Adaption of Robotic Approaches for Vehicle Localization

Kristin Schönherr, Björn Giesler
Audi Electronics Venture GmbH
85080 Gaimersheim, Germany
kristin.schoenherr@audi.de,
bjoern.giesler@audi.de

Alois Knoll
Institute of Computer Science VI, University of Technology Munich
85748 Garching b. München, Germany
knoll@in.tum.de

***Abstract*—**

Localization of a robot is a central theme of different elaborations. But the determination of an exact position for a vehicle in urban area is more complex and an extensive algorithm challenge. This paper adresses the precise localization of a vehicle by combination of different sensor information using a Kalman and Particle filter. We present a vision based approach, which handles especially the kidnapping problem by standard sensor technology of a series-production vehicle. Therefore, the fusion of GPS [1] data and odometry, like speed and turn rate, produces a good initial position, which is the basis for generating different pose hypotheses. The inaccuracy of the GPS receiver limits their range of dispersion. For the evaluation, the subsequent Particle filter matches high precise map information with the current grayscale image of a built in camera. Different approaches known from robotics engineering are validated for their feasibility in automotive applications.

***Index Terms*—kidnapping, Particle filter, Kalman filter, pose estimation**

I. Introduction

The integration rate of navigation in modern automobiles systems increases continuously. But their accuracy of pose estimation by using dead reckoning and map matching, described in [1], [2] and [3], is not precise enough for applications of driving assistant or security systems. These algorithms reduce only the lateral error but disregard the longitudinal direction. High-precision sensor systems based especially on DGPS[2] are indeed available on the market but their package size and costs do not meet the requirements of automotive applications. The availability of further sensor information in series production vehicle causes the idea of data combination for localization. Especially car-to-car communication benefits from the exchange of accurate position information for collision detection.

The localization task is often handled in robotic engineering. In particular, Particle and Kalman filter are commonly used for pose estimation there. Ashokaraj [4] described the combination of inertial sensors, encoders and ultrasonic sensors by Extendend Kalman filtering. The usage of Particle filter for robot localization is often attended by SLAM [3] algorithm, compare [5]. We have stepwise implemented and modified these approaches for vehicle localization.

The environment of a robot can be artificially adapted, that means the localization is limited to a special area, like a playing field (see [6]) or a bounded indoor scene (see [7]). Whereas the vehicle localization deals with complex and changeable outdoor scenes. The limited sensor information and the multifaceted environment is a challenge, which we want to meet. Our car is equipped with a GPS receiver and a grayscale camera. In addition odometry data like turn rate and velocity are available. Advanced map material provides apart from road network also environmental information like urban areas. We use precise maps (GIS[4]), which include building outlines. The generated vertical building edges are these landmarks, where the vehicle is positioned to. The map based model information are combined with an image of a grayscale camera for pose hypotheses evaluation. The succeeding sequence scheme, Fig.1, shows a step by step determination of a precise vehicle position.

With this paper we mainly focus on the kidnapping problem of vehicle localization.

[1]Global Positioning System
[2]Differential GPS
[3]Simultaneous Localization and Mapping
[4]Geographic Information System

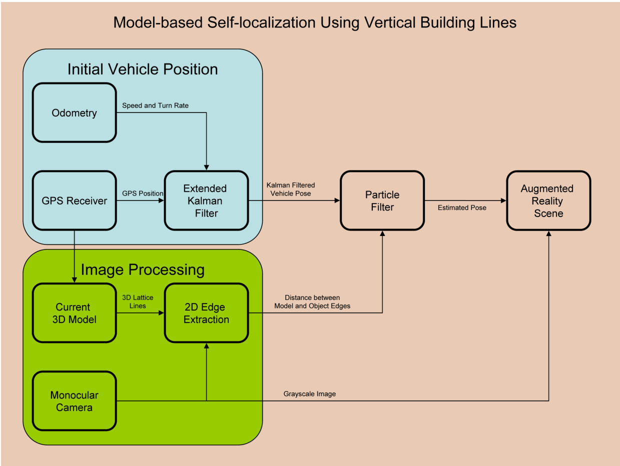

Fig. 1. Overview of the model-based self-localization solving the kidnapping problem

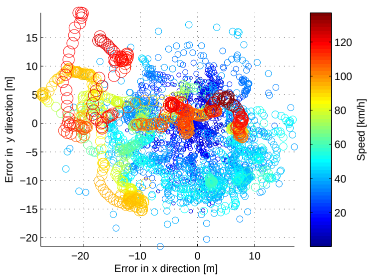

Fig. 2. Error of GPS receiver against vehicle velocity

II. Pose Estimation of a Vehicle in a Outdoor Scene

For solving the kidnapping problem of vehicle localization, the inaccuracy of the used standard GPS receiver of up to 30m has to be considered, see 2.

