

Particle Filter-based Position Estimation in Road Networks using Digital Elevation Models

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Abstract—Nowadays, the Global Positioning System (GPS) can be considered as being the de-facto standard for localization in road networks, delivering a reasonable precision at most places and being available through a huge variety of devices. Nevertheless, if signal reception is disturbed, no position estimates can be computed anymore. In this paper, we present an approach for localization in road networks which is based on a particle filter computing estimates using only basic environmental information: the road network's structure and its height profile. The approach is demonstrated in experiments of an electrical wheelchair driving through a small town.

I. INTRODUCTION

Global Navigation Satellite Systems (GNSS) such as the United States *GPS*, the Russian *GLONASS*, or the European Union's *Galileo*, give their users the ability to determine their location on earth in terms of latitude, longitude, and height. By using electronic receivers, the position is computed from traveling time of radio signals emitted from medium earth orbit satellites. Considering these systems as being the de-facto standard in outdoor localization, their drawbacks still pose scientific questions. How to deal with poor position estimates resulting from signals that are intentionally disturbed, or distorted by multiple reflections within street canyons and natural landscape features? Can a priori available spatial databases along with corresponding real-world feature measurements support, possibly even substitute, the process of estimating ones position?

In this work we argue for a straightforward application of available spatial knowledge, in order to set up a complete localization approach that gets along without any information coming from GNSS. More specifically, we describe a particle filter-based position estimation scheme that integrates barometric elevation measurements, and odometric velocity readings under the restrictive assumption to be located on a road segment. While first measurements are matched inside the *sensor model* against samples from a *Digital Elevation Model (DEM)*, latter measurements are evaluated within the *motion model*, in order to describe the progress of position

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hypotheses along street segments, modeled within a digital *Road Network*.

The remainder of this paper is structured as follows: section II presents related work in this area. Section III describes the data sets that represent the environment in which the particle filter that is described in Sect. IV operates. Finally, the experiments that have been carried out are presented in Sect. V. We conclude in Sect. VI with a qualitative assessment of the results presented and some ideas for future improvements.

II. RELATED WORK

Assuming the inaccuracy or the complete absence of position information coming from GNSS, evaluating *Geographical Information Systems (GIS)* in outdoor vehicle state estimation is appealing, because they provide large-scale and precise data that can be matched against a variety of sensorial information.

Scott and Drane [13], as well as Li et al. [8], show in their papers the improvement of raw GPS position measurements by restricting the pose estimate to a given road network. The latter work additionally matches height information coming from a digital elevation model against the three-dimensional GPS position, thereby demonstrating an even better position estimation. The mentioned approaches that are generally known as *map-matching* techniques in the GIS-community, are closely related to *road reduction filters* [16], or the *Mapping Dilution of Precision* approach to map-matched GPS [1].

With the different scenario of providing full pose estimation without any information coming from GNSS, Naval [9] describes a system that generates camera pose hypotheses by matching mountain peak image features against model features coming from a digital elevation model. The approach solely requires the camera height above ground to be known. For airborne vehicles equipped with a gyroscope and a downward facing camera, Sim et al. [15] present a localization scheme that first recovers an image DEM from aerial image pairs. Distinct features within this elevation map are subsequently matched against features coming from an a priori available model DEM. The final pose estimate is

combined from the estimated translation between the two DEMs and the attitude coming from the gyroscope.

The contribution of this paper is an outdoor self-localization approach that, in contrast to the techniques mentioned above, neither requires any GNSS pose estimates, nor other sophisticated sensorial equipment. With its ability to localize along large-scale road networks by evaluating data coming from odometry, compass, and barometer, it compares best to the work proposed by Lankenau et al. [5]. The authors present an algorithm that is capable of estimating the system’s pose along a given graph-structured representation of the environment. By evaluating translational and rotational offsets coming from odometry, the proposed system recognizes driven turns that are subsequently matched against junctions within the world model.

We will show in this paper that the developing error along straight ahead passages can be significantly reduced by considering elevation information. In addition to the qualitative improvement of localization approaches that are primarily based on odometry, our work demonstrates the successful application of a popular textbook-method such as Monte Carlo filtering for realizing a global self-localization that forgoes GNSS.

