RB5: A Low-Cost Wheeled Robot for Real-Time Autonomous Large-Scale Exploration

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***Abstract*—**

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I. Introduction

WIDELY used in cluttered environments [1]–[4], mobile robots can both substitute [5] and outperform humans in, e.g., areas that are too far or too dangerous to navigate [6]–[9]. In these areas, robots are often required to identify their surroundings by sensing the environment [10] and planning and executing complex trajectories [11], [12]. With little or no human intervention [13], this problem is known in the literature as autonomous exploration [11]. While successful in challenging indoor and outdoor environments [14], [15], autonomous exploration is especially useful in dynamic environments with no prior knowledge of the space to be covered [5], [16]. Despite recent advancements, autonomy is limited and costly in such environments. Many approaches that tackle autonomous exploration integrate commercial robots with sensing equipment that is both prohibitively expensive and difficult to maintain [8], [9], [14], [15], [17]–[20]. There is a wide range of methodologies for autonomous exploration at present [15], [21] nonetheless, which span from algorithmic foundations [15], [19], [22] to system-of-systems frameworks where, e.g., a multitude of robots integrate existing algorithms with sensors for large-scale exploration [3], [7]–[9], [18]. Recent efforts in this direction include low-cost robots for exploration [17], [23], [24] but lack terrain adaptability [17] and computational capabilities [23], [24] often required to navigate outdoors in the real-world [2], [5].

Furthermore, in areas that are ambiguous or challenging to traverse–albeit autonomous–state-of-the-art approaches rely on humans for supervision and high-level decision-making [3], [7], [8]. As a result, robots often operate close to humans or require expensive network equipment, such as a mesh of communication devices [2], [3], [9], or existing network infrastructure [25]–[27], thereby restricting autonomous exploration to indoor settings only [12], [28]–[31]. Conversely, our methodology exploits LoRa–an inexpensive long-range and low-power communication technology [32] from the internet-of-things domain–with a customized communication protocol for human intervention in, e.g., the eventuality of the robot being unable to move with the local sensory information.

Starting from the cost advantages of LoRa communication, we develop here RB5–a novel rocker-bogie-like mobile robot capable of exploring autonomously dynamic indoor and outdoor environments–and an open-source robot operating system (ROS)-based [33] exploration framework. Rocker-bogie mobile robots comprise a multi-body system with a moving base [24], [34], [35] (see Figure **??**) and provide rough terrain static adaptability [36]. They are cheaper than, e.g., legged robots in terms of cost per unit and operation, as they are able to overcome obstacles without costly computations for gait adaptation and planning [17]. Hardware-wise, RB5 maintains a lower sensory footprint with low-cost components, whereas software-wise, it integrates multiple modules into the exploration framework. Being able to operate in both unknown and GPS-denied environments, RB5 derives its position using a state-of-the-art simultaneous localization and mapping (SLAM) algorithm [37], and the trajectory with a novel methodology that extends exploration literature with a path following vector field [38] from the aerial robotics domain [39]–[41]. This allows RB5 to explore its surroundings at lower frequencies, utilizing cheaper computing hardware compared to state-of-the-art approaches [8], [9], [15], [19].

The remainder of the letter is structured as follows. In Section VI data show improved "coverage per cost" over the baseline of existing autonomous exploration system-of-systems with indoor and outdoor "in the field" experiments. Sec. IV–V describe RB5 from the hardware and software standpoints. Sec. II summarizes and compares existing literature, Sec. III formalizes the problem of autonomous exploration, and Sec. VII drafts conclusions and future directions.

II. Related Work

III. Problem Formulation

The problem considered in this work to showcase RB5 for large-scale exploration is that of exploring a bounded volume $\mathcal{Q} \subseteq \mathbb{R}^3$ with respect to an inertial navigation frame $\mathcal{O}_W$. If the notation $[n]$ denotes a set with positive naturals up to n and $[n]_{>0}$ with strictly positive naturals, we are

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interested in collision-free trajectories that explore $\mathcal{Q}$ and avoid $i \in [n]_{>0}, n \in \mathbb{N}_{\geq 0}$ obstacles $\mathcal{Q}^{O_i} \subset \mathbb{R}^3$. We can approximate the space that delimits $\mathcal{Q}$ and $\mathcal{Q}^{O_i}$ for each i with a set of vertices within which the two sets are contained.

