Out-of-Sequence Measurements Treatment in Sensor Fusion Applications: Buffering versus Advanced Algorithms

Moritz Mauthner,* Wilfried Elmenreich,† Alexander Kirchner * and Diego Boesel *

Abstract:

Out-of-sequence measurements treatment in tracking moving targets with heterogeneous sensors in a Kalman filter framework has been a widely discussed topic in the fusion community within the last years. Whereas most researchers focus on advanced algorithms to avoid the increase of system latency and worst case execution time that arises if measurements are buffered, there still lacks research on the comparison of these methods. The authors try to close this gap by analyzing the effect of buffering and advanced algorithms on the covariance matrices of the state vector after it underwent a prediction to real time.

Keywords: Buffering, Driver Assistance Systems, Sensor Fusion, Out-of-Sequence Algorithms

1 Introduction

Complex multi-sensor data fusion systems are the key technology to advanced driver assistance systems in future automobiles. New features like adaptive cruise control with steering recommendation, lane departure warning, parking pilot, and automatic emergency brake will be standard in the next car generation as electronic stability systems and anti lock braking systems are at present.

The integration of multiple heterogeneous sensors like lidar, radar, and optical cameras requires sophisticated methods of data communication and processing in order to achieve a timely accurate real-time image of the environment.

When such different types of sensors are employed in a fusion application, the system engineer has to consider different measurement frequencies and preprocessing times of each sensor type. For example, a fast lidar sensor may deliver measurements from an instant t_k, while the image preprocessing of a camera is still calculating measurements belonging to a previous instant t_{k-1}. Thus, a fusion system will first receive a measurement belonging to instant t_k and later a measurement belonging to a previous instant t_{k-1}. This out-of-sequence behavior is relevant, especially when the preprocessing and communication times become significant compared to the measurement periods.

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In this paper, we present and evaluate two approaches to this problem. The first one involves buffering of messages until all measurements taken at previous instants have finished their preprocessing. In the other approach, we use a general case of advanced algorithms (here defined as the class of algorithms, that updates our environment model with every incoming measurement, taking into account also out-of-sequence measurements).

The rest of the paper is structured as follows: Section 2 describes the problem statement. Section 3 discusses related work for this research area. We analyze the buffering approach in Section 4 and compare it to the advanced algorithms approach in Section 5. In Section 6 we will give a short example and conclude the paper in Section 7.

2 Problem Statement

We regard a system consisting of two heterogeneous sensors tracking moving targets. The achievable cycle time of a sensor depends on the complexity of the information preprocessing and the chosen hardware. Moreover, the preprocessing time may depend on the actual recorded measurements, and thus influence the cycle time. To achieve a constant cycle time, it is necessary to define the period based on the worst case execution time of the preprocessing or to design a preprocessing algorithm with *anytime behavior*. Such a preprocessing algorithm can be stopped after a predefined time interval. For the sake of discussion, we will consider sensors with constant cycle times.

Furthermore, we assume a possible out-of-sequence measurement (OOSM) problem [1, 2] in our architecture. Typically, OOSM behavior is caused by an indeterministic transmission system, where the transmission time of a message may vary so much that a message from a later measurement may overtake a newer measurement. Such behavior is caused by transmission protocols with many retries such as many Internet protocols (e. g., TCP/IP) or in networks with dynamic routing (Internet, wireless sensor networks).

However, even if communication protocols with deterministic behavior, such as time-triggered approaches like Flexray [3], TTCAN [4], TTP [5], or TTP/A [6] are used, the OOSM problem may arise.

Figure 1 depicts a situation with OOSM problem independently from communication system issues.