III. THE WORLD MODEL

A. Road Network

Ever since the availability of web applications such as *Ask Maps*, *Google Maps*, *Mapquest*, *Microsoft Bing Maps*, and *Yahoo Maps*, people can make use of comprehensive road network data in digital form. Restricted to predefined interfaces, these services do not allow for extracting the underlying datasets, thus rendering the development of stand-alone applications that work on this data impossible. With the launch of the collaborative project *OpenStreetMap (OSM)* [10], [12] in 2004, a continuously growing dataset has become freely [2] available. Based on user-recorded GPS track logs, and donated commercial datasets, e.g. the complete road dataset for the Netherlands, OSM provides maps of arbitrarily selectable regions in XML-format. This data not only contains a vector-based representation of the road network, but also a detailed classification of the types of listed road segments. Fig. 1(a) shows the complete OSM dataset for the region around Wopswede that was selected for our experimental evaluation (cf. Sect. V). Fig. 1(b) visualizes the chosen subset of road segments that is used for the selected wheelchair navigation scenario. The classes and the estimated width of the subset’s members is given in Table I.

An important operation on the road network dataset inside the sensor model of the proposed particle filter (cf. Sect. IV-B) is the computation of the closest road segment for a given position hypothesis. Assuming the $M = 1069$ road segments of the exemplary scenario in Fig. 1(b), and $N = 1000$ position hypotheses, a naive implementation of the road network data structure implies $\mathcal{O}(M*N) > 10^6$ line segment to point distance queries within a single cycle of computation of the particle filter.

TABLE I
CLASSIFICATION AND ESTIMATED WIDTH OF ROADS FILTERED FROM
OSM DATASET FOR EXPERIMENTAL EVALUATION

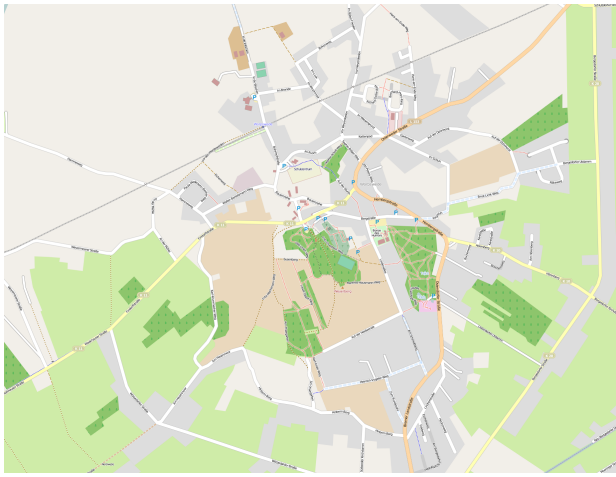
#	Class	Description	Estimated Width[m]
1	Federal Highway	generally connecting larger towns	12
2	Federal Highway Link	linking #1 to others	12
3	District Road	connecting smaller towns and villages	9
4	District Road Link	linking #3 to others	9
5	Country Road	fully developed road connecting municipals	7.5
6	Auxiliary Road	barely developed road connecting municipals	5
7	Residential Road	road accessing residential area	5
8	Living Street	traffic-calmed street with priority for pedestrians	5
9	Path	public footpath	2.5
10	Cycleway	designated cycleway	2.5
11	Track	roads for agricultural use	2.5
12	Footway	designated footpath	2.5

In order to reduce this computational payload, we sort each line segment representing a road segment from the OSM dataset into a space partitioning data structure, the so-called *PMR quadtree* [4]. Like a regular quadtree, this spatial data structure inserts its elements, in our case line segments, into buckets. Initially, the PMR quadtree consists of its root bucket, representing the whole Euclidean plane. By using a splitting rule that defines the maximal number δ of line segments to be contained within a single bucket, the line segments are inserted one-by-one into the data structure. After reaching the threshold δ for a given bucket B , four child-buckets are appended to B , representing four equal-sized quadrants of the plane represented by B . At this point, all line segments that have been contained by B are propagated down to the new child-buckets. Note that this approach leads to redundant storage of elements, since a line segment is stored in every bucket that it intersects.

