Fusion of State Estimates Over Long-haul Sensor Networks Under Random Delay and Loss

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***Abstract*—Long-haul sensor networks are deployed in a wide range of applications from national security to environmental monitoring. We consider target tracking over a long-haul sensor network, wherein state and covariance estimates are sent from sensors to a fusion center that generates a fused state. Fusion serves as a viable means to improve the estimation performance to meet the system requirement on accuracy and delay. Communications over the long-haul links, such as submarine fibers and satellite links, is subject to long latencies and high loss rates that lead to many lost or out-of-order messages and may significantly degrade the fusion performance. We propose an online selective fuser to combine the received state estimates based on estimated information contribution from the pending data. By concurrently using prediction and retrodiction, the fuser opportunistically makes timely decisions to achieve a balance between accuracy and timeliness of the fused estimate. Simulation results show that our method effectively maintains high levels of fusion performance under various communication delay and loss conditions.**

***Index Terms*—State estimation, long-haul sensor networks, delay and loss, online selective fusion, prediction and retrodiction.**

I. Introduction

In a *long-haul sensor network*, sensors are deployed spanning a large geographical area; connections to the FC are often in the range of several to tens of thousands of miles. There are many real-world applications in target monitoring and tracking, such as military surveillance/reconnaissance and air traffic control, that utilize such networks. The state estimates of dynamic targets are sent via satellite links or a combination of submarine and terrestrial connections to a remote fusion center (FC) with round trip time (RTT) of hundreds of milliseconds or even more. Latencies and losses over such links can easily lead to significant delays and jitters which may severely degrade fusion performance.

There are two competing requirements on the fused estimate produced by an FC: accuracy and timeliness. The accuracy of the fused estimate must exceed that of any single sensor, requiring that most if not all sensor estimates arrive at the FC. Meanwhile, the fused estimate must be computed and reported within a tight deadline. For instance, the position of an aircraft must be reported by the FC within a few seconds. Under extremely adverse link conditions, data sent from the remote sensors may even fail to arrive at the FC by the reporting deadline. If the FC simply ignores the missing data, the quality of the fused state could suffer; whereas waiting for all the delayed data to arrive would degrade the timeliness requirement. To tackle the problem, we design a *selective fusion* scheme that achieves a trade-off between estimation accuracy and reporting timeliness.

For ease of exposition, in this work we mainly consider targets with linear dynamics and zero-mean Gaussian measurement and noise processes, although the ideas herein can be easily extended to more complex models. We propose a novel metric for the FC to make its online selective fusion decisions based on the projected information contribution from each missing packet. In addition, the FC also draws on available estimates arriving out of order so that the missing estimates in between can be filled in quickly, further reducing the reporting delay.

The rest of the paper is organized as follows. We briefly discuss a list of related works in Section II. The optimal fusion rule with full observation is presented in Section III. We then propose our selective fusion mechanisms based on the projected differential information gain metric in Section IV. Simulation results are shown and analyzed in Section V and we conclude the work in Section VI.

II. Related Work

There has been growing interest in state estimation and fusion under uncertainty. Fixed arrival delays can be easily handled by *state augmentation* [9], where adjacent states in time are grouped together to form a "super-state". This can inflate the computation overhead as the delay becomes larger; More importantly, the dimension of the augmented state would keep changing with random delays, rendering this approach invalid. On the other hand, some studies have considered independent packet losses for one sensor-estimator. For example, [5] derives an upper bound of the packet loss rate above which the estimation error will go unbounded.

In multi-sensor state estimation problems, fusion schemes have been proposed under the condition that all packets arrive on time; see [6] and the references therein. [8] has attempted to address fusion by combining various sources of degradation (delay, loss, and packet drop) in a probabilistic manner. Aside from its high dimensionality, the underlying solution requires that probabilities of all types of degradation be known a priori, which apparently is a very unrealistic assumption. There have been studies addressing out-of-sequence measurement (OOSM) issues, as data commonly arrive out of order due to random delays. One of the focuses is on how to re-incorporate late arrivals. The initial one-step lag problem [1] has been extended to multi-lag case [2], and the single-OOSM problem in [1], [2] has been extended to multi-OOSM case [11] as well. However, efforts on multi-sensor studies are still relatively few, and time-domain constraints have not been accounted for in any of these works.

