

# CBGL: Fast Monte Carlo Passive Global Localisation of 2D LIDAR Sensor

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**Abstract**—Navigation of a mobile robot is conditioned on the knowledge of its pose. In observer-based localisation configurations its initial pose may not be knowable in advance, leading to the need of its estimation. Solutions to the problem of global localisation are either robust against noise and environment arbitrariness but require motion and time, which may (need to) be economised on, or require minimal estimation time but assume environmental structure, may be sensitive to noise, and demand preprocessing and tuning. This article proposes a method that retains the strengths and avoids the weaknesses of the two approaches. The method leverages properties of the Cumulative Absolute Error per Ray (CAER) metric with respect to the errors of pose estimates of a 2D LIDAR sensor, and utilises scan-to-map-scan matching for fine(r) pose estimations. A large number of tests, in real and simulated conditions, involving disparate environments and sensor properties, illustrate that the proposed method outperforms state-of-the-art methods of both classes of solutions in terms of pose discovery rate and execution time. The source code is available for download.

**Index Terms**—global localisation, 2D LIDAR, monte carlo, scan-to-map-scan matching

## I. INTRODUCTION

The knowledge of a mobile robot's initial pose is a prerequisite in tasks involving its navigation, especially in contexts where an observer is used for pose tracking. However, the robot's pose is not predictable or pre-settable in all conditions. This lack of predictability necessitates ad hoc estimation without prior information. Various sensor and map modalities have been investigated in the literature; from 2D and 3D LIDAR sensors [1], [2], RGBD cameras [3], and RFID equipment [4], to keyframe-based submaps [5] and metric maps [6]. In practice the latter combined with 2D LIDAR sensors have become the de facto means of mobile robot localisation and navigation due to the sensor's high measurement precision and frequency, almost no need for preprocessing, and low cost compared to 3D LIDAR sensors.

This article addresses the problem of Passive Global Localisation of a 2D LIDAR sensor in a 2D metric map, i.e. the estimation of its location and orientation within the map, under complete locational and orientational uncertainty, without prescribing robot motion commands for further knowledge acquisition. The problem is formalised in Problem P:

**Problem P.** Let the unknown pose of an immobile 2D range sensor whose angular range is  $\lambda$  be  $p(l, \theta)$ ,  $l = (x, y)$ , with respect to the reference frame of map  $M$ . Let the range sensor measure range scan  $S_R$ . The objective is the estimation of  $p$  given  $S_R$ ,  $M$ , and  $\lambda$ .

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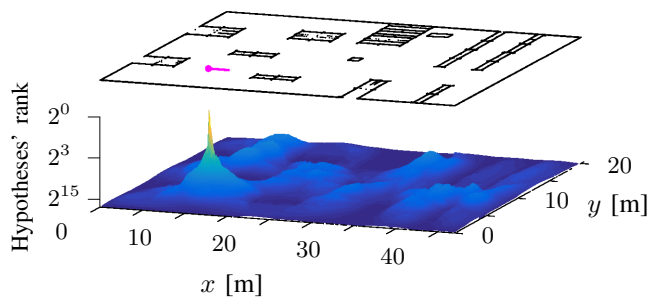


Fig. 1: Top: the map of an environment and the pose of a panoramic 2D LIDAR sensor (magenta). Given a LIDAR sensor's 2D measurement, at its core, CBGL disperses pose hypotheses within the map and ranks them ascendingly (bottom) according to the value of the Cumulative Absolute Error per Ray metric (Eq. (1)). This ranking may estimate the pose of the sensor (a) quickly due to the metric's low computational complexity, and (b) accurately due to (i) proportionality between the pose estimate error and the value of the metric for pose estimates in a neighbourhood of the sensor's pose, and (ii) lack of disproportionality outside of that neighbourhood (Fig. 2)

For the solution to Problem P this article introduces CBGL: a single-shot Monte Carlo method (a) which makes no assumptions regarding the structure or the particulars of the sensor's environment or the sensor's characteristics, (b) whose pose errors exhibit robustness to varying sensor angular range, and (c) which operates with three optionally-set and intuitive parameters, which trade accuracy for execution time. The central contributions of the article are:

- To the best of the author's knowledge the fastest Monte Carlo global localisation method that employs a 2D LIDAR that achieves higher pose discovery rates than state-of-the-art methods
- The extension and validation of the Cumulative Absolute Error per Ray metric's ability to estimate pose error hierarchies solely from real and virtual range scans, extended from scan-to-map-scan matching ( $sm2$ ) during pose-tracking, where pose estimates are "few" ( $\leq 2^5$ ) and their errors are "small", to the context of global localisation, where the set of hypotheses and their errors may be arbitrarily large
- The thorough evaluation of the proposed method against (a) established state-of-the-art localisation methods, (b) real and publicly available benchmark conditions, and (c) varying characteristics of environments and sensors, which target real conditions, that pose hindrances to global localisation methods

The rest of the article is structured as follows: Section II provides necessary definitions and the notation employed. Section III gives a brief review of solutions to problem P, and the relation of the proposed method to them. The latter's methodology is presented in section IV, its evaluation in section V, and its limitations in section VI. Section VII concludes this study.

## II. DEFINITIONS AND NOTATION

Let  $\mathcal{A} = \{\alpha_i : \alpha_i \in \mathbb{R}\}$ ,  $i \in \mathbb{I} = \langle 0, 1, \dots, n-1 \rangle$ , denote a set of  $n$  elements,  $\langle \cdot \rangle$  denote an ordered set,  $\mathcal{A}_\uparrow$  the set  $\mathcal{A}$  ordered in ascending order, the bracket notation  $\mathcal{A}[\mathbb{I}] = \mathcal{A}$  denote indexing, and notation  $\mathcal{A}_{k:l}$ ,  $0 \leq k \leq l$ , denote limited indexing:  $\mathcal{A}_{k:l} = \{\mathcal{A}[k], \mathcal{A}[k+1], \dots, \mathcal{A}[l]\}$ .

