Received: 24 April 2019 | Accepted: 29 April 2019
DOI: 10.1002/cav.1895

SPECIAL ISSUE PAPER

WILEY

Robust simultaneous localization and mapping in low-light environment

Jiawei Huang | Shiguang Liu

School of Computer Science and Technology, College of Intelligence and Computing, Tianjin University, Tianjin, China

Correspondence
Shiguang Liu, School of Computer Science and Technology, College of Intelligence and Computing, Tianjin University, Tianjin 300072, China.
Email: lsg@tju.edu.cn

Funding information
Natural Science Foundation of China, Grant/Award Number: 61672375 and 61170118; National Key Research and Development Program of China, Grant/Award Number: 2018YFC1407405

Abstract

Complex and varied illumination makes computer vision research studies difficult. This research field pays much attention to scenes with weak illumination, especially in visual simultaneous localization and mapping (SLAM). Although the current feature-based algorithm is mature, the existing SLAM method often fails because it cannot extract enough feature information in the low-light environment. In this paper, we propose a new solution to this problem, which allows our system to work in environments with the majority of lighting. We propose a multifeature extraction algorithm to extract two kinds of image features simultaneously. With such a solution, our system can work when the single-feature algorithm fails to extract enough feature points. We also add an image preprocessing step before tracking thread to cope with extremely dark conditions. Finally, we fully evaluate our approach on existing public data sets. Experiments show that the method combining multiple features can improve the robustness of the state-of-the-art algorithm under weak illumination without affecting the real-time performance.

KEYWORDS

feature, image preprocessing, low-light environment, visual SLAM

1 | INTRODUCTION

Simultaneous localization and mapping (SLAM) greatly relies on its precision and robustness. To this end, many SLAM systems currently improved their performance by using depth cameras with external sensors,[1–3] but this will cause inconvenience and hinder portability of the system. Therefore, a pure vision monocular SLAM system is still a considerable solution.

Depending on its own advantages, the monocular SLAM system based on pure vision can be used in small mobile devices such as drones, mobile phones, and virtual reality (VR). These devices will be used in various scenarios all the time. From the earliest topological SLAM system that can only be used for small work spaces to the latest achievements that can be used in a good lighting outdoor environment, the SLAM method has made great progress, but even the cutting-edge ORB-SLAM2[4] is not perfect when working in an all-weather environment. As the best-performing complete SLAM system, the ORB-SLAM2 system can show excellent results in a well-lit environment. However, when dealing with video sequences in a low-light environment, the system only uses the oriented FAST and rotated BRIEF (ORB) feature algorithm; it cannot extract enough feature points, which leads to tracking interruption. Under different lighting conditions (as shown in Figure 1), the same scene is completely different for a visual SLAM system. In addition, a SLAM process tends to fail in the scenes with weak illumination or the scenes with blurred textures. It is worth to note that most cutting-edge SLAM systems have completed the performance evaluation in the well-lit environment without considering the performance in the low-light environment.

To solve this problem, in this paper, we propose a monocular vision SLAM system with strong illumination robustness. We use ORB-SLAM2 as the main framework to retains its excellent performance and excellent loop detection ability in an ordinary environment. Firstly, we improve the visual front end of ORB-SLAM2, introduce the BRISK feature algorithm proposed by Leutenegger et al.,[5] and extract the dual features simultaneously in the SLAM visual front end to compensate for the problem that the ORB algorithm could not extract enough feature points in the low-light environment. Then, we add an input image preprocessing step at the visual front end to minimize the tracking loss by using an illumination compensation algorithm to process extremely dark images.

2 | RELATED WORK

In a low-light environment or a shadowy environment, the visual front end of the SLAM system tends to cause camera tracking failure due to visual blur or feature changes caused by illumination changes. In the past, the SLAM system would cause performance degradation because of the interference of illumination changes to the visual front segment. Therefore, it is of great research value to ensure the robustness of the visual front end of SLAM systems in an environment with complex illumination, and some related research work is also carried out.

