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GPS-Free Terrain-based Vehicle Tracking on Road Networks

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Abstract—**Prior experiments have confirmed that specific GPS-free terrain-based localization algorithms can perform vehicle tracking in real-time on a single road segment at a time. However, the ability of these algorithms to perform vehicle tracking on large road networks, i.e. across intersections and multiple road segments, has not been verified. In this study, it is shown that it is possible to build upon the existing terrain-based localization algorithms to maintain vehicle tracking in large road networks. A set of estimators based on the Unscented Kalman Filter framework is used to track the vehicle in a section of a road network, i.e. across a few road segments and an intersection. A multiple model estimation scheme, based on comparing incoming attitude measurements with a terrain map, is used to identify the road segment that the vehicle is currently traveling over. Experiments indicate that it is possible to maintain vehicle tracking as a vehicle travels across an intersection in a road network.**

I. Introduction

Several safety-critical and mission-critical applications such as path planning and navigation require the ability to accurately localize and track the position of a vehicle within a large road network [1]. While currently the de facto standard for performing these functions, the Global Positioning System (GPS) has several limitations that can impede the normal functioning of safety-critical and mission-critical applications. Specifically, poor GPS signal reception, the ability to jam GPS signals and the requirement to maintain redundancy in vehicle automation and driver assist systems necessitates the development of alternative localization and tracking techniques [2]. Previous work has shown that terrain-based vehicle tracking offers a promising alternative to the Global Positioning System (GPS) [2]. While terrain-based localization algorithms have been shown to work within a single road segment, their performance for vehicle tracking in a large road network has not been verified.

In the past, techniques for vehicle tracking on road networks have utilized a combination of dead-reckoning and GPS, along with a map-matching framework. [3] [4]. Map-matching is generally performed using tools such as neural networks [5], fuzzy logic [6], Hidden Markov Models [7], Kalman filters [8] etc. The map-matching framework essentially tries to correlate the current yaw measurement (or pose) of the vehicle with the yaw of various roads in the network to identify the road the vehicle is currently traveling on [3]. Typically, the road identification step is followed by a vehicle tracking technique to track the position of the vehicle within the identified road segment. The predominant vehicle tracking technique for this purpose is dead-reckoning, which is often fused with GPS measurements to obtain a better position estimate [8] [9]. However, the absence of GPS, combined with the errors inherent to dead-reckoning, can lead to excessive tracking errors that cannot be tolerated in safety-critical and mission-critical applications. Consequently, alternative vehicle tracking techniques for road networks are required.

The authors have previously proposed and experimentally verified a GPS-free terrain-based vehicle tracking algorithm that uses a pre-recorded terrain map and odometry to track a vehicle [2] [10] [11]. The algorithm relies heavily on the fact that the correct terrain map of the road being traversed is known. However, in certain road geometry scenarios, such as crossing an intersection, the correct terrain map may be ambiguous because the intersection leads to multiple potentially correct traversal paths, each with their own terrain maps.

In this paper, the use of a multiple model estimation framework is proposed where each of the set of potentially correct terrain maps at an intersection is considered as a possible model of the system. The proposed method relies primarily on pitch measurements, though all three attitude measurements, i.e. roll, pitch and yaw, can be used in principle. The suggested method offers several advantages over the traditional map-matching techniques which primarily rely on yaw [5] [6] [7]. Specifically, the proposed use of pitch measurements enables accurate vehicle tracking even in the absence of supplemental measurements from GPS. A key insight of this paper is to realize that the use of pitch measurements enables the discrimination of the currently traversed road segment among many choices, so as to maintain vehicle tracking across multiple roads in a large road network.

Section 2 provides a short overview of the GPS-free terrain-based vehicle tracking technique. Section 3 discusses vehicle tracking on a road network using a multiple model estimation scheme. Section 4 includes a discussion of results obtained from on-line simulation using data collected at a T-junction. Section 5 concludes the paper with a summary of the main results.

