Information Feedback for Estimation and Fusion in Long-Haul Sensor Networks

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***Abstract*—Long-haul sensor networks can be found in both civilian and military applications. In a typical long-haul sensor network, sensors are remotely deployed over a large geographical area to perform tracking and/or monitoring of one or more dynamic targets. A remote fusion center fuses the information provided by these sensors so that a final estimate of certain target characteristics – such as the position – is expected to possess much improved quality. However, imperfect communication conditions can become the bottleneck for desired estimation and fusion performance. The link-level loss and delay – such as that over a satellite channel – can easily reduce the chance that an estimate is successfully received by the fusion center, thereby limiting the potential information fusion gain and resulting in suboptimal accuracy performance of the underlying task. In this work, we explore the effect of information feedback in the context of state estimation and fusion in a communication-constrained long-haul sensor network. Different feedback configurations and schedules are proposed. In particular, the joint impact of communication delay/loss, information feedback, and computation constraints is explored by means of analytical and simulation studies.**

***Index Terms*—Long-haul sensor networks, state estimate fusion, information feedback, estimation bias, root-mean-square-error (RMSE) performance, reporting deadline.**

I. Introduction

Sensor networks have been deployed in many real-world applications for tracking and monitoring of dynamic targets. We are interested in a class of such networks, namely, the long-haul sensor networks, where the sensors are deployed to cover a very large geographical area, such as a continent or even the entire globe. A remote sensor measures certain parameters of interest from the dynamic target(s) on its own, and then sends either the measurements directly, or the state estimates it derives from the measurements (which is the case studied in this work), to the fusion center. The fusion center serves to collect data from multiple such sensors and fuse these data to obtain global estimates periodically at specified time instants. A global estimate is expected to be more accurate than those provided by the individual sensors, and this benefit is often referred to as the fusion gain. Typical examples of such long-haul sensing include the monitoring of greenhouse gas emissions using airborne and ground sensors [6], processing of global cyber events using cyber sensors distributed over the Internet [13], space exploration using a network of telescopes [14], and target detection and tracking for air and missile defense [3].

Although the structure of a long-haul sensor network is fairly simple, many challenges exist in estimation and fusion applications over such a network. When data are communicated over satellite links, for example, due to the long distances, often on a scale of tens of thousands of miles, the signal propagation time is rather significant compared to that in short-range communications. For example, the round-trip time (RTT) for signal propagation with a geostationary earth orbit (GEO) satellite is well over a half second [16]. More importantly, communication over the satellite links is characterized by sporadic high bit-error rates (BERs) and burst losses. The losses incurred during transmission or resulting from the message drop due to occasional high BERs could further reduce the number of reliable estimates available at the fusion center. As a result, the global estimates may not be promptly and accurately finalized by the fusion center, leading to degraded fusion performance and even failures to comply with the system requirements on the worst-case estimation error and/or maximum reporting delay, both crucial elements for near real-time performance in many applications.

In the literature, some prior studies have attempted to address estimation and/or fusion under variable communication loss and/or delay conditions. An upper bound of the loss rate is derived in [5], above which the estimation error goes unbounded. Some studies, including [12], [19], [20], have addressed the so-called out-of-sequence-measurement (OOSM) issue – where an OOSM is defined as a measurement that has been generated earlier but arrives later – and their common goal is to update the current state estimate with an earlier measurement without reordering the measurements and recalculating the state estimates recursively. In these studies, the data will finally arrive despite the random delay. More recently, a few studies [10], [11], [15] have exploited retransmission to recover some of the lost messages over time so that the effect of information loss can be somewhat mitigated. A dynamic online selective fusion mechanism based on the projected information gain is proposed in [8] so that the final time for fusion is dynamically determined depending on if enough information has arrived at the fusion center. A staggered estimation scheduling scheme is proposed in [9] that aims to explore the temporal domain relationships of adjacent data within an estimation interval to improve the estimation and fusion performance.

Despite all the above research efforts, one aspect for state estimation and fusion applications in a communication-constrained environment has not received enough attention, namely, information feedback from the fusion center to the individual sensors. Feedback is central to closed-loop control-based design [7], where among others, system stability and convergence is one of the major benefits. In the literature, a number of studies have been conducted in the domain of wireless sensor networks that pertain to the role of feedback: In [1] and [4], for instance, feedback is studied from an information-theoretic perspective, which is used to mitigate the effect of fading channels; in [17], on the other hand, a control-theoretical calibration algorithm is developed where the feedback is used to enhance signal detection performance in a surveillance network. Despite its importance, there have been very limited studies on the effect of information feedback in estimation and fusion performance. In the simplest form without communication constraints, the global estimates and associated error covariances generated by the FC are always sent back to the individual sensors so that the global values can supersede the local counterparts [2]. This mechanism of replacement is also the approach pursued in this study.

The main goal of this work is to investigate the impact of information feedback on estimation and fusion performance in a communication-constrained long-haul sensor network. Conventionally the fusion center simply serves as the information collector and integrator. As the fusion center is expected to output more accurate estimates under normal circumstances, we are interested in exploring when feedback of a "better" estimate can improve – and at other times worsen – the estimation/fusion performance with or without the presence of link-level communication constraints. Our major contributions include probabilistic analysis of feedback message delivery within a given time-frame and its projected effect on information fusion, and investigation, via simulation studies, of the fusion performance in a two-sensor environment with variable link-level conditions, computation constraints, as well as feedback configurations and schedules. Two types of fusers are studied and their performance under variable conditions are compared in various settings.

