# Performance Evaluation of Decentralized Estimation Systems with Uncertain Communication

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**Abstract –** *An approach for evaluating the performance of decentralized estimation systems under non-ideal communications is presented. Recent studies have shown that transmission disruptions occur frequently in tactical wireless networks due to a variety of unpredictable factors, such as unintentional interference or jamming. Yet the impact of non-ideal communications on algorithmic performance are often ignored in the fusion and tracking literature. This paper provides the beginnings of a basis for robustly assessing decentralized estimation system performance in the presence of uncertain communications through the development of a context metric - the Expected Information Rate - that characterizes problem difficulty in terms of the communication environment.*

**Keywords:** Tracking, Decentralized Data Fusion (DDF), Performance Evaluation, Context Metrics, Expected Information Rate (EIR), Distributed Kalman Filter (DKF), Covariance Intersection (CI)

## 1 Introduction

Since the early-1990s, much attention has been given to the development of techniques for fusing data from sensors and information sources in distributed architectures [1, 6, 17, 15, 13]. Continued research in this area has been driven by the US Military's vision of net-centric warfare, in which information from geographically dispersed elements of the force - be they individual sensors, sensing platforms or warfighters - is shared and combined (fused) to support decentralized command and control.

Decentralized data fusion systems have many properties, such as improved robustness, increased availability and reduced communication requirements, that make them attractive for military applications. These advantages are not without cost, however, as the primary difficulty of a decentralized architecture is properly identifying and removing information common to shared data sets. Despite the theoretical limitations of traditional Bayesian filtering approaches in general decentralized networks, numerous optimal and approximate techniques for decentralized data fusion exist. These include the Information Graph technique [6, 13], Local Fusion Tree approach [16], Covariance Intersection (CI) Filtering algorithm [10] and Channel Filtering algorithm [3]. While the performance of these algorithms has been addressed to some extent [4], very little is known about the performance of these algorithms in communication networks with non-deterministic transmission characteristics. This knowledge gap makes the challenge of identifying appropriate algorithms and predicting system performance a near impossibility for decentralized estimation system designers.

Recent studies have shown that wireless tactical networks experience significant numbers of dropped or delayed message transmissions [2]. These disruptions are due to unpredictable changes in network conditions, such as signal attenuation, unintentional interference, or jamming. However, the impact of non-ideal communications are often ignored in the literature as most fusion formulations require prior knowledge of the communication architecture or assume that fusion and communication events are deterministic [4]. Since fusion in a distributed architecture is ultimately dependent upon the characteristics of the network utilized for information sharing, any approach for predicting the performance of a decentralized fusion system must account for the stochastic nature of the underlying communication network. Thus, there is a need for methods of robustly assessing decentralized estimation system performance in the presence of uncertain communications.

Many comparisons of fusion algorithms can be found in the literature (see, e.g., [9, 8]). However, such comparative studies are typically of limited utility because little is known about the difficulty of the problem considered in the Performance Evaluation (PE) [5]. In other words, the approach of describing a specific scenario and computing performance results from simulation of that scenario provides an unsatisfactory description of algorithm performance because the complexity of the scenario is unknown. Proper characterization of problem difficulty, particularly in terms of the harshness of the non-ideal communication environment, becomes increasingly important as system designers begin to consider large scale distributed networks that exhibit truly ad hoc behavior.

This paper presents an approach for predicting the performance of a distributed estimation system when information flow is governed by non-deterministic communications. A probabilistic communication model is developed and then used to describe a stochastic form of the general fusion rule as well as a context metric that characterizes problem difficulty in terms of the stochastic communication factors. The context metric is then used to assess the performance of the Decentralized Kalman Filter (DKF), the CI algorithm and the stochastic formulation.

The structure of the remainder of the paper is as follows. Section 2 provides some necessary background on distributed fusion, including a description of the DKF and CI algorithms. Additionally, Section 2 introduces the concept of context metrics and describes the usage of such metrics in PE. Section 3 presents the stochastic formulation of the fusion rule and introduces the Expected Information Rate as a metric for problem characterization in non-ideal communication environments. Section 4 provides results from comparison of the DKF approach and CI approach using the proposed context metric. Finally, section 5 contains a summary and some concluding remarks.

# 2 Background

A decentralized data fusion system is a type of fusion system containing a set of processing nodes connected by communication links. To differentiate from architectures that are hierarchical in nature, throughout this paper attention is restricted to fully distributed, or decentralized architectures in which each node has no knowledge of the global topology and only node-to-node communication is permitted[14]. In such general network topologies, it was shown that traditional Bayesian filtering techniques can not be used to maintain consistent estimates [18]. The theoretic fundamentals of decentralized fusion explain why this is true, but application of the theoretic results of decentralized fusion remain a challenge due to the difficulty of identifying and removing common information. Despite this challenge, several decentralized data fusion techniques exist to account for or approximate the redundant information. However, application of the theory to systems with non-ideal communications remains a largely unexplored area. The remainder of this section provides necessary background on the decentralized data fusion problem and the use of context metrics to characterize problem difficulty.

