On Localization and Mapping with RGB-D Sensor and Hexapod Walking Robot in Rough Terrains

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Abstract—**In this paper, we address a problem of precise on-line localization of a hexapod walking robot operating in rough terrains. We consider an existing Simultaneous Localization and Mapping approach with a low cost structured light (RGB-D) sensor. We propose to combine this sensor and localization method with the developed adaptive motion gait that allows the robot to crawl various types of terrain, such as stairs, ramps, or small wooden blocks. Such an environment requires a full 6-DOF pose estimation to create a map of the robot surroundings and allows us to asses impact of the individual terrain types and influence of the SLAM method parametrization on the localization accuracy. The reported evaluation results indicate the relations between the terrain type, parametrization of the method and the localization accuracy.**

I. Introduction

Reliable localization is an essential prerequisite in many practical mobile robotic applications, such as intelligent navigation or exploration of unknown environment. For an autonomous operation of a mobile robot without a reliable external localization (like GPS or motion capture systems) it is necessary for the robot to perceive the environment, build its spatial representation, localize itself, and plan its motion to achieve selected goals. Such a self-localization is referred to as the Simultaneous Localization and Mapping (SLAM) problem [1].

In this work, we address the problem of visual localization of a hexapod walking robot operating in rough terrains using the structured light sensor (RGB-D sensor) with the RGB-D SLAM method based on [2]. Such a set-up represents a challenging problem where an accurate full 6-DOF pose estimation is required under presence of unpredictable camera shaking and motion blur induced by the robot locomotion.

We are emphasizing a practical verification of the method in a rough terrain scenario with different obstacles (see Fig. 1) to evaluate an impact of individual terrain types and parametrizations of the SLAM method on the localization accuracy. In the presented evaluation, we are concerned with both the closed-loop and open-loop scenarios. However, while the precision of the localization provided by SLAM methods can be significantly improved when a robot re-visits already visited locations in the closed-loop scenarios, we are more interested in the accuracy of the open-loop localization, which better fits to on-line pose estimation. The trajectories are

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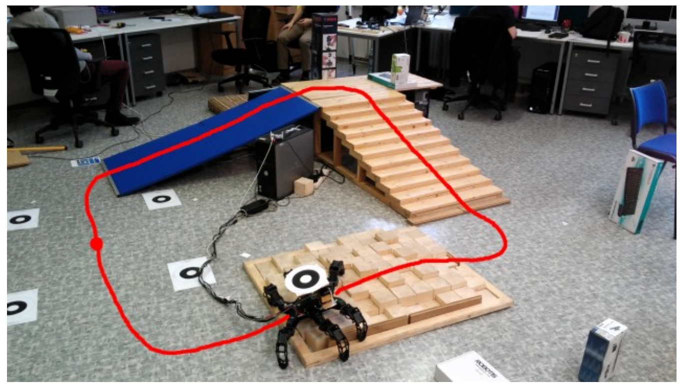


Fig. 1. Experimental set-up

compared using the established metrics of the relative pose error (RPE) and the absolute trajectory error (ATE) proposed in [3].

The paper is structured as follows. An overview of the related work on the legged robot localization in rough environment using visual SLAM methods is presented in Section II. Section III and Section IV provide a brief description of the RGB-D SLAM method and the considered hexapod walking robot controlled by an adaptive motion gait, respectively. Section V details the experimental set-up followed by the description of the established ground-truth, evaluation metrics and the particular experimental results. Discussion and concluding remarks are dedicated to Section VI.

II. Related work

The localization problem is one of the fundamental problems studied in mobile robotics, and therefore, a huge number of approaches can be found in literature. However, most of the works consider wheeled ground or aerial vehicles and only relatively smaller number of methods address challenges related to multi-legged crawling robots. Despite of that, several approaches to address the localization of the hexapod legged robot using the visual SLAM methods have been proposed.

In [4], the authors concern the SLAM problem in relation to sudden and abrupt camera motions induced by the locomotion of the hexapod robot. They propose a motion model based on the control commands of the robot to improve the tracking accuracy of the monocular SLAM system. An improved accuracy of the localization is reported, albeit relatively slow frame rate has been utilized (only 2 Hz), but only qualitative results are presented in the paper.

