

PLVS: A SLAM System with Points, Lines, Volumetric Mapping, and 3D Incremental Segmentation - A First Evaluation of PLVS I

Luigi Freda^{1*}

Indro Spinelli*

Abstract—This document presents a first evaluation of the PLVS I system [1]: a real-time system that leverages sparse SLAM, volumetric mapping, and 3D unsupervised incremental segmentation. The software is available as open-source.

I. OVERVIEW

This document presents the results of a first evaluation of the PLVS I framework, which is based on ORB-SLAM2. We refer the Reader to the PLVS report [1] for a thorough presentation of the system. The PLVS project webpage provides videos and further system design details [2].

An open-source implementation is available at github.com/luigifreda/plvs.

II. EXPERIMENTAL RESULTS

We successfully tested the PLVS framework live with different sensors (Asus Xtion Pro, ZED stereo camera, Intel Realsense, etc.) to prove its versatility. Figure 1 shows a volumetric map (custom octree-based method [1]) obtained with a tracked robot equipped with a realsense R200. Figure 2 shows the 3D reconstruction and segmentation of a laboratory we obtained live with a hand-held Asus Xtion Pro.

We measured the performance of PLVS on two different benchmarks. We evaluated the sparse RGB-D SLAM system on the TUM RGB-D dataset [3] and selected the absolute trajectory error (ATE) as metric. As for the VOLUMETRIC Mapping subsystem (VOMA) reconstruction accuracy, we used the ICL-NUIM dataset [5], which provides a ground truth for its 3D scene surfaces and camera poses.

A. Absolute Trajectory Error

Due to the non-deterministic nature of the multi-threading PLVS system, we run the system 5 times on each sequence. We consider a run failed when the tracking system gets lost for over 5% of the total number of sequence frames. A sequence is considered failed if 3 runs out of 5 failed. In case of success, we show the median RMSE value of the ATE error.

In Tab. I, we compare the performance of ElasticFusion with the one of PLVS when using only points, PLVS-P, and when using both points and lines, PLVS-PL. Note that the PLVS-P configuration is equivalent to the ORB-SLAM2 system. We used the same set of PLVS parameters on all the TUM RGB-D sequences (no fine-tuning). As reported

in the table, PLVS achieves state-of-the-art performance with trajectory estimation results on par with or better than existing SLAM systems. In particular, the combined usage of points and lines shows an improved localization robustness and a better trajectory accuracy on most sequences.

B. Volumetric Mapping Accuracy

We evaluated the surface reconstruction accuracy obtained with our framework on the ICL-NUIM dataset [5]. In our experiments, we used the available ICL-NUIM depth-maps corrupted with synthetic noise. The evaluated PLVS maps were obtained with a volumetric resolution of 0.01m.

In Tab. II, we report the average distance (expressed in meters) between each point and its nearest surface in the ground truth 3D model. The PLVS resulting performance is on par with the current state-of-the-art methods.

C. Segmentation Qualitative Results

As for the PLVS geometry-based segmentation, we provide a qualitative evaluation against our reference method [6]. While the original method runs on GPU and was specifically designed for incremental segmentation, our general purpose framework achieved comparable results running entirely on a single CPU. Some segmentation results (obtained with our custom octree-based VOMA) can be seen in Fig. 3.

D. Future Work

PLVS is an active project. The system has evolved under many aspects from the date (years ago) in which we performed our first evaluation. Now, PLVS is available in two different versions and has integrated many new improvements over time. The first version, PLVS I, is based on ORB-SLAM2, while the newest one, PLVS II, is based on ORB-SLAM3 and supports camera systems equipped with IMUs.

We are working on a new evaluation of both PLVS I and PLVS II systems. New results will be shared soon.

REFERENCES

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***Authors Contributions.** **Luigi Freda:** new concepts and methods, paper writing, design and development of all the PLVS code, code maintenance, testing and benchmarking. **Indro Spinelli:** new datasets collection, testing and benchmarking.