## 2.1 Decentralized Data Fusion

The fusion rule is often specified in a set theoretic form as the combination (union) of $n$ fusion 'events' (see e.g., [6]):

$$\Phi\left(\bigcup_{i=1}^{n} I^{i}\right) = \sum_{i=1}^{n}(-1)^{i+1}S^{i} \quad (1)$$

where $S^i$ represents the combination of $i$ event probabilities. The alternating addition and subtraction of joint probabilities serves the purpose of removing any conditional dependencies arising from shared information. For example, consider the case where two nodes, $A$ and $B$, estimate the state $x(k)$ of a target at time $k$ using a sequence of independent observations $Z_A = \{z_A(1), z_A(2), ..., z_A(k)\}$ and $Z_B = \{z_B(1), z_B(2), ..., z_B(k)\}$. Under the assumption that the posterior state $x(k)$ is independent of prior measurements given the prior state, the fusion rule from Equation 1 becomes:

$$p(x(k)|Z_A \cup Z_B) \propto \frac{p(x(k)|Z_A)p(x(k)|Z_B)}{p(x(k)|Z_A \cap Z_B)} \quad (2)$$

where $p(x(k)|Z_A \cup Z_B)$ is the joint estimate and $p(x(k)|Z_A \cap Z_B)$ is the estimate based on common information alone.

Application of the fusion rule to linear Gaussian systems yields (see [6, 13] for proofs):

$$\begin{aligned}\hat{x}_i(k) &= P_i(k)\left[\left(\sum_{j=1}^{n} P_j(k|k)^{-1}\hat{x}_j(k|k)\right)\right. \quad (3)\\ &\left. -\bar{P}_i(k)\bar{x}_i(k)\right]\\ P_i(k) &= \left[\left(\sum_{j=1}^{n} P_j(k|k)^{-1}\right) - \bar{P}_i(k)\right]^{-1} \quad (4)\end{aligned}$$

where $\hat{x}_i(k)$ and $P_i(k)$ are the mean and covariance of the fused state estimate for node $i$ at time $k$; $\hat{x}_j(k|k)$ and $P_j(k|k)$ represent the local estimate at node $j$ (i.e. after incorporation of node $j$'s sensor measurement); and, $\bar{x}_i(k)$ and $\bar{P}_i(k)$ represent the common information in the estimates being fused at node $i$ at time $k$ - i.e. are aggregates of the common information needing to be removed.

The difficulty in implementing Equations 3 and 4 occurs in identifying the common information, $\bar{x}_i(k)$ and $\bar{P}_i(k)$. If we consider a two node case once again, the challenge of removing common information in the joint estimate can be restated as determining how to combine the estimates of node A $p_A(x(k)) \sim \mathcal{N}(\hat{x}_A(k), P_A(k))$ and node B $p_B(x(k)) \sim \mathcal{N}(\hat{x}_B(k), P_B(k))$ when the cross-correlation between A and B is unknown and non-zero. The Covariance Intersection (CI) algorithm is a well known approach for such fusion operations [10]. The CI algorithm determines the convex combination of the covariances of A and B, such that the new estimate is guaranteed to be consistent - i.e. the CI-calculated covariance is greater than or equal to the actual Mean Square Error (MSE). The CI algorithm is generalizable to more than two nodes and has been used in many different data fusion and artificial intelligence applications (see e.g., [11]).

This difficulty of removing common information is circumvented in a decentralized Kalman filter (DKF) approach because by assumption each node converts its sensor measurements into independent information state and Fisher information updates:

$$\begin{aligned}y_i(k) &= H_i(k)^T R_i(k)^{-1}(z_i(k) \quad (5)\\ &\quad -H_i(k)\hat{x}_i(k|k-1))\\ Y_i(k) &= H_i(k)^T R_i(k)^{-1} H_i(k) \quad (6)\end{aligned}$$

where the measurement $z_i(k)$ is related to target state by the linear equation

$$z_i(k) = H_i(k)\,x + v_i(k) \quad (7)$$

and the noise term $v_i(k) \sim \mathcal{N}(0, R_i(k))$.