The remainder of this paper is organized as follows: In Sec. II, the system model, including the target motion and sensor measurement models as well as fusion rules, is briefly introduced. Next in Sec. III, we explore the effect of information feedback on sensor fusion under the ideal assumption that the communication link is perfect. The results therein are further developed in Sec. IV, where communication link loss, delay, and the combination of the two come into play and the resulting impact of information degradation on feedback and fusion is shown. The paper concludes in Sec. V.

II. System Model

The goal of a state estimator is to extract the state information $\mathbf{x}$ from measurements $\mathbf{z}$ that are corrupted by noise; this is done by sequentially running a filter that outputs the state estimate $\hat{\mathbf{x}}$ and its associated error covariance matrix $\mathbf{P}$ periodically. A sensor in a long-haul network assumes the role of such a filter. The fusion center, on the other hand, simply combines the estimates generated by sensors using a certain fusion rule. To formulate the estimation and fusion process, we consider that a stream of globally fused estimates is reported by the fusion center at a regular time interval T, which also coincides with the estimation interval at the sensors.

A. Target Motion and Sensor Measurement Models

We consider the nearly constant acceleration (NCA) kinematic model in one *generic* coordinate. This is because in most tracking applications, the same motion model is used for each coordinate, and the motion along each coordinate can be decoupled from other coordinates (as in a common "east-north-up" system) [2]. The motion uncertainty can be modeled by the process noise as a white stochastic process with a certain power spectral density (PSD). The continuous-time system has a state vector $\mathbf{x}$ consisting of position, velocity, and acceleration $\mathbf{x} = [p \quad v \quad a]^T$, where the derivative of acceleration is modeled by a zero-mean white jerk process noise. The system dynamics described by a discrete-time state equation with a sampling period T are given by $\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{w}_k$. The state transition matrix $\mathbf{F}$ and the covariance matrix $\mathbf{Q}$ of the stationary process noise $\mathbf{w}_k$ are defined as

$$\mathbf{F} = \begin{bmatrix} 1 & T & T^2/2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix},$$

and

$$\mathbf{Q} = \mathrm{cov}(\mathbf{w}_k\mathbf{w}_k^T) = \begin{bmatrix} T^5/20 & T^4/8 & T^3/6 \\ T^4/8 & T^3/3 & T^2/2 \\ T^3/6 & T^2/2 & T \end{bmatrix} q,$$

respectively, where q is the PSD of the continuous-time white noise.

We consider a simplified measurement model in which the sensor directly measures the position state of interest and hence only the position estimate $z_k = \mathbf{H}\mathbf{x}_k + v_k$ is available, where $\mathbf{H} = [1 \quad 0 \quad 0]$ is the measurement matrix, and the Gaussian measurement noise v has autocorrelation $\mathbb{E}[v_k v_j] = R\delta_{kj} \triangleq \sigma_v^2 \delta_{kj}$, where $\delta_{(\cdot)}$ is the Kronecker delta function.

B. Fusion Rule

It is well known that the common process noise $\mathbf{w}$ in measuring the motion of any target results in correlated errors among estimates generated by multiple sensors. The error cross-covariance is the term that describes this spatial correlation. Since it is in general very challenging to analytically derive the exact cross-covariance, we consider two types of fusers where sensor estimates are fused without any knowledge of the error cross-covariances.

1) Track-to-Track Fuser without Cross-Covariance: In tracking applications, the track-to-track fuser (T2TF) [2] is a fuser optimal in the linear minimum mean-square error (LMMSE) sense. The fused state estimate $\hat{\mathbf{x}}_F$ and its error covariance $\mathbf{P}_F$ are defined for two sensors as:

$$\mathbf{P}_F = (\mathbf{P}_1^{-1} + \mathbf{P}_2^{-1})^{-1}, \text{ and } \quad \hat{\mathbf{x}}_F = \mathbf{P}_F(\mathbf{P}_1^{-1}\hat{\mathbf{x}}_1 + \mathbf{P}_2^{-1}\hat{\mathbf{x}}_2),$$

where $\hat{\mathbf{x}}_i$ and $\mathbf{P}_i$ are the state estimates and error covariance from sensor i, respectively, The error cross-covariance $\mathbf{P}_{ij} = \mathbf{P}_{ji}^T$, the error cross-covariance between sensors i and j, has been omitted from the equations since it is unknown. This rule can be readily extended to multiple sensors. An important feature of this fuser is that $\mathbf{P}_F$ often promises an estimation error that is lower than the actual error; hence, the fuser is sometimes considered as an "optimistic fuser" in the literature [2].

