Wi-Closure: Reliable and Efficient Search of Inter-robot Loop Closures Using Wireless Sensing

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Abstract— In this paper we propose a novel algorithm, *Wi-Closure*, to improve the computational efficiency and robustness of loop closure detection in multi-robot SLAM. Our approach decreases the computational overhead of classical approaches by pruning the search space of potential loop closures, prior to evaluation by a typical multi-robot SLAM pipeline. *Wi-Closure* achieves this by identifying candidates that are spatially close to each other measured via sensing over the wireless communication signal between robots, even when they are operating in non-line-of-sight or in remote areas of the environment from one another. We demonstrate the validity of our approach in simulation and in hardware experiments. Our results show that using *Wi-closure* greatly reduces computation time, by 54.1% in simulation and 76.8% in hardware experiments, compared with a multi-robot SLAM baseline. Importantly, this is achieved without sacrificing accuracy. Using *Wi-closure* reduces absolute trajectory estimation error by 98.0% in simulation and 89.2% in hardware experiments. This improvement is partly due to *Wi-Closure*'s ability to avoid catastrophic optimization failure that typically occurs with classical approaches in challenging repetitive environments.

I. INTRODUCTION

Loop closure detection has been widely studied as a fundamental aspect of Simultaneous Localization and Mapping (SLAM) [1], [2]. The location estimate of the robot drifts over time due to the noise in the on-board odometer and loop closure detection is essential to correct for this drift by recognizing previously visited places. Without such corrections, the world as perceived by the robot may diverge substantially from reality. Similarly, if multiple robots intend to collaborate, they require a shared situational awareness consistent with reality, as obtained by multi-robot SLAM. The key to obtaining this shared understanding are inter-robot loop closures. Where regular loop closures constrain the positions of one robot itself, the inter-robot loop closure

defines spatial relations between pairs of robots. These inter-robot loop closures enable robots to merge local sensor data into a shared model of the world and obtain relative locations. A common method to find inter-robot loop closures is place recognition. However, place recognition remains challenging in practice, especially when the environment has repetitive elements [3] and when communication between robots is intermittent. We introduce *Wi-Closure* to address two persistent problems in this setting. First, since robots do not know each other's location, they may mismatch similar-looking scenes that they encountered in different locations – a problem also referred to as perceptual aliasing [1]. Second, during the short intervals that communication between robots is established, feeding a large set of inter-robot loop closures into the multi-robot SLAM pipeline puts a large strain on computational resources [4]. Repetitive elements further increase computation by falsely recognizing inter-robot loop closures. Previous work introduced pairwise consistency maximization (PCM) to prevent scene mismatching by identifying false inter-robot loop closures [5]. However, recent research demonstrates that if repetitive elements are present, catastrophic failure of the SLAM algorithm can occur even if using PCM [6]. A more robust solution to perceptual aliasing is tracking all possible (mis)matches, resulting in various hypotheses of what the world looks like [7]. Unfortunately, this is costly since multiple-hypothesis tracking and planning require high computation [8]. This makes these methods less viable for real-time execution on commonly available robot hardware.

Our approach *Wi-Closure* is a computationally lightweight method that robustly finds inter-robot loop closure candidates in perceptually aliased environments. We use spatial information from WiFi and ultra-wideband (UWB) communication signals to identify poses where robots' trajectories are in close proximity to one another. WiFi is an electromagnetic wave, and thus the receiving robot can locally derive the direction or Angle of Arrival (AOA) to the transmitting

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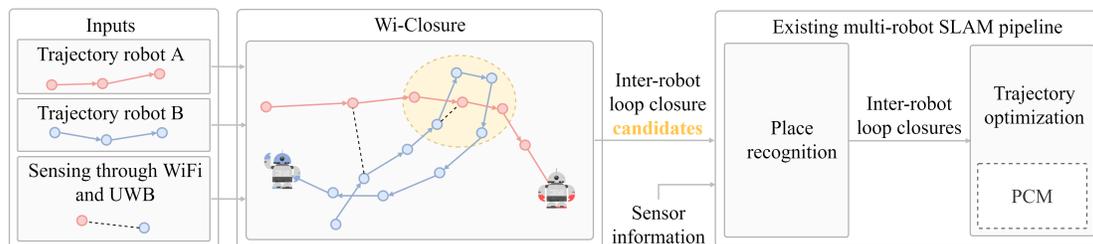
Fig. 1: *Wi-Closure* efficiently finds locations where robots' trajectories overlap, as indicated by the yellow area. Only inter-robot loop closures at these locations need to be processed by the multi-robot SLAM pipeline. This increases robustness against perceptual aliasing and decreases overall computation of the pipeline.

robot from the phase information [9]. Similarly, commercial UWB devices measure time-of-flight to estimate distance. Importantly, sensing through the communication signal has wide applicability in this setting since signals pass through obstacles (i.e. in non line-of-sight situations [10], [11]), and this doesn't require the robots to identify each other through vision-based methods, e.g. using Apriltags [12]. Our previous work [13] characterizes AOA accuracy and proves that off-the-shelf robots can compute bearing information from local displacement and WiFi signal measurements. [10] provides a toolbox for computing AOA, enabling integration with existing SLAM frameworks. Additionally, the modular set-up of *Wi-Closure* allows it to work together with other existing algorithms for place recognition and (multi-robot) SLAM modules, as depicted in Fig. 1.