Traditional feature-based SLAM systems that use scale-invariant feature transform (SIFT)[6] and speeded up robust feature (SURF)[7] are limited by the defects of a feature matching algorithm, and it is difficult to ensure the accurate localization in the environment with changing illumination. Valgren et al.[8] combined the most successful SURF variant, u-surf, with consistency checking using polar coordinate constraints, and proved that u-surf could extract more feature points in a changing environment, which was faster than the SIFT algorithm and achieved a higher success rate in a small data set. Ross et al.[9] studied the influence of illumination variation on features and proposed a new indicator for evaluating the variance of illumination of various descriptors, namely, the illumination variance ratio. By using the all-day shifting camera to detect the sensitivity of each descriptor to illumination, predefining feature keys in each image and testing only the variance of the feature descriptors, the results also show that the U-SIFT descriptor has the strongest illumination robustness.

However, a feature method at the time is still not good enough to meet the needs of a SLAM system, which should have the ability to recognize the same scene in different seasons or both day and night, so Milford et al.[10] proposed a SLAM system based on an image sequence. Instead of calculating the most likely single location in the current image, the system calculated the best candidate matching location in each local map sequence and then located it by identifying the coherent sequences of these "local best matches." However, compared with other methods, it is found that a too drastic appearance change will lead to system failure, and the overall image descriptor will also cause additional problems, such as viewpoint change sensitivity. Nuske et al.[11] proposed line-based visual localization because they were less susceptible to lighting, direction, and scale. They used fish-eye cameras to locate existing maps and test them outdoors during the day under conditions with different illumination. Although the system has certain illumination robustness, the system must rely on the environment to have enough line characteristics. Later, Pumarola et al.[12] proposed to process both point and line features in the system, and they improved the ORB-SLAM framework to enable the system to simultaneously process both ORB features and line segment features.[13] That is to say, it preserves the excellent effect of ORB-SLAM in ordinary scenes and can improve the situation that point-based methods are easy to fail, such as the scene with poor texture or blurred images (feature point disappears), which can achieve the better effect and run without significantly reducing efficiency. It has opened the way for the study of monocular SLAM systems combined with multiple features. Kim et al.[14] designed a SLAM system with illumination robustness in an environment with changing illumination for the monitoring robot Astrobee on the International Space Station with precise SLAM in varying illumination by selecting prebuilt maps of matched lighting conditions. However, because the system relies entirely on prebuilt maps, this method is only suitable for visual positioning in a fixed area.

In the field of direct SLAM, there are few studies on the low-light environment. Park et al.[15] extensively evaluated the robust direct attitude tracking method for fast illumination changes, extended the ICL-NUIM data set,[16] and provided the RGB-D sequence recorded by Kinect. This sequence allows the evaluation system to be robust to global or local illumination changes. The results show that, compared with the feature method, the classical SLAM system using a direct method can use more image information to obtain better appearance invariance.[17,18] However, this method is based on

FIGURE 1 Three kinds of lighting scenes in the ICL-NUIM data set: global illumination, local illumination, flash light

the assumption that the grayscale is invariant,[19] and the pixels changed due to the change of external illumination will be judged as abnormal by the system, resulting in insufficient robustness of the system. Therefore, this kind of system is not suitable for the complex lighting environment.

3 | OVERVIEW

Our method uses ORB-SLAM2 as the basic framework, mainly to improve its visual front end, and proposes a SLAM method combined with the multifeature extraction algorithm. The following is the basic pipeline and main modules of this paper.

As shown in Figure 2, the algorithm is divided into three main threads: tracking, local mapping, and loop detection. The tracking thread completes the feature matching between the images by calculating the image frames' feature information, thereby performing real-time camera pose estimation and determining whether to set the current frame as a keyframe. Then, the local mapping thread acquires new keyframes, generates new map points by triangulation, and performs map optimization through local or global Bundle Adjustment. Finally, the loop closing thread continuously performs loop detection and loop fusion. In the tracking thread, the ORB algorithm and the Brisk algorithm are used for feature detection and extraction, and the image frames are described by the extracted feature points. When the image frame contains enough content information, it will be used as a keyframe. In the local mapping thread, both kinds of point features are triangulated separately, and new map points are generated and integrated into the local map. Finally, the local Bundle Adjustment method is used to optimize the two features.

