Collaborative positioning using landmark maps

[Position/Short Paper]

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ABSTRACT

In this paper we deal with a strategy for a collaborative positioning of vehicles to improve their ego positioning capabilities. One way to achieve this is the sharing of the vehicle's own position and additional measurements to vehicles with known position in their surrounding area.

Under the assumption that a single vehicle is able to obtain its ego position by on-board sensors (like laser scanners and GNSS equipment) and in combination with available landmark maps, the consideration of additional measurements to other vehicles leads to a position improvement especially in case of sparse landmark maps.

Based on an available landmark map covering built-up areas and highway-like roads, a set of simulations is carried out to evaluate the resulting improvement by using relative position data among nearby vehicles. Different kinds of collaborative positioning scenarios are investigated and contrasted with ego positioning using only the landmark map.

Categories and Subject Descriptors

I.2.9 [**Artificial Intelligence**]: Robotics—*Autonomous vehicles, Sensors*; I.4.8 [**Image Processing and Computer Vision**]: Scene Analysis—*Range data, Sensor fusion*; I.5.4 [**Pattern Recognition**]: Applications—*Computer Vision*

General Terms

Algorithms, Design, Experimentation, Measurement

Keywords

Collaborative positioning, feature extraction, localization, autonomous vehicles, landmark based maps

1. INTRODUCTION

The usage of on-board sensors of vehicles such as laser scanners, cameras and radar sensors, in combination with feature and landmark maps is straightforward for positioning purposes, see e. g., [2, 10]. Since the on-board sensors typically yield relative measurements to objects along the road, the link to a global coordinate system has to be established by means of the feature and landmark maps.

The usage of feature and landmark maps for positioning purposes is well-known in robotics [4]. Investigations using landmarks such as poles of traffic signs and traffic lights for positioning has been investigated by e. g., [2, 10]. These investigations revealed that the use of landmarks can lead to positioning accuracies in the centimetre to decimetre range, which is way beyond accuracies achievable with standard GNSS. Such high accuracies are, however, needed for driver assistance systems or for autonomous driving. Despite the high potential, in situations where not enough landmarks are available, the positioning quality deteriorates or even no positioning is possible. Thus, the potential of collaborative positioning in order to bridge gaps in landmark availability will be investigated. Furthermore, collaborative positioning of nearby vehicles is worthwhile to increase the position accuracy of an existing feature and landmark map without a time-consuming update. Approaches using a vehicle-2-vehicle communication (to exchange position relevant information) for collaborative positioning instead of ego positioning can be found in e. g., [8].

The findings in an earlier study [3] were that the positioning accuracy using landmarks is very high in areas where a sufficient density in a suitable configuration is available. On the contrary, if not enough landmarks are available or if their geometric configuration is weak, then additional information (other vehicles as collaborating sensors) is beneficial to improve the accuracy. This is true for the following situation: A) *A vehicle starts in an area with no or only a few landmarks, so that a (precise) positioning is not possible. Communication with nearby vehicles helps to determine the initial position.* B) *Collaborating vehicles, also in the sense of a cluster of vehicles, have the capability to bridge gaps resulting from areas with only a low number of landmarks. In addition, convoy-driving can help to preserve their current (high) positioning accuracy and also to provide this information to joining vehicles.*

To investigate the improvement of additional position information provided by nearby vehicles typical road traffic scenarios are sketched. For all scenarios simulations are performed using extracted features from a real data set and virtually moving vehicles along a given trajectory. The results are contrasted with the ego positioning using only landmark

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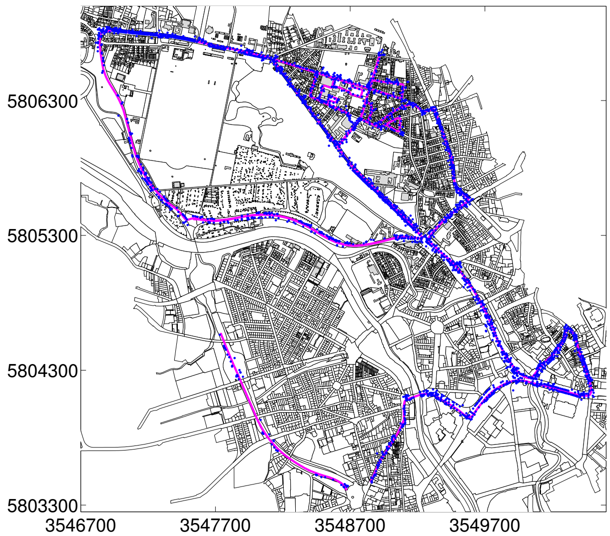

Figure 1: Sampled trajectory (magenta) and extracted pole-like objects (blue) which represent the two-dimensional landmark map.

