A Semantic Visual Slam for Dynamic Environments

Xuanhui Zhong, Hui Chai, Qian Pu, Chengji Zheng, Meng Hong, Jiaming Tian, Yaodong Wang and Min Guo

October 8, 2022

A semantic visual slam for dynamic environments

Xuanhui Zhong
School of Electrical and Mechanical Engineering
Wuhan University of Technology
*W*uhan, China
318794@whut.edu.cn

Hui Chai
School of Control Science and Engineering
Shandong University
Jinan, China
chaimax@sdu.edu.cn

Qian Pu
School of Mechanical,Electronic and Control Engineering
Beijing Jiaotong University
Beijing, China
qpu@bjtu.edu.cn

Chengji Zheng
School of Electrical and Mechanical Engineering
Wuhan University of Technology
*W*uhan, China
zcj110220@whut.edu.com

Meng Hong
School of Electrical and Mechanical Engineering
Wuhan University of Technology
*W*uhan, China
hongmeng@whut.edu.cn

Jiaming Tian
School of Electrical and Mechanical Engineering
Wuhan University of Technology
*W*uhan, China
tjming0408@whut.edu.cn

Yaodong Wang
School of Electrical and Mechanical Engineering
Wuhan University of Technology
Wuhan, China
yaodong@whut.edu.cn

Min Guo*
School of Electrical and Mechanical Engineering
Wuhan University of Technology
Wuhan, China
minguo@whut.edu.cn

***Abstract*—For autonomous robotic systems, simultaneous localization and mapping algorithm (SLAM) is one of the core technologies. Traditional simultaneous localization and mapping algorithms usually assume that the system works in a static environment. However, when there are dynamic objects in the environment, For example, people walking around indoors, etc., they will bring false observation data to the system, and the visual SLAM system will become unstable, affecting the system localization and limiting the application of visual SLAM in reality. However, if the dynamic objects occupy most of the image area, it will still affect the pose tracking. To solve this problem, this paper proposes a vision slam system adapted to dynamic environment, based on ORB-SLAM3, adding a lightweight target detection tracking network of YOLO5 at the front end to detect dynamic targets in the tracking environment, and rejecting the feature points of dynamic targets to reduce the influence of dynamic objects on the system. To avoid the lack of feature information due to excessive dynamic feature point rejection, the improved SLAM system in this paper uses Superpoint to replace ORB for feature extraction and descriptor calculation to further improve the robustness of the levy system. The experimental results of the dataset show that the improved ORB-SLAM3 system can effectively improve the robustness and accuracy of the system under dynamic environment.**

Keywords—Visiual SLAM, Object detection, Superpoint, Dynamic environment

I. INTRODUCTION

With the development of technology, autonomous mobile robots and autonomous driving technologies have made significant progress, and SLAM systems, as one of the essential core technologies in the field of autonomous mobile robots, have become the focus of research in this field in recent years. With the support of SLAM technology, mobile robots can perform position estimation and environment map construction without any a priori environmental information, which can help robots know their own position in real time. The research results mainly rely on monocular cameras, binocular cameras, and RGB-D cameras. Compared with LiDAR, the camera is able to take in more information about the environment, and visual SLAM has made many achievements in its development until now, and its performance in some specific scenes can meet the expected requirements. However, most traditional vision SLAM systems usually assume that the environment is static, and in some highly dynamic environments, traditional vision SLAM systems will affect the matching accuracy due to the presence of dynamic points, and if the proportion of dynamic points is too high in the actual environment, it will lead to the degradation of trajectory accuracy, and even the system initialization and tracking and positioning building work cannot be realized.

In this paper, based on ORB-SLAM3 we design a SLAM system that eliminates dynamic interference and has higher robustness of feature extraction, uses deep learning to detect and track dynamic objects, eliminates feature points of dynamic objects to reduce the influence of dynamic objects on localization in the real environment, and uses Superpoint to replace ORB for feature extraction and descriptor calculation on this basis. Further improving the robustness of the system, the system improves the localization accuracy of the visual SLAM system in dynamic environments on the basis of ensuring real-time performance. The main contributions of this paper are summarized as follows:

1. embedding the lightweight target detection network into the ORB-SLAM3 system, which can be used to detect the basic semantic information of tracking dynamic objects.

2. Using Superpoint to replace ORB for feature extraction and descriptor computation in ORB-SLAM3 system to ensure sufficient environmental feature information.

