The Design of a Self-Localization Estimation Method for Indoor Mobile Robots using an Improved SURF Algorithm

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***Abstract*— We present an improved self-localization estimation algorithm in this paper. The algorithm uses a modified SURF method to extract the interest points, using it to extract the orientation and a descriptor of the interest point in order to lessen the computation time. A robot using this method can estimate its indoor self-localization according to matched interest points. A number of intermediate results will also be discussed. The intermediate results show that the displacement method could correctly match the interest points in two images.**

Keywords-Ceiling Key Point Extraction; SURF (Speeded-Up Robust Features); DSP (Digital Signal Processor).

I. INTRODUCTION

Mobile robot self-localization is a mandatory task for 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. Although very simple and fast, dead reckoning algorithms tend to accumulate errors in the system since these methods only utilize the information coming from proprioceptive sensors, such as odometer readings (e.g. incremental encoders on the robot wheels). Absolute localization methods are based on exteroceptive sensor information. This method yields a stable locating error but is more complex and costly in terms of computation time. Relative localization requires a high sampling rate in order to maintain an up-to-date pose, whereas absolute localization is applied periodically with a lower sampling rate to correct relative positioning misalignments [3].

With the furthering development of science and technology, visual positioning methods play an important role in the self-localization of autonomous mobile service robots working in indoor environments [5]. Generally, prior knowledge of an indoor environment can be used to determine the position and orientation of a mobile robot via visual positioning approaches. The features used by different approaches for mobile robot localization range from artificial markers, such as barcodes, to the placement and orientation of ceiling lights and tiles, for example. Indeed, the selected visual features have significant influence on the positioning approach performance.

The remainder of this paper is organized as follows: Section II presents some of the related studies. Section III lays out the composition of the proposed algorithm. Section IV discusses some of the intermediate results. We draw our conclusions in Section V.

II. RELATED WORK

In the field of image processing, the Speeded Up Robust Features (SURF) algorithm [6] is an efficient and high-speed algorithm, which is considered to be an improved version of the Scale-invariant Feature Transform (SIFT) algorithm [10]. The SURF algorithm mainly consists of two parts: interest points extraction and an orientation and descriptor of the interest points extraction. For the interest point extraction, the SURF method uses an integral image and box filter to replace the Gaussian filter and the DoG (Difference of Gaussian) method found in the SIFT algorithm. This allows for a greatly reduced computation time.

However, in the orientation and descriptor section the SURF method scans the neighborhood region twice. In the first scan the orientation of the interest point is extracted. The second scan, according to the orientation of the interest point, is used to extract the descriptor. In low-speed devices such as a DSP board, the two scans increase the amount of computation time. Furthermore, in the case of images that only rotate and move, a simpler method can be used to obtain the orientation and descriptor.

In our paper, we use an alternative method to obtain the orientation and descriptor. This method only scans the neighborhood region interest points once. Our self-localization estimation algorithm contains three parts: interest points extraction (using SURF), orientation and descriptor extraction (using the improved method), and the interest points matching and self-localization estimation. Because there is only one scan the necessary amount of calculation is reduced.

III. THE COMPOSITION OF THE ALGORITHM

In an indoor environment, the floor is assumed to be planar. The ceiling usually consists of a series of blocks that form a chessboard pattern parallel to the floor. In this study, a camera is mounted onto the top of the mobile robot working on the floor. The camera points to the ceiling, as shown in Figure 1.

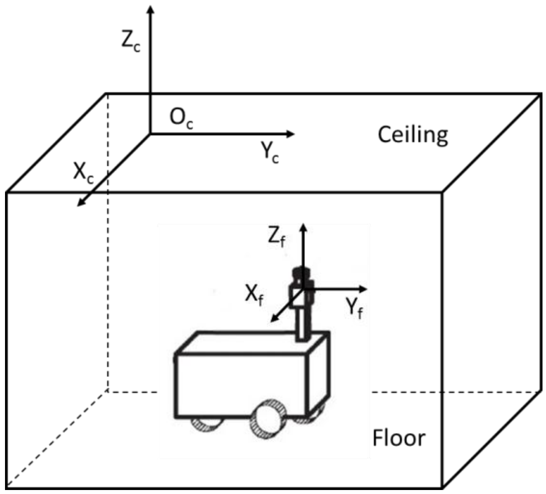


Figure 1. Ceiling based visual positioning

In our research, the SURF algorithm is used to extract the interest points. The SURF's replacement method is used to extract the orientation and the descriptors of the interest points. The self-localization of the mobile robot is then estimated according to the different positions of the same interest points in two images. The flow chart of the algorithm is shown in Figure 2. The interest points extraction section is broken down in Figure 3.