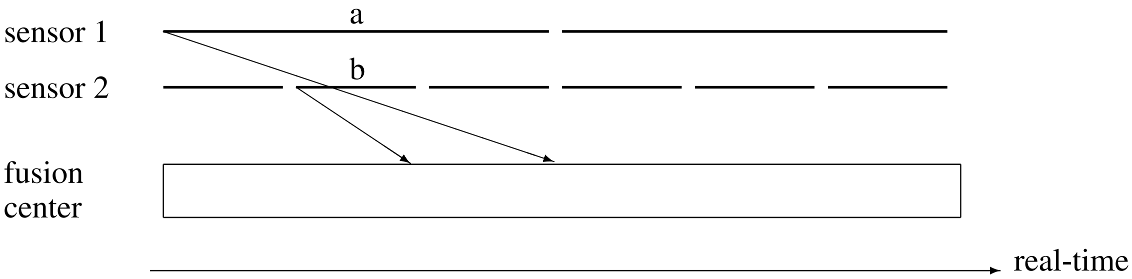

Figure 1: Origin of out-of-sequence measurements (OOSM)

We assume a system consisting of two sensors with different preprocessing times and a fusion center where the system state is updated by the newest measurement. As is depicted in figure 1, sensor 2 overtakes the measurements from sensor 1. Thus, at several instants, the fusion processor has received measurements from sensor 2 before a measurement from sensor 1, belonging to an earlier instant, arrives.

3 Related Work

Kaempchen et al. [7] discuss the maximum latency (here defined as the time difference between the instant of the composition of the image representing the surrounding environment provided by sensor fusion and the bygone instant where this image was true) that arises between measurement recording and measurement fusion, when buffering is used to guarantee chronologically ordered measurements. It is distinguished between situations where only knowledge of the maximum measurement cycle times and situations where full knowledge of the measurement cycle times is available.

The other way to solve the out-of-sequence measurements problem are advanced algorithms. These algorithms deal with one-lag and multi-lag delays, filtering and tracking, linear and non-linear systems as well as single-model and multi-model approaches.

We define t_κ as the out-of-sequence measurement time stamp and t_k as the time stamp of the measurement which updated the fusion before the out-of-sequence measurement was received.

Larsen et al. present a suboptimal multi-lag filtering algorithm for linear systems [8]. If a measurement is out-of-sequence, a correction term derived from the covariance matrices is set up, which is updated every time step. As soon as the delayed measurement comes up, this correction term is used to update the current state estimate with the delayed measurement.

Bar-Shalom presents an optimal one-lag tracking algorithm for linear systems [9]. The delayed measurement is incorporated by computing the update of the state at time t_k with the residual of the out-of-sequence measurement and the retrodicted state to the time κ as well as the covariance matrices between the states at t_k and t_κ. In [10] [11] Bar-Shalom et al. extend the presented one-lag algorithm to deal with multi-lag out-of-sequence measurements by virtually compressing the information of the updates between t_κ and t_k into one update. This approach is further extended to a multi-model approach in [12].

Mallick et al. describe an extension to the algorithm presented in [9] toward a multi-lag, single-model and a one-lag, multi-model approach [13]. In [14], Mallick et al. present a multi-lag, single-model algorithm that includes data association, likelihood computation and hypothesis management. After presenting a particle filter for out-of-sequence measurements treatment in [15], Mallick and Marrs compare in [16] particle filter (algorithm from [17]) and Kalman filter (algorithm from [18]), based on multi-lag filtering algorithms for linearized systems.

Orton and Marrs present the incorporation of out-of-sequence measurements with particle filters [17] [19] [20].

Zhang describes an algorithm in [18] that is stated to be the general case of [9] and [13]. She further differentiates between globally optimal solutions and solutions optimal for the information basis, that is available at a certain instant. In [21], she extends the before mentioned algorithms and establishes the connection to the work of Challa and Wang which will be discussed further down.

Maskel et al. present an approach similar to Zhang by trying to describe the algorithms as specific approximations to an overall framework, being optimal respectively suboptimal for the assumptions made and the information given [22].

Challa and Wang present an augmented state vector, that is a temporally staggered vector, consisting of the present state and past states. This enables the sensor fusion to incorporate measurements corresponding to past states in an optimal, elegant way but is computationally enormous expensive [23] (optimal multi-lag filtering algorithm for linear systems). To overcome the computationally expensive augmented state algorithm, Challa and Wang introduce the iterated augmented state algorithm [24]. In [25], they additionally describe the use of these algorithms in scenarios with clutter. Furthermore, Wang and Challa extend their algorithm toward an interacting multiple-model approach in [26].