Stelzer and Hirschmüller summarized their work on the legged robot locomotion in rough terrains in [5]. They developed a complete framework which uses stereo dense depth mapping in fusion with inertial measurements and legged odometry using an indirect information filter to localize the robot and map the environment. They tested their algorithm in a simple rough terrain set-up when the robot crawls a gentle ramp to a testbed filled with a gravel. Only absolute error metrics has been used to evaluate the localization accuracy in [5].

The most related work to our problem has been recently published by Dominik Belter et al. in [6] and [7]. In [7], the authors present an RGB-D SLAM method with a custom designed image processing pipeline deployed on a hexapod walking robot. The authors report an on-line performance of the algorithm with the RMSE ATE of 9.5 cm in a closed-loop scenario on a flat terrain. Although the deployed algorithm is very similar to our proposed solution, we focus on the evaluation of the accuracy in the rough terrain of about double the size in both the closed-loop and open-loop scenarios and with different types of obstacles.

On the other hand, in [6], the authors focus on the accurate mapping of unstructured terrains using Kinect–like range sensors. The provided theoretical results are supported with the practical experiments conducted with a quadrupedal legged robot in a simple rough terrain scenario. In [6], the authors focus on the accuracy of the map provided by the SLAM method and not the trajectory estimate; however, they are explicitly emphasizing the importance of a precise localization in such a type of terrain.

In comparison to the aforementioned approaches, we present a more thorough evaluation in a larger scenario with different types of terrains the robot is crawling on. We are also interested in determining the relations between the absolute trajectory error, relative pose error, parametrization of the SLAM method and the impact assessment of individual terrain types on the localization accuracy.

III. RGB-D SLAM

The RGB-D SLAM method considered in the addressed problem of localization of the hexapod crawling robot is based on [2]. It benefits from using a scale information of 3D depth sensing with the strengths of detection and tracking of image salient points to create a dense 3D representation of the environment. The system is visualized in Fig. 2 and it operates as follows.

First, salient image points are extracted from the RGB image. The OpenCV library [8] is utilized for the feature detection, description, and matching of various feature types. For feature extraction one of the SURF [9], FAST [10]–BRIEF [11] or ORB [12] image features can be used.

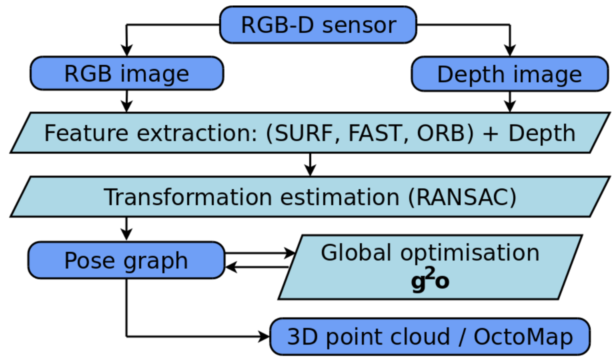


Fig. 2. Overview of the RGB-D SLAM system

Then, the 3D position of the features is obtained by extracting the depth measurement from the depth image at the coordinates of the particular feature. Note, only the features with a known depth information are further processed. The depth information provided by the structured light sensor might not be available at certain parts of the image, e.g., due to the sunlight, maximum and minimum distance or presence of the features on the edges and borders of obstacles.

After the extraction and 3D projection of the image features, the pairwise feature correspondences between the current frame and a subset of previously mapped frames are computed using the feature matching. This subset consists of n_p directly preceding frames, n_g graph neighbouring frames, and n_r random frames from the whole trajectory which are used for discovering large loop-closures.

An estimation of the rigid transformation is computed between successfully established frame-to-frame correspondences using the RANSAC algorithm [13]. Then, the frame is added as a node to the pose graph (map) of the SLAM method. The node contains the estimated 6-DOF pose of the frame together with the set of the detected image features and the estimated dense point cloud given by the depth measurement. The edges of the pose graph represents the pairwise rigid transformations between the individual frames.

The pairwise transformations between the RGB-D sensor poses in the pose graph are optimized using the $\mathbf{g^2o}$ graph optimisation framework [14] to further optimize the trajectory and provide a reliable localization The $\mathbf{g^2o}$ framework provides a globally consistent trajectory estimation which is especially beneficial in loop-closures when the robot revisits some previously visited area that is mapped in the constructed pose graph representation of the operational environment.