Problem (Exploration)**.** Consider sets of vertices $V := \{\mathbf{v}_1, \mathbf{v}_2, \dots\}$, $O_i := \{\mathbf{o}_{i,1}, \mathbf{o}_{i,2}, \dots\}$ with $i \in [n], \mathbf{v}_j, \mathbf{o}_{i,k} \in \mathbb{R}^2$, $\forall j \in [|v|]$, $k \in [|o_i|]$ a point w.r.t. $\mathcal{O}_W$. Let V enclose $\mathcal{Q}$, O_i $\mathcal{Q}^{O_i}$ per each i. The *exploration problem* is the problem of finding the coverage that visits each point $\mathbf{p} \in \mathcal{Q} \cap \mathcal{Q}^{O_1} \cap \mathcal{Q}^{O_2} \cap \dots \cap \mathcal{Q}^{O_n} := \mathcal{Q}^V$.

Here the notation $|\cdot|$ denotes the cardinality and $\mathbb{R}$, $\mathbb{Z}$ are reals and integers. Bold notation is used for vectors.

Let ϕ be a path function, i.e., a function RB5 tracks as it explores its surroundings in $\mathcal{Q}^V$, avoiding the obstacles $\mathcal{Q}^{O_i}$.

Definition III.1 (Path function)**.** $\phi : \mathbb{R}^2 \to \mathbb{R}$ is a two-dimensional continuous and differentiable *path function* of the x, y components of $\mathbf{p}$.

Definition III.2 (Coverage)**.** Given a tuple with a path function and its time component, $\langle \phi, t \rangle$, the *coverage* is the collection of multiple tuples.

The large-scale exploration framework (see Sec. V) derives ϕ at each sampling step and adds it to the global "coverage stack". The process ends once $\mathcal{Q}^V$ is covered.

IV. RB5 Mechanical Design

V. Large-Scale Exploration

There is a large body of work for robot exploration [15], [19], [21], [22], [42]. While the majority exploits the concept of frontiers [43], i.e., boundaries between known and unknown space, mixed approaches are emerging [15], [44], [45]. Especially useful in the presence of diverse sensing modalities, e.g., involving raw sensory data, topologies, semantics, etc., they have multiple advantages for real-world environments [15], [46]. We propose a mixed approach for RB5 large-scale exploration framework, combining frontier- and sampling-based methods, similar to some recent approaches [43], [44], [19].

The framework evaluates local frontiers at each step, samples the environment, and determines feasible candidate path functions ϕ that intersect $\mathcal{Q}^V$ (see Definition III.1). The next ϕ is selected so that the frontier is the largest, but other costs are possible (see Sec. VII). The framework then derives a path-following vector field that points to ϕ at any point and guides the robot utilizing the gradient descent algorithm. This allows RB5 to, e.g., follow the covering path for longer and in real-time compared to approaches that utilize frontiers only, decreasing computational and cost requirements (see Sec. VI).

To derive the path-following vector field, let the gradient of ϕ be defined

$$\nabla \phi := \begin{bmatrix} \partial \phi(\mathbf{p}) / \mathbf{p}_x \\ \partial \phi(\mathbf{p}) / \mathbf{p}_y \end{bmatrix}, \tag{1}$$

where $\partial \phi / \mathbf{p}$ is the differntial, and $\mathbf{p}_x$, $\mathbf{p}_y$ are the x and y compoenents of $\mathbf{p}$. It points in the direction where ϕ maximally locally increases. To assign the direction to each point, we use the construct of vector fields, which is common in other motion planning literature [38], [40], [42]

$$\Phi(t, \phi) := \bigcup_{\mathbf{p}(t) \in \mathcal{Q}} \nabla \phi(\mathbf{p}(t)). \tag{2}$$

We modify the vector field in Equation (2) to point to the contour of the path function ϕ rather than its local maxima

$$\Delta \phi(\mathbf{p}(t)) := E \nabla \phi(\mathbf{p}(t)) - k_e \phi(\mathbf{p}(t)) \nabla \phi(\mathbf{p}(t)), \tag{3}$$

where $E \nabla \phi$ points perpendicularly to the gradient and $\phi \nabla \phi$ to ϕ at $k_e \in \mathbb{R}_{>0}$ rate [40]. E is the following direction, i.e.,

$$E = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \tag{4}$$

is counterclockwise and $-E$ clockwise directions [41].