¹ [luigifreda\[@\]gmail\[dot\]com](mailto:luigifreda[@]gmail[dot]com)

Dataset	PLVS-P RMSE	PLVS-P LOST	PLVS-PL RMSE	PLVS-PL-LOST	ElasticFusion-RMSE	Frame Drops
freiburg1 360	0.209709	0	0.095676	0	0.108	1.6%
freiburg1 desk	0.01561	2	0.015792	0	0.02	3.1%
freiburg1 desk2	0.02302	1	0.039633	0	0.048	3.2%
freiburg1 floor	-	5	-	5	-	11.8%
freiburg1 plant	0.014714	0	0.020575	0	0.022	1.3%
freiburg1 room	0.063147	0	0.06036	0	0.068	0.7%
freiburg1 rpy	0.021416	0	0.018436	0	0.025	4.0%
freiburg1 teddy	-	4	0.043727	1	0.083	1.3%
freiburg1 xyz	0.009729	0	0.009692	0	0.011	0.8%
freiburg2 360 hemisphere	-	4	0.144988	1	-	2.2%
freiburg2 360 kidnap	-	5	-	5	-	1.2%
freiburg2 coke	-	4	0.510676	1	-	2.0%
freiburg2 desk	0.008305	0	0.013404	0	0.071	2.5%
freiburg2 dishes	0.043513	0	0.032529	0	-	2.2%
freiburg2 large no loop	0.210336	0	0.525601	0	-	1.8%
freiburg2 large with loop	-	3	-	3	-	2.4%
freiburg2 metallic sphere	-	5	0.721055	0	-	1.7%
freiburg2 metallic sphere2	0.227863	2	0.121611	0	-	1.2%
freiburg2 pioneer 360	-	5	-	5	-	61.6%
freiburg2 pioneer slam	-	5	-	5	-	52.7%
freiburg2 pioneer slam2	-	5	-	5	-	52.3%
freiburg2 pioneer slam3	-	5	-	5	-	32.3%
freiburg2 rpy	0.00312	0	0.003056	0	0.015	2.1%
freiburg2 xyz	0.003798	0	0.006609	0	0.011	1.5%
freiburg3 cabinet	-	5	-	5	-	4.1%
freiburg3 large cabinet	-	3	0.043743	0	0.099	3.9%
freiburg3 long office household	0.010322	0	0.011873	0	0.017	4.9%
freiburg3 nostructure notexture far	-	5	-	5	-	4.7%
freiburg3 nostructure notexture near withloop	-	5	-	5	-	3.9%
freiburg3 nostructure texture far	0.043296	0	0.030099	0	0.074	4.0%
freiburg3 nostructure texture near withloop	0.022714	0	0.022261	0	0.016	3.5%
freiburg3 structure notexture far	0.038519	0	0.021302	0	0.03	3.5%
freiburg3 structure notexture near	0.023198	0	0.020095	2	0.021	3.7%
freiburg3 structure texture far	0.010575	0	0.011232	0	0.013	4.7%
freiburg3 structure texture near	0.01057	0	0.015167	0	0.015	4.9%
freiburg3 teddy	-	5	-	4	0.049	4.2%

TABLE I: ATE RMSE on the evaluated static scenes of the TUM RGB-D dataset [3]. In the PLVS system, we used the same parameters over all the sequences. The *Frame Drops* column report the percentage of missing frames (that were never recorded by the original capturing device) as provided in the ElasticFusion paper [4].

System	kt0	kt1	kt2	kt3
PLVS-Octree	0.008	0.019	0.028	0.008
PLVS-Chisel	0.013	0.024	0.025	0.011
PLVS-FastFusion	0.078	0.123	0.105	0.093
PLVS-Octomap	0.107	0.047	0.025	0.012
PLVS-VoxelGrid	0.057	0.062	0.066	0.040
ElasticFusion	0.007	0.007	0.008	0.028
DVOSLAM	0.032	0.061	0.119	0.053
RGB-DSLAM	0.044	0.032	0.031	0.167
MRSMap	0.061	0.140	0.098	0.248
Kintinuous	0.011	0.008	0.009	0.150

TABLE II: Comparison of the surface reconstruction accuracies on the evaluated synthetic sequences of the ICL-NUIM dataset [5]. The reported values are the average distances (expressed in meters) between each point an its nearest surface in the ground truth 3D model. The compared values are extracted from the ElasticFusion paper [4].

