Track Based Multi Sensor Data Fusion for Collision Mitigation

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Abstract – This paper presents a high level fusion approach suitable for automotive sensor networks with redundant field of views. The advantage of this method is that it ensures system modularity and allows benchmarking, as it does not permit feedbacks and loops inside the processing. The proposed algorithm deals with the issue of multidimensional assignment as the test vehicle comprises four forward looking sensors. The work described here is part of the research work in the project PReVENT/ProFusion² where the proposed algorithm has been tested in two experimental vehicles. The paper also contains results with respect to data fusion performance for the case of collision mitigation application using several testing scenarios in real conditions.

Keywords: data fusion, heterogeneous sources, track level fusion, collision mitigation

1 Introduction

In this paper a track level fusion architecture is proposed that takes the information provided by four sensorial systems and provides as output the global fused objects describing the vehicle environment. The architectural level where this operation takes place is the intermediate level between the measurements and the applications, mentioned often as the perception layer. This approach is referred in the next as: Track Level Fusion (TLF).

Related work on multi sensor data fusion for preventive safety has been carried out in a series of research activities such as the projects ARCOS [1], EUCLIDE [2], PAROTO [3], and CARSENSE [4]. These first fusion systems in automotive safety were using a limited number of sensors and were focused in one particular application (e.g. forward collision warning). However, in IP PReVENT more sophisticated fusion systems are being tested with a group of integrated applications, characteristic example is the LATERAL SAFE subproject with eleven sensors observing holistically the rear and side areas of the vehicle [5]. In ProFusion² innovative research on sensor data fusion takes place and prominent car manufacturers offer useful test cases where several independent sets of sensorial systems are used [6]. This approach is being tested in two specific prototype vehicles. Here the results using data of the Volvo Technology Corporation sensor equipped truck with main test case the multidimensional assignment are presented.

The structure of the paper is the following: Section 2 presents the test vehicle where the algorithms were applied. Section 3 describes the fusion algorithm and the road geometry estimation method followed. The evaluation scenarios and the results are given in Section 4. Finally Section 5 closes the paper.

2 Test Vehicle

2.1 Description of the vehicle

The test vehicle platform is based on a Volvo FH12 420 Globetrotter truck. Within the IP PReVENT sub-project COMPOSE, it has been equipped with a laser scanner at the front left corner for the application of rear-end collision mitigation by braking. Within ProFusion², an extended sensor set is investigated for the same application, covering the area in front of the host vehicle. The main components of the ProFusion² perception system are

- An IBEO laser scanner, mounted in the front left corner of the truck, shared with SP COMPOSE
- A lane camera and vision system, developed in the SP SAFELANE
- A long range radar (LRR), shared with the SP SAFELANE
- A short-range radar (SRR) system, shared with the SP APALACI.
- An automotive PC hosting the data fusion platform.

The perception system provides the decision system with the objects detected ahead of the own vehicle. With help of the lane camera an improved object-to-lane assignment is investigated. Based on the fusion system a decision is made if a collision is likely or unavoidable. If a collision is detected to be likely, the driver is warned, if an impact has become unavoidable, the vehicle is braked automatically to mitigate the consequences of an impact.
3 Algorithm

The algorithmic part of track level fusion is separated in methods for measurement data preprocessing, object tracking algorithms, road border estimation algorithm and track to track fusion approach. In this section brief description of these generic approaches will be given.

3.1 Measurement data preprocessing

Data preprocessing takes place in a first place so that afterwards the tracking algorithms to be applied in the measurement points of interest. This practically means that the moving vehicles are usually needed for the tracking algorithms, while the rest of the points can feed a road border estimation algorithm or can be omitted as belonging to clutter.

For sensors like the LRRs in the demonstrator vehicles, the data selection preprocessing is straightforward as the measured velocities are reliable and moving targets can easily be separated and enter the tracking algorithm. For the case of sensors that their velocity and angle measurements or estimates are not reliable, specific data processing steps were considered. Here we present two such cases.

Angle measurement of SRR network

It was observed that the angular measurements of a forward looking two-sensor SRR network were deteriorating as the range of the measurement was increasing. For that reason a range based association of the two sensor measurements took place and an extraction of their common angle measurement followed. This means that a merged object for the SRR network is afterwards feeding a tracking algorithm.

