

Tiny LiDARs for Manipulator Self-Awareness: Sensor Characterization and Initial Localization Experiments

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Abstract—For several tasks, ranging from manipulation to inspection, it is beneficial for robots to localize a target object in their surroundings. In this paper, we propose an approach that utilizes coarse point clouds obtained from miniaturized VL53L5CX Time-of-Flight (ToF) sensors (*tiny LiDARs*) to localize a target object in the robot’s workspace. We first conduct an experimental campaign to calibrate the dependency of sensor readings on relative range and orientation to targets. We then propose a probabilistic sensor model, which we validate in an object pose estimation task using a Particle Filter (PF). The results show that the proposed sensor model improves the performance of the localization of the target object with respect to two baselines: one that assumes measurements are free from uncertainty and one in which the confidence is provided by the sensor datasheet.

I. INTRODUCTION

Collaborative robots are required to operate in highly dynamic environments while ensuring safety. Consequently, localization is essential for them to maintain awareness of their changing surroundings and adapt their actions accordingly. In particular, LiDAR systems have been widely utilized in the literature for tasks such as object location and Simultaneous Localization and Mapping (SLAM), thanks to their reliability and ability to provide high-density measurements [1], [2].

Recently, miniaturized LiDARs based on Time-of-Flight (ToF) technology have garnered significant interest as a cost-effective (£6.50 each) and lightweight (approximately 1 g) alternative to traditional LiDAR systems [3]. These sensors have so far mainly been employed in obstacle and collision avoidance, pre-touch sensing, in-hand manipulation, object detection, and gesture recognition [4]–[11]. Their characteristics, though, along with their extremely compact form factor, make them particularly suitable for distributed integration into the robot body, facilitating medium-range distance sensing (typically up to a few meters), enhancing spatial awareness [12]–[14] and extending their range of applications to object localization and SLAM. The advantage of the ease of integration comes at the cost of significantly lower spatial resolution of the sensor measurements compared to traditional LiDAR (most recent models provide an 8×8 depth map). In addition, ToF sensors typically feature a pyramidal Field of View (FoV), which results in increasingly

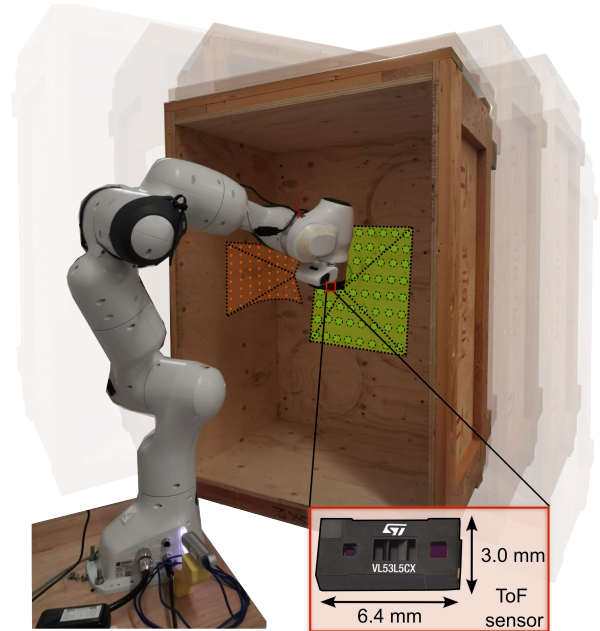


Fig. 1. Robot estimating the pose of the crate using a Particle Filter based on measurements collected with miniaturized ToF sensors. The faded crates illustrate the estimated poses associated with particles. Each sensor provides an 8×8 depth map of the surface falling into the FoV, which can be converted into a small Point Cloud. A picture of the sensor used in this paper and its dimensions are also reported.

coarse spatial resolution the higher the distance to the target (see Figure 1). Their use with existing state-of-the-art algorithms performing SLAM or localization presents idiosyncratic challenges, as these algorithms are designed to work with much higher-density point clouds of the surrounding environment.