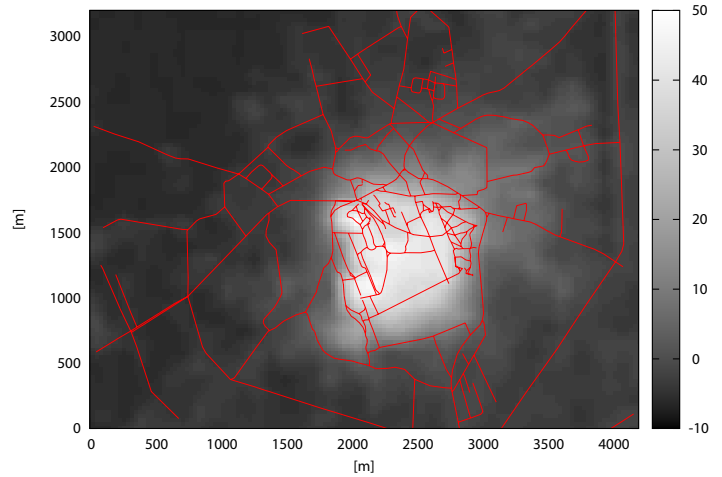
Hoel et al. show in [4] an algorithm to find the closest line segment from a given PMR quadtree w.r.t. a given point, that has the computational complexity of $\mathcal{O}(\delta)$, provided the line segments to be uniformly distributed over the given map region. This yields an upper bound of $\mathcal{O}(\delta * N)$ closest road segment to position hypothesis queries for our particle filter, making the PMR quadtree the first choice for the spatial data structure of the road network.

B. Digital Elevation Model

In order to model the three-dimensional characteristics of the earth, DEMs rasterize the earth’s surface by a grid of squares and assign a height value to each square. The measurement of the elevation is commonly done by remote sensing techniques such as airborne or spaceborne optical stereo sensors [14], or traditional surveying approaches. Since former approaches suffer from image quality disturbed by cloud cover or lack of sunlight, and latter approaches are too complex to densely map the earth’s surface, interferometric synthetic aperture radar (*InSAR*) measurements



(a) Rendering of the complete OpenStreetMap dataset [10] for Worpsswede. The depicted information is from August 2009, and available under the *Creative Commons Attribution-ShareAlike 2.0 license* [2].



(b) Digital Elevation Model dataset from [17] with superimposed subset of OpenStreetMap data, characterizing roads and paths allowed for wheelchair or bicycle navigation. The elevation of the underlying landscape ranges from $-2m$ (dark gray) to $51m$ (light gray).

Fig. 1. Illustration of a-priori available information used by the particle filter presented in this work. Both maps represent the same area around Worpsswede, a typical municipal in Northern Germany with about 9500 residents. The width and the height of the maps are about $4.2km$ and $3.2km$ respectively.

have become the state of the art in producing DEMs. In the year 2000, the *Shuttle Radar Topography Mission* [11], or *SRTM* for short, recorded high-quality elevation data of the earth's surface between latitudes $60^\circ N$ and $57^\circ S$. Available to the public [17] this data comes along as DEMs with a square resolution of $1arcsec$ ($\sim 30m$) for the continental United States, and with a resolution of $3arcsec$ ($\sim 90m$) for the rest of the world. The maximal relative vertical error of 90% of the provided data is given by $\pm 6m$ within a horizontal distance of $200km$ around a given measurement point. Furthermore, the maximal absolute vertical error is given by $\pm 16m$ w.r.t. all measurement points. SRTM DEMs with a square resolution of $3arcsec$ are shipped as tiles covering $1^\circ lon * 1^\circ lat$ (WGS84 data), containing $1201 * 1201 = 1442401$ elevation squares. An illustration of a part of the SRTM DEM that was used in an experimental test run (cf. Sect. V) is given in Fig. 1(b).

IV. STATE ESTIMATION

State estimation is realized using a Monte-Carlo approach [3] since it is able to deal with non-linear motion models (cf. Sect. IV-A) as well as with the occurrence of multiple hypotheses (cf. Sect. IV-D).

The state X_t to be estimated and thus the content of every particle $x_t^{[m]}$ within a set of M particles is a simple pose in 2-D:

$$x_t^{[m]} := \langle px_t^{[m]}, py_t^{[m]}, \theta_t^{[m]} \rangle \quad (1)$$

Due to the motion model which is constrained to the road network (as described in the subsequent section), only a small subset of the theoretically possible state space is used.

