Saturation-Aware Angular Velocity Estimation: Extending the Robustness of SLAM to Aggressive Motions*

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***Abstract*— We propose a novel angular velocity estimation method to increase the robustness of Simultaneous Localization And Mapping (SLAM) algorithms against gyroscope saturations induced by aggressive motions. Field robotics expose robots to various hazards, including steep terrains, landslides, and staircases, where substantial accelerations and angular velocities can occur if the robot loses stability and tumbles. These extreme motions can saturate sensor measurements, especially gyroscopes, which are the first sensors to become inoperative. While the structural integrity of the robot is at risk, the resilience of the SLAM framework is oftentimes given little consideration. Consequently, even if the robot is physically capable of continuing the mission, its operation will be compromised due to a corrupted representation of the world. Regarding this problem, we propose a way to estimate the angular velocity using accelerometers during extreme rotations caused by tumbling. We show that our method reduces the median localization error by 71.5 % in translation and 65.5 % in rotation and reduces the number of SLAM failures by 73.3 % on the collected data. We also propose the Tumbling-Induced Gyroscope Saturation (TIGS) dataset, which consists of outdoor experiments recording the motion of a lidar subject to angular velocities four times higher than other available datasets. The dataset is available online at `https://github.com/norlab-ulaval/Norlab_wiki/wiki/TIGS-Dataset`.**

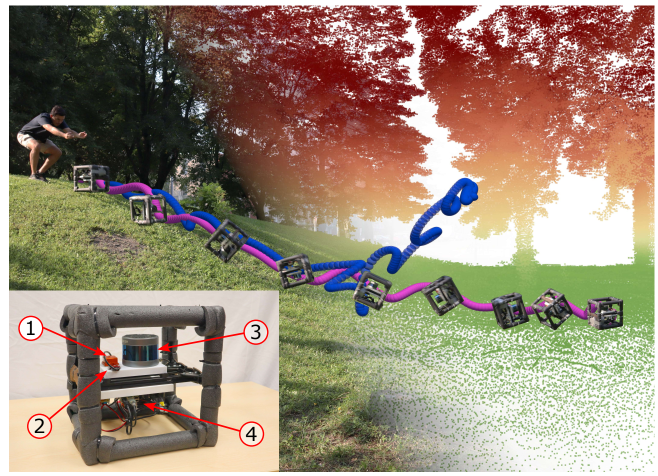

Fig. 1. Our robot localization system tumbling down a steep hill. At the top is a picture of the event and the reconstructed point cloud. The blue trajectory represents a SLAM-estimated trajectory relying on raw gyroscope measurements. In pink is a similar trajectory, this time estimated relying on our angular velocity estimation approach. The rugged perception rig is shown in the bottom left. The numbers in the red circles correspond to (1) XSens MTi-30 IMU, (2) VectorNav VN-100 IMU, (3) RoboSense RS-16 lidar, and (4) Raspberry Pi 4.

I. INTRODUCTION

For many robot applications, operations are conducted in a remote, or dangerous environment, meaning human intervention is impossible [1]. Hardware improvements have significantly reduced potential failure due to collisions, especially for aerial systems [2]. However, software systems, especially for robot localization, will typically not recover from falls, drops, and collisions [3]. Therefore, increasing mobile robot localization robustness to such events is key to enabling autonomy in human-denied environments.

Inspired by work on control, such as Williams *et al.* [4], we define aggressive motions for perception as being near the dynamic limits that the system can sustain. With this definition, navigation on highways would not cause aggressive motions despite its high velocities. On the contrary, a robot tumbling down a steep hill, as shown in the top part of Figure 1, exemplifies well this definition of aggressive motions because of the repeated collisions and fast angular velocities that are sustained. Such motions cause skew in lidar scans [5] and saturation in gyroscope measurements [6]. Deskewing algorithms correct these distortions using an estimate of the intra-scan lidar motion. However, in many Simultaneous Localization And Mapping (SLAM) systems, the prior attitude for optimization and estimate for intra-scan lidar motion is obtained by integrating Inertial Measurement Unit (IMU) measurements [7]–[10]. Therefore, gyroscope saturations lead to wrong optimization priors, inaccurate deskewing, and thus, to SLAM failure, as shown by the blue trajectory. In this work, we propose to leverage the theory related to Gyro-free (GF) Inertial Navigation System (INS) [11] to estimate angular velocities during gyroscope saturations. To validate our approach without damaging robots, we built a rugged lidar-inertial rig, shown in the bottom left. We generated a dataset of the rig tumbling down a steep hill, saturating gyroscope measurements to analyze our solution. Thus, the contributions of this work are:

1) A novel method to estimate robot angular velocities during gyroscope saturation periods; and
2) The Tumbling-Induced Gyroscope Saturation (TIGS) dataset, consisting of 32 distinct runs of a custom per-

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ception rig tumbling down a steep hill, reaching angular velocities up to $18.6\,\mathrm{rad/s}$.