In [27], Anxi et al. present a unified suboptimal one-lag, multi-lag and mixed-lag (consider a sequence with two out-of-sequence measurements 1 and 2 with $t_{\kappa_1} < t_{\kappa_2}$ and $t_{k_1} > t_{k_2}$) out-of-sequence algorithm.

4 Latency due to Out of Sequence Measurements Treatment by Buffering respectively Advanced Algorithms

We consider a system of two sensors that measure with constant cycle times a and b and a phase shift between the starting points of a and b of the size c_0. We assume that the processing time for measurement fusion can be neglected. To generate a real-time image, the state has to be predicted over the interval I_{RT-ST} as shown in figure 2.

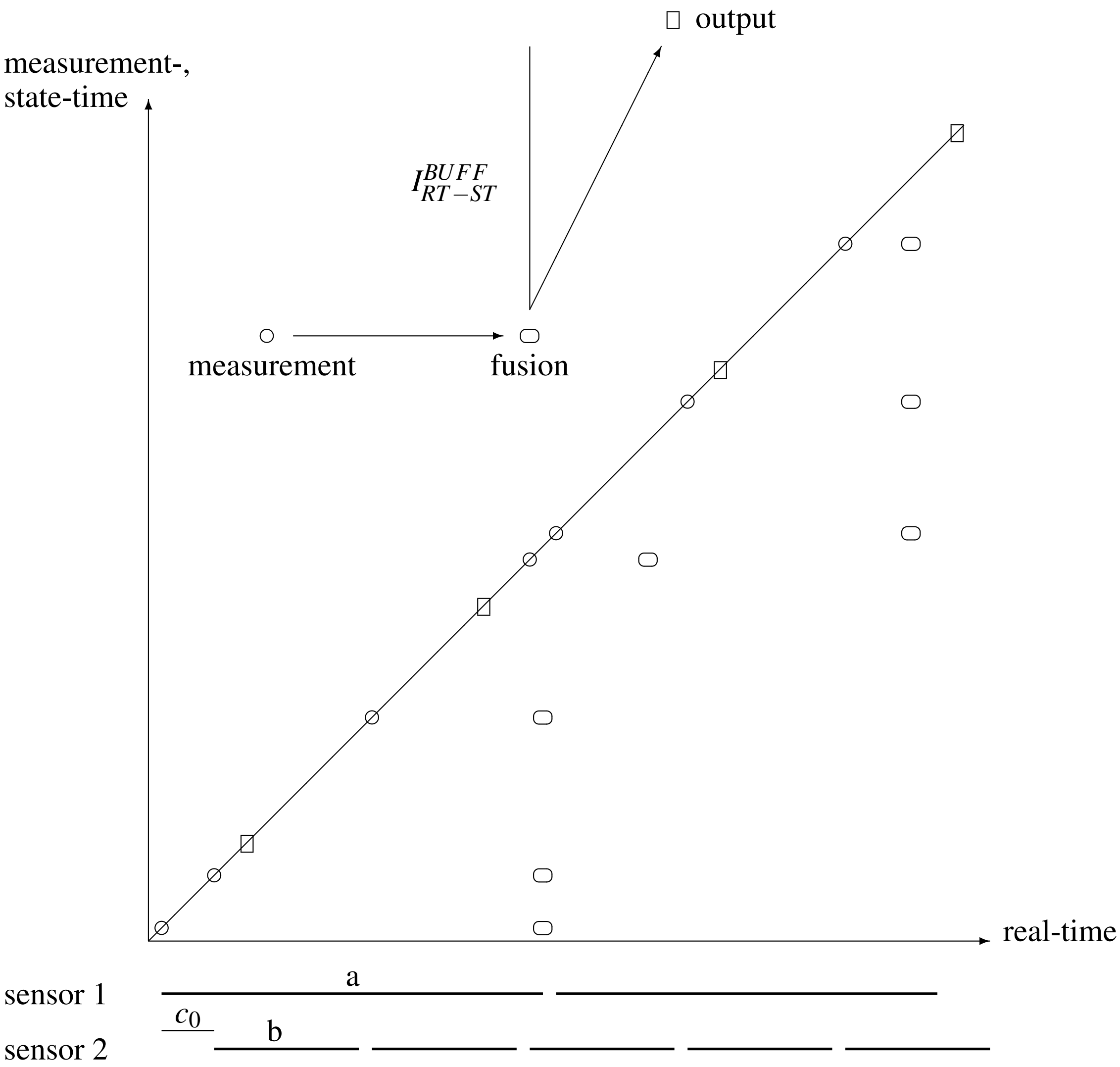

Figure 2: Temporal estimation to generate cyclic output with buffering to treat OOSM

