SLAM-BASED MULTI-SENSOR BACKPACK LIDAR SYSTEMS IN GNSS-DENIED ENVIRONMENTS

Dedong Zhang[1,2], *Zheng Gong*[2,3], *Yiping Chen*[3], *John Zelek*[2], *Jonathan Li*[1, 2,3*]

[1] Department of Geography and Environmental Management, University of Waterloo, Waterloo, Ontario N2L 3G1, Canada – {dedong.zhang, junli}@uwaterloo.ca

[2] Department of Systems Design Engineering, University of Waterloo, Waterloo, Ontario N2L 3G1, Canada – {jzelek, junli}@uwaterloo.ca

[3] Fujian Key Laboratory of Sensing and Computing for Smart Cities, School of Informatics, Xiamen University, Xiamen, Fujian 361005, China – gongzheng@stu.xmu.edu.cn, chenyiping@xmu.edu.cn

***Abstract* -. The backpack LiDAR system is a highly efficient device for indoor positioning and navigation. With the use of multi-sensor interactions inside of the backpack, it can solve the problem of undetermined trajectories or locations in a GNSS-denied environment. This paper presents a multi-sensor-based backpack LiDAR system for mapping in GNSS-denied environments. With this device, we solve the problem of inaccurate positioning caused by the inability to receive GNSS signals in a small-sized lidar portable device, also reduces the cumulative error caused by the IMU module through the analysis of the vibration pattern. Through the demonstration of the results, the method is of great significance for 3D reconstruction of the indoor environment and object detection.**

***Index Terms*—backpack LiDAR, GNSS-denied, IMU, Pattern recognition**

I. INTRODUCTION

In recent years, with the demand for high-quality map information, many scientific research teams have begun to conduct in-depth research on real-time 3D object detection [1,2,3]. And one of the challenging tasks for this series of study is to detect 3D objects in a Global Navigation Satellite System (GNSS)denied environment. The GNSS-denied environment is the environment that generally hard to receive signals from the GNSS, such as underground tunnels, in-building parking lots, or other indoor environments [4]. The backpack LiDAR is undoubtedly the best solution for low-cost, high-efficiency indoor mapping, 3D reconstruction, and object tracking [5,6,7,8]. Since the portable LiDAR equipment is in the preliminary stage of research, there is no unified and effective model platform for the GNSS-denied environment. Through long-term and in-depth study, we have proposed a multi-sensor backpack LiDAR system. The multi-sensor complementary feature effectively solves the positioning problem in the GNSS-denied environment.

This article, we will introduce the hardware design of the backpack LiDAR system and discuss the use of wavelet transform to process the vibration noise of the Inertial Measuring Unit (IMU) data for the GNSS-denied environment. The rest of this paper is organized as follows. Section II introduces the hardware setup of the device and presents data extracted by the backpack. Section III describes the proposed method. Section IV presents and discussed the experimental results. Section V concludes the paper.

II. PLATFORM DESCRIPTION

The machine platform is mainly composed of three parts: (1) Sensor, which acquires the data. The sensors here primarily refer to LiDAR, panoramic camera and IMU. (2) Control platform, which mainly consists of an NVIDIA's embedded Linux development platform featuring a Tegra K1 SOC (CPU + GPU + ISP in a single chip). (3) Power supply system, the entire backpack LiDAR system is powered by a lithium battery at the bottom; the battery can provide the backpack for 3 hours of working power. Fig. 1 shows the hardware diagram of our backpack LiDAR system.

The system will process the simultaneous localization and mapping (SLAM) algorithm to output the 3D point cloud image on the tablet (Fig. 7). However, the vibration will inevitably occur during the movement of the human body, and these vibrations will cause serious errors to LiDAR and IMU. Therefore, in this article, we will analyze the error generated by some of the sensors used in the process, and use the wavelet transform to optimize the cumulative error of the vibration.