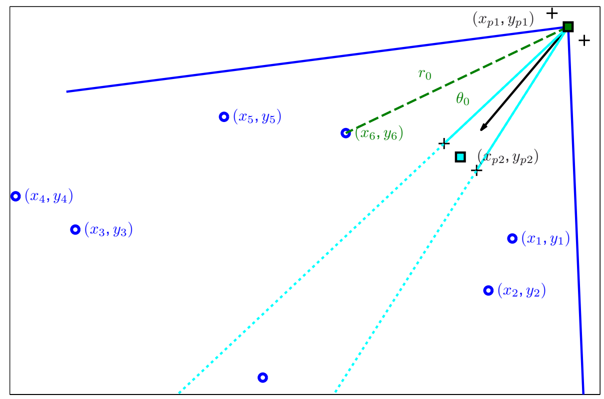

Figure 2: Sketch of the measurement model. The vehicle (p1, green square) observes poles (blue) according to its fov indicated by the blue lines. The fov is partiality occluded by the ahead driving vehicle (p2, cyan square) indicated by the cyan lines.

maps on the basis of error ellipses.

2. DATA

The data used in this contribution was acquired by the Streetmapper mobile mapping system [7]. The data comprises a 21.7 km long trajectory through densely built-up regions and highway-like roads in the area of Hannover, Germany. From the available dense 3D point cloud were extracted 2658 pole-like objects fully automatically [1]. By these features a two-dimensional landmark map was built up which is used throughout the simulations. The accuracy of position for the extracted objects is in a range of 12 cm [3]. For simulation purposes, the Streetmapper trajectory was sampled with positions every 10 m which yields in total 2141 vehicle positions for the subsequent simulations.

Fig. 1 shows the trajectory (magenta) and the extracted pole-like objects (blue) which are not equally distributed along the trajectory. For the built-up regions and especially in the area of inner-city junctions a sufficient number of poles are available. This leads to the expectation of positioning accuracies in centimetre range. Along the highway-like roads the number of poles is obviously smaller. Here positioning accuracies in decimetre range or even no positioning are expected, cf. [1, 3].

3. PROPOSED APPROACH FOR COLLABORATIVE POSITIONING

The general positioning approach is based on the matching of poles [1]. For each position of a vehicle the visible poles are selected according to the field of view (fov) which is defined by the on-board sensors. The corresponding measurement model is outlined with its basic equations in the following and Fig. 2 illustrates the situation. We start with the assumption of measurement errors for range and angle as well as inaccurate pole positions.

The observations are measured distances r_i and angles θ_i towards i poles (x_i, y_i) in the fov. The unknowns are given by the vehicle position (x_p, y_p) and orientation θ_p. Measurement residuals are denoted by v and they have to be minimized. Thus, the set of observation equations are (cf. Fig. 2)

$$r_i + v_{r_i} = \sqrt{(x_i - x_p)^2 + (y_i - y_p)^2} \tag{1}$$

$$\theta_i + v_{\theta_i} = \operatorname{atan2}(y_i - y_p, x_i - x_p) - \theta_p. \tag{2}$$

Eq. 1–2 represent the standard polar measurement model which is also well known in robotics [9]. To account for the measurement errors of the extracted pole position $(x_{i,0}, y_{i,0})$ by means of the method described in [1], the positions are introduced in a Gauss-Markov model as observed unknowns

$$x_{i,0} + v_{x_{i,0}} = x_i \quad \text{and} \quad y_{i,0} + v_{y_{i,0}} = y_i. \tag{3}$$

In addition to [1], direct measurements of the vehicle ego position (for instance by the on-board GNSS equipment) are introduced which allows two extra observation equations

$$x_{p,0} + v_{x_{p,0}} = x_p \quad \text{and} \quad y_{p,0} + v_{y_{p,0}} = y_p. \tag{4}$$

The major modification of the so far outlined observation equation system is the consideration of ahead and oncoming vehicles. Therefore, again measured distances and angles towards ahead and oncoming vehicles and their known positions are available as additional observations. Since the same on-board sensors are used for the observation of poles and the other vehicles, the observation equations are identical to the outlined ones in Eq. 1–3. In total this leads for m observed poles to $3+2\cdot m$ unknowns and $2+4\cdot m$ observation equations plus $2\cdot l$ unknowns and $4\cdot l$ observation equations per l ahead and oncoming vehicles.

This modification requires the consideration of occlusions resulting from ahead and oncoming vehicles during the selection of poles in the fov (cf. Fig. 2).