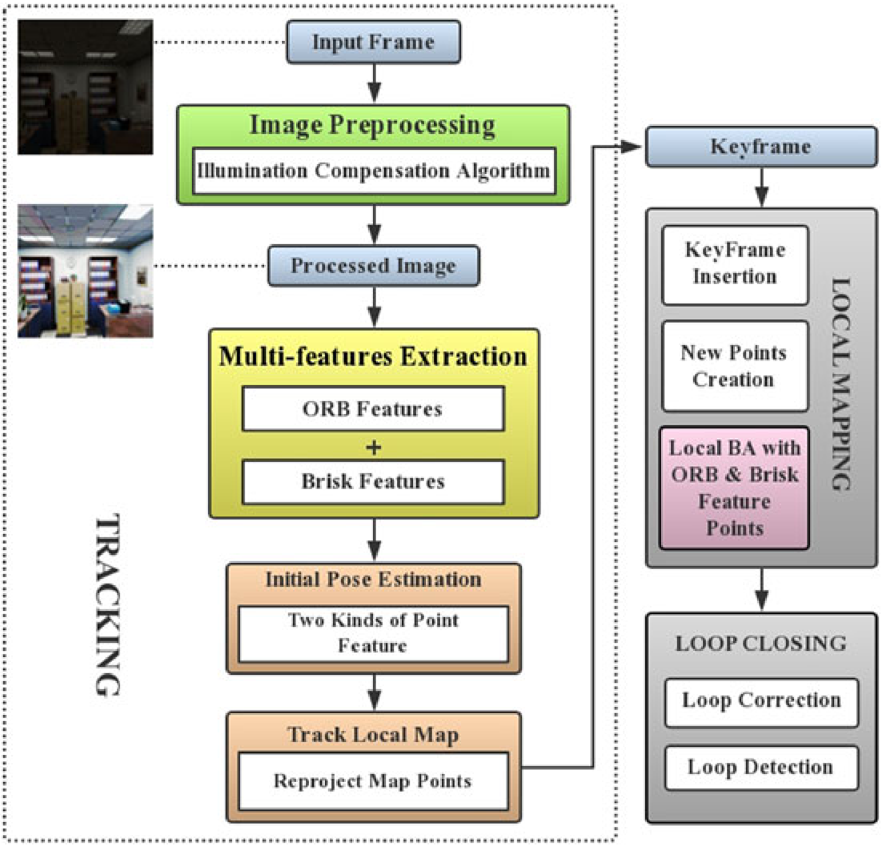

FIGURE 2 Our system pipeline, including three threads: tracking, local mapping, and loop closing. We mainly modified the tracking thread to improve the illumination robustness by adding the image preprocessing module and the multifeature extraction algorithm. ORB = oriented FAST and rotated BRIEF; BA = Bundle Adjustment

Because we also use point feature as our compensatory feature, some of the algorithms of the existing paper can be used directly for other modules in our system.

4 | METHOD

4.1 | Multifeature extraction

4.1.1 | Image feature description with two features

ORB-SLAM2 uses ORB as the feature extraction and description algorithm of image frames. ORB uses FAST (features from accelerated segment test)[20] to detect feature points and then uses the BRIEF algorithm to calculate descriptors of a feature point. The most obvious feature of the ORB algorithm is the high calculation speed, which is mainly due to the detection speed of the FAST corner point, and the unique binary string representation of the BRIEF algorithm not only saves storage space but also greatly shortens the matching time. This saves a lot of computing space for the entire SLAM system. Although the algorithm has the advantage of fast speed, the cost of this advantage is to sacrifice the detection effect. Obviously, for blurred or especially dark images, ORB features are not easy to extract enough feature points or the extracted feature points are not uniform.

In order to solve this problem, we introduce a feature matching algorithm to supplement the number of feature points extracted under such conditions. Because the image frame has been preprocessed, we have tested the processed image with the existing feature algorithm. We choose the Brisk algorithm[5] to obtain a great feature extraction effect while ensuring real-time performance of SLAM, which performs best in the registration of blurred images. To this end, we then modify the tracking thread of ORB-SLAM2. When the tracking thread obtains the preprocessed image frame for feature extraction, we extract both ORB and Brisk features. Firstly, in order to ensure that the two features can be uniformly extracted and efficient, we reduce the number of ORB feature points extracted from the original ORB-SLAM2 by half and then perform the Brisk feature extraction on each layer of the image pyramid according to the image pyramid. Finally, the image feature description is performed using all feature points in the image.

4.1.2 | Bundle Adjustment with Two Features

In optimization threads, we use the bundle adjustment algorithm to continuously correct the generated trajectory. The single-feature SLAM method optimizes the local BA by associating the feature points in the keyframe with the map points. However, there are two kinds of feature information in our system, so we can use both features to perform BA together to enhance its effectiveness. However, this is not easy work; the two features may interfere with each other in calculating, which may lead to unnecessary errors. Therefore, we improve the traditional BA algorithm in this paper.