II. RELATED WORK

In this section, we list recent work in the literature focused on localization and mapping under aggressive motions. In particular, we explain how they were not tested and would not work in cases where gyroscope saturations occur. Then, we highlight existing GF-INS methods, aiming to estimate the angular velocity of a robot when gyroscope measurements are saturated. Lastly, we analyze lidar SLAM datasets and demonstrate that they are not suited to test our angular velocity estimation method.

1) SLAM robust to aggressive motions: Several SLAM algorithms were proposed to overcome the challenges posed by aggressive motions. In the FAST-LIO2 SLAM algorithm [9], an Iterated Extended Kalman Filter (IEKF) enables state estimation when navigating at high speeds in noisy and cluttered environments. In their algorithm, after the prediction step, the authors back-propagate the estimated state to deskew the point cloud. Their method was tested at angular speeds up to $21.7\,\mathrm{rad/s}$, without specifying accelerations. However, they did not mention any gyroscope saturation in their work. Another algorithm robust to aggressive motions is the DLIO SLAM algorithm [10]. In DLIO, scans are deskewed using the lidar motion estimated by integrating IMU measurements with a constant jerk and angular acceleration model. After roughly aligning the scan with the map through deskewing, the scan alignment is refined using the Generalized Iterative Closest Point (GICP) [12] registration algorithm. Their method was tested at angular velocities up to $3.6\,\mathrm{rad/s}$ and linear accelerations up to $19.6\,\mathrm{m/s^2}$. DLIO was not tested under saturated gyroscope measurements. Although promising, the aforementioned methods have a major drawback preventing their use in the context of a tumbling robot: they use IMU measurements to compute the prior for their optimization process. If IMU measurements are incomplete because of saturations, they might lead the optimization to converge far from the true solution.

An approach to tackle sensor failures is introduced in the LOCUS SLAM algorithm [13]. They introduce a health-monitoring module in their method to detect sensor malfunctions. In contrast, we propose a way to not only detect but also recover from gyroscope failures, as robots do not have a direct alternative for such measurements. To the best of our knowledge, the only algorithm that was specifically designed for aggressive motions is our previous work [5]. In it, we introduced a SLAM algorithm that takes into account the skewing uncertainty during registration. This allowed our localization and mapping algorithm to give more importance to certain portions of a scan that were less affected by scan skewing. However, since our method was not robust to gyroscope saturation, we limited our experiments to angular speeds up to $11\,\mathrm{rad/s}$ and linear accelerations up to $200\,\mathrm{m/s^2}$. As can be seen, none of the SLAM algorithms presented previously were designed for gyroscope saturation. This motivates the need for an angular velocity estimation method relying on other sensory measurements. Such methods can be relied upon in the case of gyroscope saturations during aggressive motion.

2) Angular Velocity Estimation: Several solutions have been proposed to estimate gyroscope measurements during saturation periods. In the work of Dang *et al.* [14], the authors propose a smoothing algorithm to estimate saturated gyroscope measurements. They use an optimization algorithm based on the presence of zero-velocity intervals for motion tracking. Their method is well-suited in situations in which short gyroscope-saturated time windows happen during a continuous motion contained between zero-velocity periods. However, their method was not designed for cases where repeated collisions are sustained (e.g., when tumbling). Alternatively, Tan *et al.* [15] introduce an Extended Kalman Filter (EKF) exploiting the sinusoidal structure of magnetometer measurements to estimate the angular velocity of a monocopter, despite gyroscope saturations. In a situation where repeated collisions are sustained, a sinusoidal structure in magnetometer measurements cannot be assumed. Moreover, in robotics, magnetometers are often disregarded as their measurements are biased by proximal magnetic sources [16]. Another approach is explored in the work of Pachter *et al.* [11], where GF INS theory is laid down to allow the estimation of the position, orientation, linear velocity, and angular velocity of an object in 3D using only accelerometers. Following this work, Lee *et al.* [6] proposed an EKF to estimate the angular velocity of a rotating plate using three accelerometers, which they validated experimentally. This solution was developed for aerospace applications and was not tested inside a SLAM framework. Since accelerometer-based methods have more potential than other work presented previously, we will build on these solutions to improve the robustness of SLAM algorithms under saturated gyroscope measurements.

