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.

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,
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 $b'(s')$ over states $s'$,
based on the belief $b$ over states $s$, the observation $o$, action
$a$, transition and observation models $T$ and $O$, and a new term
for incorporating measured distance $m$, $M$.

$$b'(s') = M(m|s')O(o|s')T(s'|s,a)b(s)$$  

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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