Work has been done to address this drawback by pairing the ToF with other sensors, as in [15] with a monocular camera and in [11] with an RGB-D camera. In this work, we present an approach for localizing large objects in the robot’s workspace. Unlike the aforementioned works, our method relies solely on using ToF sensors. The sensor used in this work provides a small 8×8 depth map as output and is capable of sensing the relative distance from objects up to 4 m. The localization is achieved by applying a Particle Filter (PF) algorithm to a probabilistic beam model of the sensor. We draw inspiration from [16]. Their work focused on 2D in-hand localization of a small object at a very short distance; therefore, compared to our case, their sensor measurements

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were less affected by uncertainties related to distance from the target. We decided to deal with such uncertainties by performing a systematic sensor characterization to (i) correct the raw sensors measurements and (ii) build a more accurate probabilistic sensor model that accounts for the observed noise.

In summary, this work tackles the problem of localizing an object in the workspace of a robot manipulator equipped solely with ToF sensors. The probabilistic model, enhanced by our extensive sensor characterization, has been validated through comparative experiments to quantitatively analyze the improvement in the localization accuracy with respect to two baseline methods – the first relies on information provided by the sensor datasheet, while the second assumes measurements are free from uncertainty.

This work is organized as follows. We first introduce the notation and scope of the work in Section II and describe the characterization process in Section III. Section IV outlines our experimental setup and Section V details our results. Conclusion follows.

II. TOF-BASED LOCALIZATION

We aim to determine the position of an object in the surroundings of a robotic manipulator using coarse and noisy measurements. To this end, we accommodate sensor noise by identifying a probabilistic sensor model that we then exploit in a Monte Carlo Localization (MCL) algorithm using a PF. In this section, we first detail the sensor model for the localization task and then briefly describe the MCL algorithm¹.

A. Probabilistic Sensor Model

The miniaturized ToF sensor utilizes K separate beams that measure the environment at different fixed directions, resulting in a detection volume. As a result, at the sampling time t , the sensor produces K distance measurements $z_t^k \in \mathbb{R}$ in the direction of the k -th beam. We collect the measurements at time t in the set $Z_t = \{z_t^1, \dots, z_t^K\}$.

The inaccuracy over z_t^k is conditioned on the ToF sensor pose with respect to a target object o_t , and on the environment itself. Since the sensors are rigidly attached to the robot, their state is intertwined with the robot state $r_t \in SE(3)$, corresponding to the Cartesian pose of the frame to which the ToF is rigidly connected. Accordingly, we define the sensor model $p(z_t^k | r_t, o_t)$ to represent the conditional probability of the observation z_t^k given the state r_t and the object o_t .

Given the nature of the ToF sensors, the model $p(z_t^k | r_t, o_t)$ mirrors the beam range finder model [17] that is widely used for range sensors and contemplates the effect that noise and unexpected objects have on range estimation. In our case, we want the model to mainly handle the sensor noise. Indeed, the robot does not interact with the environment, i.e., has no effect on o_t , and the object is supposed to be fixed over time. For this reason, in the following, we will refer to the object without a subscript.

¹We refer the reader to [17] for a more exhaustive treatment on localization methods and stochastic sensor modeling.

We can then express the sensor noise as a Gaussian distribution centered at the *true* range value z_t^{k*} and with variance σ^2 . The true range value can be computed with a ray-casting technique given the pose r_t of the robot. Conversely, the variance is estimated by characterizing the sensor. Therefore, we have $p(z_t^k | r_t, o) \sim \mathcal{N}(z_t^{k*}, \sigma^2)$ and $p(Z_t | r_t, o) = \prod_{k=1}^K p(z_t^k | r_t, o)$ as we assume the likelihood of the individual beam to be independent from the others as is commonly done in the literature [17].

B. Monte Carlo Localization

The probabilistic model described above is integrated into the MCL algorithm to update the belief function of the object's pose. To describe the object pose x_t , we define a set of M particles $X_t = \{x_t^1, \dots, x_t^M\}$, with the $x_t^j \in SE(3)$ representing the pose of the object in the Cartesian space.

In our case, the belief function $\text{bel}(x_t)$ given by the particles is formally defined as

$$\text{bel}(x_t) = p(x_t | Z_{1:t}), \quad (1)$$

where $Z_{1:t}$ denotes the sequence of sensor observations up to time t . The belief is updated according to the weights the MCL assigns to each particle based on the measurements [17]. To this end, for each particle, the probabilistic sensor model is used to estimate the likelihood of the observations given the object pose associated with the particle. In fact, for a given x_t^j , knowing the pose of the robot r_t , it is possible to estimate the true measurements z_t^{k*} and compute $p(Z_t | r_t, o)$. The weights computed by the MCL play a role in the resampling phase during which new particles are drawn.