An example of the output of this approach is given in Figure 2. With blue and cyan dots the measurements from the SRR sensors are given, with magenta crosses are the output of the merging of the two sensors points. With green is the input of the laser scanner as an idea of where the object is moving, as a more reliable sensor. The figure is a cumulative plot of approximately 25 scans. Of interest is the object appearing at (4,4)m and moving to about (23,4)m. The detections of the SRRs even though they are not corresponding to the same point on the vehicle seem to clearly draw away as the distance increases. The merged point is a more realistic representation of the actual object (according to laser scanner measurements) and those objects are tracked to provide the output of the SRR network track array.

Object selection for laser scanner

As it is also shown in Figure 2 laser scanner (green polygons) provides detections for cars or other vehicles moving in the road but it also detects lines corresponding to road boundaries or road environment (i.e. buildings, trees etc). Therefore, it was absolutely necessary to classify these measurement polygons in order to exploit in the best possible manner this very useful information. The velocity information was proved to be unreliable for identifying moving vehicles out of this amount of information, and consequently the effort was concentrated in geometric searching for predefined shapes in laser scanner measurements.

The algorithm searches for lines horizontal or vertical and “L” shapes of various orientations. The vertical (I-shapes) and L-shapes usually correspond to vehicles were dimensions information can also be extracted. The selection of data that are candidates for road borders estimation is based on the following idea: take into account data that lie within two parallel strips, one on the left side and the other on the right side of the ego vehicle, ignoring other data. This way the first measurement set is formulated. The second step is to locate other vehicles that are moving within these strips of interest, using a specific algorithm that searches for closely parallel moving points, and exclude these measurements from being used in borders estimation.
In Figure 3 several representable examples of laser scanner polygon measurements that were characterized as vehicles are given.

3.2 Tracking algorithm

Modeling
The basic model used in the different cases of tracking implemented is the constant acceleration (CA). This model was proved to be adequate for the cases that were examined. The measurements used include measurement vectors of: range-azimuth-range rate, coordinate x-coordinate y-range rate and coordinate x-coordinate y-length-width. In the first two cases where the measurement space is non-linear the EKF approach was used, while in the latter simple Kalman Filter use was possible.

Data association
The problem of data association is the assignment of sensor measurements to one of the existing tracks and the problem is formulated as in [7]. The assignment problem that is the problem of finding the best association between tracks and measurements minimizing a cost function is solved with two methods: the GNN and the probabilistic JPDA. The former is one-to-one measurement to track assignment, while the latter uses more than one measurements to update one track, and more than one track to be updated (with different probabilistic weights) by the same measurement.

The data association in LRR tracking algorithm work in 2 modes; the GNN and the JPDA, using 1-to-1 and N-to-1 measurements to track assignment. The final decision of the DA approach to be implemented depends on the quality of the measurements by each sensor. Typically GNN is adequate for LRR tracking.

Track Management
According to the results of 1-1 assignment, if a track has been associated with a measurement it has a “hit” in the current scan; otherwise it has a “miss”. The values of “hits” and “misses” are stored for each track and are attached to it. The track consists of the state vector, the covariance matrix and the ID vector.

For confirmation and deletion of tracks, the algorithm presented in Figure 4 is followed. When a new track is confirmed or an existing track is deleted, the tracked object list is updated accordingly. Each tracked object is defined by its state vector, ID vector and covariance matrix. Track management is the last step before the filtering step, after track management the tracks with an existing track-measurement pair are updated by the filtering equations. This method of DA is applied in the GNN-auction (1-1) case.

In the probabilistic method track probability values are calculated normalizing the weights of association of every existing track with all measurements available in current scan. If the probabilities of no association of a track with one of the existing measurements in the current scan surpass a threshold - e.g. 0.5 - this track is deleted. All tracks are regarded as confirmed tracks in the JPDA case.

Track Initialization
The issue of filter initialization is very important in tracking applications. Each measurement not associated with one of the existing tracks is becoming a new track, and it is initialized according to available measurements. The missing information is calculated using the available parameters and making some assumptions that are reflected to the initial estimation errors.

