The Line Leading the Blind: Towards Nonvisual Localization and Mapping for Tethered Mobile Robots

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Abstract—Mobile robots supported by an electromechanical tether can safely explore extremely rugged terrain in resource-limited environments. While a tether provides power, wired communication, and support on steep surfaces, it also reduces maneuverability; in cluttered environments the tether will contact obstacles, forming intermediate anchor points. In order for the robot to avoid tether entanglement, it must localize itself with respect to any added anchor points. Accordingly, we present a first approach towards nonvisual localization and mapping that utilizes tether measurements and wheel odometry to jointly estimate vehicle trajectory and tether-to-obstacle contact points. The proposed method is inspired by FastSLAM, where instead of updating a map of landmarks, tether length and bearing measurements are used to update sequential lists of anchor points for every particle representing a belief of the robot’s trajectory. Results from both simulation and experiment using our Tethered Robotic eXplorer (TReX) demonstrate that (i) our method is more accurate than odometry alone, and (ii) we are able to map intermediate anchor points nonvisually.

I. INTRODUCTION

Deploying mobile robots in extreme conditions requires a consideration of limitations imposed by power and communication. Environments such as cliffs, caves, and disaster zones all require increased power budgets and offer reduced, or nonexistent, communication infrastructure. In these circumstances, an electromechanical tether can support a robot by providing a safe and reliable source of power and wired communication. The main disadvantage of using a tether, other than limited range and management complexity, is the inherent requirement that ingoing and outgoing paths be roughly similar. When navigating cluttered environments, the tether is likely to come into contact with one or more obstacles. Since every tether-to-obstacle contact forms an intermediate anchor point (IAP), the sequence and location of IAPs must be recorded for safe navigation. If done accurately, the continuity between topological spaces is ensured (i.e., the paths are homotopic). Path continuity is critical when the robot is backtracking, as it must sequentially detach from all active IAPs (excluding the initial anchor) in order to avoid entanglement.

Localization of a tethered robot and its IAPs is critical to operational safety. However, the use of vision-based localization methods, such as those relying on passive/active cameras, will not always be an apt fit when the operational environment is either poorly illuminated or compromised by smoke, dust, or vapor.

Nonvisual methods for localizing tethered robots are currently limited due to a reliance on preexisting infrastructure. Dead-reckoning is also not an option, as measurements are susceptible to unbounded drift, even under ideal conditions. Past papers have used tether measurements to aid in localization only, but none have formulated the tethered simultaneous localization and mapping (SLAM) problem to jointly estimate the robot’s trajectory and IAPs. Accordingly, we have developed the first nonvisual SLAM technique that uses just tether length, tether bearing-to-anchor measurements, and wheel odometry.

Our method uses a particle filter based on FastSLAM [1], where each particle’s estimated measurement is weighted against the actual measurement, allowing for iterative resampling to yield more probable hypotheses of the robot trajectory and IAP locations. As a first step, we consider this SLAM problem in the context of a planar environment (extensions to 3D are not addressed). Results from both simulation and experiments with TReX, our climbing and steep-terrain mapping platform shown in Figure 1, demonstrate that our algorithm outperforms odometry alone, and is capable of mapping unknown IAPs encountered in cluttered environments.

This paper is structured as follows. Section II presents related work on tethered robotics. Section III introduces the TReX platform. Section IV details the algorithm. Section V and VI evaluate results from simulation and experiment. Section VII is a discussion of lessons learned. Section VIII outlines future work, and Section IX offers conclusions.
II. RELATED WORK

Historically, research in tethered robotics has focused on two discrete threads: the mechanical design/testing of tethered mobile robots, and tether-constrained path planning. The most notable tethered robots to be designed and operated in extreme terrain are Dante II [2] and Axel II [3]. McGarey et al. [4] provides a detailed review of tethered mobile robots.