III. SENSOR CHARACTERIZATION

A sensor model explicitly represents measurement noise through a conditional probability distribution. In addition, it is important to account for other sources of errors that can affect sensor readings. For ToF sensors, like other range sensors [18], [19], various factors can introduce errors in measurements. These factors include the distance to the target, the relative orientation between the sensor and the target, ambient light conditions, environmental temperature, and the physical properties of the target, such as its color and material. Nonetheless, characterizing the sensor for each of these sources is non-trivial. As our use-case consists of an indoor object localization, we characterized the sensor only considering its distance from the target and its orientation. Being an initial study, we designed our experiments so that lighting conditions, environmental temperature, and material properties do not vary.

In this section, we first describe the experimental setup used for the characterization. Then, details on the experimental procedure follow with a description of how the obtained results are integrated into the probabilistic sensor model.

A. Experimental Setup for ToF Characterization

This work uses VL53L5CX ToF sensors from STMicroElectronics², featuring a square FoV with a diagonal of 65°,

²Sensor datasheet available at: <https://www.st.com/resource/en/datasheet/vl53l5cx.pdf> [2025].

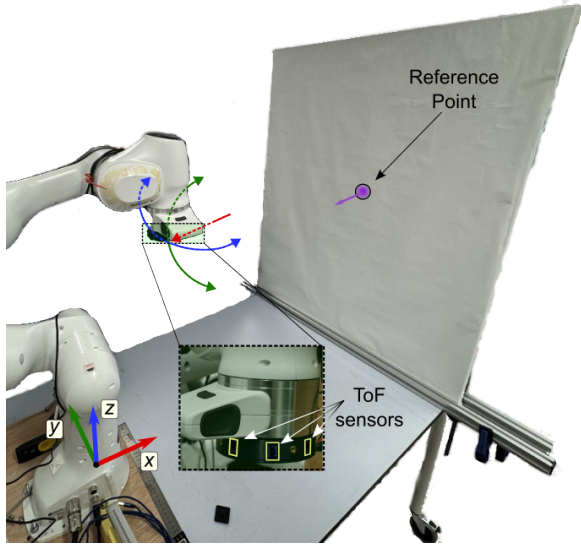


Fig. 2. A board is wrapped with a white vinyl film and placed in front of the robot at a fixed distance. The robot is commanded to move: in the x direction in the 20 mm to 800 mm range as highlighted with the red arrow; around the z -axis along a circular segment path of 50° by keeping a 200 mm distance from the reference point as indicated with the blue arc; around the y -axis along a circular segment path of 50° by keeping a 200 mm distance from the reference point as indicated with the green arc.

a measurement range of 20 mm to 4 m and an acquisition frequency of 15 Hz. Each ToF sensor measures distance along 64 individual beams evenly distributed within the detection volume and provides an 8×8 matrix, with each element representing the distance in the direction of a specific beam. Assuming the direction of the beams is known from the specifications, distance measurements can be converted into a small Point Cloud (PC) data structure.

For the characterization, three sensors were mounted on the end-effector of a Franka Robotics Panda robotic arm using a 3D-printed support with a circular shape; hence the precise relative placement between the robot and the support, as well as between the support and the sensors, was given by the CAD model. A flat board wrapped in a white vinyl film was placed orthogonal to the x -axis of the robot base frame as shown in Figure 2. The distance from the robot base was measured using a measuring tape as in [19], with a resolution of 10^{-3} m; while a proper orientation of the target was ensured by using a protractor with a resolution of 0.1° .

The robot was commanded to move its end-effector to different distances from the target, while also varying its orientation. All the readings are expressed with respect to the common reference frame associated with the robot base (see Figure 2). Similar to [16], the robot pose is assumed to be known with no uncertainties. Given the known position of the target board with respect to the robot and knowing the exact position of the ToF sensor with respect to the end-effector, we computed the distance between the reference point on the board (see Figure 2) and the sensor, i.e., the true range z^* . In all the experiments, the reference point was kept close to the center of the board, so that all ToF measurements intersected the board in each test position.