Simply put, in the rapid interest points detection method, the NMS (Non-Maximum Suppression) method used after obtaining the Fast-Hessian matrix in the conventional SURF algorithm is changed to a Non-minimum suppression method to obtain the feature points whose gray value is high. In addition, the conventional order of the box filter scale [6] is changed to 75, 51, and 99. Not only does this remove the impact of the image edge, reducing the amount of calculation, but also leads to an increase in the interest points. The interest points extraction results are shown in Figure 6.

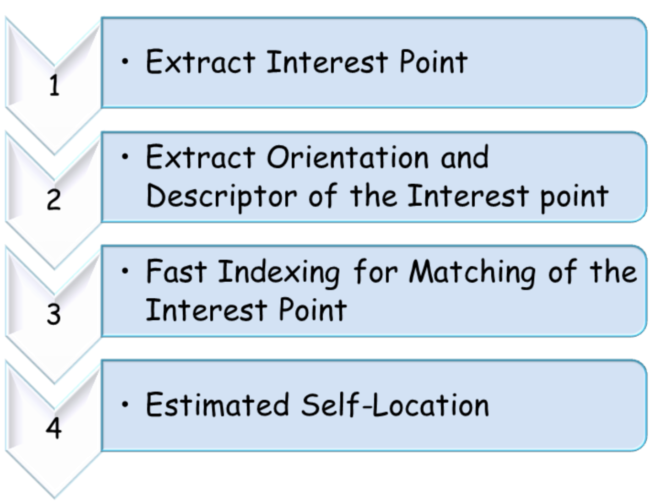


Figure 2. The SURF algorithm flow chart

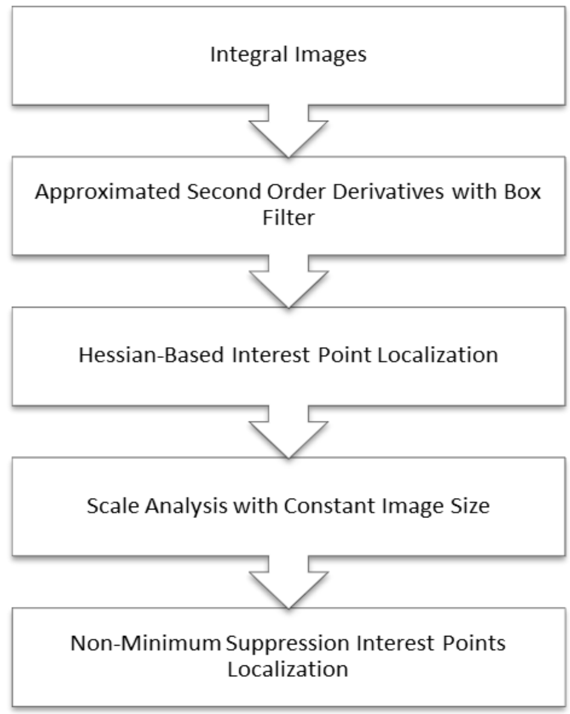


Figure 3. The interest points extration

Regarding the orientation and descriptor extraction, our descriptor method is similar to that of the SIFT algorithm. The flow chart describing the replacement algorithm is shown in Figure 4. The details regarding this algorithm can be found in [11].

To date, in a simple environment, for the case of the translation and rotation of the image obtained from the ceiling, the replacement algorithm has been verified to be feasible. The results from the replacement algorithm are shown in Figure 7.