Based on the trajectory estimate given by the pose graph, an environmental map can be generated by projecting the sensor depth measurements directly in a form of a point cloud or a voxelized OctoMap [15]. The whole method evaluated in this paper is implemented using the ROS [16] framework.

IV. HEXAPOD ROBOT

The RGB-D SLAM is considered with a hexapod walking robot visualized in Fig. 3 based on a low-cost PhantomX

Mark II hexapod platform. The robot has six legs, each with three joints motorized with the Dynamixel AX-12 intelligent servos. Each servo drive has a P-type position controller and provides the control unit with its current position and applied torque through a serial interface. This feedback is further utilized in an adaptive motion gait [17] which allows the robot to traverse various terrains.

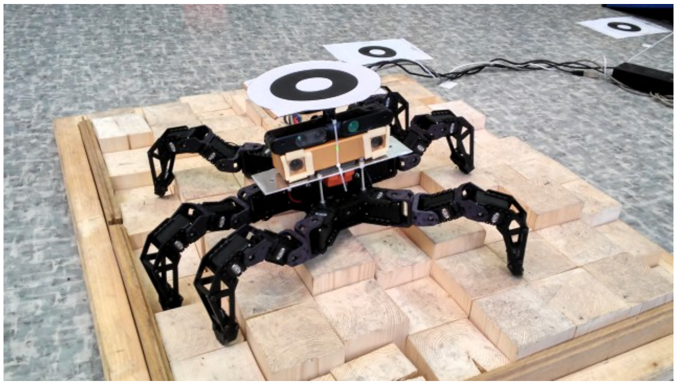


Fig. 3. The hexapod robot with mounted RGB-D ASUS Xtion Pro live (used in the presented localization approach) and stereo Bumblebee 2 cameras (not utilized in the presented results)

The adaptive motion gait [17] is based on a regular tripod gait, but utilizes a feedback from the servo drives to sense the contact of the legs with the ground throughout the gait cycle. One gait cycle consists of the phases of rising the three legs off the ground, moving them forward, dropping the legs on the ground, and finally moving and leveling the whole body to cope with the position of the legs and the shape of the terrain. During the drop phase, the position error readings from the servo drives are utilized to detect the contact point of a leg with the surface which allows to stop the movement of the leg and avoid high torque values at the joints. No additional sensors, like touch sensors, are utilized for the motion control.

The considered hexapod walking platform with the RGB-D sensor represents an off-the-shelf solution. Our original motivation is to address the localization and mapping problem in rough terrain with such a minimalistic set-up and demonstrate that such a relatively inexpensive robotic system is capable of exploration mission to create a map of a priori unknown environment. The achieved results are reported in the following section.

V. Experimental Results

In general, SLAM system produces a trajectory estimate together with the map of the environment. Although a good trajectory estimate does not imply a reliable map of the environment (e.g., of dynamic environments), we focus on the evaluation of the localization precision only.

A. Experimental set-up

The experimental evaluation has been performed on a laboratory test-track simulating rough terrain conditions, see Fig. 1. The test track consists of a square path of approximately 9 m length involving a plain ground, a set of stairs, a ramp and a pile of irregularly height wooden blocks.

Such a scenario constitutes a set of different challenges for the visual SLAM method. The pile of irregularly height wooden blocks simulates an uneven terrain where the SLAM method mainly needs to deal with the angular rotation of the camera. During the ascend the robot motion is subjected to slippage when the camera pose changes abruptly and randomly and during the descent the robots RGB-D sensor is inclined to the ground and only limited number of features in the close distance is visible. The turns represent another significant challenge for the SLAM system due to the motion blur.

The hexapod robot has been guided by a human operator along the path using the adaptive motion gait [17]. Asus Xtion Pro live RGB-D sensor rigidly mounted to the robot was connected to a desktop computer which recorded the dataset using the ROS framework [16]. Raw RGB stream and the depth stream have been recorded and saved for further evaluation with the RGB-D SLAM. Altogether three individual closed loop trajectories have been performed, each of them taking 10–12 minutes. Note, an average speed of the robot is 0.014 $m.s^{-1}$. All of the presented results have been computed using the dual-core Intel Core i3–M330 (2.13GHz).