Wi-Closure also addresses a major challenge to wireless sensing, namely multipath propagation of the wireless signal. Multipath refers to the phenomenon where the signal bounces off of various objects to arrive at the receiver from different angles. Consequently, the AOA measurement may include multiple directions, of which at most one is the direct-line path to the other robot. We address this issue with PCM, since only the true direct paths will give consistent pairs of AOA measurements over time. In our hardware experiments, after collecting 4 AOA measurements with in total 3 direct paths and 17 multipaths, we are able to accurately distinguish all direct paths from the multipaths.

Our numerical and hardware experiment results demonstrate that our method efficiently prunes the search space of loop closure candidates by **99.0%** in simulation and **78.7%** in hardware experiments. Our results also demonstrate robustness against perceptual aliasing by rejecting up front inter-robot loop closures between distinct places, and leads to a reduction in absolute trajectory estimation error of **98.0%** in simulation and **89.2%** in hardware.

We summarize the contributions of this paper as follows:

1) We introduce a resource efficient approach, *Wi-Closure*, to detect inter-robot loop closures in perceptually aliased environments, based on spatial information from the communication signal. It can work in tandem with existing place recognition methods.

2) We address the challenging situation of multipath propagation of the communication signal with PCM.

3) We demonstrate the merits of our approach in terms of robustness against false inter-robot loop closures and improved computation time in simulation with the KITTI dataset and in hardware experiments in an indoor office environment with repetitive features.

II. RELATED WORK

For decades, the majority of research on loop closure detection has focused on the case of a single robot [14], [15]. Recently however, loop closure detection algorithms are being adapted to fleets of robots, to ensure reliable and efficient retrieval of shared map and location estimates [5], [16]. We leverage previous work on sensing over the communication signal to address two open problems: 1) the expensive computation of loop closure detection amongst long-run trajectories from different robots, and 2) the mismatching of trajectories in environments with repetitive features.

Wireless sensing Research has shown that spatial information can be obtained from wireless signals [9], [17]. Many works use UWB sensors to obtain ranging information between two robots by measuring the time-of-flight of the ultra-wideband signal. [18], [19] use the ranging information amongst robots to improve the joint position estimate even without being in line of sight of each other. Recently, [10] also introduced sensing relative direction from the WiFi communication signal to the robotics community, requiring only a single WiFi antenna and movement of the robot. These innovations avoid the need of bulky equipment and anchors as used in classical works [20] to estimate position.

Range-only SLAM Previously, [21] used UWB sensors in a multi-robot SLAM setting coined range-only SLAM, where distance measurements are directly used as inter-robot loop closures. This avoids the problem of perceptual aliasing, but it only introduces connections between the maps of the robots where they are communicating. These connections can be sparse since in realistic scenarios the communication is intermittent. Then, combining communication measurements with place recognition can increase the accuracy of the map. Place recognition however requires high computation and is susceptible to perceptual aliasing. To our knowledge, we are the first to address these problems in place recognition using information from the communication signal.

Computation in loop closure Researchers sought to reduce computation of loop closure detection, e.g. with low dimensional and easily obtainable visual descriptors [22], and efficient look-up trees to match scenes [14]. Unfortunately, these methods are susceptible to mismatching maps in perceptually aliased environments [6]. Authors in [23] investigate if selecting only the most informative inter-robot loop closures can reduce overall computation, but the efficiency of this method is also affected by perceptual aliasing.

Perceptual aliasing Although repetitive scenes are pervasive in many environments, classical place recognition approaches find it notoriously difficult to deal with them. Researchers have focused on simultaneously representing all possible matches as multiple hypotheses in one framework [24] or reject outliers in the SLAM back-end [25]. However, to properly use these multiple hypotheses to determine the best course of action for the robot, we need computationally expensive methods such as data-association belief space planning (DA-BSP) [8], [26].

We observe that many methods have a trade-off between robustness against perceptual aliasing and computation: increased robustness requires large computation, while computationally efficient methods decrease robustness or perform worse in repetitive environments. Our approach aims to improve both computation and robustness against perceptually aliasing. By sensing relative angles and distance information over communication signals, we efficiently pinpoint where inter-robot loop closures connect scenes that are likely in the same location.