3. A SLAM system that eliminates dynamic feature points and uses a deep network model to extract feature points to compute descriptors is successfully constructed based on ORBSLAM3, which can effectively improve the accuracy and robustness of the system in dynamic environments.

The rest of the paper is structured as follows: chapter 2 reviews related work by other researchers; chapter 3 details the framework structure of the improved SLAM and describes the proposed approach; chapter 4 reports the experimental results evaluated on the TUM dataset; finally, future work is proposed in summary in section 5.

II. Related Works

A. Semantic slam

One of the larger difficulties faced by visual SLAM in practical applications is the dynamic interference problem in the lower complex environment. In recent years, many researchers have been studying the robustness of visual SLAM systems in dynamic environments, and the key to solving this problem is how to accurately detect and reject dynamic feature points in real time. Researchers have proposed methods for this problem such as multi-view geometry-based methods, deep learning-based methods for target detection, semantic segmentation, optical flow/scene flow-based methods, etc. Bescos et al. [1] proposed DynaSLAM, which uses CNN for pixel-wise segmentation of dynamic objects in key frames without extracting that part of features in the case of monocular and binocular cameras, and for RGBD cameras case, dynamic objects are detected using a multi-view geometric model and a deep learning based algorithm. Yu et al. [2] proposed DS-SLAM, which combines a semantic segmentation network with a moving consistency checking method to filter out dynamic objects in the scene and improve the robustness and accuracy of the system in dynamic scenes. Kim et al. [3] proposed a robust dense visual odometry calculation method based on background model, which uses the depth scene to calculate the background model while estimating the camera's own motion and using a representative background model with a nonparametric model to filter out dynamic feature points and improve the system stability. Zhang et al. [4] proposed a semantic segmentation combined with optical flow network dynamic SLAM system to detect the motion of dynamic objects by optical flow and eliminate dynamic feature points to improve system accuracy. Zhang et al. [5] proposed a semantic SLAM system to identify dynamic objects in the environment by YOLO and construct a semantic map to filter out dynamic feature points to improve system stability. Li et al. [6] proposed a real-time depth-edge-based RGB-D SLAM system, which is based on frame-to-keyframe alignment, using only depth-edge points and reducing the influence of dynamic objects on the system by representing the likelihood of a point becoming part of the static environment with the static weight of the keyframe edge points. Zhao et al. [7] used an optical flow science approach to check the potential in dynamic regions and background regions under the assumption of spatio-temporal consistency of the two images,and determine the correspondence of points from two consecutive images to eliminate the influence of dynamic points on the system. Liu et al. [8] proposed a new semantic-based real-time dynamic VSLAM algorithm, which effectively uses the semantic segmentation results for dynamic target detection and outlier removal while maintaining the real-time nature of the algorithm. Sun et al. [9] proposed a new motion segmentation algorithm for RGB-D, where motion segmentation uses vector quantized depth images and applies maximum a posteriori estimation to vector quantized depth images to accurately determine the foreground. Scona et al. [10] proposed a robust dense RGB-D SLAM method for detecting moving targets in dynamic environments while reconstructing the background structure, simultaneously estimating camera motion as well as probabilistic static/dynamic segmentation of the current RGB-D image to reduce the overall drift. Zhang et al. [11] proposed a new dense RGB-D SLAM method that uses optical flow residuals to highlight the dynamic semantics in RGB-D point clouds for more accurate dynamic/static segmentation.Dai et al.[12] proposed a point cloud correlation-based segmentation method to separate static and dynamic points, which uses the correlation between map points to separate points belonging to static scenes and points belonging to different motion objects into different classes to improve the robustness and accuracy of the system for motion estimation in dynamic environments.

B. Feature Extraction

Cong et al. proposed the use of Superpoint for feature extraction in UAV SLAM with accurate extraction and high computational efficiency. Tang et al.[15] proposed a deep learning based network GCNv2 for generating keypoints and descriptors. Kang et al.[17] proposed the use of shallow convolutional neural networks to extract feature points and enhance the SLAM system.

III. System Introduction

In this chapter, we will introduce the improved ORB-SLAM3 in detail.This chapter is divided into three main aspects. First, the improved system framework is introduced; second, the added target detection method is introduced; and finally, Superpoint feature extraction is introduced.

