Probabilistic Radar Scan Matching for Robot Teach and Repeat

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Abstract—Teach and repeat is a robotics paradigm in which a robot is to repeatedly traverse a predefined, taught route. A central component of teach and repeat robotics is the localisation of a robot with respect to a locally consistent map rather than a globally consistent one as in many SLAM applications. This localisation is dependent on the ability to match sensor scans to determine motion.

In this paper we investigate the use of a microwave radar sensor coupled with a probabilistic scan matching method for a teach and repeat application with a mobile robot. The use of microwave radar is motivated by it's resilience to adverse weather conditions, which provides an advantage over many currently used sensors such as LIDAR. The use of a probabilistic framework for scan matching is motivated by issues such as initialisation errors associated with commonly used optimisation based scan matchers.

This work demonstrates efficacy in the use of radar with a probabilistic scan matcher for the localisation in a teach and repeat setting.

I. INTRODUCTION

Within the field of robotics, teach and repeat is a paradigm in which a robot learns a specific task or route well enough to regularly repeat the task or route. Teach and Repeat robotics makes use of sensor data to localise to the local maps procured in the teach phase. Such an approach to mobile robotics is particularly useful in scenarios where a robot repeatedly executes the same “mission” such as in a warehouse environment [1].

One of the key differences between the SLAM(Simultaneous Localisation and Mapping) framework and the teach and repeat framework is the necessity of a globally consistent map. Unlike SLAM which takes a global localisation approach [2], the teach and repeat paradigm localises within a locally consistent map, however progress has been made to allow for variations within these local maps [3].

An important feature of teach and repeat robotics is the ability to match, or register successive scans procured from the robots sensors. This allows the robot to determine in which way it has moved since the last localised point. By finding the transform between successive(not necessarily contiguous) scans, a map may be built by storing the transforms between points of interest, known as Keyframes.

Many existing scan matching algorithms use optimization techniques to find a solution to the scan matching problem, however some of these optimization based techniques are not robust to initialisation error [4]. It is also noteworthy that scan matching optimisation problems are seldom convex [5], resulting in multiple sub optimal solutions and lengthy run times. These issues are avoided by taking a probabilistic approach to scan matching, as demonstrated in this work. By placing the problem within a probabilistic framework, the problem of initialization error can be avoided.

Another key contribution of this paper the use of microwave radar for robot teach and repeat. Recent research indicates the use of LIDAR(Light Detection and Ranging) sensors and visual odometry, however these methods are not robust to adverse weather conditions, for example LIDAR can be affected by rain and fog, causing noisy reflectances [6]. Visual odometry can be affected by large appearance changes in a scene, for instance lighting changes [7].

This paper presents a probabilistic scan matching method using radar with an application to the teach and repeat paradigm. Then proceeding by presenting a short evaluation of existing pertinent work, followed by an explanation of the methods used. Finally presenting a summary of results and a closing conclusion.

The robot used in this work is a Europa2, part of a EU project to develop robots to perform tasks such as delivery, cleaning and surveying. The Europa2 is displayed below with the sensor used in this work indicated.
II. PREVIOUS WORK

Optimization based scan matching algorithms are widely used in robotics for localization and mapping. A prominent algorithm is ICP(Iterative Closest Point) which uses the Euclidean distance metric between two scans points as a measure of a candidate transforms suitability [8]. The algorithm iteratively minimises this distance metric. However, the performance of ICP is dependent on the quality if its initial “guess”, as a result ICP may converge to a suboptimal or incorrect solution for an erroneous initialisation [4]. In addition, ICP is prone to failure when presented with noisy data, as is produced by many radar devices [9]. A variant of ICP is ICL(Iterative Closest Line), a method that instead of matching points, matches points to lines between the reference and query scans [4]. Like ICP, the quality of a solution yielded by ICL is dependent on the initial guess at the correspondence between the scans.

In addition to the aforementioned iterative optimization based methods, there have been approaches based on the use of phase correlation. An example is the use of the Fourier-Mellin transform to perform phase correlation in the frequency domain to match two radar scans. The rationale is that a shift of coordinate frames is transformed in the Fourier domain as a linear phase difference [9]. This method proved to be efficacious within a SLAM framework and indicates a useful application of Microwave Radar to robot localisation.