In contrast to the above works, our study is more of an online decision-making process under tight constraints on accuracy and delay. Addressing a higher degree of system uncertainty, we focus on the impact of missing packets on current estimation accuracy and timeliness, regardless of their delay/loss patterns. As such, our scheme is more adaptive and can be applied under most circumstances.

III. Optimal Fusion with Fully Received Local State Estimates

We consider the following multi-sensor discrete linear system (k and i are time and sensor indices, respectively):

$$\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{w}_k, \qquad E[\mathbf{w}_k\mathbf{w}_l^T] = \mathbf{Q}\delta_{k-l}, \tag{1}$$

$$\mathbf{y}_k^i = \mathbf{H}_k^i\mathbf{x}_k + \mathbf{v}_k^i, \qquad E[\mathbf{v}_k^i(\mathbf{v}_l^i)^T] = \mathbf{R}^i\delta_{k-l}, \tag{2}$$

where $\mathbf{F}$ is the state transition matrix and $\mathbf{H}$ is the measurement matrix[1]. The vector $\mathbf{x}$ denotes the state of the target and $\mathbf{y}$ the sensor measurement. The process noise $\mathbf{w}$ and measurement noise $\mathbf{v}$ are white and independent (δ is the Kronecker delta function), whose variances are $\mathbf{Q}$ and $\mathbf{R}$ respectively.

The well-known Kalman filter (KF) consists of a set of equations [9] that recursively estimate the states of such a dynamic linear system. In the equations, $\hat{\mathbf{x}}_{k|k-1}^i$ and $\hat{\mathbf{x}}_{k|k}^i$ denote respectively the a priori and a posteriori estimates by sensor i at time k and are periodically updated at each time step. These notations also apply to $\mathbf{P}$, the *error covariance matrix* of the estimate, defined as $\mathbf{P}_k^i = E[(\hat{\mathbf{x}}_k^i - \mathbf{x}_k)(\hat{\mathbf{x}}_k^i - \mathbf{x}_k)^T]$. $\mathbf{P}^{-1}$ is often called the *information matrix*. Kalman filters are minimum-mean-square-error (MMSE)-optimal as the trace of $\mathbf{P}$ – the estimation error – at each step is minimized.

In the multi-sensor scenario, the updates from the KFs by the individual sensors are sent to the FC so that global fusion can be performed. If we define the above parameters similarly for the FC ("*G*" denotes "global"), we have the following optimal fusion rule:

$$\hat{\mathbf{x}}_{k|k-1}^G = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1|k-1}^G \tag{3}$$

$$\mathbf{P}_{k|k-1}^G = \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}^G\mathbf{F}_{k-1}^T + \mathbf{Q} \tag{4}$$

$$(\mathbf{P}_{k|k}^G)^{-1} = (\mathbf{P}_{k|k-1}^G)^{-1} + \sum_{i=1}^{n}\left((\mathbf{P}_{k|k}^i)^{-1} - (\mathbf{P}_{k|k-1}^i)^{-1}\right) \tag{5}$$

$$(\mathbf{P}_{k|k}^G)^{-1}\hat{\mathbf{x}}_{k|k}^G = (\mathbf{P}_{k|k-1}^G)^{-1}\hat{\mathbf{x}}_{k|k-1}^G + \sum_{i=1}^{n}\left((\mathbf{P}_{k|k}^i)^{-1}\hat{\mathbf{x}}_{k|k}^i - (\mathbf{P}_{k|k-1}^i)^{-1}\hat{\mathbf{x}}_{k|k-1}^i\right) \tag{6}$$