In figure 3, the effect of measurement preprocessing and buffering on I^{BUFF}_{RT-ST} for synchronous measuring ($a = n \cdot b$, $c_0 = 0$) and in figure 4 for asynchronous ($c_0 \neq 0$) measuring is demonstrated.

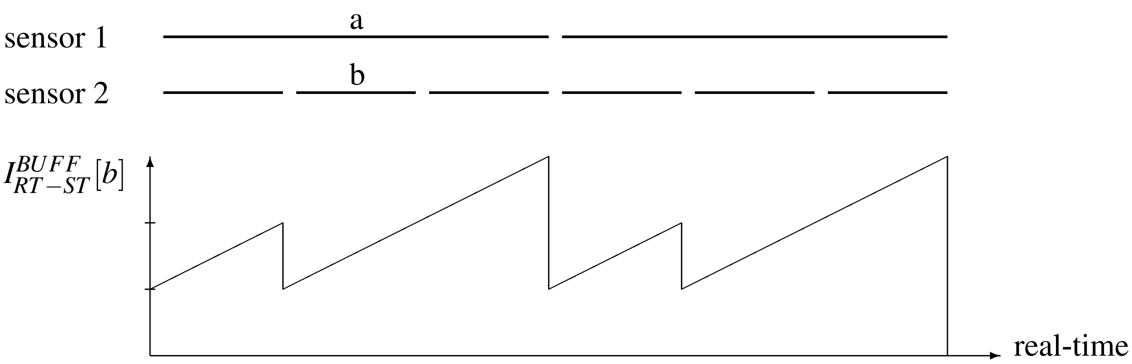

Figure 3: I_{RT-ST}^{BUFF} with $a = n \cdot b$ (n integer) and $c_i = 0$

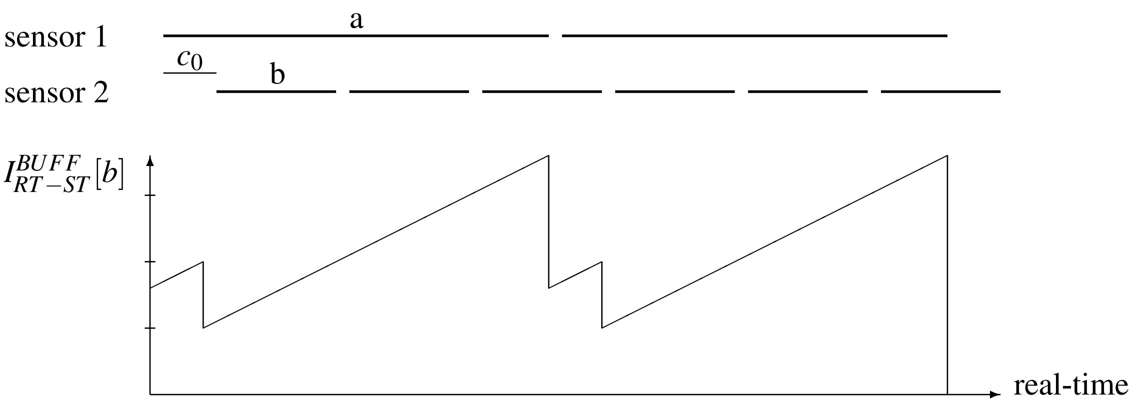

Figure 4: I_{RT-ST}^{BUFF} with $a = n \cdot b$ (n integer) and $c_i = const.$

The key idea is that every measurement must be stored in a buffer until all measurements that are from an earlier time have finished their preprocessing. For sensor 1 this interval is equal to the preprocessing time a whereas sensor 2 is additionally delayed by waiting for sensor 1 to finish its preprocessing. The time of the fusion state becomes equal to the measurement recording time when a measurement has been processed in the fusion algorithm. The fraction of the integral of I_{RT-ST}^{BUFF} and the analysed interval time a are used to compare the synchronous and the asynchronous case. In the case of $a = n \cdot b$ (n integer) and $c_0 = 0$, the minimum, mean and maximum of I_{RT-ST}^{BUFF} can be computed by