B. Ground truth

A reliable ground truth for each of the three trajectories has been established by the RGB-D SLAM and verified by the independent 3D position estimation provided by the WhyCon [18] external motion tracking system. The WhyCon system provides a 3D position of the robot based on tracking a circular pattern attached to the robot, therefore this estimation has been utilized to verify the full 6-DOF pose localization determined by off-line frame-by-frame data processing of the created dataset with the RGB-D SLAM. The considered RGB-D SLAM parametrization for the ground truth processing was the SURF feature extractor detecting 600 features and keeping 400 best matches with a very long comparison horizon of $n_p = 16$, $n_g = 4$ and $n_r = 4$. Additional parameters like RANSAC stopping criteria and optimisation precision were set to the best values. Such a processing took more than 6 hours per one trajectory resulting in the trajectory estimate which was compared to the WhyCon reference.

First, the trajectories provided by the SLAM and the reference system were time synchronized and their starting points collocated. Then the rigid transformation of the estimated SLAM trajectory was found by minimization of the root mean squared distance error between the individual trajectories. Only the rotational component of the rigid transformation has been optimized with the fixed orbit of the collocated starting point.

The ground truth RMSE estimation error for trajectories T_1, T_2, and T_3 is 0.040 m, 0.043 m, and 0.036 m respectively which is marginal and therefore the information about the robot 6-DOF pose from the frame-by-frame RGB-D SLAM processing is considered as the ground truth in the evaluation presented in the rest of this paper.

C. Methodology

The trajectories are evaluated using the established metrics of the relative pose error (RPE) and the absolute trajectory error (ATE) proposed in [3].

For the purpose of the evaluation, we assume that the estimated trajectory $\mathbf{X} = \{\mathbf{X}_1, \mathbf{X}_2 \cdots, \mathbf{X}_n\} \in \mathrm{SE}(3)$ and the ground truth trajectory $\hat{\mathbf{X}} = \{\hat{\mathbf{X}}_1, \hat{\mathbf{X}}_2 \cdots, \hat{\mathbf{X}}_n\} \in \mathrm{SE}(3)$ consist of the same number n of the time synchronized poses. The $\mathbf{X}_k$ and $\hat{\mathbf{X}}_k$ are the 6-DOF estimated pose and ground truth pose at the time k, respectively, given by the equation

$$\mathbf{X}_k = \begin{pmatrix} \mathbf{R}_k & \mathbf{t}_k \\ \mathbf{0} & 1 \end{pmatrix}, \tag{1}$$

where $\mathbf{R}_k$ and $\mathbf{t}_k$ are the rotation matrix and 3D coordinates of the pose $\mathbf{X}_k$ with respect to the origin.

The relative pose error (RPE) $\mathbf{E}_k$ represents the local accuracy of the trajectory and it is given by the equation

$$\mathbf{E}_k = \left(\hat{\mathbf{X}}_k^{-1}\hat{\mathbf{X}}_{k+1}\right)^{-1}\left(\mathbf{X}_k^{-1}\mathbf{X}_{k+1}\right). \tag{2}$$

By further decomposition of $\mathbf{E}_k$ according to (1) into the translational and rotational components we obtain the translational RPE_t as the Euclidean norm of the translational component and the rotational RPE_ϕ as the Euler angle bound with the rotational component, respectively.

The absolute trajectory error (ATE) compares an absolute distance between the synchronized trajectories and it is given as

$$\mathbf{E}_k = (\hat{\mathbf{X}}_k)^{-1}(\mathbf{X}_k). \tag{3}$$

However; prior the evaluation of the ATE it is necessary to align the trajectories. The alignment is done by finding a rigid transformation that minimizes the square root of the ATE for the given trajectory. Only a rotational component of the rigid transformation is optimized with a fixed orbit around a collocated starting point.

D. Results

Results of the thorough evaluation of the RGB-D SLAM are reported in this part. The main goal of the evaluation is to determine the influence of the RGB-D SLAM parametrizations and terrain types on the quality of the localization both in closed-loop and open-loop scenarios. With respect to the practical application scenarios of the mobile robotics we are also concerning the processing speed as one of the parameters.

The considered set-up of the operational environment allows us to measure the influence of individual terrain types on the localization error. In order to evaluate the above mentioned relations we firstly divided the trajectories into individual segments according to the terrain type. The five recognized terrain types are:

- Plain (the start and finish plane ground);
- Rot (individual turns along the path);
- Hill (the irregular hill of wooden blocks);
- Stairs (the ascending stairs);
- Ramp (the descending slope).