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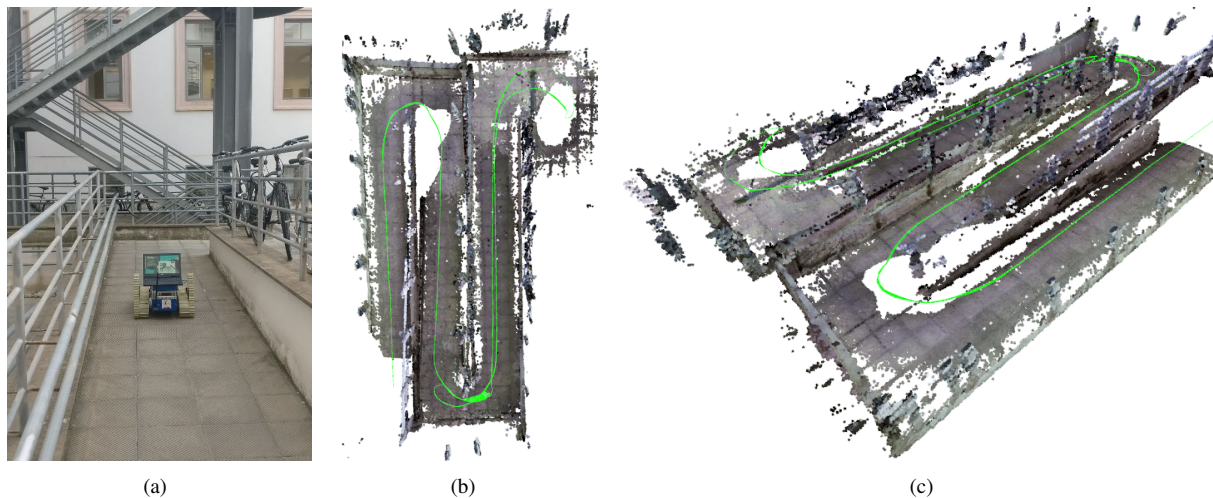


Fig. 1. The robot equipped with a realsense R200 and the built volumetric map (based on our custom octree-based VOMA).

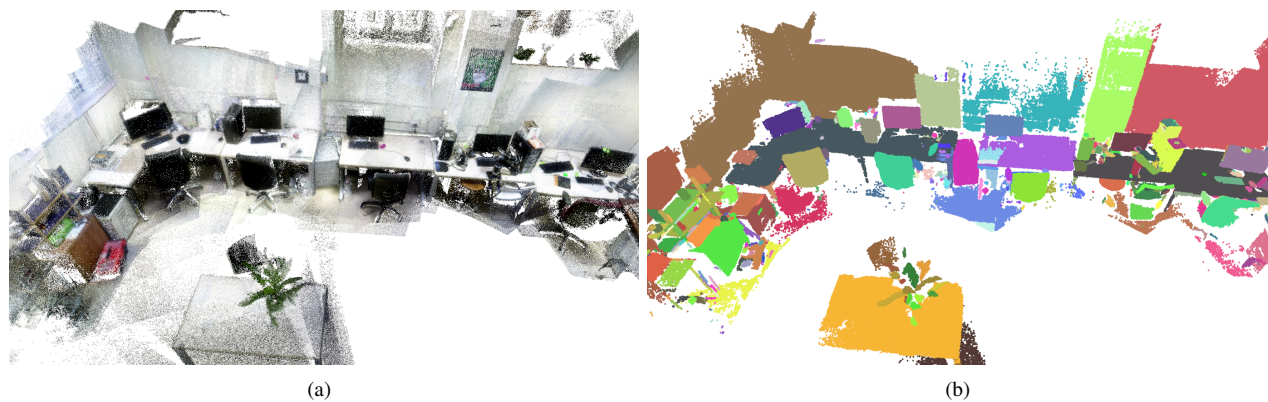


Fig. 2. Segmentation performed on big office environment

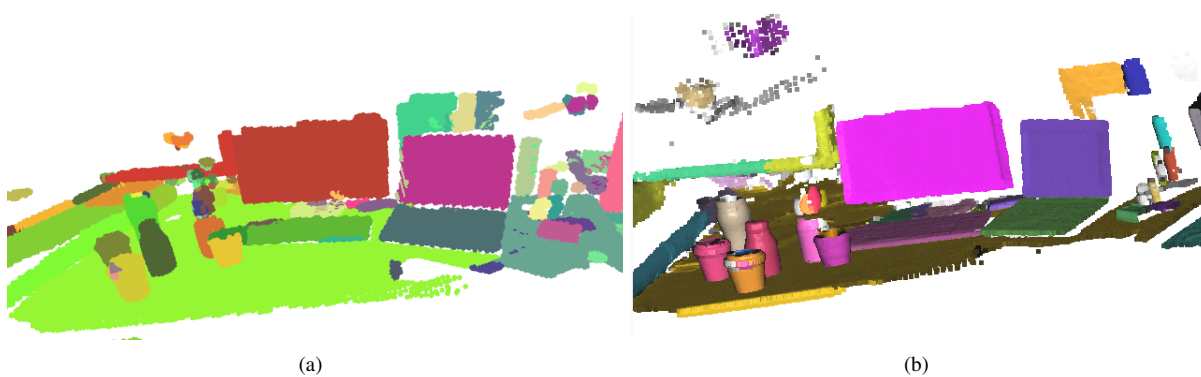


Fig. 3. Incremental segmentation detail (a) PLVS (b) inSeg [6]