Known from robotic localization, there are two main probabilistic methods existant for state estimation, more precisely Kalman and Particle filter. We use a combined approach of both, which is discussed here. The main focus of localization lies on the x- and y-position of the vehicle and its orientation.

A. Kalman Filter

The estimation of the vehicle position using the Kalman filter in the way of sensor data fusion is a common and promising method. All information of the odometry, like speed and turn rate, a single camera and a GPS receiver could be combined with this probabilistic method. The video data of the grayscale camera plays a special role in filtering. The matching of reality and model information is possible by using this method. The handling of landmarks by using the Kalman filter leads to an extension of the state vector and results in a significantly increased processing effort. Because of the initially described position variation by the GPS receiver a landmark based Kalman filter is not able to exactly determine the vehicle position. The high variability of the GPS position will be averaged by the Kalman filter, but still the alignment between model edge and object edge within the image results in wrong correspondences and produces local maxima. The kidnapping problem itself can not be mastered utilizing this approach. The Particle filter is the appropriate method solving this issue. Still the Kalman filter in combination with the odometry data and the GPS signal is a solution to determine the initial position and orientation for the subsequent Particle filter process. With the utilization of the CTRV[5] model from [8] it is possible to estimate the vehicle position and direction. This system model describes a turn movement by a segment of a circle, in which turn rate and velocity are constant. The state vector x_{t_k} consists of position information x and y, rotation angle γ, velocity v and turn rate ω. The state transition equation (1) includes a non linear process, thus the utilization of the Extended Kalman filter is necessary. The time-discrete prediction step is defined in the form of

$$\underline{x}^*_{t_k} = g_A(\underline{x}_{t_k}) \tag{1}$$

$$P^*_{t_k} = A_{t_k} P_{t_{k-1}} A^T_{t_k} + Q_{t_{k-1}}, \tag{2}$$

where P_t is the covariance matrix of the state vector and A_t the Jacobian matrix of g_A. Th gaussian process noise is expressed by Q_t. In the subsequent correction step the sensor information of the GPS receiver and the odometry data will be combined. This fusion represented by the correction step is only allowed if the independent measurement data was synchronized before. Basis for the correction are measured information about speed, turn rate from the odometry and GPS position. A compass for angle measurement is not available. The update step is described by the following equations

$$\underline{x}_{t_k} = \underline{x}^*_{t_k} + K_{t_k}(\underline{y}_{t_k} - \underbrace{C_{t_k}\underline{x}^*_{t_k}}_{\underline{y}^*_{t_k}}) \tag{3}$$

$$K_{t_k} = P^*_{t_k} C^T_{t_k} (C_{t_k} P^*_{t_k} C^T_{t_k} + R_{t_k})^{-1} \tag{4}$$

$$P_{t_k} = (I - K_{t_k} C_{t_k}) P^*_{t_k} \tag{5}$$

[5]Constant Turn Rate and Velocity

where K_t is the Kalman gain and R_t the sensor noise. With this approach the inital vehicle direction and position can be estimated which is used as starting point for the Particle filter.

B. *Particle Filter*

The key idea of the Particle filter is to approximate the posterior density $p(x_{k-1}|z_{1:k-1})$ at time $t = k-1$ by a set

$$S_k = \left\{ x_{k-1}^{(i)} | \omega_{k-1}^{(i)}, i = 1, ..., N \right\} \qquad (6)$$

of N state samples x_i or particles and their corresponding weights ω_i. Estimates are computed based on these particles and weights.

The following steps of the Particle filter update the particle set to represent the posterior density $p(x_k|z_{1:k})$ for the current time k, compare Fig. 3.

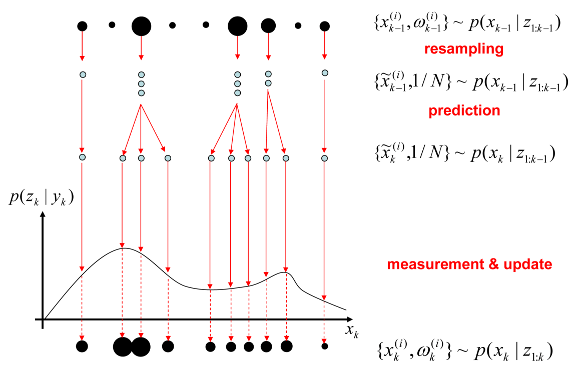

Fig. 3. Steps of the Particle filter algorithm

- Normalize the particle weights.
- Get a new distribution by the elimination of particles with low importance ratios and multiplication of particles with high importance ratios.
- Add small random values to each parameter to move multiple particles slightly for better space covering.
- Adapt each particle according to prediction.
- Update the particle weights with respect to the current measurements z_k.
- Repeat from step 1

The iteration process over time produces particle clustering especially around groundtruth data. Based on the known deviation of the urban vehicle position the estimation of the Kalman filter can be transferred into the Particle filter where it is refined . The estimated deviation is the basis for the scattering of pose hypotheses in terms of particles. The Particle filter state to be estimated includes therefore position information x and y, rotation angle γ.