Fig. 4 shows the individual segments on top of the ground truth trajectory T_3. It also shows an example of the estimated trajectory (open-loop SURF 2.5 Hz) and its ATE_t (grey interconnections).

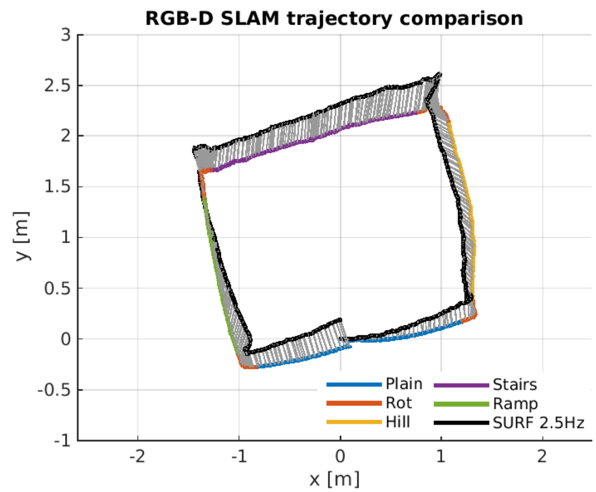
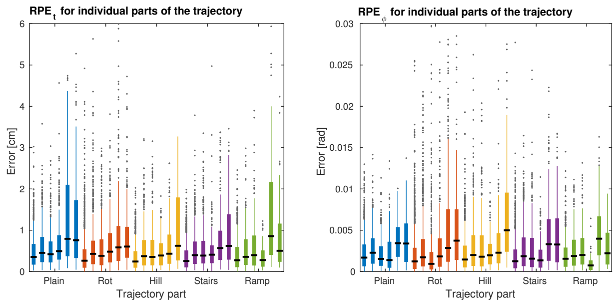


Fig. 4. An estimated trajectory with ATE_t and the ground-truth trajectory divided into individual segments

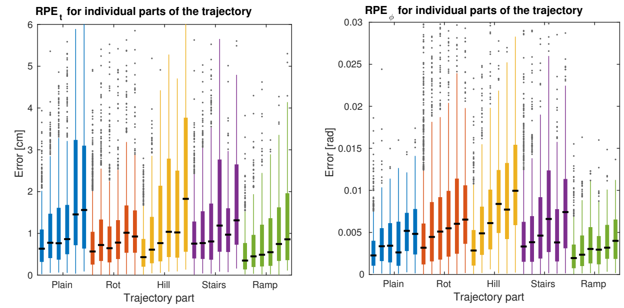
Afterwards, we have processed the dataset with the RGB-D SLAM in both open-loop and closed-loop fashion. The considered parametrizations used for the evaluation of the RPE and ATE are SURF, FAST–BRIEF and ORB feature extractors detecting maximum of 500 features per image and keeping the 300 best matches. The comparison horizons were selected as $n_p = 3$, $n_g = 3$ and $n_r = 0$ for open-loop scenarios and $n_r = 3$ for closed-loop scenarios, which is much less computationally demanding than the parametrization used for the construction of the ground truth. In the evaluation the datasets have been processed frame-by-frame with a skip step from the set of 6 different frame rates {10, 5, 3.3, 2.5, 2, 1.6} in Hz, which gives altogether 36 different parametrizations. In total, 87 trials on all of the three datasets have been performed. The evaluation results are summarized in Table I. For better readability of the results, Table I presents the quantitative results for the trajectory T_3 only.

Table I lists the aggregated RPE for the whole trajectory estimates; however, in order to evaluate the influence of a particular terrain type on the localization accuracy, we evaluated the RPE for each trajectory segment. Note, we have done the evaluation of the influence of the terrain types using the open-loop processing of the dataset. The RPE for individual terrain types is visualized in the plots in Fig. 5a, Fig. 5b, and Fig. 5c. Each plot depicts the RPE for the individual trajectory segments considered with a particular parametrization, where each bar represents a distribution of the RPE for a particular terrain type (color and x-axis labels) and processing speed.

