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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.

cost camera based localisation system as a replacement for the GNSS measurements along the GNSS denied region; while for GNSS available regions, we determine global vehicle location using standard GNSS measurements. Our proposed camera based localisation solution uses pre-mapped visual features for vehicle relocalisation in GNSS denied regions. The effectiveness of the proposed method was evaluated on real-world data.

Related Work

GIS methods to create and use DSMs and to perform operations on geometries have existed for a long time and have been used in many studies [9,10,11]. Environment agency (United Kingdom) have published models at up to 25cm resolution derived from their national LiDAR programme[3]. To enable positioning a receiver needs contact to at least four GPS satellites [12]. A comprehensive, well documented, user friendly Python library for calculation of astronomical movements including earth-based satellites is provided as open source by Skyfield [8]. Effort has already been made to understand how obstructions in the environment affect GNSS accuracy. Examples include Kastendeuch's method to estimate sky view factors (SVF) for complex geometries from a digital elevation model (DEM), which considers slopes and transmittance of objects. This method has been developed for climatological purposes to understand radiative exchange using an SVF equation and a polygonised finite sky dome, the result of which expresses the proportion of radiation leaving the sky [5]. Another is Deep et al's attempt to develop a Signal-to-Noise Ratio (SNR) prediction model using a DEM and a 3D model generated using Total Station, with similar applications of understanding satellite signal propagation in mind [6]. Of note is the University of Nottingham's Mapping Obscuration of GNSS in Urban Landscapes (MOGUL) work, which created algorithms for deriving horizon masks from on board vehicle cameras; such masks illustrate percentage of available view of sky at a specified point [4].

Vision based localisation has been extensively studied in the field of mobile robotics, where a variety of systems have been proposed that range from full vision only mapping and localisation (visual SLAM [13]), to multi-sensor fusion based approaches that use visual odometry. Visual SLAM based approaches localise a mobile robot by tracking features and constructing maps using visual features that are extracted from a camera. The map constructed in visual SLAM is used to aid localisation of the vehicle by solving a nonlinear optimisation problem [13]. While such approaches have shown to perform well on a wide range of mobile robotics problems, the absolute accuracy of such systems cannot be guaranteed as visual SLAM systems can only ideally (ideal performance may also not be guaranteed for real world data) compute a metrically consistent trajectory for the mobile robot (i.e. the estimated trajectory from visual SLAM is similar to the actual trajectory by a special Euclidean SE(3) transformation). The works in [14,15,16] also propose similar full visual SLAM solutions that are similar to the work in [13]. In order to improve the absolute vehicle location accuracy, the work in [17] proposed a fusion based visual localisation system that utilised pre-mapped visual features as a replacement to GNSS measurements.

The pre-mapped visual features were constructed using both camera data and GNSS measurements (that were noisy). While the work in [17] demonstrated long range and accurate vehicle localisation, the approach replaced GNSS for the entirety of the route (they did not consider partitioning route into GNSS available/denied regions), thereby reducing computational efficiency (in particular, increased memory required). To this end, the **primary contributions** of this paper are as follows:

1. Demonstrating a method to map estimated GNSS availability across the United Kingdom. Using widely available datasets and proven open-source GIS tools detailed measures are achieved by combining horizon masks generated from digital surface models with satellite locations computed using the Skyfield API.
2. Informed by GNSS availability, we propose to pre-map regions that have been identified as GNSS denied such that vision based location measurements (using pre-mapped visual features) can then be used in such regions. If GNSS is determined to be available in a specific region, we would rely on the GNSS measurements, thereby improving both the accuracy and scalability of the overall localisation system.

In subsequent sections we first introduce the GIS based GNSS forecasting tool that we use in order to determine GNSS availability. We then introduce our proposed hybrid GNSS/Visual localisation system that we term geotagged visual localisation.

GIS Based GNSS Forecasting

GNSS plays an important part in the navigation and location parts of operating a CAV. Adequate connectivity and signal trust is key to the understanding of where the vehicle is located alongside other sensor information. By far the most common reasons for poor accuracy of GNSS signals are direct signal blockage by buildings, bridges, and trees, and multipath signals reflected off buildings, walls or the landscape. The latter plays a significant part in degradation of positional accuracy and is influenced by the materials and angles of surfaces in complex ways. Far less common causes are radio interference and jamming; major solar storms; satellite maintenance or manoeuvres creating temporary gaps in coverage; and improperly designed devices that do not comply with GPS Interface Specifications [7].