3) Aggressive Motion Datasets: In order to demonstrate the improvement of SLAM reached through our speed estimation method, a dataset with aggressive motions and gyroscope saturations is required. We studied the lidar SLAM datasets that are the most used and that contain the most aggressive motions, namely the Newer College [17] and Hilti-Oxford [18] datasets. Because of its importance in the literature, we also studied the KITTI dataset [19]. The maximum angular velocity in all these datasets combined is $4.7\,\mathrm{rad/s}$ and the maximum linear acceleration in all datasets combined is $30.7\,\mathrm{m/s^2}$. Since the motions in these datasets are not aggressive enough to cause gyroscope saturations, we propose the Tumbling-Induced Gyroscope Saturation (TIGS) dataset, which consists of a perception rig tumbling down a hill, with angular velocities up to $18.6\,\mathrm{rad/s}$ and linear accelerations up to $157.8\,\mathrm{m/s^2}$.

III. THEORY

To increase the robustness of SLAM algorithms to a robot tumbling or colliding with its environment, we develop a method that allows estimating the angular velocity of a robot when its gyroscope measurements are saturated. The only prerequisite of our angular velocity estimation method is an estimate of the robot's Center Of Mass (COM) location. We provide the uncertainty of the estimated velocity to allow its use in probabilistic frameworks (e.g., Bayesian filtering). We then describe the SLAM framework in which our method is inserted. Our angular velocity estimation method implementation is freely available online to facilitate replicability.[1]

A. Angular Velocity Estimation

Inertial measurements during an event of a robot tumbling down a hill are shown in Figure 2. Gyroscope saturations usually occur during the middle section of the tumbling, when the angular velocities are at their highest. Accelerometers, on the other hand, tend to saturate less and, even if they do saturate, it is for a short period (e.g., during a collision), as opposed to gyroscopes, which can saturate for several seconds. We therefore have two distinct cases during which to estimate saturated gyroscope measurements: *i)* during free-fall and *ii)* during collisions. Indeed, the plateaus in the angular speed curve correspond to free-fall periods whereas the fast changes correspond to collisions, as indicated by the spikes in the acceleration curve.

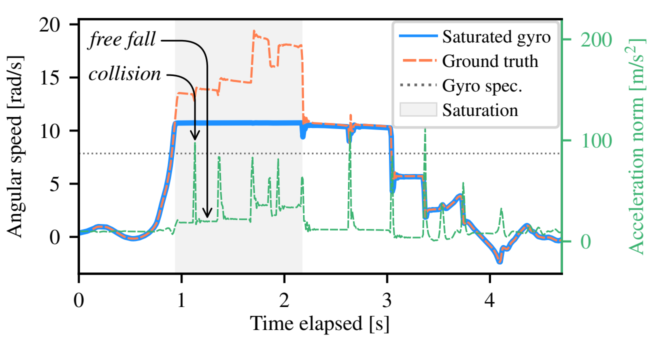

Fig. 2. The angular speed is shown through time for the saturated gyroscope axis of a robot tumbling down a hill. Light gray zones indicate the gyroscope saturation periods. In blue are the measurements from a saturated gyroscope, in orange are the ground truth angular speeds, and in dashed green is the norm of the measured acceleration. We show the manufacturer-specified gyroscope saturation point in dark gray. Examples of collisions with the ground and free-fall events are highlighted.

The modeling of collisions still being an open problem, it is challenging to estimate the angular velocity from accelerometer measurements during collisions. Therefore, our approach is split into two steps. First, we estimate the angular velocities assuming that we are in free fall. Then, we smooth the estimated velocities with a physically-motivated motion prior to obtain more accurate estimates during collisions. As shown in Figure 2, collisions are much shorter than free-fall periods, meaning that the robot is indeed in free fall during most of the gyroscope saturation period. The following assumptions are made to estimate saturated gyroscope measurements during free fall:

Assumption 1: The IMU is not located along the robot's rotation axis;

Assumption 2: The measured linear acceleration at the robot's COM is null;

Assumption 3: The rotation axis remains unchanged between two IMU measurements;

Assumption 4: The rotation axis passes through the robot's COM;

Assumption 5: Only one axis of the gyroscope is saturated at once.

