VISUAL ODOMETRY FOR TRAILER OFF-TRACKING ESTIMATION

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Abstract

Application of articulated and Long Combination Vehicles (LCVs) in challenging off-highway applications is possible with the use of path-following trailer steering. This requires an accurate estimate of trailer off-tracking, but it has been shown that that existing methods for this are not applicable on roads with low friction or significant camber or grade. Here we propose an off-tracking measurement concept using stereo visual odometry which is applicable to off-highway environments. Simulation results demonstrate the theoretical accuracy of the system as well as the effects of camera placement and stereo baseline. Rear-mounted cameras are shown to yield the best precision, with RMS off-tracking measurement errors of 7–36 mm, while side-mounted cameras offer practical benefits such as scope for multiple-trailer configurations. Integration drift errors were shown to be bounded in time due to the relative nature of the off-tracking measurement.

Keywords: Articulated HGVs; off-tracking; visual odometry; stereo vision; trailer steering

1. Introduction

The efficiency of road freight vehicles increases significantly with the size and mass of the vehicle, allowing for more payload to be transported per litre of fuel spent (OECD/ITF, 2011). Opportunities for such efficiencies include the use of tractor-semitrailer configurations instead of short rigid vehicles, and the use of Long Combination Vehicles (LCVs) instead of conventional articulated lorries.

The effectiveness of LCVs in reducing CO_2 reduction and improving logistics efficiency has been widely demonstrated, and they have been the subject of new schemes and legislation in a number of countries. Most notable is the Australian Performance-Based Standards (PBS) scheme (NTC, 2008), which is also the basis for a PBS trial in South Africa (Nordengen *et al.*, 2014).

LCVs are well-suited to on-highway applications but are limited by off-tracking behaviour in more challenging scenarios such as logging, military supply and farm collections. For these applications most LCVs require active trailer steering to achieve acceptable manoeuvrability, where accurate trailer tracking fidelity can be critical.

Trailer off-tracking is demonstrated in Figure 1(a) for a tractor-semitrailer combination. The ‘path-following’ trailer steering concept of Jujnovich (2005) is illustrated in Figure 1(b). This has been shown to effectively minimise off-tracking through active steering control while minimising trailer tail swing. This strategy can be used on tractor-semitrailer (Jujnovich *et al.*, 2013) or multiple-trailer combinations (Roebuck *et al.*, 2013) to ensure accurate path-following performance. Trailer off-tracking estimation is fundamental to the operation of this strategy.

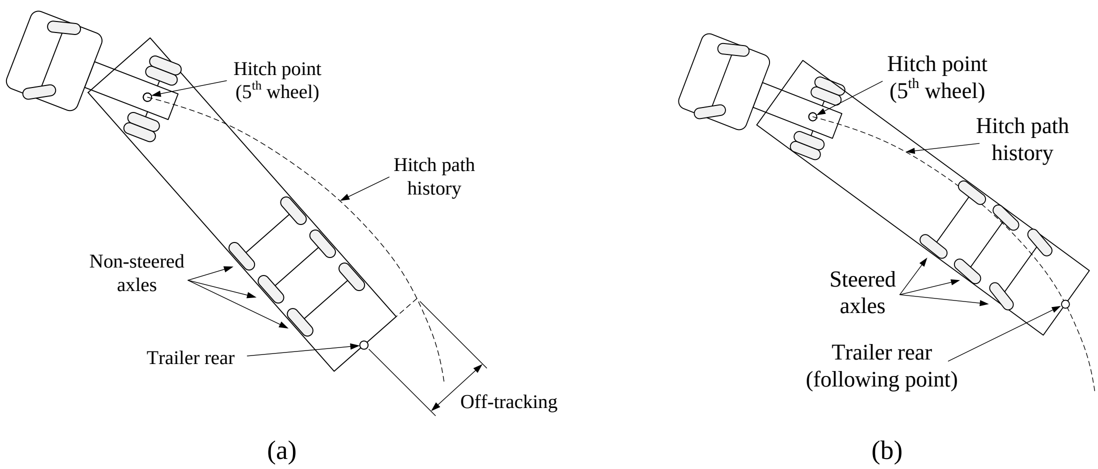


Figure 1 – (a) Trailer off-tracking behaviour with non-steered axles; (b) the path-following trailer steering strategy