The stochastic model is given by the uncertainties of the observations σ_r, σ_θ and σ_x, σ_y for the observed poles and the ahead and oncoming vehicles as well as σ_{p_x}, σ_{p_x} for the own vehicle position. These standard deviations form the cofactor matrix $\mathbf{Q}_{ll}$ of observations. By using the law of propagation of uncertainties, the resulting cofactor matrix

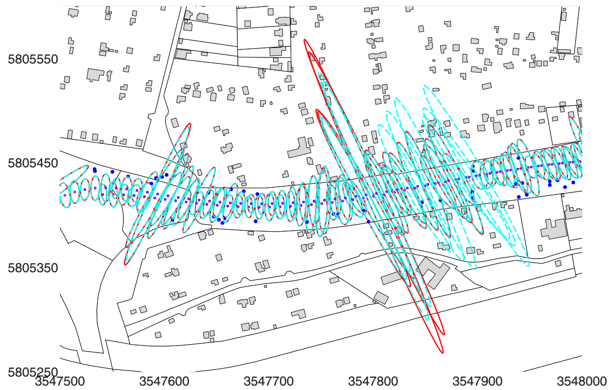

Figure 3: On-board GNSS position for ahead and oncoming vehicles and no additional information for selected vehicle position (cyan) versus only landmark based positioning (red). Note that all error ellipses in this and other figures are scaled by a factor of 100.

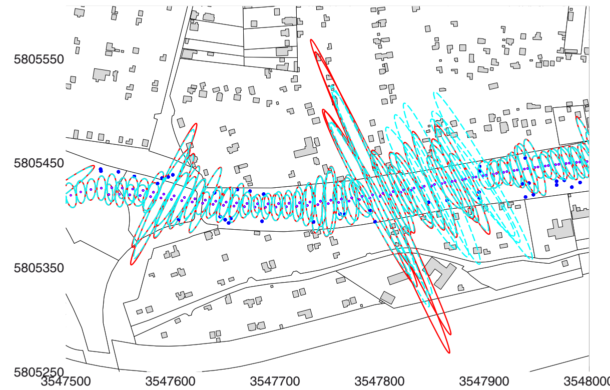

Figure 4: On-board GNSS position for ahead and oncoming vehicles and GNSS based ego position for selected vehicle position (cyan) versus only landmark based positioning (red).

$\mathbf{Q}_{xx}$ of the unknowns and thus the vehicle's position accuracy is given by $\mathbf{Q}_{xx} = \left(\mathbf{A}^T \cdot \mathbf{Q}_{ll}^{-1} \cdot \mathbf{A}\right)^{-1}$. Here, $\mathbf{A}$ is the design matrix which contains the partial derivatives of the observation equations (Eq. 1–4) for the unknowns and thus provides information of the observation geometry.

4. SIMULATIONS

The simulations are carried out with the introduced measurement model in the previous section. Since the emphasis is to show the benefit of a collaborative positioning instead of using only ego positioning we do not present a variation of on-board sensor configurations, instead is referred to [1].

The on-board sensor providing range and angle measurements was assumed to be available in front of the car, pointing in the driving direction. The opening angle was set to $85\,^\circ$ and the measurement range was set to 100 m, according to the specifications of an existing automotive grade laser scanner [6]. Ahead and oncoming vehicles are considered in a range of up to 25 m. The selected accuracies in the simulations are $\sigma_r = 0.05\,\mathrm{m}$, $\sigma_\theta = 1\,^\circ$ and $\sigma_x = \sigma_y = 0.10\,\mathrm{m}$ for the observed poles. Optional measurements of the ego position of the vehicles by means of on-board GNSS equipment were assumed with an accuracy of $\sigma_{p_x} = \sigma_{p_x} = 2.50\,\mathrm{m}$, which is a reasonable assumption in case of augmented GNSS using e. g., WAAS, EGNOS.

For the selected vehicle whose position should be determined two scenarios can be distinguished in terms of the ahead and oncoming vehicles:

1. The ego position of ahead and oncoming vehicles is determined by means of on-board GNSS equipment.
2. The ego position of ahead and oncoming vehicles is determined by means of landmark based approaches as proposed in [1].

For both outlined scenarios, two distinct situations are possible for the selected vehicle. Either, no additional position information is available, or the vehicle has an a priori information from GNSS equipment regarding its position and corresponding accuracy.

All above outlined scenarios are compared with the unmodified landmark based positioning [1] without consideration of additional ego position information or ahead and oncoming vehicles. The comparison is done on basis of error ellipses which are scaled by a factor of 100.