A. System Framework

The conventional ORB-SLAM3 has excellent performance in most practical situations under static environment assumptions, and the accuracy is further improved compared with ORB-SLAM2 [14] by introducing IMU combined with vision; realizing a multiple sub-map system, reconstructing the sub-map when following a loss, and merging with the previous sub-map when looping back to improve the system robustness [13]. However, the problem of poor positioning accuracy or even failure still exists in dynamic environments. For this reason, we choose to add a target detection tracking thread to ORB-SLAM3 and use Superpoint to replace ORB to extract feature points. An overview of the improved ORB-SLAM3 system is shown in Fig. 1:

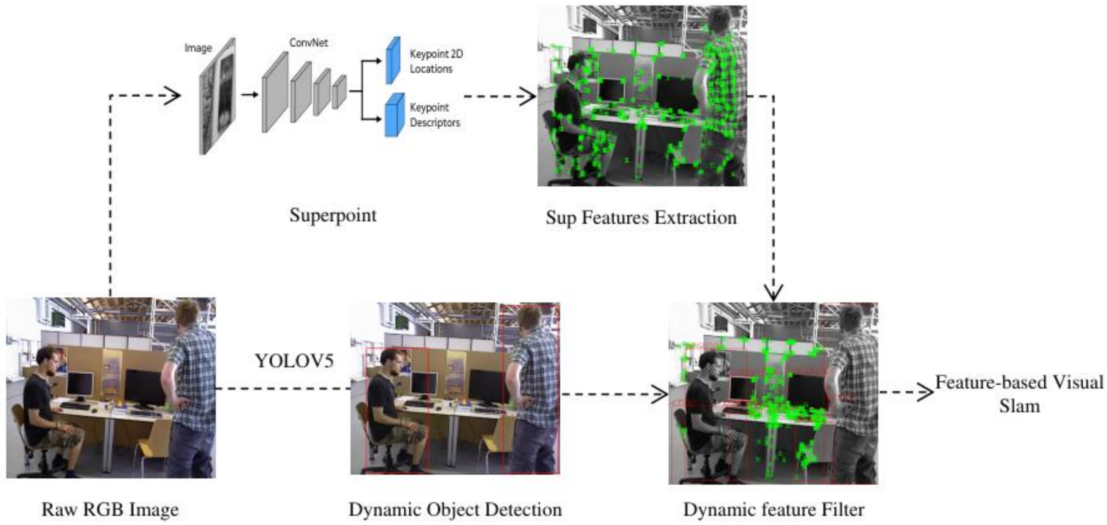

Fig. 1 System framework overview, based on the original ORB-SLAM3 front-end, add YOLO5 to provide semantic information to detect and track dynamic targets, add Superpoint convolutional neural network instead of ORB to extract feature points, eliminate dynamic feature points and keep only static feature points.

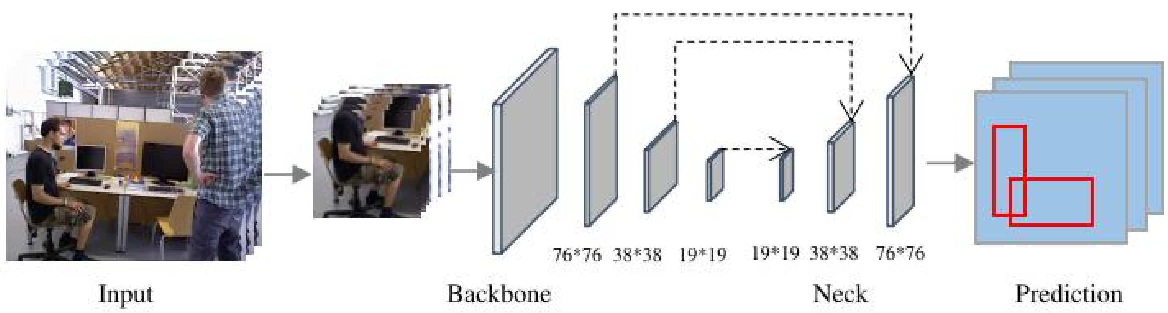

Fig. 2 YOLO5s convolutional neural network model overview diagram, mainly contains Input, Backbone, Neck, Prediction four parts

