Proceedings of the
2007 IEEE Intelligent Vehicles Symposium
Istanbul, Turkey, June 13-15, 2007

Extending Onboard Sensor Information by Wireless Communication

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Abstract— **New algorithms for the integration of data, which is obtained by wireless communication, in an onboard sensor based vehicle environment model are introduced. The system receives the dynamic state and additional information of objects via wireless communication with latency. The dynamic state is filtered and predicted to the current time. Afterwards, a track-to-track fusion of received objects and objects, which are measured by onboard sensors, is performed. This association is based on the object's position, orientation, velocity as well as the object's history. In addition, the probability of an unmeasured object is considered. The complete system is evaluated with ground truth data.**

I. Introduction

SEVERAL advanced driver assistance systems are already available in modern cars. Additional systems are in the focus of research and development for future cars. Today, driver assistant systems usually are directly connected to one or several exclusively used sensors. The increasing number of driver assistant systems will cause the need of sharing sensors in the future. The application of a common sensor data processing unit seems to be useful and efficient.

This work is based on algorithms for laser scanner sensor data preprocessing, tracking, and classification. These algorithms create a common vehicle environment model, which can serve multiple applications simultaneously. The environment model contains multiple objects, accompanied by information about object size, orientation, velocity, and class. In addition, map information can be integrated. The pose of the host vehicle in the map is estimated with landmarks detected by the laser scanner [1]. Unfortunately, some information can not or hardly be measured by onboard sensors.

Recent research also focuses on the usage of wireless communication for advanced driver assistant systems [2]-[4]. Such systems usually use GPS or differential GPS positions for the localization of both, the host vehicle and other road users. Sometimes, very precise and expensive real time kinematic GPS (RTK GPS) sensors are applied. Pure communication based systems are feasible for a wide range of functions. However, there are some disadvantages, which were already partly mentioned in [4]. Firstly, the GPS position is quite inaccurate, if not measured by expensive RTK GPS sensors. Secondly, due to incomplete equipment rate, unequipped road users can not be detected. It will take a lot of time, until a sufficient penetration rate is achieved for cars, but it is questionable if pedestrians will ever be equipped with communication technology. Finally, latencies caused by GPS sensors and communication time have to be considered.

For this reason a fusion of onboard sensor information and wireless communicated information seems to be advisable. The resulting extended environment description can benefit from both, precise position and velocity estimates of all objects, which are close to the host vehicle, and additional information received by wireless communication. The additional information can improve the sensor's view in two ways: It can extend the systems field of view, since communication is less affected by occlusions than sensors. It is also possible to add information, which can not be measured by onboard sensors, to the measured objects.

There are two sources of received object information. Equipped vehicles can directly send the information. But it is also possible to send information about objects, which are measured by sensor equipped stationary road side platforms or other vehicles.

Two object types have to be distinguished. Objects, whose data is received by wireless communication, are called "received objects". Objects, which are measured by onboard sensors, are called "measured objects". This work concentrates on the main fusion task: the association of measured objects and received objects. For this purpose both object types are tracked. Afterwards, corresponding objects are associated. Methods to provide a consistent output in terms of an extended vehicle environment model are discussed.

Manuscript received April 15, 2007. This work was supported in part by IBEO Automobile Sensor GmbH.
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1-4244-1068-1/07/$25.00 ©2007 IEEE.

II. Differential GPS Position Error

If object information is sent by wireless communication, the corresponding position usually has to be estimated by GPS. Two types of differential GPS receivers were analyzed to estimate the available position accuracy. Two equipped vehicles were used. The GPS position of one vehicle was transformed into the sensor coordinate system of the other vehicle. The difference between the quite precise measured position and the transformed received position describes the relative position error, which is relevant for advanced driver assistant systems. The experiments have shown a quite low accuracy. Relative errors of up to 5 m were typical for suburban and rural roads. Urban scenarios even showed relative errors of up to 10 m due to multipath problems and less available satellites.

Figure 1 illustrates this problem by an example. The standard situation of oncoming traffic can look very dangerous, if the inaccurate GPS position indicates an oncoming vehicle on the lane of the host vehicle. Several safety applications will fail, if this GPS position is used. This problem can be solved by information fusion with onboard sensors, if the received objects are associated to precise onboard sensor position and velocity data.