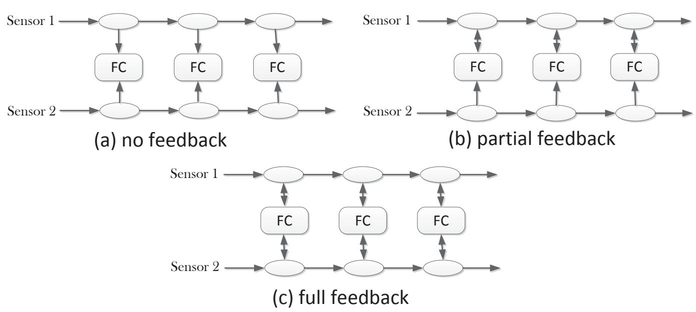


Fig. 1: Different information feedback mechanisms with two sensors: (a) no feedback; (b) partial feedback (to Sensor 1 only); and (c) full feedback. The horizontal arrows indicate time evolution, whereas the vertical ones indicate the direction of information flow

2) Fast Covariance Intersection (CI) Algorithm: In another fusion method – the covariance intersection (CI) algorithm – the geometric intersection of the individual covariance ellipses is considered as the error covariance of the fused estimate. The intersection is characterized by the convex combination of sensor covariances:

$$\mathbf{P}_F = (\omega_1 \mathbf{P}_1^{-1} + \omega_2 \mathbf{P}_2^{-1})^{-1}$$
$$\hat{\mathbf{x}}_F = \mathbf{P}_F \left(\omega_1 \mathbf{P}_1^{-1} \hat{\mathbf{x}}_1 + \omega_2 \mathbf{P}_2^{-1} \hat{\mathbf{x}}_2\right), \quad \omega_1 + \omega_2 = 1$$

where $\omega_1, \omega_2 > 0$ are weights to be determined (e.g., by minimizing the determinant of $\mathbf{P}_F$). Recently, Wang and Li [18] proposed a fast CI algorithm where the weights are found based on an information-theoretic criterion so that ω_1 and ω_2 can be solved for analytically as follows:

$$\omega_1 = \frac{D(p_1, p_2)}{D(p_1, p_2) + D(p_2, p_1)}$$

where $D(p_A, p_B)$ is the Kullback-Leibler (KL) divergence from $p_A(\cdot)$ to $p_B(\cdot)$, and $\omega_2 = 1 - \omega_1$. When the underlying estimates are Gaussian, the KL divergence can be computed as:

$$D(p_i, p_j) = \frac{1}{2}\left[\ln \frac{|\mathbf{P}_j|}{|\mathbf{P}_i|} + \mathbf{d}_X^T \mathbf{P}_j^{-1} \mathbf{d}_X + Tr(\mathbf{P}_i \mathbf{P}_j^{-1}) - k\right]$$

where $\mathbf{d}_X = \hat{\mathbf{x}}_i - \hat{\mathbf{x}}_j$, k is the dimensionality of $\hat{\mathbf{x}}_i$, and $|\cdot|$ denotes the determinant. This fast-CI fuser can also be extended to more than two sensors [18], although the equations are somewhat more involved. It is important to note that this fuser, or any CI-based fuser, is pessimistic in the sense that $\mathbf{P}_F$ indicates a worse-than-actual error performance. This can be useful in practice since $\mathbf{P}_F$ provides a conservative measure of the error performance.

III. Information Feedback and Its Impact on Fusion without Communication Constraints

In this section, we consider information feedback under the assumption that the communication medium is ideal; that is, every message can be successfully delivered to its intended destination with no or negligible delay. As such, we can single out the effect of instantaneous feedback on information fusion. Our focus here is on effects of computation constraints in the form of sensor estimation bias.

A. Feedback Configurations

In terms of to which sensor(s) a feedback message is being sent back, there exist different feedback configurations. For ease of presentation, here we consider only a two-sensor fusion scenario in this work, although the ideas can be similarly extended to multi-sensor fusion as well. In Fig. 1, a two-sensor scenario is shown with the ovals representing sensor estimates and rectangles fused estimates. In (a), as in conventional fusion settings, information exchange is one-way, meaning that no information feedback from the fusion center to the individual sensors exists. In contrast, the partial feedback to Sensor 1 in (b) and to both sensors in (c) serve to pass the global information generated by the fusion center to the individual sensor(s). Upon receiving a feedback message (containing the fused estimate and its associated error covariance matrix), a sensor substitutes the globally fused information for its own, which is further used as the input for its next-step filtering. An important note here is that under the ideal communication assumption, the fusion center can immediately obtain a fused estimate; in addition, any feedback message can be received by the sensor(s) with no delay[1] as well, thereby affecting its subsequent filtering.

Having introduced different feedback configurations, we next investigate the effect of information feedback with perfect communications. Variable sensor bias profiles that reflect the computational constraints are studied.

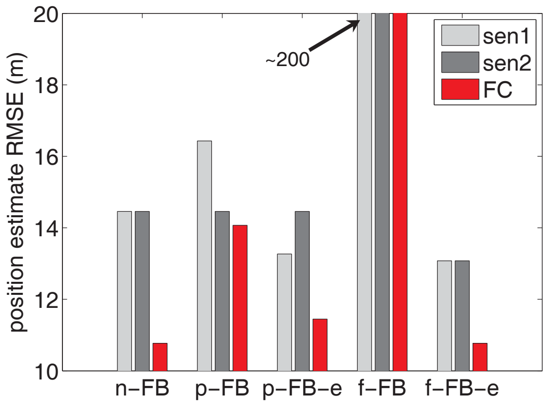
B. Feedback with Unbiased Sensor Data

We first consider the case with both sensors yielding unbiased estimates. A representative case is investigated throughout the work that has the same parameters as in [9]: T = 1 s, q = 1 $\mathrm{m}^2/\mathrm{s}^3$, and σ_v = 20 m for both sensors. The effects on position RMSE estimation performance of the sensors and on fusion performance at the fusion center are shown in Fig. 2.