Additionally, every particle carries information as the identifier $r_t^{[m]}$ of the current road segment, a cluster identifier $c_t^{[m]}$ (cf. Sect. IV-D), and its age $a_t^{[m]}$ (i.e. the number of survived resampling steps, cf. Sect. IV-C).

A. Motion Model

The state transition of a single particle through motion is

$$u_t^{[m]} := d_t \quad (2)$$

with d_t being the distance traveled since the last motion update step. Due to the constraint to move along roads only, we always assign

$$\theta_t^{[m]} = \alpha_t^{[m]} \quad (3)$$

with $\alpha_t^{[m]}$ being the direction of the road currently closest to a particle, gained from a lookup in the quadtree, as described in Sect. III-A. To keep our approach as general as possible, d_t is a simple distance and not a two-dimensional offset or a pose, although our test platform (cf. Sect. V-A) would be able to provide the latter. The most common case to expect, e.g. in cars or bicycles, is a one-dimensional odometer. A two-dimensional offset $v_t^{[m]} = (v_x^{[m]}, v_y^{[m]})^T$, thereby an updated sample position, is computed as follows:

$$v_t^{[m]} = M_\theta^{[m]} (d_t + a_1 n_x^{[m]}(d_t), a_2 n_y^{[m]}(d_t))^T \quad (4)$$

$$px_t^{[m]} = px_{t-1}^{[m]} + v_x^{[m]} \quad (5)$$

$$py_t^{[m]} = py_{t-1}^{[m]} + v_y^{[m]} \quad (6)$$

with $M_\theta^{[m]}$ being a rotation matrix describing $\theta_t^{[m]}$, $n_{x,y}^{[m]}$ a noise function sampled from a triangular distribution, and a_1 and a_2 being two scalars for the generated noise in different directions. Equation 4 does not only move a sample along a road but also in a small amount perpendicular to the road's center. This noise distributes the samples randomly over the whole width of street segments and causes samples of a cluster to proceed at different roads at a branch (Eqn. 3). Nevertheless, free motion far from any road is limited by the sensor model, as described in the following section.



Fig. 2. The *Bremen Autonomous Wheelchair Rolland* driving along different roads during the experimental test runs. The particle filter explicitly models street widths for different classes of roads (cf. Table I). The roads above are classified as residential road, living street, path, and footway (left to right).

B. Sensor Model

To carry out the particle filter’s resampling step (which is assumed to be known, and therefore it is not described in this paper), each sample’s weighting $w_t^{[m]}$ needs to be computed according to the sensor model

$$z_t := \langle elv_t, dist_t^0, dir_t \rangle \quad (7)$$

with elv_t being the altitude measured by a barometer and dir_t the global orientation measured by a compass. The distance $dist_t^0$ is a virtual measurement to keep all samples along the roads. As this is an assumption about the driver’s behavior and not a real sensor measurement, $dist_t^0$ is always zero. By this construct, a sample’s distance $dist_t^{[m]}$ (which is based on state variables) to the next road segment (also considering its width) can easily be incorporated in the sensor model for computing $w_t^{[m]}$:

$$\delta_{elv}^{[m]} = |elv_t - elevationModel(px_t^{[m]}, py_t^{[m]})| \quad (8)$$

$$\delta_{dir}^{[m]} = |dir_t - \theta_t^{[m]}| \quad (9)$$

$$w_t^{[m]} = \mathcal{N}(\delta_{elv}^{[m]}, \sigma_{elv}^2) \mathcal{N}(dist_t^{[m]}, \sigma_{dist}^2) \mathcal{N}(\delta_{dir}^{[m]}, \sigma_{dir}^2) \quad (10)$$

Since the digital elevation map consists of discrete tiles, the function *elevationModel* computes the expected height at a sample’s position by bilinear interpolation. As shown in Sect. V, in some cases, it is already possible to successfully track a position using only the measured orientation dir_t and the road distance. The latter cannot be measured directly but can be regarded as a constraint to keep the samples roughly on the road network; some deviation remains allowed to overcome imprecisions in the road network model.