**Definition I. Pose and pose estimate.**—The object of localisation is the estimation of the—fundamentally-unknown—3DoF pose  $\mathbf{p}$  of a sensor or robot:  $\hat{\mathbf{p}} = (\hat{\mathbf{l}}, \hat{\theta})$ , where  $\hat{\mathbf{l}} = (x, y) \in \mathbb{R}^2$  is its location on the 2D plane and  $\hat{\theta} \in [-\pi, \pi]$  rad its orientation relative to the positive  $x$  axis.

**Definition II. Range scan captured from a 2D LIDAR sensor.**—A range scan  $\mathcal{S}$ , measured by a 2D LIDAR sensor, consisting of  $N_s$  rays over an angular range  $\lambda \in (0, 2\pi]$ , is an ordered map of angles to distances between objects and the sensor within its radial range  $r_{\max}$ :  $\mathcal{S} : \Theta \rightarrow \mathbb{R}_{\geq 0}$ ,  $\Theta = \{\theta_n \in [-\frac{\lambda}{2}, +\frac{\lambda}{2}] : \theta_n = -\frac{\lambda}{2} + \lambda \frac{n}{N_s}, n = 0, 1, \dots, N_s-1\}$ . Angles  $\theta_n$  are expressed relative to the sensor's heading, in the sensor's frame of reference [7].

**Definition III. Map-scan.**—A map-scan is a virtual scan that encapsulates the same pieces of information as a scan derived from a physical sensor (Def. II). Contrary to the latter it refers to distances within a map  $M$  of an environment rather than within the environment itself; the latter is represented by  $M$  usually in Occupancy Grid or ordered Point Cloud form. A map-scan  $\mathcal{S}_V^M(\hat{\mathbf{p}})$  is derived by locating intersections of rays emanating from a sensor's pose estimate  $\hat{\mathbf{p}}$  and the boundaries of  $M$ .

**Definition IV. The Cumulative Absolute Error per Ray metric.**—Let  $\mathcal{S}_p$  and  $\mathcal{S}_q$  be two range scans, equal in angular range  $\lambda$  and size  $N_s$ . The value of the Cumulative Absolute Error per Ray (CAER) metric  $\psi \in \mathbb{R}_{\geq 0}$  between  $\mathcal{S}_p$  and  $\mathcal{S}_q$  is given by

$$\psi(\mathcal{S}_p, \mathcal{S}_q) \triangleq \sum_{n=0}^{N_s-1} \left| \mathcal{S}_p[n] - \mathcal{S}_q[n] \right| \quad (1)$$

**Definition V. Pose densities.**—The locational and angular density,  $d_l, d_\alpha \in \mathbb{N}$ , of a pose set  $\mathcal{H} = \{\hat{\mathbf{p}}_i\}$  respectively denote the mean number of pose estimates dispersed on a given map  $M$  per unit area of space and per angular cycle.

**Definition VI. Admissibility of solution.**—A pose estimate  $\hat{\mathbf{p}}(\hat{\mathbf{l}}, \hat{\theta}) \in \mathbb{R}^2 \times [-\pi, +\pi)$ , may be deemed an admissible solution to Problem P iff  $\|\mathbf{p} - \hat{\mathbf{p}}\|_2 \leq \delta_0$  and  $\|\mathbf{l} - \hat{\mathbf{l}}\|_2 \leq \delta_l$  and  $|\theta - \hat{\theta}| \leq \delta_\theta$ , where  $\delta_l, \delta_\theta, \delta_0 \in \mathbb{R}_{>0}$ :  $\delta_l^2 + \delta_\theta^2 = \delta_0^2$ .

## III. RELATED WORK

The literature concerning the solution to the problem of global localisation with the use of a 2D LIDAR sensor is rich. A recent and comprehensive survey on global localisation may be found in [8], while a brief overview is given below.

In broad terms global localisation approaches may be divided into two categories: (a) approaches that operate in feature space, that is, methods that extract features from measurements and the map and establish correspondences between them, and (b) approaches that directly exploit only raw measurements. In the latter category a number of methods solve the problem in an iterative Bayesian Monte Carlo fashion, i.e. by dispersing hypotheses within the map and updating the belief of the robot's pose by incorporating new measurements as it moves until estimate convergence [9]–[13]. However, the requirement of motion (a) may give rise to safety concerns (the robot may not even be visible), and (b) increases estimation time. The Monte Carlo method proposed in this article operates directly in measurement space as well but, in contrast, is not iterative, and does not require motion or more than one measurement. As a result CBGL is a single-shot global localisation approach that is able to process more hypotheses in less time, resulting in an improvement in the number of correctly estimated locations, and making it able to compete against (traditionally faster) feature-based approaches in terms of execution time.

Research on the feature-based approaches has been more extensive due to the richness, adaptability, and efficacy of methods originated in the computer vision field, and their low execution time. Relevant methods mainly perform detection of key-points in a measurement, followed by the calculation of a distinctive signature, which is then matched to similarly- and pre-computed place-signatures [1], [14]–[20]. In principle, however, unstructured environments cannot be relied upon for the existence of features due to their absence or their sparse and fortuitous distribution (although Deep Neural Network approaches have demonstrated increased performance in place recognition with the use of 3D LIDARs [21]–[23]). Structured environments, on the other hand, manifest different features depending on the particularities of the environment, where features may be present but not in a sufficiently undisturbed state by sensor noise or map-to-environment mismatch. Furthermore, feature-based methods require the tuning of parameters in a per-environment basis, which hinders the range and degree of their applicability and efficacy. In contrast CBGL (a) makes no assumptions on- and exploits no environmental structure and (b) uses three parameters, whose setting is optional and intuitive.