With respect to path planning, most research has been confined to simulation. In the early 1990s, the tethered robot problem was first considered for 2D obstacle navigation [5]. A decade later, theoretical approaches were proposed to address tethered path planning for multiple robotic agents operating in 3D environments [6]. In the 2000s, a path-planning algorithm for climbing robots operating in rocky, lunar environments was investigated [7]. Unfortunately, the algorithm relied on the use of preexisting terrain models, and was never field tested. Recently, interest in path planning for tethered robots has resurfaced. The idea of homotopic path planning and control in the presence of obstacles has been demonstrated on a cabled robot [8]. The discretization of the robot’s operating environment to consider the impact of tether-to-tether and tether-to-obstacle interactions was recently proposed [9]. Other work has evaluated the problem of shortest path planning given a tether constraint caused by obstacle interaction [10]. Extending this idea, a computationally efficient, tethered path-planning algorithm based on a heuristic A* search has been shown [11].

All of the aforementioned methods of tethered path planning are fundamentally reliant on accurate localization of the robot [12]. Although tethers can be considered a constraint to mobility, they are actually beneficial for use in low-cost, non-visual localization. Tether measurements have been used for brute-force, line-of-sight localization in prior work [13][14]. Both of these methods do not attempt to localize IAPs, nor do they account for noise in tether measurement. The most developed work on the topic has demonstrated localization only using tether length, IMU data, and wheel odometry to track a pipe inspection robot [15].

III. THE TReX PLATFORM

Given that few robotic platforms are capable of accurately measuring the length and orientation of an attached tether, work on tether-based localization has been limited in the literature. TReX was developed as a steep-terrain, harsh-environment rover capable of generating a 3D point-cloud of its surroundings, while accurately measuring tether orientation. TReX has a suite of integrated tether measurement sensors, and uniquely allows passive measurement of the tether’s bearing-to-anchor regardless of vehicle orientation or direction of tension. Figure 2 indicates the specific sensors used for measuring tether orientation on TReX. McGarey et al. [4] outlines the complete TReX design and platform testing in more detail.

IV. METHODOLOGY

In this paper, we are interested in producing nonvisual localization information using only the robot’s tether length, tether bearing-to-anchor measurements, and wheel odometry. As such, an accurate bookkeeping of tether-to-obstacle contacts in the environment is necessary. The contact history is critical in determining how tether length is distributed in the environment (i.e., tether length is a function of the location and sequence of all active IAPs). The bearing-to-anchor measurement can be measured directly since it is a function of the most current IAP alone.

We can generate a list of IAP locations in the context of a SLAM problem. First, an appropriate representation of uncertainty in the robot’s pose and tether measurement must be determined based on the expected environment and noise distribution. When a robot believes it has added a potential IAP, it may have uncertainty about the detection (i.e., was the measurement caused by a new IAP, or simply noise?) and about wrap direction (i.e., which side of an obstacle did the robot drive?). Any doubt in the passing direction implies a multi-modal uncertainty distribution, since the robot can now exist in two discrete positions on either side of a newly added IAP. Consequently, a representation of the joint pose and map uncertainty as a uni-modal distribution could be a poor approximation. Instead, we propose a tether-based version of FastSLAM [1], which represents the robot’s trajectory using a finite number of particles and the landmark map using Gaussians. From a high level, this algorithm iterates through the following steps:

1) propagate particles using wheel odometry,
2) calculate weights based on tether measurements,
3) update the map and IAP list,
4) resample most likely particles by weight.

We will spend the rest of this section highlighting the modifications that were necessary to make FastSLAM work for our scenario. For this problem we assume that IAPs are zero-radius points and that the tether is taut and therefore perfectly straight.