III. PROBLEM FORMULATION

Consider a team of robots operating in an unknown environment, initially unaware of their relative positions to each other. Each robot locally estimates its trajectory from on-board sensors such as IMU. Once robots come into communication range, they attempt to identify how their trajectories are positioned with respect to each other. Classically, this is done through place recognition. Usually, place recognition requires communication and matching of all of the robots' observations. However, this naive approach is fundamentally limited to a search time complexity of $\mathcal{O}(m \log(n))$ for matching m measurements of one robot with n measurements of the other robot, and it is susceptible to perceptual aliasing. *Wi-Closure* leverages wireless sensing to address these two problems: it identifies which locations have high opportunity to match, before further processing only this subset of locations by a place recognition algorithm. Specifically, the spatial information measured from the communication signal enables *Wi-Closure* to identify which locations are nearby each other, and uses this to construct an "exchange graph" as defined in [27].

A. The exchange graph

We consider a classical graph-SLAM setup of a team of robots. Let two robots be identified by their local coordinate frames $\alpha, \beta \in \Omega$, with Ω the set for all robots. These two robots will be used to further illustrate the problem and approach, without loss of generalization to larger multi-robot settings. Each robot estimates its trajectory $\mathcal{T}^{\alpha}$ with respect to its local frame α. A trajectory is defined by a set of N poses $\mathcal{T}^{\alpha} = \{T_i^{\alpha} : T_i^{\alpha} \in SE(d), i = 0, \ldots, N\}$, with $SE(d)$ the d-dimensional Special Euclidean Lie group. Pose T_i^{α} consists of a rotation matrix in the Special Orthogonal Lie group $R_i^{\alpha} \in SO(d)$ and translation vector $\mathbf{x}_i^{\alpha} \in \mathbb{R}^d$. A translation between poses of different trajectories, e.g. between $T_i^{\alpha} \in \mathcal{T}^{\alpha}$ and $T_j^{\beta} \in \mathcal{T}^{\beta}$, is defined as $\mathbf{t}_{i\alpha}^{j\beta} \in \mathbb{R}^d$.

The exchange graph of robot α and β is an undirected bipartite graph $G = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \mathcal{V}_1 \cup \mathcal{V}_2$ and sets $\mathcal{V}_1$ and $\mathcal{V}_2$ correspond to the poses in trajectories $\mathcal{T}^{\alpha}$ and $\mathcal{T}^{\beta}$ respectively. An edge $e \in \mathcal{E}$ connects two vertices iff measurements at the corresponding poses will be exchanged and matched. Each edge is thus identified by the tuple of poses it connects across robots α and β's trajectories, i.e. $e_{ij} = (T_i^{\alpha}, T_j^{\beta})$, and represents a "candidate" inter-robot loop closure between these poses. The naive place recognition approach has a complete graph, i.e. exchanging and matching measurements for all poses. In contrast, *Wi-Closure* selects a subset of candidate inter-robot loop closures $\mathcal{E}_{WiFi} \subset \mathcal{E}$. Assuming that there is an underlying set of truly correct - but unknown - inter-robot loop closures $\mathcal{E}_{true}$, then we define set $\mathcal{E}_{WiFi}$ to contain "high-opportunity locations" if $\mathcal{E}_{WiFi} \supset \mathcal{E}_{true}$. The goal is to achieve this while making $|\mathcal{E}_{WiFi}|$ as small as possible. After all, rejected edges $e \notin \mathcal{E}_{WiFi}$ save computation (they are no longer exchanged and matched), and do not introduce outlying pose associations through perceptual aliasing.
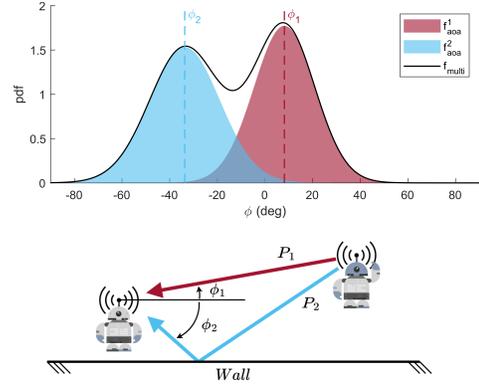

Fig. 2: The communication signal can reach the robot through different paths $\mathcal{P} = \{P_1, P_2\}$, resulting in multiple Gaussian modes f_{aoa}^i in the AOA measurement f_{multi}.