It has been shown that under adverse road conditions of low friction, camber and grade, the performance of the path-following system degrades significantly due to errors in off-tracking estimation (Miao *et al.*, 2014). In response to this Miao developed a ‘ground-watching’ navigation concept to measure trailer off-tracking using two cameras mounted beneath the trailer (Miao, 2015).

The ground-watching concept is limited by the road surface condition and so has limited practical application. The present work proposes an alternative strategy for off-tracking estimation using visual odometry which is not reliant on the surface conditions of the road. The system uses three-dimensional visual information from the road-side landscape as a motion reference for the trailer.

The contributions of this paper are as follows:

1. A novel application of visual odometry for trailer off-tracking estimation is demonstrated.
2. Simulation results demonstrate theoretical system performance, and give insight into design considerations for further development.
3. Unlike global positioning visual odometry applications, errors are shown to be bounded in time.

2. Related Work

A review of the literature pertinent to the current topic follows.

2.1 Path-Following Trailer Steering

A path-following active steering concept for rigid trucks was proposed by Hata *et al.* (1989) to reduce off-tracking without increasing tail swing. This concept was extended by Notsu *et al.* (1991) for a steered semitrailer, in which the rear of the trailer actively followed the front of the tractor.

More recently, Jujnovich and Cebon (2013) developed a path-following semitrailer steering system in which the rear of the trailer follows the path of the 5^{th} wheel or hitch point. This was achieved by comparing heading angles at the front and rear of the trailer in a low-speed control strategy.

This work was extended by Cheng *et al.* (2009), using a ‘virtual driver’ at the rear of the trailer and an LQR control strategy. The system was applicable to low and high speeds, minimising a cost function with respect to either off-tracking or high-speed stability. This work was extended by Roebuck *et al.* (2013) for multiple trailers.

2.2 Path-Following in High Slip Environments

Miao and Cebon (2014) showed how the performance of trailer path-following control is severely degraded in off-highway conditions such as low friction, camber and grade. Off-tracking errors of up 0.6 m were observed for a conventional tractor pulling a path-following steered semitrailer subjected to combinations of adverse conditions in a standard 450° roundabout manoeuvre.

Miao (2015) proposed a ground-watching navigation system to estimate off-tracking in these conditions. The concept used two ground-watching cameras beneath the trailer, one at the 5^{th} wheel and the other at the trailer rear. Performance of the system was demonstrated in vehicle tests with a tractor-semitrailer. Open-loop off-tracking estimation errors of 0.05 m were obtained, giving closed-loop path-following errors of less than 0.1 m.

Other applications of path-following in high slip environments include agricultural vehicles and planetary exploration. Cariou *et al.* (2010) developed a system to guide a towed agricultural implement (*i.e.* a trailer) along a predefined path, controlled with steer inputs from the towing vehicle. The system utilises high precision RTK-GPS, an articulation angle sensor and a kinematic vehicle model.

Helmick *et al.* (2004) proposed a visual odometry-based path-following system for a Mars rover in high-slip environments. Visual odometry data was merged with IMU data using a Kalman filter. This was complemented with kinematic measurements based on wheel speed and steer angles.

2.3 Visual Odometry and Heavy Vehicles

Visual odometry is the estimation of the pose and motion of a camera through a three-dimensional scene. Advances in visual odometry algorithms have resulted in its widespread use in the areas of autonomous road vehicles and mobile robotics. Compared to other odometry systems such as wheel speed sensors and GPS, visual odometry offers high precision, low-cost hardware, and independence from traction conditions.

