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], [38], and the trajectory with a novel methodology that extends exploration literature with a path following vector field [39] from the aerial robotics domain [40]–[42]. 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], [43]. While the majority exploits the concept of frontiers [44], i.e., boundaries between known and unknown space, mixed approaches are emerging [15], [45], [46]. 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], [47]. We propose a mixed approach for RB5 large-scale exploration framework, combining frontier- and sampling-based methods, similar to some recent approaches [44], [45], [19].

The framework evaluates local frontiers at each step, samples the environment, and determines feasible candidate path functions ϕ that intersect $\mathcal{Q}^V$ (Definition III.1). The next ϕ is selected so that the frontier is largest, but other costs are also 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 increases. To assign such direction to each point, we

Algorithm 1 Real-time autonomous large-scale exploration

1: **for all** $t \in \mathcal{T}$ **do**
2: **if** $\mathcal{P} \cap \mathcal{Q} = \{\varnothing\}$ **then return** $\langle \phi, t \rangle$
3: $\mathcal{Q}_t^V := O_{1,t}, O_{2,t}, \dots, O_{n,t}, V_t \leftarrow$ sensors readings
4: **if** $\mathcal{Q}_t^V \neq \mathcal{Q}_{t-1}^V$ **then**
5: $\{\phi_{1,t}, \phi_{2,t}, \dots\} \leftarrow \phi$s in Def. III.1, inters. $\mathcal{Q}^V \cap h(\mathcal{Q}_t^V)$
6: **if** $\phi_t := \{\phi_{1,t}, \phi_{2,t}, \dots\} = \{\varnothing\}$ **then** RB5 is stuck
7: **else**
8: $\phi_t \leftarrow \arg\max_\phi l(\phi_t, t, \mathcal{Q}_t^V)$ in Eq. (6)
9: $\langle \phi, t \rangle \leftarrow \langle \phi, t \rangle \cup \langle \phi_t, t \rangle$ in Def. III.2
10: $\mathcal{P} \leftarrow \mathcal{P} \cup h(\mathcal{Q}_t^V)$
11: **end if**
12: **end if**
13: $\varphi(t, \mathbf{p}(t)) \leftarrow \varphi(t-1) + \theta \Delta \phi(\mathbf{p}(t))$ in Eq. (3)
14: **end for**

use the construct of vector fields similarly to other motion planning literature [39], [41], [43]

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

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 [41]. E is the following direction, i.e.,

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

is the counterclockwise, $-E$ the clockwise direction [42].

Let thus the path following of vector field from Eq. (2) be

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

The path-following vector field is included in the pseudocode in Algorithm 1, Line 13.

The cost l in Line 8 is evaluated by taking the function ϕ that selects the largest frontier, e.g., if there are no obstavcles ϕ is a line that interset RB5 current point $\mathbf{p}$ and the mid-point between the field-of-view. Formally

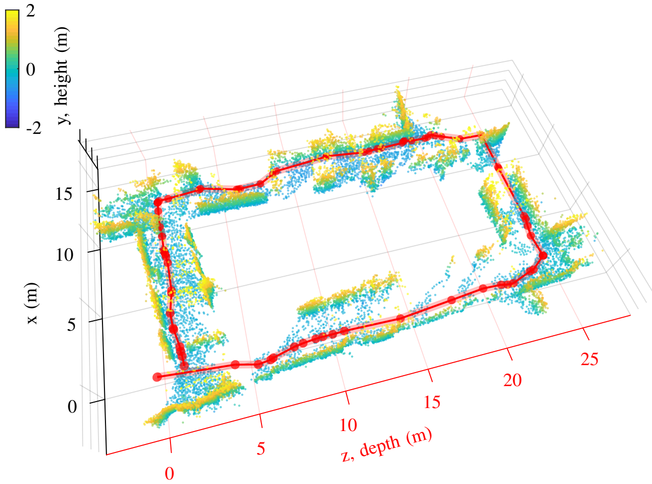
$$l := \{\|\mathbf{p}_1 - \mathbf{p}_2\| \mid \exists\, \mathbf{p}_1, \mathbf{p}_2 \in \mathcal{Q}_t^V \text{ s.t. } \mathbf{p}_1 \neq \mathbf{p}_2, \phi(\mathbf{p}_1 - \mathbf{p}_2) \approx 0\}, \tag{6}$$