B. Candidate loop closures from wireless measurements

Wi-Closure determines two poses $T_i^{\alpha} \in \mathcal{T}^{\alpha}$ and $T_j^{\beta} \in \mathcal{T}^{\beta}$ to be a candidate inter-robot loop closure, if these are potentially located close to each other. In other words, the Mahalanobis distance d_{MH} between the poses is small.

$$\mathcal{E}_{WiFi} = \{(T_i^{\alpha}, T_j^{\beta}) : d_{MH}(T_i^{\alpha}, T_j^{\beta}) < D\} \quad (1)$$

$$d_{MH}(T_i^{\alpha}, T_j^{\beta}) = \sqrt{(\mathbf{t}_{i\alpha}^{j\beta\top}) \, \Sigma_{i,j}^{-1} \, \mathbf{t}_{i\alpha}^{j\beta}} \quad (2)$$

where $\Sigma_{i,j}$ denotes the covariance matrix of $\mathbf{t}_{i\alpha}^{j\beta}$.

Estimating $\mathbf{t}_{i\alpha}^{j\beta}$ requires information on how the trajectories are related to each other. *Wi-Closure* gains this spatial information from the communication signal between the robots. Consider the situation where UWB and WiFi signals are available between the robots at poses T_k^{α} and T_p^{β}. Note that these poses are not necessarily the same as T_i^{α} and T_j^{β}, as evaluated in Equation 1. Then, these signals provide measurements on respectively the distance d between robots, and the relative direction ϕ of the signal-transmitting robot with respect to the signal-receiving robot. We adopt the following formulation of the communication measurements from [28] as (conditional) probability density functions $f_{uwb}(d|T_k^{\alpha}, T_p^{\beta})$ and $f_{aoa}(\phi|T_k^{\alpha}, T_p^{\beta})$.

$$f_{uwb}(d|T_k^{\alpha}, T_p^{\beta}) = c_1 \exp\left(\sigma_{k,p}^{-2}(d - \|\mathbf{t}_{k\alpha}^{p\beta}\|_2)^2\right) \quad (3)$$

$$f_{aoa}(\phi|T_k^{\alpha}, T_p^{\beta}) = c_2 \exp\left(-\kappa_{k,p}\mathbf{u}^T(\phi) \frac{\mathbf{t}_{k\alpha}^{p\beta}}{\|\mathbf{t}_{k\alpha}^{p\beta}\|_2}\right) \quad (4)$$

where $c_1 = \frac{1}{\sqrt{2\pi\sigma_{k,p}^2}}$, $c_2 = \frac{1}{2\pi I_0(\kappa_{k,p})}$ and $\mathbf{u} = \begin{bmatrix} \cos\phi \\ \sin\phi \end{bmatrix}$.

Here, $I_0(.)$ is the modified Bessel function of the first kind of order zero, $\sigma_{k,p}^2$ the variance of the distance measurement, and $\kappa_{k,p}$ a concentration parameter computed as the inverse of the AOA variance.

Importantly, this formulation from [28] models the AOA measurement as a single Gaussian. However, this may not realistically represent the AOA measurement in practice due to multipath propagation of the signal. Objects in the environment can reflect the communication signal, causing it to arrive at the robot via different paths as shown in Fig. 2. We parameterize these paths by the set of binary variables $\mathcal{P} = \{P_1, P_2, ..., P_n\}$, where $P_m = 1$ indicates that path m is the direct path between the robots, while $P_m = 0$ if m is a

multipath. The multimodal AOA measurement f_{multi} can be approximately modeled as a sum over multiple Gaussians.

$$f_{multi}(\phi|T_k^\alpha, T_p^\beta) = \sum_{m=1}^{|\mathcal{P}|} f_{aoa}^m(\phi|T_k^\alpha, T_p^\beta, P_m = 1)p(P_m = 1)$$

$p(P_m = 1)$ is the probability that path P_m is the direct path, but *Wi-Closure* does not require it to be directly computed.

For each multimodal AOA measurement at most one path is the true direct path, and only direct paths lead to a correct estimate of $\mathbf{t}_{i\alpha}^{j\beta}$ and subsequently of $\mathcal{E}_{WiFi}$. An important component of *Wi-Closure* is therefore how to determine the set of direct paths from multiple AOA measurements.

IV. APPROACH

The approach of *Wi-Closure* consists of two major parts. The first module detects the direct paths in the multimodal communication measurements. Then, the second module uses this information in a branch-and-bound algorithm to quickly find the set $\mathcal{E}_{WiFi}$.