For these reasons, it will be necessary to model the built and natural environment along the route a CAV will drive as well as predicting where the satellites will be positioned in relation to the CAV at the time of driving. The model created

[3] https://data.gov.uk/dataset/f0db0249-f17b-4036-9e65-309148c97ce4/national-lidar-programme

as part of ServCity is strategic and will not include multipath signals, solar storms, or bad weather. To predict the availability of GNSS in a specific location we propose the following process for the GPS forecasting routines.

Modelling the View of Sky

Simplistically the view of sky modelling can be illustrated as in Figure 1. Figure 2 demonstrates a model of the view of sky at sample locations along a street, derived by tracking the altitude of the horizon as a function of:

- Viewpoint (vehicle antennae location x, y and height).
- Azimuth or 'compass-direction' (a 360-degree view). See Figure 3.
- Surrounding built and natural environment in the form of a high-resolution digital surface model (DSM) within 500m of view point. See Figure 4.

FIGURE 1 The view of sky is the part of space that is not blocked by buildings, vegetation, and the topology of the landscape. The defining features that block the view need not be the closest or the tallest within a certain distance, but is defined as the one with the largest angle to the horizon.

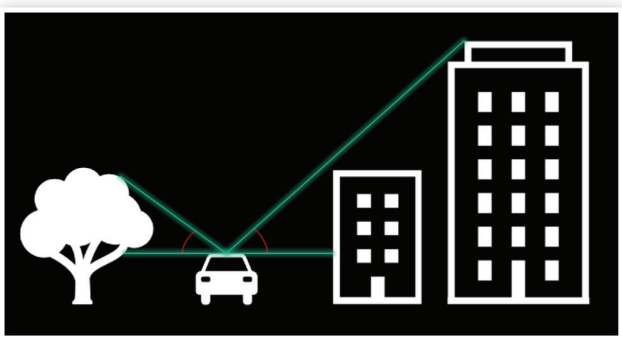


FIGURE 2 The horizon is modelled as a shape that fits inside a circle where the perimeter represents 0 degrees above theoretical horizon and the centre represents 90 degrees (directly above). The contour of the horizon represents the angle to the altitude in the direction of view - the smaller the hole in the donut the less sky is visible from the observation point.

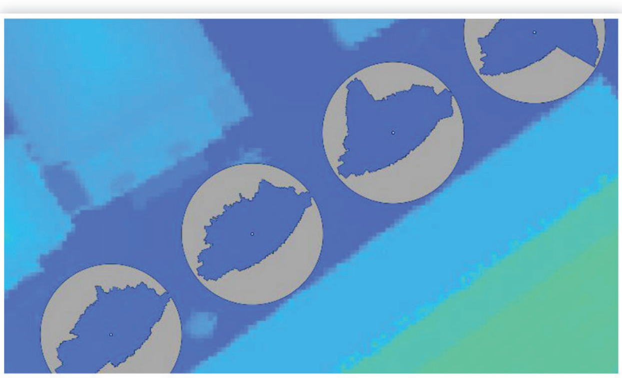


FIGURE 3 Viewpoints are marked with a white dot on the road. Example of radial lines covering every 2 degrees of the circle are computed for one point. Building and road polygons from Ordnance Survey MasterMap Topography Layer © Crown copyright and database rights 2021 OS 100063502.

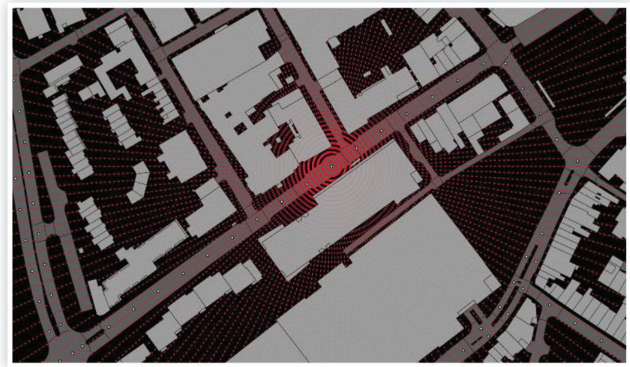
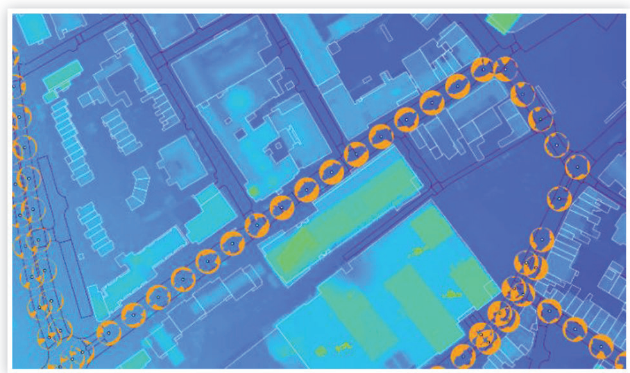


FIGURE 4 Using SAGA GIS to extract a profile along the DSM for each of the radial views. A horizon altitude can be calculated for each line. DSM from the National LiDAR Programme ©2021 Environment Agency. Building and road polygons from Ordnance Survey MasterMap Topography Layer © Crown copyright and database rights 2021 OS 100063502.