Let thus the path-following equivalent of Eq. (2) be

$$\Phi_\phi(t, \phi) := \bigcup_{\mathbf{p}(t) \in \mathcal{Q}} \Delta \phi(\mathbf{p}(t)). \tag{5}$$

Algorithm 1 Derivation of the exploration coverage $\langle \phi, t \rangle$

```
1:  for all t ∈ T do
2:    if P ∩ Q = {∅} then return ⟨φ, t⟩
3:    Q_t^V := O_{1,t}, O_{2,t}, ..., O_{n,t}, V_t ← sensor readings
4:    if Q_t^V ≠ Q_{t−1}^V then
5:      {φ_{1,t}, φ_{2,t}, ...} ← φs in Def. III.1, inters. Q^V ∩ Ψ(Q_t^V)
6:      if φ_t := {φ_{1,t}, φ_{2,t}, ...} = {∅} then RB5 is stuck
7:      else
8:        φ_t ← arg max_φ l(φ_t, t, Q_t^V) in Eq. (7)
9:        ⟨φ, t⟩ ← ⟨φ, t⟩ ∪ ⟨φ_t, t⟩ in Def. III.2
10:       P ← P ∪ Ψ(Q_t^V)
11:     end if
12:   end if
13:   φ(t, p(t)) ← φ(t − 1, p(t − 1)) + θΔφ(p(t)) in Eq. (3)
14: end for
```

The path-following vector field is summarized in the pseudo-code in Algorithm 1, with the gradient descent in Line 13. The vector $\varphi \in \mathbb{R}^2$ points RB5 in the direction of the path function ϕ with a scalar step size $\theta \in \mathbb{R}_{>0}$. The algorithm runs at the highest frequency $\mathcal{T} := \{t_0, t_0 + h, \dots\}$ with a time-step $h \in \mathbb{R}_{>0}$. Practically, there might be different hs at different times (see Sec. VI). In Line 2, the algorithm evaluates if the bounded volume $\mathcal{Q}$ is covered utilizing the covered volume $\mathcal{P} \subseteq \mathbb{R}^3$. The latter is updated in Line 5, where the function $\Psi : \mathbb{R}^{2n} \times \mathbb{R}^2 \to \mathbb{R}^{3n} \times \mathbb{R}^3$ maps the vertices to the volume. The vertices of $\mathcal{Q}_t^V$ in Line 3 are derived from sensor readings, assuming the presence of a low-cost depth camera. The framework read the camera's point cloud, clustering the obstacles $O_{1,t}, O_{2,t}, \dots$ by checking if the distance between consecutive points in space is within a given threshold $\varepsilon \in \mathbb{R}_{>0}$ and deriving their vertices. The vertices of the space at time instant t, V_t are simply the limits of the sensor's field of view.

The remaining lines compute the feasible path functions $\{\phi_{1,t}, \phi_{2,t}, \dots\}$ by intersecting the space $\Psi(\mathcal{Q}_t^V)$ with possible candidate trajectories that have their final points laying at the edges of $\mathcal{Q}_t^V$, i.e., splines of the form

$$a(x - \mathbf{p}_x)^3 + b(x - \mathbf{p}_x)^2 + c(x - \mathbf{p}_x) + d - y = 0, \tag{6}$$

where $a, b, c \in \mathbb{R}$ are the coefficients of the spline. The best trajectory is then derived via the cost l in Line 8, utilizing the intersection of the largest frontier. For instance, if there are no obstacles, Eqs. (6–7) are such that ϕ is a line parallel to the direction of RB5. Formally

