Proceedings Paper:

Ma, K., Zhu, J., Dodd, T.J. et al. (2 more authors) (2015) Robot Mapping and Localisation for Feature Sparse Water Pipes Using Voids as Landmarks. In: Towards Autonomous Robotic Systems. 16th Annual Conference, TAROS 2015, September 8-10, 2015, Liverpool, UK. Lecture Notes in Computer Science , 9287 . Springer International Publishing , pp. 161-166. ISBN 978-3-319-22415-2

https://doi.org/10.1007/978-3-319-22416-9_19

Robot Mapping and Localisation for Feature Sparse Water Pipes using Voids as Landmarks

Ma Ke[1,2], Juanjuan Zhu[2], Tony Dodd[1], Richard Collins[2], and Sean R. Anderson[1]

[1] Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield, UK, S1 3JD
[2] Department of Civil and Structural Engineering, University of Sheffield, Sheffield, UK, S1 3JD

Abstract. Robotic systems for water pipe inspection do not generally include navigation components for mapping the pipe network and locating damage. Such navigation systems would be highly advantageous for water companies because it would allow them to more effectively target maintenance and reduce costs. In water pipes, a major challenge for robot navigation is feature sparsity. In order to address this problem, a novel approach for robot navigation in water pipes is developed here, which uses a new type of landmark feature - voids outside the pipe wall, sensed by ultrasonic scanning. The method was successfully demonstrated in a laboratory environment and showed for the first time the potential of using voids for robot navigation in water pipes.

Keywords: Robot navigation, mapping, localisation, water pipes

1 Introduction

Water, a highly precious resource, is distributed to buildings by networks of pipes. As pipe materials age they are prone to damage, which can cause wastage of water and bacterial infiltration. Water distribution systems therefore require inspection, maintenance and repair [1]. However, water pipes are usually buried and so are difficult to access. Robotic systems have great potential for inspecting these inaccessible pipelines [2]. Whilst there are many techniques for robot pipe inspection itself [3], an as yet unsolved problem is accurately locating damage in pipes once found, to effectively target repair. This problem can be addressed by robot navigation algorithms, specialised to water pipes, which is the focus of this paper.

There are a number of challenges for robot navigation in water pipes. Firstly and most importantly the water pipe is a feature sparse environment. Most current robot navigation systems deal with indoor and outdoor environments, which contain numerous landmark features. However, pipe walls lack features that can be used as landmarks. Secondly, in pipes standard range and bearing sensors can only detect features that are nearby due to the close and enclosing proximity of the surrounding pipe wall. Thirdly, unlike indoor or outdoor navigation, the in-pipe robot has a very restricted route (moving either forward or backward), which limits the perspective of the robot on landmark features. Therefore, robot navigation in water distribution pipes is a difficult problem.

Robot navigation is often performed using simultaneous localisation and mapping (SLAM), which is where the location of the robot and the map features are represented in the state vector of a state-space model [4]. State estimation techniques are then used to construct the map and localise the robot, using e.g. the extended Kalman filter [5] or the Rao-Blackwellised particle filter [6]. Although these techniques are well-developed, they have rarely been applied in the water pipe environment. Mapping and localisation has been attempted in water pipes based on cameras and inertial measurement units (IMUs) [7, 8]. However, the use of cameras is limited by the lack of visual features, and IMUs are subject to drift, meaning that the navigation problem has yet to be adequately solved.

For in-pipe navigation, the feature sparsity problem motivates the development of sensing techniques that can transform the water pipe into a feature-rich environment. The aim of this paper is to improve water pipe navigation by exploiting a novel type of feature - voids that occur outside the pipe wall. Ultrasonic signals can penetrate the wall of plastic pipes to detect the depth between the outside soil and the pipe (and plastic pipes are now typically used by water utilities, especially in the UK). Significant gaps between the pipe wall and soil - voids - can be used as landmark features for navigation. Ultimately, these features can be used to build maps, localise the robot and fuse with standard sensing based on cameras and IMUs.

In this contribution we develop a novel framework for mapping and localisation in water pipes using voids as features, detected by ultrasonic scanning through the pipe wall, and demonstrate the approach experimentally in a laboratory environment. The experimental results show that ultrasonic sensing can be used to successfully build a map based on soil depth outside the pipe wall, and the navigation algorithm can be used to localise using voids as features.

2 Methods

This section describes the navigation algorithm using voids as features, as well as the experimental setup and data used to evaluate the algorithm performance.