If each node communicates $y_i(k)$ and $Y_i(k)$ with the other nodes, the fusion rule becomes (see e.g., [12]):

$$\begin{aligned} \hat{x}_i(k) &= P_i(k)\Big[P_i(k|k-1)^{-1}\hat{x}_i(k|k-1) \quad (8) \\ &\quad + \sum_{j=1}^{n} y_j(k)\Big] \\ P_i(k) &= \left[P_i(k|k-1)^{-1} + \sum_{j=1}^{n} Y_j(k)\right]^{-1} \quad (9) \end{aligned}$$

## 2.2 Context Metrics for PE

Numerous comparative studies of fusion algorithms can be found in the literature. For example, Gan & Harris recently performed a comparison of two common Kalman-filter based measurement fusion methods [9]. After a theoretical analysis, they show that the state estimation covariances of the two methods are identical over a variety of process noise levels. In another study, Farina et al. consider a non-linear filtering problem and compare several filtering methods, including the Benes Filter, Extended Kalman Filter and Particle Filter [8]. Performance in this paper is assessed using the mean estimation error and the standard deviation of the estimation error over many independent trials of a single scenario.

In both of these studies, simulation is used as a primary means for comparing algorithm performance. However, performance results from simulation alone are insufficient for evaluating algorithmic performance because in addition to measures of performance (MOPs), an understanding of the difficulty of the scenario(s) considered is needed. To fill this gap and provide a more thorough methodology for fusion algorithm performance evaluation, Chong proposed collecting context metrics that characterize problem difficulty in addition to traditional MOPs [5]. Chong's proposed PE approach is shown in Figure 1.

Context metrics are used to describe the complexity of the problem as it pertains to the MOP under consideration. If the $p$ parameters of a problem are given by the set $C = \{C_1, C_2, ..., C_p\}$, a performance metric can be thought of as a function of these parameters, such that $m = f(C)$. Certain values of the problem parameters may result in equivalent values of the performance metric - e.g., $m_a = f(C^1) = f(C^2)$ - and the possible values of $C$ can be partitioned into sets of problem parameter values (e.g. $a = \{C^1, C^2\}$) that are equivalent with respect to the performance metric $f$. The resulting set of equivalent classes define the context metric values of the problem. In other words, the context metrics

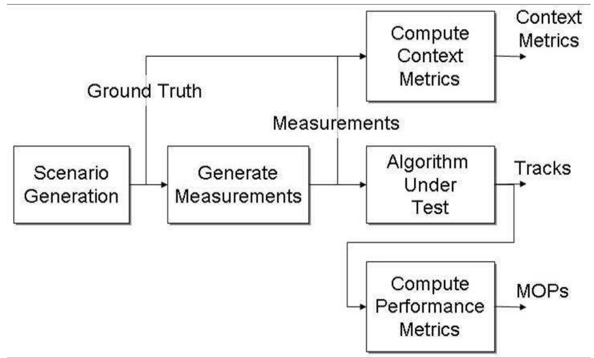


Figure 1: Steps in PE include collecting both traditional MOPs, such as probability of correct association, as well as context metrics that characterize problem difficulty in terms of that MOP (from [5])

consist of the set $\{a, b, ...\}$, where $a = \{C^1, C^2, ...\}$ for MOP value $m_a$, $b = \{C^k, ...\}$ for MOP value $m_b$, etc...

To make this concept more understandable, consider a scenario in which a single target is observed by a single sensor. We are interested in assessing the state estimation performance of a particular tracking algorithm and select the Root Mean Square (RMS) Position Error as a suitable metric. While there are many factors that affect state estimation performance, we restrict consideration to two problem parameters - namely, target mobility ($MOB$) and sensor revisit rate ($RATE$). Intuitively, the tracking problem becomes more difficult as sensor revisit rate is reduced and target mobility is increased. To capture this notion in terms of context metrics, we would assess the RMS Position Error under different values of $MOB$ and $RATE$ to identify equivalent classes of problem parameters. The resulting equivalent classes would form the set of context metrics for the problem and could be used to compare performance of different tracking algorithms.

# 3 Formulation

The theoretic formulation of decentralized fusion given in Equations 1-3 convey the importance of removing duplicate information. However, even in the linear Gaussian case, identifying such information is non trivial because it requires a genealogy of past fusion events and state estimates. This challenge is further compounded by the probabilistic nature of the communication network, which prevents analysis of information flow as in the Information Graph technique [6, 13]. Accounting for the non-determinism of fusion and transmission events requires a stochastic communication model. This model and its application to the fusion rule and context metrics are described in the following subsections.

## 3.1 Communication Model

The non-determinism of communication events is due to many unpredictable changes in network conditions, such as signal attenuation, unintentional interference, jamming or even bandwidth availability. To describe the probabilistic behavior of the underlying network, two important aspects are considered: 1) Message transmission probability; and 2) Message delay probability [4].