In sum the proposed method retains the positive qualities of the two main approaches to global localisation and avoids their pitfalls: it uses multiple hypotheses for robustness against uncertainty, assumes no motion, environmental structure, or parameter tuning in a per-environment or sensor basis, and is robust against noise. The motivation of CBGL originates from seeking to achieve a greater degree of universality, reliability, and portability across multiple

and disparate environments, by aiming to economise on the use of resources (environmental assumptions; number, type, and cost of sensors; number of measurements; time). The proposed method is most akin to the two tested methods in [24]: all three are single-shot 2D LIDAR-based Monte Carlo approaches, but CBGL computes a measure of the alignment of the measurement to the virtual scan captured from each hypothesis *before* scan-to-map-scan matching, which occurs subsequently and only for a small subset of the most-aligned virtual scans to the measurement. This, along with the low computational complexity of the alignment measure that CBGL utilises, greatly diminish its execution time. So far this alignment measure (Def. IV) has only been tested against the context of `sm2` in pose tracking, i.e. for pose hypotheses in a neighbourhood of the sensor's true pose [25], [26].

#### IV. THE CBGL METHOD

##### A. Motivation

The proposed method's motivation lies in the simple but powerful fact that in general is exhibited through fig. 2: Let a pose estimate of a 2D LIDAR sensor be in a neighbourhood of its true pose within a given map (Def. I); then the value of the CAER metric (Def. IV) between the scan measured by the sensor (Def. II) and the map-scan captured from the estimate within the map (Def. III) is proportional to both the estimate's location error and orientation error. In other words comparing any two pose estimates residing in a neighbourhood of the sensor's pose in terms of a scalar value is enough to establish a pose error hierarchy between them. Moreover, this scalar locus metric is directly derivable and calculable from the assumptions of Problem P, with low computational complexity  $\mathcal{O}(N_s)$ .

The relationships of proportionality between the CAER metric of a pose estimate and its location and orientation errors have been discovered and successfully exploited in the context of non-global localisation, and specifically in pose-tracking, for the production of lidar odometry [25] and the reduction of localisation's pose estimate error [26]. In this context, estimate errors are close to the origin, i.e. in contrast to the arbitrary distribution of hypotheses' errors in Monte Carlo global localisation methods.

The above motivate investigation on whether the CAER metric could prove equally beneficial in settings more uncertain than pose-tracking, that is, where the location and orientation of pose estimates extend farther away from the sensor's true location and orientation. Fig. 11 (top) shows the relations between the total errors of hypotheses and their (a) CAER values (left) and (b) resulting ranks (right), which resulted from an experimental procedure similar to that which produced fig. 2.

##### B. The CBGL System

In order to test the efficacy of the CAER metric in aiding the solution of Problem P, we introduce the CAER-Based Global Localisation system (CBGL).<sup>1</sup> Given map  $M$ ,

<sup>1</sup>For a rigorous mathematical formulation of the hypothesis underpinning CBGL see [27].

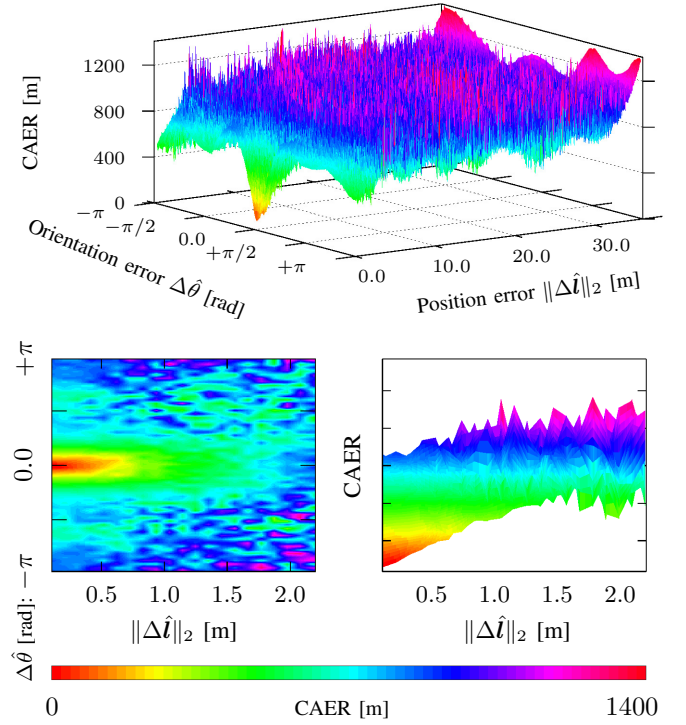


Fig. 2: Top: without loss of generality, a typical plot of the Cumulative Absolute Error per Ray metric (Eq. (1)) of  $10^6$  hypotheses dispersed in the map of environment WAREHOUSE (Fig. 1 and section V-B). Bottom: focused view on hypotheses with location error close to the origin

CBGL first generates a set of pose hypotheses  $\mathcal{H}$  (Def. I). Their positions are randomly generated uniformly within the map's traversable space, while orientations within  $[-\pi, \pi)$  rad. Then from these poses it computes map-scans (Def. III). Given these map-scans and a LIDAR's 2D measurement  $\mathcal{S}_R$  (Def. II), CBGL subsequently computes the CAER value (Def. IV) associated with each pose hypothesis. It then ranks them in ascending order and selects the  $k$  estimates with the least CAER values in an attempt to estimate the  $k$  hypotheses with the least pose error (Alg. II). Estimation in this sense rests on the motivation of subsection IV-A.

One challenge is choosing such  $k$ ,  $d_l$ , and  $d_\alpha$  (Def. V) that, given pose estimate error requirements  $\delta_l$ ,  $\delta_\theta$ , CBGL produces admissible pose estimates (Def. VI) while being executed in timely manner. Given the method's Monte Carlo nature, optimistically, the only option for increasing the accuracy of the final pose estimate by a factor of two would be to double locational density  $d_l$ ; instead of doing that—and thereby doubling the method's execution time—subsequent to the estimation of the pose estimates with the  $k$  lowest CAER values, CBGL utilises scan-to-map-scan matching (`sm2`) [26], [28], followed by the estimation of the one pose estimate with the lowest CAER value within the group of  $k$  matched estimates.