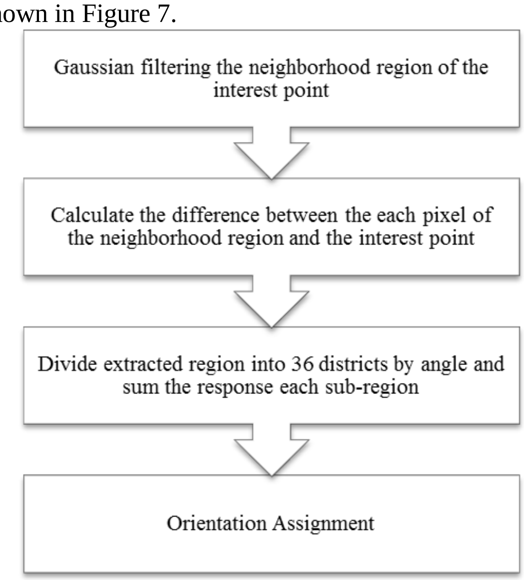
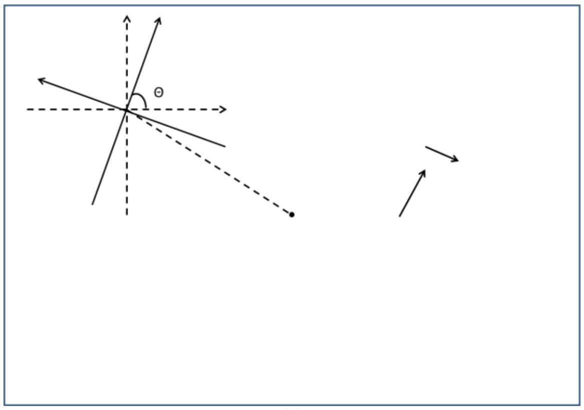


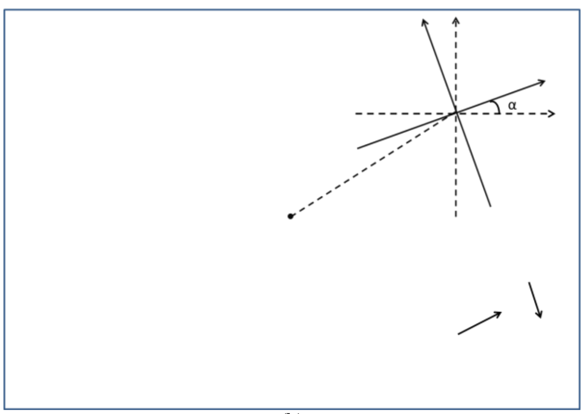
Figure 4. The modified algorithm flow chart

The self-localization estimation method is illustrated in Figure 5.

The two illustrations shown in Figures 5(a) and 5(b) show differences obtained over a small time interval. Figure 5(a) illustrates a baseline before the camera is moved. After the camera is moved (5 seconds), Figure 5(b) illustrates the position and orientation differences. We assume that there are three interest points and a center point. The center point represents the self-localization of the mobile robot. One point amongst three interest points have two coordinates (Dash Line Coordinate System and Solid Line Coordinate System).



(a)



(b)

Figure 5. The self-localization estimation method

The dashed line coordinates represent the image coordinates whereas the solid line coordinates represent the interest points. The X-axis of the solid line coordinate represents the orientation of the interest point.

The center point's coordinate *(x, y)* in the dashed line coordinate system can be changed to the solid line coordinate system $(\hat{x}, \hat{y})$ by:

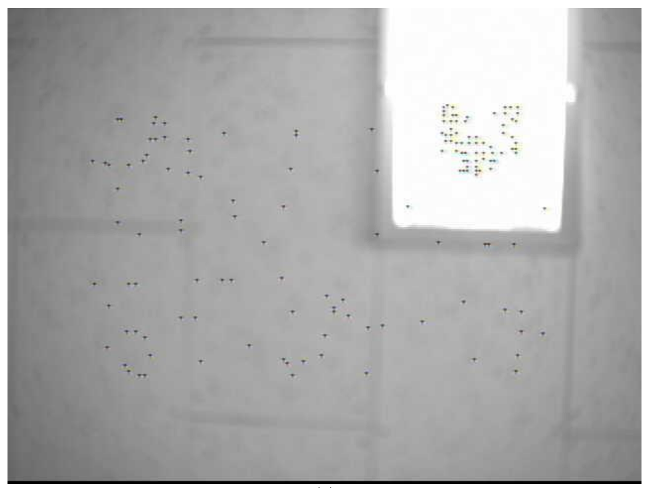
$$\begin{bmatrix} \hat{y} \\ \hat{x} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} y \\ x \end{bmatrix} \qquad (1)$$