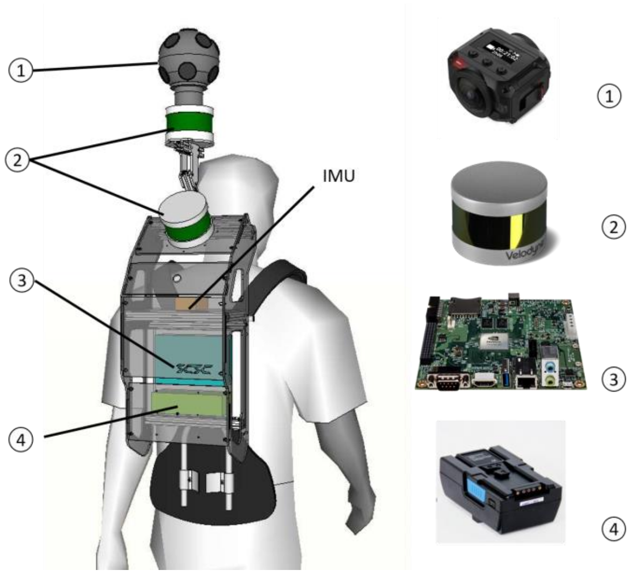

Fig.1 Sensor setup of backpack LiDAR. (1) panoramic RGB camera (2) Dual Velodyne VLP-16 Laser Scanner, (3) Jetson Tk1 embedded system, (4) Lithium battery

A. Software Description

Because of the size limitation of the wearable system, all data manipulation and data storage are done through a handheld tablet. As shown in Figure 2, the embedded system uses the LINUX UBUNTU system to control external devices (LiDAR, camera, IMU, UART). The tablet receives the data information sent by the embedded system through WIFI, and displays the real-time data output, and can also adjust the sensor usage according to the machine status information.

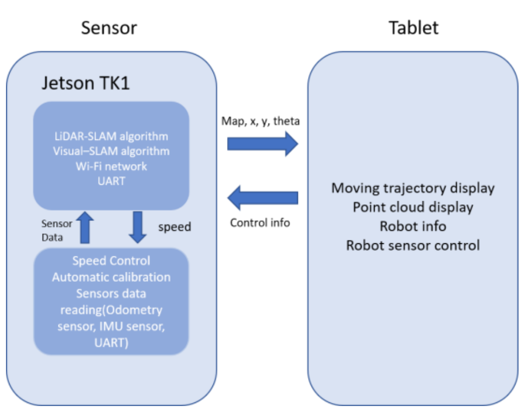

Fig. 2 Software architecture diagram of our backpack platform.

It should be noted that since each sensor can operate independently. How to synchronize multi-sensor systems is an essential task. And because there is a big gap between the systematic errors of different sensors, the system will introduce system errors by various sensors. In this article, we will focus on eliminating the cumulative error of the vibration of the IMU sensor.

B. IMU Data Classification

In the calculation process using multi-sensor fusion, the Inertial Measuring Unit (IMU) data is unstable due to the IMU accuracy and cumulative error, and without the correction of the position by the GNSS signal, the IMU data will no longer be worthy of trust after more than a few seconds of operation. During data processing, we optimize the three parts of the data separately: velocity, acceleration, and angular rotation. And according to the walking state, the IMU data are divided into five types: smooth straight, go up the stairs, go down the stairs, left turn, and right turn. Fig. 3 shows the process of collecting data from a lidar backpack in a real-world environment.

Fig. 3 Scanning an indoor using a backpack LiDAR.

As a representative backpack LiDAR data, we used a set of straight-line walking data for testing. This data contains 107 frames of images and IMU data for a straight-line walking at a constant speed. The total data size is 0.4 GB, and the entire data length is about 12 seconds.

In the IMU data, the algorithm mainly focusses on the noise reduction of the vibration. As for the analysis of the data, we focus on velocity, acceleration, and rotation respectively. Further, because the selected data set is in the linearly walking state, the velocity of forward, the acceleration of the x-axis, and the rotation of the x-axis are not considered as the focus of noise cancellation. Figs. 4 and 5 show the velocity, acceleration, and rotation of the backpack during the walking process.

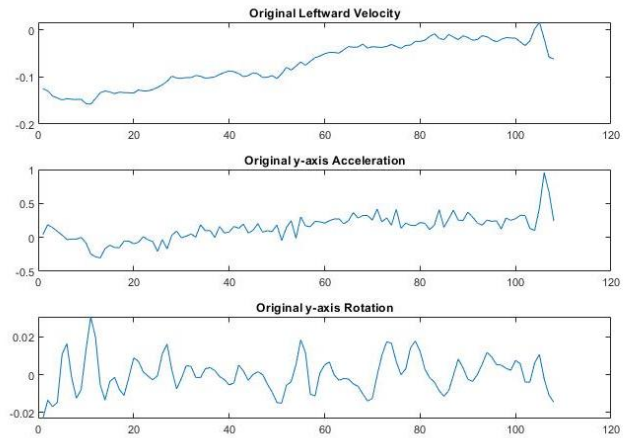

Fig 4. Original leftward velocity (top), original y-axis acceleration (middle) and original y-axis rotation (bottom).