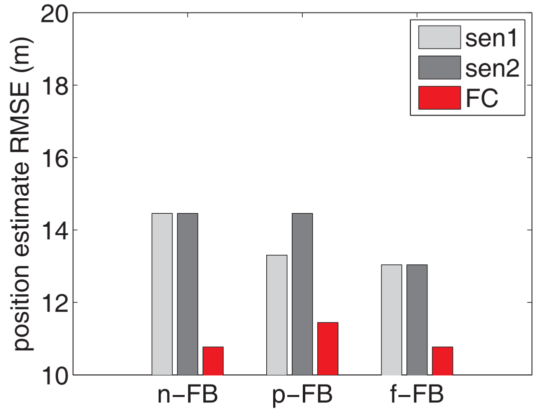
In (a), the performance of the track-to-track fuser (T2TF) is shown. The "n", "p", and "f" in the labels stand for no, partial, and full feedback configurations, respectively. When there is no feedback, the fused estimate has on average 25.5% less position RMSE than the individual sensors, or equivalently, 44.5% less MSE after fusion[2]. On the other hand, in both "p-FB" and "f-FB" cases, where a fused estimate $\hat{\mathbf{x}}_F$ and the associated error covariance $\mathbf{P}_F$ are sent back, the resulting fusion performance is poor, especially for the full feedback case (with an RMSE approaching 200). It can be shown that this feedback mechanism, as in the partial feedback (to Sensor 1) case, is equivalent to artificially reducing the $\mathbf{P}$ of the other sensor (Sensor 2) to half of its value at each fusion step; in the full feedback case, $\mathbf{P}$ of both sensors are artificially halved, thereby leading to rapid filter divergence and extremely large fusion errors. As such, two modified feedback schemes are introduced, namely, "p-FB-e" and "f-FB-e", where "e" means that an elevated $\mathbf{P}$ – in this case, $2\mathbf{P}_F$ – is sent back by the fusion center along with the fused estimate $\hat{\mathbf{x}}_F$. Without further specification, in the rest of the paper, we always assume such elevated feedback as the default setup for the T2TF.

[1]Or at least this delay is negligible compared to the estimation interval.

[2]Note that in the ideal case without error cross-covariance, this value would be 50%.



(a)



(b)

Fig. 2: Position estimate RMSE performance under variable feedback configurations without communication and computation constraints for (a) T2TF and (b) fast-CI fuser

Next in (b), the performance with the fast-CI fuser is similarly shown. The default setup without feedback yields basically the same error performance as in the T2TF case. Interestingly, this fuser doesn't undergo the above-described filter divergence problem when $\hat{\mathbf{x}}_F$ and $\mathbf{P}_F$ are taken by the sensor(s). In addition, as has been observed in the T2TF case (with elevated $\mathbf{P}$), feedback effectively reduces the sensor estimation errors; however, the fusion performance becomes slightly worse with partial feedback to sensor 1 and remains nearly the same with full feedback to both sensors. This effect can be somewhat explained by the geometric meaning of the CI fuser. Since the fusion result is described by an ellipse that contains the intersection of the two ellipses corresponding to errors of both sensors, when a fused estimate is initially sent back and supplants data of Sensor 1, the area corresponding to the next-step fused estimate would at least contain the intersection of error ellipses of Sensor 2 and the fusion center[3], now an even larger ellipse, hence an increased error. In the full-feedback case, the expanding and shrinking of ellipses occur simultaneously, albeit in different directions, resulting in nearly identical intersection regions.

In the case with no information feedback, both sensors and the fusion center are in their respective steady state, meaning statistically the estimation errors remain stable over time. However, feedback brings sensors and the fusion center to their respective quasi-steady state, and once the feedback is withdrawn, the errors will promptly revert to their true steady-state values. It is to be understood that all performances under feedback are not steady-state behaviors, since in the latter, as long as one sensor's error performance is improved, the fused estimate will experience reduced errors as well. In all, with unbiased state estimates, feedback serves to disrupt the steady state of the individual sensors; although the sensor error performance is somewhat improved, there's no immediate benefit in improving the quality of fused estimates.

[3]In fact the updated Sensor 1 estimate would be described by a different ellipse than the fusion center's from the previous step. But the net effect is still a larger new intersection region.

C. Feedback with Biased Sensor Data

Now we focus on the case where the quality of one sensor (Sensor 1 in this work) estimates is compromised due to persistent measurement biases. In particular, a biased measurement z_k^b at time k consists of both deterministic and random elements: $z_k^b = \mathbf{H}\mathbf{x}_k + v_k + b_k + v_k^b$, where b_k is the fixed bias and v_k^b is the random element such that $\mathbb{E}[(v_k^b)^2] = R^b$ and R^b is the associated bias variance. To measure the effect of both deterministic and random biases, we consider a joint bias term $\tilde{v}_k$ that satisfies $\tilde{v}_k^2 = b_k^2 + (v_k^b)^2$ as the metric for bias. In the example to be used in our subsequent studies, b_k is selected to be 96% of the average bias $\tilde{v}_k$ and the random bias term v_k^b can be easily generated as well. An important point here is that Sensor 1 is not aware of its measurement bias; therefore, $\mathbf{P}_1$ it generates is an over-optimistic description of its actual estimation error.

