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Simultaneous Localization and Mapping of Mobile Robot Based on Image Enhancement

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***Abstract*—For the camera optical system aberration, scene image observed by the robot will be disturbed by noise such as illumination, motion, and other noise interference, which will bring visual positioning error, lead to wrong expression of topological structure for the environment, and affect the robustness of Simultaneous Localization and Mapping (SLAM). How to control the accumulation effectively and enhance the effectiveness, robustness and real-time of visual SLAM is a challenging research topic. The fuzzy image set is constructed according to the blurred image. This paper proposed a processing techniques of fuzzy image based on image enhancement. (1) The threshold algorithm is employed to improve the histogram equalization algorithm in image enhancement field. (2) The fuzzy set of illumination is constructed offline and the gray scale histogram of the original image is stretched in nonlinear to increase the dynamic range of the gray value of the pixel. (3) The illumination fuzzy set is integrated into the SLAM, and then the visual odometry, closed-loop detection module of SLAM are tested on the basis of the quantitative experiment in the actual scene. The experimental results show that the proposed algorithm is robust to SLAM and have good real - time performance.**

Keywords-Simultaneous Localization and Mapping (SLAM); image enhancement; histogram equalization algorithm; threshold algorithm; mobile robot

I. INTRODUCTION

Mobile robots have been widely applied in the fields of service, industrial, medical, rescue, and military tasks [1]. Simultaneous Localization and Mapping well known as SLAM is creatively proposed for autonomous robots navigating in partially or fully unknown environments [2], which is one of the most frequently applied approaches for providing an environmental representation for mobile robots, and it has been a core technique enabling the autonomy of robots, such as autonomous vehicles and AUV [3].

In general, SLAM can be described as estimating the robot trajectory and constructing the map simultaneously where the robot is moving based on the control inputs and observations [4]. Visual sensors are attractive for SLAM due to their rich information, low cost and low power, many studies have been performed on visual SLAM. Visual SLAM is one of the key technologies to realize autonomous robot navigation and a hot topic in the field of robot autonomous navigation.

With the rapid development of unmanned applications, the visual sensor is susceptible to noise interference such as light and motion, which affects the robustness of SLAM. Illuminated blurred images not only affect feature extraction, feature matching and closed-loop detection in visual SLAM, but also reduce the quality of environmental maps, which is not conducive to visual navigation [5].

This paper uses the histogram equalization algorithm in the image enhancement technique. First, we transform the image, and construct a blurry image of the image. The fuzzy image set is constructed to identify and match the feature points of the fuzzy image and identify the feature points in the fuzzy image. It solves the interference of environmental factors. Compared with other fuzzy image processing methods, this algorithm reduces the time complexity of image restoration. The illumination fuzzy set can be composed of off-line time, which ensures the real-time performance of the system and ensures the accuracy of visual odometer and closed-loop detection.

II. RELATED WORK

The problem of simultaneously localizing a mobile robot and building a map of its surrounding environment has been introduced for the first time by Smith et al (1986) and since then it has received attention considerably. Over the past decade, a large variety of SLAM approaches have been proposed, such as the Kalman filter SLAM, the particle filter SLAM, and many variants of them [6].

The Kalman Filter based SLAM is the earliest approach to solve SLAM and recursively estimates the Gaussian density over the current pose of the robot and the position of all landmarks. Due to the simplicity of algorithm. The limitation of KF SLAM is that the kinematic model of robot is usually non-linear and the uncertainty cannot in principle be assumed to be Gaussian if there are ambiguities about the feature which is related to the measure [7-10].

The second family of algorithms is Particle Filter (PF) based SLAM [11-13]. PF is one of the most popular methods employed for tracking, which is non-parametric filter and derived from Monte Carlo, can solve the nonlinear and non-Gaussian problems, which has been widely used in many different navigation environments from indoor to outdoor, undersea and underground for mobile robots [14-18].

Feature based methods have been introduced to reduce the computational complexity of processing each pixel. This is done by matching only salient image locations, referred to as features. Descriptors associated with each feature and are used to provide quantitative measurements of similarity to other key points [19-20].