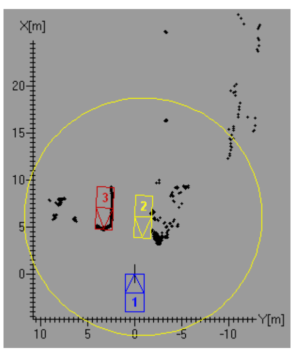

Fig. 1. GPS position error: A blue box (1) describes the position of the test vehicle. The yellow box (2) and ellipse show the received position of the second vehicle and its uncertainty (3σ). The correct object position is indicated by the red box (3). The usage of the GPS position seems to be insufficient for a wide range of driver assistant systems. All laser scanner measurements are indicated by black dots. A pure distance based association of the received object information to sensor measurements will fail due to the high GPS position error.

III. Wireless Data

The introduced methods require information about the following properties of received objects: A unique object ID is used to distinguish different received objects. The UTC (Coordinated Universal Time), which is obtained from GPS, is used for synchronization. The properties position in WGS84 coordinates (global coordinates using the World Geodetic System 1984) with uncertainties, orientation to north, velocity, and yaw rate are used to filter and predict the objects' dynamic states. This information is also used for association purposes.

The following properties are used to improve or extend the onboard sensor based vehicle environment model: The precise object size and class can directly improve the estimates, which are obtained from the onboard sensors. Additional information like mass, activated turn lights, gas or brake pedal positions can extend the information about measured objects. It seems also useful to communicate the expected route, if an object uses a navigation system.

IV. System Overview

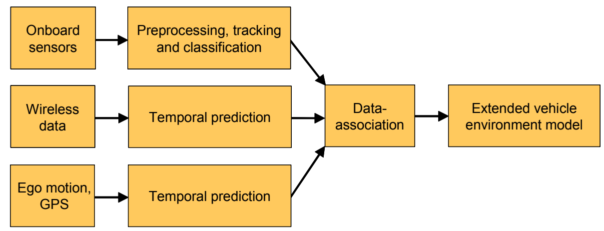

Fig. 2. System overview: The system performs tracking and classification of objects, which are observed by onboard sensors. Object information obtained from wireless communication is filtered to predict the object state to the time of the current sensor measurements. In addition, the host vehicle's position has to be predicted. The data association algorithms fuse information of all sources and provide the extended vehicle environment model.

The system layout is illustrated by Figure 2. The onboard sensors measure objects in the vehicle's environment. The sensor data is preprocessed, the objects are tracked and classified. Details about tracking and classification can be found in [5]. The result of these parts is a sensor based environment model, which contains objects accompanied by information about the size, position, velocity, and class.

This environment model is enhanced by data obtained from wireless communication. Object data is received with corresponding differential GPS and motion data. An object state filter is used to estimate and predict the dynamic state of the received objects as well as the host vehicle. A data association is performed to fuse measured objects with received objects. The result is the extended vehicle environment model.

V. Object State Filter

Several latencies complicate the task of data association. Firstly, GPS has a low update rate. Usually, a position is measured once a second. Secondly, some time is necessary for measuring of the position and for the wireless communication. For this reason, the received object information will correspond to past measurements of the onboard sensors. Unfortunately, the objects move significant distances between the measuring time of the GPS position and time of the current onboard sensor measurements. The corresponding position differences are illustrated by Figure 3.

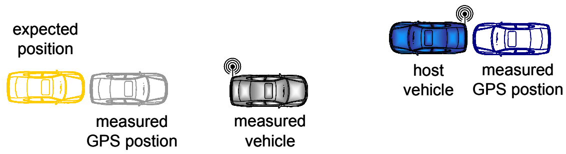

Fig. 3. Position error, caused by measurement and transmission delay: Usually the received positions and the last GPS position of the host vehicle correspond to past sensor measurements. If the received position is used directly, the object will be expected very far away from its correct position. Therefore, the received information and the host vehicles position have to be predicted to the current time.