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II. GPS-FREE TERRAIN-BASED VEHICLE TRACKING

This section provides an overview of the GPS-free terrain-based vehicle tracking framework. At the heart of the framework is the idea that, as a vehicle travels over a road, attitude measurements (pitch or roll or yaw or combinations thereof) obtained from an inertial measurement unit are sent to the tracking algorithm, which then correlates them to a pre-recorded terrain map. Specifically, the algorithm uses an Unscented Kalman Filter (UKF) to track the current position of the vehicle [12] [13]. The current position (or state) of the vehicle is defined as the distance of the vehicle from the last traversed intersection. The system model is given by (1), which represents the propagation of the system state, i.e. the current position of the vehicle:

$$x_{k+1} = x_k + u_k + w_k \tag{1}$$

where x_{k+1} denotes the position of the vehicle at time $k+1$, x_k denotes the position of the vehicle at time k, u_k denotes the distance moved by the vehicle as determined through odometry, and w_k denotes the zero-mean Gaussian process noise in odometry measurements. The measurement model is given by (2), which relates the current position of the vehicle with the corresponding attitude measurement.

$$y_k = f_{NL}(x_k) + v_k \tag{2}$$

where y_k denotes the attitude measurement at time k and is a nonlinear function of the vehicle position at time k, and v_k denotes the measurement noise at time k. The nonlinear function (or *terrain map*) is defined as a lookup table stored in a database that relates the position along a road to a pre-recorded attitude measurement.

An Unscented Kalman Filtering framework is used to estimate the current vehicle position, as discussed in [14]. A short overview of the algorithm is included here. The sigma points, as described in [15], are initialized according to (3) as follows:

$$X_{k-1} = [x_{k-1}, x_{k-1} + C, x_{k-1} - C] \tag{3}$$

where $C = \alpha\sqrt{N_s \cdot P_{k-1}}$, α is an algorithm parameter, N_s is the number of system states, and P_{k-1} is the covariance of the position estimate at time $k-1$.

The time update (or *prediction*) step propagates the system states forward in time according to (4), (5) and (6) as follows:

$$X_k^- = X_{k-1} + u_k \tag{4}$$

$$x_k^- = X_k^- \cdot W_m \tag{5}$$

$$P_k^- = [X_k^- - x_k^-] W_c [X_k^- - x_k^-]^T + Q \tag{6}$$

where X_k^- denote the *a priori* sigma points, x_k^- denotes the *a priori* position estimate, P_k^- denotes the *a priori* position covariance, and W_m, W_c and Q are algorithm parameters.

Next, the measurement update (or *correction*) step processes the newly obtained measurement in order to provide a correction for the *a priori* position estimate and covariance according to (7), (8), (9), (10) and (11) as follows:

$$Y_k = f_{NL}(X_k^-) \tag{7}$$

$$y_k = Y_k \cdot W_m \tag{8}$$

$$P_{yy,k} = [Y_k - y_k] W_c [Y_k - y_k]^T + R \tag{9}$$

$$P_{xy,k} = [X_k^- - x_k^-] W_c [Y_k - y_k]^T \tag{10}$$

$$K = P_{xy,k} \cdot P_{yy,k}^{-1} \tag{11}$$

Here, (7) represents the terrain map lookup step, where the *a priori* sigma points are used to recover the corresponding attitude measurements at those locations, y_k denotes the effective attitude measurement at the *a priori* position estimate x_k^-, and K represents the filter gain. Finally, the *a posteriori* position and covariance estimate are given by (12) and (13) as follows:

$$x_k = x_k^- + K \cdot (\theta_k - y_k) \tag{12}$$

$$P_k = P_k^- - K \cdot P_{yy,k} \cdot K^T \tag{13}$$

where θ_k denotes the attitude measurement obtained at time k. The filtering scheme represented by (3) – (13) is used to track a vehicle on a given road segment using attitude measurements, odometry and the correct terrain map. The next section discusses how this scheme may be extended to maintain vehicle tracking in a large road network.