The elevation elv_t is needed for those scenarios in which the direction alone cannot resolve any ambiguities at branches. In addition, it increases the precision of the overall estimate (cf. Sect. V).

C. Sensor Resetting

Regarding self-localization, the so-called *robot kidnapping* is a common problem caused by transformations not covered by the robot’s motion model, e. g. by carrying the robot to a different place during normal operation. Such classical kidnapping operations do not occur in our scenario but something causing a similar effect might happen: the robot might lose its way, e. g. by letting many samples take a wrong

branch, or the distribution might fall behind the real position or be ahead of it respectively.

By adding new samples computed from recent measurements to the probability distributions, the so-called sensor resetting [7], the Monte-Carlo approach is able to recover quickly from kidnapping actions. Due to the lack of unique features in our scenario, these samples are randomly added on streets within a certain frame, having the rotation of the last orientation measurement. The frame is an axis-aligned bounding box around all samples which have a minimum age $a_t^{[m]}$. This reduces the insertion of samples on misleading road segments. To allow an extension beyond this scope, the bounding box can be scaled by a user-defined factor.

In our implementation, a fixed number of samples is added after each resampling step.

D. Clustering

After each execution cycle of the particle filter, a resulting pose needs to be determined as output. As our approach tracks a pose from a known starting position, an overall average of all samples appears to be a reasonable choice. However, adding new samples or splitting the distribution at road branches leads to a multimodal distribution. In such cases, averaging might produce wrong results and thus tracking different clusters is mandatory. For this purpose, we chose the *Particle History Clustering* approach [6] that integrates into the particle filter process and produces reasonable results in linear time. It originally only provides cluster merging operations, so we extended it by a splitting operation based upon changes of samples’ road assignments $r_t^{[m]}$.

V. EXPERIMENTAL EVALUATION

A. Platform & Sensor Equipment

The *Bremen Autonomous Wheelchair Rolland* has been used as the experimental platform for this work. Rolland is based on the power wheelchair *Xeno* by the German manufacturer *Otto Bock Healthcare* (cf. Fig. 2 for photos taken during the test runs). The drive wheels of Rolland are equipped with wheel encoders with a resolution of approximately $2mm$ driving distance per tick. A micro controller board is counting the encoder ticks and sends them to the laptop which integrates the kinematic equations. Because of the

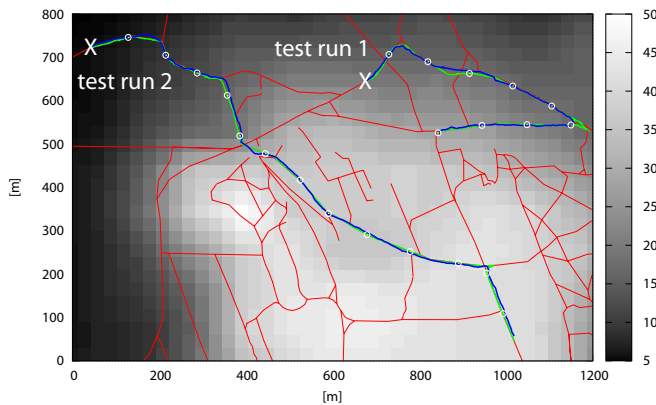


Fig. 3. Reference trajectories (blue) and estimated trajectories (green) of two experimental test runs conducted in Worpswede. The underlying elevation information is a bilinear interpolation of the raw SRTM data source, and illustrated by shaded $30m \times 30m$ squares. Heights are given in m . Both experiments have been carried out by evaluating measurements coming from a barometer (elv_t in Eqn. 7), odometers (d_t in Eqn. 2), and a compass (dir_t in Eqn. 7). Test runs started at the position marked by an x . White circles are placed every $100m$ along the reference trajectory.

drifting odometry rotation, we use the *XSens MTx* orientation tracker for measuring the orientation of the wheelchair. Its integrated compass measures the earth’s magnetic field and outputs the orientation between the sensor-fixed coordinate system and an earth-fixed reference coordinate system. Note that we evaluate basic magnetometer measurements, and no gyroscope-stabilized yaw estimations. We further ignore the magnetic declination throughout this work, i.e. the deviation between magnetic north and true north, since it is negligible with $< 1^\circ$ for most parts of Germany.