Although the use of cameras for vehicle odometry is commonplace in autonomous vehicles (see for example (Geiger *et al.*, 2011; Sibley *et al.*, 2010)), little work has been done with heavy vehicles. In addition to the work of Miao (2015), some work has explored trailer articulation angle measurement using both mono and stereo vision methods (de Saxe & Cebon, 2015; Harris, 2013), with precision in the order of 1°.

3. Method

Miao's ground-watching concept (2015) assumes an unchanging road surface with static features. This assumption is invalidated if the road surface is soft and disturbed by the passing vehicle or if the surface is reflective as in the case of standing water or snow. These road conditions are an important consideration in off-highway applications.

The method in this paper is to fix a stereo camera pair to the trailer to obtain visual odometry data from the road-side surroundings. These data can be manipulated to estimate trailer off-tracking by finding the relative trajectories of the 5th wheel and trailer follow point.

Off-tracking measurement error needs to be in the region of 0.1 m for suitable path-following control (Cheng, 2009; Jujnovich & Cebon, 2013).

3.1 Visual Odometry

The VISO2-S visual odometry algorithm of Geiger *et al.* (2011) was used in this work, and is freely available online. Details of the algorithm may be found in the reference and can be summarised into the following steps:

1. A stereo image pair is obtained and corner-like features are detected in each image.
2. 'Circular' feature matching is performed, comparing features between left and right images (normal stereo matching) as well as between current and previous image pairs. Features are accepted if matching succeeds through the full loop of four images.

3. A ‘bucketing’ process (Kitt, *et al.*, 2010) divides the images into a rectangular grid, and each ‘bucket’ may only store a maximum number of features. This ensures a good distribution of features in the image, minimising the effects of bias and of moving objects.
4. Ego-motion is estimated by minimising the sum of re-projection errors. This requires calibration parameters for the stereo camera pair. Gauss-Newton optimisation is performed with respect to R and **T**, the rotation matrix and translation vector respectively.
5. The ego-motion estimation incorporates a RANSAC strategy to remove outliers.
6. A constant acceleration Kalman filter is used to minimise noise.

In (Geiger *et al.*, 2012), the VISO2-S algorithm was shown to yield 2.44% translation error and 0.0114 °/m rotation error in the ‘KITTI’ dataset, using a stereo baseline of 0.5 m. The algorithm runs at 20 fps on a single processing core.

A mono camera version of the algorithm exists but is less accurate, less computationally efficient, and relies on scene assumptions. The use of two cameras was not deemed to be a limiting factor in this application and so the stereo system was adopted. For practical applications stereo vision remains the preferred solution with only a marginal increase in cost.

Using a representative trailer length of 14 m (from hitch to rear), translation drift of 2.44% would result in 0.0224 × 14 m = 0.3136 m of lateral off-tracking error between the hitch point and the rear of the trailer (approximately one tyre width). It is expected that this error could be reduced by increasing the stereo baseline.