Matching allows for (a) the correction of the pose of true positive estimates by scan-matching the map-scan captured from a pose estimate against the range scan measured by the real sensor, (b) by the same token the potential divergence

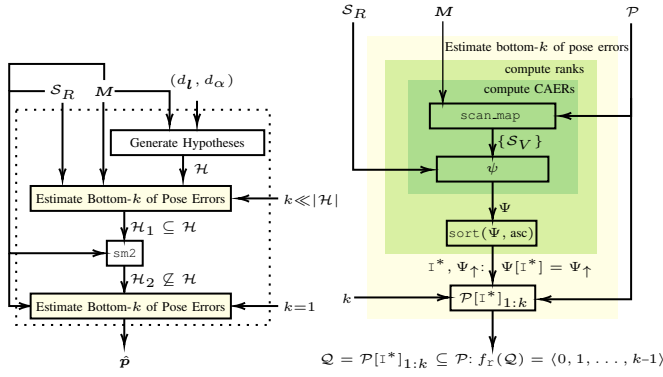


Fig. 3: CBGL in block diagram form. Left: Given map  $M$ , CBGL first generates a set of pose hypotheses  $\mathcal{H}$ . Then it estimates the  $k$  hypotheses with the least pose error (right; Alg. II). As a final step, it scan-to-map-scan matches these to  $S_R$  for finer estimation (sm2; Alg. III). CBGL's output pose estimate is that with the minimum CAER among the  $k$  matched estimates

of spurious, false positive, pose estimates, and hence their elimination as pose estimate candidates, (c) the production of finer pose estimates without excessive increase in execution time, and (d) the decoupling of the final pose estimate's error from the method's chosen densities. The principle of sm2 is depicted in fig. 4.

CBGL's output pose estimate is that with the least CAER among the  $k$  matched estimates. CBGL is described in block diagram form in fig. 3 and in pseudocode in Algorithm I.

#### Algorithm I CBGL

**Input:**  $S_R, \lambda, M, (d_l, d_\alpha), k$   
**Output:** Pose estimate of sensor measuring range scan  $S_R$

- 1:  $A \leftarrow \text{calculate\_area}(\text{free}(M))$
- 2:  $\mathcal{H} \leftarrow \{\emptyset\}$
- 3: **for**  $i \leftarrow 0, 1, \dots, d_l \cdot A - 1$  **do**
- 4:  $(\hat{x}, \hat{y}, \hat{\theta}) \leftarrow \text{rand}(): (x, y) \in \text{free}(M), \hat{\theta} \in [-\pi, +\pi]$
- 5: **for**  $j \leftarrow 0, 1, \dots, d_\alpha - 1$  **do**
- 6:  $\mathcal{H} \leftarrow \{\mathcal{H}, (\hat{x}, \hat{y}, \hat{\theta} + j \cdot 2\pi/d_\alpha)\}$
- 7: **end for**
- 8: **end for**
- 9:  $\mathcal{H}_1 \leftarrow \text{bottom\_k\_poses}(S_R, M, \mathcal{H}, k, \lambda)$  (Alg. II)
- 10:  $\mathcal{H}_2 \leftarrow \{\emptyset\}$
- 11: **for**  $k \leftarrow 0, 1, \dots, |\mathcal{H}_1| - 1$  **do**
- 12:  $\hat{h}' \leftarrow \text{sm2}(S_R, \lambda, M, \mathcal{H}_1[k])$  (Alg. III—e.g. x1 [26])
- 13:  $\mathcal{H}_2 \leftarrow \{\mathcal{H}_2, \hat{h}'\}$
- 14: **end for**
- 15: **return**  $\text{bottom\_k\_poses}(S_R, M, \mathcal{H}_2, 1, \lambda)$

## V. EXPERIMENTAL EVALUATION

This section serves the testing of the performance of state of the global localisation art methods and CBGL with regard to solving Problem P in static environments, varying environmental conditions, sensor configurations, and map representations. With regard to CBGL, its three required parameters are set to  $(d_l, d_\alpha, k) = (40, 2^5, 10)$  after initial experimental tests with the dataset used in subsection V-A. The rationale of choosing appropriate  $d_l, d_\alpha$  is depicted in

#### Algorithm II bottom\_k\_poses

**Input:**  $S_R, M, \mathcal{H}, k, \lambda$

**Output:** Set of  $k$  poses of  $\mathcal{H}$  with least CAER values,  $\mathcal{H}_\nabla$

- 1:  $\Psi \leftarrow \{\emptyset\}$
- 2: **for**  $h \leftarrow 0, 1, \dots, |\mathcal{H}| - 1$  **do**
- 3:  $\mathcal{S}_V^h \leftarrow \text{scan\_map}(M, \mathcal{H}[h], \lambda)$
- 4:  $\psi \leftarrow 0$
- 5: **for**  $n \leftarrow 0, 1, \dots, |S_R| - 1$  **do**
- 6:  $\psi \leftarrow \psi + |S_R[n] - \mathcal{S}_V^h[n]|$  (Eq. (1))
- 7: **end for**
- 8:  $\Psi \leftarrow \{\Psi, \psi\}$
- 9: **end for**
- 10:  $[\Psi_\uparrow, \mathcal{I}^*] \leftarrow \text{sort}(\Psi, \text{asc})$
- 11:  $\mathcal{H}_\nabla \leftarrow \{\emptyset\}$
- 12: **for**  $h \leftarrow 0, 1, \dots, k - 1$  **do**
- 13:  $\mathcal{H}_\nabla \leftarrow \{\mathcal{H}_\nabla, \mathcal{H}[\mathcal{I}^*[h]]\}$
- 14: **end for**
- 15: **return**  $\mathcal{H}_\nabla$

#### Algorithm III sm2

**Input:**  $S_R, \lambda, M, \hat{p}$

**Output:**  $\hat{p}$  + correction that aligns  $\mathcal{S}_V^M(\hat{p})$  to  $S_R$

- 1:  $\mathcal{S}_V \leftarrow \text{scan\_map}(M, \hat{p}, \lambda)$
- 2:  $\Delta p \leftarrow \text{scan\_match}(S_R, \mathcal{S}_V)$  (e.g. ICP [29], FSM [25])
- 3: **return**  $\hat{p} + \Delta p$