III. METHODOLOGY

A. Radar and Data Preprocessing

The sensor used in this work is a Navtech CTS350-X Microwave Radar. For the purposes of this research, no other sensor data was used.

<table>
<thead>
<tr>
<th>Specifications of the Navtech CTS350-X.</th>
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<tbody>
<tr>
<td>Maximum Range</td>
</tr>
<tr>
<td>Range Resolution</td>
</tr>
<tr>
<td>Field of View</td>
</tr>
<tr>
<td>Scan Rotation Rate</td>
</tr>
</tbody>
</table>

Due to a high level of background noise being present in the microwave radar scans, CA-CFAR(Cell Averaging - Constant False Alarm Rate) filtering has been applied to the raw radar data. CA-CFAR is a simple algorithm for dynamically setting a threshold at which returns are considered to be true detections [10].

The algorithm operates in a sliding window manner, taking for each CUT(Cell Under Test) a block of sample cells either side of the CUT to be averaged over to set the threshold. However, it should be noted that a neighbourhood within this block immediately adjacent to the CUT is not taken in to account to avoid the corruption from the CUT itself. For a CUT to be deemed a valid return, it must be greater than both its adjacent cells and some constant multiple of the local average [10]. For a radar beam FFT binned, the following pseudocode is appropriate:-

```plaintext
for i = 0 to cellCount do
    avgReturn = 0
    count = 0
    for j = i - sampleCells to i + sampleCells do
        if j not guard cell then
            avgReturn = avgReturn + FFT_DATA[i]
            count ++
        end if
    end for
    if not (avgReturn ≥ MULT * FFT_DATA[i]) then
        FFT_DATA[i] = 0
    end if
end for
```

B. Scan Matching

The configuration of a mobile robot in a planar environment may be described by a 3-vector \( x = (x, y, \theta) \) whose components \( x, y \) and \( \theta \) represent its relative cartesian position and orientation respectively. Given two consecutive states of the robot \( x_{n-1} \) and \( x_n \) a common problem is to find a rigid body transformation \( T \) such that \( x_n = Tx_{n-1} \). It follows that this rigid body transform corresponds to the transformation between sensor scans following some control action \( u \) being performed. The rigid body transform \( T \) can be found by matching scans \( z_{n-1} \) and \( z_n \). As such, the rigid body transform problem can be solved via the solution to the scan matching problem. The process of the robots observation models can be represented by the following graphical model [5]:-
In the above, the vectors $x_{n-1}$ and $x_n$ represent state, $u$ is a control vector, $z_{n-1}$ and $z_n$ are radar scans. At this point it should be noted that the scan $z_{n-1}$ is the reference scan to which matching is performed.

The graphical model presented above allows the formulation of the problem in terms of a distribution over the robots position, as follows:-

$$p(x_n|x_{n-1}, u, z_n, z_{n-1}) \propto p(z_n|x_n, z_{n-1})p(x_n|x_{n-1}, u)$$

As per the graphical model, the distribution is proportional to the product of two distributions, an observation distribution and a motion distribution. The scan matching problem is concerned with the approximation of the former, the likelihood of the current scan given the current state and the previous scan.

Intuitively, the likelihood of a scan given a previous scan and current state is proportional to the displacement between the scans. As such, via Bayes Theorem the problem may be stated as follows:-

$$p(z_n|x_n, z_{n-1}) \propto p(T|z_n, z_{n-1})$$

Which allows for a search over a discretised set of candidate transforms. Performing this discretised search allows for constraints on the search space to be enforced. The maximum likelihood solution is then given by the transformation that maximises the following:-

$$p(T|z_n, z_{n-1}) \propto \prod_{i=0}^{N} e^{-\left(\frac{d_{n}^{i} - d_{n-1}^{i}}{\sigma}\right)^2}$$

Or in log space, as may be more computationally attractive:-

$$p(T|z_n, z_{n-1}) \propto \sum_{i=0}^{N} \left(\frac{d_{n}^{i} - d_{n-1}^{i}}{\sigma}\right)^2$$

Where the spread parameter $\sigma$ is a precomputed MLE for each 0.25m distance interval of the radar. For every possible range, a maximum likelihood estimation has been made of the noise floor. $d_n^i$ represents the dB return of the $i^{th}$ point in the $n^{th}$ scan.