TABLE I
STANDARD DEVIATION OF READINGS AT DIFFERENT RANGES

Range (mm)	Standard Deviation (%)	Trend
20	40.0	Maximum deviation
25	1.4	Sudden drop from 20 mm
60	1.2	Linear decrease from 25 mm
100	0.6	Linear decrease from 60 mm
100 - 800	0.6	Constant deviation

The experimental procedure described in the remainder of the section was performed for the three ToF sensors, one at a time.

B. Range Characterization

For the range characterization, the robot was positioned so that the normal of the ToF sensor of interest was orthogonal to the target at a distance of 20 mm. As indicated in the datasheet, below this threshold the sensor does not provide reliable data. Starting from this pose, the robot was commanded to move backward in steps of fixed length up to a distance of 800 mm. For the first 200 mm the robot moved in 5 mm increments and then in 10 mm ones.

We acquired 100 sensor samples at each commanded pose, resulting in 100 sets of measurements, each composed of 64 values corresponding to the number of beams. We averaged each set – compensated for beam angle by the sensor’s firmware – to estimate the trend of the average $\bar{z}$ range and its standard deviation in the x direction (see Figure 2) over the 100 samples at different distances. Figure 3 shows the trend of the mean recorded at different ranges against the ground truth distances and the mean deviation recorded at each pose. The measurements are linearly correlated with the ground truth values with a deviation and an offset with respect to the ideal sensor measures (i.e., the precise measurements referring to the robot’s pose without noise and error), represented by the green bisector line. Therefore, we interpolated the data to find this correlation and found that the true range z^* (in mm) can be linked to the measured range $\bar{z}$ according to the following equation:

$$z^* = 0.963 \times \bar{z} - 18.15 \text{ [mm]}. \quad (2)$$

The discrepancy between measured data and the fitting line is on average below 1% with a maximum of 17.5% observed at 20 mm. It is worth noting that in the 100 mm to 800 mm range, the standard deviation associated with the readings varies constantly by 0.6% of the measured range. Conversely, a maximum 40% deviation is observed at 20 mm. It then linearly drops to 1.4% at 25 mm and to 1.2% at 60 mm; it eventually reaches 0.6% at 100 mm in a linear fashion. We report these results in Table I. The obtained results were repeatable across tests performed for the 3 different sensors. Therefore, there is no need for a tailored function for each to model the range error and estimate the noise distribution.

Notably, these results are significantly different from the sensor datasheet. In particular, the registered offset as well as the deviation from an ideal sensor measuring the true range

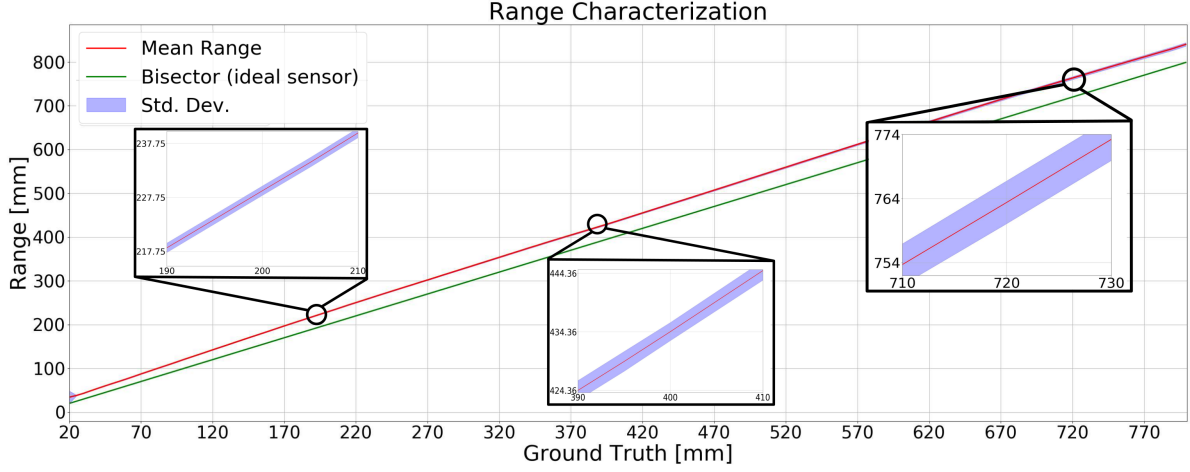


Fig. 3. The plot presents the estimated range along with the deviation and zoom-ins to highlight how the deviation changes at different ranges. The green bisector line represents an ideal sensor with perfect accuracy, illustrating the deviation of the real sensor from ideal behavior.