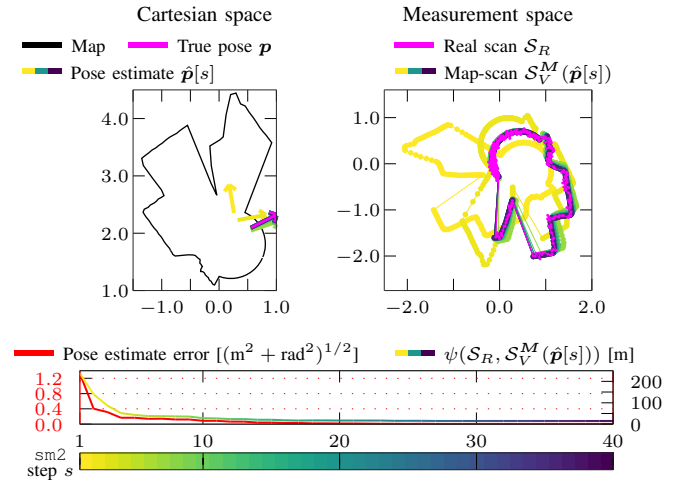


Fig. 4: Depiction of the process of scan-to-map-scan matching (sm2) in principle, which takes place for all  $\hat{p} = \mathcal{H}_1[k] \in \mathcal{H}_1$ . The registration of map-scan  $\mathcal{S}_V^M(\hat{p}[s])$  to  $S_R$  at step  $s$  results in pose  $\hat{p}[s+1]$ . Its error is, in principle, reduced compared to  $\hat{p}[s]$ , and the next map-scan is captured from it. The process is iterative and completes upon estimate convergence



|      | Position Err. [m] |       | Orientation Err. [rad] |       | Exec. Time [sec] |      |
|------|-------------------|-------|------------------------|-------|------------------|------|
|      | Mean              | std   | Mean                   | std   | Mean             | std  |
| ALS  | 0.500             | 0.265 | 1.956                  | 1.167 | 6.15             | 5.32 |
| CBGL | 0.041             | 0.045 | 0.011                  | 0.019 | 1.61             | 0.06 |

TABLE I: Mean and standard deviation of (a) errors of ALS and CBGL with regard to position and orientation and (b) their execution times, with regard to experiments in real conditions

fig. 5;  $k$  is chosen as such in order to retain a high-enough true positive discovery rate without significant increase in execution time. The locational threshold  $\delta_l = 0.5$  m is used as a tighter solution admissibility criterion determinant than that of [24]; the threshold itself was determined through experimental procedure with a YDLIDAR TG30 sensor (footnote 3). References to sets  $\mathcal{H}_*$  are made to fig. 3 (left) and lines 6, 9, and 13 of Algorithm I. All tests are performed with a processor of 12 threads and a clock speed of 4.00 GHz.

#### A. Experiments in real conditions

The first type of test is conducted using a Hokuyo UTM-30LX sensor, whose angular range is  $\lambda = 3\pi/2$  rad and radial range  $r_{\max} = 30.0$  m, in the Electrical and Computer Engineering Department’s Laboratory of Computer Systems Architecture (CSAL), of the Aristotle University of Thessaloniki, an Occupancy Grid map of which is depicted in fig. 6. The sensor was mounted on a Robotnik RB1 robot, which was teleoperated within the environment while scans were being recorded. This resulted in  $N_E = 6669$  range scans, whose number of rays are downsampled by a factor of four before being inputted to CBGL and Advanced Localization System (ALS) [30]. The latter implements Free-Space Features [1] and, contrary to CBGL, is not a single-shot method; however, it is selected for comparison against CBGL due to the fact that it is the only state of the art global localisation method which exhibits feasible execution times with respect to the collected range dataset’s volume (see bottom of fig. 8b for indicative execution times of state of the art methods). CBGL’s internal `sm2` method is chosen to be PLICP [31] due to its low execution time and the sensor’s non-panoramic field of view. The top of fig. 7 depicts the proportion of output pose estimates from each method whose position and orientation error is lower than outlier thresholds  $\delta_l$ ,  $\delta_\theta$ ; at the bottom they are depicted exclusively for CBGL’s output and its internal pose sets. Table I provides a summary of the magnitude of pose errors and execution times of the two methods.

From the experimental evidence it is clear that CBGL manages to produce admissible solutions to Problem P 991 times out of a thousand for an outliers’ locational threshold  $\delta_l = 0.5$  m when an angular threshold  $\delta_\theta$  is not considered, and (b) CBGL outperforms ALS in terms of (i) position and orientation errors, (ii) number of pose estimates within all locational and angular thresholds, and (iii) execution time.

#### B. Simulations against sources of uncertainty

The second type of test concerns the main limiting factor of global localisation methods, i.e. uncertainty—: arising e.g.