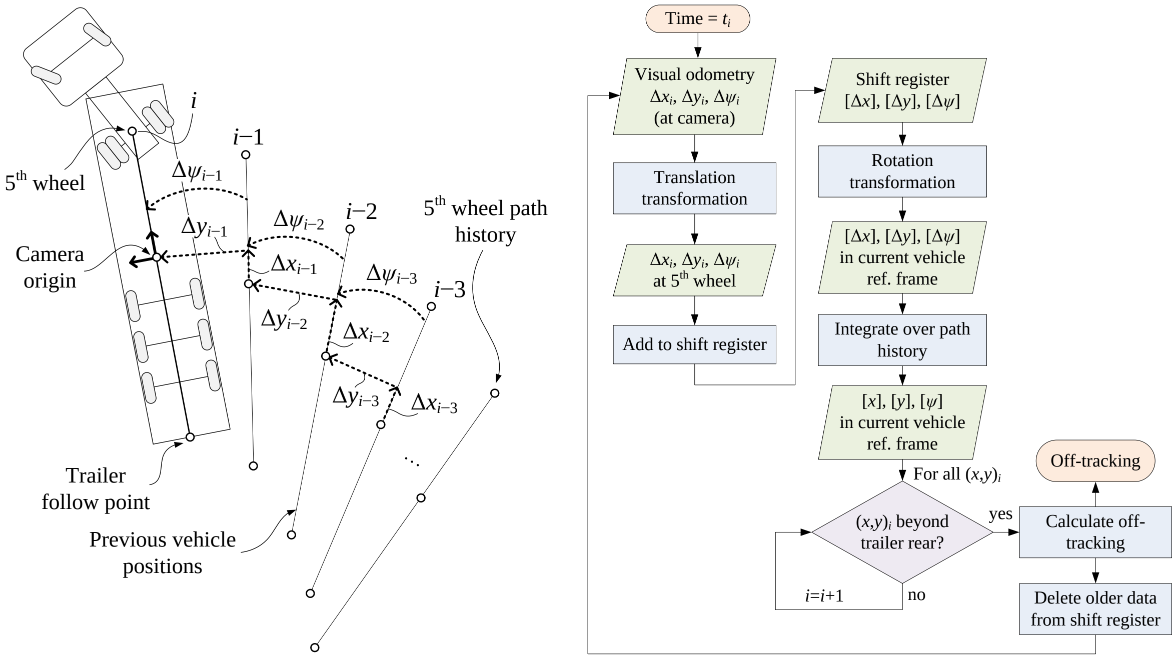
3.2 Off-tracking

The goal is to calculate off-tracking between the rear of the trailer and the 5th wheel trajectory, given visual odometry data from a stereo camera pair fixed to the trailer. Visual odometry data are given in the form of a rotation matrix, R, and translation vector, **T**, at each time step. R and **T** are relative to the prior vehicle location and reference frame. Off-tracking is measured perpendicular to the longitudinal axis of the trailer.

Figure 2(a) illustrates the piecewise yaw-plane motion of a tractor-semitrailer combination at time steps i, $i-1$, $i-2$, *etc.* The camera origin has been arbitrarily assumed to be at some distance along the trailer longitudinal axis. The raw visual odometry data is shown in the form of Δx, Δy and $\Delta\psi$: incremental translation and rotation at each step.

To calculate off-tracking from visual odometry data, the incremental motion must first be transformed to incremental motion at the 5th wheel. Then this motion needs to be updated at each time step to match to coordinate frame of the current vehicle position, i. Translation data may then be integrated over the length of the trailer to calculate off-tracking.

A shift register is used to store motion data to allow for integration over the trailer length. Initially the shift register will grow. Once one trailer length has passed, off-tracking can be calculated and any data beyond the rear of the trailer can be discarded. Thereafter the shift register size will vary with the speed and path of the vehicle as outdated data is removed. The method is summarised in Figure 2(b).



(a) (b)

Figure 2 – (a) Raw visual odometry data for arbitrarily located cameras; (b) flowchart illustrating the calculation of trailer off-tracking from odometry data

Integration drift is inherent in visual odometry systems and is a result of integrating incremental odometry data relative to a global reference frame. In this application integration is performed only in a relative sense from the hitch to the rear of the trailer. As a result integration drift is bounded by the length of the trailer and will not grow with time. Further, any significant outliers in the visual odometry data will be removed from the shift register after one trailer length has passed.

3.3 Wide-Baseline Stereo

Increasing the baseline of a stereo camera pair can improve depth accuracy and hence odometry accuracy (Olson & Abi-Rached, 2010). However the extent to which this can be utilised is limited due to the increasing difference in perspective between the two cameras. This will negatively affect feature matching between stereo image pairs. For this reason standard stereo vision algorithms are often adapted for wide-baseline applications (see for example (Olson & Abi-Rached, 2010)).

There is also a practical limitation for passenger vehicles and mobile robots, where the camera baseline cannot practically exceed the dimensions of the vehicle or robot, or even some proportion of it. Goods vehicle are an application where wide-baseline stereo vision may be practical, given the larger vehicle dimensions.