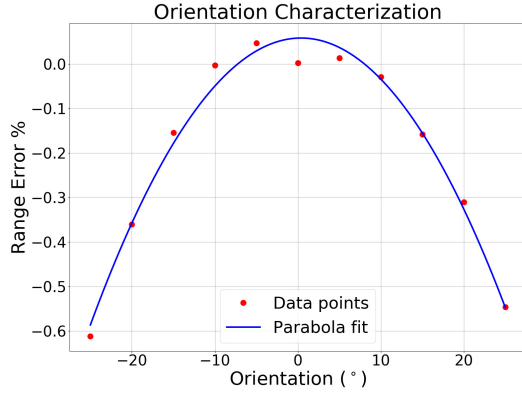


Fig. 4. The figure shows the percentage error of the measurements on the distance estimation at different orientations along with the interpolation curve.

are not mentioned. Furthermore, the reported deviation at different distances is generally greater or less informative. As an example, in the 20 mm to 200 mm range a deviation of 15 mm is reported, which implies a deviation that varies from 75% to 0.075%.

The results reported herein are used in a twofold way in the probabilistic model – firstly, raw ToF measures are corrected based on the measured distance; secondly, the σ for the given distance is assigned by Table I via linear interpolation.

C. Orientation Characterization

Similar to procedures performed for other sensors [18], [19], we also characterized how the measurements are affected by the relative orientation between the ToF sensor and targets. The robot’s end-effector was kept at a constant distance from the target and commanded to move over a circular path to cover different orientations. The explored range was chosen such that all the beams intersected the target. During this procedure, the normal of the sensor

intersected the reference point to the board as shown in Figure 2. Also in this experiment, both the relative error and the standard deviation are computed. The circular segment path had a radius of 200 mm with respect to the reference point. The angle of the circular sector spanned from -25° to 25° , covered in 5° increments while the robot moved. This path is defined for the x - y and z - y planes. Similar to the previous experiment, for each pose, we acquired and averaged 100 samples.

Figure 4 reports the recorded errors on the range estimation for the different orientations considered when moving in the x - y plane. For this plot, range measurements were first compensated according to the range error observed in the previous characterization and then the error of the measured range with respect to the ground truth was computed. As can be seen from the plot, a parabolic curve interpolates well the results. In particular, a second-order polynomial was fitted to interpolate the data as follows:

$$e_{xy} = -10^{-3}\theta^2 + 7.78 \times 10^{-4}\theta + 0.06, \quad (3)$$

in which θ represents the orientation.

The experiments on the y - z plane yielded similar results. Therefore, the error induced by the orientation of the ToF sensor with respect to the target can be approximated with the elliptic paraboloid:

$$e = -10^{-3}(\theta^2 + \phi^2) + 7.78 \times 10^{-4}\sqrt{(\theta^2 + \phi^2)} + 0.06. \quad (4)$$

In this case, θ is the angle in the x - y plane as in (3) and ϕ indicates the angle in the y - z plane. This equation is used to correct the range measure and adopted for the sensor model as before. Conversely, the standard deviation of the measure observed in these tests is not considered, as it was one order of magnitude smaller than the one observed in the range calibration (i.e., $< 10^{-1}$ mm).

IV. LOCALIZATION EXPERIMENTS

The proposed model based on sensors’ characterization – which we will refer to as Probabilistic Sensor Model (PSM) –

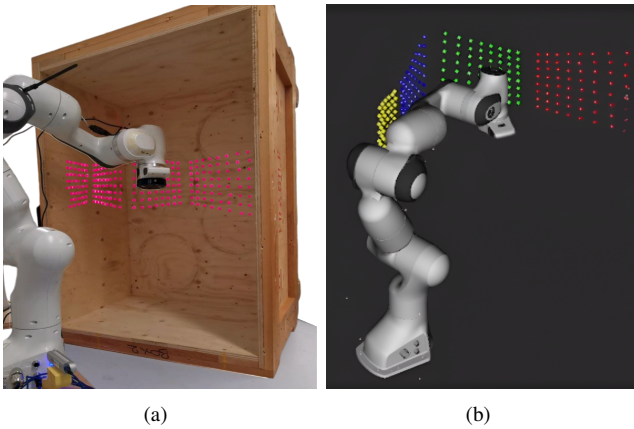


Fig. 5. PC reconstructed from ToF measurements at a given robot pose for the crate. (a) Real robot equipped with ToF sensors whose measurements are overlaid on the crate. (b) RViz visualization. A different color of the points is used to discriminate the different ToF unit generating the measurement.