III. MULTIPLE MODEL ESTIMATION FRAMEWORK FOR LARGE ROAD NETWORKS

This section discusses the multiple model estimation framework in the context of vehicle tracking on large road networks. It has been established that in order to effectively track a vehicle using terrain data, three elements are required, viz. (a) odometry, (b) attitude measurements over the current location, and (c) an accurate terrain map that has pre-recorded information which relates attitude data to the locations along the road. However, as a vehicle navigates across a large road network, certain road geometry situations may arise that raise doubts as to the veracity of the terrain map at hand. Specifically, as a vehicle moves across an intersection and onto a different road, the new terrain map may be any one of the terrain maps corresponding to the roads that lead away from the intersection. As a consequence, in this scenario the correct terrain map is unknown. Since it is known that one of a set of terrain maps is the correct map, a multiple model estimation framework may be used to maintain vehicle tracking.

The starting point of the multiple model estimation framework is the filtering scheme discussed in the previous section. In the GPS-free terrain-based vehicle tracking problem, a specific terrain map was used in (7) to provide the measurement update. However, in the current scenario the correct terrain map is unknown. On the contrary, a set of potentially correct terrain maps is available and one of them must be chosen to maintain accurate vehicle tracking. In order to solve this problem, N UKF estimators must be set up to run simultaneously, where N is the number of roads leading away from the intersection. Each estimator is tasked with tracking the vehicle based on the terrain map assigned to it, while a separate algorithm tries to identify the estimator that possesses the 'correct' terrain map. The 'correct' terrain map is defined as the terrain map within a set of potentially correct maps that best represents the terrain that the vehicle is currently traveling over.

Each estimator i is assigned an initial probability $P_0^i = 1/N$ that denotes the probability that the terrain map (or model) used in *its* measurement update step (7) is the correct one. As new attitude measurements are received, these are compared against the terrain map in each estimator and the corresponding probabilities are updated. If T_i represents the event that the terrain map (or model) used in estimator i is the correct one, then the probabilities are propagated according to (14) as follows [16]:

$$P(T_i|\theta^k) = \frac{P(T_i|\theta^{k-1})\, f(\theta_k|T_i,\theta^{k-1})}{\sum_{j=1}^{N} P(T_j|\theta^{k-1})\, f(\theta_k|T_j,\theta^{k-1})} \quad (14)$$

where $P(T_i|\theta^k)$ denotes the posterior probability that the terrain map used in estimator i is correct given all attitude measurement up to time k, and $f(\theta_k|T_i,\theta^{k-1})$ denotes the likelihood of making an observation θ_k given the terrain map in estimator i and the attitude measurements θ^{k-1} up to time $k-1$. The likelihood function $f(\theta_k|T_i,\theta^{k-1})$ is assumed to be a Gaussian with mean y_k and covariance $P_{yy,k}$ obtained from (8) and (9).

This algorithm can be better understood with a graphical aid. Fig.1 depicts a situation where a vehicle has just crossed an intersection and has two potentially correct terrain map candidates to choose from. Only one of these terrain map candidates actually represents the terrain that the vehicle is now travelling over. As the vehicle progresses forward, it receives terrain measurements that can be used to identify the correct terrain map. When measurement $\Theta(k)$ is received at time k, the likelihood that it belongs to either of Gaussian distribution A or B is determined. In Fig. 1, the likelihood that the measurement $\Theta(k)$ is a result of the vehicle traveling over the terrain represented by Candidate 1 is greater than that of it being a result of the vehicle traveling over terrain represented by Candidate 2. The likelihoods are incorporated into a probability measure that is calculated recursively with each new measurement, using (14).

As the vehicle progresses forward, only the correct terrain map fares favorably since the incoming attitude measurements better match the effective attitude predicted in (8) resulting in a higher likelihood. Consequently, the probability of that terrain map being correct goes to one, while the probabilities of the remaining terrain maps being correct go to zero. These remaining estimators are then eliminated and vehicle tracking is maintained using the single estimator that uses the correct terrain map. The correct position estimate that is output by the multiple model estimation scheme is the one that corresponds to estimator which uses the correct terrain map. In this regard, the estimation scheme differs from traditional multiple model estimation schemes where the final state estimate output is usually a weighted average of the state estimates obtained from each model. While this may be prudent in many cases, in the current context of vehicle tracking it is not advisable due to two reasons: (a) a weighted average of final position estimates may put the vehicle at a location that does not lie on a road, and (b) as a vehicle moves through multiple sequential intersections, the number of potential pathways and as result, the number of required estimators, would grow exponentially unless they are eliminated in the manner discussed above.