Assumption 1 is necessary to enable angular velocity estimation from the measured centripetal acceleration. Assumption 2 stems from the fact that the acceleration perceived by a body in free fall is null and on the underlying assumption that the force caused by air friction is negligible. Assumption 3 is supported by the high acquisition rate of IMU measurements, which is typically 100 Hz or more, and by the angular momentum preventing the axis of rotation from changing quickly. Assumption 4 relies on the fact that when no external forces act on a body, it rotates about its COM. This is again based on the underlying assumption that we are in free fall and that the force caused by air friction is negligible. Assumption 5 is not strictly necessary, but allows us to compute a simple and precise estimate of the angular speed of a saturated gyroscope axis. Moreover, in our experiments described in Section IV-A, we did not encounter situations in which more than one gyroscope axis was saturated at once.

The important variables are illustrated in Figure 3 where an IMU is linked to the robot's COM by $\boldsymbol{t}$ and rotates at an angular speed $\omega = \|\boldsymbol{\omega}\|$ around the unit rotation axis $\boldsymbol{e}$. The $\boldsymbol{r}$ vector orthogonally links the IMU to $\boldsymbol{e}$. The rotational coordinate frame $\mathcal{R}$ is at the same location as the IMU, but rotated to have its x axis perpendicular and pointing to the rotation axis $\boldsymbol{e}$ and its z axis in the same direction as $\boldsymbol{e}$. As the axis-angle representation states, the rotation axis $\boldsymbol{e}$ can be recovered from the angular velocity $\boldsymbol{\omega} = [\omega_x, \omega_y, \omega_z]^T$ such that $\boldsymbol{\omega} = \omega\boldsymbol{e}$. Drawing from the work of Pachter *et al.* [11], the Coriolis formula states that

$$\boldsymbol{a}_I = \boldsymbol{a}_C + \dot{\boldsymbol{\omega}} \times \boldsymbol{r} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{r}), \tag{1}$$

where $\boldsymbol{a}_I$ is the linear acceleration at the location of the IMU, $\boldsymbol{a}_C$ is the linear acceleration at the robot's COM, and $\dot{\boldsymbol{\omega}}$ is the angular acceleration of the robot. All angular velocity and linear acceleration measurements are expressed in a common coordinate frame.

Since accelerometers measure proper acceleration, the measured acceleration $\tilde{\boldsymbol{a}}_I$ at the location of the IMU is equal to

$$\begin{aligned} \tilde{\boldsymbol{a}}_I &= \boldsymbol{a}_I - \boldsymbol{g} \\ &= (\boldsymbol{a}_C - \boldsymbol{g}) + \dot{\boldsymbol{\omega}} \times \boldsymbol{r} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{r}) \\ &= \tilde{\boldsymbol{a}}_C + \dot{\boldsymbol{\omega}} \times \boldsymbol{r} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{r}), \end{aligned} \tag{2}$$

where $\boldsymbol{g}$ is the gravity force vector and $\tilde{\boldsymbol{a}}_C$ is the measured acceleration at the robot's COM. Using Assumption 2, Equation 2 simplifies to

$$\tilde{\boldsymbol{a}}_I \approx \dot{\boldsymbol{\omega}} \times \boldsymbol{r} + \boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{r}). \tag{3}$$

Equation 3 is the key to allowing the computation of angular velocity during gyroscope saturation periods. The first term

[1] https://github.com/norlab-ulaval/saturated_gryo_speed_estimation

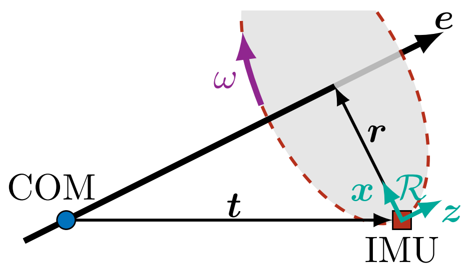

Fig. 3. Illustration of important quantities in our angular velocity estimation method. The COM is indicated by a blue dot. The IMU is indicated by a red square. The axis of rotation $\boldsymbol{e}$ is assumed to pass through the robot's COM. The vector $\boldsymbol{t}$ joins the COM and the IMU and the rotation lever arm $\boldsymbol{r}$ joins the IMU to the axis of rotation. The angular speed ω of the IMU around $\boldsymbol{e}$ is indicated in purple. The x and z axis of the rotational frame $\mathcal{R}$ are illustrated in green.