B. Dynamic detection

The task of the target detection model is to detect objects in the image and determine their location coordinates, as seen in Fig. 1, the red two-dimensional bounding box indicates the location of the dynamic object, the mainstream detection network is divided into single-order network and dual-order network. Single-order networks extract features directly in the network to predict the classification and location of objects, characterized by fast speed and low accuracy compared to dual-order networks; dual-order networks need to be classified and regressed into Region Proposal (RP) for each RP to return results, which is slower but more accurate. The common single-order networks are YOLO series, SSD, RetinaNet, YOLO as the pioneer of single-order network, with the iterative update in recent years, its real-time and target detection effect is gradually improved, YOLO5 uses Mosaic data enhancement in the model training stage, the pictures are randomly scaled, randomly cropped, randomly arranged in a way to stitch the rich detection object background and small targets, which greatly improves the network training speed and reduces the model memory. To ensure the real-time performance of visual Slam and improve the detection efficiency, this paper selects the faster lightweight single-order network model YOLO5s, and the target detection is outlined in Fig. 2.

yolo5s contains four parts: Input, Backbone, Neck and Prediction. The images are input in standard size, and pre-processed in Input module with data enhancement, adaptive anchor frame calculation, adaptive image scaling, etc. The original images are uniformly scaled to standard size and sent to Backbone module. In the Backbone module, we first perform isolated sampling and stitching to split the image into multiple low-resolution images and then perform feature extraction for later target detection. box's loss function:

$$CIOU\_Loss = 1 - CIOU = 1 - (IOU - \frac{Distance\_2^2}{Distance\_C^2} - \frac{v^2}{(1-IOU)+v})$$

v is the aspect ratio impact factor is the aspect ratio impact factor, the formula is as follows:

$$v = \frac{4}{\pi^2}(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w^p}{h^p})^2$$

Where IOU denotes the intersection ratio of two boxes to be calculated, $Distance\_2$ denotes the Euclidean distance between the center point of the predicted box and the center point of the real box, and $Distance\_C$ is the diagonal distance of the smallest box that can enclose two boxes. Compared with the previous generations of Bounding box loss function, $CIOU\_Loss$ integrates the geometric factors such as overlap area, centroid distance, aspect ratio, etc. In the case that the prediction box and the real box do not overlap, IOU is 0, the gradient can still be calculated. Finally, NMS non-maximum suppression is used to determine whether the same object is detected by the detection frame and eliminate the redundant detection frames.

C. Superpoint feature Extraction

ORB is used for feature extraction of ORB-SLAM3 vision front-end based on its small computational effort and possesses rotation and scale invariance, however, in scenes with low texture and obvious illumination changes, the extraction of tracking feature points is generally effective, and the system may even fail to initialize due to the insufficient number of feature points. Therefore, in this paper, while eliminating dynamic feature points to optimize the SLAM system, we use superpoint to replace ORB for feature extraction to further improve the robustness of the visual slam system. The method adopts a self-supervised full convolutional network framework, in which feature detection and descriptor computation share a single encoder to enhance the association between them and reduce computation, and adopts a sub-pixel convolution upsampling method to reduce model computation in feature extraction. In terms of descriptor computation, a semi-dense descriptor is first obtained by using the UNC-like method to reduce the memory consumption of algorithm training and the running time of the algorithm, and then the descriptors are obtained by interpolating all the pixels with double cubic polynomials and then by normalizing the descriptors with L2. Fig. 3 shows the comparison results between ORB extracted feature points and superpoint extracted feature points.

The two images in the experiment (a)(b) are the same image in the TUM dataset. (a) is the feature points extracted by the traditional ORB-SLAM3 based on Oriented FAST and Rotated BRIEF (ORB), and it can be seen that there are almost no feature points extracted from the strong light area in the upper left corner of the image and the weak light area in the middle part of the upper edge of the image. In our improved SLAM system, it is obvious that the feature points extracted by Superpoint have more number of feature points and are evenly dispersed, which has stronger robustness.