As shown in Figure 5(b), there are two new coordinates $(\hat{x}_a, \hat{y}_a)$ and $(\hat{x}_b, \hat{y}_b)$. According to the characteristics of the invariant properties [10], $(\hat{x}_a, \hat{y}_a)$ and $(\hat{x}_b, \hat{y}_b)$ are in the same coordinate system. In fact, the location change of the mobile robot is from $(\hat{x}_a, \hat{y}_a)$ to $(\hat{x}_b, \hat{y}_b)$. The relative displacement of the mobile robot can therefore be expressed simply as:

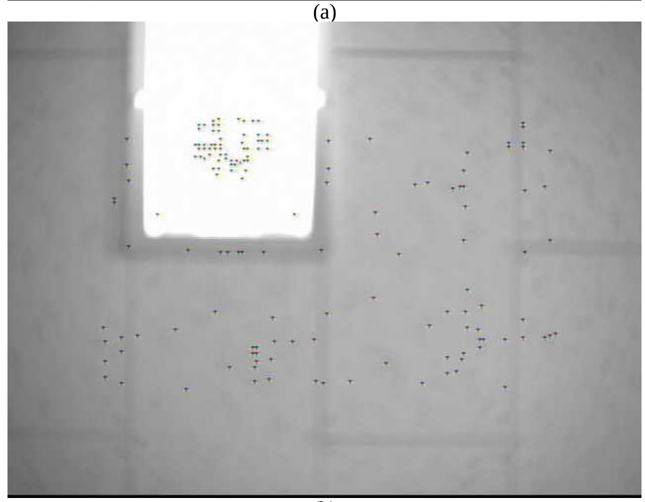
$$D = \sqrt{(\hat{x}_a - \hat{x}_b)^2 + (\hat{y}_a - \hat{y}_b)^2} \qquad (2)$$

IV. THE INTERMEDIATE RESULTS

In this section we discuss some intermediate results. Figure 6 shows the extracted interest points results. The black dots represent the interest points. The captured image after camera moved is shown in Figure 6(b). Comparing the two images, most of the interest points are retained.



(a)



(b)

Figure 6. The extracted interest points simulation results: (a) before and (b) after the camera moved

Because the interest points being matched by the results from the DSP is not very intuitive, Figure 7 shows the results which were simulated using the same method in MatLAB.

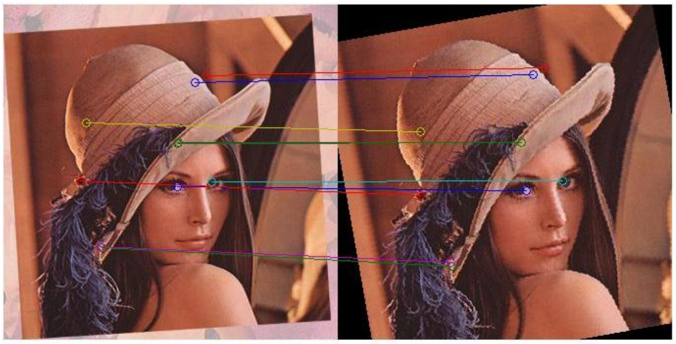


Figure 7. Descriptor extraction and matching using our improved algorithm in MatLAB

V. CONCLUSION

In this study, we used Non-minimum suppression to replace Non-maximum suppression in interest points extraction. As a result, we present a modified SURF algorithm used to extract the orientation and descriptor of the interest points. The simulation results verify the modified algorithm has good interest point matching results. In future work, we will write a program to verify the proposed self-localization estimating design in a DSP board. We will also address camera rotation in regards to the self-localization algorithm and verify it.

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