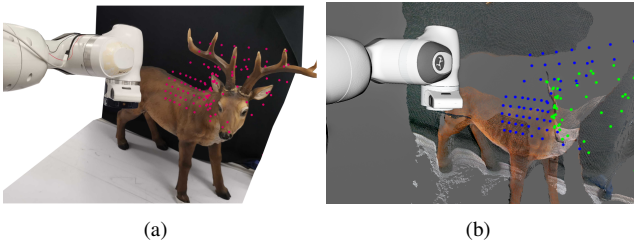


Fig. 6. PC reconstructed from ToF measurements at a given robot pose for the deer statue. (a) Overlay of ToF sensors measurements on the statue. (b) RViz visualization. The denser PC for the deer was acquired using an Intel Realsense D415 depth camera mounted on the right side of the robot's base.

is validated on two different object localization tasks, where we want to estimate the pose $x_o \in SE(2)$. As the objects lie on a flat surface, their height and out-of-plane orientation are fixed; we thus limit our study to position and orientation in the 2D x - y plane without loss of generality. Figure 5(a) and Figure 6(a) respectively show a crate and a statue of a deer placed in the robot workspace. With the crate, we reproduce a toy example of an inspection task for which the robot's end-effector is inside the space to explore. The crate presents strong features, e.g., corners and planes, that should be easy to detect with the ToF. Conversely, the deer statue allows us to test a more complex object with intricate features, which could be challenging due to the limited resolution of the sensors.

We benchmark PSM against two other methods. The first corresponds to the beam model in Section II built on the sensor datasheet – referred to as DataSheet (DS). The second method – Ideal Sensor (IS) – assumes the ToF is free of uncertainties in its measurements.

A. Data collection

ToF data were acquired with 4 different sensors embedded in the same 3D-printed support as in Section III. Regarding the crate, throughout the entire data collection, its pose was kept stable and measured from the reference frame placed at

the robot's base with measuring tape and a protractor. Since we know the crate shape, we can ray-cast every recorded sensor pose to measure the true distances between the sensor and the crate. Similarly, the statue was kept in a known pose for the data collection – measured with an Intel RealSense D415 depth camera and an AprilTag tag [20] – while the mesh adopted for the ray-casting was adapted from the dense PC collected in [21].

For both objects, the robot was commanded in diverse poses – 10 for the crate and 6 for the statue – to collect measurements from the ToF sensors. An example of the output of the 4 sensors at a given robot pose is shown in Figure 5(a) in the form of a PC for the crate. The deer statue only fell in two sensors' FoV given its size – see Figure 6(a). In the following, we refer to *data sample* to indicate the set of measurements collected at a given pose.

The poses for the crate were chosen to ensure that most sensor beams fell on the object. Raw measurements corresponding to distances higher than 600 mm were considered outside the crate volume and thus filtered out. Similarly, we surrounded the statue in a prismatic volume to reject the measurements.

It is worth noting that a more complete system may require a planner that moves the robot to the next position depending on the collected data [21] as well as a robust algorithm for scene segmentation. However, these aspects are out of the scope of this paper. In these experiments, we are only interested in benchmarking the use of ToF in the localization task; therefore, we collected offline data samples in different robot poses to evaluate how performance in the localization task is affected by: (i) the number of ToF sensors; (ii) the number of data samples.

B. Experiment Details

In line with what is presented in Section II, a PF approximates the belief of the object pose x_o [22].

The generic particle is $x_t^j = \{x, y, \gamma\}$, where $\{x, y\} \in \mathbb{R}^2$ represents the planar position of the reference frame rigidly attached to the object, and $\gamma \in \mathbb{R}$ its orientation in the plane (as shown in Figure 2).