(a)ORB-SLAM3 (b)Ours

Fig. 3 Comparison of traditional ORB-SLAM3 feature extraction and improved SLAM feature extraction

TABLE I. RESULTS OF ABSOLUTE TRAJECTORY ERROR (ATE)

Dataset sequences	ORB-SLAM3		Dyna-SLAM		Ours		Improvements against ORB-SLAM3	
	RMSE	*STD*	*RMSE*	*STD*	*RMSE*	*STD*	*RMSE*	*STD*
fr3/w/xyz	0.3948	0.1892	0.0164	0.0086	0.0127	0.0069	96.78%	96.35%
fr3/w/rpy	0.6429	0.2740	0.0354	0.0190	0.033	0.0188	94.49%	93.14%
fr3/w/half	0.3914	0.0954	0.0296	0.0157	0.0268	0.0143	93.15%	85.01%
fr3/s/static	0.2039	0.0807	0.0108	0.0056	0.0083	0.0043	95.93%	94.67%

TABLE II. RESULTS OF ROTATIONAL RELATIVE POSE ERROR (RPE)

Dataset sequences	ORB-SLAM3		Dyna-SLAM		Ours		Improvements against ORB-SLAM3	
	RMSE	*STD*	*RMSE*	*STD*	*RMSE*	*STD*	*RMSE*	*STD*
fr3/w/xyz	8.3007	5.7019	0.6284	0.3848	0.6137	0.1786	92.61%	96.87%
fr3/w/rpy	8.9483	7.6020	0.9849	0.5701	0.5144	0.2323	94.25%	96.94%
fr3/w/half	6.3572	5.1356	0.7842	0.4012	0.7099	0.2324	88.83%	95.47%
fr3/s/static	0.3121	0.2075	0.3416	0.1642	0.1647	0.0818	47.23%	60.58%

IV. EXPERIMENTAL RESULTS

The performance of the improved SLAM for dynamic scenes will be described in detail in this chapter. We chose four different scenes from the TUM dataset [16] to test the proposed method in this paper. The experimental computing platform configuration is AMD-5800X, GTX2060 and 16GB RAM, and the SLAM is running on ubuntu 20.04. The TUM RGB-D dataset is composed using the Microsoft Kinect sensor collection, which is often used in the SLAM field for system performance evaluation. The four datasets chosen are dynamic datasets in TUM, where fr3_walking_xyz describes two people walking, sitting, and talking to each other in a scene, which is considered a highly dynamic scene, fr3_walking_rpy describes the same scene as fr3_walking_xyz, but the two cameras move differently, fr3_ walking_half dataset, the camera does hemispheric trajectory movement to collect data, fr3_siting_static describes two people doing some simple sitting and talking actions.

A. Experimental evaluation criteria

Absolute trajectory error is the direct difference between estimated and real poses, which can reflect the algorithm accuracy and global consistency of trajectory very intuitively. The program first aligns the real and estimated values according to the timestamp of poses, then calculates the difference between each pair of poses and finally outputs it in the form of a graph, which is very suitable for evaluating This criterion is ideal for evaluating the performance of visual SLAM systems. The relative pose error is used to calculate the difference between the pose changes within the same two timestamps, which is suitable for estimating the drift of the system. The magnitude of the absolute trajectory error and the relative pose error can be determined by the root mean square error and the standard deviation.

B. Evaluation accuracy

We use ATE and RPE as evaluation criteria, and both use root mean square error and standard deviation to compare data with ORB-SLAM3 and Dyna-SLAM, respectively, and the experimental data are shown in Table 1 and Table 2, where Table 1 shows the data results related to ATE and Table 2 shows the data results related to RPE. From Table 1-Table 2, we can see that the improved SLAM can lead to the improvement of most dynamic sequence performance of TUM. Compared with the conventional ORB-SLAM3, the RMSE and STD errors can be reduced by up to 96.78% and 96.35% in terms of absolute trajectory errors, and the trajectory accuracy is also improved to some extent compared with Dyna-slam.We provide ATE plots of two challenging high dynamic scenarios fr3_walking_xyz and fr3_walking_half datasets in ORB-SLAM3 and our improved system. From the real trajectories and predicted trajectories provided by the datasets, the improved algorithm in this paper can effectively handle the impact of dynamic targets on the trajectory estimation and localization of the SLAM system .

