

Time-to-Collision Estimation in Automotive Multi-Sensor Fusion with Delayed Measurements

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Abstract This paper presents a time-to-collision estimation in the context of multi-sensor fusion. Several asynchronous sensors are fused where the measurements arrive at the fusion unit out-of-sequence, i.e., some measurements are temporally more delayed than others. The adequate out-of-sequence handling is crucial for time-critical applications such as pre-crash systems. Several methods are discussed and compared with respect to accuracy and computational costs. In addition, a reduced out-of-sequence algorithm for practical application is derived. The performance of the pre-crash system is evaluated using real-world data from crash tests. To this end, a soft crash target is used with a position ground truth accurate to the centimeter and a contact sensor as temporal ground truth.

Keywords Driver assistance systems · Pre-crash · Multi-sensor fusion · Out-of-sequence · Time-to-collision

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1 Introduction

Future driver assistance and safety systems have to face more and more challenging tasks, like autonomous driving or active collision avoidance. In order to guarantee the required ASIL level, more than one sensor has to be used to compensate a possible failure of one sensor. Advanced sensor fusion techniques are therefore, crucial.

This paper deals with sensor fusion algorithms in time-critical contexts, specifically in a pre-crash system that calculates a time-to-collision. In order to quickly react to an imminent collision, it is important to avoid all additional delays in the filtering and to integrate all measurements immediately upon arrival. This is not always fulfilled in state-of-the-art fusion systems, as will be discussed in the following.

In sensor fusion, a frequent problem is the so-called out-of-sequence problem, which means that one sensor is slower than another. I.e., the pre-processing time between the raw measurement and the arrival at the fusion system differs for each sensor. This means that the original order of the measurements is not guaranteed in the fusion system.

Figure 1 shows an example of an out-of-sequence problem with two sensors. Here the measurement from time t_{k_0} is the oldest, but arrives third at the fusion system, which makes it a delayed measurement, a so-called out-of-sequence measurement (OOSM). Methods to deal with these out-of-sequence measurements are required, as will be discussed in this chapter.

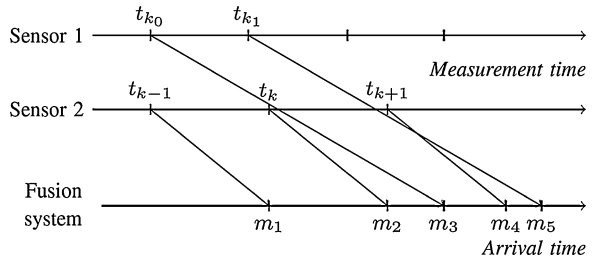
2 Filtering with Out-of-Sequence Measurements

2.1 Problem Description

The well-known Kalman filter [1] estimates the state at time t_k by doing a prediction from time t_{k-1} to time t_k , yielding an *a priori* state estimate $x_{k|k-1}$ with corresponding estimation error covariance $P_{k|k-1}$, followed by an innovation with the latest measurement z_k , which gives an *a posteriori* state estimate $x_{k|k}$ with covariance $P_{k|k}$. It is assumed that all measurements

$$Z^k := \{z_1, \dots, z_k\}$$

Fig. 1 Out-of-sequence problem with two different asynchronous sensors



arrive at the fusion unit in the correct temporal order. However, when more than one sensor is used, measurements in practical applications often are out-of-sequence: After the innovation with z_k , an older measurement z_{k_0} arrives. This out-of-sequence measurement cannot be directly integrated using the standard Kalman filter. Therefore, advanced OOSM algorithms have to be used, which will be described in the following.

2.2 Out-of-Sequence Algorithms

The simplest method to deal with out-of-sequence measurements is the so-called *Buffering*, which simply stores all measurements first without using them. Only when all sensors have provided at least one measurement, the oldest measurement can be integrated, since no OOSM can be missing by then any more [2]. However, Buffering is clearly an undesirable algorithm in time-critical applications, since additional delays make the system slow and not all information is used at most times. Quick reactions like emergency braking are not possible.

Another straight-forward method is *Reprocessing* (see for example [3, 4]). Here all measurements are processed immediately upon arrival. In case an OOSM arrives, all later measurements are integrated again, thus correcting the error due to the previously missing OOSM. Clearly this is the most accurate algorithm, but also the most expensive one, therefore in practical applications cheaper algorithms are needed that perform comparably.

One advanced OOSM algorithm is the so-called *Retrodiction* [5]. Upon OOSM arrival, a backward prediction in the past to the OOSM timestamp is calculated, followed by an innovation with the OOSM. A practical modification called *Reduced Retrodiction* is given in the following chapter.

Another method to deal with OOSM is the *Forward-Prediction Fusion and Decorrelation (FPFD)*. Other than the Retrodiction, it does not use a backward prediction, but a decorrelation step in information space. See [6, 7] for details.

Both Retrodiction and FPFD have much lower computational costs than Reprocessing at comparable performance [3, 4]. Therefore, Retrodiction or FPFD should be used instead of Buffering or Reprocessing. A practical comparison of these algorithms will be given in “Flexible environment perception for advanced driver assistance systems”.

