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Topological Robot Localization in a Pipe Network

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***Abstract*—Topological localization is advantageous for robots with limited sensing ability in pipe networks, where localization is made difficult if a robot incorrectly executes an action and arrives at an unknown junction. Novel incorporation of measurement of distance travelled is used in a Hidden Markov Model based localization method, which is shown to improve accuracy.**

***Index Terms*—Robot Localization, Topological Localization, Pipe Inspection Robots.**

I. Introduction

Water pipe infrastructure is in regular need of maintenance, the cost of which may be reduced by precisely locating faults using robots for autonomous, persistent monitoring of a network. A principal challenge for this robotic system is to localize itself and faults in the network. This work is on *topological* localization for a single robot in a network of pipes. While metric information would be required for precise localization of a fault, topological localization to a single discrete pipe or junction would be sufficient for navigation and for localizing a fault to a part of the network. Metric localization is poorly suited to pipes, as parametric methods like Kalman filters poorly describe the multimodal probability distribution of robot position, and non-parametric methods like particle filters require high computational power from the robot with limited power and size.

Early work in robot localization was done in a topological map [1], as was early work on localization in a pipe network [2]. Recent work on topological localization incorporates some geometric information [3], and recent work on localization in pipes also uses both metric and topological information [4].

This work investigates challenges to localization by the possibility of the robot incorrectly executing an action, and presents the incorporation of measurement of distance into the localization method. The rest of the paper will describe the model of uncertainty in robot motion, and describe the novel addition to the typical localization method. Simulation has been used to evaluate the method, and to investigate the effect of uncertainty parameters on the localization accuracy.

II. Problem Definition

The robot moves in a network of pipes shown in Fig. 1. The network has a range of topologies at smaller scales. It is assumed that the topology and approximate geometry of the network are known. At a junction, the robot chooses a direction at random relative to its own unknown orientation.

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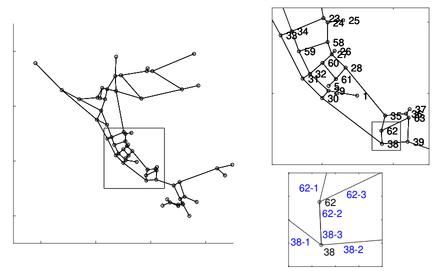

Fig. 1. The example network of pipes used in simulation, consisting of 63 nodes, each connected to 1, 3, or 4 other nodes. Inset is a smaller part of the network with labelled junction indices. The further inset shows the labelled pipes in blue, where each pipe with two labels, one for each node.

This action could be chosen to best inspect the network, however this would not affect localization so is neglected.

The robot state is defined by three components. The first component is the robot's discrete position, which is the junction index. The second component is the robot's discrete direction which is the index of the pipe which it has arrived from, allowing use of information about the robot's choice of action. The third component is the robot's previous position, allowing information about the length of the journey between junctions to be used, as described later. The latter two components are distinct when there are multiple paths between two positions. The robot state is only updated at junctions or at ends of pipes,

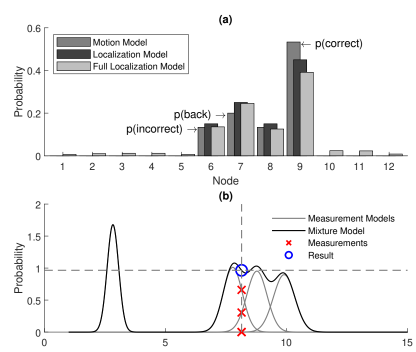

Fig. 2. (a) An example of the discrete probability distribution for robot motion, in this case from node 7 in a 12 node network. Shown is the motion model used to simulate the robot motion, the estimate of this distribution used for localization, and the full localization model considering the probability of missing a node. (b) An example continuous probability distribution over possible measurements of distance between a pair of nodes.

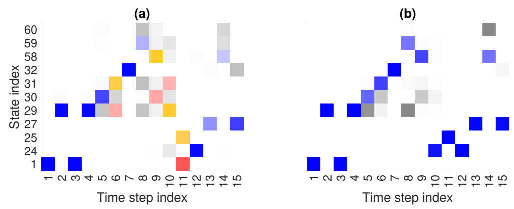

Fig. 3. An example of the use of the localization method in the map in Fig. 1. Each column shows the belief vector over a subset of the discrete states at that time step, where each value represents the probability of being in the corresponding state. The darkness of the colour corresponds to the value of belief in the state. The largest belief value is highlighted in blue if it is correct and red otherwise, where the correct value is shown in orange. (a) The result found without using the measured distance between states, (b) The improved result found when using the distance.

and the robot's position and orientation are not considered in transitions between these states.