For measuring the reference GNSS position, and the elevation of our experimental platform, we use a *Garmin GPSMap 60CSx*. Its WAAS/EGNOS¹ enabled GPS receiver outputs one position estimate per second, and has a specified positional accuracy of $3 - 5m$ in 95% of all measurements. The handheld device integrates a barometer-based altimeter with a documented accuracy of $\pm 3.048m$, and a resolution of $30.48cm$. We configured the altimeter not to be recalibrated by GPS elevation during operation, but calibrated the device manually by the height taken from the DEM at the starting position of our experimental test runs.

B. Conducted Test Runs

The particle filter-based position estimation approach described in Sect. IV has been experimentally evaluated by two real world test runs, conducted on the streets of Worpswede, a small town in Northern Germany² (cf. Fig. 1 for an illustration of the available world model). Measured by GPS ground truth, test run 1 and 2 had a length of $906m$ and

$1364m$ respectively. During the experiments, the wheelchair drove on a variety of road types (cf. Table I and Fig. 2), while the system recorded GPS reference positions, odometric velocity readings, barometric elevation measurements, and compass orientation. In an offline analysis that processed approx. 36 seconds of real world data in one second when using 1000 samples, we tested the proposed localization approach with two different sensor models. The first one solely comprised orientation information, and the second one comprised orientation information and elevation data, as described in Eqn. (7). In both evaluations of the two test runs, we initialized each sample with the GPS reference position.

C. Discussion

For the case of using orientation information and elevation data within the sensor model, average localization errors against GPS ground truth are given by $7.58m$ for test run 1, and $7.73m$ for test run 2 respectively (cf. Fig. 3 for the resulting trajectories). Without using elevation information, we find average localization errors of $8.14m$ in test run 1, and $15.18m$ in test run 2. Figure 4(a) shows the complete error plots of both test runs, as well as the development of the measured elevation and the bilinear interpolated model-elevation at the GPS reference position. Although the particle filter was able to track the wheelchair’s position using the complete and the reduced sensor model, large differences among the resulting error plots can be seen for test run 2 between $600m$ and $1100m$ of traveled distance. The different behavior of both localization runs can be explained by the low number of junctions within this interval. Localization without considering the elevation profile along this straight ahead section results in a stretching cloud of particles, each of which not being able to compensate for the developing error due to missing crossings.