A. Direct paths in communication measurements

Due to the multipath propagation problem in communication signals, the AOA measurement determining factor f_{multi} can be multimodal, while only one mode can correspond to the direct path. *Wi-Closure* uses PCM to find the set of direct paths. The PCM method first determines for a pair of inter-robot loop closures whether they are consistent with each other [5]. As shown in Fig. 3, two communication measurements are consistent with each other if we can traverse them and the odometry backbone of the robot trajectories in a closed loop (green arrow). Let $p_{j\beta}^{i\alpha}$ be a rigid body transformation in $SE(d)$ defined by some communication measurements $f_{uwb,1}$ and $f_{aoa,1}$. Similarly, $p_{l\beta}^{k\alpha}$ is estimated from $f_{uwb,2}$ and $f_{aoa,2}$. Consider these in conjunction with transformations $p_{k\alpha}^{i\alpha} = (T_i^\alpha)^{-1}(T_k^\alpha)$ and $p_{j\beta}^{l\beta} = (T_l^\beta)^{-1}(T_j^\beta)$. Then, the loop is closed if the following equality holds.

$$\epsilon_{loop} = (p_{j\beta}^{i\alpha})^T\ p_{k\alpha}^{i\alpha}\ p_{l\beta}^{k\alpha}\ p_{j\beta}^{l\beta} = I \qquad (5)$$
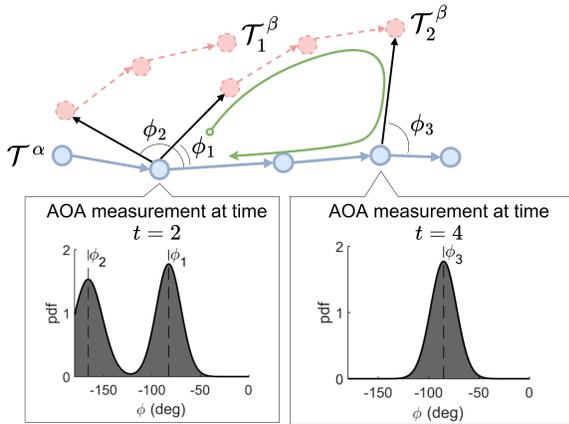

Fig. 3: From robot α's perspective, at time $t = 2$ the trajectory of robot β could be either at $\mathcal{T}_1^\beta$ or $\mathcal{T}_2^\beta$ due to the multipath in the AOA measurement (black arrows). By additionally using the AOA measurement at time $t = 4$, PCM determines that the paths corresponding to ϕ_1 and ϕ_3 are direct paths, since they can form a loop (green arrow). Therefore, $\mathcal{T}_2^\beta$ is robot β's real trajectory.

To account for noise in the transformation estimates, we identify consistent loops using the Mahalanobis distance d_{PCM}. For this we use Lie algebra to express the transformation as a vector $\xi_{loop} \in \mathfrak{se}(d)$ with logarithm map $\xi_{loop} = \log(\epsilon_{loop})$.

$$d_{PCM} = \sqrt{\xi_{loop}^\top \Sigma_{loop}^{-1} \xi_{loop}} \qquad (6)$$

where Σ_{loop} is the covariance matrix corresponding to ξ_{loop}.

Given a large set of f_{aoa}, consistency d_{PCM} is computed for each pair of wireless measurements. PCM then identifies the largest set of wireless measurements that are *all* consistent with each other. These most likely consist of only direct paths, and thereby constitute the set $\mathcal{P}_{direct}$.

B. Efficiently find trajectory overlap

A branch-and-bound algorithm efficiently finds clusters where trajectories overlap, obtaining a set of edges $\mathcal{E}_{BB} \supset \mathcal{E}_{WiFi}$ of the exchange graph. As shown in Fig.4, our approach first bounds the area traversed by robots α and β, and keeps edges within $\mathcal{E}_{BB}$ only if the corresponding poses lie within the overlapping area. These poses are divided into smaller clusters, for which the process is repeated.

The branch-and-bound algorithm may reject two poses T_i^α and T_j^β from $\mathcal{E}_{BB}$, if their spacing $||\mathbf{t}_{i\alpha}^{j\beta}||$ is larger than d_{buffer}. By design of d_{buffer} we enforce that rejection from $\mathcal{E}_{BB}$ implies rejection from $\mathcal{E}_{WiFi}$, such that $\mathcal{E}_{WiFi} \subset \mathcal{E}_{BB}$.

$$||\mathbf{t}_{i\alpha}^{j\beta}|| > d_{buffer} \implies d_{MH}(T_i^\alpha, T_j^\beta) > D \qquad (7)$$