For this reason, the motion after the last known GPS position has to be estimated. It is necessary to combine the velocity and the yaw rate of objects with the GPS positions. This estimation must be performed for both, the host vehicle and the measured object.

The motion estimation is performed with an Extended Kalman Filter [6] using a turn model in the global WGS84 coordinate system [7] [8]. This leads to the state vector:

$$x = (\varphi \quad \lambda \quad v \quad \psi \quad \omega)^T$$

with latitude φ, longitude λ, velocity v, orientation ψ, and yaw rate ω. The altitude h is not filtered, because it is assumed to be constant between successive GPS measurements. The corresponding process model is given by:

$$x_{k+1} = x_k + \begin{bmatrix} \frac{v}{r_\varphi \omega}(\sin(\omega T + \psi) - \sin(\psi)) \\ \frac{v}{r_\lambda \omega}(\cos(\psi) - \cos(\omega T + \psi)) \\ 0 \\ \omega T \\ 0 \end{bmatrix}$$

The values of the radius of curvature in the meridian r_φ and the radius of curvature in the prime vertical r_λ can be calculated by:

$$r_\varphi = \frac{a(1-e^2)}{(1-e^2\sin^2\varphi)^{\frac{3}{2}}} + h$$

$$r_\lambda = \left(\frac{a}{\sqrt{1-e^2\sin^2\varphi}} + h\right)\cos\varphi$$

$$e^2 = \frac{a^2 - b^2}{a^2}$$

with the WGS84 geoid's semi major axis a and semi minor axis b.

The motion estimation also has to consider the GPS measurement latency. The output of the GPS receiver usually corresponds to a measurement time several hundred milliseconds before. Due to this latency, some of the last velocity and yaw rate measurements are newer than the measured GPS position (Figure 4). Unfortunately, the Extended Kalman Filter expects the measurements in a chronological order.

A simple idea to consider this fact is to keep the motion measurements until the GPS data is measured. This idea will ignore several motion measurements, which are already available. This will result in a quite uncertain state estimation.

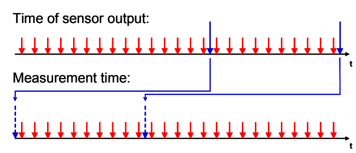

Fig. 4. GPS latency: The output of the GPS receiver (blue arrows) corresponds with a measurement time several hundred milliseconds ago. Therefore, the GPS measurements are older than the last velocity and yaw rate measurements (red arrows).

A more accurate approach considers all available measurements. A backup of the dynamic state and the covariance matrix is stored after each GPS measurement. Afterwards all available motion measurements are incorporated into the Kalman Filter. In addition, all motion measurements after the last GPS measurement are stored in a buffer. If a new GPS measurement is available, the backup will be used and all measurements are incorporated in chronological order. Again, the backup of the dynamic state and the covariance matrix is performed after the incorporation of the GPS measurement.

Finally, the dynamic object state of received objects and the host vehicle is predicted to the time of the current sensor measurements for association purposes.

VI. Data Association

The received objects are assigned to object tracks of measured objects if possible. This procedure is divided into several steps. First, the dynamic state of a received object has to be transformed from WGS84 to the vehicle coordinate system. Afterwards, the number of assignable measured objects is reduced by a gating of the position. Based on the transformed uncertainty of the received object's dynamic state, association probabilities for each assignable measured object are calculated conditioned on the assumption, that the object was measured. Afterwards, the probability of an unmeasured object is incorporated by numerical integration of occluded areas. A temporal filter stabilizes the association probabilities. These probabilities are stored in the environment model for later output.