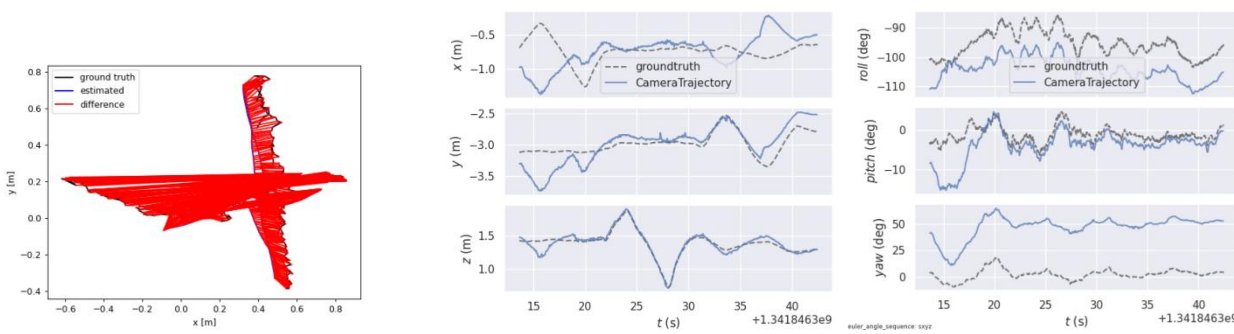

Fig. 4 The performance of the conventional ORB-SLAM3 system in the TUM dataset fr3_walking_xyz sequence, (a) plot of ATE, (b) plot of curve fit of the estimated trajectory of the camera with the real trajectory in x-direction, y-direction, and z-direction translation, and (c) plot of curve fit of the camera doing roll, pitch, and yaw motion.

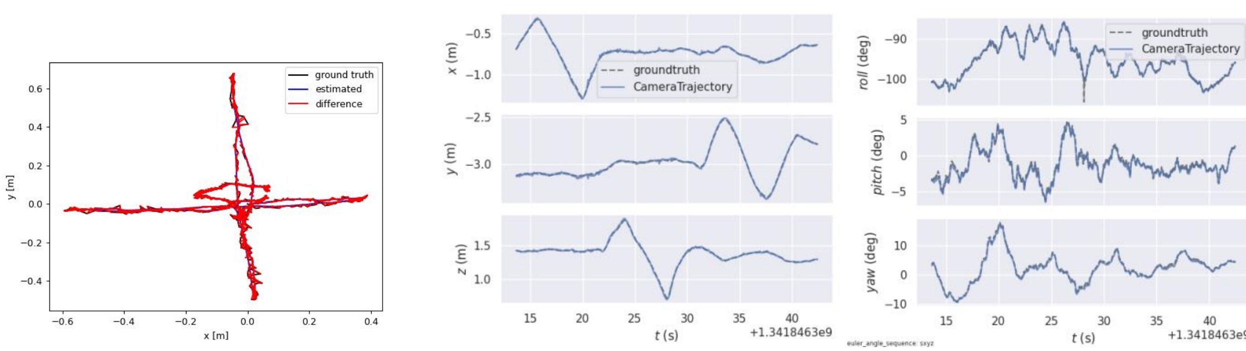

Fig. 5 The performance of our improved ORB-SLAM3 system in the TUM dataset fr3_walking_xyz sequence is shown in (a) plot of ATE, (b) plot of curve fit of the estimated trajectory of the camera with the real trajectory in x-direction, y-direction, and z-direction translation, and (c) plot of curve fit of the camera doing roll, pitch, and yaw motion.

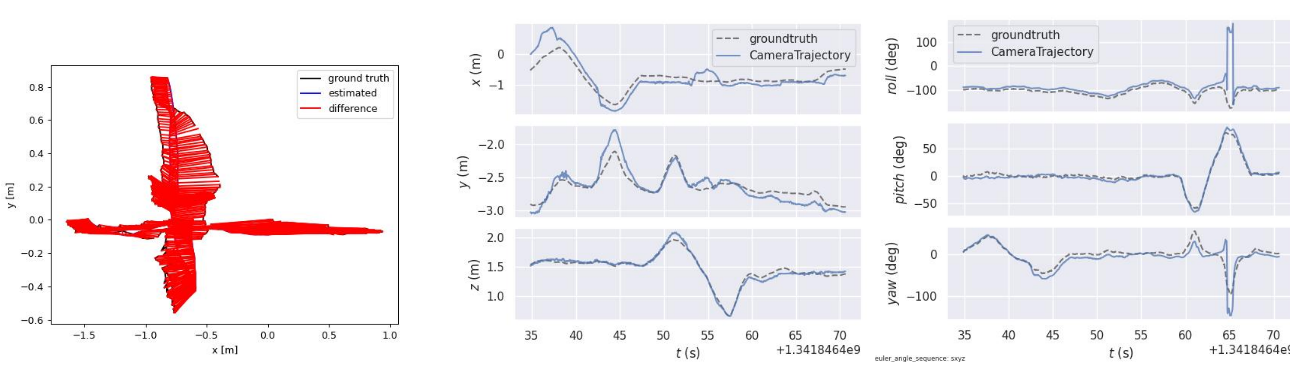

Fig. 6 The performance of the conventional ORB-SLAM3 system in the TUM dataset fr3_walking_half sequence, (a) figure shows the ATE plot, (b) figure shows the curve fit of the estimated trajectory of the camera with the real trajectory in x-direction, y-direction and z-direction translation, (c) figure shows the curve fit of the camera doing roll, pitch and yaw motion.