Fig. 3 shows the RMSE performance under variable Sensor 1 measurement bias levels and feedback configurations (the T2TF and fast-CI fusers yield the same performance). As expected, the estimation error increases rapidly as the overall bias level goes up. The resulting fused estimates also experience degraded error performance, which after a certain point, becomes even worse than using Sensor 2 alone. With information feedback from the fusion center, the error performance of Sensor 1, again, can be improved significantly. Unlike the no-bias case, as the bias level increases, the fused estimates start to possess a better quality when the feedback is sent back to Sensor 1 only (labeled as "p-FB-1") than no- or full-feedback case. This demonstrates that the major benefit of information feedback is to counteract sensor measurement/estimation bias. Of course, the premise is that feedback has to be selectively sent to the right sensor (i.e., biased sensor); otherwise, it can actually worsen the performance when feedback is sent to the better sensor (e.g., Sensor 2 here). This calls for the design of bias detection mechanisms, which is beyond the scope of this work. Another interesting observation is that although the fusion performance under different partial and full feedback configurations varies, the effects on the individual sensors remain largely the same; that is, the effect of feedback on Sensor 1 is independent of that on Sensor 2 and vice versa.

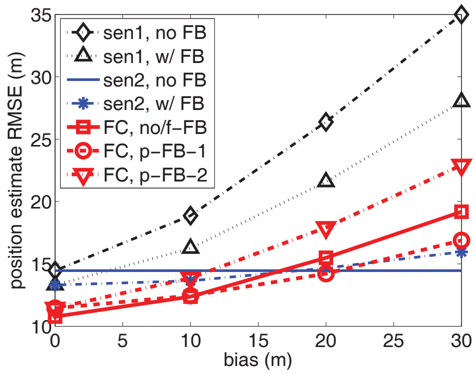


Fig. 3: Position estimate RMSE performance under variable feedback configurations and bias levels without communication constraints (both T2TF and fast-CI fusers)

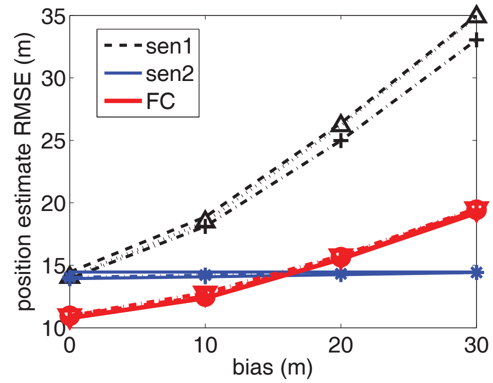


Fig. 4: Position estimate RMSE performance under variable feedback configurations and bias levels with fixed RTT = 1 s (both T2TF and fast-CI fusers)

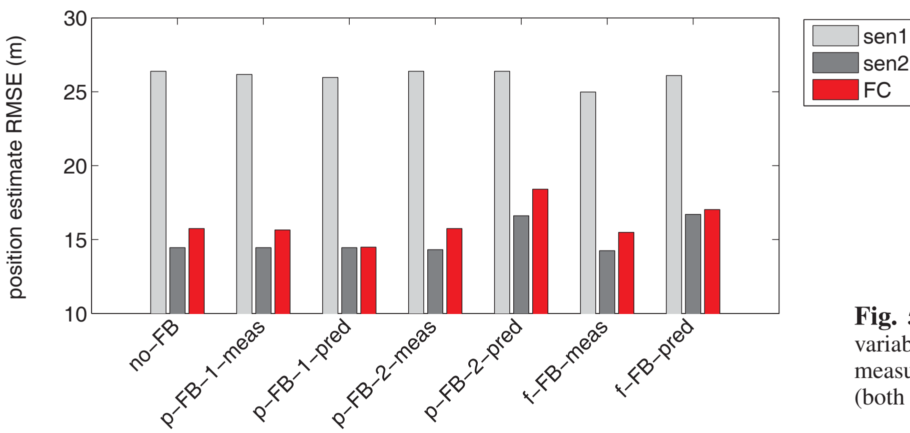


Fig. 5: Position estimate RMSE performance with variable feedback configurations and update methods, measurement bias of Sensor 1 = 20 m, RTT = 1 s (both T2TF and fast-CI fusers)

IV. Information Feedback with Communication Constraints

Now we turn our attention to information feedback in the context of communication constraints. Specifically, we consider the impact of feedback on fusion performance with (1) fixed communication delay, (2) communication loss, and (3) a combination of random loss and delay. We assume the sensors can take measurements and then in turn generate and send out their state estimates in a timely manner; it is the communication loss and delay between any sensor and the fusion center that may result in unavailable state estimates at the latter. Doing so allows us to focus mainly on evaluating different information feedback schemes at the fusion center in order to potentially improve estimation/fusion performance.