2.1 Robot navigation algorithm

Problem statement The problem that we address here is: (i) to construct a map $g(\mathbf{x}_k)$ for the water pipe environment, that can be used to transform from robot pose $\mathbf{x}_k \in \mathbb{R}^{n_x}$ at time-step k to sensor measurements $\mathbf{y}_k \in \mathbb{R}^{n_y}$, where $g : \mathbf{x}_k \to \tilde{\mathbf{y}}_k$, where typically the robot pose $\mathbf{x}_k = [x\ y\ \theta]^T$, i.e. $\mathbf{x}_k$ contains the spatial location in x-y co-ordinates and heading θ, and $\tilde{\mathbf{y}}_k$ is the noise-free sensor output; and (ii) localise the robot by obtaining the estimate of the pose distribution $p(\mathbf{x}_k|\mathbf{y}_k)$.

Robot dynamics and measurement model We assume that the dynamics of the water pipe robot can be represented by a state-space model, with state dynamics

$$p(\mathbf{x}_k|\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) \Leftrightarrow \mathbf{x}_k = A\mathbf{x}_{k-1} + B\mathbf{u}_{k-1} + \mathbf{w}_k \tag{1}$$

where $\mathbf{u}_k \in \mathbb{R}^{n_u}$ is the input, assumed to arise from an actuator such as a motor, A is the state transition matrix, B is the input matrix and $\mathbf{w}_k \sim N(0, Q)$ is the state noise. For this investigation we set the state dimension to $n_x = 1$ to only represent the location of the ultrasonic probe in 1-dimension (moving forwards and backwards along a line), with no heading information. The dynamics are described by $A = 1$, $B = [-1\ 1]$, and $\mathbf{u}_{k-1} = [m_{k-1}\ m_k]^T$, where m_k is a motor encoder value - effectively the dynamic model predicts ultrasonic probe location using distance travelled obtained from a motor encoder.

The state-space measurement model is

$$p(\mathbf{y}_k|\mathbf{x}_k) \Leftrightarrow \mathbf{y}_k = g\left(\mathbf{x}_k\right) + \mathbf{v}_k \tag{2}$$

where $\mathbf{v}_k \sim N(0, R)$ is the measurement noise. In this case, we use only a single ultrasonic probe, hence $n_y = 1$, although the framework as presented above readily permits the extension to multiple sensors. The nonlinear function $g(.)$ in this case is the mapping from probe location, x_k, to soil depth y_k, which by definition is the map of soil depth over space (see Results, Fig. 2(a)).

Estimation of robot location In order to estimate the location of the probe, i.e. the distribution $p(\mathbf{x}_k|\mathbf{y}_k)$, we used a sequential Monte Carlo algorithm, specifically the bootstrap version of the particle filter, based on sequential importance resampling [9]. Firstly, the particle filter samples are initialised from the prior, which is the starting location of the robot,

$$\mathbf{x}_0^{(i)} \sim p(\mathbf{x}_0), \quad i = 1, \ldots, n_s \tag{3}$$

where n_s is the number of samples, and the weights associated with these particles are initialised to $w_0^{(i)} = \frac{1}{n_s}$, for $i = 1, \ldots, n_s$. The particle filter algorithm then iterates through the following steps at each sample-time k:

1. The location is predicted by samples drawn from the state equation, Eq. 1,

$$\mathbf{x}_k^{(i)} \sim p(\mathbf{x}_k|\mathbf{x}_{k-1}^{(i)}, \mathbf{u}_{k-1}), \quad i = 1, \ldots, n_s \tag{4}$$

   where we make the standard assumption that the state equation can be used as the importance distribution of the particle filter [9].
2. The weights are updated as

$$w_k^{(i)} \propto p(\mathbf{y}_k|\mathbf{x}_k^{(i)}), \quad i = 1, \ldots, n_s \tag{5}$$

   where from the assumption of Gaussian noise $\mathbf{v}_k$ on the sensor output,

$$w_k^{(i)} = \exp\left(-\frac{1}{2}\left(\mathbf{y}_k - \hat{\mathbf{y}}_k^{(i)}\right)^T R^{-1}\left(\mathbf{y}_k - \hat{\mathbf{y}}_k^{(i)}\right)\right), \quad i = 1, \ldots, n_s \tag{6}$$

where the map $g(.)$ is used to predict the soil depth from the sensor location, $\hat{\mathbf{y}}_k^{(i)} = g\left(\mathbf{x}_k^{(i)}\right)$. The weights are then normalised to sum to unity.
3. The final step is a check for particle degeneracy by counting the effective number of particles - if less than some threshold γ resampling is performed using the stratified resampling algorithm [9].