A. Adapting FastSLAM

Multi-modal uncertainty can be handled by an implementation of Monte Carlo Localization (MCL) [16], where many samples of the robot pose (i.e., particles), each with a different map of tether/obstacle interactions, jointly represent the state distribution. Upon resampling, particles with a pose and map compatible with observations and expected motion are
likely to survive. Our method is inspired by FastSLAM [1], which incorporates a similar particle-filtering technique to MCL. The fundamental benefit of using FastSLAM is that the joint likelihood of the robot’s trajectory (represented using a finite number of samples) and IAP locations is factored. In SLAM, measurements are a function of just one robot pose and a single landmark, allowing FastSLAM to maintain separate landmark estimates inside each particle representing a hypothesis for the robot’s trajectory. In our proposed augmentation of FastSLAM, conditional independence amongst IAPs is approximated, as the measurement may involve multiple IAPs. Specifically, the tether length measurement is a function of just one robot pose and all active IAPs (i.e., any IAP currently in contact with the tether), while the bearing-to-anchor measurement is a function of one robot pose and only the current IAP (i.e., the most recently added IAP). While an assumption is made that the uncertainty contribution of previously added IAPs to the length measurement is quite small, we recognize that our approximation can introduce localization error increasing with the number of encountered obstacles. As per FastSLAM, conditional independence is given by the following posterior factorization,
\[ p(x, \ell, v) = \prod_{\text{particles}} \prod_{\text{Gaussians}} p(x, \ell, v), \]
where the joint likelihood of robot trajectory, x, and list-based map of IAPs, \( \ell \), is inferred from tether measurements, y, and wheel odometry measurements, v, from time 1 to time K (the maximum time step). We note that IAP correspondences are an implied part of the map estimate and have been left out for clarity of notation. The further factorization of the right-hand factor in Equation (1) into a product of smaller Gaussians, one for each landmark, is exact in SLAM, but only approximated for our problem. The conditional-independence approximation limits uncertainty influence to the current IAP in our measurement. Any tether wrapped around prior IAPs is considered a ‘fixed’ component of the measured length. Thus, our measurement likelihood is approximated as
\[ p(y_k|\ell_n) \approx p(y_k|x_k, \ell_n), \]
where only the current IAP, \( \ell_n \), can influence the likelihood at time k. Like all IAPs, \( \ell_n \), is a Gaussian with a 2×1 mean, \( \mu_n \), and a 2×2 covariance, \( \Sigma_n \), distributed as
\[ \ell_n \sim \mathcal{N}(\mu_n, \Sigma_n). \]
Accordingly, the measurement approximation implies that the map likelihood becomes:
\[ p(\ell|x, y) \approx \prod_{n=1}^{N} p(\ell_n|x, y), \]
where N is the maximum number of IAPs observed. Since the robot is not expected to encounter more than tens of IAPs during a single traverse (due to the finite tether length), our approximation still allows for reasonable localization accuracy.

B. Splitting Particles to Represent Tether History

In landmark-based SLAM, exteroceptive measurements are made with a passive or active camera, and thus, many landmarks may be added, updated, or unobserved during a single time step. Conversely, tether-based SLAM is limited to a single measurement at any given time that can involve all the active IAPs (i.e., tether length is a function of all the IAPs contacting the tether). However, we make the approximation that our measurement only involves the current IAP. We do so using a ‘direct’ bearing-to-anchor measurement and an ‘indirect’ range measurement (i.e., the ‘free’ length of tether connecting the robot to the current IAP only), which are used to determine if an IAP has been added, updated, or deleted from a given particle’s list of encountered obstacles (Section IV-D provides details).

In order to decide when to add, update, or delete an IAP, each particle is split into three copies just after resampling – each representing one of the decisions (i.e., add, update, or delete). A particle storing n currently active IAPs will generate three copies of itself with lists containing \( n+1 \), \( n \), and \( n-1 \) quantities of IAPs. During the next resample, the best third of the split particles will be most likely to survive. For example, if the measurements are indicative of an added IAP, then the copied particles with \( n+1 \) IAPs will be favored during resampling with higher probability.

C. Weighting Particles and Updating Maps

Prior to updating lists of IAPs, each particle’s importance factor, or weight, is calculated using the uncertainty from the previous time step. That weight is proportional to the likelihood of the current measurements given a particle’s trajectory and prior map according to
\[ w_k^m \approx \int p(y_k|x_k^m, \ell_n^m) p(\ell_n^m|x_k^m, y_k^m) d\ell_n^m, \]
where the integrated measurement likelihood for a particle with superscript m is used to produce a weight, \( w_k^m \).

In accordance with FastSLAM, an Extended Kalman Filter (EKF) is then used to update each particle’s map, where IAPs are represented as discrete Gaussians. A nonlinear observation model is used to generate a mean (i.e., the 2D position of an IAP), while a linear approximation of the same model is used to compute a covariance. The process for adding or deleting an IAP is equivalent to the initialization of a landmark in FastSLAM. In this section, we have shown the subtle changes needed to make FastSLAM work for our purposes. For a detailed description of the FastSLAM algorithm and EKF update for landmark Gaussians see [17].