Wide baselines were considered as part of this investigation. In this case the distance to scenery is assumed to be sufficiently large that no alterations to the stereo matching algorithm were necessary. Calibrating a stereo pair in practice becomes more challenging for wide baselines but this was not addressed in this study.

4. Simulation Overview

To assess the feasibility and theoretical accuracy of the system, simulations were carried out in the Autodesk Inventor CAD environment ("Inventor Professional 2013," 2013). Visually representative virtual road and roadside environments were constructed including a gravel road, grassy roadsides, trees, shrubs, fences, and distant clouds, as shown in Figure 3(a).

Road width was set to 5 m (within the U.K. rural road design guidelines), and the size of objects and textures were chosen to be representative. Soft ambient lighting and shadows were incorporated and all scenery was stationary.

A virtual stereo camera pair was made to follow a straight road path at a fixed slip angle, representative of a trailer moving with constant off-tracking (due to a cambered road surface for example). This is illustrated in Figure 3(b). These cameras have no distortion and their intrinsic parameters may be set manually, and known precisely without calibration.

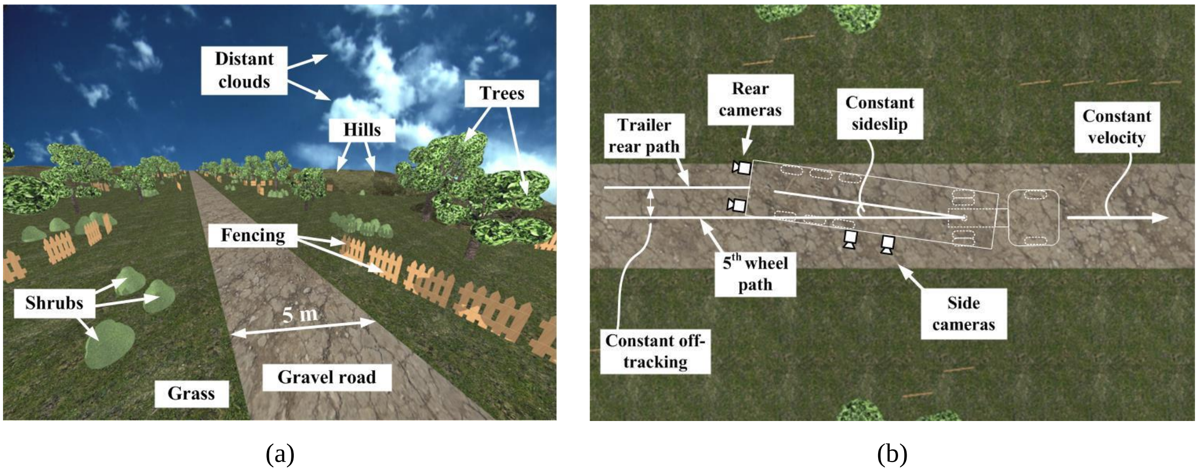


Figure 3 – CAD simulation environment: (a) Overview of CAD environment; (b) testing arrangement with constant sideslip (*e.g.* on a cambered road)

Simulations were carried out with five different slip angles (0.0, 2.5, 5.0, 7.5, 10.0 m) and three stereo baselines (0.5, 1.5, 2.5 m). Rear- and side-mounted camera arrangements were considered.

Each run was 100 m in length with a constant speed of 5 m/s. Images were captured at a resolution of 1344 × 391 at 10 frames per second (fps). The cameras were located 3 m above ground level with zero tilt and roll angles relative to the ground. The trailer length from 5th wheel to follow point was taken to be 14 m which is representative of a U.K. semitrailer.

The default input parameters for VISO2-S were used, including 200 RANSAC iterations per optimisation, outlier flow and disparity thresholds of 5 pixels, a bucket size of 50 × 50 pixels and a maximum of 2 features per bucket.