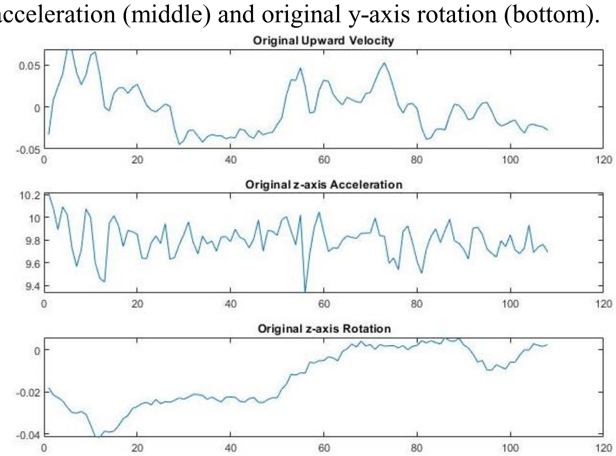

Fig 5. Original leftward velocity (top), original z-axis acceleration (middle) and original z-axis rotation (bottom).

III. Method

The data were processed in four steps (see Fig. 6), including IMU data classification, Wavelet transformation, threshold adjustment, and inverse wavelet transformation.

Step 1: The data were divided into three categories: velocity, acceleration and angular rotation.
Step 2: A wavelet transform was performed on the data signal under the assumption that the noise in the data signal conforms to the Gaussian distribution.
Step 3: The threshold was then adjusted, and the modified signal was restored using the inverse wavelet transform.
Step 4: The noise-reduced signal was compared with the original signal and continue to adjust the threshold until the data meets the optimal noise reduction criteria.

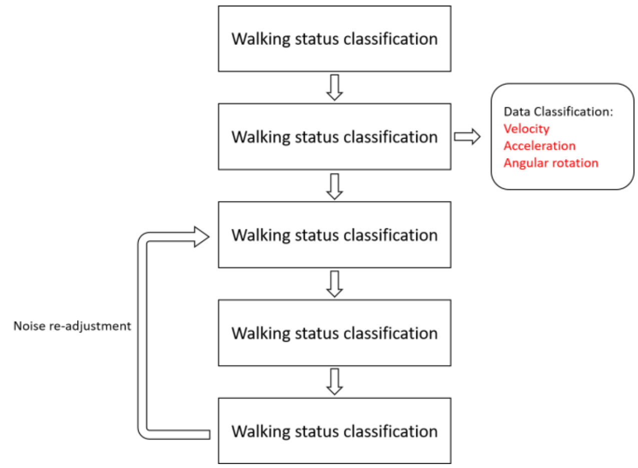

Fig 6. Flowchart for IMU signal algorithmic process.

IV. Results and Discussion

Figs.7 and 8 show the experimental results. Fig. 7 shows a LiDAR backpack that effectively extracts the interior features of a building, including ceilings, walls, and floors, in a three-story building. It can notice clearly that the point cloud image is not affected by the operator's walking up the floor vibration, and the floors can be correctly parallel to each other. As shown in Fig 8, the proposed method has a relatively higher efficiency in correcting the acceleration. At the same time, it has an effect on both the velocity and the correction of the rotation.

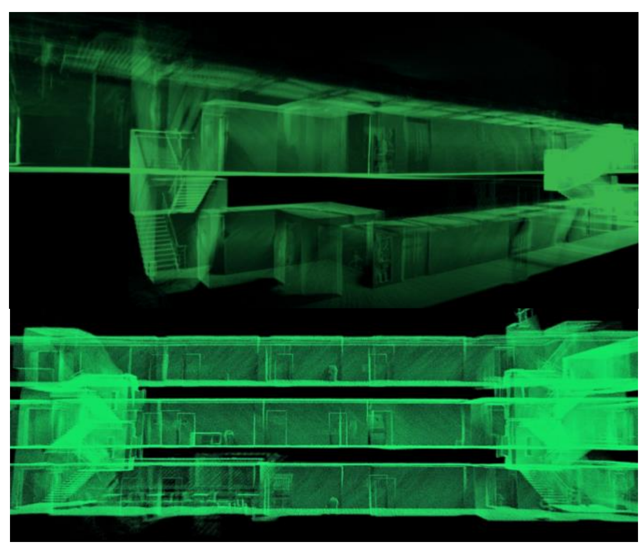

Fig 7. 3D mapping point cloud result after SLAM.