To implement the localisation algorithm the following parameters were used: $n_s = 300$, $\sqrt{Q} = 7$, $\sqrt{R} = 120$, and $\gamma = 0.6n_s$.

In the absence of any detected void, i.e. when the observed soil depth is below some small threshold ρ (here $\rho = 100$), the samples are predicted at each time step k with no correction. This results in an increasing spread of samples until a void feature is encountered, which then corrects the location estimate.

2.2 Experimental setup

In the laboratory setup an ultrasonic transducer was moved through a water bath over plastic pipe material to emulate the water pipe environment. The base of the water bath was covered in soil, with the plastic pipe material resting on top (Fig. 1). At certain locations in the soil, voids were inserted to create landmark features for evaluating the navigation algorithm.

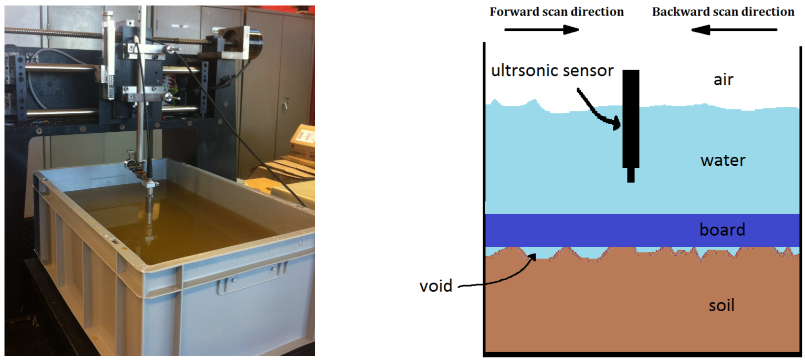
The ultrasonic transducer had a central excitation frequency of 10 MHz and focal distance of 75 mm, mounted to the gantry of a stepper motor driven scanning table. The transducer was pulsed at a rate of 160 pulse/s using PC mounted pulser-receiver and digitisation cards. The location of the transducer was recorded for each pulse. The reflected ultrasound was windowed such that the reflections extending from the upper pipe surface to approximately 80 mm past the lower surface of the pipe could be observed and digitised at a rate of 100 MSamples/s.

3 Results

To evaluate the use of voids as features for navigation, an ultrasonic probe was used to scan soil beyond plastic pipe material, in a setup that was designed to emulate the water pipe environment (Fig. 1). When the sensor was moved from left-to-right, the soil depth was measured and the void map was created (Fig. 2(a)). After the sensor reached the right end point, the map construction was finished, including voids, and was then used for localisation when moving from right-to-left.

To evaluate results, the motor location from the x-y table was used as the ground truth because it is highly accurate. To illustrate the effectiveness of localisation using voids a degraded version of the motor signal was used in the state equation to predict location, where the motor position was corrupted by white noise and a sinusoidal term.

The key result on the localisation is that when there is no void, the samples increasingly spread, but once a void is present, the location estimate is corrected,



(a) (b)

Fig. 1: Experimental setup in the laboratory environment. (a) Ultrasonic sensing probe, mounted on an x-y motorised arm in a water bath. At the base of the water bath is a layer of soil, over which is a plastic board of similar width and material to water pipe. (b) Diagram of the lab setup shown in panel (a).