In particular, we define the *information gain matrix* $\mathbf{J}_k$ and *information gain vector* $\mathbf{j}_k$ at the FC to be the sum of those at the individual sensors:

$$\mathbf{J}_k^G \triangleq (\mathbf{P}_{k|k}^G)^{-1} - (\mathbf{P}_{k|k-1}^G)^{-1} = \sum_{i=1}^{n}\left((\mathbf{P}_{k|k}^i)^{-1} - (\mathbf{P}_{k|k-1}^i)^{-1}\right), \tag{7}$$

$$\mathbf{j}_k^G \triangleq (\mathbf{P}_{k|k}^G)^{-1}\hat{\mathbf{x}}_{k|k}^G - (\mathbf{P}_{k|k-1}^G)^{-1}\hat{\mathbf{x}}_{k|k-1}^G = \sum_{i=1}^{n}\left((\mathbf{P}_{k|k}^i)^{-1}\hat{\mathbf{x}}_{k|k}^i - (\mathbf{P}_{k|k-1}^i)^{-1}\hat{\mathbf{x}}_{k|k-1}^i\right). \tag{8}$$

Similar results can be found in [4], [10]; [3] has shown that the above fusion rule is equivalent to the centralized solution where the FC has received all the raw measurements and hence is MMSE-optimal. In our distributed fusion, only state estimates (instead of measurements) and their corresponding error covariances are sent to the FC for fusion. This has practical benefits. Raw measurement data often arrive in larger volumes than processed state estimates. Sending measurements directly not only consumes more bandwidth but also renders the data being sent more prone to link latency and loss.

IV. Selective Fusion With Projected Differential Information Contribution (PRODIC) and Retrodiction

With full observation of the sensors' data, the error covariance at the FC is often much lower than that at the individual sensors. However, severe delay and loss may significantly limit such fusion gain. In this section, we propose an information metric to guide the FC through the selective waiting and fusion process. We also combine forward information gain projection and backward retrodiction so that the FC can obtain an accurate estimate much faster.

A. Selective Fusion – Design Considerations

With incomplete collection of the sensors' estimates, in Eqs. (7) and (8), fewer than n terms are actually incorporated and the resulting a posteriori $\mathbf{P}$ is higher than that in the full-observation case. If one-step predicted values – that is, the a priori estimates – substitute for the missing data, the effect is exactly the same as that of simply ignoring the missing packets: $\mathbf{P}_{k|k}^i = \mathbf{P}_{k|k-1}^i$ and $\hat{\mathbf{x}}_{k|k}^i = \hat{\mathbf{x}}_{k|k-1}^i$ leading to $\mathbf{J}_k^i = 0$ and $\mathbf{j}_k^i = 0$, respectively. Therefore, prediction alone may cause the error covariance to shoot up within a short amount of time if there are many missing estimates.

Alternatively, the FC can defer the final reporting for D_{max} – the reporting deadline – and collect all the estimates that have arrived by then. This deadline is often set for the worst performance that the system could tolerate. Generally, it is preferable to report the estimate as early as possible which is especially critical for surveillance tasks. Owing to packet loss and long arrival delays, however, the average waiting time could be well approaching D_{max}, even if some estimates would not measurably improve the accuracy at all. Passively waiting for every missing packet not only significantly increases the reporting delay but may hardly benefit the overall accuracy when the packets being awaited carry little information. It would be a more viable option that the FC selectively waits for *some* missing

[1] These matrices are often known from the underlying system.

packets before finalizing a global estimate. Stated differently, at any time step, the FC should decide whether each delayed packet is still "worth" waiting for. The goal is to balance both the accuracy and timeliness requirements.