Filtering
The basic filtering approach in LRR tracking is the EKF or KF and GNN method for data association, as object extraction was taking place before tracking and each track is updated by one measured object.

3.3 Road geometry estimation

The amount of information available from the scanning of the laser scanner allows the estimation of the road geometry.

Two identical clothoid curves [8] with the same parameters \( c_0 \) and \( c_1 \), but different offsets \( y_{0l} \) and \( y_{0r} \),
can describe the road. Thus, the state vector \( x_{RB} \) that
describes the road is:
\[
x_{RB} = (c_o, c_i, y_o, y_r)^T
\]
A discrete time model is defined for the update of this
vector using the ego-vehicle parameters. The parameters
used are the velocity \( V \), the (direction) angle difference
between current and previous angle \( \delta \theta \) and the turn rate
\( \omega \). According to the value of \( \omega \) the values \( \Delta x \) and \( \Delta y \)
of the ego-vehicle transposition that takes place in \( T \)
seconds are computed. Two cases are distinguished:
(a) When the ego-vehicle’s turn rate is significant and consequently affects the vehicle’s trajectory:
\[
\Delta x = \frac{V}{\omega} \sin(\delta \theta), \quad \Delta y = \frac{V}{\omega} (1 - \cos(\delta \theta))
\]
(b) When the turn rate is negligible, it is assumed that the vehicle is moving on x-axis (direction of velocity) entirely, therefore \( \Delta x \approx VT \) and \( \Delta y \approx 0 \).
The state equation for the update of road parameters is
defined as:
\[
x_{RB}(k+1) = \Phi_{RB}(k) \cdot x_{RB}(k) + G_{RB}(k)w_{RB}(k)
\]
The transition matrix from scan \( k \) to scan \( k+1 \) \( \Phi_{RB} \) and
the input vector \( G_{RB} \) are respectively:
\[
\Phi_{RB} = \begin{bmatrix}
1 & \Delta x & 0 & 0 \\
0 & 1 & 0 & 0 \\
\frac{\Delta x^2}{2} & \frac{\Delta x^3}{6} & 1 & 0 \\
\frac{\Delta x^2}{2} & \frac{\Delta x^3}{6} & 0 & 1
\end{bmatrix}, \quad G_{RB} = \begin{bmatrix}
0 \\
0 \\
\Delta y \\
-\Delta y
\end{bmatrix}
\]
The estimation covariance matrix is:
\[
P(k+1|k) = \Phi_{RB}(k)P(k|k) \Phi_{RB}^T + Q(k), \text{ with the process noise covariance defined as:}
\]
\[
Q_{RB} = \mathbb{E}(\delta x \delta x^T) = \begin{bmatrix}
E(c^2_o) & E(c_c) & 0 & 0 \\
E(c_c) & E(c^2_i) & 0 & 0 \\
0 & 0 & E(y^2_o) & 0 \\
0 & 0 & 0 & E(y^2_r)
\end{bmatrix}
\]
The parameters that affect the above equation are the
curvature rate standard deviation \( E(c^2_i) = s_i^2 \) and offset
standard deviation \( E(y^2_o) = s_o^2 \). The non diagonal elements of the covariance matrix are:
\[
E(c_c) = E(c_c) = E(c^2_i l) = s^2_i E(l) \quad \text{and} \quad \]
\[
E(c^2_i) = E(c^2_i l^2) = s^2_i E(l^2). \]
In order to compute the mean value for the curve’s length, the elementary offsets \( \Delta x \) and \( \Delta y \) are used, which leads to:
\[
E(l) = \sqrt{(\Delta x^2 + \Delta y^2)} = \left\{ \frac{V}{\omega} \sqrt{2(1 - \cos(\delta \theta))} \right\}^{\frac{1}{2}}
\]
for cases (a) and (b) respectively. Since \( E(l^2) = (E(l))^2 \)
and \( \alpha \) equals \( E(l) \); then \( Q_{RB} \) becomes:
\[
Q_{RB} = \begin{bmatrix}
\quad \quad a^2 s^2_c & a s^2_c & 0 & 0 \\
\quad a s^2_c & s^2_c & 0 & 0 \\
0 & 0 & s^2_o & 0 \\
0 & 0 & 0 & s^2_o
\end{bmatrix}
\]
The set of measurements that are assigned as candidates for
road geometry estimation are assumed known in this
paragraph. These measurements generate a \((N_l + N_r)\)1-
dimensional measurement vector, in the general case,
where \( N_l \) and \( N_r \) refer to the measurements of the left and
the right side of the road respectively. Each measurement
refers to its x and y coordinates in the road plane. From
the \( N_l \) pairs \((x_{li}, y_{li}), i = 1, ..., N_l\) and the \( N_r \) pairs
\((x_{ri}, y_{ri}), i = 1, ..., N_r\) a measurement vector is
formulated:
\[
y_{RB} = \left( y_{l1}, ..., y_{lN_l}, y_{r1}, ..., y_{rN_r} \right)^T
\]
It should be mentioned that the y-coordinates are taken as measurements of road geometry, as more sufficient\(^1\) to
errors comparing to x-coordinates. The later are used in
the formation of the measurement matrix of the following
equations. According to this vector, the measurement
matrix \( H \) that associates it with the state vector is
computed so as:
\[
y_{RB}(k) = H_{RB} x_{RB}(k+1) + u_{RB}
\]
\[
H = \begin{bmatrix}
x_{li} & x_{li} & 2 & 6 & 1 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
x_{rli} & x_{rli} & 2 & 6 & 1 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
x_{lnr} & x_{lnr} & 2 & 6 & 0 & 1 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
x_{rnr} & x_{rnr} & 2 & 6 & 0 & 1
\end{bmatrix}
\]
The measurement error covariance matrix \( R \)
corresponding to the Gaussian zero mean noise \( u_{RB} \)
is selected as a diagonal matrix with dimensions
\((N_l + N_r) \times (N_l + N_r)\) with its diagonal elements
having the value of y-measurement standard deviation.