D. Initializing Potential IAPs

Given the robot pose and tether measurement, the position of a newly detected IAP can be determined by forming an ellipse. The intersection of an ellipse and a line drawn in the direction of the bearing-to-anchor measurement gives the position of a new IAP. The ellipse detection model is shown in Figure 3. The geometry of an ellipse is important because
it represents all the potential locations for a newly added IAP given a tether length and two known foci (i.e., the positions of the robot and the known current IAP). The process for determining a unique location from all potential points on the boundary of an ellipse is detailed as follows.

First, the measured tether length is segmented into two distances; a ‘free’ distance, $d_{f,k}$, joining the current IAP location, $\mu_{n}$, and robot pose, $x_k$, and a ‘fixed’ distance, $d_{w,k}$, the summed distance between all the active IAPs (not including the ‘free’ distance). Assuming that $d_{f,k}$ is greater than the distance between $x_k$ and $\mu_n$, the location of a newly added IAP, $\mu_{n+1}$, can be found uniquely:

$$
\mu_{n+1} = \begin{bmatrix} x_k \\ y_k \end{bmatrix} - d_{f,k} \begin{bmatrix} \cos(\phi_k + \theta_k) \\ \sin(\phi_k + \theta_k) \end{bmatrix},
$$

where the sub-segment, $d_{1,f,k}$, a component of $d_{f,k}$, is the distance from $x_k$ to $\mu_{n+1}$, as shown in Figure 3. That distance is determined as follows:

$$
d_{1,f,k} = \frac{\|x_k - \mu_n\|^2 - (d_{f,k})^2}{2(d_{f,k}) - \|x_k - \mu_n\| \cos \psi_k}.
$$

The error angle, $\psi_k$, is formed between $\phi_k$ (in the global frame) and a line drawn between $x_k$ and $\mu_n$. If the distance between $x_k$ and $\mu_n$ is greater than $d_{f,k}$, then an ellipse cannot be formed. In this case, a particle will not be allowed to add an IAP, and instead, will wait until the formed ellipse is properly conditioned (i.e., eccentricity $< 1$).

V. SIMULATED RESULTS

Our tether-based localization and mapping algorithm was evaluated using simulated data. For one hundred trials, a random set of static IAPs were distributed in a planar environment. Ground truth trajectories were generated, ensuring that the outgoing and return paths were homotopy equivalent. The robot’s sensor measurements were recorded throughout driving and Gaussian noise was applied for use in our estimation. The estimator had no prior knowledge of IAP quantities or positions. A single trial from the set of one hundred was selected to illustrate the effective performance of our algorithm. Figure 4(a) compares the complete trajectory of our estimate with odometry and ground truth. Figure 4(b) provides position error as a function of tether deployed. A time-lapse animation of this trial is shown in Figure 5, which illustrates how particles are propagated and IAPs are mapped in real time. These figures demonstrate that our method outperforms odometry alone. Figure 4(c) illustrates the percentage localization error at the end of the trajectory.
for all hundred trials as a histogram of Euclidean errors. Despite the varying conditions, our method is statically more accurate than odometry using simulated data.

VI. EXPERIMENTAL RESULTS

Three experiments were performed with TReX navigating through a set of bollards serving as static IAPs. In each experiment, the robot was attached to a single initial anchor and was piloted on a trajectory encountering unknown IAPs (the sequence of IAPs is different for each experiment). Ground truth positions for the IAPs and robot were collected using a total station (Leica TDRA6000). A prism mounted on the rotational axis of the robot allowed the total station to output a continuous position estimate throughout data collection. An annotated time-lapse image taken for each experiment is shown in Figure 6. Most importantly, the IAP sequence for each experiment is provided for reference. The figure also highlights the outgoing trajectory driven, with the assumption that we retrace that trajectory to return to the initial anchor. We note that all but the ‘Two Roads’ experiment use IAP 1 as the initial anchor.

As with the simulated result, the performance of our algorithm on experimental data is shown qualitatively by trajectory maps in Figure 7, and quantitatively by position error plots in Figure 8. Our method outperforms odometry in all experiments. The odometry was generally poor as a result of the robot being acted upon by tether tension on the flat floor, resulting in a sliding motion that is not measured by wheel odometry (wheel slippage resulting from tether tension is currently an unexplored problem in robotics). However, our estimate is able to recover from sliding motion because of the tether-length constraint. While our solution generally exhibits some drift in rotation (i.e., the trajectory appears to be rotated in some areas), the beginning and end of each trajectory closely match ground truth. This suggests that the more IAPs our robot encounters, the more our solution will drift. However, returning to the initial anchor allows for rewinding accumulated pose error.