B. PRODIC as the Information Metric

Applying stationarity of the state transition matrix, we define a function h that links together two successive a posteriori $\mathbf{P}$:

$$\mathbf{P}_{k|k}^{-1} = h(\mathbf{P}_{k-1|k-1}^{-1}, \mathbf{J}_k). \tag{9}$$

We name the information metric Projected differential information contribution (PRODIC), which measures the potential information contribution of a delayed packet should it return now. The following steps calculate $\Delta\mathbf{P}_{k,k-d}^{i}$ at time k, which is the PRODIC of the missing packet from the sensor i with time-stamp $k-d$:

Step 1: Add the expected information gain $\mathbf{J}_{k-d}^{i}$ of the missing packet to the information matrix $\mathbf{P}_{k-d}^{G}$:

$$(\mathbf{P}_{k-d,temp}^{G})^{-1} = (\mathbf{P}_{k-d}^{G})^{-1} + \mathbf{J}_{k-d}^{i}; \tag{10}$$

The "temp" means that the associated $\mathbf{P}^{G}$ is only updated *temporarily* to obtain the PRODIC of the missing packet (which has not actually arrived).

Step 2: Recursively propagate the change of $\mathbf{P}_{k-d}^{G}$ in Step 1, through the intermediate steps, to the current time k. From time $T_n = k-d+1$, $k-d+2$, ..., up to k, calculate

$$(\mathbf{P}_{T_n,temp}^{G})^{-1} = h\left((\mathbf{P}_{T_n-1,temp}^{G})^{-1}, \mathbf{J}_{T_n}^{G}\right); \tag{11}$$

In this step, all the $\mathbf{J}^{G}$ terms of these intermediate time steps remain the same.

Step 3: Calculate the differential information gain

$$\Delta\mathbf{P}_{k,k-d}^{i} = \mathbf{P}_{k}^{G} - \mathbf{P}_{k,temp}^{G}. \tag{12}$$

After the recursion in Step 2 has proceeded to the current time k, Eq. (12) measures the difference between $\mathbf{P}_{k,temp}^{G}$ – the updated $\mathbf{P}_{k}^{G}$ with the *supposed arrival* of the missing packet – and the current $\mathbf{P}_{k}^{G}$.

Note that the PRODIC is calculated separately for each delayed packet of time $k-d$. Doing so (with a linear complexity) would greatly reduce the computational overhead should the FC consider all possible combinations of packet arrivals (with an exponential complexity). After considering the PRODIC of one missing packet, the FC has actually found the least amount of information to be gained among all the possible arrival patterns that include at least this particular pending packet. Therefore, PRODIC is a conservative measure of information gain for awaiting an individual packet.

The FC compares the PRODIC value of a missing packet with a cutoff threshold th. If the PRODIC value exceeds the threshold, the FC still considers the information carried by the missing packet important for reducing the estimation error and will continue waiting for the estimate. As long as the reporting deadline has not been reached, the global estimate will be finalized only when the FC decides not to wait for any of the pending estimate for the corresponding time instant.

For convenience of implementation, the FC can use a fixed normalized threshold, for example, the desired percentage of error reduction, so that

$$\frac{\Delta\mathbf{P}_{k,k-d}^{i}}{\mathbf{P}_{k}^{G}} = 1 - \frac{\mathbf{P}_{k,temp}^{G}}{\mathbf{P}_{k}^{G}} > th \tag{13}$$

implies the packet can potentially improve the current $\mathbf{P}_{k}^{G}$ more than the threshold level and thus will be awaited.

The online decisions made by the FC are largely affected by the availability of the estimates from the sensors with better accuracy guarantees. When the FC has received all or most packets from these sensors, further improvement from the missing ones is small or negligible. On the other hand, with the data from these better sensors missing, $\mathbf{P}^{G}$ would inflate, elevating the normalized PRODIC of these packets; what often ensues is the decision to continue waiting for these missing packets.