\(^1\) Range sensors detect angular position of targets
(consequently y-coordinates) with less confidence
comparing to range parameter (and x-coordinates).
The state vector’s initialization takes place at the first scan or more often when the previous scan was a scan of ‘deletion’ (i.e. no data was present for a number of successive scans). In the initialization process the parameters \(c_0\), \(c_1\) are set to zero and the offset parameters are set to their previous estimated values. A state vector is deleted when a series of ‘miss’ (i.e. 3) scans of no measurement data for both sides of the road is completed. Instant deletion and re-initialization of state vector occurs when curvature exceeds a design threshold. The algorithm is adjusted so as to give geometry segments of equal length on both sides of the road, while it can give results for the one or both sides even if data exist only in the one side.

**Measurements to road geometry assignment**

Although road geometry estimation models approximate sufficiently the road parameters, they can be proved useless if there is no measurement data or they are of poor quality in high clutter environments. The measurement set selection to be assigned is of crucial importance for the overall performance of a road geometry estimation algorithm. The selection of data that are candidates for road geometry estimation is based on the following idea: take into account data that lie within two parallel strips, one on the left side and the other on the right side of the ego vehicle, ignoring other data. This way the first measurement set is formulated. The second step is to locate other vehicles that are moving within these strips of interest, using a specific algorithm that searches for closely parallel moving points, and exclude these measurements from being used in road geometry estimation. Then whether these data are sufficient for this kind of estimation is checked. In the case that a small measurement set (e.g. less than 4 points) is selected, it is ignored because the probability of wrong estimation based on these measurements is high.

The formulation of the above mentioned two strips is described in the next. Each strip has constant width and takes its shape according to the middle clothoid (with zero offset). The middle clothoid represents an estimation of the road geometry. These two strips are shifting away or getting closer to the ego vehicle according to where the data of interest are.

A particular care is taken in case sufficient data exist only for one side of the road. On this occasion a pre-calculated estimation of the road width is used.

**3.4 Track fusion algorithm**

The track arrays of each demonstrator architecture are inserted in the fusion algorithm where they firstly are aligned temporally and spatially. There are several methods to update 2 or more tracks (using state and covariances) with track-to-track fusion; some of them are summarized in the following lines.