When performing camera pose estimation, for the jth ORB point feature in the ith key frame $a_{i,j}$, the reprojection error can be expressed as

$$e_{i,j} = a_{i,j} - \tilde{a}_{i,j}, \tag{1}$$

where $\tilde{a}_{i,j}$ is the reprojected point for $a_{i,j}$. For the newly added Brisk point feature in the key frame, we calculate the reprojection error in the same way, which can be expressed as

$$E_{i,j} = b_{i,j} - \tilde{b}_{i,j} \tag{2}$$

$$\tilde{b}_{i,j} = \pi(b_j, \theta_i, k), \tag{3}$$

where θ_i is the pose of the ith key frame, and k is the camera internal parameter.

By calculating the reprojection error of both features, we can then use the BA strategy to optimize the camera pose for each frame. We introduce a cost function in Pumarola et al.,[12] which integrates the two kinds of errors as

$$C = \sum_{i,j} H\left(e_{i,i}^{\top}\Phi_{i,j}^{-1}e_{i,j} + E_{i,i}^{\top}\Phi_{i,j}^{\prime -1}E_{i,j}\right), \tag{4}$$

where H is the Huber robust cost function and $\Phi_{i,j}$, $\Phi'_{i,j}$ are the covariance matrices associated to the scale.

4.2 | Image preprocessing

The experimental results show that the multifeature extraction algorithm does greatly enhance the robustness of SLAM in a low-light environment. However, in some extreme cases (such as an extremely dark environment), we find that both feature algorithms may not extract enough feature information at the same time. Considering the working needs of the SLAM system, we propose a solution to cope with such situations. We consider preprocessing the obtained video frame by introducing the illumination compensation algorithm in the field of image processing to improve the illumination intensity of the extremely dark image and highlight the feature information in the image.

Firstly, we use a variety of illumination compensation algorithms as candidate algorithms and analyzed the effects one by one. Because there is no discriminant algorithm, the system will preprocess each input image frame, so it is required to have sufficient high similarity for the image obtained under different illuminations in the same scene and can acquire enough features that match. We experiment with gamma correction algorithm,[21] logarithmic transformation algorithm,[22] Retinex algorithm,[23] and histogram equalization algorithm[24] for image feature points extraction under different illumination conditions. Finally, experiments show that, in the same scene, two images under different illumination conditions can obtain the most uniform feature matching by histogram equalization, which is the most suitable method for application in this paper.

For each frame obtained, we first shift the image nonlinearly and redistribute the image pixel values so that the number of pixel values within a certain gray range is approximately equal. Then, the contrast of the peak portion in the middle of the original histogram is enhanced, and the contrast of the valley portion on both sides is lowered, and the histogram of the output image is a flat segmented histogram. For the low-light image, the most feature matching can be obtained on it after being processed. Its calculation formula can be expressed as