There are four sources of uncertainty in the robot motion: *Incorrect action* execution, *return* to the previous junction, not detecting a junction and *missing* it without updating the state, and normally distributed *noise* in the time taken to travel between junctions. The three discrete components of this model are illustrated as a discrete probability distribution in Fig. 2(a). As the state transition model is difficult to compute exactly, for a given network a Monte Carlo method is used to approximate the transition probability between each state.

The robot makes two observations: the number of exits from a junction, and the distance moved since its last state update. For a given state transition there are a number of routes and corresponding distances. The probability distribution over possible noisy distance measurements is given by a sum of Gaussian distributions, shown in Fig. 2(b). Odometry used to observe this distance could be done using wheel encoders, vision, or simply using the control input and time taken.

III. Methods

The discrete probability distribution, or belief, over the possible robot states is desired. The belief is a vector summing to one where each value represents the probability of being in the corresponding state. The forward algorithm is used to compute the belief as a Hidden Markov Model (HMM). Using the given state definition, this is equivalent to a second order HMM. The localization model parameters are set to be somewhat incorrect estimates of the values in the motion model described previously, so that the robot does not have exact knowledge of the true motion model. The typical form in Equation 1 computes the updated belief $\boldsymbol{b}'$ over states $\boldsymbol{s}'$, based on the belief $\boldsymbol{b}$ over states $\boldsymbol{s}$, the observation o, action a, transition and observation models T and O, and a new term for incorporating measured distance m, M.

$$\boldsymbol{b}'(\boldsymbol{s}') = M(m|\boldsymbol{s}')O(o|\boldsymbol{s}')T(\boldsymbol{s}'|\boldsymbol{s}, a)\boldsymbol{b}(\boldsymbol{s}) \tag{1}$$

TABLE I
Effect of each parameter on the localization error metrics.

	incorrect action		return probability		miss probability		noise magnitude	
Error Metric	ρ[a]	g[b]	ρ	g	ρ	g	ρ	g
Total Error	-0.41	0.00	-0.20	-0.04	**0.98**	**0.83**	**0.99**	**1.96**
Mislocalization	-0.46	0.00	-0.61	-0.05	**0.98**	**0.37**	**0.99**	**0.66**
Relocalization Time	-0.01	0.00	**0.69**	**1.50**	**0.95**	**7.47**	**0.96**	**13.4**

[a]The correlation coefficient ρ between the metric and the parameter.
[b]The linear fit gradient g is the magnitude of the effect of the parameter.

IV. Results

An example of the localization performance is shown in Fig 3. This illustrates the improvement found when incorporating measured distance between junctions. The robot is simulated moving 1000 times between junctions in the network shown in Fig. 1 using the robot definitions given previously, and the state is estimated after each move. The *total* error is measured as the proportion of steps at which the estimation is incorrect. The effect of the four parameters is investigated by performing the simulation for different values of each, giving 256 sets of measurements in total. Over the 16 parameter sets representing lower uncertainty, the median total error without use of measured distance is 0.60 (with an interquartile range of 0.17). This is reduced to 0.18 (with an interquartile range of 0.11) with the use of measured distance.

The *total* error can be decomposed into two parts: the proportion of steps where an initial *mislocalization* occurs, and the mean number of steps before successfully *relocalizing*. Table I shows two measures of the effect of each parameter on the result for these metrics: the correlation coefficient and the gradient of a linear fit. The probability of missing a junction and measurement noise have a strong effect on all metrics, and the probability of incorrectly returning to the previous node has an effect on the relocalization. The probability of correctly executing an action does not affect the accuracy. These results give a measure of the hardware requirements for localization.

V. Conclusion

Simulations show that a Hidden Markov Model based method is able to effectively localize a robot in a discrete network where there is a possibility of the robot missing nodes in the network, using noisy measurements of distance travelled between nodes. Variation in the measurement noise and the probability of missing a node is shown to have a large effect on the localization effectiveness.

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