A. Information Feedback with Fixed Communication Delay

Without loss of generality, we focus on the case where the RTT of the network is set to be a fixed 1 s, with each way (sensor $\rightarrow$ FC or FC $\rightarrow$ sensor) taking up exactly 0.5 s. Following this setup, half a second after both sensor estimates are sent out, the fusion center receives and combines them to obtain a fused estimate. Immediately, this estimate is sent back to the desired sensor(s). Suppose all processing delays are negligible, a sensor will receive the fused estimate one second after sending out its own. Because the estimation interval is also 1 s, the sensor needs to update this fused estimate (for the previous estimation epoch) to its current estimate. We now investigate how fusion performance will change with such delayed feedback and response.

Fig. 4 shows the estimation and fusion performance under variable feedback configurations and bias profiles as in the previous section. Compared to the results in Fig. 3, changes in fusion performance after feedback become much less visible regardless of the bias level. The main reason for this result is that in order to update the previous feedback message forward by 1 s, the sensor has used its latest measurement – which is exactly the biased one feedback attempts to improve. Another way to examine the effect is to count how many times a biased measurement is used in the sensor estimation process. Without communication delay, it is used just once for generating a new estimate; with RTT = 1 s, however, it is used an additional time to update the feedback message over time. As a result, the fusion performance is hardly affected by feedback.

Alternatively, to bypass the biased measurement, Sensor 1 can use one-step prediction to update the delayed feedback message. In Fig. 5, the performance comparison between updates using measurements (“-meas”) and those using prediction (“-pred”) is shown under different feedback configurations and a measurement bias = 20 m. Of interest to us is the case where feedback is sent back to Sensor 1, which in turns uses prediction to forward the feedback message by one second. It turns out this approach yields better fusion performance than others, and the difference will become more apparent with even higher biases.

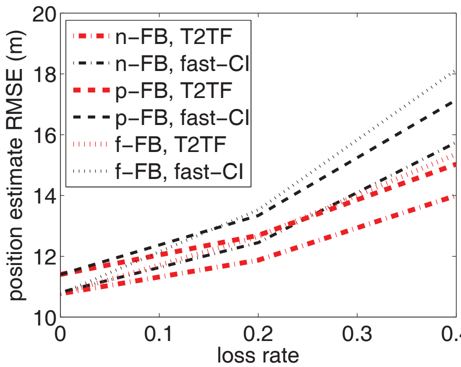


Fig. 6: Position estimate RMSE performance with variable feedback configurations and link-level communication loss rates, no measurement bias

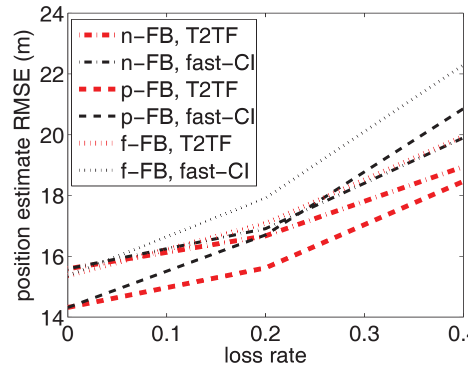


Fig. 7: Position estimate RMSE performance with variable feedback configurations and link-level communication loss rates, measurement bias of Sensor 1 = 20 m

B. Information Feedback with Communication Loss

Next we explore the fusion performance under information feedback with link-level message loss. Suppose each message sent by a sensor is lost en route to the fusion center with probability p that is independent of other messages. Likewise, any feedback message sent by the fusion center is also subject to the same loss rate.

With the presence of communication loss, the feedback process becomes much less certain in terms of the quality of any fused estimate to be sent back. If in the case of a lost message from a sensor, the fusion center applies prediction from the previously available estimates for that sensor, then a fused estimate at time k could be obtained from (1) available $\hat{\mathbf{x}}_1$ and $\hat{\mathbf{x}}_2$ at k; (2) available $\hat{\mathbf{x}}_1$ but a predicted estimate from an earlier time for Sensor 2; (3) available $\hat{\mathbf{x}}_2$ but a predicted estimate from an earlier time for Sensor 1; and (4) predicted estimates from (possibly different) earlier times for both sensors. Although it is possible to probabilistically combine the long-term error values (as found in the previous section) for these different scenarios to approximate the errors after fusion, we again resort to simulations for evaluation of the fusion performance.

In Fig. 6, tracking errors under variable loss rates and feedback configurations are plotted for both T2TF and fast-CI fusers when there's no measurement bias. Across the board, the fusion errors increase fairly quickly as the communication loss worsens, reflecting the link between information loss and reduced fusion gain. Whereas the fast-CI fuser generates estimates of the same quality as those from T2TF when there is no loss, the estimates from the former become increasingly error-prone as the loss rate increases. When the loss reaches 40%, the fast-CI fuser always outputs worse estimates than the T2TF, regardless of feedback configurations. This demonstrates the higher sensitivity of fast-CI fuser to information loss compared to its T2TF counterpart. Another interesting observation is that with increasing communication loss, partial feedback starts to outperform full feedback for both types of fusers. This is because under higher loss, full feedback tends to resemble partial feedback – and partial becomes more of "no feedback" – thereby assuming the relationship of those configurations under lossless situations.