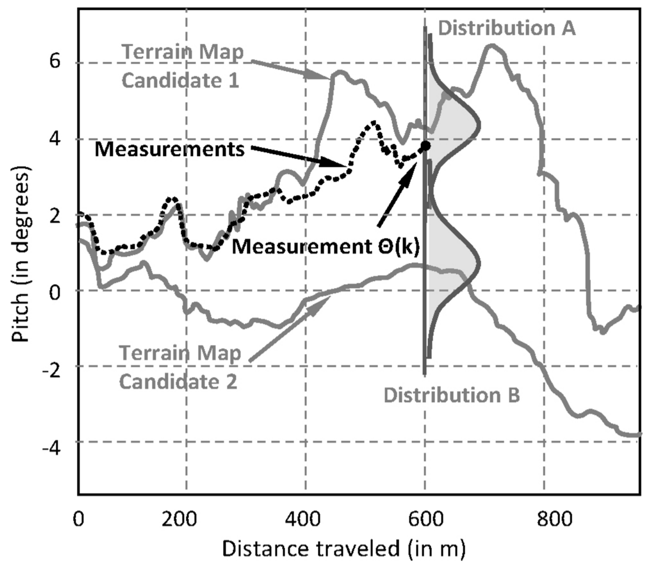

Fig. 1. Selection of correct terrain map. Newly available measurements are compared against the possible terrain maps to determine the correct map of the terrain that the vehicle is currently traveling over.

IV. Experiments and Results

This section discusses experiments and results obtained from field testing the described multiple model estimation implemented at a T-junction. The experiment was performed at the intersection of Rock Rd. and Buffalo Run Rd. in State College, PA. Fig. 2 depicts the intersection where the experiment was carried out [17]. The experiment consists of two phases: (a) the data collection phase, and (b) the test run phase.

In the data collection phase, two terrain maps were generated: one for the vehicle taking a right turn at the intersection from Buffalo Run Rd. onto Rock Rd. (Terrain Map 01) and another for the vehicle traveling straight through the intersection on Buffalo Run Rd. (Terrain Map 02). The attitude data collected for the two routes are included as Fig. 3. It is observed that there is a significant difference in the pitch profiles of the two roads after the intersection.

Next, in the test run phase, the vehicle position was tracked as the vehicle traveled on Buffalo Run Rd. and took a right turn at the intersection on to Rock Rd. The set of operations that execute in the vehicle tracking algorithm in such a scenario, i.e. when an intersection is encountered, include (a) recognizing that an intersection has been reached, (b) constructing multiple estimators, one for each road leading up to the intersection, (c) tracking the vehicle position on each road leading up to the intersection, based on the corresponding terrain maps, (d) selecting the estimator that is using the correct terrain map based on the method outlined in Section 3, and (e) eliminating the remaining estimators and continuing to track the vehicle using the selected estimator.

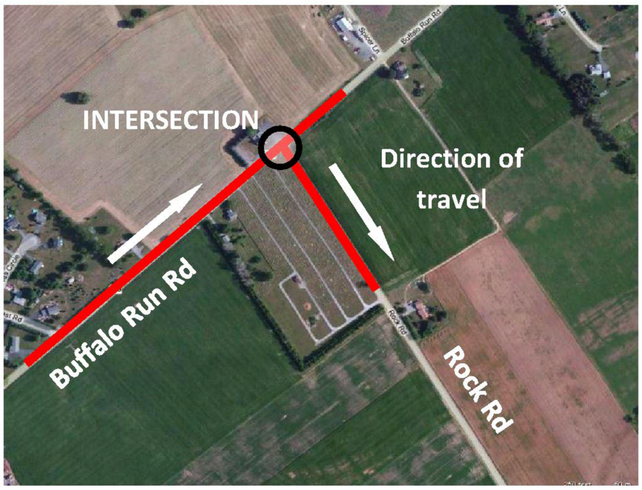

Fig. 2. Site of the experiment at the intersection of Rock Rd and Buffalo Run Rd. Two terrain maps were created, one each for (a) taking a right turn at the intersection From Buffalo Run Rd. onto Rock Rd., and (b) going straight through the intersection on Buffalo Run Rd.