of the sum is the tangential acceleration of the IMU and is oriented into the page in Figure 3. The second term of the sum is the centripetal acceleration and is oriented in the same direction as the x axis of the rotational coordinate frame $\mathcal{R}$ in Figure 3. Therefore, expressing the accelerometer measurements $\tilde{\boldsymbol{a}}_I$ in the coordinate frame $\mathcal{R}$ and using Equation 3, we can deduce without further approximation that

$$^{\mathcal{R}}\tilde{\boldsymbol{a}}_I \approx \begin{bmatrix} \|\boldsymbol{\omega} \times (\boldsymbol{\omega} \times \boldsymbol{r})\| \\ -\|\dot{\boldsymbol{\omega}} \times \boldsymbol{r}\| \\ 0 \end{bmatrix} = \begin{bmatrix} \omega^2 r \\ -\dot{\omega} r \\ 0 \end{bmatrix}, \tag{4}$$

where $\omega = \|\boldsymbol{\omega}\|$, $r = \|\boldsymbol{r}\|$ and $\dot{\omega} = \|\dot{\boldsymbol{\omega}}\|$. The last equality in Equation 4 holds because $\boldsymbol{r}$ is orthogonal to $\boldsymbol{\omega}$ by definition and to $\dot{\boldsymbol{\omega}}$ due to Assumption 3. From here, the angular velocity can be estimated from either the x or y component of the acceleration vector. However, computing the angular velocity via the angular acceleration $\dot{\boldsymbol{\omega}}$ would lead to integrating noise and thus lead to a worse estimate. In order to compute the magnitude of the angular velocity vector $\|\boldsymbol{\omega}\|$, the magnitude of the lever arm $\|\boldsymbol{r}\|$ must be determined. Using Assumption 4, as can be seen in Figure 3, $\boldsymbol{r}$ can be retrieved with

$$\boldsymbol{r} = (\boldsymbol{t} \cdot \boldsymbol{e})\boldsymbol{e} - \boldsymbol{t}. \tag{5}$$

The axis of rotation $\boldsymbol{e}$ is usually determined using the angular velocity $\boldsymbol{\omega}$, but this is not possible in the present case, since the measurement of one of the gyroscope axis is saturated. Using Assumption 3, the axis of rotation of the previous estimated angular velocity is used instead. Lastly, without loss of generality, let us assume that the gyroscope is saturated on the x component. Using Assumption 1 and Assumption 5, we can retrieve the saturated measurement ω_x using

$$\omega_x = \sqrt{\frac{\tilde{a}_x}{\|(\boldsymbol{t} \cdot \boldsymbol{e})\boldsymbol{e} - \boldsymbol{t}\|} - \omega_y^2 - \omega_z^2}, \tag{6}$$

where $\tilde{a}_x$ is the x component of $^{\mathcal{R}}\tilde{\boldsymbol{a}}_I$, ω_y and ω_z are the unsaturated gyroscope measurements. Because of noise in accelerometer measurements, the computed angular speed might be below the saturation point, which we know is not possible. To solve this, the maximum between the magnitude of the estimated angular speed and the saturation point is kept. The sign ambiguity of the computed angular speed can be resolved by looking at the sign of the saturated gyroscope measurement. The last issue that can be encountered is that, again because of noise in accelerometer measurements, the term under the radical in Equation 6 can be negative. In that case, we simply reject the estimate.

We now smooth the angular velocity estimates computed previously with Gaussian Processes (GPs) using a physically-motivated motion prior. GPs allow us to get more accurate angular velocity estimates during collisions when one or many of the five assumptions stated above are broken during a short duration. Similarly as done by Tang *et al.* [20], a white-noise-on-jerk motion prior is used. To account for the possibly abrupt changes in angular velocity, the diagonal entries of the angular jerk power spectral density matrix are set to a high value $q_{\ddot{\omega}}$. The unsaturated gyroscope measurements are assigned a covariance of σ^2_{ω}, which can be computed using the IMU specifications. The valid angular speed estimates are given a higher covariance, $\sigma^2_{\hat{\omega}}$, which is a parameter of our method. Employing GPs for smoothing has the advantage of yielding both the mean and covariance of the estimated angular velocity as functions of time. The STEAM library, from Anderson *et al.* [21], was used to carry out these computations.