5. Results

Sample views of the virtual environment from the rear and side camera pairs are shown in Figure 4. Locations of matched features are shown in each image. The side-mounted cameras give a narrower distribution of feature depths. RMS and mean errors for the simulations are shown in Figure 5 for side and rear cameras and for all slip angles and baselines considered.

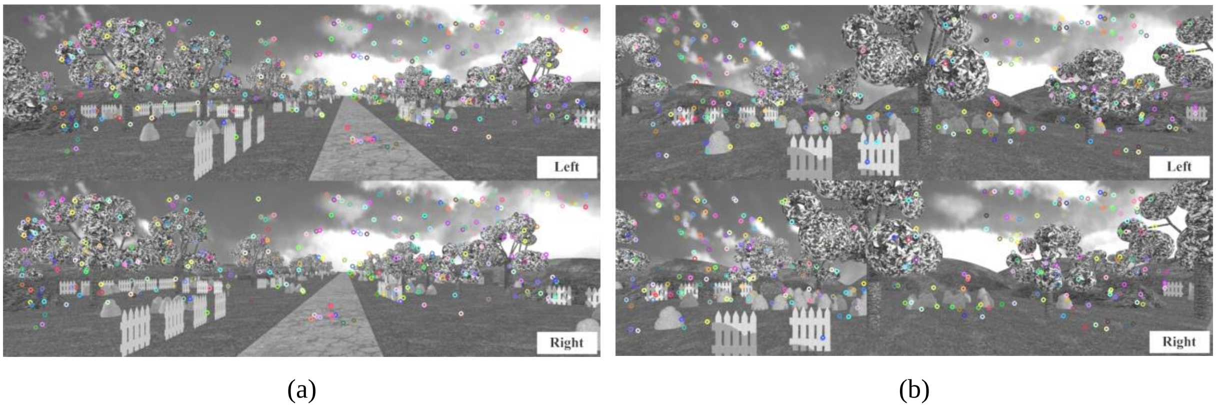


Figure 4 – Rear (a) and side (b) camera views at 10° slip angle and 2.5 m baseline

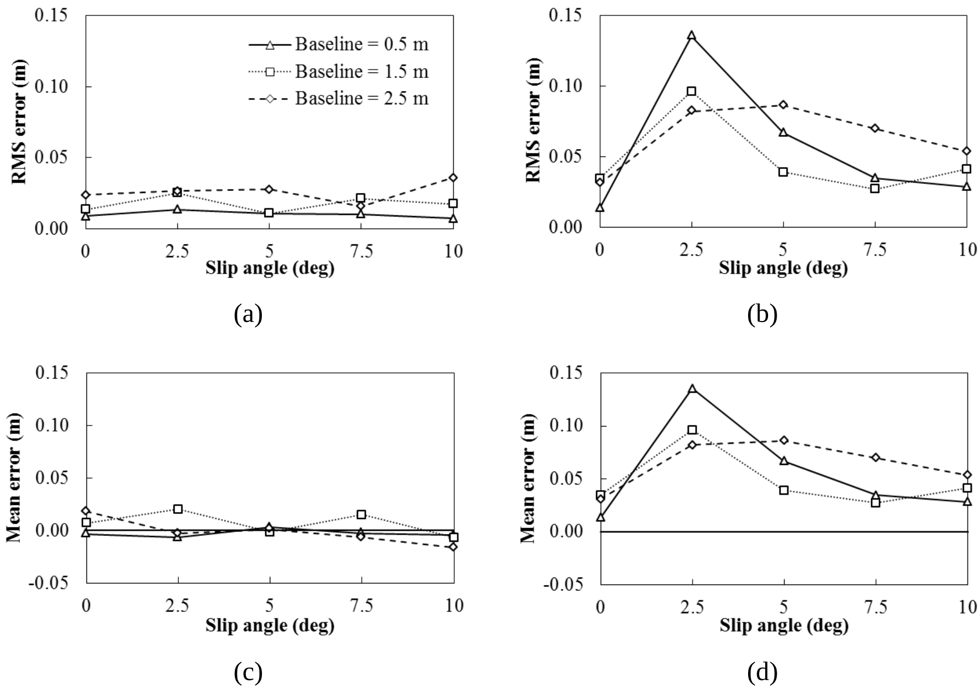


Figure 5 – Simulation results: RMS errors for (a) rear cameras and (b) side cameras; mean errors for (c) rear cameras and (d) side cameras