$$MIN\left(I_{RT-ST}^{BUFF}\right) = b, \tag{1}$$

$$\bar{I}_{RT-ST}^{BUFF} = \frac{b^2 + \frac{1}{2}a^2}{a} \tag{2}$$

and

$$MAX\left(I_{RT-ST}^{BUFF}\right) = a. \tag{3}$$

In the case of $a = n \cdot b$ (n integer) and $c_0 \neq 0$ we get

$$MIN\left(I_{RT-ST}^{BUFF}\right) = b, \tag{4}$$

$$\bar{I}_{RT-ST}^{BUFF} = \frac{bc_0 + a(b-c_0) + \frac{1}{2}a^2}{a} \tag{5}$$

and

$$MAX\left(I_{RT-ST}^{BUFF}\right) = a + b - c_0. \tag{6}$$

It is worth noting that $\bar{I}_{RT-ST}^{BUFF}$ is not a steady function of b and c_0 and only $\lim_{c_0 \to b} \bar{I}_{RT-ST}^{BUFF}$, but not $\lim_{c_0 \to 0} \bar{I}_{RT-ST}^{BUFF}$, leads from $\bar{I}_{RT-ST}^{BUFF}$ with $a = n \cdot b$ (n integer) and $c_0 \neq 0$ to $a = n \cdot b$ (n integer) and $c_0 = 0$.

If we abandon the restriction that the cycle time of one sensor is a multiple of the cycle time of the other sensor ($a \neq n \cdot b$, n integer), the interval that has to be analysed becomes the least common multiple of a and b ($lcm(a,b)$) (see figure 5).

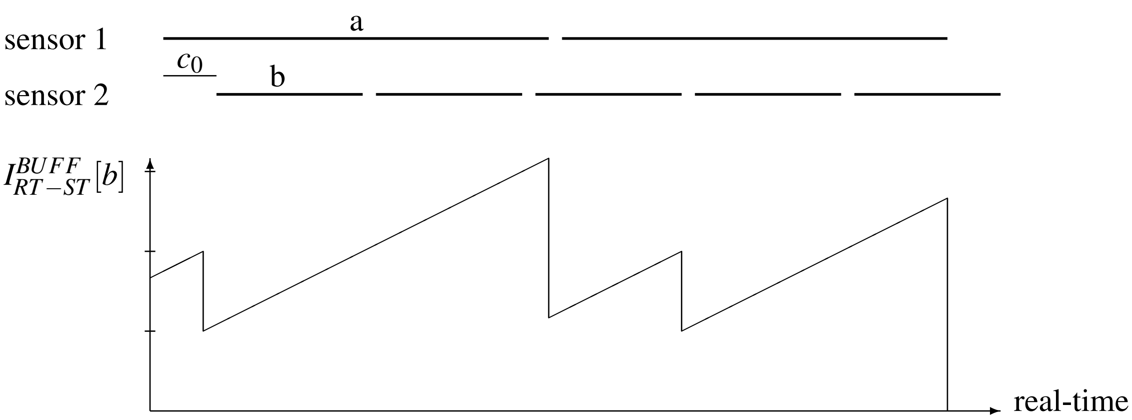

Figure 5: I_{RT-ST}^{BUFF} with $a \neq n \cdot b$ (n integer) and $c_i \neq const$.