B. *SLAM framework*

The SLAM framework in which our angular velocity estimation method is inserted is divided into four steps which are described briefly in this section. For more details, refer to our previous work [5]. **1) Intra-scan trajectory estimation:** Using the estimated angular velocities computed in Section III-A and accelerometer measurements, the trajectory of the IMU is estimated. To do so, first, the angular velocities and linear accelerations are passed through a Madgwick filter [22] to estimate the orientation of the IMU throughout the scan. These orientations are used to express all measurements in a gravity-oriented coordinate frame, allowing us to remove the gravity vector from accelerometer measurements. Then, accelerometer measurements are integrated, and resulting displacements are added to the position computed in the previous registration to estimate the position of the IMU throughout the scan. Finally, this position and orientation information is used in combination with the extrinsic calibration between the IMU and lidar to compute the trajectory of the latter during the scan. **2) Deskewing:** As lidar sensors typically assume they are static during scans [5], point positions need to be corrected with respect to intra-scan motion. We use the estimated position of the lidar frame during the scan to transform every measured point in the coordinate frame of the lidar at the start of the scan. **3) Uncertainty-aware registration:** Using the Time-based Weighting (TW) model and registration algorithm described in [5], the deskewed scans are registered to the reconstructed map of the environment. This weighting model takes the uncertainty of the deskewing into account for the registration algorithm by assigning a larger weight to scan points that are likely less affected by skewing. As the estimated displacement of the lidar during the scan is used as prior alignment for the registration algorithm, the quality of IMU measurements has a major influence on the robustness of registration. **4) Merge and map maintenance:** The registered deskewed scan is then merged into the map of the environment and maintenance operations are performed. These maintenance operations are surface normal computation and removal of points with a deskewing uncertainty above σ_p^2.

IV. RESULTS

In this section, we describe the experimental setup used to build our dataset. We show that our angular speed estimation method significantly reduces angular velocity error in the case of gyroscope-saturating motions. We then show the robustness improvement for our SLAM framework, both for localization and mapping. Lastly, we compare the range of motions in our dataset to those in other SLAM datasets.

A. Experimental setup

To validate the improvements reached through our approach while minimizing hardware damage and replacement costs, we created a rugged perception rig, which is shown in Figure 1. A RoboSense RS-16 lidar was used to record the 3D point clouds at a frequency of 10 Hz. For angular velocity measurements, we used two different IMUs, with distinct gyroscope saturation points. The first IMU is an XSens MTi-30, with a gyroscope saturating at 10.5 rad/s, despite the Xsens specification sheet stating a saturation point of 7.85 rad/s. The second IMU is a VectorNav VN-100, with a gyroscope saturating at 34.9 rad/s according to its specification sheet. Its angular velocity measurements are used as ground truth since we did not reach its gyroscope saturation point in our dataset. Lastly, we used a Raspberry Pi 4 embedded computer to record all sensor data. All SLAM results were computed offline, using the `norlab_icp_mapper` library [23]. The COM of the rig was evaluated manually, by balancing the rig on a single point on each face. The constants that were introduced in Section III are set to $q_{\dddot{\omega}} = 10^6$, $\sigma_{\bar{\omega}}^2 = 2.74\times10^{-5}$, $\sigma_{\hat{\omega}}^2 = 3.65$ and $\sigma_p^2 = 1$. To evaluate our method, we built the TIGS dataset, including a total of 32 distinct runs, consisting of pushing the rig to roll down a steep hill, mimicking a tumbling robot. One of the runs of our dataset can be seen in Figure 1. A ground-truth map was built by moving the sensor rig slowly, thus limiting skew in the scans.

B. Angular velocity estimation

Using the angular velocity estimation method described in Section III-A, the angular velocity of the platform was estimated for all the runs in our dataset. An example is shown for a single run in the left subplot of Figure 4. The speed estimation error during gyroscope saturation periods with and without our method is shown for all runs in our dataset in the right part of Figure 4. Only periods of saturation are studied (i.e., the light gray area), as angular velocities are the same with or without our speed estimation method outside saturation zones. When accounting for all runs, our approach reduces the angular velocity error median by 83.4 %, when compared to saturated gyroscope measurements. As expected, our angular velocity estimation approach significantly reduces angular velocity error under gyroscope saturations, especially for extreme values.