2.3 The Reduced Retrodiction Algorithm

The Retrodiction algorithm [5] was derived under the assumption that at the latest timestamp t_k , an innovation with a measurement z_k is done. Based on this estimate $x_{k|k}$, the Retrodiction to an out-of-sequence timestamp t_{k_0} is calculated. However,

in practical applications, there may not be an innovation at every timestamp, even if a measurement arrives. For example, a gating procedure may exclude all measurements if the Mahalanobis distance is too big. In this case, the Retrodiction must be calculated based on the predicted *a priori* estimate $x_{k|k-1}$ instead of the *a posteriori* estimate $x_{k|k}$. Therefore, the derivation of a modified Retrodiction is needed, called Reduced Retrodiction in the following.

2.3.1 Reduced State and Covariance Retrodiction

In the usual Retrodiction algorithm, the retrodicted state is derived from the system dynamics

$$x_k = F_{k,k_0}x_{k_0} + v_{k,k_0}$$

by inverting the system matrix F_{k,k_0} , where v_{k,k_0} denotes the process noise between t_{k_0} and t_k . The state at the OOSM timestamp t_{k_0} can therefore be calculated as [5]

$$x_{k_0|k} = F_{k,k_0}^{-1} [x_{k|k} - v_{k,k_0|k}],$$

with the expected *a posteriori* process noise

$$v_{k,k_0|k} = E[v_{k,k_0} | Z^k] = Q_{k,k_0} H_k^T S_k^{-1} \gamma_k.$$

Here Q_{k,k_0} denotes the process noise covariance, H_k is the measurement matrix, and $\gamma_k = z_k - H_k x_{k|k-1}$ is the residual with corresponding covariance S_k . However, if at time t_k no innovation with z_k has been done, the state Retrodiction reduces to

$$x_{k_0|k-1} = F_{k,k_0}^{-1} [x_{k|k-1} - v_{k,k_0|k-1}] = F_{k,k_0}^{-1} x_{k|k-1},$$

since the *a priori* expectation value for the process noise is zero:

$$v_{k,k_0|k-1} = E[v_{k,k_0} | Z^{k-1}] = 0.$$

The corresponding reduced covariance Retrodiction can be calculated as

$$P_{k_0|k-1} = F_{k,k_0}^{-1} [P_{k|k-1} - Q_{k,k_0}] \left(F_{k,k_0}^{-1} \right)^T.$$

This completes the reduced state and covariance Retrodiction.

2.3.2 Reduced OOSM Innovation

After the Retrodiction to the past timestamp t_{k_0} , the innovation with the OOSM z_{k_0} and simultaneously the prediction to the latest timestamp t_k are done. Again, this OOSM innovation reduces in case no innovation has been done at time t_k . The

cross covariance between state and measurement as in [5] is needed, where some terms now vanish in the reduced form:

$$P_{k,k_0|k-1}^{xz} = [P_{k,k-1} - Q_{k,k_0}] F_{k,k_0}^T H_{k_0}^T.$$

The modified Kalman gain then is

$$W_{k_0} = P_{k,k_0|k-1}^{xz} S_{k_0}^{-1}.$$

With that, the reduced OOSM state innovation is as usual

$$x_{k|k_0} = x_{k|k-1} + W_{k_0} [z_{k_0} - H_{k_0} x_{k|k-1}].$$

The corresponding reduced OOSM covariance innovation is

$$P_{k|k_0} = P_{k|k-1} - P_{k,k_0|k-1}^{xz} S_{k_0}^{-1} \left(P_{k,k_0|k-1}^{xz} \right)^T.$$

With this step, the reduced OOSM innovation is completed.

3 Practical Evaluation

3.1 System Description and Sensor Setup

The proposed algorithms, including the Reduced Retrodiction derived in the previous section, are tested using data from crash tests with a soft crash target (see Fig. 2b). In this paper, a frontal collision scenario with constant velocity is evaluated. The sensor vehicle is equipped with a moncamera, two short range radars and a long range radar, as shown in Fig. 2a. Whereas the moncamera is used for classification only, the radars result in an out-of-sequence problem that has to be accounted for. The ground truth is provided by an inertial measurement unit for accurate positioning as well as a contact sensor on the front bumper for the exact timestamp of the collision.

In order to apply OOSM algorithms, the temporal characteristics of each sensor (such as cycle time and measurement delay) have to be known. Methods to temporally calibrate the sensors can be found in, e.g., [8].

3.2 Results

This chapter shows the results from the different OOSM algorithms. The proposed Reduced Retrodiction is combined with the usual Retrodiction and applied depending on whether an innovation has been done or not.