For each set of measurements Z_t (see Section II), we compute its average $\bar{z}_t$ and correct its value by using (2) and (4) retrieved from the characterization experiments. We also associate the standard deviation value for the given range and thus compute the likelihood $p(\bar{z}_t | x_t^j, o)$ for each particle x_t^j , i.e., the normal distribution centered at the true range value z_t^* . The true range is retrieved with a ray-casting technique between the known sensor pose and the object as devised by the particle. The likelihood value is then used to update the j -th weight. When more than one ToF is used, the associated likelihoods are obtained in the same way and then multiplied before updating the weights.

When considering the DS method, we do not correct the distance measure as there is no indication of this in the datasheet. Conversely, the standard deviation is provided as a function of the measured distance. Therefore, if the difference between z_t^* and $\bar{z}_t$ for the j -th particle is smaller

TABLE II
CRATE LOCALIZATION RESULTS WITH RESPECT TO THE NUMBER OF ACQUISITIONS

Method	Number of Data Samples									
	2		4		6		8		10	
	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)
PSM (ours)	0.031 ± 0.011	0.926 ± 0.630	0.049 ± 0.010	0.760 ± 0.280	0.040 ± 0.009	0.974 ± 0.520	0.055 ± 0.034	0.556 ± 0.454	0.049 ± 0.008	1.352 ± 0.183
DS	0.069 ± 0.004	1.488 ± 0.194	0.069 ± 0.005	1.132 ± 0.312	0.065 ± 0.004	1.610 ± 0.273	0.067 ± 0.004	1.396 ± 0.402	0.068 ± 0.011	1.378 ± 0.713
IS	0.068 ± 0.003	1.336 ± 0.171	0.068 ± 0.005	1.256 ± 0.476	0.064 ± 0.008	1.488 ± 0.317	0.067 ± 0.005	1.316 ± 0.345	0.063 ± 0.006	1.312 ± 0.489

TABLE III
CRATE LOCALIZATION RESULTS WITH RESPECT TO THE NUMBER OF ToF SENSORS AND THE NUMBER OF ACQUISITIONS

Method	Number of ToFs / Number of Data Samples											
	2 / 4		2 / 6		3 / 4		3 / 6		4 / 4		4 / 6	
	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)
PSM (ours)	0.048 ± 0.012	0.522 ± 0.221	0.040 ± 0.016	0.370 ± 0.199	0.038 ± 0.014	0.298 ± 0.412	0.038 ± 0.014	0.798 ± 0.450	0.032 ± 0.009	0.412 ± 0.250	0.036 ± 0.021	0.888 ± 0.682
DS	0.068 ± 0.006	1.688 ± 0.206	0.071 ± 0.012	1.094 ± 0.278	0.071 ± 0.009	1.444 ± 0.237	0.069 ± 0.008	1.706 ± 0.348	0.066 ± 0.005	1.056 ± 0.221	0.070 ± 0.008	1.678 ± 0.381
IS	0.072 ± 0.006	1.498 ± 0.329	0.063 ± 0.010	1.360 ± 0.437	0.070 ± 0.008	1.370 ± 0.145	0.068 ± 0.004	1.248 ± 0.550	0.070 ± 0.007	1.210 ± 0.270	0.070 ± 0.006	1.588 ± 0.224

TABLE IV
DEER LOCALIZATION RESULTS WITH RESPECT TO THE NUMBER OF ToF SENSORS AND THE NUMBER OF ACQUISITIONS

Method	Number of ToFs / Number of Data Samples							
	1 / 4		1 / 6		2 / 4		2 / 6	
	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)	e_x (m)	e_y (°)
PSM (ours)	0.027 ± 0.004	1.232 ± 0.417	0.029 ± 0.008	1.596 ± 0.593	0.033 ± 0.007	1.585 ± 0.195	0.033 ± 0.004	1.401 ± 0.399
DS	0.030 ± 0.006	1.374 ± 0.424	0.030 ± 0.008	1.397 ± 0.317	0.034 ± 0.010	1.659 ± 0.094	0.029 ± 0.009	1.612 ± 0.437
IS	0.027 ± 0.006	1.362 ± 0.400	0.033 ± 0.010	1.324 ± 0.385	0.035 ± 0.006	1.449 ± 0.169	0.030 ± 0.007	1.658 ± 0.361