$$S_i = T(r_i) = \sum_{i=0}^{k-1} \frac{n_i}{n}, \tag{5}$$

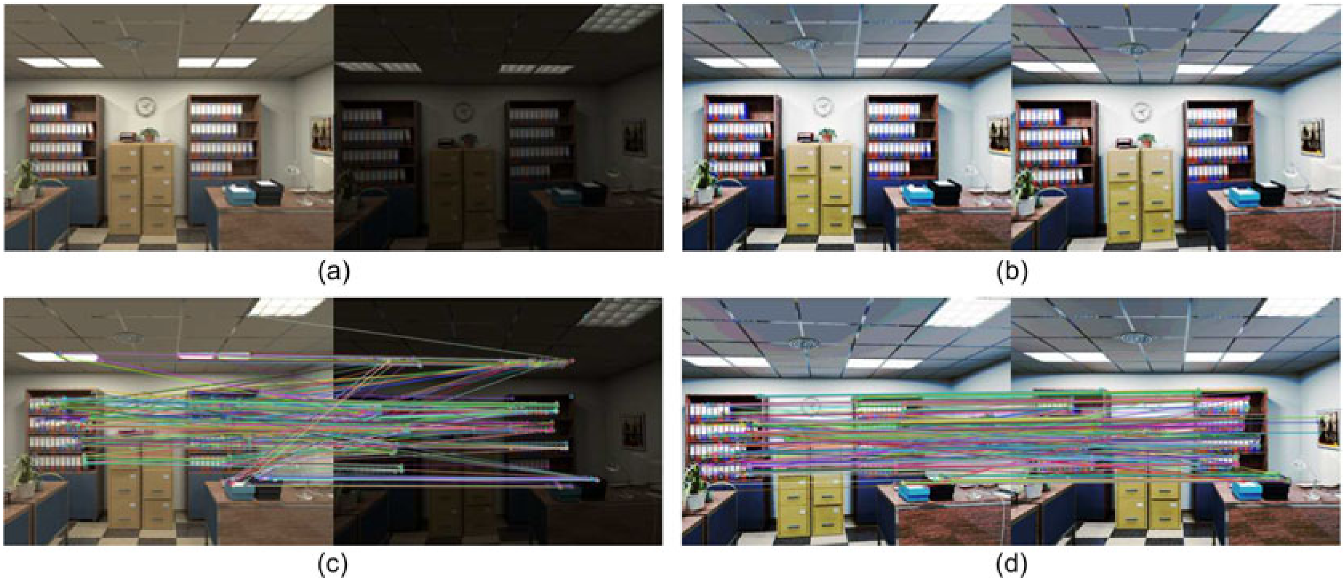

FIGURE 3 (a) is the two pictures obtained under different lighting conditions in the scene, whereas (c) is the result of performing feature matching on (a). (b) is the result of illumination compensation for the two images in (a), whereas (d) is the result of feature matching for (c). It can be seen that (d) can obtain greater matching than (c)

where n is the sum of the pixels in the image, n_i is the number of pixels in the current gray level, and k is the total number of gray levels in the image. Figure 3 shows the results of feature matching before and after preprocessing of the input video image. It can be seen that the video frame is processed by the histogram equalization algorithm; then, the feature matching can obtain more matching pairs, and more uniformly distributed feature points can be extracted from the low-light image.

5 | EXPERIMENTAL RESULTS

To test the positioning accuracy and illumination robustness of our SLAM algorithm, we evaluated two sets of classical open experimental data sets. We first use the TUM RGB-D indoor handheld image sequence to evaluate the SLAM trajectory accuracy of the proposed system and then use the ICL-NUIM synthetic data set to evaluate the illumination robustness of the SLAM system.

We completed all tests on a platform with Intel Core i5-6300HQ (2.30 GHz) and 8-GB RAM. After the experimental test, we found that, due to the randomness of each module of the SLAM system, there may be a large deviation from the start of the map initialization, and the subsequent threads may also have certain errors, resulting in a certain degree of fluctuation in the final experimental results. Therefore, our final experimental data are obtained by calculating the average of the results from five experiments.

5.1 | Localization accuracy in the TUM RGB-D data set

TUM RGB-D data sets are real video data sets recorded by handheld cameras. Because of its rich scenes and its own trajectory evaluation tools, it is a reliable SLAM evaluation tool. We selected 10 video sequences for experiments, including various types of real scenes and various camera motion postures. Furthermore, the SLAM system with the best effect is selected for a comparative test, and the experimental results are evaluated by calculating the absolute trajectory error.

Our goal is to get our system up to the same accuracy as ORB-SLAM2 in good illumination. The experimental results in Table 1 showed that we have achieved better results than expected. The SLAM trajectory error obtained by our method in each scene is smaller than the existing advanced methods (as shown in Figure 4). Especially in f1-XYZ, f1-desk, and f2-XYZ, the accuracy is greatly improved. Moreover, in the f3-str-tex-far scenario, ORB-SLAM2 could not generate a complete trajectory.

TABLE 1 Absolute keyframe trajectory root mean square error (RMSE)

TUM RGB-D benchmark	ORB-SLAM2	Ours
f1-xyz	0.03724	0.02071
f1-rpy	0.03287	0.04134
f1-desk	0.03873	0.01280
f1-desk2	0.04926	0.03121
f2-xyz	0.14216	0.03464
f2-rpy	0.03724	0.03746
f3-sit-halfshp	0.27237	0.24727
f3-sit-xyz	0.34892	0.32485
f3-str-tex-far	-	0.84901
f3-str-tex-near	0.24902	0.24900

Note. The accuracy of SLAM trajectory is evaluated under the TUM data set, and the absolute trajectory error is calculated by using the ATE algorithm. The main purpose is to evaluate the accuracy of our systems in ordinary environments.