III. VISUAL SLAM

The visual SLAM system consists of two parts: front-end (graph construction) and back-end (graph optimization).

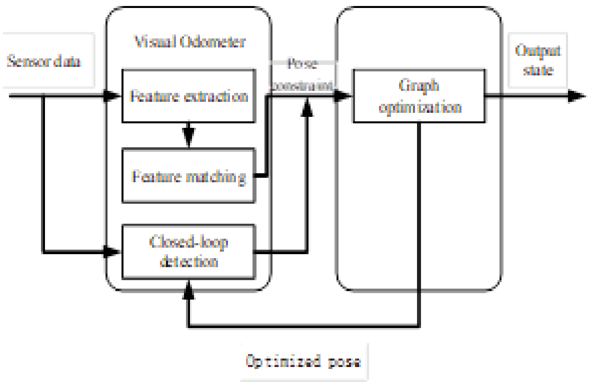

Figure 1. Visual SLAM system

The visual SLAM system includes

A. Sensor Data Extraction

In visual SLAM, sensor data processing includes reading and pre-processing of camera images, while reading and synchronizing sensor information of the robot.

B. The Front End is a Graph Construction

The front end is known as visual odometer. Based on the image data of the vision sensor, camera motion between adjacent images is estimated to construct a partial map. Including feature extraction, feature matching and so on. Loop closure detection mainly solves the problem that the position estimation drifts with time, and judges whether the robot is in the environment that has been visited before according to the observation data.

C. The Back End is Graph Optimization

The node represents the robot pose, while edges encode either odometry or loop closure constraints, others represent the transformation matrix and the covariance matrix encoding the uncertainty associated with these transformations. The essence of back end optimization is nonlinear optimization.

D. State Output.

Construct a map consistent with the environment.

IV. STRUCTURAL MODEL AND COMPOSITION PARAMETERS OF ILLUMINATION FUZZY SET

Image enhancement technology is the preprocessing stage of image analysis. The histogram equalization algorithm is the core algorithm in the field of image enhancement.

A. Histogram Equalization Theory

The histogram equalization algorithm is the image enhancement technique based on the cumulative distribution function. The basic idea is to nonlinearly stretch the gray histogram of the original image, redistribute the image pixel values, and increase the number of pixels in the image. The gray value is expanded to combine the gray values with a small number of pixels, thereby increasing the dynamic range of the pixel gray value, achieving the contrast effect.

Let the total number of pixels of the image $f(x,y)$ be n, a total of L gray levels, r_k is the kth gray value of the image $f(x,y)$, and n_k is the number of pixels of the gray level r_k, The probability of occurrence of kth level gray value is:

$$p(r_k) = \frac{n_k}{n} \tag{1}$$

The cumulative distribution function of the normalized image gray scale r is mapping function

$$s = T(r) \qquad r, s \in [0,1] \tag{2}$$

where r is the normalized image gray level, $r = 0$ is black, $r = 1$ is white; s is the normalized gray level of the enhanced image: $T(r)$ is the cumulative distribution function of r, $T(r)$ needs to meet the following conditions

When $0 \le r \le 1$, $0 \le \mathrm{T}(\mathrm{r}) \le 1$.

The inverse transformation from s to r can be expressed as $r = T^{-1}(s)$, $0 \le s \le 1$.

The transformation function expression for a digital image

$$s_k = T(r_k) = \sum_{i=0}^{k} p_r(r_i) = \sum_{i=0}^{k} \frac{n_i}{n} \qquad 0 \le r_i \le 1, 0 \le k \le L-1 \tag{3}$$

Histogram equalization is to use the accumulation function to adjust the gray value of the image and improve the contrast of the image. Assuming that the gray level is an image of n levels, and the frequency of the gray level k is P_i, the information amount (entropy) of the gray level

$$I(i) = P_i \log \frac{1}{P_i} = -P_i \log P_i \tag{4}$$

The amount of information (entropy) contained in the entire image

$$H = \sum_{i=0}^{n-1} I(i) = -\sum_{i=0}^{n-1} P_i \log P_i \tag{5}$$

It can be shown that when $P_0 = P_1 = \cdots P_{n-1} = \frac{1}{n}$, H has a maximum value, that is, when the image has a uniformly distributed histogram, the information entropy H is the largest. To make images with high contrast and multiple gray tones, histogram equalization techniques are often used.