Regarding the selection of fusion method for two tracks update several methods were examined, starting from Simple Fusion (Singer [9]) that implies that the tracks are uncorrelated thus it is a suboptimal method. The Weighted Covariance Fusion (Bar-Shalom [10]), [7] accounts for correlation between trackers (common process noise) producing the cross covariance matrix from the 2 existing covariance matrices. The fusion finally selected when reliable tracks are available is the Covariance Intersection method (Julier & Uhlmann [11]). Covariance Intersection method deals with the problem of invalid incorporation of redundant information. The fused state and covariance are calculated as:

\[
P_f = \left[ w P_1^{-1} + (1-w) P_2^{-1} \right]^{-1}
\]

\[
x_f = P_f \cdot \left[ w \cdot P_1^{-1} \cdot x_1 + (1-w) \cdot P_2^{-1} \cdot x_2 \right]
\]

where \(w\) in the interval [0,1].

The Covariance Union method (Uhlmann [12]) solves the problem of information corruption from spurious estimates. Covariance Union method guarantees consistency as long as the system and measurement estimates are each consistent, but it is computationally demanding and we decided to not use it. Covariance intersection method is a conservative solution but superior to weighted covariance method.

However in many cases the covariance of obviously not reliable tracks was leading to inaccurate estimates, and therefore a constant predefined weight was used for these cases.

**4 Evaluation Scenarios and Results**

**4.1 Description of scenarios**

The scenarios for the evaluation of ProFusion2 have been chosen in accordance to the COMPOSE evaluation. However, some modifications have been made, since in this case the perception performance is evaluated instead of the application performance.

The scenarios are described in [Error! Reference source not found.](in an overview).

**Scenario 1 – Stationary Performance**

Scenario 1 consists of both a stationary host vehicle and a stationary target vehicle. This scenario aims at investigating the perception performance in terms of detection and positioning accuracy.

**Scenario 2 – Car accelerating from stationary**

In scenario 2, the stationary host vehicle is observing an accelerating target vehicle. This scenario is chosen for investigating track stability for highly dynamical targets.

**Scenario 3 – Car overtaking truck**

Scenario 3 considers the stationary host vehicle being overtaken by a moving target vehicle. This scenario is chosen for investigating track initiation time.
<table>
<thead>
<tr>
<th>Number</th>
<th>Relevant traffic scenario</th>
<th>Evaluation Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Stationary car ahead</td>
<td>Detection and Positioning accuracy</td>
</tr>
<tr>
<td>2</td>
<td>Car accelerating from stationary</td>
<td>Quality of velocity and acceleration measurements, track quality (stability)</td>
</tr>
<tr>
<td>3</td>
<td>Car overtaking truck, $v_{\text{target}} = 40 \text{ km/h}$</td>
<td>point of detection (distance)</td>
</tr>
<tr>
<td>4</td>
<td>Approach to stationary car, $v_{\text{host}} = 40 \text{ km/h}$</td>
<td>point of detection (distance), track quality (stability)</td>
</tr>
</tbody>
</table>

Table 1: Scenarios for PF2-COMPOSE / SAFELANE truck use-case

**Scenario 4 – Approach to stationary car**
In scenario 4, the host vehicle approaches a stationary target vehicle. This scenario is relevant for application performance for Collision Mitigation.

For evaluation, each of the scenarios has been driven three to six times. Data has been recorded for offline analysis of the fusion algorithms.

**4.2 Results of track-based fusion**

The main results for the track-based fusion approach are summarized in Error! Reference source not found. In total, the relevant object has been detected in 16 of 18 scenarios (89%). The missed detections were most likely caused due to a long range radar sensor not detecting the object in question well. Concerning false alarms, in total 130 clutter detections have been made. They can be classified into 86 systematic clutter detections caused by close misdetections of the laser scanner sensor system. The remaining 44 clutter detections were distributed stochastically. This yields a rate of 10.5 systematic clutter detections per minute and 5.4 stochastic clutter detections per minute.

**Scenario 1 – Stationary Performance**
The fusion system performs with good stability and detection rate of stationary objects. A false detection close to the left side of the truck is present in all tests. When the stationary car is positioned close enough for the SRR to detect it, detections become a slightly worse, both in terms of stability, position accuracy and false detections.