We achieve above property by defining d_{buffer} as

$$d_{buffer} = D \cdot \sigma_{UB} \qquad (8)$$

with D the threshold for the Mahalanobis distance from Equation 1 and σ_{UB} an upper bound to the uncertainty $\Sigma_{i,j}$ in $\mathbf{t}_{i\alpha}^{j\beta}$. In addition to poses T_i^α and T_j^β, consider poses T_k^α and T_l^β which are connected through a communication measurement. Then, leveraging noise propagation we rewrite

$$\Sigma_{i,j} \approx \Sigma_{i,k} + J_{k,l}^T(\Sigma_{k,l} + J_{l,j}^T\Sigma_{l,j}J_{l,j})J_{k,l} \qquad (9)$$

with $J_{k,l}$ a change-of-basis matrix from the old basis defined in local frame k to the basis in frame l. $J_{l,j}$ is similarly defined. This allows distributed computation of σ_{UB} as

$$\sigma_{UB}^2 = \max_{i\in\{1,...,|\mathcal{T}^\alpha|\}} \rho(\Sigma_{i,k}) + \rho(J_{k,l}^T\Sigma_{k,l}J_{k,l})$$
$$+ \max_{j\in\{1,...,|\mathcal{T}^\beta|\}} \rho(J_{k,l}^T J_{p,j}^T\Sigma_{p,j} J_{p,j} J_{k,l})$$

with $\rho(\cdot)$ the spectral radius. Given the derived σ_{UB}, the d_{buffer} is used to determine whether a pose from one robot can possibly be matched with a location inside the trajectory bounds of the other robot, as shown in the Fig. 4. The process won't terminate terminate until each cluster only contains few points or the region is too small. The union of these clusters forms $\mathcal{E}_{BB}$, and final loop closure candidates can be identified in the next section.

C. Identifying inter-robot loop closures

Finally, inter-robot loop closure candidates $\mathcal{E}_{WiFi}$ are obtained by computing the Mahalanobis distance for all remaining pose-pairs in $\mathcal{E}_{BB}$. From Equation 1 this requires computation of $\mathbf{t}_{i\alpha}^{j\beta}$ and corresponding covariance matrix $\Sigma_{i,j}$, which is done as follows. For each pose pair (T_i^α, T_j^β), we choose one nearest communication measurement connecting the trajectories at poses T_k^α and T_l^β. The commu-
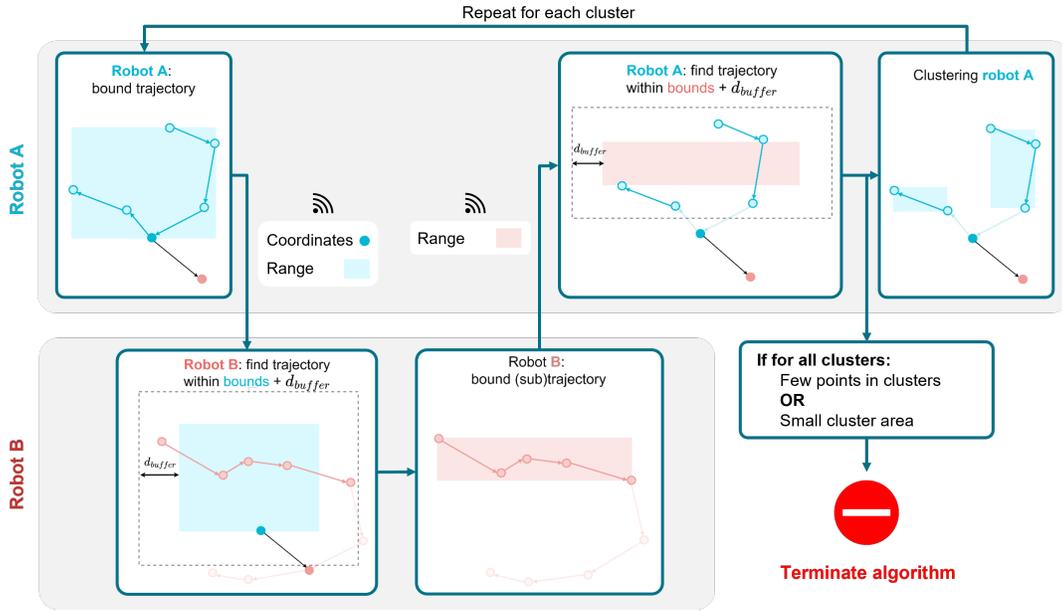
Fig. 4: Finding area where trajectories overlap by iterative refinement of overlapping bounding boxes.

nication measurement is chosen such that the path between T_i^α and T_j^β through T_k^α and T_l^β is shortest. Then, pose and uncertainty information is propagated from T_i^α to T_j^β.

$$T_i^j = T_p^j \; T_k^p \; T_i^k \tag{10}$$

$$\Sigma_{i,j} \approx \Sigma_{i,k} + J_{k,l}^T (\Sigma_{k,l} + J_{l,j}^T \Sigma_{l,j} J_{l,j}) J_{k,l} \tag{11}$$

with Jacobians J defined as in Equation 9. Then, $\mathbf{t}_{i\alpha}^{j\beta}$ is the translation vector of pose T_i^j. These estimates allow us to compute the Mahalanobis distance for all $(T_i^\alpha, T_j^\beta) \in \mathcal{E}_{BB}$, and obtain set $\mathcal{E}_{WiFi}$.