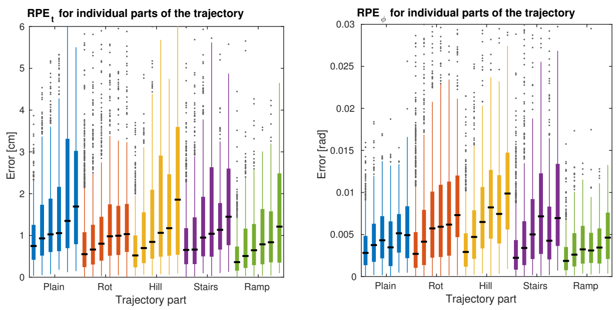
The aggregated results of the RPE evaluation for the individual terrain types for all the performed open-loop tests on all of the three dataset trajectories are listed in Table II together with their standard deviations σ_{RPE_t} and $\sigma_{\mathrm{RPE}_\phi}$.



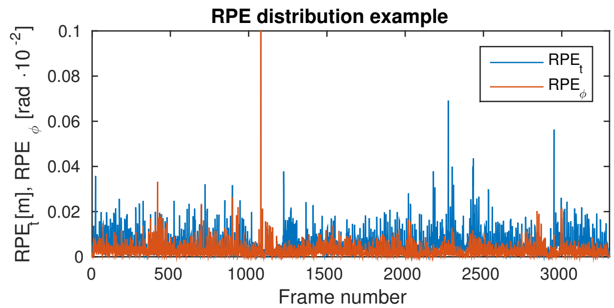
(a) SURF



(b) FAST–BRIEF



(c) ORB



(d) RPE distribution – SURF 5 Hz

Fig. 5. (a), (b), (c) RPE for individual segments of the trajectory estimated using the particular extractor from left to right for 10, 5, 3.3, 2.5, 2, and 1.6 fps. (d) Illustration of the RPE distribution in time for the open-loop SURF 5 Hz parametrization

TABLE I
TRAJECTORY ESTIMATION RESULTS

Extractor	**SURF**						**FAST–BRIEF**						**ORB**					
fps	10	5	3.3	2.5	2	1.6	10	5	3.3	2.5	2	1.6	10	5	3.3	2.5	2	1.6
Open loop																		
RPE$_t$ [cm]	0.40	0.56	0.56	0.56	0.95	0.95	0.76	1.00	1.09	1.33	1.40	1.66	0.79	1.06	1.27	1.48	1.45	1.74
RPE$_\phi$ [rad$\cdot 10^{-2}$]	0.22	0.31	0.26	0.23	0.50	0.50	0.41	0.53	0.62	0.71	0.73	0.83	0.36	0.52	0.67.	0.74	0.77	0.89
ATE$_t$ [cm]	23.00	27.20	8.54	20.66	21.57	14.66	80.20	20.81	14.21	12.81	21.38	39.29	44.13	65.17	27.05	20.11	17.78	24.13
ATE$_\phi$ [rad]	0.19	0.22	0.18	0.22	0.19	0.20	0.41	0.30	0.17	0.18	0.25	0.25	0.18	0.44	0.26	0.17	0.18	0.16
End distance [cm]	35.24	36.27	19.05	30.50	33.48	22.08	117.21	31.92	29.53	27.15	32.89	48.71	137.53	56.49	75.17	41.03	36.02	70.39
Closed loop																		
RPE$_t$ [cm]	0.59	0.54	1.20	1.00	1.16	1.46	0.70	1.00	1.11	1.42	1.38	1.26	0.78	1.11	1.32	1.47	1.50	1.80
RPE$_\phi$ [rad$\cdot 10^{-2}$]	0.30	0.28	0.69	0.61	0.64	0.81	0.28	0.55	0.63	0.83	0.71	0.62	0.40	0.59	0.73	0.79	0.79	0.92
ATE$_t$ [cm]	2.74	1.01	7.98	12.23	7.48	10.02	20.90	18.54	14.77	23.07	13.50	12.21	24.15	37.12	27.49	41.88	18.77	31.60
ATE$_\phi$ [rad]	0.19	0.06	0.17	0.19	0.15	0.12	0.22	0.34	0.22	0.19	0.23	0.09	0.22	0.37	0.07	0.15	0.32	0.27
End distance [cm]	0.33	0.57	2.13	20.75	0.99	1.99	33.76	3.30	2.09	4.60	2.36	1.68	6.72	3.84	3.19	4.08	4.25	2.85

