IET Intelligent Transport Systems

Research Article

Longitudinal error improvement by visual odometry trajectory trail and road segment matching

ISSN 1751-956X
Received on 23rd May 2018
Revised 5th September 2018
Accepted on 24th September 2018
doi: 10.1049/iet-its.2018.5272
www.ietdl.org

Dayang Nur Salmi Dharmiza Awang Salleh[1] ✉, Emmanuel Seignez[1]
[1]*SATIE, ENS Cachan, CNRS, Universite Paris Sud, 91400 Orsay, France*
✉ *E-mail: dayang-nur.salmi-dharmiza@u-psud.fr*

Abstract: As one of the key requirements in the intelligent vehicle, accurate and precise localisation is essential to ensure swift route planning during the drive. In this study, the authors would like to reduce the longitudinal positioning error that remains as a challenge in accurate localisation. To solve this, they propose a data fusion method by integrating information from visual odometry (VO), noisy GPS, and road information obtained from the publicly available digital map with particle filter. The curve of the VO trajectory trail is compared with road segments curve to increase longitudinal accuracy. This method is validated by KITTI dataset, tested with different GPS noise conditions, and the results show improved localisation for both lateral and longitudinal positioning errors.

1 Introduction

Accurate vehicle localisation has been immensely researched for years, in the development towards the autonomous vehicle. While the technology has started to develop and been in the market in recent years, it does not stop the motivation for further research. Besides its application for an autonomous vehicle, the current positioning and routing technology in vehicles should also be improved. There are still many issues that need to be addressed as the road network structure is becoming more complex with urban development and this frequently causes interruptions in localisation and path planning.

While low-cost GPS is widely used for localisation, it suffers from several conditions such as the multipath and non-line-of-sight effects especially in urban areas due to the dense buildings or other constructions like tunnels and bridges [1]. Zair *et al.* [2] proposed to overcome GPS signal problem to improve its accuracy by detecting and removing the outliers. This resulted in reliable GPS data, but the method consumes complex computation and the results are inconsistent particularly in biased GPS noise. Therefore, data fusion with other sensors is desirable to overcome this problem. Data fusion for vehicle localisation can be from several sensors and among those are LIDAR, GNSS receiver, camera sensor, Inertial Measuring Unit (IMU), and a radar sensor. In addition, the digital map can also be used as an input for the data fusion. These data and information can be used together, without requiring prior computation or data compensation, to provide new information of an estimated state.

For instance, Hata *et al.* [3] proposed curb detection by 3D-LIDAR fused with motion estimation by GPS/IMU. The paper presented a novel method for curb detection by using multilayer LIDAR to extract curb structure even with the existence of obstacles. Although the localisation performance is good, it still suffers from longitudinal error and the system is quite expensive. As our research motivation, we would like to reduce the localisation system cost by avoiding high cost sensors such as LIDAR and RTK GPS although they can easily provide accurate positioning for the vehicle [4, 5]. Generally, sensors used for localisation can be divided into two – passive and active sensors. LIDAR is an example of an active sensor since it transmits light pulse and detects the reflected light. Active sensors are not only more expensive, but they also consume more energy. Therefore, we would prefer passive sensors for cost optimisation in vehicle localisation.

Meanwhile, Gu *et al.* [6] have proposed a low-cost localisation method by passive sensors data fusion from 3D-GNSS, inertial sensor and camera sensor. The inertial sensor is used to smooth the positioning trajectory, but the drift makes it difficult to achieve accurate localisation. Thus, camera sensors are utilised for lane marking detection to reduce lateral positioning error while observing lane-keeping or lane-changing behaviour. The results show submeter positioning accuracy, but the method highly relies on the availability of 3D maps and it does not consider GNSS signal outage. On the other hand, Brubaker *et al.* [7] presented an interesting localisation technique by only using a camera for visual odometry (VO), matched with the digital map by a probabilistic model. It has an interesting approach that achieved a positioning error average of about 3 m, but it failed to perform well in ambiguous road networks. Besides, these works did not include further quantitative analysis on lateral and longitudinal errors. The lateral error can usually be improved because vehicles do not move vertically, and it can be compensated by using road width information obtained from lane marking on both sides of the road as presented in [8]. However, the longitudinal error remains a problem for localisation especially when the vehicle is moving on a straight path or road without intersections.

Most of the work in vehicle localisation [9–11] utilised stop lane marking or intersection detection to correct the longitudinal position and overcome this problem but there is a possibility of occluded lane markings or roads without lane markings that can degrade the localisation performance. Previously, the authors of [3, 6, 11] proposed map matching approach by processing the image for road lane markings extractions and curb detection to compare with a road curve on the map. These localisation methods can reduce longitudinal error by profiting the vehicle's heading variation and slower speeds at intersections, which contribute to more accurate results. In fact, many studies performed an evaluation on residential road drive with intersections to compensate the VO drift after each turn [12–16]. This leaves a research gap of what will happen if the road network is a stretch of long straight road, with higher speed, or without intersections? Thus, a new strategy is required to address the longitudinal problem in such road condition.

Zeng *et al.* in [17] also presented a curve matching method whereby they performed curve comparison from GPS data with map roads. However, since GPS data typically contains noise – unless a high precision GPS device is used – it needs to be filtered to obtain a functional curve for comparison. Hence, using a similar concept, we utilise curve comparison with the road network on the map but by using VO trajectory with the assumption that the VO trajectory curve often complies with road curve. Besides, by VO