C. Information Gain from Retrodiction

Because the estimates from some sensors often carry larger potential information gain, the FC generally has to wait long enough if estimates from these sensors are missing. *Retrodiction* ("backward prediction"), also known as *smoothing*, has been studied in the estimation literature. Conventionally, an earlier *existing* estimate is retrodicted using subsequent measurements so that its accuracy is improved. We propose a novel use of retrodiction to *proactively interpolate* intermediate missing data. After one or more subsequent packets of an unavailable one have been received, the FC retrodicts the missing one. While waiting for missing packets, the FC applies retrodiction, from the current time k to time $k-d$ whose global estimate is to be reported next, for *all* the estimates – including the available ones – in between. The idea is illustrated in Fig. 1, where $d = 2$.

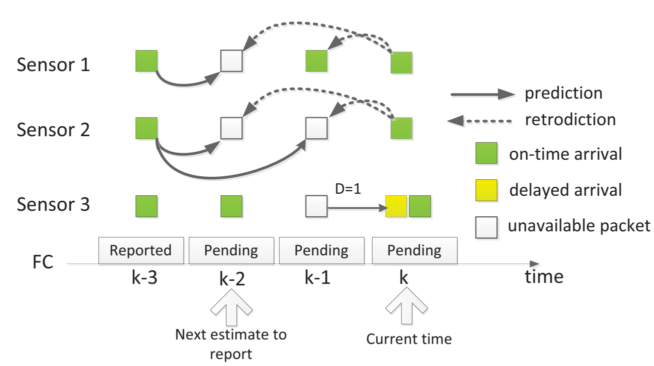


Fig. 1: Selective fusion concept: There are three sensors. Since applying prediction-only estimates results in a higher error variance, to reduce the accuracy degradation, the FC may decide to wait for the delayed packet while applying retrodiction if subsequent packets arrive. Note both available and unavailable estimates are retrodicted. The terminating time for retrodiction always corresponds to the next pending estimate to be reported.

We apply the fixed-interval Rauch-Tung-Streibel (RTS) retrodiction algorithm [9], which is known to be computationally efficient. The algorithm is especially suited for our scenario because state estimates appearing in the equations are sent directly to the FC. The following steps iteratively propagate the newly gained information, due to the on-time arrival of estimate at time k from sensor i (we denote the associated packet as P_k^i), backward to time $k-d$.

Step 0: Initialize the backward smoother.

$$\mathbf{P}_{k,retr}^i = \mathbf{P}_{k|k}^i; \tag{14}$$

$$\hat{\mathbf{x}}_{k,retr}^i = \hat{\mathbf{x}}_{k|k}^i; \tag{15}$$

From time $T_n = k$, $k-1$, ..., up to $k-d$, recursively calculate the values through the following three steps:

Step 1: backward smoothing gain

$$\mathbf{G}_{T_n-1}^i = \mathbf{P}_{T_n-1|T_n-1}^i \mathbf{F}_{T_n-1}^T (\mathbf{P}_{T_n|T_n-1}^i)^{-1}; \tag{16}$$

Step 2: $\mathbf{P}^i$ of the smoothed estimate

$$\begin{aligned}&\mathbf{P}_{T_n-1,retr}^i = \\ &\mathbf{P}_{T_n-1|T_n-1}^i - \mathbf{G}_{T_n-1}^i (\mathbf{P}_{T_n|T_n-1}^i - \mathbf{P}_{T_n,retr}^i)(\mathbf{G}_{T_n-1}^i)^T;\end{aligned} \tag{17}$$

Step 3: smoothed estimate

$$\hat{\mathbf{x}}_{T_n-1,retr}^i = \hat{\mathbf{x}}_{T_n-1|T_n-1}^i + \mathbf{G}_{T_n-1}^i (\hat{\mathbf{x}}_{T_n,retr}^i - \hat{\mathbf{x}}_{T_n|T_n-1}^i). \tag{18}$$

In these equations, $\mathbf{P}_{retr}^i$ denotes the a posteriori $\mathbf{P}^i$ after retrodiction. The algorithm is applied to each sensor separately, so that the process is also in line with the packet-level PRODIC calculation. In contrast to conventional studies, retrodiction in our scheme has the dual benefits of improving existing estimates and interpolating missing ones. From the equations, a string of missing estimates can be improved by just one subsequently available one. For example, in Fig. 1, at time k, having been retrodicted by packet P_k^2, P_{k-1}^2 can further retrodict P_{k-2}^2. This can potentially reduce the reporting delay significantly.