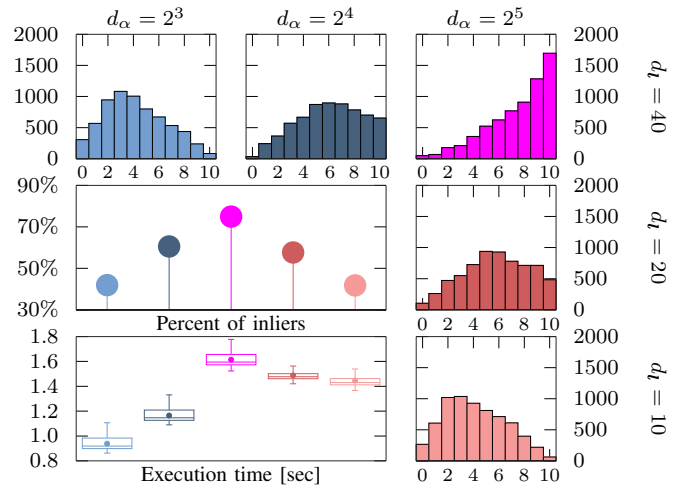


Fig. 5: Top row and right column: histograms of the number of times out of  $N_E = 6669$  CBGL global localisation attempts when exactly  $n \in [0, k] = [0, 10]$  pose estimates belonging to set  $\mathcal{H}_1$  (fig. 3 and line 9 of alg. I) exhibited pose errors lower than  $\delta_0 = (\delta_l^2 + \delta_\theta^2)^{1/2} = (0.3^2 + 0.4^2)^{1/2} = 0.5$  (m<sup>2</sup> + rad<sup>2</sup>)<sup>1/2</sup>. For densities  $(d_l, d_\alpha) = (40, 2^5)$  (top right) this number is strictly increasing with  $n$ , which would be retrospectively an aspect to be expected of a global localisation method. Denser configurations adhere to the same pattern as well but would require more execution resources.

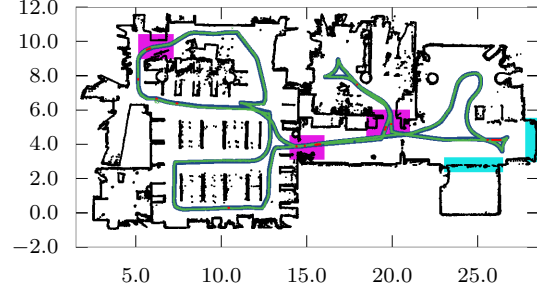


Fig. 6: The map of the real environment CSAL (black), the trajectory of the sensor (blue), and CBGL’s estimated positions of the sensor (green). A total of  $N_E = 6669$  pose estimations take place, 99.1% of which result in position errors lower than  $\delta_l = 0.5$  m. See fig. 7 for the respective percentages of position and orientation errors for varying admissibility thresholds  $\delta_l$  and  $\delta_\theta$ . Estimation is performed for each sensor pose independently of previous estimates and measurements. Sensor poses for which CBGL’s output exhibits position error larger than  $\delta_l$  are marked with red, sources of great range noise with cyan, and regions around doors with purple

from spurious measurements, repeatability of surroundings, missing or corrupted range information, or their combinations. For this reason the experimental procedure of [24] is extended here for the two methods tested therein, i.e. Passive Global Localisation-Fourier-Mellin Invariant matching with Centroids for translation (PGL-FMIC) and- Point-to-Line ICP (PGL-PLICP), and then for ALS, Monte Carlo Localisation (MCL) [9], and General Monte Carlo Localisation (GMCL) [12]. All methods are tested against the two most challenging environments, i.e. WAREHOUSE and WILLOWGARAGE, in which a panoramic range sensor is placed at 16 different poses, respectively  $p_*^W$  and  $p_*^G$ , for  $N = 100$  independent attempts at global localisation per

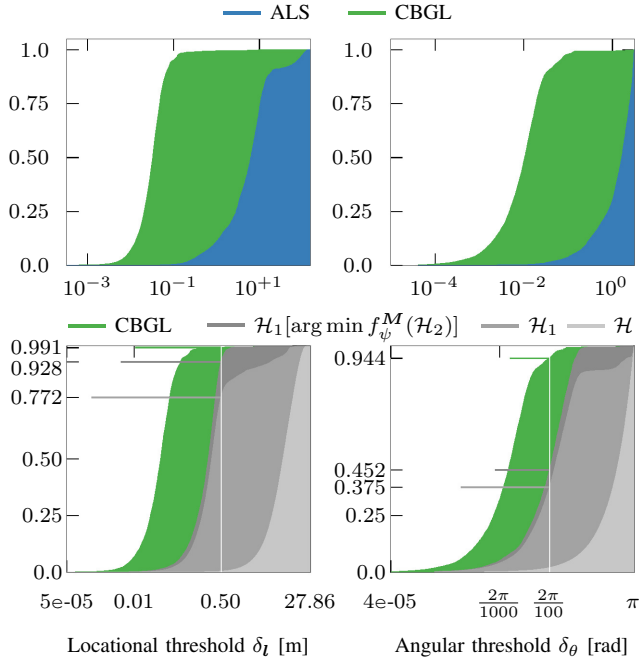


Fig. 7: Proportions of pose estimates whose position and orientation error is lower than corresponding thresholds  $\delta_l$  and  $\delta_\theta$ . Top: ALS vs CBGL. Bottom: CBGL and internal pose estimate sets. Approximately 77% of all bottom- $k$  pose estimates—the contents of  $\mathcal{H}_1$  sets, as described in section IV—exhibit position errors lower than  $\delta_l = 0.5$  m for  $k = 10$ , and so do over 99% of CBGL’s final pose estimates. The improvement in position and orientation induced by scan-to-map-scan matching is captured by the difference between the output (i.e.  $\mathcal{H}_2[\arg \min f_\psi^M(\mathcal{H}_2)]$ ) and  $\mathcal{H}_1[\arg \min f_\psi^M(\mathcal{H}_2)]$

pose. The tests are conducted with the use of a sensor whose number of rays  $N_s = 360$ , maximum range  $r_{\max} = 10.0$  m, and noise  $\sim \mathcal{N}(0, 0.05^2)$  [m, m<sup>2</sup>]. CBGL’s internal sm2 method is chosen to be  $\times 1$  due to the periodicity of the range signal,  $\times 1$ ’s robust pose errors compared to sm2 state of the art methods, and its greater ability in matching scans captured from higher initial displacements than ICP alternatives [26]. The latter translates to the need for smaller initial hypothesis sets: for each environment the locational density is set to  $3e+04$  divided by the free space area of each environment. For Monte Carlo approaches MCL and GMCL the number of initial hypotheses is also set to  $3e+04$ .