$$\mathcal{E}_{WiFi} = \{(T_i^\alpha, T_j^\beta) \; : \; d_{MH}(T_i^\alpha, T_j^\beta) < D\} \tag{12}$$

$$d_{MH}(T_i^\alpha, T_j^\beta) = \sqrt{(\mathbf{t}_{i\alpha}^{j\beta})^\top \; \Sigma_{i,j}^{-1} \; \mathbf{t}_{i\alpha}^{j\beta}} \tag{13}$$

V. EXPERIMENTS

In this section, We evaluate *Wi-Closure* through simulation and hardware experiments. Our results show that *Wi-Closure* can efficiently and robustly detect loop closures while processing large trajectories in batches and in repetitive environments. Our approach also successfully handles the multipath phenomenon of the wireless signal in practice.

A. Simulation experiments

Simulations are performed on the KITTI 08 dataset modified by [29], where a trajectory is split into sections to emulate the multiple robot case with trajectory overlap. Since this dataset does not contain measurements from the wireless signal, we simulate these based on the groundtruth (GPS) trajectory. We use a standard deviation of $0.5 \; m^2$ for distance and $10 \deg$ for AOA, based on previous work characterizing these measurements [10]. All comparisons are performed on a desktop computer running an Intel i9 5.2GHz processor in Ubuntu Linux 18.04. We assess the efficacy of *Wi-Closure* by comparing the performance of the multi-robot DiSCo-SLAM pipeline with and without using *Wi-Closure*. The performance is assessed based on absolute trajectory error

(ATE) and the number of correctly and falsely included inter-robot loop closures. To determine which loop closures are true and false, we use a GPS-based groundtruth trajectory and define true inter-robot loop closures as positions that are at a maximum distance of $35 \; m$, such that the LiDAR scans with a range of $30 \; m$ overlap for 20%.

Originally, [29] tuned the parameters of the DiSCo-SLAM algorithm such that it has good performance against mismatching on the modified KITTI 08 dataset. However, we argue that parameters do not necessarily generalize to other environments (as we show in our hardware experiments). We, therefore, consider a worse set of parameters in this comparison. Then, we show that while the original DiSCo-SLAM pipeline fails with this parameter set, using the same set of parameters and adding Wi-Closure can still recover good performance.

Table I shows that including *Wi-Closure* in the multi-robot SLAM pipeline results in a lower ATE. Fig. 6 shows that the baseline approach includes too many false loop closures resulting in catastrophic failure. Also, without *Wi-Closure*, DiSCo-SLAM processes all 1,099,101 position pairs as possible loop closures, of which 5,544 are true loop closures. Meanwhile, *Wi-Closure* substantially reduces this search space to 7,049 inter-robot loop closures, of which 3,631 are true positive loop closures. This comes at a cost of missing 1,913 potential loop closures.

As a result, the whole pipeline takes 896 seconds for the baseline algorithm, whereas adding *Wi-Closure* reduces it to 464 seconds. of which 53 seconds are caused by added computation of the *Wi-Closure* module.

B. Hardware experiments

We evaluate our approach on a dataset collected in an unfinished shell space as shown in Fig. 5 with repetitive features. We deploy two customized Locobot PX100, which are installed with a Velodyne VLP-16 LiDAR, a MicroStrain
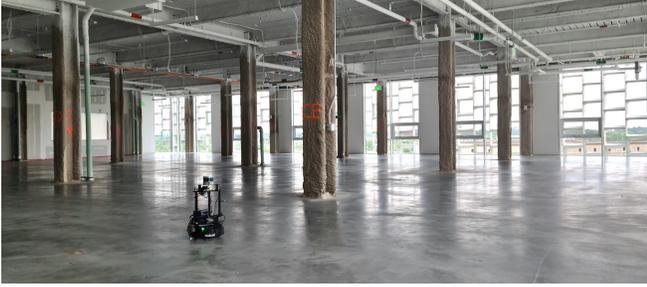
Fig. 5: The $25m \times 23m$ testing field for hardware experiments with highly repetitive features including identical pillars.

3DM-GX5-AHRS IMU, DWM1001 UWB, 5dBi Antenna, and Intel NUC 10. We process the AOA measurements using the WiFi sensing Toolbox from our earlier work [10]. To accompany the scale of the test field, we limit the range of the LiDAR to **10** meters otherwise the LiDAR would be able to cover the testbed in one shot. For the purpose of computing the ground truth error, we set up 5 UWB nodes in the space to localize the robot in real time.