TABLE II
AGGREGATED RPE FOR INDIVIDUAL TERRAIN TYPES

Terrain	Plain	Rot	Hill	Stairs	Ramp
RPE$_t$ [cm]	1.03	0.85	0.89	0.93	0.70
σ_{RPE_t} [cm]	1.00	1.24	0.98	0.91	0.75
RPE$_\phi$ [rad$\cdot 10^{-2}$]	0.35	0.54	0.52	0.47	0.30
$\sigma_{\mathrm{RPE}_\phi}$ [rad$\cdot 10^{-2}$]	0.28	1.26	0.56	0.56	0.26

The results indicate a higher RPE is exhibited for the stairs terrain and during the fast turns. However, the differences are only marginal thus the evaluation did not provide unambiguous results in terms of determining the influence of the terrain type on the RPE. This is likely related to the used adaptive motion gait which was originally designed with stress on a smooth motion in various terrains.

Notice, a low value of the RPE does not imply a low value of the ATE, e.g., the 5 Hz SURF trajectory represents an estimation with the low RPE but due to few outliers in pose estimation the overall ATE is high (as it is shown in Fig. 5d).

This issue is partially addressed by enabling the loop-closure detection ($n_r > 0$), when the robot recognizes previously mapped areas. In such a case, the whole trajectory estimate is optimized based on the newly established frame to frame correspondences, which affects mostly the individual outliers. The loop-closing performed best with the SURF feature extractor, while very poorly with the ORB extractor due to the poor discriminability of the ORB features in the given environment. In all cases, there is a huge improvement in the end distance which stands for the Euclidean distance between the last poses of the ground truth and the estimated trajectory.

Regarding the processing speed and its influence on the localization accuracy we processed the dataset frame-by-frame with a different skip-step. Fig. 6 shows the aggregated RMSE RPE for all the segments according to the frame rate for the individual open-loop parametrizations of the RGB-D SLAM method.

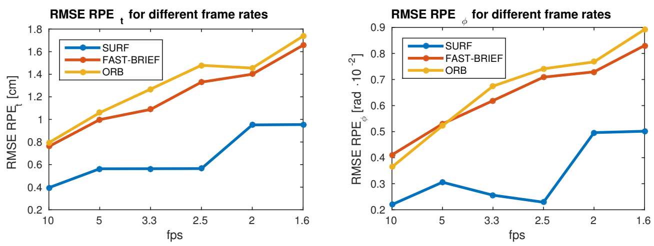


Fig. 6. RMSE RPE comparison

The results indicate that the RPE is directly influenced by the frame rate except for the RPE$_\phi$ and SURF feature extractor. By focused examination of the dataset we revealed that for the 3.3 and 2.5 fps the dropped frames coincide with the sudden abrupt change in the camera pose, and therefore, the SURF parametrization exhibits an overfitting of the trajectory data (see also Fig. 5a). Nevertheless, this comparison gives us a direct relation between the RPE, RGB-D SLAM parametrization, and the frame rate.

On the given evaluation hardware, we are capable of an on-line processing of the trajectories with the frame rate lower than 3.3 Hz for the SURF extractor and lower than 5 Hz for the FAST–BRIEF and ORB extractors. Note, the evaluation hardware is only dual-core and does not provide a GPU acceleration capabilities, thus the presented results support the algorithm is deployable for on-line estimation of the robot pose in an autonomous navigation mission in rough terrains.

VI. Conclusion

In this paper, we address the problem of a precise localization of a hexapod walking robot operating in a rough terrain. The proposed combination of the existing RGB-D SLAM approach with the adaptive motion gait and considered set-up of the operational environment allowed us to study the relations between the RGB-D SLAM parametrization, localization error, and terrain types in a closed-loop as well as open-loop scenarios. The focused examination of the influence of individual terrain types on the localization accuracy did not bring unambiguous results which is likely related to the used adaptive motion gait originally designed with stress on a smooth motion in various terrains. The results show that a low relative pose error does not imply a low absolute trajectory error and vice versa, but they indicate a high absolute error is usually implied by a limited number of outliers in the pose graph. In such a situation, it might be beneficial to fuse the localization estimate with the inertial measurements or odometry data as proposed in [5] or [4], or to model the spatial uncertainty of the point features as in the most recent work [19] which is a subject of our future work. Besides, the loop closing can significantly improve the overall performance of the localization, and therefore, we also aim to consider active sensing in our future work.

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