For the general case, the minimum, mean and maximum of I_{RT-ST}^{BUFF} can be computed by

$$MIN\left(I_{RT-ST}^{BUFF}\right) \geq b, \tag{7}$$

$$\bar{I}_{RT-ST}^{BUFF} = \frac{\sum_{i=1}^{lcm(a,b)/a}\left(bc_i + a(b-c_i) + \frac{1}{2}a^2\right)}{lcm(a,b)} \tag{8}$$

with

$$c_i = \begin{cases} c_{i-1} + \lceil \frac{a-c_{i-1}}{b} \rceil b - a & \text{if } 0 \neq c_{i-1} + \lceil \frac{a-c_{i-1}}{b} \rceil b - a \\ b & \text{if } 0 = c_{i-1} + \lceil \frac{a-c_{i-1}}{b} \rceil b - a \end{cases} \tag{9}$$

and

$$MAX\left(I_{RT-ST}^{BUFF}\right) \leq a + b. \tag{10}$$

The same analysis can be done to compute $MIN\left((I_{RT-ST}^{BUFF})^2\right)$, $\overline{(I_{RT-ST}^{BUFF})^2}$, $MAX\left((I_{RT-ST}^{BUFF})^2\right)$ and higher orders.

The advanced algorithms for out-of-sequence measurements treatment rely on the possibility to update the state vector with an delayed measurement by estimating or computing the correlation between the delayed measurement and the actual state. Therefore we can update the state vector with every incoming measurement without further delay. The minimum, mean and maximum of $\left(I_{RT-ST'}^{OOSM}\right)^n$ can be computed by

$$MIN\left(I_{RT-ST'}^{OOSM}\right) = b^n, \tag{11}$$

$$\bar{I}_{RT-ST'}^{OOSM} = \frac{\left(\int_0^b (b+x)^n \cdot dx\right)}{b} \tag{12}$$

and

$$MAX\left(I_{RT-ST'}^{OOSM}\right) = (2b)^n. \tag{13}$$

5 Comparison of the Predicted Covariance Matrices

If we want to compare the error covariance matrices of these two methods, we get

$$P_{RT}^{BUFF} = F(I_{RT-ST}^{BUFF}) \cdot P_{ST}^{BUFF} \cdot F(I_{RT-ST}^{BUFF})^T + Q(I_{RT-ST}^{BUFF}) \tag{14}$$

for buffering and

$$P_{RT}^{OOSM} = F(I_{RT-ST'}^{OOSM}) \cdot P_{ST'}^{OOSM} \cdot F(I_{RT-ST'}^{OOSM})^T + Q(I_{RT-ST'}^{OOSM}) \tag{15}$$

for the advanced algorithms.

From the results gained in section 4, we can conclude that the mean of $Q(I_{RT-ST}^{BUFF}(n,n))$ has to be bigger than the mean of $Q(I_{RT-ST'}^{OOSM}(n,n))$. On the other hand, it is clear, that the mean of $P_{ST}^{BUFF}(n,n)$ must be smaller than $P_{ST'}^{OOSM}(n,n)$. Under the assumption, that for a given system a is known and $Q(I_{RT-ST}^{BUFF}(n,n))$ and $Q(I_{RT-ST'}^{OOSM}(n,n))$ are polynomials, the means of $Q(I_{RT-ST}^{BUFF}(n,n))$ and $Q(I_{RT-ST'}^{OOSM}(n,n))$ can be easily calculated. As an analytical approach to determine $F(I_{RT-ST}^{BUFF}) \cdot P_{ST}^{BUFF} \cdot F(I_{RT-ST}^{BUFF})^T$ and $F(I_{RT-ST'}^{OOSM}) \cdot P_{ST'}^{OOSM} \cdot F(I_{RT-ST'}^{OOSM})^T$ does not seem reasonable, $F(I_{RT-ST}^{BUFF}) \cdot P_{ST}^{BUFF} \cdot F(I_{RT-ST}^{BUFF})^T$ and $F(I_{RT-ST'}^{OOSM}) \cdot P_{ST'}^{OOSM} \cdot F(I_{RT-ST'}^{OOSM})^T$ have to be computed numerically for the considered system.