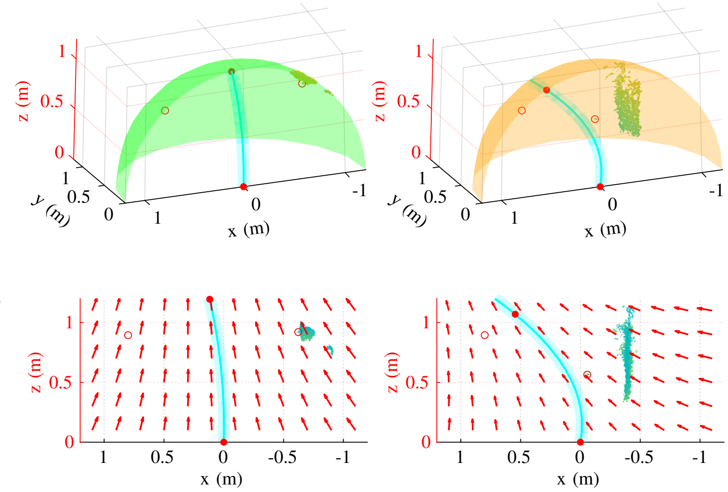
where the condition $\phi(\mathbf{p}_1 - \mathbf{p}_2)$ is evaluated on a given $\varepsilon \in \mathbb{R}_{>0}$, i.e., $|\phi(\mathbf{p}_1 - \mathbf{p}_2)| < \varepsilon$.

In Line 5 the function $h : \mathbb{R}^{2n} \times \mathbb{R}^2 \to \mathbb{R}^{3n} \times \mathbb{R}^3$ maps the vertices to the volume.

VI. Field Experiments

VII. Conclusion and Future Directions

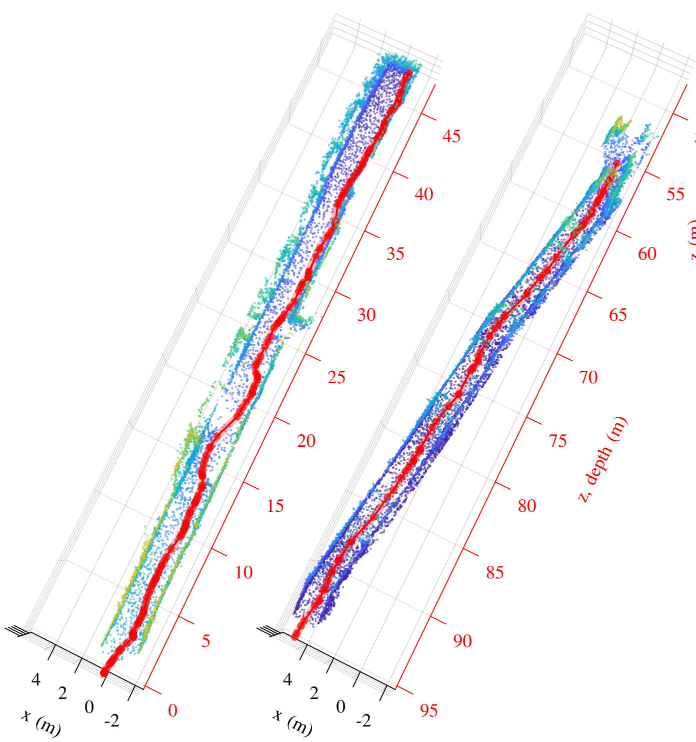


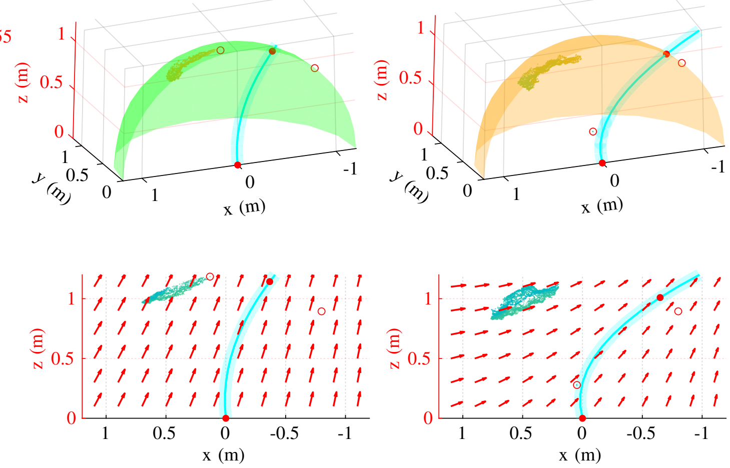


(b) . . . . (c) . . . .

(a) . . . .

Fig. 1: . . . .





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

(a) . . . .

Fig. 2: . . . .

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