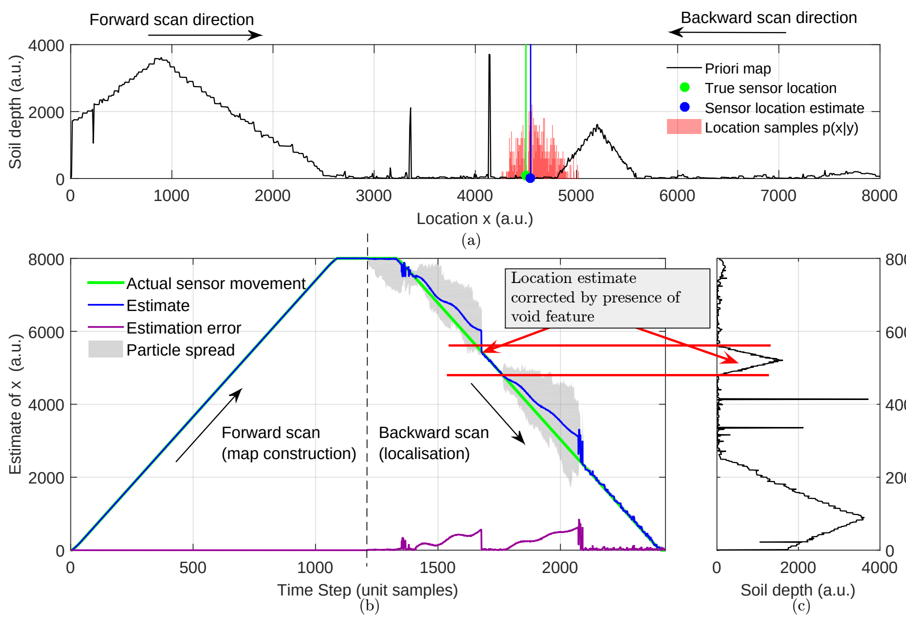


Fig. 2: Mapping and localisation experimental results. (a) Map of the soil depth outside the pipe wall, which corresponds to the observation function $g(.)$. The location estimate in blue corresponds to the sample with the maximum weight. (b) Mapping and localisation results where the map is constructed on the forward pass and localisation is performed on the backward pass. The location estimate in blue corresponds to the sample with the maximum weight. (c) Map of soil depth as shown in panel (a) but orientated to correspond to panel (b).

e.g. see time step $k = 1650$ in Fig. 2(b). Beyond time step $k = 1700$, when the void is passed, the samples diverge again. At $k = 2100$, the probe reaches another void, and all sample estimates once more converge on the true location. Crucially, this demonstrates the effectiveness of using voids as features for robot navigation.

4 Summary

The aim of this paper was to develop the use of a new type of feature, voids, for use in water pipe robot navigation. The navigation framework was successfully demonstrated in a laboratory experimental setup. In the future, this approach could be combined with multiple sensors, in order to transform water pipes from a feature sparse to a feature rich environment.

Acknowledgments The authors gratefully acknowledge that this work was supported by the EPSRC, UK, grant Assessing the Underworld (EP/K021699/1) and a PhD scholarship award to Ke Ma by the University of Sheffield.

References

1. T. Hao, C. Rogers, N. Metje, D. Chapman, J. Muggleton, K. Foo, P. Wang, S. R. Pennock, P. Atkins, S. Swingler, *et al.*, “Condition assessment of the buried utility service infrastructure,” *Tunnelling and Underground Space Technology*, vol. 28, pp. 331–344, 2012.
2. J. Moraleda, A. Ollero, and M. Orte, “A robotic system for internal inspection of water pipelines,” *IEEE Robotics & Automation Magazine*, vol. 6, no. 3, pp. 30–41, 1999.
3. J. M. Mirats Tur and W. Garthwaite, “Robotic devices for water main in-pipe inspection: A survey,” *Journal of Field Robotics*, vol. 27, no. 4, pp. 491–508, 2010.
4. H. Durrant-Whyte and T. Bailey, “Simultaneous localization and mapping: part I,” *IEEE Robotics & Automation Magazine*, vol. 13, no. 2, pp. 99–110, 2006.
5. M. G. Dissanayake, P. Newman, S. Clark, H. F. Durrant-Whyte, and M. Csorba, “A solution to the simultaneous localization and map building (SLAM) problem,” *IEEE Transactions on Robotics and Automation*, vol. 17, no. 3, pp. 229–241, 2001.
6. M. Montemerlo, S. Thrun, and B. Siciliano, *FastSLAM: A scalable method for the simultaneous localization and mapping problem in robotics.* Berlin Heidelberg: Springer-Verlag, 2007.
7. D. Krys and H. Najjaran, “Development of visual simultaneous localization and mapping (VSLAM) for a pipe inspection robot,” in *International Symposium on Computational Intelligence in Robotics and Automation, 2007. CIRA 2007*, pp. 344–349, IEEE, 2007.
8. H. Lim, J. Y. Choi, Y. S. Kwon, E.-J. Jung, and B.-J. Yi, “SLAM in indoor pipelines with 15mm diameter,” in *IEEE International Conference on Robotics and Automation, 2008. ICRA 2008.*, pp. 4005–4011, 2008.
9. S. Sarkka, *Bayesian Filtering and Smoothing.* Cambridge, UK: Cambridge University Press, 2013.