4.1 Vehicles with GNSS based ego position

Fig. 3 shows the results for the first scenario where no further information is available for the selected vehicle. The error ellipses of the unmodified landmark based positioning (red) correspond for most of the vehicle positions to the error ellipses of the collaborative positioning approach (cyan). For most of the vehicle positions the additional information provided by the ahead and oncoming traffic does not increase the position accuracy because of the inaccurate additional information in comparison to the landmark map. However, a position accuracy improvement can be noted for a small number of vehicle positions. These improvements result from the additionally available observations and more over from an improved observation geometry.

Fig. 4 also shows the results for the first scenario but in addition the vehicle's own position is also observed by means of GNSS equipment. In general, the same findings as for the simulation without further information about the vehicles own position can be reported. For the small number of vehicle positions a further improvement of the position accuracy can be noted.

It is noteworthy that for vehicle positions with weak constellation in the landmark map, additional information for either ahead and oncoming vehicles or even the vehicle itself lead to an improvement of the vehicle's position accuracy.

4.2 Vehicles with landmark based position

Fig. 5 shows the results for the second scenario where no further information is available for the selected vehicle. The error ellipses of the unmodified landmark based positioning are drawn in red. One can clearly see the improvement of the position accuracy for the collaborative positioning approach (cyan). The reason for that can be found in the position accuracy of the ahead and oncoming traffic which is in the range of the accuracy of the landmark map or even better.

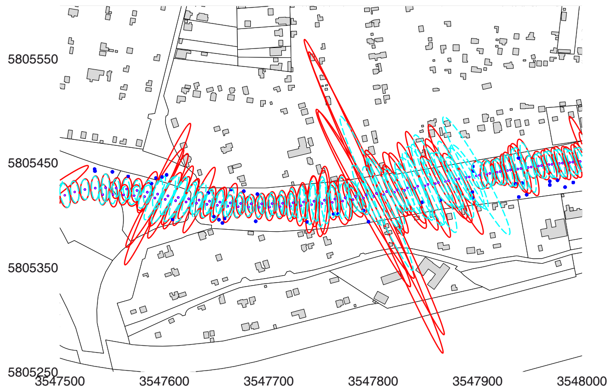

Figure 5: Landmark based positioning for ahead and oncoming vehicles and no additional information for selected vehicle position (cyan) versus only landmark based positioning (red).

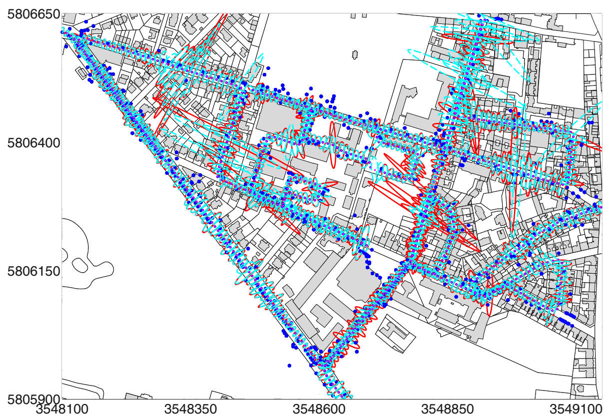

Figure 6: Landmark based positioning for ahead and oncoming vehicles and GNSS based ego position for selected vehicle position (cyan) versus only landmark based positioning (red).

If the selected vehicle has GNSS available in addition, this will lead to no further significant improvement of the position accuracy. The reason can be found in the different accuracy levels of the landmark map, the ahead and oncoming vehicles in comparison with the GNSS position accuracy. Hence, this low GNSS accuracy does not affect the position accuracy of the vehicle obtained by the landmark map.

The same conclusion can be drawn from Fig. 6. The results are obtained for the second scenario and in addition the vehicle's own position is also observed by means of GNSS equipment. Red error ellipses indicate the unmodified landmark based positioning and the cyan ones stand for the collaborative positioning approach.

5. CONCLUSIONS AND OUTLOOK

The collaborative positioning leads to an improvement of the ego positioning by means of landmarks. In particular, the inclusion of additional position information is beneficial in case of small numbers of landmarks and geometrically weak landmark constellations. Thereby, the observation geometry can be strengthened.

In the current simulation, the ego position of one vehicle was determined based on the information in its local environment, i. e., the goal was a precise positioning of one object. In the future, the integrated positioning of all objects will be investigated, where all the vehicles and their mutual observations can be considered similar to a geodetic network, which leads to a network adjustment task [5]. Also the application of state-space filtering will be investigated to account for the vehicle's motion model. The investigations will be extended to a larger test area which will be acquired with a mobile mapping system of the institute. Facades will be integrated as additional features to improve the landmark maps. Validations of the collaborative positioning by ahead and oncoming vehicles will be carried out under real world conditions either with vehicles or small-scale robots.

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