The maximum range of the sensor is such that the geometry of environment WAREHOUSE causes (disorderly) extended lack of sampling of the sensor’s surrounding environment, which limits available information and may therefore produce spurious measurements and increase ambiguities between the ranks of candidate estimates. In WILLOWGARAGE, on the other hand, almost all sensor placements result in complete sampling of its surroundings, but the sensor is purposefully posed in such conditions as to challenge the localisation methods’ ability to perform fine distinctions between similar surroundings. Figure 8a depicts the percentage of outputs whose position error is lower than  $\delta_l = 0.5$

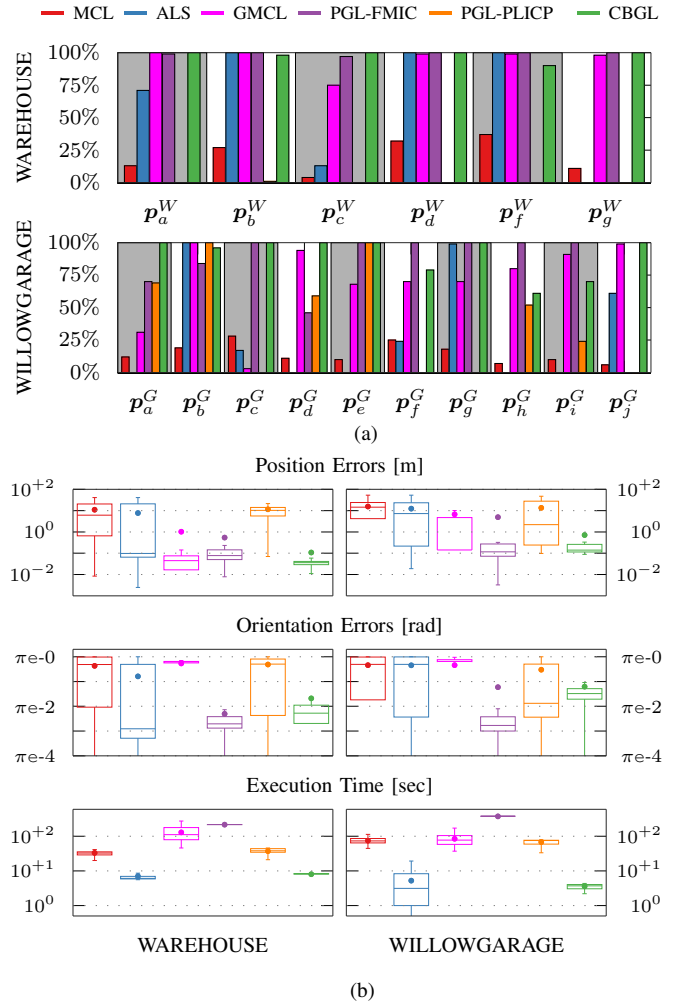


Fig. 8: (a) Percent proportions of pose outputs whose position error is lower than  $\delta_l = 0.5$  m per tested environment, pose, and method. Overall CBGL (green) features the highest number of inlier poses. (b) Distribution of position errors, orientation errors, and execution times per tested environment and algorithm in seconds for  $N_s = 360$  rays. CBGL’s execution time is at least eighteen times lower than other Monte Carlo approaches in WILLOWGARAGE and four times lower in WAREHOUSE

m per tested pose, and fig. 8b depicts the overall distribution of position errors, orientation errors, and execution times per tested environment and algorithm. Although the cardinality of set  $\mathcal{H}$  is equal in both environments, CBGL’s execution times are uneven due to  $\times 1$ ’s increased execution time when dealing with scans with missing range information. ALS is more robust against missing information than against repeated surroundings, while PGL-PLICP exhibits the inverse tendency. Notwithstanding the aforementioned sources of uncertainty, CBGL manages to exhibit the overall highest number of poses whose position error is below  $\delta_l = 0.5$  m.

### C. Simulations against environmental and sm2 algorithmic disparity

The third type of test aims to inquire how the performance of CBGL scales with respect to increasing environment

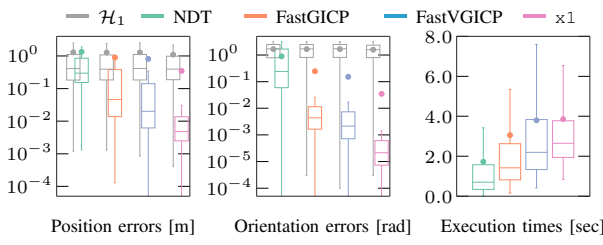


Fig. 9: Distributions of positional and orientational errors and of execution time of CBGL for varying choices of scan-to-map-scan matching methods. The errors of CBGL’s internal  $\mathcal{H}_1$  set are virtually unaffected by the decrease in angular range  $\lambda$  ( $\lambda_{\text{NDT}} = \lambda_{\text{FastGICP}} = \lambda_{\text{FastVGICP}} = 3\pi/2 \neq \lambda_{x1} = 2\pi$ )

area (and therefore to increased number of hypotheses), environment diversity, sensor angular range, and choice of overlying  $\text{sm2}$  method. CBGL is tested once in each of  $N_E \simeq 4.5\text{e}+04$  environments, generated via the evaluation procedure of [26], which utilises five established and publicly available benchmark datasets provided courtesy of the Department of Computer Science, University of Freiburg [32]. Each coordinate of the Point Cloud map of each environment is corrupted by noise  $\sim \mathcal{N}(0, 0.05^2)$  [m, m<sup>2</sup>]. The angular range of the range sensor varies according to the overlying  $\text{sm2}$  method used: for Normal Distribution Transform (NDT) [33], Fast Generalised ICP (FastGICP) [34], and Fast Voxelised Generalised ICP (FastVGICP) [35]:  $\lambda = 3\pi/2$  rad; for  $x1$ :  $\lambda = 2\pi$  rad. Measurement noise is  $\sim \mathcal{N}(0, 0.03^2)$  [m, m<sup>2</sup>]. As in subsection V-A the choice of pose densities and  $k$  is  $(d_l, d_\alpha, k) = (40, 2^5, 10)$ .