A. Dynamic state transformation

The dynamic state of the received objects has to be transformed to the host vehicle's coordinate system, when an association is performed. The calculation of the transformed dynamic state $\mathbf{x_R}$ of the received object is performed by the function:

$$\mathbf{x}_R = \begin{bmatrix} x_R \\ y_R \\ v_R \\ \psi_R \end{bmatrix} = \mathrm{f}\left(\varphi_{host} \quad \lambda_{host} \quad \psi_{host} \quad \varphi_{obj} \quad \lambda_{obj} \quad \psi_{obj} \quad v_{obj}\right) = \mathrm{f}(\mathbf{x})$$

$$\mathbf{x}_R = \mathrm{f}(\mathbf{x}) = \begin{pmatrix} r_\varphi \cos(\psi_{host})(\varphi_{obj} - \varphi_{host}) + r_\lambda \sin(\psi_{host})(\lambda_{obj} - \lambda_{host}) \\ r_\varphi \sin(\psi_{host})(\varphi_{obj} - \varphi_{host}) - r_\lambda \cos(\psi_{host})(\lambda_{obj} - \lambda_{host}) \\ v_{obj} \\ \psi_{host} - \psi_{obj} \end{pmatrix}$$

The transformation is also applied to the corresponding uncertainties. For this purpose, the covariance matrix $\mathrm{cov}(\mathbf{x})$ is obtained from the object state filters of the host vehicle and the received object. The Jacobian $\mathbf{J_f}$ of $\mathbf{f}$ is needed for the transformation of this covariance matrix:

$$\mathrm{cov}(\mathbf{x}_R) = \mathrm{cov}\begin{bmatrix} x_R \\ y_R \\ v_R \\ \psi_R \end{bmatrix} = \mathrm{J_f}(\mathbf{x})\mathrm{cov}(\mathbf{x})\mathrm{J_f}(\mathbf{x})^T$$

B. Gating

A validation region of the positions of measured objects is defined based on the transformed covariance matrix. The matrix elements with respect to the position constitute a two dimensional covariance matrix. This matrix can define an elliptical validation region (3σ ellipse) [9]:

$$\left(\begin{bmatrix} x_M \\ y_M \end{bmatrix} - \begin{bmatrix} x_R \\ y_R \end{bmatrix}\right)^T \left(\mathrm{cov}\begin{bmatrix} x_R \\ y_R \end{bmatrix}\right)^{-1} \left(\begin{bmatrix} x_M \\ y_M \end{bmatrix} - \begin{bmatrix} x_R \\ y_R \end{bmatrix}\right) \le \gamma \qquad (1)$$

All measured objects with the position $(x_M, y_M)^T$ will be assignable to a received object with the position $(x_R, y_R)^T$, if equation (1) is true for a given threshold γ.

C. Association Probabilities

The association probabilities are calculated for each received object independently. The probability of each assignable measured object is calculated based on the transformed covariance matrix and the Euclidean distance between the dynamic state vectors of the measured object and the received object.

The first step is the calculation of the conditional association probability of the measured object k given the event M that the received object was measured by onboard sensors. This probability is conditioned on the number of measured objects n in the validation region and their position [9]:

$$P(k|M) = \frac{e_k}{\sum_{j=1}^{n} e_j}$$

where each e_i is calculated from the assumed Gaussian probability density function of the dynamic state of the received objects:

$$e_i = \exp\left(-\frac{1}{2}\left(\mathbf{x}_{M,i} - \mathrm{f}(\mathbf{x})\right)^T \mathrm{cov}(\mathbf{x}_R)^{-1}\left(\mathbf{x}_{M,i} - \mathrm{f}(\mathbf{x})\right)\right)$$

The second step is the calculation of the (unconditioned) association probability. This can be performed with Bayes' theorem:

$$P(k|M) = \frac{P(M|k)P(k)}{P(M)} = \frac{1 \cdot P(k)}{P(M)}$$

$$P(k) = P(k|M)P(M)$$

This calculation needs an estimation of the current probability $P(M)$, that the received object is measured at the moment. This estimation is described in the next subsection.

D. Occlusion Detection

The probability of occlusion is calculated for discrete areas in the vehicle environment based on the measurements of the laser scanner. The radial measuring principle of the laser scanner leads to a discretization in polar coordinates with the tangential step size $\Delta\alpha$ and radial step size Δr. The corresponding probability of occlusion is $P(r, \alpha)$.