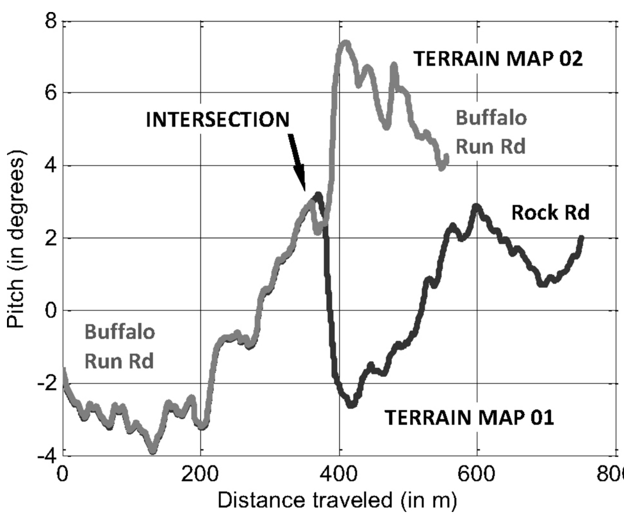

Fig. 3. Attitude data collected during terrain map generation process for Buffalo Run Rd. and Rock Rd. Notice the difference in pitch values after the vehicle crosses the intersection.

In this proof of concept study, two estimators were run simultaneously as the vehicle neared the intersection. Each estimator used its own unique terrain map as part of the Unscented Kalman Filter framework needed to track the vehicle. The tracking performance is included in Fig. 4. The first plot indicates the vehicle tracking error when Terrain Map 01 was used, whereas the second plot indicates the vehicle tracking error when Terrain Map 02 was used. Since Terrain Map 01 corresponds to the route that the vehicle *actually* took during the test run, vehicle tracking is maintained and the tracking error remains bounded under 3.5 meters. On the other hand, since Terrain Map 02 corresponds to the other route which the vehicle did *not* take, it is expected that the vehicle tracking performance will be poor, as is observed.