**Scenario 2 – Car accelerating from stationary**
The fusion system has good tracking of the moving object, although quite some false detections (reflections).

**Scenario 3 – Car overtaking truck**
The overtaking car is generally detected quickly, but false detections on the close left side of the truck are interfering and makes it hard make a certain identification. After the initial detection, the car is tracked quite well, but with some stability issues. The lateral positioning is a bit unstable until the long range radar detects the car.

\[2\] Note that for the clutter evaluation every single reported target independent of minimal report duration has been counted.
Table 2: Evaluation result for track-based fusion approach

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Scans</th>
<th>Scans with presence of road geometry data</th>
<th># of successful road geometry estimations</th>
<th># of failed road geometry estimations</th>
<th>Success</th>
<th># of successful road geometry estimations</th>
<th># of failed road geometry estimations</th>
<th>General Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highway1</td>
<td>2479</td>
<td>2310</td>
<td>2274</td>
<td>10</td>
<td>99,56%</td>
<td>121</td>
<td>74</td>
<td>96,61%</td>
</tr>
<tr>
<td>Highway2</td>
<td>1538</td>
<td>1491</td>
<td>1460</td>
<td>13</td>
<td>99,12%</td>
<td>17</td>
<td>48</td>
<td>96,53%</td>
</tr>
<tr>
<td>Orbital</td>
<td>4408</td>
<td>4046</td>
<td>2568</td>
<td>15</td>
<td>99,42%</td>
<td>1687</td>
<td>138</td>
<td>96,53%</td>
</tr>
<tr>
<td>Rural</td>
<td>689</td>
<td>657</td>
<td>534</td>
<td>17</td>
<td>96,91%</td>
<td>101</td>
<td>37</td>
<td>92,16%</td>
</tr>
<tr>
<td>Urban/Mixed</td>
<td>3079</td>
<td>2794</td>
<td>927</td>
<td>107</td>
<td>89,65%</td>
<td>1454</td>
<td>591</td>
<td>77,33%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>12193</strong></td>
<td><strong>11298</strong></td>
<td><strong>7763</strong></td>
<td><strong>162</strong></td>
<td><strong>97,96%</strong></td>
<td><strong>3380</strong></td>
<td><strong>888</strong></td>
<td><strong>91,39%</strong></td>
</tr>
</tbody>
</table>

Table 3: Road geometry estimation results

Except for the systematic clutter close to the left side of the truck, false detections are not a problem. 

**Scenario 4 – Approach to stationary car**
The stationary car is generally detected 65-70 m away and remains detected (with some instability) until 15-20 meters away. Not very many false detections have been encountered. Clutter to the left side of the truck is not a big problem. In some tests, the car is not detected at all, most likely to a lacking detection of the long-range radar sensor.

### 4.3 Results of road geometry estimation

The results of the road geometry estimation algorithm are summarised in the following table. The algorithm has been tested in 5 different kinds of roads. The results comes in terms of (a) flag OFF where the sensors data are present and reliable, (b) flag ON where the sensors data in the road borders area are very few and unreliable quite often. As it is expected the results in the first case are far better with the performance in highways to reach 99% success and in urban and mixed roads to be 96 and 89% respectively. In the case (b) the results are worst with the relevant numbers to be 96% in highways, 92% in rural and 77% in urban environments. Summarising the overall performance of the algorithm is 98% in case (a) and 91% in (b), and can be judged as sufficient.

## 5 Conclusion

A track level fusion approach for objects and road geometry estimation for collision mitigation application for a truck has been presented. The approach regarding object estimation demonstrated overall good performance with a minor number of clutter targets on detection level. On the other hand, it has to be taken into account that the selected sensor set-up had a quite inhomogeneous distribution of perception quality. With respect to object sensing, one quite capable sensor has
been complemented by two less performing sensors with either some risk of introducing false alarm or even the risk of missed detections in some scenarios. In these terms, the investigations made and results achieved can also be seen as an analysis of the cooperative data fusion of sensors of different perception quality level. The performance in road geometry estimation when the sensors data are sufficient and enough is quite good.

References