A time-lapse animation of just one of the experiments is shown in Figure 9. The sequence of figures illustrates the particle filter running on data collected from the ‘Telephone Cord’ experiment. More importantly, the sequence shows our mapping result in more detail. Despite demonstrating a reasonable localization result, our map is less accurate than we would expect given our result from simulation (see Figure 5). Specifically, the estimated map is not aligned with ground truth and has many more IAPs than are actually present. A detailed discussion of reasons for poor experimental mapping results, as well as probable causes, are provided in the following section. Later, Section VIII provides potential solutions to these problems in the context of future work.

VII. EXPERIMENT DISCUSSION

The difference in performance of our algorithm on simulated and experimental data is linked to (i) error in tether measurement, and (ii) deficiencies in the algorithm that were not observed in simulation.

With respect to (i), the following list captures problems that can be attributed to estimation errors in experiment.

- Length error: An encoder mounted to a pulley on the tether arm is used to measure length. This measurement is subject to unbounded drift since the encoder is not absolute, and the tether can slip on the pulley.
Fig. 6. A time-lapse image of each experiment is shown. The trajectory is represented by a color overlay with arrows showing the outgoing direction. The circle markers indicate IAPs. A different trajectory was driven in each experiment. The start, middle, end, and in the case of the ‘Two Roads’ experiment, revisit point (i.e., re-observation of the most distant IAP), is indicated for each trajectory. The IAP sequence is ordered by time of observation starting/ending with the initial anchor. We note that initial anchor for the ‘Two Roads’ experiment was IAP 2 and IAP 1 for the other experiments.

Fig. 7. Localization results from three experiments demonstrate that our estimate outperforms odometry alone. The estimate is taken from the mean of the most likely particles. The estimated trajectory has been smoothed in all the maps because our use of a particle filter means that the estimate can be noisy (the general shape has not changed). The estimated IAPs are not shown on this map for sake of clarity (Figure 9 provides an example of real-time mapping for the ‘Telephone Cord’ experiment). Instead, the positions of ground truth IAPs are shown. We also draw a dashed line to provide an understanding of how the tether is configured for the ground truth robot (e.g., the tether line joins the initial IAP to the most distant robot pose through all the active IAPs). We note that the x and y axes are switched for the ‘Telephone Cord’ trajectory map for the purpose of presentation.

Fig. 8. The RMS position error for our estimate and odometry are shown as a function of deployed tether length. The important point is that our estimate outperforms odometry in all cases by simply incorporating tether measurements. Specifically, our solution rolls off accumulated error upon returning to the initial anchor. The odometry from the ‘Telephone Cord’ experiment converges with ground truth near the end of the trajectory (briefly outperforming our estimate). However, this is an example of odometry getting lucky, as dead reckoning methods usually drift without bound.
Fig. 9. **Experiment Particle Filter Animation:** This time-lapse animation illustrates the particle filter running on data collected from the ‘Telephone Cord’ experiment. We note that our ground truth is position only, so it is shown without orientation. The key point of this illustration is to show that while our estimated trajectory is better than odometry (see Figure 8), the mapping result is much noisier than we would expect. In simulation (see Figure 5), the quantity and position of IAPs closely resembled ground truth. In experiment, we encounter many more outliers and false detections, meaning that the drift error increases as a function of the amount of tether deployed. A full discussion of this problem and possible causes is provided in Section VII.

- **Bearing-to-anchor error:** Friction in the tether arm results in bias, which causes outlier measurements of IAPs. This type of noise is difficult to quantify as it depends on many variables including tether tension, wheel slip, tether wrap direction, and the radial distance from the IAP being measured. On steep terrain, the friction in the arm is easily overcome, but on flat, smooth terrain (e.g., the concrete floor) the error contribution is not negligible.