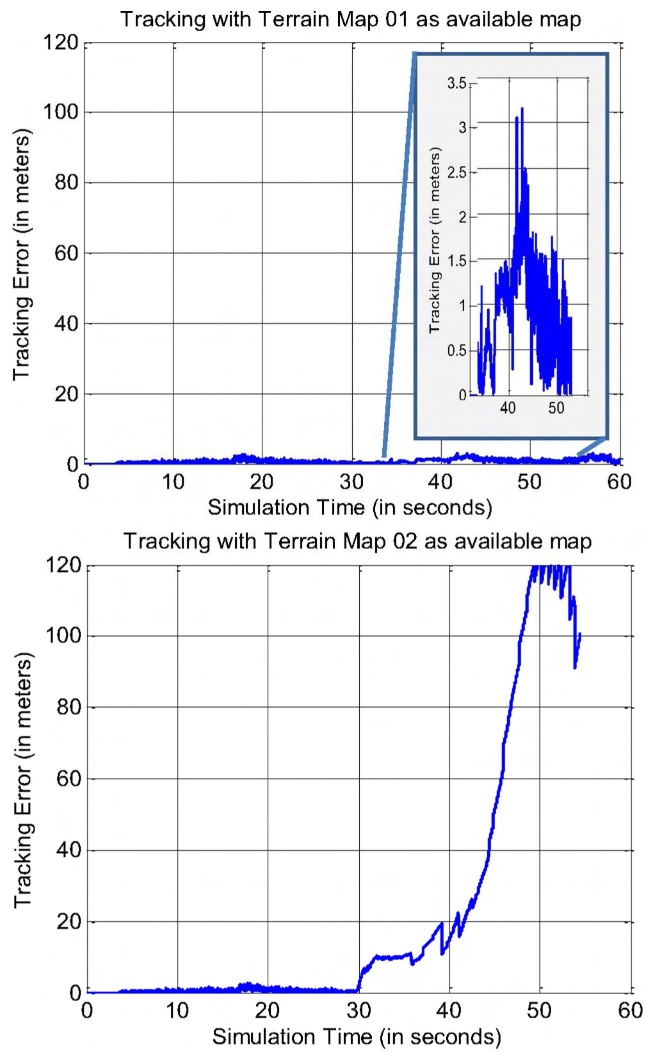

Fig. 4. Vehicle tracking performance with two different terrain maps using on-line simulations. (a) Using the correct terrain map (01). Incoming measurements match the terrain map and tracking is maintained. (b) Using incorrect terrain map (02). Incoming measurements do not match the terrain map and tracking is lost.

To calculate the absolute tracking error, the algorithm's output was compared to ground truth, i.e. the position coordinates obtained from GPS measurements. Note that neither the absolute tracking error nor the GPS coordinates themselves were used in the tracking algorithm. The tracking error plots in Fig. 4 are only used to demonstrate the behavior of the algorithm, rather than describe its internal logic. Specifically, since one of the applied constraints is that position estimates from GPS are not available, in practice there are no means to calculate the tracking error or identify which estimator is tracking correctly. In other words, in the absence of ground truth, either estimator could be tracking the vehicle equally well. In such a scenario, the estimator that is performing the "correct" tracking can only be found by comparing the currently observed measurements with the pre-recorded map and calculating the appropriate probability values. This is indeed the process being used, as described in Section 3. The experimental results obtained from using this multiple model estimation approach are included below.

Fig. 5 depicts the probabilities that the terrain map being used in each estimator is representative of the terrain that the vehicle is actually traveling over. The probabilities are calculated recursively as described in (14). It is observed that before the intersection is reached both estimators are equally likely since the terrain maps in both estimators are identical up to the intersection. However, after crossing the intersection, while the incoming attitude measurements are similar to the pre-recorded attitude in Terrain Map 01, they do not match the observations in the Terrain Map 02. Thus, the estimator that is providing the correct position estimates is the one that is using Terrain Map 01 and the probability of Terrain Map 01 being correct goes to 1, while the probability of Terrain Map 02 being correct goes to zero. The position estimates from the estimator using Terrain Map 01 may then be used for various applications such as navigation or path planning, while the second estimator is eliminated.

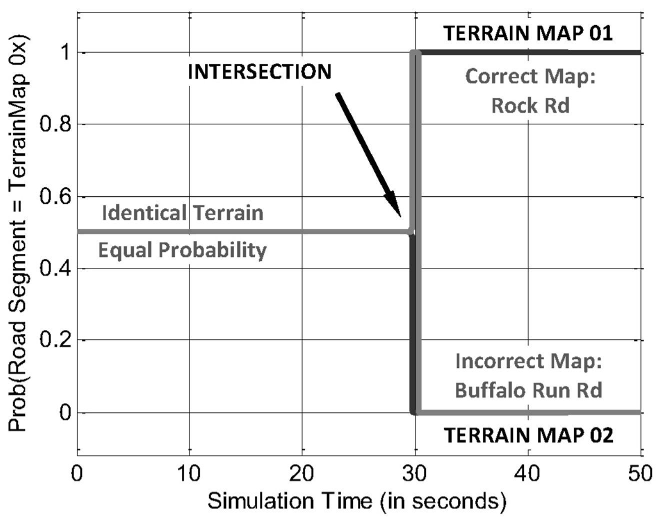

Fig. 5. Probability associated with each terrain map candidate. The probability associated with the correct terrain map goes to 1 in a short time after the intersection is crossed, while the probability associated with the second terrain map goes to zero.

V. CONCLUSIONS

The above work provides a proof of concept that the GPS-free terrain-based vehicle tracking algorithm can be extended to large road networks. Specifically, the work shows the feasibility of using pitch data for discriminating the road being traversed in a network (similar to yaw), as well as tracking the vehicle within the identified individual road segment. In summary, the above experiment and on-line simulations indicate that the terrain-based algorithm and the multiple model estimate framework can be used to maintain tracking across intersections in a road network even in the absence of GPS.

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