63	0.88	2.73	0.91	2.7232	0.9153	0.0068	0.0053
3	3-1	5.28	2.58	5.375	2.58	5.3699	2.5802	0.0051	0.0002
	3-2	1.58	0.71	1.68	0.69	1.6648	0.6891	0.0152	0.0009
4	4-1	12.98	1.07	13.08	1.1	13.0742	1.0743	0.0058	0.0257
	4-2	10.67	0.7	10.66	0.63	10.6628	0.6388	0.0028	0.0088
5	5-1	1.45	1.15	1.45	1.04	1.4452	1.0398	0.0048	0.0002
	5-2	14.96	4.4	14.93	4.28	14.927	4.2903	0.003	0.0103
6	6-1	15.17	4.2	15.27	4.19	15.2688	4.2063	0.0012	0.0163
	6-2	16.72	1.13	16.87	1.08	16.8656	1.0746	0.0044	0.0054
Average Error:								0.0069	0.009025

From the simulation results of Table 1, the average errors of the proposed algorithm generated are all below 1[cm]. It is enough to satisfy the accuracy for the self-localization estimation of indoor environments.

5. Concluding Remarks

A new algorithm for estimating relative self-localization of indoor mobile robot was proposed. The algorithm calculated the estimation of its relative self-localization through a series of the transformation of a coordinate system. Some errors were caused in the image matching because the image and interest points are influenced by an illumination, or rotation etc. In this paper we simply analyzed the error and proposed a new method to reduce them. Moreover, we also showed the effectiveness of the proposed algorithm through some simulation examples. In future works, we will analyze the detailed reasons for why the errors are caused. And we will also study the systematic method to remove them.

Acknowledgements

This research was supported (in part) by the Daegu University Research Grant.

References

[1] D. C. K. Yuen and B. A. MacDonald, "Vision-Based Localization Algorithm Based on Landmark Matching, Triangulation, Reconstruction, and Comparison", IEEE Transactions on Robotics, vol. 21, no. 2, **(2005)**, pp. 217-226.

[2] A. Kitanov, "Mobile robot self-localization in complex indoor environments using monocular vision and 3D model".

[3] N. A. Andersen, L. Henriksen and O. Ravn, "Visual positioning and docking of non-holonomic vehicles", Proc. 4th Int. Symp. Experimental Robot, vol. 223, **(1995)**, pp. 140-149

[4] K. -C. Chen and W. -H. Tsai, "Vision-Based Autonomous Vehicle Guidance for Indoor Security Patrolling by a SIFT-Based Vehicle-Localization Technique", IEEE Transactions On Vehicular Technology, vol. 59, no. 7, **(2010)**.

[5] S. -Y. An, J. -G. Kang, L. -K. Lee and S. -Y. Oh, "SLAM with Visually Salient Line Features in Indoor Hallway Environments", Journal of Institute of Control, Robotics and Systems, vol. 16, no. 1, **(2010)**.

[6] P. Sala, R. Sim, A. Shokoufandeh and S. Dickinson, "Landmark Selection for Vision-Based Navigation", IEEE Transactions on Robotics, vol. 22, no. 2, **(2006)**.

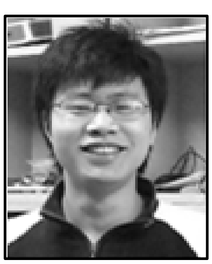
[7] L. Juan and O. Gwun, "A Comparison of SIFT, PCA-SIFT and SURF", International Journal of Image Processing (IJIP), vol. 3, no. 4, **(2010)**.

[8] X. Xiong and B. -J. Choi, "A Replacement Algorithm of Fast Computing Interest Point's Orientation and Descriptor in SURF for Self-localization Robot", G. Lee, *et al.*, (Eds.): ICHIT **(2012)**, LNCS 7425, Springer-Verlag Berlin Heidelberg, pp. 339-349.

[9] D. G. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", International Journal of Computer Vision, **(2004)**.

[10] H. Bay, A. Ess, T. Tuytelaars and L. Van Gool, "Speeded-Up Robust Features (SURF)", **(2008)**.

Authors



Xing Xiong received his B.S. degree in automation engineering at NanJing Institute of Technology, and M.S. degree and Ph.D from Daegu University. He is currently Doctor Course in the School of Electronic Engineering from Daegu University. His research interests include intelligent control and embedded systems.

Byung-Jae Choi received his B.S. degree in Electronic engineering at Kyungpook National University, and M.S. degree and Ph.D from Korea Advanced Institute and Technology. He is currently Professor in School of Electronic and Electrical Engineering from Daegu University. His research interests include intelligent control theory and its applications.