- **Real-time measurement model:** Since we are not accounting for the error contribution of previously added IAPs, our model is not equipped to deal with outliers. In simulation, this model is reasonable since our measurement noise is Gaussian, meaning that we have many fewer outliers than in experiment. In experiment, we see that non-Gaussian measurement noise results in outlier IAPs being initialized at a greater frequency, meaning that we are likely to sample particles with outliers in their maps. If an outlier is introduced early on in the mapping process, we have no way to go back and correct the mistake.

- **Assumptions:** To set up the problem we made two assumptions that in retrospect, are not realistic. First, we assume that the tether is perfectly straight when taut, meaning that our length measurement is exactly the sum of distances between active IAPs. In reality, any cable or tether will not only stretch when tension is applied but will also sag under its own weight, forming a catenary curve. Then, we make an assumption that IAPs are zero-radius points, when in reality they are not. This assumption implies an inherent measurement bias as the tether wraps around any bollard, which affects the bearing-to-anchor measurement accuracy. While these assumptions simplify the problem for purpose of investigation, we are underestimating their error contribution.

With respect to (ii), the following deficiencies in our algorithm were observed in experiment.

- **Sample Impoverishment:** As a consequence of iteratively resampling particles, many of the samples will have the same parent particle. Therefore, any mapping mistakes made early on will be hard to recover from, as errors cannot be back corrected. Increasing stability would require many more particles. However, this is a naïve approach because it becomes computationally intractable to run the algorithm in real time, especially considering that each particle is split into three just after resampling.

- **Outliers:** Due to errors in tether measurement as previously discussed, our IAP initialization step is prone to generate
outliers. Our method is online and has no form of outlier rejection, which means that performance can vary greatly between trials.

- **Large-Scale Loop Closure:** In the proposed algorithm, loop closure is only done when sequentially deleting IAPs (i.e., reobserving previously added IAPs that are still active). This is why we can reduce error by returning to and reobserving the initial anchor point at the end of the trajectory. However, large-scale loop closure is currently an unsolved problem because we have no way to associate newly added IAPs that were previously observed and are no longer active. An example can be found in the “Two Roads” experiment (see Figure 7), where the most distant IAP is visited twice from two different approaches (i.e., roads). If we were able to associate these observations, our map would better align with ground truth.

VIII. Future Work

Given the results of experiments with the TReX platform, we aim to solve the aforementioned problems in future versions of tether-based localization and mapping. The problems indicate that two important changes are needed. For one, we need to address our approximation of conditional independence between IAPs. It appears that we should instead use a measurement model that accounts for uncertainty across all active IAPs instead of just the current one. In other words, the tether length measurement should be a function of one robot pose and all active IAPs. This idea leads to a second change, which is that a batch formulation would be a more appropriate approach to this type of SLAM problem. The benefit of a batch approach will be that (i) we could use all the measurements to optimize the robot trajectory and locations of detected IAPs, and (ii) we can employ outlier detection to reject unlikely measurements of IAPs. Beyond these changes, we need to properly account for measurement drift in tether length, and attempt to characterize bearing-to-anchor bias. Lastly, future experiments with TReX will be conducted in more challenging environments, including steep cliffs, meaning that we will need to adapt our algorithm to work in three dimensions.

IX. Conclusion

This paper introduces the first nonvisual, tether-based localization and mapping technique. The algorithm uses tether measurements and odometry to localize a robot better than odometry alone, while providing a map of tether-to-obstacle contact points (i.e., IAPs). Our method is based on FastSLAM and uses many particles, each representing a belief of the state, that store discrete maps of IAPs represented by individual Gaussians. By splitting all particles into three just after resampling, we represent the likelihood of adding, updating, or deleting IAPs. Using tether length and bearing-to-anchor measurements, an ellipse-based model for initializing IAPs is also detailed. Our algorithm was evaluated in both simulation and experiments with our TReX robot. The results demonstrate that our method outperforms odometry alone. Above all, we hope to have introduced a new and challenging problem in robotics that will lead to further developments in localization and mapping for tethered mobile robots.

ACKNOWLEDGMENT

This work was made possible with funding and support from Fulbright Canada, Natural Sciences and Engineering Research Council of Canada (NSERC), NSERC Canadian Field Robotics Network (NCFRN), and the Collaborative Research and Training Experience Program (CREATE).

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