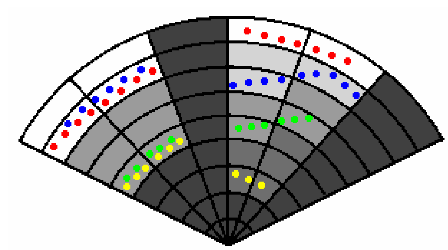

Fig. 5. Occlusion detection: The algorithm estimates occlusion probabilities of discrete areas in polar coordinates based on the four horizontal layers of the laser scanner. The probabilities are indicated by gray values between black (not occluded) and white (occluded). The circles are sensor measurements. The corresponding layer is indicated by color. The occlusion probability of an area rises with the number of layers with corresponding measurements between the area and the sensor (center).

The four horizontal scan layers of the sensor allow the distinction of five discrete probabilities of occlusion: not occluded, occluded in 1, 2, 3 or 4 layers. The calculation is applied to each of the discrete angles α_i separately and starts at the sensor. The occlusion probability is *0* in the area between the sensor and the first laser scanner measurements. The probability is *0.25* in the area between these measurements the laser scanner measurements of a second layer and so on. The principle is illustrated in Figure 5.

The occlusion probability of a received object is estimated by numerical integration of the occluded area under the Gaussian pdf in the elliptical gate (Figure 6).

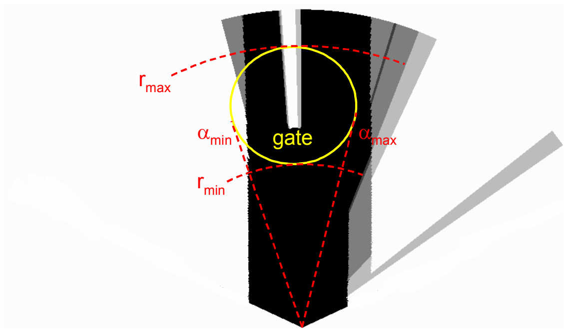

Fig. 6. Occlusion probability: The occlusion detection calculates occlusion probabilities of discrete areas. These probabilities are displayed as in Figure 4 (white: certainly occluded, black certainly not occluded). The occlusion probability of a received object is calculated by integration of the occlusion probabilities under the assumed Gaussian pdf in the elliptical gate.

The occlusion probability of the received object is calculated by:

$$1 - P(M) = P(\overline{M}) = \sum_{r=r_{min}}^{r_{max}} \sum_{\alpha=\alpha_{min}}^{\alpha_{max}} P(r,\alpha) A(r,\alpha) g(r,\alpha)$$

with the discrete area size:

$$A(r,\alpha) = \frac{\Delta\alpha}{2\pi}\left(\pi(r + 0.5\Delta r)^2 - \pi(r - 0.5\Delta r)^2\right)$$

and the value of the Gaussian pdf:

$$g(r,\alpha) = \frac{1}{2\pi\sqrt{\det(\mathrm{cov}(\mathbf{x}_R))}} e^{-\frac{1}{2}\Delta\mathbf{x}(r,\alpha)^T \mathrm{cov}(\mathbf{x}_R)^{-1} \Delta\mathbf{x}(r,\alpha)}$$

Here the distance between the center of the Gaussian and the center of the area is evaluated:

$$\Delta\mathbf{x}(r,\alpha) = \begin{pmatrix} x_R \\ y_R \end{pmatrix} - \begin{pmatrix} r\cos\alpha \\ r\sin\alpha \end{pmatrix}$$

E. Temporal Filter

Unfortunately, these association probabilities are insufficient for a robust association of measured objects and received objects. There are ambiguities caused by similar dynamic states of measured objects. The association can be significantly improved by an additional evaluation of the object's history. For this purpose the association probabilities are stabilized by a temporal mean filter.

This modification will only achieve high association rating of a measured object, if it performs a similar motion like the received object.

VII. Extending the Environment Model

The received objects are stored together with the estimated object state and additional information directly in the internal database of the system. The filtered association probabilities are stored in this database, as well. Thereby, the output of the framework, which is the extended vehicle environment model, can be adapted to the requirements of different applications.

Usually, a consistent environment model with a single association to each received object is required by the applications. Therefore, the association to the object with the maximum association probability will be given to the application. This is only reasonable, if a minimum association probability threshold *s* is exceeded.

