Robust Vehicle Localisation with Digital Maps
COMP2550 Project Proposal

Sam Toyer
u5568237@anu.edu.au

April 24, 2015

Overview

Localisation—the task of determining the position of an object relative to its environment—is a common problem in robotics and related fields. In outdoor environments, a common solution is to use a satellite-based navigation system like GPS, which is usually able to provide a latitude and longitude estimate within metres of the ground truth.

However, in some applications—especially applications in areas where GPS reception is poor—GPS is not sufficient on its own, and other sources of information must be used to infer location. For road vehicle localisation, street maps are excellent for this purpose: since cars almost always travel on roads, raw GPS fixes can be "snapped" to the most likely true position of the vehicle on the road network in a process called map matching. With the recent availability of free, accurate maps from the OpenStreetMap[1] project, map matching has become an attractive technique for improving the performance of existing localisation techniques.

The objective of this project is to develop a robust algorithm to estimate the position of a vehicle on a road network from GPS data and odometry. The algorithm should maintain good performance even with poor GPS reception, and should be adaptable to other localisation tasks—pedestrian localisation, for example—where use of digital maps could improve performance.

Such an algorithm has a wide range of applications, ranging from improving the performance of visual road classifiers by providing improved prior information about the position of roads in the image (Álvarez et al., 2014) to assisting visually impaired people to navigate outdoors (Oh et al., 2004).

[1] `http://www.openstreetmap.org/`

Related work

Map matching in vehicles—where vehicles are localised under the simplifying assumption that their true position coincides *exactly* with that of a road—is a well studied problem with a range of preexisting solutions. The most popular family of solutions are heuristic methods which follow some variation on the following three-step structure:

1. Estimate the vehicle's position using GPS or dead-reckoning.
2. Consider all road segments in the map and choose the one which the vehicle seems most likely to be on given the current GPS fix and the previous map-matched position.
3. Estimate the position of the vehicle within the chosen segment.

Approaches of this kind include those of Ochieng et al. (2003), Velaga et al. (2009) and Quddus et al. (2006). These algorithms can be highly accurate—for instance, Quddus et al. report that they were able achieve a horizontal accuracy of better than 5.5m for 95% of observations using an algorithm following the structure described above, which compares favourably with the 32m horizontal accuracy of naively matching to the nearest point on the road network

Although these approaches are popular, one of their common weaknesses is poor mismatch handling: since segments are usually selected recursively—with the algorithm only matching to segments close to the previously matched one—an incorrectly selected road segment can cause subsequent road segments to be selected incorrectly. Such mismatches can easily happen immediately after the initialisation of the algorithm, since the first match cannot be made using data from previous, presumably correct matches, and thus is more likely to be incorrect. This problem has prompted algorithm designers to take special precautions like observing many GPS fixes before performing an initial match (Syed and Cannon, 2004).

Probabilistic algorithms are able to sidestep this problem by modelling vehicle position not as a single "best guess", but as a probability distribution over all possible vehicle states. Thus, when there are multiple roads on which the vehicle could plausibly be travelling, the algorithm will assign them each similar probability and allow probability mass to converge on a single segment later, rather than choosing one segment arbitrarily and suffering incorrect subsequent matches.

The most common probabilistic approach to map matching is particle filtering, as exemplified by Selloum et al. (2009) and Chausse et al. (2005). Particle filters approximate the distribution of possible vehicle positions using a large number of "particles", each of which represent one possible state of the vehicle. Initially, these particles are spread uniformly over the road network. Then, at each time step, the particle positions are updated according to observed vehicle motion, and each particle is assigned a weight reflecting how well it corresponds to GPS readings and other available data. The particles are then resampled to produce a new particle distribution which reflects these weights, after which the algorithm loops back to the particle position update stage. Over time, the position of the particles should converge to the true vehicle position.

Particle filters can be adapted to work without GPS (Gustafsson et al., 2002), or in situations like pedestrian navigation where the true position of the localisation target is not guaranteed to coincide with that of a mapped feature like a road or footpath (Oh et al., 2004), which is a major advantage over the traditional "three-step" map matching methods described above. However, current applications of particle filtering to vehicle localisation, including those of Selloum et al. and Chausse et al., have used augmented GPS systems and specialised maps which are not widely available. As a result, a promising avenue of research—and in fact the one which this project will pursue—is to adapt particle filtering to perform well with commonly available street maps and regular GPS receivers.