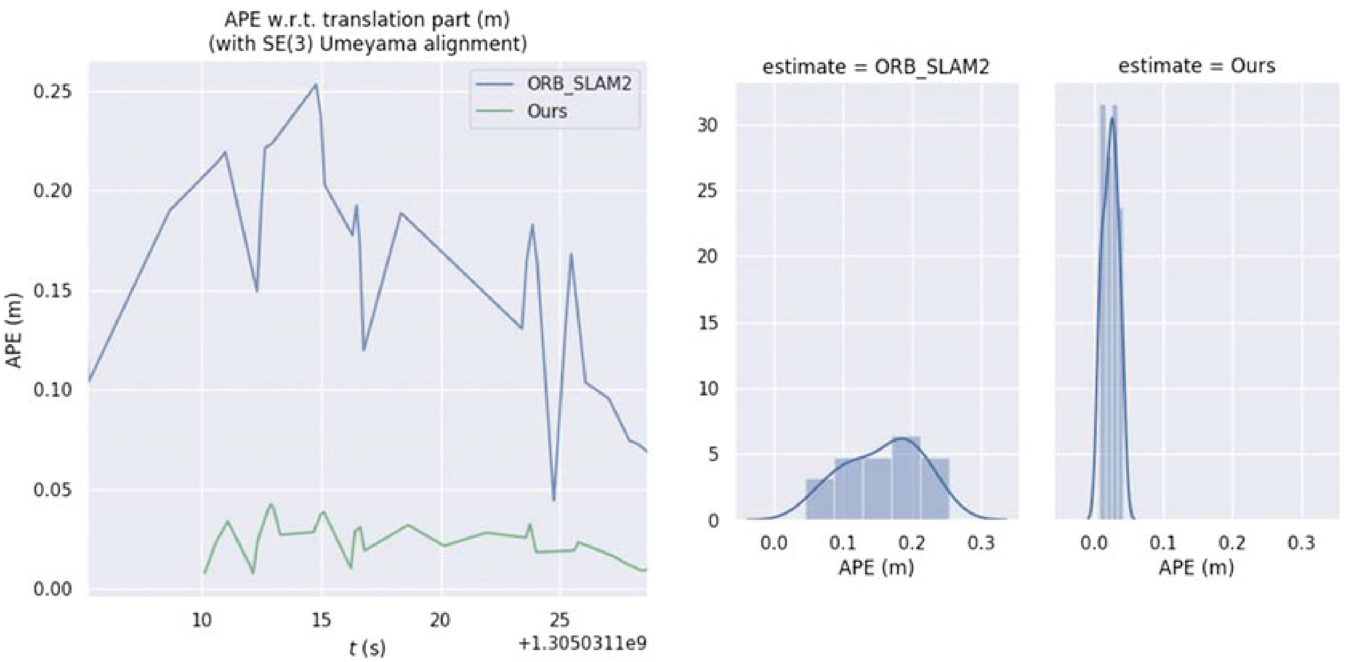

FIGURE 4 The absolute pose error of two trajectories from ORB-SLAM2 and our system. ORB = oriented FAST and rotated BRIEF; SLAM = simultaneous localization and mapping; APE = Absolute pose error

5.2 | Illumination robustness in the ICL-NUIM

Because the current real-time video data sets are mostly recorded in a well-lit and stable environment, it is not suitable for the illumination robustness evaluation of the proposed algorithm. Therefore, we have completed the experiment using the ICL-NUIM data set. The ICL-NUIM data set is an indoor video sequence synthesized by software. It can simulate different lighting environments and provide relevant trajectory true values. Therefore, we use this data set to study the performance of the system under the illumination change environment. The trajectory error is used as an evaluation index. We selected six scenarios of three lighting modes (good illumination, globally varying illumination, localized illumination) for six experiments.

In this set of experiments, the advantages of our system are highlighted. As can be seen from Table 2, in the low-light scenes of ETHl/syn1-flash, ETHl/syn2-flash, and ETHl/syn2-global, the traditional ORB-SLAM2 failed due to tracking

TABLE 2 Trajectory error root mean square error (RMSE)

ICL-NUIM benchmark	ORB-SLAM2	Ours
ETHl/syn1	0.26842	0.24531
ETHl/syn1-local	0.30623	0.20187
ETHl/syn1-global	0.42399	0.40285
ETHl/syn1-flash	-	0.44520
ETHl/syn2	0.15154	0.14624
ETHl/syn2-local	0.23728	0.17575
ETHl/syn2-global	-	0.15625
ETHl/syn2-flash	-	0.16982

Note. The illumination robustness of SLAM system is evaluated under the ICL-NUIM data set. Syn1 and Syn2 are two indoor scenes, and each includes three illumination modes (global illumination, local illumination, and flash). We evaluate the performance by calculating track error RMSE.

loss, whereas our system can eventually generate a complete trajectory although the accuracy is lower than that in a good lighting environment, indicating that our system does have good illumination robustness.