6 Example

As an example, a system with cycle time $a = 160\ ms$, that is governed by the following expressions:

$$F(t_k) = \begin{bmatrix} 1 & (t_{k+1} - t_k) \\ 0 & 1 \end{bmatrix} \tag{16}$$

$$Q(t_k, t_{k+1}) = \begin{bmatrix} \frac{(t_{k+1}-t_k)^3}{3} & \frac{(t_{k+1}-t_k)^2}{2} \\ \frac{(t_{k+1}-t_k)^2}{2} & t_{k+1}-t_k \end{bmatrix} \cdot q \tag{17}$$

with $q = 100\frac{m^2}{s^3}$

$$H(t_k) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{18}$$

$$R_{sensor1}(t_k) = \begin{bmatrix} 0.01m^2 & 0 \\ 0 & 0.001\frac{m^2}{s^2} \end{bmatrix} \tag{19}$$

and

$$R_{sensor2}(t_k) = \begin{bmatrix} 0.1m^2 & 0 \\ 0 & 0.01\frac{m^2}{s^2} \end{bmatrix} \tag{20}$$

is considered.

With $a = 160\ ms$, the maximum, mean and minimum of $\overline{(I^{BUFF}_{RT-ST})^3}$ as well as $\overline{(I^{OOSM}_{RT-ST'})^3}$ are plotted in figure 6 against b. Interesting is the fact that the minima and maxima of $\overline{(I^{BUFF}_{RT-ST})^3}$ are eye-catching for b with $a = n \cdot b$ (n integer). This is due to the fact that $c_i = const.$ for b with $a = n \cdot b$ (n integer).

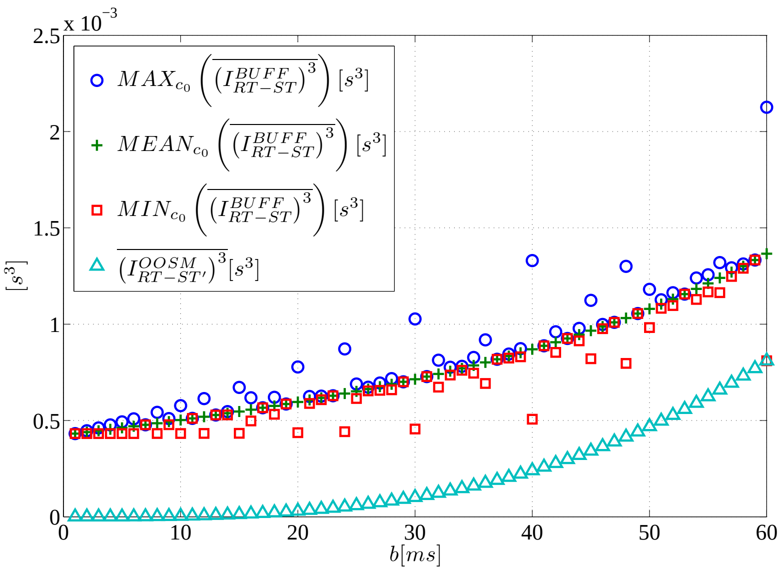

Figure 6: Maximum, mean and minimum of $\overline{(I^{BUFF}_{RT-ST})^3}$ and $\overline{(I^{OOSM}_{RT-ST'})^3}$ by variation over c_0 for $a = 160\ ms$ against b

We visualize the maximum, mean and minimum of $\overline{P^{BUFF}_{RT}}(1,1)$ and $\overline{P^{OOSM}_{RT}}(1,1)$ as well as $\overline{P^{BUFF}_{ST}}(1,1)$ and $\overline{P^{OOSM}_{ST'}}(1,1)$in figures 7 and 8.

It is worth noting, that for this example the $\overline{P^{BUFF}_{RT}}(1,1)$ is bigger than $\overline{P^{OOSM}_{RT}}(1,1)$, whereas it is vice versa for the state-time error covariance matrices. Furthermore, the characteristics