The challenge when using the Particle filter is the determination of the probability of each particle, see equation

$$w_t^{(i)} = p(z_t | x_t^{(i)}). \qquad (7)$$

In this context the probability (weight) will be named as importance factor w. With the utilization of the video image information, the distances between model and object edges build its input values, see [9]. As basis for the determination of these distance values the RAPiD[6] algorithm [10] known from object tracking is used. Therefore the visible model edges are being projected into the image domain and divided into segments of the same length. Afterwards the algorithm searches for object edges of image features along the normal vectors based on the created interpolated points, see also [11], [12] and [13]. The approach of determining the distance values is being transferred from the RAPiD algorithm to Particle filter with the purpose of identifying the weight. However the model edges are limited to vertical building edges as shown in Fig. 4

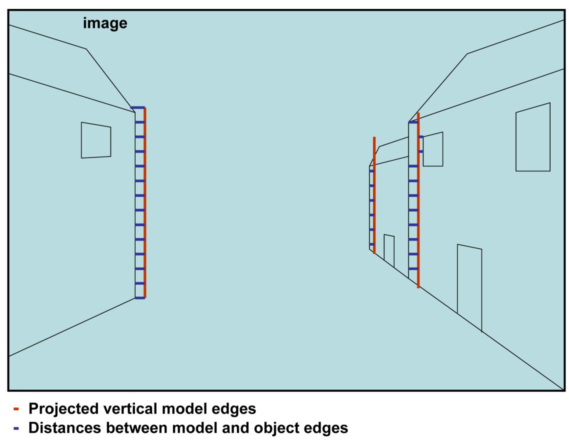

Fig. 4. Image with projected model edges and distance values

The building outlines of the map material are used for generating vertical model edges. The 3D model creation is based on the assumption of a minimum building height of 10m. The point of view separates visible and non visible edges. The disregard of horizontal model edges is caused by obstacles like parking cars near ground and the guess of the building height.

[6]Real-time Attitude and Position Determination

III. Results

For our vision-based pose estimation we compare the results of the Particle filter with precise position information of high value reference sensors, which are additionally integrated in our test vehicle. Therefore the usage of complexe outdoor scenes is possible for evaluating the described approach. The generated particles are hypotheses of position information. The vehicle direction is set to precise reference data in order to restrict the envelope of the Particle filter and allow a selective analysis. In addition there is no movement of the vehicle. Fig. 6 shows the convergence behavior of the particles. The denser the particles are concentrated in a specific area the higher the probability of the density function is approximated. The clustering of the particles near groundtruth position implicates a well designed importance factor and supports our vision-based approach, compare Fig. $6f$. The clustering area after few Particle filter steps is clear smaller than the inacurracy of the GPS receiver. This cluster has a size of circa 2m x 2m, which delivers a precise position estimation in lateral and longitudinal direction. On closer examination of the best weighted particle (red point) compared to groundtruth position (green point), see Fig. $6f$, we get a $\Delta x = 0.02m$ and $\Delta y = 0.5m$. The considered outdoor scene is well structured and supports the vision based approach. But if we use a scene with ambiguities due to adjacent homogeneous building fronts, the result of the Particle filter is unsatisfactory. The Fig. 5 shows a vast area of particles with similar weights, which results in generation of one or more less concentrated particle cluster(s).

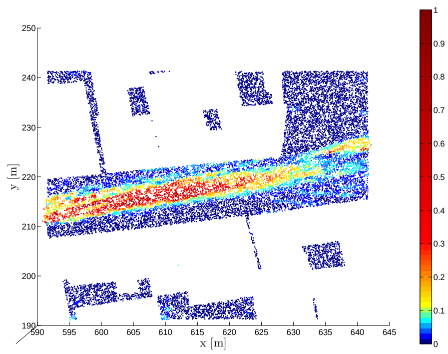

Fig. 5. Weighted particles of a homogeneous outdoor scene

IV. Conclusion

In this paper the utilization of roboter localization approaches for pose estimation of a vehicle in outdoor scenes has been shown. The transfer of distance values by RAPiD algorithm into the evaluation of the Particle filter generates a multi modal probability density function, where the maximum describes the current vehicle position. The utilization of the Kalman filter prior to the Particle filter results in a limitation of the scattering area. Finally the Particle filter provides a solution for the kidnapping problem by vision-based weighting calculation. Further work will increase the degree-of-freedom of the Particle filter and optimize the combined approach for more robustness and efficiency.