Fig. 7 shows similar results with the exception that there is a measurement bias of 20 m at Sensor 1. Partial feedback is shown only for Sensor 1. As expected, all errors are higher than those in the no-bias case. What stands out here is among all schemes the persistently best tracking performance with partial feedback to Sensor 1 using T2TF. Although initially the fast-CI fuser also performs well with partial feedback, its tracking accuracy deteriorates with increasing communication loss, which eventually becomes even worse than the no-feedback scenario.

C. Information Feedback with Random Loss and Delay

Now we are ready to explore the effect of both information feedback and random loss and delay as experienced in long-haul sensor networks. In particular, we focus on the effect of information loss, due both to link-level communication loss and imposed early time cutoff, on information feedback.

1) Loss and Delay Profiles: The communication loss and delay characteristics are determined by the long-haul link conditions. Loss is again assumed to be independently encountered with probability p. The latency that a message undergoes before arriving at the fusion center may consist of the initial detection and measurement delay, data processing delay, propagation delay, and transmission delay, among others. For ease of analysis, suppose that a pdf $f(t)$ can model the overall delay t that a message experiences before being successfully received by the fusion center. One typical example is that of the shifted exponential distribution:

$$f(t) = \frac{1}{\mu} \exp^{-\frac{t-T_I}{\mu}}, \text{ for } t \geq T_I,$$

in which T_I serves as the common link and processing delay, which is the minimum delay that a message must experience to reach the fusion center, and μ is the mean of the random delay beyond T_I that can be affected by factors such as weather and terrain. This simple probabilistic model enables us to measure the performance of information delivery over a period of time. In addition, the delay over the reverse link (FC $\rightarrow$ sensor) is assumed to follow the very same distribution as outlined above. Without loss of generality, we let $T_I = \mu = 0.5$ s as in [11]. As such, the average RTT is 2 s, an even worse link scenario than that studied in Sec. IV-A.

2) Timing of Feedback Message Delivery: Suppose a reporting deadline D is defined as the maximum allowable time for the fusion center to fuse the available sensor estimates. With negligible

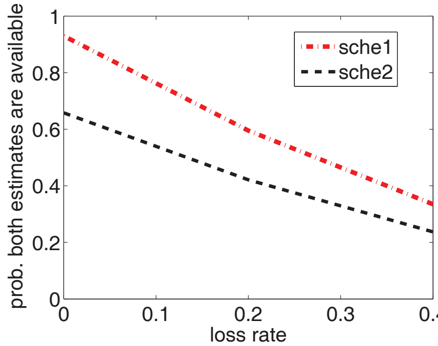


Fig. 8: Probabilities of having both sensor estimates available for fusion under two feedback schedules

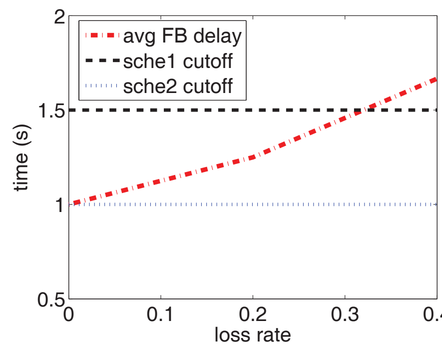


Fig. 9: Average feedback message communication delay and cutoff time for two feedback schedules

computation time, this is also the moment when the fused estimate is sent back to the sensor(s). When there's no loss, the average amount of time it takes for the feedback message to arrive is $T_I+\mu$; with the initial period D, the total average latency between the time when the feedback message is received and the (prior) time instant the message describes is $D+T_I+\mu$. A sensor then would have to either use prediction or measurements to project this delayed fused estimate to its next pending estimate, with an average number of $\lceil\frac{D+T_I+\mu}{T}\rceil$ prediction steps, or alternatively, using each measurement $\lceil\frac{D+T_I+\mu}{T}\rceil$ times (See Sec. IV-A). As such, to reduce the potential negative effect from error increase due to prediction and/or measurement bias, it is preferable to use a smaller D. However, with the deadline cut short, the fusion center is using less information for fusion, which may have a more adverse effect on tracking performance. In our two-sensor case, for instance, the probability that the fusion center can obtain both sensor estimates by the reporting deadline is $(1-p)^2F^2(D)$, where $F(\cdot)$ is the corresponding cdf of $f(\cdot)$, and a decrease in D may in turn significantly reduce this probability as well. We will explore the trade-off of selecting different D values next.

3) Fusion Performance with Different Feedback Schedules with Loss and Delay: To study the effect of information feedback on fusion with random loss and delay, we consider two feedback schedules: in the first schedule ("sche1"), both the deadline D and feedback cutoff time are set to be 1.5 s; whereas in the second ("sche2"), both are set as just 1 s. Here the feedback cutoff time effectively serves to disregard any feedback message received thereafter. In Figs. 8 and 9, the effects of these two schedules on original and feedback message deliveries are shown.

From the figures, we observe that by reducing the total amount of time allowed for communication (as from "sche1" to "sche2"), the probability that both sensor estimates are available at the fusion center is reduced by 30% for all loss rates. On the other hand, as the loss rate increases, the expected time to receive a feedback message becomes longer, even surpassing the assigned feedback communication time in "sche1" when the loss goes above 30%. The overall effect is that for "sche2", the fused estimates used for feedback are of worse quality to begin with, which are also less likely to be actually received and incorporated by the sensor(s) afterward. As such, any benefit from a shorter assigned communication time, i.e., to reduce the effect of prediction and/or measurement during the sensor update of the feedback message, is largely offset and overruled by the negative effect of information loss due to early cutoff.