C. Teach and Repeat

Mapping is the first stage in the teach and repeat process. A map of the environment in which the robot is to perform its localisation during future repeats consists of a set of keyframes. A keyframe is a snapshot of the world that represents some point of interest. A keyframe pair consists of two of these snapshots along with the transform between them. For trajectory following, a keyframe pair could be collected after travelling some set distance. At this point it is pertinent to again highlight the difference in mapping strategies between SLAM and teach and repeat. SLAM performs localisation to a globally consistent map, whereas the keyframing approach used in this teach and repeat exercise performs localisation only to a single keyframe at a time. As such, whereas SLAM relies on global consistency, teach and repeat with keyframing relies on local consistency.

With a set of keyframes collected, a mobile robot is able to determine its location with respect to what is known about the environment. For instance, in an environment where a robot is to follow a simple trajectory, it can use the collected keyframes to determine its location and if it has reached the target state, i.e. the end of the path.

IV. RESULTS

In the first stage the robot(above) was manually driven along a straight path of 11m to collect keyframes to build the known map to which it is to localise to in future runs. In future runs, the robot deviates from its path and attempts to localise on return to the closest keyframe. Performance is assessed in terms of distance to the end point of the initial keyframe collecting run. As the deviations from the simple run become larger, some keyframes will not be able to be localised to. As such, the assessment is on the ability to re-localise after going off track. Deviations from the straight path are in steps of 0.5m

![Fig. 5: Paths taken.](image)

One metric used is the difference in distances from the last keyframe to the target and the last localised scan to the target. In addition, different permutations of map and live dataset from the corpus have been used, so in some runs the map would have a deviation from a straight path also.

The first experiment run was to test the ability to re-localise to a straight path after deviating from it by some set distance. Below are the distances from the target position for single runs of a set deviation form the no deviation
TABLE II: Distances from target at end of run for straight path.

<table>
<thead>
<tr>
<th>Deviation from straight map</th>
<th>Distance $l_2$ from Target</th>
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</thead>
<tbody>
<tr>
<td>0m deviation</td>
<td>0.25m</td>
</tr>
<tr>
<td>0.5m deviation</td>
<td>0m</td>
</tr>
<tr>
<td>1m deviation</td>
<td>0.25m</td>
</tr>
<tr>
<td>1.5m deviation</td>
<td>0.25m</td>
</tr>
<tr>
<td>2.0m deviation</td>
<td>0m</td>
</tr>
</tbody>
</table>

It can be seen that localisation is performed with an error range of 0m to 0.25m following a range of deviations from course, demonstrating the ability to re-localise once a known keyframe is within sight..

In addition to the deviations from the straight path, different permutations of the data collected have been used to assess different map/live scan scenarios.

TABLE III: Average distances from target at end of run for deviations in map.

<table>
<thead>
<tr>
<th>Map used (deviation from original)</th>
<th>Average $l_2$ from Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Deviation as Map</td>
<td>0.13m</td>
</tr>
<tr>
<td>0.5m Deviation as Map</td>
<td>0.526m</td>
</tr>
<tr>
<td>1m Deviation as Map</td>
<td>0.332m</td>
</tr>
<tr>
<td>1.5m Deviation as Map</td>
<td>0.253m</td>
</tr>
<tr>
<td>2.0m Deviation as Map</td>
<td>0.142m</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

To conclude, this paper has demonstrated the feasibility of the use of probabilistic scan matching of microwave radar images within a teach and repeat framework. It was demonstrated that localisation is possible even when deviating from what is known from the teach phase. In many cases, even with deviations from known paths, localisation is possible to within 0.5m.

REFERENCES