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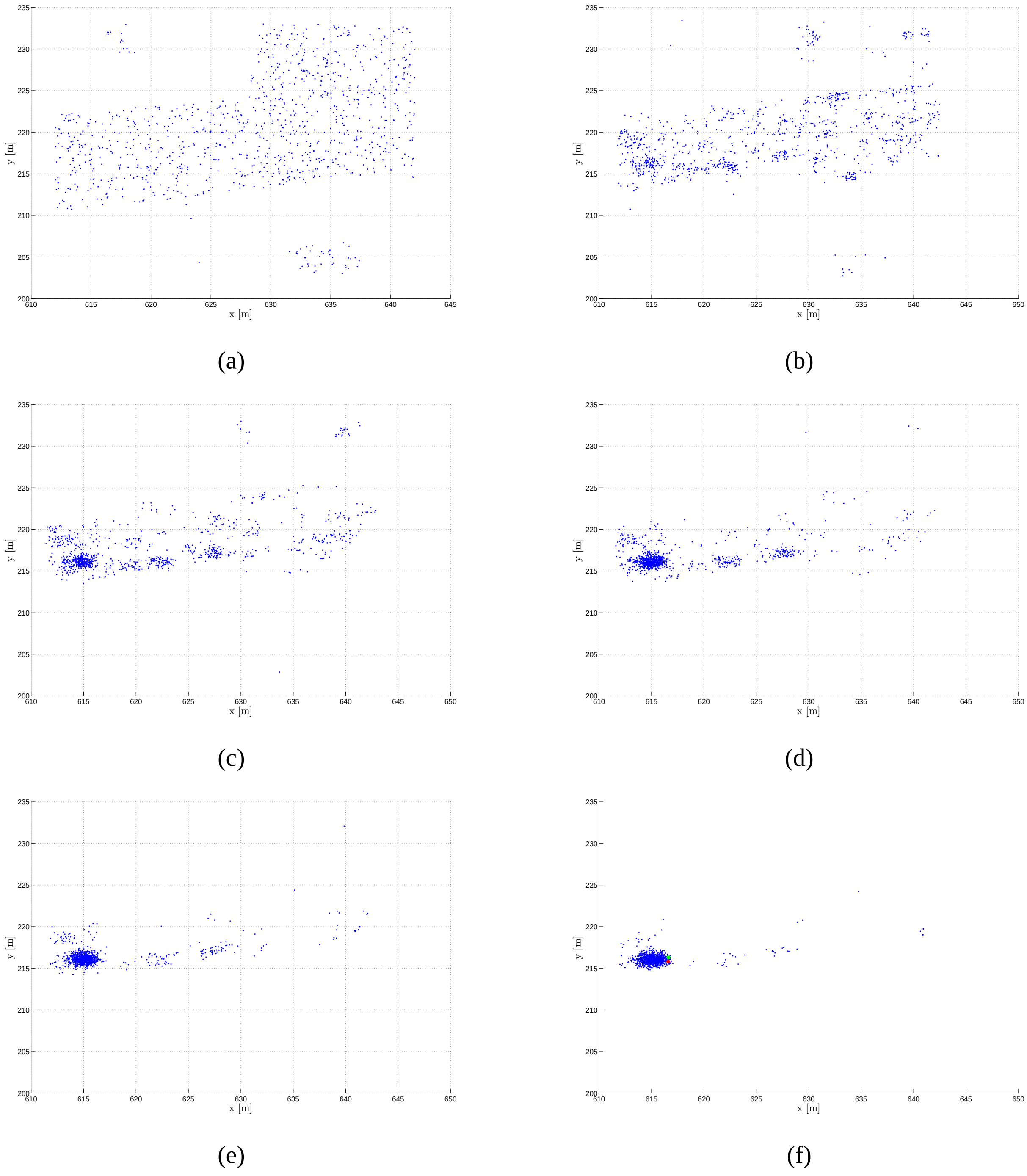

Fig. 6. The figures show the located particles. $a)$ Initial random sample step of the Particle filter relating to GPS position. No particles inside of building outlines, $b)$ - $f)$ Particle clustering after each filter cycle, where $f)$ additionally includes groundtruth position(green) and best weighted particle (red)