6 | CONCLUSION

In this paper, we proposed a monocular vision SLAM system for the low-light environment. We use the state-of-the-art ORB-SLAM2 as the basic framework and then improved the algorithm of its visual front end. First, the images are preprocessed by using the illumination compensation algorithm, and then, the two kinds of point features are extracted to complete the interframe matching so that our SLAM system can improve the robustness in the low-light environment and, to some extent, improve the positioning accuracy in the common scene. We conducted a number of experiments on the TUM RGB-D and ICL-NUIM data sets. The experimental results also showed that the proposed system is superior to the existing SLAM methods.

However, as we modify the ORB-SLAM2 system and add computing modules, the computational cost also increases. In future work, we will further optimize the algorithm mentioned in this paper, so that the image preprocessing method and multifeature extraction algorithm can work together better and reduce the computational cost. We also considered the impact of the environment with too much light on the SLAM system because, as far as we know, it is difficult to extract good feature information from the overexposure image.

ACKNOWLEDGEMENTS

The authors would like to thank the anonymous reviewers for their insightful comments. This work was supported by the Natural Science Foundation of China under Grants 61672375 and 61170118, and the National Key Research and Development Program of China (2018YFC1407405).

ORCID

Jiawei Huang https://orcid.org/0000-0002-1066-7883
Shiguang Liu https://orcid.org/0000-0003-2353-5318

REFERENCES

1. Liu R, Zhang J, Yin K, Wu JX, Lin R, Chen S. Instant SLAM initialization for outdoor omnidirectional augmented reality. Proceedings of the 31st International Conference on Computer Animation and Social Agents; 2018 May 21–23; Beijing, China. New York, NY: ACM; 2018. p. 66–70.
2. Ji P, Zeng M, Liu X. Geometric primitives based RGB-D SLAM for low-texture environment. Proceedings of the 31st International Conference on Computer Animation and Social Agents; 2018 May 21–23; Beijing, China. New York, NY: ACM; 2018. p. 59–65.