Results show the rear cameras yield RMS errors in the range 0.009–0.036 m, with the side cameras yielding consistently higher errors. The better performance of the rear cameras is likely due to the higher range of feature depths, providing more precision to the stereo triangulation calculations.

The rear cameras also show a favourable mean error response (0.001–0.02 m), indicating little or no bias. The side cameras show a clear bias in all runs. This is possibly due to the fact that for slip angles less than 45°, pixel movement due to off-tracking has a higher component in the image plane for rear cameras versus side cameras.

The effect of stereo baseline is not conclusive, but Figure 5 suggests a small negative effect of increasing the baseline. The small loss in performance is likely due to the loss in feature matches due to the higher perspective difference.

This is illustrated in Figure 6 which shows the feature matching statistics. The mean number of feature matches and the percentage of these which are inliers are shown. Increasing the baseline reduces both these figures as expected.

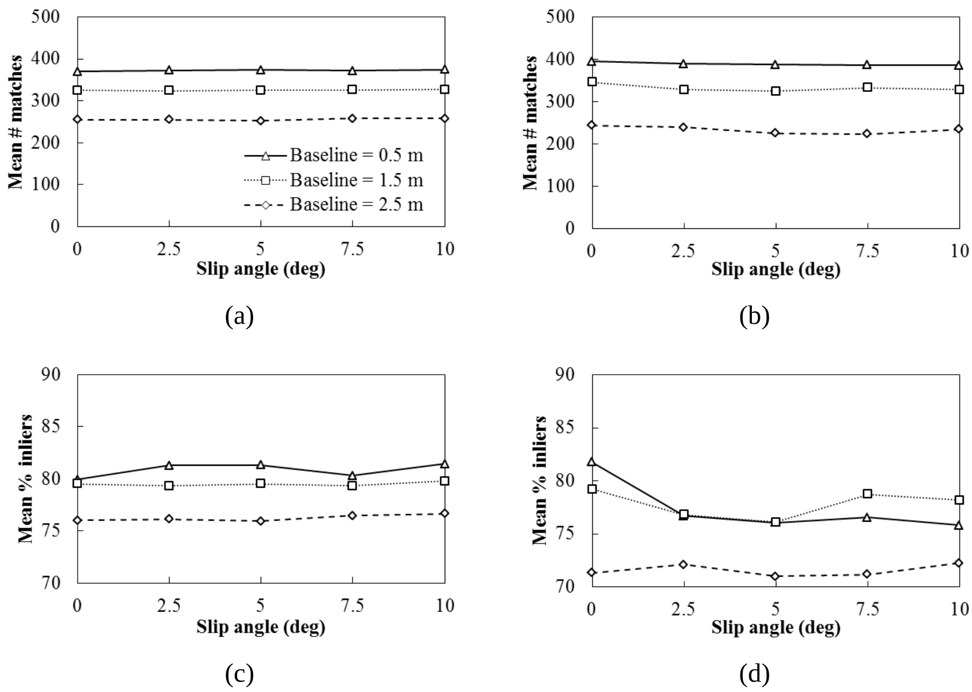


Figure 6 – Simulation results: mean number of feature matches for (a) rear cameras and (b) side cameras; mean % inliers for (c) rear cameras and (d) side cameras

These drops in feature matches only appear to have a small effect on accuracy in these simulation conditions. In conditions with fewer feature points this may become more pronounced. It is expected that a wide baseline will improve performance in the presence of real-world noise and camera calibration errors due to more precise triangulation.