B. *Threshold Adjustment Histogram Equalization Theory*

Since the traditional histogram equalization algorithm performs T operations on every point of the image, it is a global processing method. It has the advantages of simple algorithm and fast calculation speed, but since it performs the same processing for all pixels, ignoring the local features of the image edge will affect the image denoising processing and edge detection effect.

The point processing technique can be expressed as $g(x,y)=T[f(x,y)]$, where $f(x,y)$ is the original image pixel intensity, and $g(x,y)$ is the histogram equalization. The obtained image pixel intensity, T is the gradation transformation function, G_i is set as the threshold, (G_i,G_j) represents the gradation range, and (g_i,g_j) represents the intensity range, within the gradation range (G_i,G_j), the gradation conversion formula for $f(x,y)$ is

$$g(x,y)=g_i+(g_j-g_i)\frac{T[f(x,y)]-T[G_i]}{T[G_j]-T[G_i]} \tag{6}$$

C. *Composition of Illumination Fuzzy Sets*光照模糊集的合成

The histogram equalization technique using threshold adjustment is used to expand the gray value of the number of pixels in the image. The image is converted into three grayscale images.

$$X=[X_R \quad X_G \quad X_B] \tag{7}$$

Set $L(X)$ to the histogram equalization operation on the original sharp image, and the gradation conversion formula by $f(x,y)$,and r is the histogram equalization operation coefficient, and the control coefficient k is adjusted to control the brightness of the image to obtain a fuzzy set of the illumination image.

$$X_R=L(m_R \quad n_R \quad k) \tag{8}$$

$$X_G=L(m_G \quad n_G \quad k) \tag{9}$$

$$X_B=L(m_B \quad n_B \quad k) \tag{10}$$

V. EXPERIMENTAL RESULTS AND ANALYSIS

This section feature extraction, feature matching and loop-closure detection as three key aspects. The degree of influence of the illumination blurred image on the visual SLAM system is quantitatively analyzed. Removal of illumination blur noise interference in SLAM system using SLAM algorithm based on illumination fuzzy set.

A. *Influence of Illumination Blur on Visual SLAM*

1) *Influence of illumination blur on feature extraction*

Taking the camera image as the research object, the SIFT feature extraction and matching algorithm is used to extract the features of the two frames.

Figure 2. SIFT identification of normal images

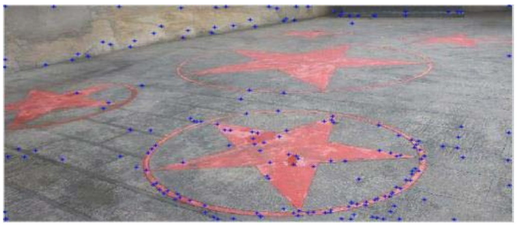

Figure 3. SIFT identification of overexposed image

Extract feature for normal and overexposed images respectively. Fig. 2 extracts 454 SIFT feature, Fig. 3 extracts 216 SIFT feature. As the degree of illumination blur increases, the number of SIFT feature points in image extraction decreases sharply.

2) *Influence of illumination blur on feature matching*

Figure 4. Comparison of original image and light blurred image

As shown in Fig. 4, the original clear image and the illumination blurred image have 16 matching points, the number of matching is small, and the illumination blur intensity is too large, which will seriously affect the visual odometer result. The motion trajectory of the robot in SLAM drifts greatly.

3) *Influence of illumination blur on loop closure detection*

Due to the influence of blurring, Fig. 2 and Fig. 3 are identical scenes, but there is a lower matching degree. The number of matching points is just 16, which is prone to false negative in the closed loop detection. Similarly, two scenes with large differences, due to the influence of illumination blur, which is mismatched into the same scene, and prone to false positives. This situation will increase the probability of closed loop detection failure and affect the stability of the visual SLAM system.