Predicting the Positions of GNSS Satellites

Skyfield API for Python[4] was used to predict the positions of relevant GNSS satellites. An example of output is shown in Figure 5. Azimuth and altitude were calculated for every location in 5 minute intervals covering the relevant time period as a function of:

- Location (latitude, longitude, elevation) using WGS84 coordinate system.
- Local date and time for starting the calculations.
- Most recent general perturbations (GP) information for GPS satellites in the form of Two-Line Element Sets (TLEs) (downloaded from CelesTrak[5]).

[4] http://rhodesmill.org/skyfield/
[5] http://celestrak.com/NORAD/elements/gps-ops.txt

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.

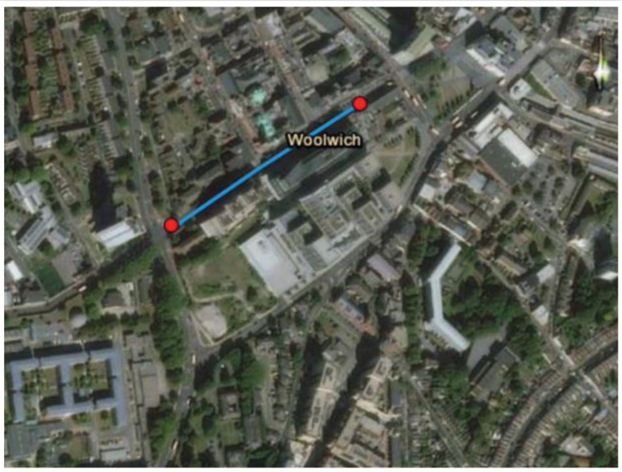
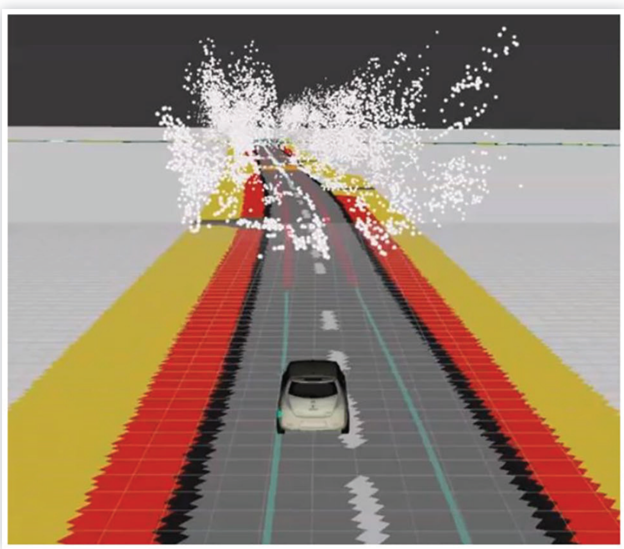


FIGURE 28 Current vehicle position shown on HD map. Furthermore, both the color of the centerlines and the pre-mapped visual features (shown by point cloud) are used to determine the operating mode of the localisation system. That is, the green colored centerline indicates RTK-GPS is available, while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

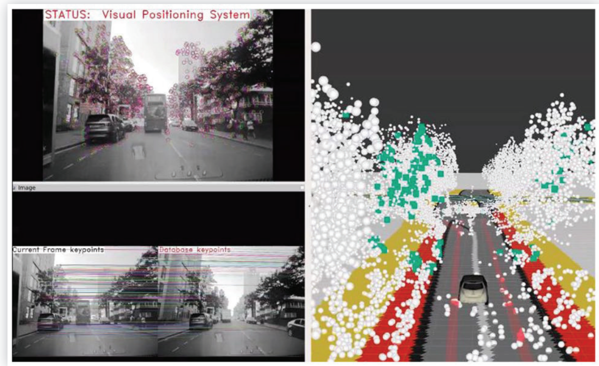


Figure 28 and Figure 29 shows the demonstration of the geo-tagged visual localisation system. In particular, Figure 28 illustrates the transition boundary of the ego-vehicle from RTK-GPS enabled region to RTK-GPS disabled region. Furthermore, the proposed geo-tagged visual localisation system was able 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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