Figure 9 illustrates that, with the exception of NDT, all versions of CBGL exhibit mean positional errors less than 1.0 m; its combination with  $x1$  exhibits a mean error of approximately 0.5 m. The evidence illustrate that CBGL is robust to sensor angular range, as the distributions of errors between bottom- $k$  ( $\mathcal{H}_1$ ) sets are virtually indistinguishable for  $k = 10$ . Figure 10 shows the execution time of CBGL combined with FastVGICP and  $x1$  as a function of environmental area, and that with  $x1$ ’s timing breakdown with respect to (a) CBGL’s total time minus  $\text{sm2}$  time and (b) computing map-scans, as proportions of total execution time.

## VI. CHARACTERISATION & LIMITATIONS

Range scans with panoramic angular ranges induce fewer pose ambiguities in pose estimate rankings than those with non-panoramic field of view. In the latter case this means that, given the evidence of subsections V-A and V-C where  $\lambda = 3\pi/2$  rad, the choice of  $k = 10$  largely inhibits the propagation of ambiguities to the output (fig. 9). However, non-panoramic sensors coupled with repeated environment structures may give rise to the conditions of fig. 11 (bottom). Other sources of potential, large pose errors for CBGL are portrayed in fig. 6: Regions coloured with cyan indicate closed glass doors, wherein high range errors in  $S_R$ —which result from premature and arbitrary reflections of the LIDAR’s light on glass—form major discrepancies with regard

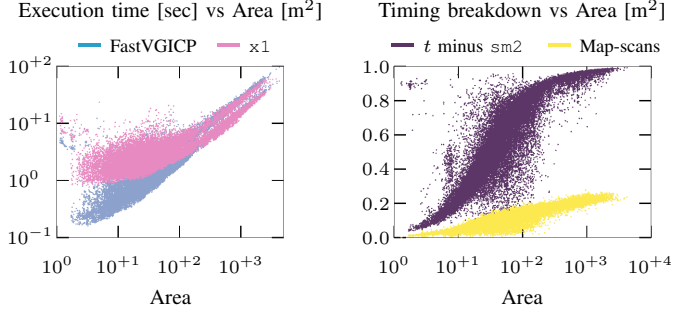


Fig. 10: Left: CBGL’s execution time with respect to environment area for two choices of overlying scan-to-map-scan matching methods. In rough terms  $\mu_t^{\text{CBGL}} [\text{sec}] \simeq 10^{-2} \cdot \text{area} [\text{m}^2]$  for areas larger than 200 m<sup>2</sup>. Right: Proportion of CBGL  $\circ x1$ ’s total execution time spent on (a) all operations up to and except for matching, and (b) computing map-scans, with respect to area

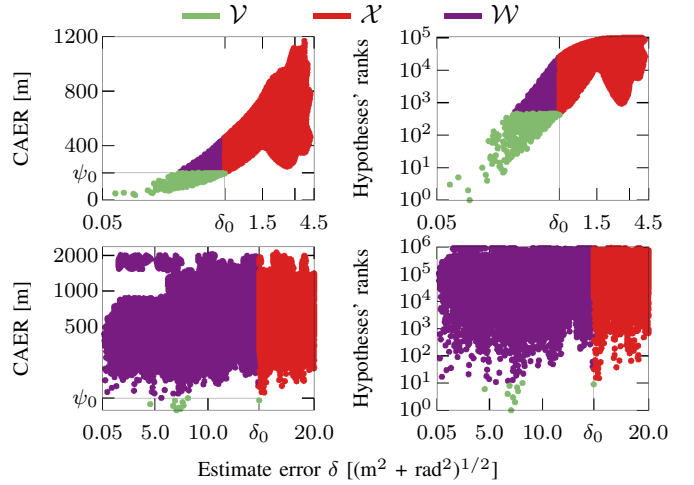


Fig. 11: Top: In principle there is at least one admissible pose estimate ( $\delta \leq \delta_0$ ) for any choice of  $k$  (Alg. II) in  $\mathcal{H}$ . However,  $k$  sets threshold  $\psi_0$  on the CAER of estimates in  $\mathcal{H}$ , and therefore it sets  $\mathcal{V}$ :  $\mathcal{V} \cup \mathcal{X} \cup \mathcal{W} = \mathcal{H}$ . In case of (a) repetitions of the immediate environment of the sensor more than once in a given map, and (b) non-panoramic angular range of a sensor, as witnessed in environment WILLOWGARAGE (pose  $p_i^G$ ; subsection V-B), it is possible that a choice of  $k$  may starve  $\mathcal{V}$  of admissible poses. See [27] for details on  $\mathcal{V}$ ,  $\mathcal{X}$ , and  $\mathcal{W}$

to map-derived virtual ranges; these subsequently propagate to CAER values and ultimately corrupt the estimation of pose error hierarchies derived from these values. Discrepancies of this kind arise also in regions coloured purple, which indicate vicinities around doors. In these areas the non-linear contour of ranges, combined with the fact that from different position estimates different parts of the environment become visible (and therefore small changes in position may result in large discrepancies between real and virtual scans)—these factors may cause to require higher values of locational density  $d_l$  or values of  $k$  in order to suppress highly erroneous pose estimates propagated to the output.

## VII. CONCLUSIONS AND FUTURE STEPS

This article has presented a single-shot Monte Carlo approach to the solution of the passive version of the global localisation problem with the use of a 2D LIDAR

sensor, titled CBGL. CBGL allows for the fast estimation of the sensor's pose within a metric map by first dispersing hypotheses in it and then leveraging the proportionality of values of the Cumulative Absolute Error per Ray (CAER) metric to the pose errors of the hypotheses, for estimates in a neighbourhood of the sensor's pose. CBGL was evaluated in various real and simulated conditions and environments; it was found to be superior to Monte Carlo and feature-based approaches in terms of number of inlier pose estimates and execution time. Future steps will aim at the extension of the CAER metric for the use with 3D LIDAR sensors in service to a solution of the problem of their global localisation in 6DoF. The C++ ROS code of the proposed method is available at <https://github.com/li9i/cbgl>.

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