An example time history is shown in Figure 7(a), at 7.5° slip and 2.5 m baseline. The reference value is shown as a dashed line. No cumulative drift is apparent in these or any of the other results. Instances of *temporary* error drift were observed in some results, for example in Figure 7(b) (side cameras, 5° slip, 1.5 m baseline). Here drift develops in region ‘A’, with constant error in the range 74–88 m (region ‘B’).

The source of this can be seen in Figure 7(c), in the visual odometry data in the camera Z-direction, where Z in this case is in the direction of off-tracking measurement. While the data exhibit predominantly zero-mean noise, in region ‘A’ there is a distinct sequence of biased outliers (circled) relative to the dashed reference value.

The sum of the magnitudes of these outliers equates to a cumulative error of about 0.08 m, which is comparable to the observed off-tracking error in region ‘B’. The effect disappears after approximately one trailer length has passed (14 m) and the corrupting data points are discarded from the shift register.

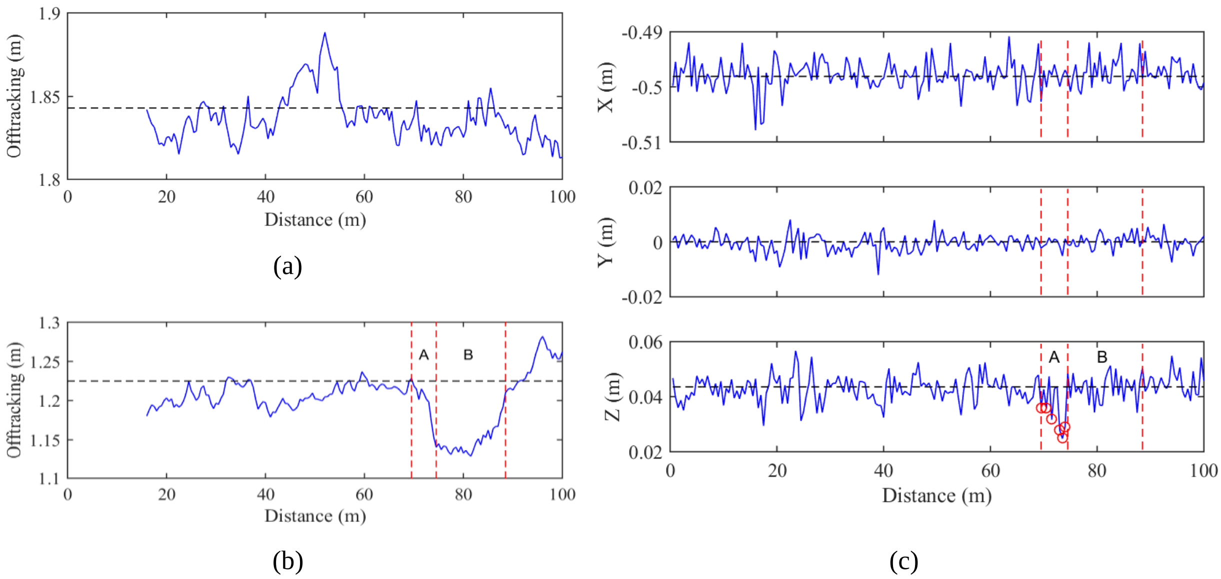


Figure 7 – (a) Rear camera off-tracking results, 7.5° slip, 2.5 m baseline; (b) side camera off-tracking results, 5° slip, 1.5 m baseline; (c) visual odometry data for (b)

6. Conclusion

This work has demonstrated a proof-of-concept for trailer off-tracking estimation using visual odometry. The performance demonstrated is theoretical but informative for further development.

In reality, camera calibration parameters will not be known exactly, the density and depth of features will differ, and images may include lighting and blur disturbances. Moving scenery is not expected to have a significant effect on performance due to the bucketing step of the VISO2-S algorithm.

Future work will focus on implementing the system on a tractor-semitrailer vehicle combination, and assessing its performance in representative off-highway environments. More analysis will be conducted on the effects of camera location, orientation and baseline on performance and practicality.

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