V. Performance Evaluation

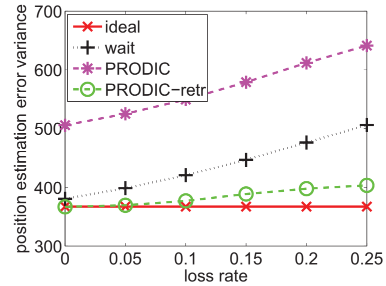
A. *Simulation Setup*

We consider tracking of a target whose motion follows the near-constant-acceleration model [7]. The target state consists of its position, velocity, and acceleration. Our goal is to reduce the position estimate MSE and the reporting time. As our default setup, there are a total of three sensors, whose measurement noise standard deviations are all 50 m. The process noise PSD is 0.5 m^2/s^3 and the normalized sampling time and reporting deadline are 1 and 10, respectively. The PRODIC threshold is set to 5%. In our study, packet loss and delay are two independent processes. While the packet loss is generated as an independent Bernoulli process, delays follow (memoryless) exponential distribution. The default loss rate and normalized arrival delay are set to be 10% and 3, respectively. Next we study the impact of each factor separately.

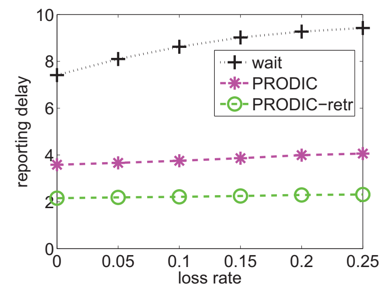
B. *Comparison of Different Online Fusion Schemes*

We compare the following online fusion schemes in our simulation study:

- Maximal waiting ("wait"): the FC finalizes the estimate after all missing estimates arrive or the reporting deadline is reached, whichever is first;
- Selective fusion based on PRODIC but without retrodiction ("PRODIC"):

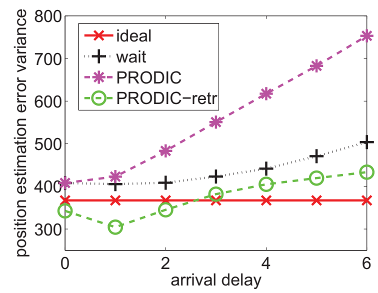


(a)

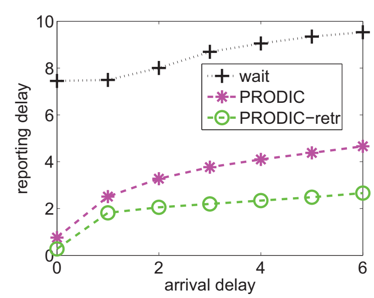


(b)

Fig. 2: Loss rate vs. (a) position error variance and (b) reporting delay



(a)



(b)

Fig. 3: Arrival delay vs. (a) position error variance and (b) reporting delay

- Selective fusion based on PRODIC with modified RTS retrodiction ("PRODIC-retr");
- We also consider the full-observation case ("ideal") as a baseline scenario for comparison with other schemes, in which the reporting delay is always zero and hence there is no retrodiction.

