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Geotagged Visual Localisation System for Urban Automated Vehicles

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Abstract

Vehicle localisation is one of the fundamental building blocks of automated driving systems. Although, high-end satellite navigation systems can provide centimetre-level accuracy, they are limited to applications where there is sufficient satellite signal visibility. One example where signals from navigational satellites might deteriorate is urban canyons which are characterised by high rise, high density residential and commercial buildings. To overcome the limitations of satellite navigation systems, most state-of-the-art localisation solutions fuse information from multiple sensors such as GNSS, LiDAR, camera, accelerometer, and wheel encoder with the purpose of creating a full 3D map of the operating environment. Although this approach provides accurate and reliable results, it is bounded in terms of data efficiency and scalability. With these limitations in mind an alternative methodology is proposed. More specifically, as opposed to existing approaches, the proposed system eliminates the need for creating full 3D maps by activating a visual localisation system only in geographical areas where the accuracy of satellite navigation systems might deteriorate, particularly urban canyons. The existence of urban canyons is pre-determined depending on the visibility of sky which is calculated using a digital surface model (DSM) of the environment. As a result, 3D maps are created only in challenging GNSS denied areas which makes the overall localisation and map systems much lighter improving the data efficiency and scalability. The paper will be covering the technical details of the proposed solution and will be showing the efficacy of the approach with results obtained in real-world urban environments.

Introduction

Rapid urbanization and large private car ownership have resulted in significantly more congested roads that has led to ever increasing levels of pollution. Autonomous vehicles (AVs) have been proposed as a solution to alleviate congestion by providing ride sharing services that would reduce the number of cars being driven on roads while moving similar quantities of people around. Furthermore, AVs have the potential to reduce the number of yearly traffic accidents by incorporating predictable and safe driving routines that minimize the potential for accidents. To this end, the UK government has spearheaded the development of AV technology by funding over 70 research projects under Connected Autonomous Vehicle[1] (CAV) initiative [2]. ServCity is one such project where UK government funding has been used to form a consortium with members from both academia and industry to tackle the technical and societal challenges of urban AV services [3]. Some of the technical goals of the project are the development and improvement of the following critical components for autonomous vehicles: vehicle perception, localisation (the focus of this paper), mapping, path planning and control systems. Vehicle localisation is critical for safe roll-out of level-5 AV systems, where current production level vehicle localisation systems rely on GNSS for accurate localisation. However, the accuracy of GNSS[2] measurements can significantly degrade if there is no line-of-sight between the GNSS satellites and vehicle receiver, where such cases can arise in urban canyons (we also refer to regions where GNSS measurements degrade due to limited line-of-sight as **GNSS denied** regions).

To this end, in order to improve the robustness of GNSS systems, we first propose to estimate a-priori the likelihood of regions that are GNSS denied by proposing a digital surface model that compute the GNSS satellites visibility (that is, line-of-sight between satellite and vehicle receiver). If a region is categorised as GPS denied, we propose a **low**

[1] CAV generalises AV technologies by enabling vehicle to vehicle communication. CAV technologies require additional components such as secure vehicle to vehicle communication [1].

[2] The acronyms GNSS and GPS are used interchangeably in this paper.

FIGURE 27 Satellite image of test route (red points and blue line) that was determined to be GNSS denied using the GIS based GNSS forecasting tool.