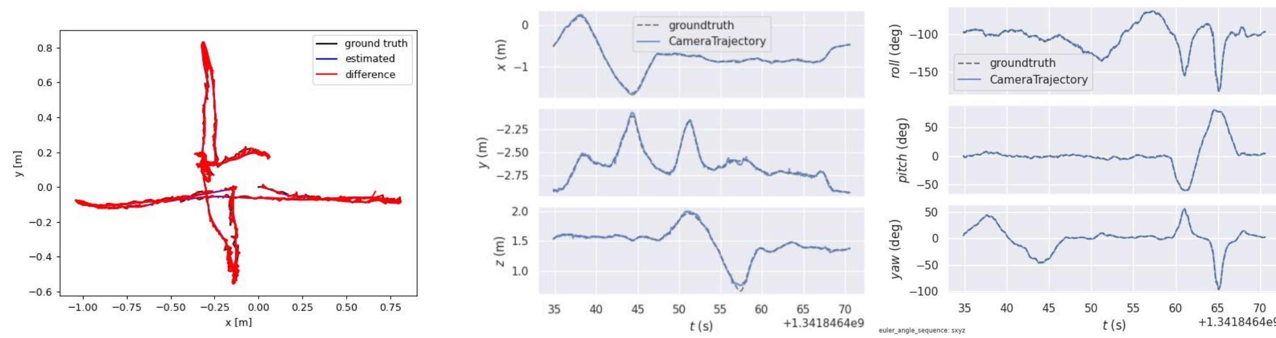

Fig. 7 The performance of our improved ORB-SLAM3 system in the TUM dataset fr3_walking_half sequence is shown in (a) plot of ATE, (b) plot of curve fit of the estimated trajectory of the camera with the real trajectory in x-direction, y-direction, and z-direction translation, and (c) plot of curve fit of the camera doing roll, pitch, and yaw motion.

As shown in Fig.4 Fig.5, (a) the red part in the figure shows the error between the ground-truth and the estimated trajectory of the system, in the fr3_walking_xyz sequence, the difference between the estimated trajectory of the traditional ORB-SLAM3 and the ground-truth provided by the dataset is large, and the error of the estimated trajectory of the improved SLAM system in this paper is significantly (b) In (b), from the real curves of camera motion in x, y and z directions and the curve fitting plots obtained from the system estimation, the improved SLAM system estimation in this paper is more accurate. (c) In the figure, from the real curves of the camera doing roll, pitch, ywa motion and the curve fitting plot obtained from the system estimation, the improved SLAM system in this paper is more accurate in estimation. The results show that the improved system is more robust in the dynamic environment.

As shown in Fig.6 Fig.7. In the fr3_walking_half sequence, it can be seen from the plot in (a) that the difference between the estimated trajectory of the conventional ORB-SLAM3 and the real trajectory provided by the dataset is large, while the error of the estimated trajectory of the improved SLAM system in this paper is significantly smaller, and in (b), from the real motion curves of the camera in the x, y, and z directions and the curve fit plots obtained from the system estimation The improved SLAM system in this paper has a higher accuracy in estimation. (c) In the figure, from the real curves of the camera doing roll, pitch, and yaw motion and the curve fitting plots obtained from the system estimation, the improved SLAM system in this paper is estimated more accurately. The results show that the improved system is more robust in the dynamic environment.

V. CONCLUSIONS

In this paper, a real-time semantic SLAM system is proposed that can reduce the impact of dynamic targets on camera pose estimation. We add the YOLO dynamic target detection tracking thread to the original ORB-SLAM3 system to remove the influence of dynamic feature points on the accuracy of the SLAM system, and use Superpoint to replace ORB to extract feature points, which experimentally proves that more and evenly dispersed feature points can be obtained, which further improves the robustness of the SLAM system to some extent. The improved system is tested on several dynamic sequences of the TUM RGB-D dataset. The results show that the improved SLAM outperforms the conventional ORB-SLAM3 in terms of accuracy and robustness.