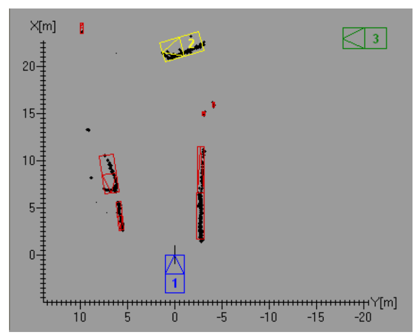

Fig. 7. Extended vehicle environment model: The test vehicle (1) measures several objects in the environment with the laser scanner (black points). The sensor based tracking and classification algorithms estimate objects for these measurements (red boxes). This environment description is extended in two ways by wireless communication: If information is received about an object, which already is measured by the laser scanner, the information will be added to the measured object (2). If the received object is not in the field of view of the sensors, the object will be added as an additional object to the environment description (3).

If an association seems to be unreasonable, it will be assumed that the received object is not measured by the onboard sensors. Thus, the received object is passed to the application in addition to the measured objects (Figure 7). This additional object will be combined with very high uncertainties due to the uncertain GPS position and the communication latency.

If an association uncertainty is required, the filtered association probabilities will also be handed over to the application.

As a second output option, it is also possible to provide an application with all assignable objects, the corresponding association probabilities and the received objects. Thus, the application can decide how to use all the information. This second option is not analyzed by the following system performance evaluation section.

VIII. Results

The complete system performance is evaluated with test data. Several sequences with equipped test vehicles in urban and suburban scenarios as well as on highways were evaluated. The correct association was labeled manually and compared to the algorithm's results.

Offline tests simulated different delays for the communication of the measured real world data. This experiment shows the influence of the communication delay to the association performance.

Two corresponding measures were calculated for each simulated communication delay: the rate of correct associations indicates the ratio of correct associations to possible associations. The mean number of wrong associations per frame gives an indication about false alarms. Different combinations of the two measures can be obtained by selecting different thresholds for the minimum association probability, which restricts the output of an association. The results are illustrated by Figure 8.

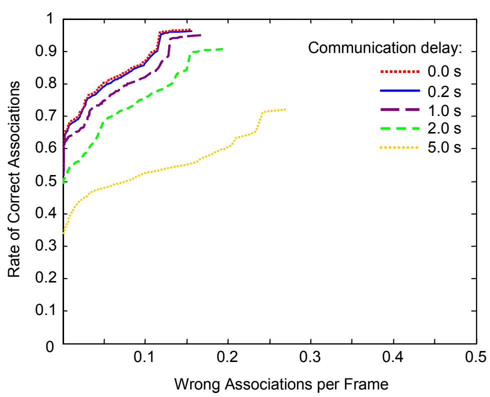

Fig. 8. Results: Several simulated communication delays were compared. The plots show the rate of correct associations over the mean number of wrong associations per frame. Different combinations of the measures are obtained by changes of the threshold for the minimum accepted association probability.

The experiments showed only minor differences between the optimum of no communication delay and the realistic value of 200 ms. Communication delays higher than 1 s cause a significant loss of association performance.

A good association performance could be achieved with the realistic value of 200 ms. If the application can not accept false associations, between 60 and 70 percent of all possible associations were achieved. If false alarms can be tolerated, the performance will rise up to 97 percent.

IX. Conclusion

A real time system for the extension of an onboard sensor based vehicle environment model with data of wireless communication was introduced. The extension is based on received data of objects. The system filters the dynamic state of these objects. An association of received objects and objects, which are measured by onboard sensors, is performed. If an association is reasonable, additional information of the received object can be added directly to the measured object. Otherwise, the received object will be passed to the applications in addition to the measured objects. The performance of the system was evaluated with ground truth data.

Although a laser scanner was equipped as onboard sensor, the proposed algorithms may also work with other sensors like RADAR or sensor fusion approaches.

The presented framework is developed to handle received objects, which are localized by differential GPS. However, it is also possible to handle object data with better localization. The position uncertainties are directly considered. A better localization can be achieved by using digital maps, for example [1]. This will increase system performance and robustness, because the gating will reject more measured object than in the case of high position uncertainties. In addition, the association probabilities are more suitable.

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