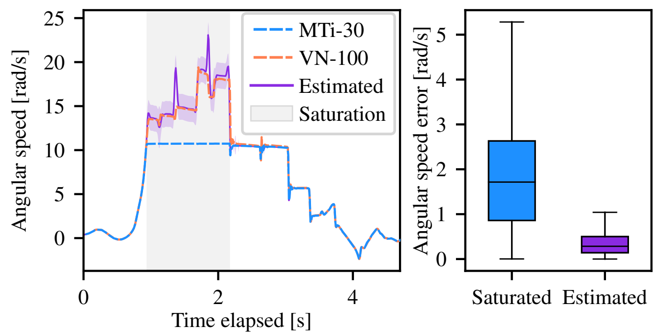

Fig. 4. The left plot shows an example of the angular speed through time for the saturated gyroscope axis for a single run of our experiments. In dashed blue are the measurements from an MTi-30 gyroscope, in dashed orange are the measurements from a VN-100 gyroscope, and in purple are the angular speeds estimated using our method. The purple-shaded area represents three standard deviations above and below the estimated speed. The right plot shows the error in angular speed without (in blue) and with (in purple) our method during saturation periods for all runs.

C. Impact on SLAM

Using no prior map of the environment, our SLAM algorithm described in Section III-B was run on each of the 32 runs in our dataset. The localization errors with and without our angular velocity estimation method are illustrated in Figure 5. Here, the localization error corresponds to the error in the estimated transformation between the initial and final poses of the rig. The ground-truth transformation for each run was found by registering the first and last scan in the ground-truth map, as the perception rig is static at these times. Our angular velocity estimation approach improves the baseline SLAM algorithm localization error median by 71.5 % for translation and 65.5 % for rotation. As localization error build-up can lead to navigation and detection failure [3], reducing this error in the event of the vehicle tumbling down a hill is critical. Additionally, reducing the localization error facilitates vehicle recovery, enabling it to resume its mission.

To investigate the impact of our method on mapping, we analyze a map built with our SLAM system for every run in our dataset. We built on prior work from Chung *et al.* [24] for the Defense Advanced Research Projects Agency (DARPA) Subterranean Challenge to evaluate mapping quality. Our map overlap metric is the percentage of reconstructed map points that are within a threshold distance from a point belonging to the ground-truth map. In the present case, we chose the threshold distance to be 0.25 m as opposed to the 1 m from the work of Chung *et al.* [24] to reflect the much smaller scale of our experiments. Indeed, the distance traveled in our runs is between 5 m and 10 m, compared to between 150 m and 250 m in the case of the DARPA Challenge. The mean overlap of the maps built without our angular velocity estimation method is 77.2 %, as opposed to 92.1 % with our method. The result for a specific run is shown in Figure 6. We selected this run since the increase in mapping performance was significant when our SLAM algorithm relied on our speed estimation method. Additionally, with saturated gyroscope measurements, we observe a failure of the mapping for $46.9\,\%$ of the runs, as opposed to $12.5\,\%$ when relying on our speed estimation method. We define mapping failures as cases where scan registration errors are apparent in the reconstructed map. This clearly shows that our angular velocity estimation method increases mapping robustness in the case of a robot tumbling down a hill. This result is especially useful in the case of exploration, with no prior knowledge of the environment. Fixing the map remotely or autonomously is a complex endeavor, thus a broken map puts the system at risk of failure.

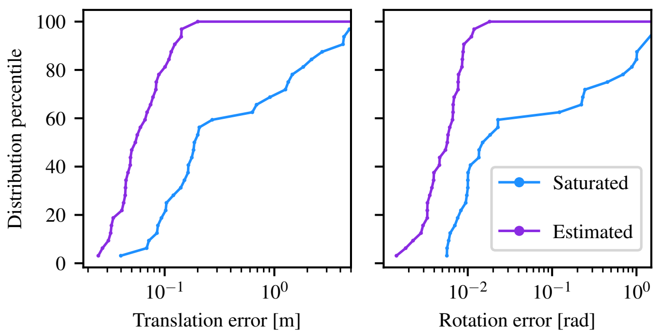

Fig. 5. Localization error for every run in the dataset. The percentiles of translation error distribution is shown on the left plot and percentiles of rotation error distribution is shown in the right plot. The blue and purple lines represent the percentiles of the localization error distribution when relying on saturated measurements and our speed estimation method, respectively. Errors on both subplots are shown with a log scale.