REFERENCES

[1] B Bescós, JM Fácil, Civera J , et al. DynSLAM: Tracking, Mapping and Inpainting in Dynamic Scenes[C]// 2018:1-1.

[2] Yu C , Liu Z , Liu X , et al. DS-SLAM: A Semantic Visual SLAM towards Dynamic Environments[C]// 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2018.

[3] Kim, Deok-Hwa, Jong-Hwan. Effective Background Model-Based RGB-D Dense Visual Odometry in a Dynamic Environment[J]. IEEE Transactions on Robotics: A publication of the IEEE Robotics and Automation Society, 2016.

[4] Zhang J , Henein M , Mahony R , et al. VDO-SLAM: A Visual Dynamic Object-aware SLAM System[J]. 2020.

[5] Zhang L , Wei L , Shen P , et al. Semantic SLAM Based on Object Detection and Improved Octomap[J]. IEEE Access, 2018, PP:1-1.

[6] Li S , Lee D . RGB-D SLAM in Dynamic Environments using Static Point Weighting[C]// International Conference on Robotics and Automation. IEEE - Institute of Electrical and Electronics Engineers, 2017.

[7] Zhao L , Liu Z , Chen J , et al. A Compatible Framework for RGB-D SLAM in Dynamic Scenes[J]. IEEE Access, 2019, PP(99):1-1.

[8] Liu Y , Miura J . RDS-SLAM: Real-Time Dynamic SLAM Using Semantic Segmentation Methods[J]. IEEE Access, 2021, PP(99):1-1.

[9] Sun Y , Ming L , Meng Q H . Improving RGB-D SLAM in dynamic environments: A motion removal approach[J]. Robotics and Autonomous Systems, 2016, 89:110−122.

[10] Scona R , Jaimez M , Petillot Y R , et al. StaticFusion: Background Reconstruction for Dense RGB-D SLAM in Dynamic Environments[C]// 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018.

[11] Zhang T , Zhang H , Li Y , et al. FlowFusion: Dynamic Dense RGB-D SLAM Based on Optical Flow[C]// International Conference on Robotics and Automation. IEEE, 2020.

[12] Dai W , Zhang Y , Li P , et al. RGB-D SLAM in Dynamic Environments Using Point Correlations[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020, PP(99):1-1.

[13] Campos C , Elvira R , JJG Rodríguez, et al. ORB-SLAM3: An Accurate Open-Source Library for Visual, Visual-Inertial and Multi-Map SLAM[J]. 2020.

[14] Mur-Artal R , JD Tardós. ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras[J]. IEEE Transactions on Robotics, 2017.

[15] C. H. Quach, M. D. Phung, H. V. Le and S. Perry, "SupSLAM: A Robust Visual Inertial SLAM System Using SuperPoint for Unmanned Aerial Vehicles," 2021 8th NAFOSTED Conference on Information and Computer Science (NICS), 2021.

[16] Sturm J, Engelhard N, Endres F, et al. A benchmark for the evaluation of RGB-D SLAM systems[C]//2012 IEEE/RSJ international conference on intelligent robots and systems. IEEE, 2012: 573-580.

[17] Tang J, Ericson L, Folkesson J, et al. GCNv2: Efficient correspondence prediction for real-time SLAM[J]. IEEE Robotics and Automation Letters, 2019,

Authors' background

Name	*Prefix*	*Research Field*	*Email*	*Personal website*
Xuanhui Zhong	MasterStudent	Robotics	318794@whut.edu.cn	
Hui Chai	AssociateProfessor	Robotics	chaimax@sdu.edu.cn	https://faculty.sdu.edu.cn/chaihui2/zh_CN/index.htm
Qian Pu	Lecture	System control	qpu@bjtu.edu.cn	
Chengji Zheng	MasterStudent	Robotics	zcj110220@whut.edu.cn	
Meng Hong	MasterStudent	Robotics	18171392754@163.com	
Jiaming Tian	MasterStudent	Robotics	tjming0408@whut.edu.cn	
Yaodond Wang	MasterStudent	Robotics	yaodong@whut.edu.cn	
Min Guo*	AssociateProfessor	Robotics	minguo@whut.edu.cn	http://smee.whut.edu.cn/rsgz/szdw/201901/t20190103_351129.shtml