Mobile Robot Localization in the presence of Unexpected Objects

Mobile Robot Localization is one of the important problems in Autonomous Robotics, and through the years, researchers have developed very effective techniques for the same. However, we are seeking to deploy smaller autonomous robots, across more challenging environments. This requires an efficient localization algorithm that can function in dynamic and unstructured environments.

The report proposed an enhancement to the widely used Endpoint sensor model for Range Finders also called the Likelihood field model for Monte Carlo Localization, making the model capable of performing in a dynamic environment. The technique is based on the principle of Outlier Rejection, is advantageous in that, it does not employ the computationally expensive ray tracing algorithm that other approaches do. Experimental results are provided which demonstrate that the developed technique is capable of functioning reasonably well in an environment filled with unexpected obstacles, and outperforms the raw Likelihood field model in the same.

for reading in readingSet:

  if !(reading = z_{max}) :

    $p = q = 0$

    for *particle* in *particleSet*:

      $p = p + z_{random} * p_{random}(z)$

      $q = q + p_{Hit}(z) + z_{random} * p_{random}$

    if (p/q) > thresh: **reject**

    else: **accept**

Proposed algorithm in pseudo-code

Results and Learnings:

For evaluation, log from the 'Department_DIIGA' dataset was used. The occupation density of unexpected objects in the area of the map explored by the robot was used as a metric. The dataset had a minimal presence of un-modelled objects; hence, additional un-modelled objects were simulated on the explored area of the map (540 m^2) at random positions and orientations. The objects taken were rectangles of 400 mm x 200 mm, approximating a human's dimensions at ~1.5 feet. The laser range readings that would get affected by these objects were selectively corrupted.

MCL with both the raw likelihood field model, as well as the model with added outlier rejection, were tested on the corrupted data sets. When using the raw likelihood field model or Endpoint model, the robot was able to localize without many failures, only up to 0.25% occupation density. At densities greater than 0.25%, the localization failed to the extent, that the belief completely lost track of the robot pose. In contrast, MCL with added outlier rejection, successfully performed upto an occupation density of 1.05%, wherein some extent of failures took place, but eventually the robot regained track of its pose. In the corrupted data set for 1.05% occupancy, there were several instances of localization wherein the number of corrupted readings exceeded 50%, also touching 100% on many counts. In fact, the failures, occurred only when either greater than 90% of the readings were corrupted for an extended duration of time, or no information was available in the uncorrupted readings to discern its pose in a certain direction, over several instances of localization. The likely cause of this is that, when over several instances of localization, readings are absent to tell the robot about its position in one or more directions, gradually the particle filter diverges, and after a point, localization failure occurs. Having said that, this happens only over several instances of localization, as the particle filter is able to cope with intermittent absence of data for localization. Another related observation, is the effect of "tightness" of the motion model. The smaller the variance coefficients in the motion model, the lesser the particle filter diverges, over each instance of unavailability of suitable localization information. When the variance coefficients were doubled, intermittent failures were observed even at the 0.25% occupation density level, in spite of using Outlier rejection. Additionally, in practice, the proposed technique should be able to survive even a further higher occupation density of people, since, due to the presence of Obstacle avoidance schemes, the robot would not go very close to the un-modelled objects, in a manner that most of its readings get blocked, preventing it from localizing. Further evaluation of the technique in more realistic scenarios would give a more accurate quantification of the performance.

Conclusion:

The key contributions of this work have been firstly, showing that the problem of Localization in a dynamic environment can be solved using range finders reasonably well even without the use of expensive ray tracing, and secondly proposing a technique that is simple to add to the widely used Endpoint sensor model. Moreover, since the technique does not make any additional assumptions about the structure and nature of the environment i.e. presence of linear features, etc., it also remains suitable for use in unstructured environments.

Some distinct aspects of Monte Carlo Localization (MCL) were also experienced in the course of this work, one of those being the need to inflate the noise parameters. An idea has been proposed for the same, as future work.