VI. CONCLUSIONS AND FUTURE WORK

A. Conclusions

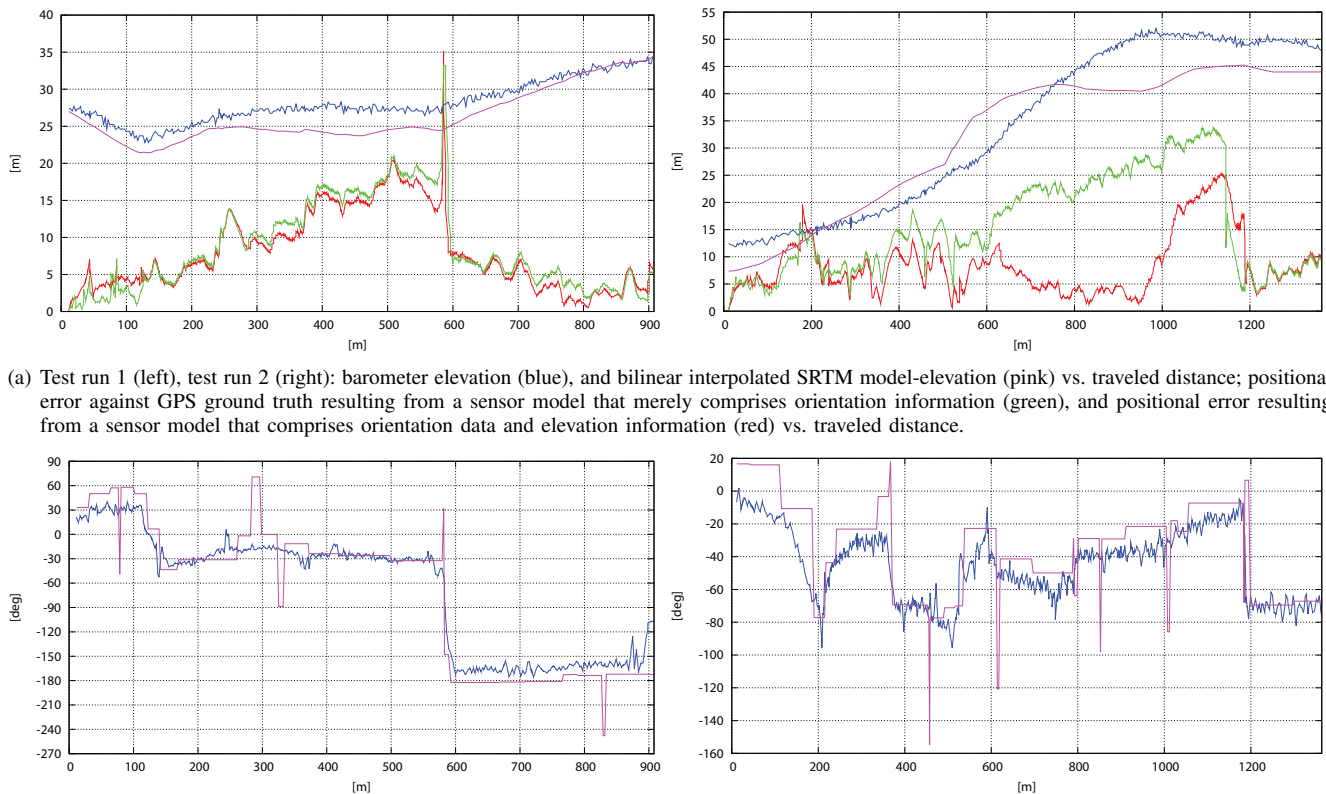
This work has presented a particle filter-based position estimation approach that is capable of tracking a vehicle’s position by evaluating data coming from odometry, compass, and barometer. Under the restrictive assumption of being located on mapped parts of the street network, the proposed localizer clearly benefits from a sufficiently variable elevation profile along the driven course. However, ambiguous situations are still challenging, e.g. a road splitting into two roads under sharp angles, accompanied by a flat elevation profile in this area. Such cases have been tackled by a carefully parameterized sensor model, and the particle history clustering approach. The later strategy has shown to be well suited to assess emerging clusters of multimodal distributions.

B. Future Work

A strong support for the results presented should be available with the evaluation of more exhaustive test data. We plan to equip a bicycle with the necessary sensorial equipment, in order to evaluate localization test runs of greater distances, covering a broader spectrum of road types

¹The *Wide Area Augmentation System* (WAAS), and the *European Geostationary Navigation Overlay Service* (EGNOS) are satellite-based augmentation systems that improve the accuracy of the basic GPS signal. Both systems use ground-based reference stations that detect inaccuracies of the basic GPS signal, and send correction messages to geostationary satellites that forward these messages to the GPS receivers. WAAS and EGNOS typically improve the accuracy of GPS from $10 - 20m$ to $1 - 3m$.

² $53^\circ 13.304' N, 8^\circ 55.684' E$



(a) Test run 1 (left), test run 2 (right): barometer elevation (blue), and bilinear interpolated SRTM model-elevation (pink) vs. traveled distance; positional error against GPS ground truth resulting from a sensor model that merely comprises orientation information (green), and positional error resulting from a sensor model that comprises orientation data and elevation information (red) vs. traveled distance.

(b) Test run 1 (left), test run 2 (right): compass orientation (blue), and orientation of OSM street segment closest to GPS reference position (pink) vs. traveled distance. Peaks in the street segment's orientation result from a temporarily association of the GPS reference position to a wrong road.

Fig. 4. Evaluation of two experimental test runs conducted in Worpsswede. The length of test run 1 is 908m, and the length of test run 2 is 1364m.

and elevation profiles. An algorithmic improvement is aiming for a successful demonstration of localization from scratch, requiring no positional initialization of the involved samples. Eventually, this will require using more detailed world models, e.g. employing the recently available ASTER-SRTM. Still in its developing phase, this DEM promises $1arcsec^2$ -sized elevation squares for most of the world's land surfaces.

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