We don't require the robots to take the wireless measurements continuously, but rather intermittently as needed. The frequency is mostly determined by the scale of the task and the discretization of the trajectories. In the hardware experiment, we only collected the 4 wireless measurements which already provide convincing results. The UWB measurements are only taken continuously for ground truth purposes. Two robots are set up at different locations without knowing each other's frames. They traverse the space collecting LiDAR scans and IMU data. Every 10 meters one robot collects AOA and ranging measurements to the other robot. Trajectories have two rendezvous points to provide loop closure opportunities. Again, we compare computation time and ATE with and without *Wi-Closure*, and we assess if loop closures are filtered correctly.

We directly apply original DiSCo-SLAM parameters from [29], and show that the original method fails in our environment while adding *Wi-Closure* recovers performance.

As shown in Table II, our approach successfully reduces the computation time of the whole SLAM pipeline by 4.3 times and reduces the trajectory error by 89.2%. Fig. 7 shows the optimized trajectories. Because of the repetitiveness of the pillars, the original algorithm fails in a challenging environment. Similar to the simulation results, applying our approach substantially reduces the search space from 1,848 loop closures to only 119 of which 115 are true inter-robot loop closures. Consequently, our method increases speed and prevents failure of the algorithm.

Also, our approach successfully handles the multipath phenomenon in our hardware experiment. Each of the four AOA measurements contains five multipath. *Wi-Closure* is able to distinguish all three direct paths from the 17 multipath, leading to consistent optimization results as shown in Fig. 7.

VI. CONCLUSION

In this paper we propose an efficient and robust loop closure finding method *Wi-Closure*, utilizing light-weight information from the wireless signal between robots. We properly handle the multipath phenomenon, and are able to exclude the majority of false loop closures. This drastically reduces processing time of the muli-robot SLAM pipeline and increases the robustness of the results.

ACKNOWLEDGEMENT

TABLE I: Loop Closure (LC) performance comparison between *Wi-Closure* and DiSCo-SLAM in the KITTI Dataset.

	Baseline	*Wi-Closure*
ATE (m)	66.1	1.3
Correctly rejected false LC (%)	N/A	99
Missed true LC (%)	0	1
Total Computation Time (s)	896	411
Total Wi-Closure time (s)	N/A	53

TABLE II: Loop Closure (LC) performance comparison between *Wi-Closure* and DiSCo-SLAM in hardware experiments.

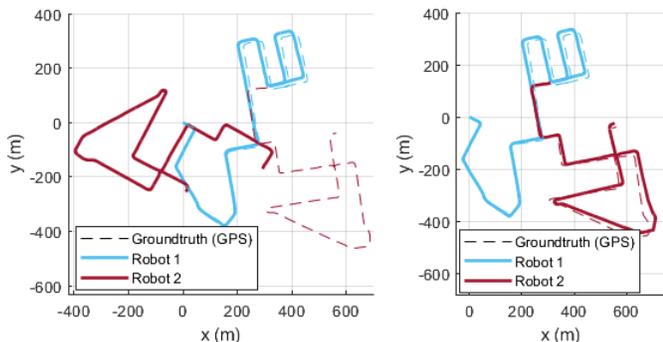|	Baseline	*Wi-Closure*
ATE (m)	17.6	1.9
Correctly rejected false LC (%)	N/A	78.7
Missed true LC (%)	0	15
Total Computation Time (s)	155	36
Total Wi-Closure time (s)	N/A	0.5 seconds

Fig. 6: Simulation results in KITTI 08 dataset. Left: optimized trajectory from DiSCo-SLAM without *Wi-Closure*. Right: optimized trajectory from DiSCo-SLAM using *Wi-Closure*.
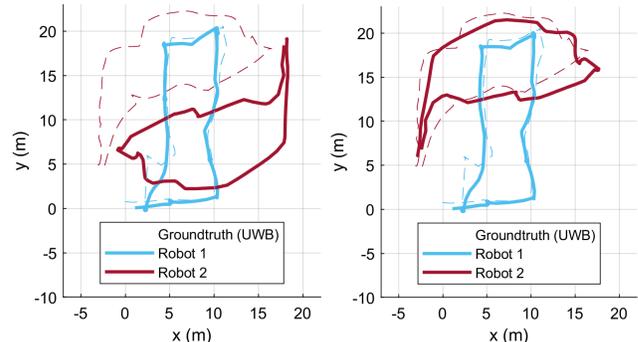

Fig. 7: Hardware experiment results. Left: optimized trajectory from DiSCo-SLAM without using *Wi-Closure*. Right: optimized trajectory from DiSCo-SLAM using *Wi-Closure*.

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