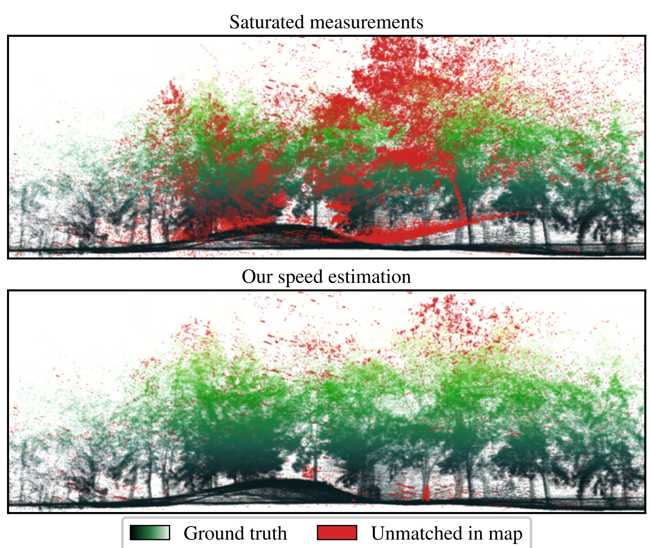

Fig. 6. Side view of the ground-truth map built for the dataset. The color map is proportional to point height. Mapping outliers from the fourteenth run are displayed in red. The top map shows the mapping outliers when relying on saturated measurements. The bottom map shows the mapping outliers when using our speed estimation method. Outlier points are defined as points that are farther than $0.25\,\mathrm{m}$ from the ground-truth map.

D. The TIGS Dataset

To show how our Tumbling-Induced Gyroscope Saturation (TIGS) dataset covers a larger spectrum of aggressive motions than other SLAM datasets, we present the distributions for observed linear accelerations and angular velocities in Figure 7. We compare to the KITTI [19], Newer College [17] and Hilti-Oxford [18] datasets. One can observe that our dataset covers a significantly larger spectrum of aggressive motions, characterized by high linear accelerations and angular velocities. Indeed, the maximum recorded linear acceleration for the TIGS dataset is $127.1\,\mathrm{m/s^2}$ over the highest linear acceleration observed in the compared datasets. Since the saturation point of the VN-100 accelerometer was reached for some collisions, the increase in linear acceleration that was really sustained is probably higher than this number. Furthermore, the maximum angular speed for the TIGS dataset is $13.9\,\mathrm{rad/s}$ over the highest angular speed observed in the compared datasets. Our dataset is the only one with angular speeds over the specified saturation point of the Xsens gyroscope, thus allowing us to evaluate SLAM pipelines under saturated gyroscope measurements.

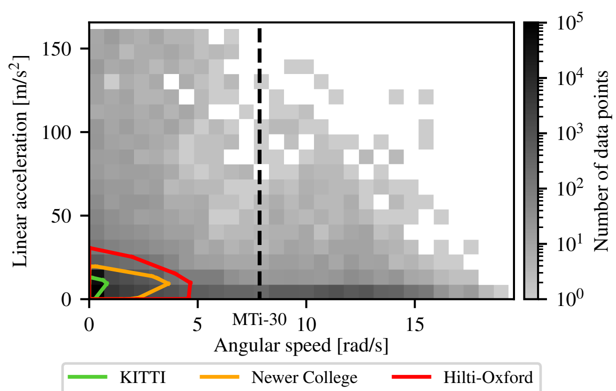

Fig. 7. Density map of the TIGS dataset. The color represents the number of data points acquired at the specific angular speeds and linear accelerations. The outlines represent the distributions in linear accelerations and angular velocities for similar datasets. In green is the KITTI dataset, in orange is the Newer College dataset, and in red is the Hilti-Oxford dataset. The dashed line represents the manufacturer-specified saturation point of the MTi-30 gyroscope.

V. CONCLUSION

In this paper, we introduced a novel method to estimate angular speed under saturated gyroscope measurements. We validated our method through 32 runs mimicking a robot tumbling down a hill, with angular speeds reaching up to $18.6\,\mathrm{rad/s}$ and linear accelerations up to $157.8\,\mathrm{m/s^2}$. Our system was able to perform SLAM under these aggressive motions with $73.3\,\%$ fewer failures than without our speed estimation method. We release our dataset, called TIGS, to allow evaluation of SLAM frameworks under aggressive motions. Future work will focus on investigating the benefits of adding IMU constraints to the lidar scan registration cost function to further increase SLAM robustness to aggressive motions.

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