than the σ provided by the datasheet, the likelihood is computed; otherwise, a null weight is given to the particle. As a matter of fact, the datasheet assumes that the measure follows a Gaussian distribution centered at the estimation itself, thus the likelihood will always be maximum or null depending on the distance between the measure and the true value. Similarly, in the IS case, where the measure is assumed to be free from uncertainty, the measure belongs to a Gaussian centered in the measure itself, though with a very small deviation, i.e., in the order of the sensor resolution range (1 mm). In this case, if the distance between the estimation obtained with the ray-casting and the averaged sensor measure is below 1 mm, the likelihood value is computed and the weight is updated with a non-zero value.

V. RESULTS AND DISCUSSION

Our analysis first considers a single ToF sensor and different numbers of data samples. Then, for a fixed number of data samples, we analyze the effect of increasing the number of ToF sensors. All PF experiments initialize and draw 500 particles from a Gaussian distribution centered close to the ground truth and with an uncertainty of 0.15 m and 6° for position and angle. We performed five localization trials for each method by re-initializing the PF. We compare each method by its absolute translation and rotation error – e_x and e_y – defined as the norm of the difference between the true and estimated pose of the object.

In Table II we report the trend of the mean errors and their standard deviation, related to the localization tests conducted with the crate when considering a single ToF sensor with respect to an increasing number of data samples. For each set of experiments, the lowest position and angular error are highlighted in light blue. The results demonstrate that PSM outperforms the other two methods, thus validating

the characterization we performed. Specifically, across all experiments, PSM consistently delivered better performance, with a position error about 0.02 m smaller on average. Increasing the number of data samples does not significantly affect localization performance. The same behavior is also observed for the two baseline methods. Although average error values slightly oscillate, PSM consistently delivers better performance. The oscillations in the position error Table II are below 10 mm in most of the cases, which is in line with the sensor noise we observed from the characterization experiments. A similar behavior is also observed in Table III when multiple sensors and different data samples are considered. Also, in this case, there are small oscillations in the errors while increasing the number of ToF sensors. However, as expected, PSM consistently outperforms the two baselines. It also appears that the number of ToF sensors does not significantly affect the localization accuracy.

With more samples – whether collected by the same sensor at different times or jointly by multiple sensors – the localization performance is expected to improve as more discriminative features are considered. Nevertheless, the crate we used in the localization experiment is a simple object that contains strong local features (planes and corners) that may be captured by a single ToF and with a small number of samples. Conversely, the irregular shapes and fine details of the deer make ToF measurements challenging, thus limiting the effectiveness of using PSM. With fewer sensor beams intersecting the statue in each data sample (as shown in Figure 6), fewer measurements are captured, reducing the impact of the PSM corrections. As a result, while PSM generally outperforms the other methods, the difference in performance is less pronounced for the deer statue, with all three methods yielding similar results, i.e., $e_x < 0.035$ m and

$e_\gamma < 1.8^\circ$.

It is also interesting to note that, across the different tests, there is little performance difference between the DS method (built on datasheet information) and the IS method, where no uncertainty is modeled. This motivates proper sensor characterization as discussed herein.

VI. CONCLUSION

In this paper, we propose a method to localize a target object in the manipulator workspace by using coarse information provided by *tiny LiDARs*, i.e., the miniaturized VL53L5CX ToF sensors. We first characterize the sensors to assess how noise is affected by distance and orientation to the target. Then, we exploit the characterization curves and use an MCL algorithm to estimate the pose of objects. The characterization not only provides information on the sensor's accuracy but also allows for an improvement in the localization task with respect to two baselines where measurements are considered with no uncertainty or with the one from the sensor's datasheet. The characterization in this work was done by considering just a white vinyl film wrapped around a flat board. Future work will focus on understanding how different physical properties of the target might affect the sensor readings. Additionally, the effects of environmental lighting and temperature should be further investigated.

In the proposed analysis, we localized a crate and a deer statue with respect to the robot base. In this context, we found that, in this setting, a single ToF sensor is sufficient to achieve the task. Future analyses will evaluate this aspect by considering different, more complex objects as this may require a more sophisticated model for the sensor, taking into account other crucial sources of error, such as multipath interference or light scattering [23], [24]. We aim to address these challenges in our future work.

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