$$l := \left\{ \|\mathbf{p}_1 - \mathbf{p}_2\| \mid \exists\, \mathbf{p}_1, \mathbf{p}_2 \in \Psi(\mathcal{Q}_t^V) \text{ s.t. } \mathbf{p}_1 \neq \mathbf{p}_2, \phi(\mathbf{p}_1 - \mathbf{p}_2) \approx 0 \right\}, \quad (7)$$

where the condition $\phi(\mathbf{p}_1 - \mathbf{p}_2)$ is evaluated on a given $\varepsilon \in \mathbb{R}_{>0}$, i.e., $|\phi(\mathbf{p}_1 - \mathbf{p}_2)| < \varepsilon$.

Using the algorithm, the framework provides a way to explore space $\mathcal{Q}$ and avoid obstacles $\mathcal{Q}^{O_i}$. There are configurations at which there are no feasible trajectories nonetheless, e.g., if $\{\phi_{1,t}, \phi_{2,t}, \dots\} = \{\varnothing\}$ in Line 6. In this scenario, the framework allows a human to intervene via standard wireless and LoRa communication technology. RB5 can then be teleoperated on long distances–studies from the internet-of-things domain [32], [47] report a range of up to five kilometers in an urban setting–and with a relatively inexpensive hardware equipment (two LoRa bundles). The framework we propose utilizes a web interface to parse human commands into our custom communication protocol which utilizes the LoRa physical layer's payload to transfer φ's x and y components.

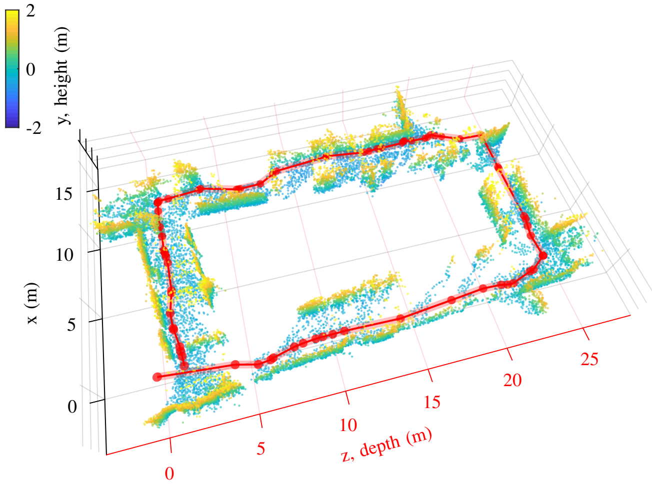
To derive a map of the environment and to keep the track of RB5 within it in Line 13, the framework uses a state-of-the-art visual SLAM algorithm from the literature [37]. RB5's location is also used to determine whether the exploration is complete in Line 2 and to asses exploration-to-cost (see Fig. **??**).

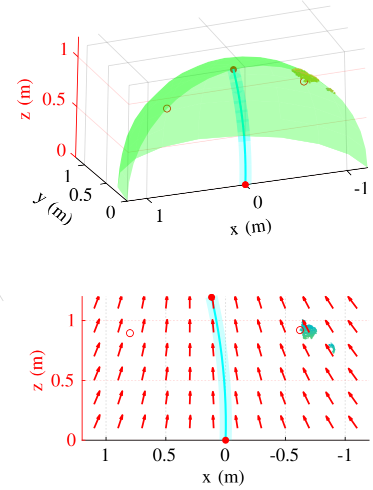
The framework is distributed under the popular open-source CC BY-NC-SA license[1]. It is composed of three distinct components. A "ground robot" ROS2 [33] package implements the communication with a base station using either the IEEE 802.11 wireless communication or long-range LoRa protocols. The package further implements the serial communication with the microcontroller (a Teensy (R) board implemented in Arduino) and the vertices detection (see Algorithm 1). A "ground navigation" ROS package collects point clouds from an RGB-D sensor (an Intel (R) RealSense (TM) Depth Camera [48] D435) and other data from the SLAM algorithm [37] and ports them into ROS2. Finally, a "base server" implements the necessary functionality for remote human intervention. Both "ground robot" and "ground navigation" are implemented in C++ in ROS2 and ROS respectively, whereas "base station" is in PHP and JavaScript.