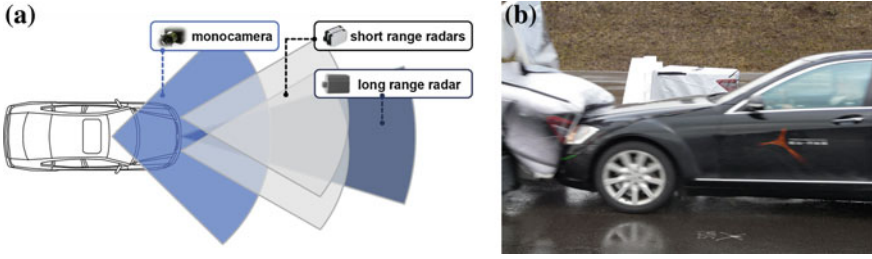


Fig. 2 **a** Sensor setup with monocamera as well as short and long range radars. **b** Crash test with a soft crash target. The temporal ground truth is provided by a contact sensor on the front bumper

First, the one-sigma-volume of the estimation error covariance of all trackers is shown in Fig. 3. This volume can be interpreted as the uncertainty of the corresponding tracker. Clearly Buffering yields a very uncertain state estimate, since the measurements used are mainly outdated. The covariance volume is much bigger than with all of the other trackers. Due to this uncertainty, Buffering should not be used in case a high reliability of the fusion system is needed. Therefore, Buffering is not considered in the following evaluation any more.

The next plot, Fig. 4, shows the position error of the different OOSM algorithms. Clearly all methods perform nearly identical. This is due to the fact that in the one-step lag case, i.e., the case when the OOSM lags behind only one measurement, the algorithms are equivalent [5–7]. In the multi-step lag case, like in this test setup, the algorithms differ slightly, but the results are still very similar.

This shows that due to their lower computational costs, FPDF or Retrodiction should be preferred to Reprocessing. Clearly the derived Reduced Retrodiction (included in the usual Retrodiction) performs satisfactory as well.

Finally the time-to-collision estimation is evaluated. The estimation error can be seen in Fig. 5. Again, the differences in the OOSM algorithms are neglectable, all algorithms yield sufficiently precise time-to-collision estimates. Again, this shows the advantages of the cheaper OOSM algorithms Retrodiction and FPDF compared to Reprocessing, as well as the accuracy of the derived Reduced Retrodiction algorithm.

Fig. 3 One-sigma-volume of the estimation error covariance of the different trackers. The crash time is depicted by the vertical black line

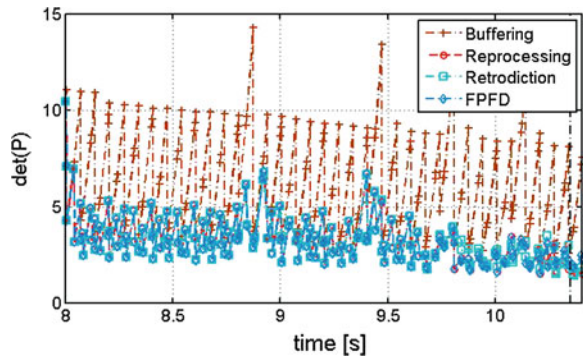


Fig. 4 Position error of the different trackers. The crash time is depicted by the vertical black line

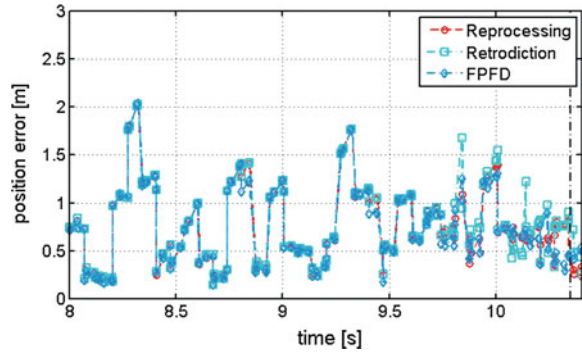
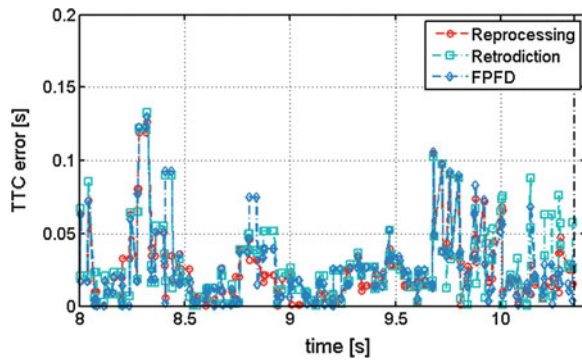


Fig. 5 Error in the time-to-collision estimation of the different trackers. The crash time is depicted by the vertical black line



4 Conclusion and Outlook

This paper has demonstrated the effects of different out-of-sequence algorithms in practical applications. A time-to-collision based on the different algorithms was evaluated using real-world data from crash tests. A modification of the main out-of-sequence algorithm for practical applications, the so-called Reduced Retrodiction, was derived. This modification was validated and its applicability was shown.

Future work will concentrate on the application of OOSM algorithms not only in state estimation, but also in existence estimation. This topic of current research is discussed in [9, 10] and will be further investigated in the future.

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