B. Visual SLAM Based on Fuzzy Set

Figure 5. Light blurred image (parameter 0.2)

Figure 6. Light blurred image (parameter 0.7)

Figure 7. Light blurred image (parameter 3)

Figure 8. Light blurred image (parameters 8)

To adjust the histogram equalization parameter as shown in Fig. 5 to Fig. 8, the blurred image obtained by illumination. Each picture corresponds to a histogram of the three components of red, green and blue. As shown in Fig. 9 to Fig. 11, which is a histogram of the red, green and blue color components.

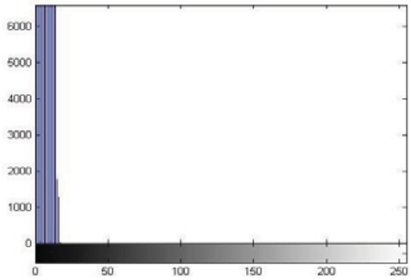

Figure 9. Red histogram (parameter 0.2)

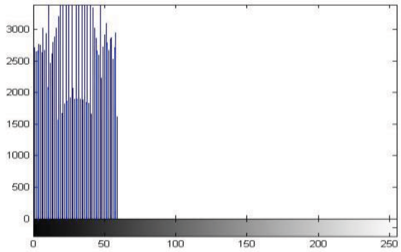

Figure 10. Green histogram (parameter 0.2)

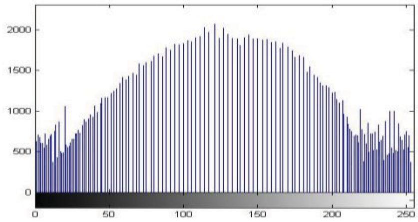

Figure 11. Blue histogram (parameter 0.2)

As the brightness of the matched two images approaches, the matching effect increases rapidly. The histograms of the respective color components are counted corresponding to the four images in the above experiment. When the two images match results getting better and better, their histograms are increasingly similar.

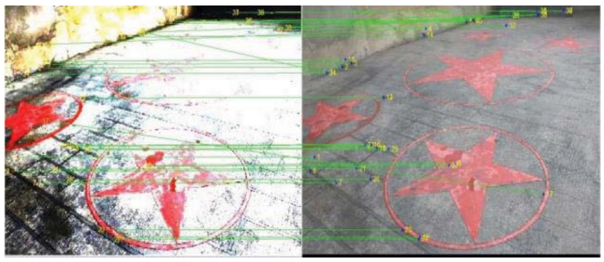

Figure 12. Comparison of Fuzzy Sets and Fuzzy Images

The matching effect between fuzzy set and fuzzy image is shown in Fig. 12. The number of matching points reaches 52 pairs, which is 3.25 times of the initial matching, which takes 0.14s/frame, which helps the robot to better identify its position. The effects of blurred images on feature point recognition, matching and closed-loop detection in visual SLAM are well removed, and the accurate calculation of SLAM is realized.

As the cumulative distribution function increases, the recognition experiments of over-exposed and over-dark images have been carried out. The effectiveness of algorithm for illumination blurred image recognition is verified by comparing the recognition algorithm with the improved algorithm and SIFT algorithm. When the cumulative distribution function value is 0.7, the matching algorithm is 52. The correct rate is 98%, and the matching effect is the best.

VI. Conclusion

调整阈值模拟图像模糊

In this paper, the histogram equalization algorithm based on threshold adjustment is used to simulate the image blur effect caused by illumination. The number of feature matching is 52 pairs, which is 3.25 times of the initial match and the correct rate reaches 98%. The efficiency of the SIFT matching of image recognition is significantly improved, and the robustness of the SLAM system is greatly enhanced. It takes 0.14s/frame and has good real-time performance. The processing and analysis of fuzzy images is a difficult problem in the field of vision and image. Taking SIFT algorithm as an example, this paper proposes a processing technique that can effectively identify illumination blurred images, which can be applied to other fuzzy image recognition problems. It is generally applicable to various types of visual SLAM techniques such as monocular and binocular.

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