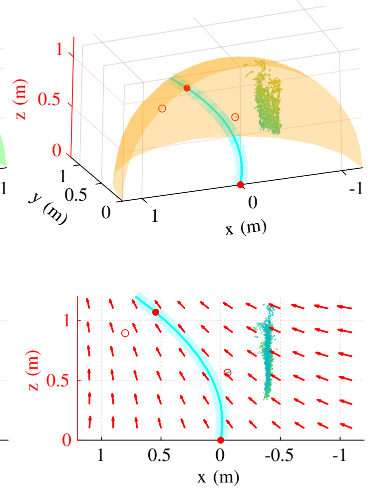
VI. Field Experiments

VII. Conclusion and Future Directions

[1] github.com/adamseew/ytcg_ground-based



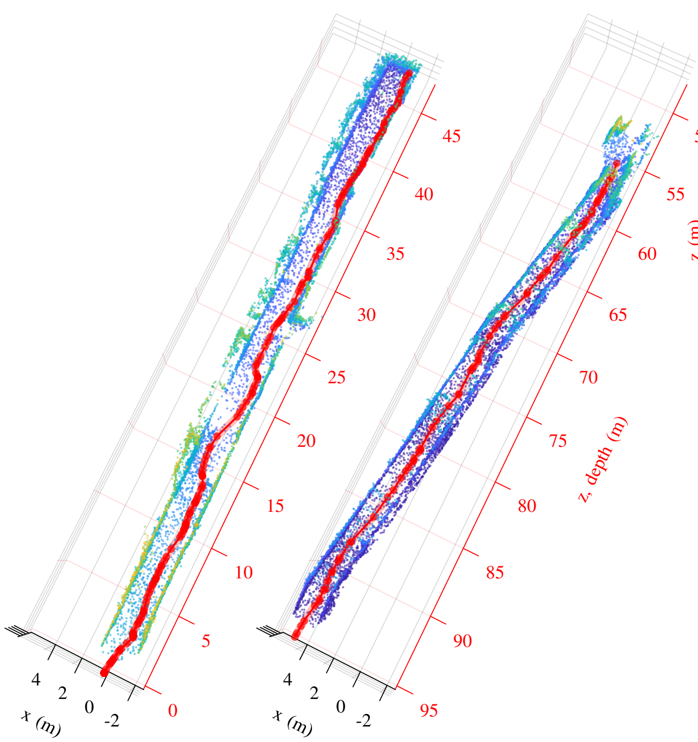


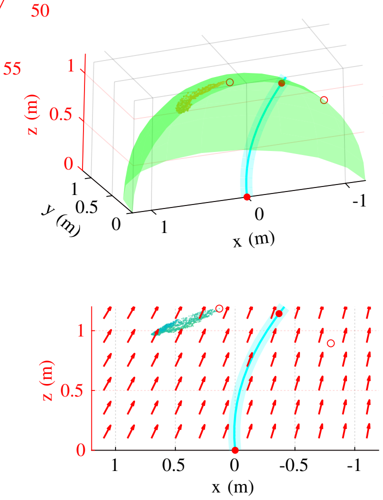


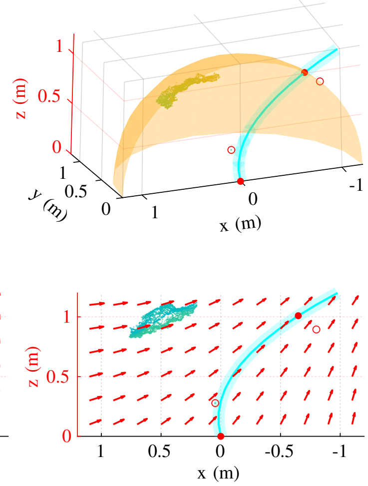
(b) . . . . (c) . . . .

(a) . . . .

Fig. 1: . . . .







(b) . . . . (c) . . . .

(a) . . . .

Fig. 2: . . . .

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