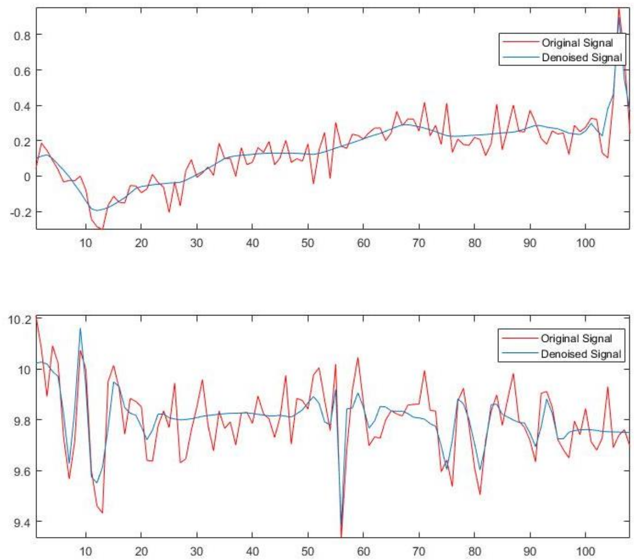

Fig 8. Comparison of acceleration on the y-axis. Notice that the red line is the original signal, and the blue line is after noise reduction. And the figure below shows the comparison of acceleration on the z-axis.

It is noted that the method we provide does not change the overall trend of velocity and rotation, which makes the algorithm could also applicable to other walking states.

V. Concluding Remarks

We have developed a multi-sensor LiDAR backpack based on the GNSS-denied environment. The platform can effectively realize the reconstruction of the indoor 3D environment and can effectively control the vibration error generated by the user during the traveling. The wavelet transform algorithm that can be used on a backpack-mounted IMU module, making the module significantly less noisy and suitable for all walking modes. Due to the characteristics of the walking itself, the vibration modes in the IMU data can be summarized, and the noise problem could be eliminated by algorithms. The LiDAR backpack effectively reconfigures the indoor environment and is equally applicable to multi-floor environments. Our method can eliminate the vibration error generated by the IMU itself in a short time, but further research is needed on the accumulated error caused by the system for a long time. In this experiment, only the wavelet transform method is used to eliminate noise. In the future work, other signal denoising methods need to be demonstrated.

References

[1] X. Chen, H. Ma, J. Wan, B. Li, and T. Xia. Multi-view 3D object detection network for autonomous driving. In IEEE CVPR, volume 1, page 3, 2017. 1, 2

[2] Z. Deng and L. J. Latecki. Amodal detection of 3D objects: Inferring 3D bounding boxes from 2D ones in rgb-depth images. In Conference on Computer Vision and Pattern Recognition (CVPR), vol. 2, pp. 2, 2017. 1, 2

[3] C. R. Qi, H. Su, K. Mo, and L. J. Guibas. Pointnet: Deep learning on point sets for 3D classification and segmentation. Proc. Computer Vision and Pattern Recognition (CVPR), IEEE, 1(2):4, 2017. 1, 2, 3

[4] N. Panigrahi, S. R. Doddamani, M. Singh, B. N. Kandulna: A method to compute location in GNSS denied area. International Conference on Electronics, Computing and Communication Technologies (CONECCT), IEEE, 2015

[5] H. A. Lauterbach, D. Bormann, R. Heb, D Eck: Evaluation of a Backpack-Mounted 3D Mobile Scanning System, Remote Sensing, October 2015,7,13753-13781

[6] M. Bosse, R. Zlot, P, Flick: Zebedee: Design of a spring-mounted 3-D range sensor with application to mobile mapping. IEEE Trans. Robot. 2012, 28, 1104–1119.

[7] A. Nüchter, D. Borrmann, J. Elseberg, D. Redondo: A backpack-mounted 3D mobile scanning system, Remote Sens., 2015, 7(10), 13753-13781

[8] N. Corso, A. Zakhor: Indoor localization algorithms for an ambulatory human operated 3Dmobile mapping system. Remote Sens. 2013, 5, 6611–6646.