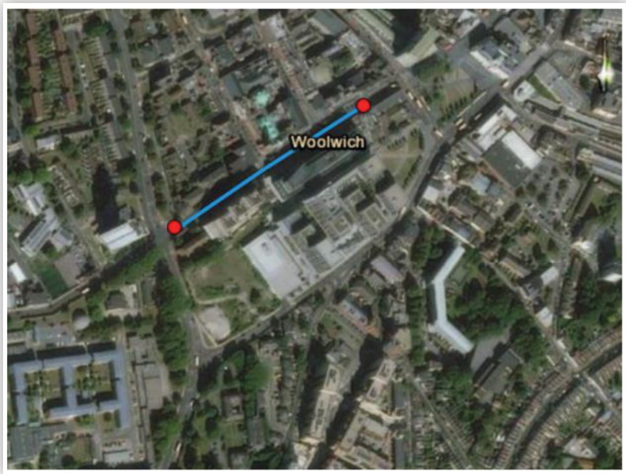
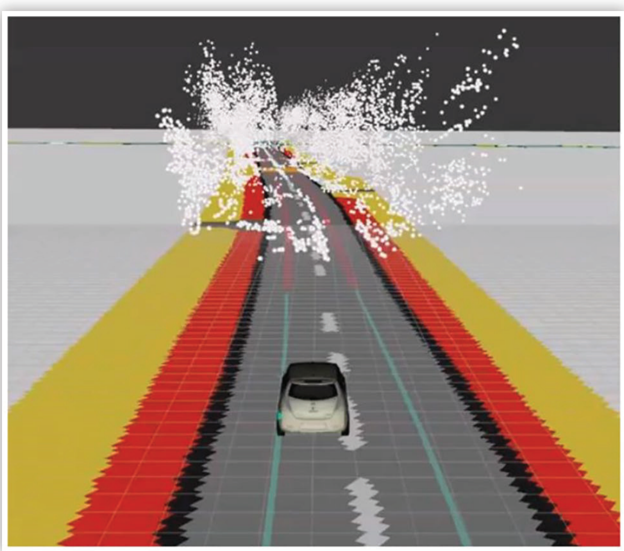


FIGURE 28 Current vehicle position shown on HD map. Furthermore, both the color of the centerlines and the pre-mapped visual features (shown by point cloud) are used to determine the operating mode of the localisation system. That is, the green colored centerline indicates RTK-GPS is available, while the red centerline and pre-mapped visual features (point cloud data) illustrate RTK-GPS is unavailable.



a high definition HD map (developed for the ServCity project) such that the geo-tagged localisation system can determine the correct mode of operation (i.e. RTK-GPS enabled or RTK-GPS disabled modes). It should be noted that our system stores approximately 30MB of visual feature data for every 100m of a given route. The approximate length of the identified GNSS denied route is 300 meters, where the total length of the route that we considered is approximately 6000m. To this end, we can achieve significant reduction in memory storage requirements for our proposed localisation system via the identification of GNSS denied routes.

FIGURE 29 The figure shows the following: 1) the status of the geo-tagged visual localisation system and visual features (keypoints) used in the visual odometer (shown in top left panel); 2) the matched visual features used by the visual positioning system to estimate an accurate vehicle pose (shown in bottom left panel); and 3) the current vehicle position shown on a HD map and the 3D position of the pre-mapped visual features (shown in right panel).

Figure 28 and Figure 29 shows the demonstration of the geo-tagged visual localisation system. In particular, Figure 28 illustrates the transition boundary of the ego-vehicle from RTK-GPS enabled region to RTK-GPS disabled region. Furthermore, the proposed geo-tagged visual localisation system was able to maintain lane-level accurate estimation of the vehicle pose for the entire length of the GNSS denied route. This can be further seen from the demonstration in Figure 29 where the estimated current pose of the vehicle (shown in the right panel of Figure 29) was aligned with lane markings on the HD map.

Conclusions

We have demonstrated that by using GIS modelling of GNSS availability we can obtain a potentially scalable solution for identifying routes that need to be pre-mapped for more accurate localisation. We further demonstrated that by capturing visual features and storing them along GNSS denied routes, we can generate more robust and accurate estimates of the vehicle's location. Future work on predicting GNSS denied routes will focus on adding more measurements, such as GNSS satellite trajectories, for even more accurate prediction of GNSS availability. Future work on visual localisation will focus on vehicle-to-vehicle collaboration, whereby information shared between multiple vehicles will be leveraged for even more accurate localisation.

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