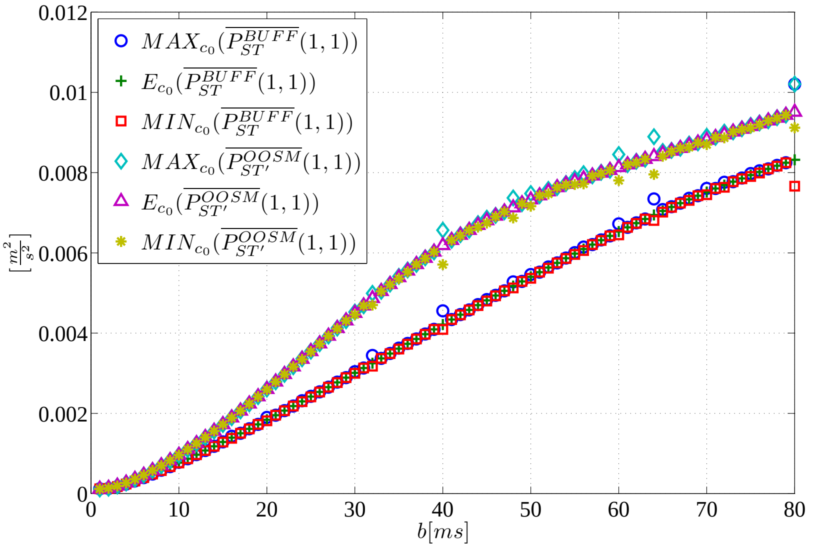

Figure 7: Maximum, mean and minimum of $\overline{P_{ST}^{BUFF}}(1,1)$ and $\overline{P_{ST}^{OOSM}}(1,1)$ by variation over c_0 for $a = 160$ ms against b

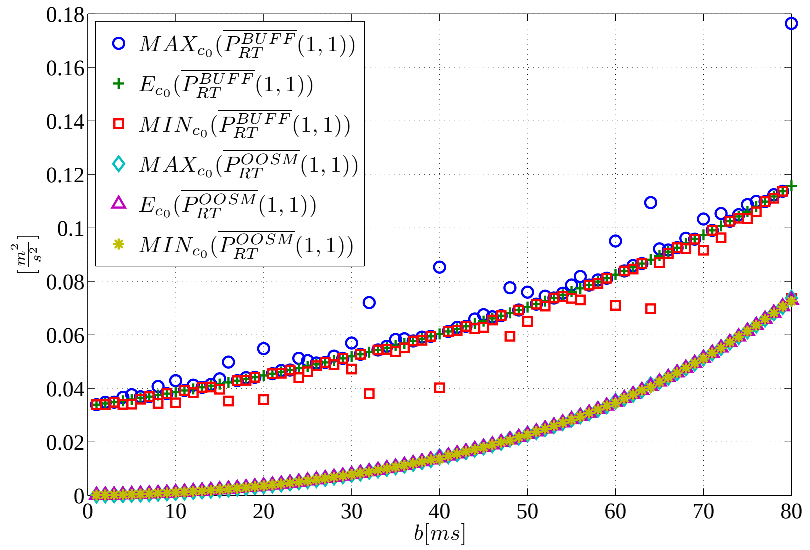

Figure 8: Maximum, mean and minimum of $\overline{P_{RT}^{BUFF}}(1,1)$ and $\overline{P_{RT}^{OOSM}}(1,1)$ by variation over c_0 for $a = 160$ ms against b

of $\overline{(I^{BUFF}_{RT-ST})^3}$ and $\overline{(I^{OOSM}_{RT-ST'})^3}$ can be found in figure 8 as well, which means that buffering is preferably done in systems where $a = n \cdot b$ (n integer) and sensors are triggerable.

This is due to the fact that, for buffering, the state is updated at fewer real-time instants than for the advanced algorithms, whereas the information is richer. When it comes to the real-time error covariance matrix, the prediction from state-time to real-time can, depending on q and F, over weigh this effect.

7 Conclusion

We have motivated the need for an out-of-sequence measurement treatment in sensor fusion systems. Even when using a deterministic communication protocol, the out-of-sequence measurements problem will arise when sensors have different cycle times.

We have shown how buffering and advanced algorithms depend on the cycle times of the sensors and the possibility to synchronize the measurements. We have compared both approaches and have explained, how the preference of one approach depends on the underlying model. We have hinted at the possibility, that the simple buffering approach can be competitive to the advanced algorithms approach if the measurement cycles of sensors 1 and 2 follow the equation $a = n \cdot b$ (n integer) and the sensor measurements can be synchronized.

In further work we will analyse the effect of a sensor fusion processing time, that can no longer be neglected.

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