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Todd Hester and Peter Stone "Negative Information and Line Observations for Monte Carlo Localization"

The paper discusses its motivation clearly and concisely within the abstract. It is attempting to *"extend the general Monte Carlo localization algorithm"* by utilizing new line observation and negative information techniques to be used *"both on a Sony AIBO ERS-7 robot and in simulation"*. The paper excellently challenges the paradigm of the traditional MCL algorithm using a clear example about Notre Dame to be used as a landmark for negative information while trying to localize on a map of Paris.

However, the paper fails to examine the crisis in the field that the current solutions using MCL fail to solve. It mentions a new method but doesn't quantify the level of the issue that previous papers don't solve. It requires a brief analysis of previous examples where the author has run traditional MCL algorithms and ran into this issue. A statement like "worlds that have ambiguous landmarks prove to not provide any increase in certainty of its true pose or speed in its computation. However, using an intelligent algorithm, we should be able to see large increases in performance from environments that have repeated landmarks" would demonstrate to the reader that the previous methods might have potential for improvement which could be investigated using this paper.

The author has attempted to take previous knowledge and methods used in papers and integrate them together into an overall better algorithm. They claim to have used their own use of line observations which is *"simpler than previous algorithms [8], [9], but very effective at localizing the robot"*. The author claims that using a new method that observes lines as atomic entities instead of using individual line pixels allows them to *"make better use of the information provided by the orientation of the lines, as well as freeing us from having to pre-calculate tables of expected line pixel observations for every location in the world"*. They provide no substantial evidence for why their line observation is at all an improvement over the previous method deeming this area of the paper relatively mute until further analysis can be shown. A benchmark that compares the overall quality of its computation to the previous method would allow us to make an evaluation on its academic contribution to science.

The second area addressed in their adaptation of the MCL algorithm is their improved version of Hoffmann et al.'s previous method to use negative information to increase pose certainty. A clear problem was hypothesised in Hoffmann et al.'s method where information may be missed due to *"reasons such as image blurring or occlusions"* and may be perceived as negative information. The paper proposes a very simple solution to check if the absence of an expected object in the robot's sensor is indeed correct or if the frame collected by the sensor is faulty. The solution is to check multiple (stored as t) frames before affecting the pose probability due to negative information.

The negative information algorithm adaptation was tested against the previous method within the confides of the testing area and shown to produce reasonably positive results. As this is solely an improvement based on error correction, I hypothesise that the improvements shown by the new method will be proportional to the quality of the camera and be largely affected by the environment it's placed in.

A further dive into the testing on new environments for the negative information algorithm would also be appreciated to give us greater confidence in the results. The author finds it *"interesting to note that using negative information caused more improvement in angular errors than using line observations"*. I theorise that the large improvements on accuracy of pose angles solely due to negative information was a lot to do with the setup of the environment where all distinct landmarks were visible from all areas of the map. This allowed the algorithm to cut out x degrees (x being the FOV of Sony Aibo ers-7's camera) of poses when any landmark isn't viewed given any location on the pitch. In a more complex environment where LOS (Line Of Sight) is interrupted in areas to distinct landmarks, the information of not viewing said landmark is far less valuable. Using the example from the author in their introduction, not viewing Notre Dame allows us to rule out all poses in Paris that would be able to see Notre Dame. However, the topology of Paris with it being a city encompassing high buildings everywhere means just because you are facing Notre Dame given any location, doesn't mean you can see it and therefore should not rule out that location based on the information that you can't see Notre Dame. As all locations on the tested environment can see every landmark if facing the correct angle, the angle of the pose can be reasonably accurately estimated based purely off the negative information algorithm.

Finally, the author claims to have made *"some small but significant improvements to the re-seeding and re-sampling portions of the algorithm"* but provides little information on the improvements made and provides no benchmark of their improvements so it is unlikely that any major discoveries were made there.

There is merit here to taking different adaptations of the MCL algorithm and optimising every area to work harmoniously together. However, no significant scientific advances have either been made or been benchmarked within this paper. Merely merging the previous methods together holds little value in a research paper and the adaptations to these methods are either trivial or untested.

Further testing should be done as a scientific paper to benchmark all claimed improvements on MCL to give us a good understanding on the quality of the specific contributions listed. Additionally, testing on different environments will give us some more scenarios in the real world where the technology could be adapted to. Just using the singular data set given to us from 1 test environment makes it very difficult to hypothesise how this technology would perform in alternate scenarios.