Technical approach

As mentioned above, this project take a particle filter-based approach to localisation. Initially, this approach will be adapted from the method presented by Selloum et al. (2009), where map information is incorporated by clamping the weights of all off-road particles to zero. Other map-based priors will then be considered, including the lane-centered Gaussians employed by Chausse et al. (2005).

The algorithm will be evaluated using the data set supplied by Brubaker et al. (2013), which is itself derived from the KITTI Vision Benchmark Suite.[2]This data set includes approximately 40km of traces produced by driving a vehicle fitted with a highly accurate GPS unit through various urban environments. It also includes OpenStreetMap-derived map data for each of the regions corresponding to these traces.

The chosen data set does not include noisy data typical of low-cost GPS receivers, so GPS-like noise will have to be introduced artificially. This approach has the advantage of allowing the algorithm's performance—as measured by horizontal positioning error—to be evaluated with varying levels of noise.

Project plan

In order to evaluate progress, the project will be divided into several milestones:

1. Completion of the basic programming work required to evaluate the algorithm, including cleaning and parsing of the data set and production of simulated GPS noise.
2. Implementation of the particle filter and production of comparisons between the implemented filter and raw GPS localisation.
3. Synthesis of results into a paper.
4. Further investigation of techniques for improving the efficiency and performance of the particle filter so that it can yield accurate location predictions in real time.

The first three milestones should be easily achievable within the five to six week time frame available before the final report is required, and the fourth milestone will allow for the productive use of any time which remains after these milestones are complete.

It is anticipated that, at its conclusion, this project will have produced a robust vehicle localisation algorithm which significantly outperforms raw GPS localisation by making use of freely available digital map data. However, in the event that this goal is not achieved, it will still be possible to report useful negative results regarding the application of particle filtering to map-aided vehicle localisation in scenarios where specialised maps of the kind used in previous studies are not available.

[2] `http://www.cvlibs.net/datasets/kitti/index.php`

References

J. M. Álvarez, A. M. López, T. Gevers, and F. Lumbreras. Combining priors, appearance, and context for road detection. *IEEE Transactions on Intelligent Transportation Systems*, 15(3):1168–1178, 2014.

M. A. Brubaker, A. Geiger, and R. Urtasun. Lost! leveraging the crowd for probabilistic visual self-localization. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 3057–3064. IEEE, 2013.

F. Chausse, J. Laneurit, and R. Chapuis. Vehicle localization on a digital map using particles filtering. In *Intelligent Vehicles Symposium, 2005. Proceedings. IEEE*, pages 243–248. IEEE, 2005.

F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P.-J. Nordlund. Particle filters for positioning, navigation, and tracking. *Signal Processing, IEEE Transactions on*, 50(2):425–437, 2002.

W. Y. Ochieng, M. Quddus, and R. B. Noland. Map-matching in complex urban road networks. *Revista Brasileira de Cartografia*, 2(55), 2003.

S. M. Oh, S. Tariq, B. N. Walker, and F. Dellaert. Map-based priors for localization. In *Intelligent Robots and Systems, 2004.(IROS 2004). Proceedings. 2004 IEEE/RSJ International Conference on*, volume 3, pages 2179–2184. IEEE, 2004.

M. A. Quddus, R. B. Noland, and W. Y. Ochieng. A high accuracy fuzzy logic based map matching algorithm for road transport. *Journal of Intelligent Transportation Systems*, 10(3):103–115, 2006.

A. Selloum, D. Betaille, E. Le Carpentier, and F. Peyret. Lane level positioning using particle filtering. In *Intelligent Transportation Systems, 12th International IEEE Conference on*, pages 1–6. IEEE, 2009.

S. Syed and M. Cannon. Fuzzy logic-based map matching algorithm for vehicle navigation system in urban canyons. In *ION National Technical Meeting, San Diego, CA*, volume 1, pages 26–28, 2004.

N. R. Velaga, M. A. Quddus, and A. L. Bristow. Developing an enhanced weight-based topological map-matching algorithm for intelligent transport systems. *Transportation Research Part C: Emerging Technologies*, 17(6):672–683, 2009.