Performance results are shown again in Figs. 10 and 11 to validate our analysis above. In Fig. 10, the fusion errors are plotted for both schedules and both types of fusers under variable loss rates. The curves largely resemble those in the loss-only case in the previous subsection, although here the errors are variably higher due to communication delay and early cutoff. As has been seen earlier, performance degradation is more severe for the fast-CI fuser as loss increases. In addition, the performance difference between two feedback schedules is larger for CI fuser than that of T2TF, reflecting the higher sensitivity to information loss (now due to early cutoff) of the former. As this is the no-bias case, from (a) no feedback to (b) partial feedback a slight decrease in fusion accuracy is observed.

In contrast, in Fig. 11, with a measurement bias of 20 m added at Sensor 1, the improvement from partial feedback to Sensor 1 is apparent for T2TF under longer time cutoff ("sche1"), although this improvement becomes very small as the loss rate goes beyond 30%. On the other hand, the same partial feedback under "sche2" hardly benefits the fusion performance at all, due to the information loss introduced by early cutoff (thereby showing more effects of "no feedback" scenario). The performance of the fast-CI fuser under "sche1" is comparable to that of the T2TF under "sche2" – again demonstrating better tolerance of information loss by the latter – and with an earlier cutoff, the fast-CI fuser performs even worse with partial feedback than no feedback at all[4]. These results conform with our earlier analysis on the effect of information loss due to message loss and early time cutoff.

V. Conclusion

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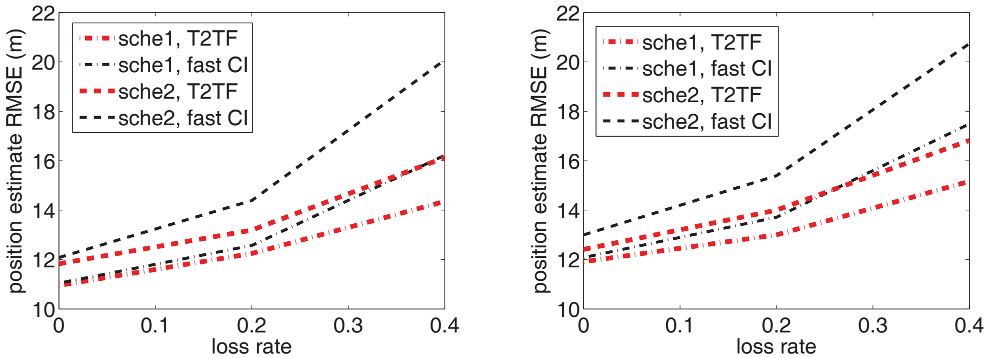
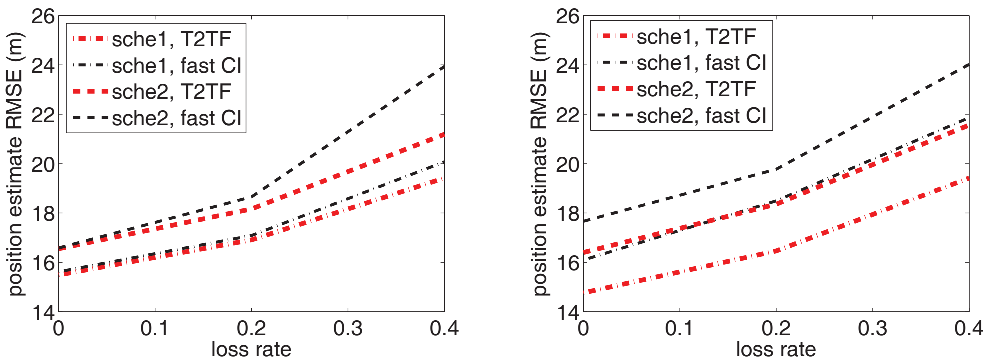
In this work, we have investigated the effect of different information feedback configurations and schedules in the context of variable communication link-level loss and delay conditions as well as sensor computation constraints. Numerical and simulation studies with a two-sensor fusion example are used to demonstrate the benefits and limitations of information feedback as applied in a long-haul sensor network. Having concluded that the main advantage of information feedback is in combating bias, we are

[4]Another interesting point is that even without link-level loss, the CI-fuser outputs estimates of higher errors than the T2TF in Fig. 11 as opposed to nearly identical errors between the two in Figs. 4 and 5, where the RTT is much smaller.



(a) (b)

Fig. 10: Position estimate RMSE performance with variable feedback schedules and link-level communication loss and delay, no measurement bias: (a) no feedback, (b) partial feedback



(a) (b)

Fig. 11: Position estimate RMSE performance with variable feedback schedules and link-level communication loss and delay, measurement bias of Sensor 1 = 20 m: (a) no feedback, (b) partial feedback to Sensor 1

interested in designing dynamic information feedback schemes that incorporate bias detection and estimation in the context of multi-sensor fusion in future work. Also of interest are other feedback mechanisms beyond simple replacement. Other extensions of this study may include incorporation of more complex target maneuvering models and measurement models as well as correlated link communication statistics.

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