1) Loss Rate: Setting other parameters at their default values, the packet loss rate is varied from 0 to 0.25. From the results

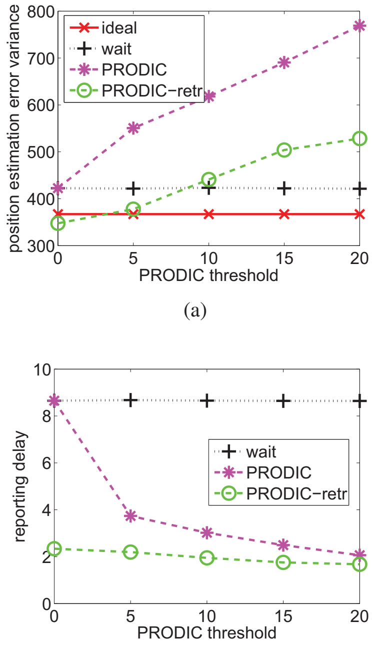


Fig. 4: PRODIC threshold (in percentage) vs. (a) position error variance and (b) reporting delay

shown in Fig. 2, with its average reporting time approaching the deadline, the "wait" scheme takes advantage of the extra waiting time to collect much delayed estimates and thus reduces the estimation error. The PRODIC scheme can effectively reduce the reporting delay; however, the estimation error is still relatively high. Compared to other schemes, PRODIC-RTS is less sensitive to change in the loss rate. At the highest loss rate 25%, the error variance increases only by about 7% from the zero-loss case. This demonstrates the effectiveness of our design, which exploits retrodiction to reduce the estimation error upon packet loss. Besides, the change in reporting delays as the loss rate increases is negligible (it stays slightly above 2). From this perspective, our PRODIC-RTS is robust to packet loss.

2) Arrival Delay: We vary the normalized packet arrival delay from 0 to 6. In Fig. 3, similar trends can be observed, with some minor exceptions. When there is no arrival delay, no retrodiction is performed so that the estimates can be reported immediately; as the arrival delay goes up to one, the error variance decreases thanks to retrodiction. As the arrival delay increases even more, the error variance also increases, though not as fast as in other schemes. As can be seen, retrodiction has effectively reduced the estimation errors with significantly longer delays.

Although it may first seem surprising that the reporting delay is well below the average arrival delay (e.g., when the arrival delay equals 6, the reporting delay is 2.5), the result is attributed to both the randomness of the arrival delay and the selective fusion process. There exist packets whose arrival delays are smaller than the average and hence can retrodict other missing ones comparatively faster. With the improved estimates following retrodiction, the FC may decide to terminate its waiting much earlier, disregarding all the remaining pending packets. In contrast, the reporting delay in the "waiting" case often approaches the reporting deadline D_{max} due to the near constant presence of missing packets.

3) PRODIC Threshold: In the above simulations, we have kept the PRODIC threshold at 5%; that is, only when a pending packet can potentially reduce the current estimate error by at least 5% would the FC decide to wait for it. In reality, the FC can tune the threshold according to the current accuracy level. In Fig. 4, the threshold varies from zero (i.e., to wait for all) to 20%. The results can be easily interpreted: As the threshold goes up, the requirement on each packet is relaxed, fewer packets need to be awaited, and hence reduced accuracy and reporting delay follow; and vice versa. It is interesting to note that when the threshold is zero, PRODIC scheme is reduced to the "waiting" case; PRODIC-RTS, on the other hand, does not incur inflated waiting time thanks to retrodiction.

To sum up, our PRODIC-RTS scheme, combining features such as information gain projection, selective waiting, and proactive retrodiction, often yields accuracy performance comparable to that under the full-observation case while incurring very little reporting delay, demonstrating its robustness against degradation in transmission links such as severe loss and delay.

VI. Conclusion

In this work, we have considered state estimation over a long-haul sensor network. To meet the stringent requirements on accuracy and timeliness, while accounting for severe data latency and loss inherent over long-haul links that exert a negative impact on fusion performance, we have proposed an information metric (PRODIC) and a modified application of the RTS retrodiction algorithm, so that the fusion center can make its online decisions to efficiently fuse the information contributed by the remote sensors. Simulation results have validated the advantages of our design under variable transmission delays and loss rates.

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