3. Zhu Z, Yang S, Dai H, Li F. Loop detection and correction of 3D laser-based SLAM with visual information. Proceedings of the 31st International Conference on Computer Animation and Social Agents; 2018 May 21–23; Beijing, China. New York, NY: ACM; 2018. p. 53–58.
4. Tardos JD, Mur-Artal R. ORB-SLAM2: an open-source SLAM system for monocular, stereo, and RGB-D cameras. IEEE Trans Robotics. 2017;33:1255–1262.
5. Leutenegger S, Chli M, Siegwart R. BRISK: binary robust invariant scalable keypoints. In: Metaxas DN, Quan L, Sanfeliu A, Van Gool LJ, editors. Proceedings of the 2011 International Conference on Computer Vision; 2011 Nov 6–13; Barcelona, Spain. Washington, DC: IEEE Computer Society; 2011. p. 2548–2555.
6. Lowe DG. Distinctive image features from scale-invariant keypoints. Int J Comput Vision. 2004;60:91–110.
7. Bay H, Ess T, Tuytelaars T, Van Gool L. Speeded up robust features (SURF). Comput Vis Image Underst. 2008;110:346–359.
8. Valgren C, Lilienthal A. SIFT, SURF & seasons: appearance-based long-term localization in outdoor environments. Robot Auton Syst. 2010;58:149–156.
9. Ross P, English A, Ball D, Corke P. A method to quantify a descriptors illumination variance. Paper presented at: Australian Conference on Robotics and Automation (ACRA 2014); 2014 Dec 2–4; Melbourne, Australia. Melbourne, Australia: Australian Robotics and Automation Association; 2014.
10. Milford M, Wyeth GF. SeqSLAM: visual route-based navigation for sunny summer days and stormy winter nights. Paper presented at: IEEE International Conference on Robotics and Automation; 2012 May 14–18; Saint Paul, MN. Piscataway, NJ: IEEE; 2012.
11. Nuske S, Roberts J, Wyeth G. Robust outdoor visual localization using a three-dimensional-edge map. J Field Robot. 2009;26:728–756.
12. Pumarola A, Vakhitov A, Agudo A, Sanfeliu A, Moreno-Noguer F. PL-SLAM: real-time monocular visual SLAM with points and lines. Paper presented at: IEEE International Conference on Robotics and Automation (ICRA); 2017 May 29–Jun 3; Singapore. Piscataway, NJ: IEEE; 2017. p. 4503–4508.
13. Von Gioi RG, Jakubowicz J, Morel JM, Randall G. LSD: a line segment detector. IPOL. 2012;2:35–55.
14. Kim P, Coltin B, Alexandrov O, Kim HJ. Robust visual localization in changing lighting conditions. Paper presented at: IEEE International Conference on Robotics and Automation (ICRA); 2017 May 29–Jun 3; Singapore. Piscataway, NJ: IEEE; 2017. p. 5447–5452.
15. Park S, Schöps T, Pollefeys M. Illumination change robustness in direct visual SLAM. Paper presented at: IEEE International Conference on Robotics and Automation (ICRA); 2017 May 29–Jun 3; Singapore. Piscataway, NJ: IEEE; 2017. p. 4523–4530.
16. Handa A, Whelan T, McDonald J, Davison AJ. A benchmark for RGB-D visual odometry, 3D reconstruction and SLAM. Paper presented at: IEEE International Conference on Robotics and Automation (ICRA); 2014 May 31–Jun 7; Hong Kong. Piscataway, NJ: IEEE; 2014. p. 1524–1531.
17. Engel J, Schöps T, Cremers D. LSD-SLAM: large-scale direct monocular SLAM. In: Fleet DJ, Pajdla T, Schiele B, Tuytelaars T, editors. Computer vision – ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014. Proceedings, Part II. Cham, Switzerland: Springer; 2014. p. 834–849.
18. Forster C, Pizzoli M, Scaramuzza D. SVO: fast semi-direct monocular visual odometry. Paper presented at: IEEE International Conference on Robotics and Automation (ICRA); 2014 May 31–Jun 7; Hong Kong. Piscataway, NJ: IEEE; 2014. p. 15–22.
19. Ojala T, Pietikäinen M, Mäenpää T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell. 2002;7:971–987.
20. Rosten E, Drummond T. Machine learning for high-speed corner detection. In: Leonardis A, Bischof H, Pinz A, editors. Computer vision – ECCV 2006: 9th European Conference on Computer Vision, Graz, Austria, May 7–13, 2006. Proceedings, Part I. Berlin, Germany: Springer; 2006. p. 430–443.
21. Chiu YS, Cheng FC, Huang SC. Efficient contrast enhancement using adaptive gamma correction and cumulative intensity distribution. Paper presented at: IEEE International Conference on Systems, Man, and Cybernetics; 2011 Oct 9–12; Anchorage, AK. Piscataway, NJ: IEEE; 2011. p. 2946–2950.
22. Jiao L, Sun Z, Sha A. Partially overlapped sub-block logarithmic transformation of images under non-uniform illumination. Comput Eng Appl. 2011;47(9):196–199.
23. Rahman Z, Jobson DJ, Woodell GA. Retinex processing for automatic image enhancement. J Electron Imaging. 2004;13:100–111.
24. Abdullah-Al-Wadud M, Kabir MH, Dewan MA, Chae O. A dynamic histogram equalization for image contrast enhancement. IEEE Trans Consumer Electron. 2007;53:593–600.

AUTHOR BIOGRAPHIES

Jiawei Huang received his BE degree from the School of Applied Mathematics, Chengdu University of Information Technology, in 2017. He is currently working toward his ME degree at the School of Computer Science and Technology, College of Intelligence and Computing, Tianjin University. His research interests include computer graphics and SLAM.

Shiguang Liu received his PhD degree from the State Key Laboratory of CAD & CG, Zhejiang University, Hangzhou, China, in 2007. He is currently a professor at the School of Computer Science and Technology, College of Intelligence and Computing, Tianjin University, Tianjin 300350, China. His research interests include image/video editing, computer graphics, visualization, and virtual reality.

How to cite this article: Huang J, Liu S. Robust simultaneous localization and mapping in low-light environment. *Comput Anim Virtual Worlds*. 2019;30:e1895. https://doi.org/10.1002/cav.1895