The message transmission probability can be thought of as the probability of successful message delivery. For an arbitrary communication topology consisting of nodes $i$ and $j$, the probability that a transmission from node $i$ to node $j$ at some time $k$ is successful is modeled as a Bernoulli process. Assuming that this process is stationary for all $k$, the message transmission probability between $i$ and $j$ is denoted as $\mu^{ij}$.

The message delay probability describes the probability that a transmission from node $i$ will be received by node $j$ given some delay, where delay is described in terms of the number of time steps, $m$. A stationary Poisson process is used to model the probability that a transmission from $i$ to $j$ is received in $m$ time steps

$$\mu^{ij}_{k_j-k_i=m} = \mu^{ij}_{k_j|k_i} = \frac{\lambda^m_{ij}\exp(-\lambda_{ij})}{m!} \tag{10}$$

where $\lambda_{ij}$ is the mean number of time steps of delay between nodes $i$ and $j$. Assuming independence of the transmission probabilities and delay probabilities, the total probability that a message sent from node $i$ at time $k_i$ is received at node $j$ at time $k_j$ is

$$\mu^{ij}_{k_j,k_i} = \mu^{ij}\cdot\mu^{ij}_{k_j|k_i} \tag{11}$$

## 3.2 Stochastic Fusion Rule

The above communication model can be used in conjunction with the theoretic formulation of decentralized fusion in Equations 1-3 to develop a stochastic form of the fusion rule. At each time step, the possible message transmission patterns between the nodes in the network can be enumerated. An example of a few of the possible outcomes for transmissions between two nodes - Node 1 and Node 2 - are shown in Figure 2.

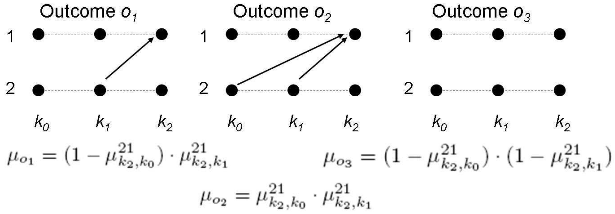


Figure 2: Illustration of some possible communication outcomes for messages received by Node 1 at time $k_2$. The arrows represent successful message transmission events.

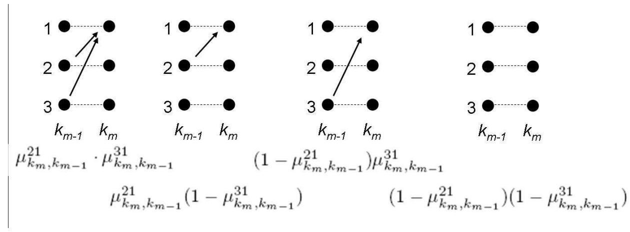


Figure 3: Enumeration of possible communication outcomes in a 1-step history ($L = 1$) for messages received by Node 1.

For a set of $S_o$ messages received by node $i$ at time $k_m$, the probability of any particular outcome $o$ is:

$$\mu_o = \prod_{l\in L}\left[\prod_{i\in S_0, i\neq j}\mu^{ij}_{k_m,k_{m-l}}\cdot \prod_{i\in\neg S_o, i\neq j}\left(1-\mu^{ij}_{k_m,k_{m-l}}\right)\right] \tag{12}$$

where $L$ is the amount of history over which to search. For example, consider the complete 1-step history ($L = 1$) for messages received by Node 1 shown in Figure 3.

For each of the $O$ possible transmission patterns, the expected fusion result of a linear Gaussian model, over all communication events can be given as (see e.g., [4]):

$$\hat{x}_i(k) = \sum_{o\in O}\mu_o P^o_i(k)\left[\sum^n_{j\in S_o} P_j(k|k)^{-1}\hat{x}_j(k|k) - \bar{P}_i(k)\bar{x}_i(k)\right] \tag{13}$$

$$P_i(k) = \sum_{o\in O}\mu_o\left[\left(\sum^n_{j=1}P_j(k|k)^{-1}\right)-\bar{P}_i(k)\right]^{-1} \tag{14}$$

where $P^o_i(k)$ refers to the covariance of the $o^{th}$ outcome at node $i$ at time $k$. This stochastic formulation does not resolve the issue of accounting for redundant information, meaning that a decentralized fusion technique (unless otherwise stated, the CI algorithm is used throughout this paper to account for redundant information). However, this model does account for uncertain communication events and is therefore useful in the prediction of distributed estimation system performance.

## 3.3 Expected Information Rate

Many different factors affect the performance of a data fusion algorithm. For example, reducing revisit rate and increasing target mobility will degrade the state estimation performance of a target tracking algorithm (see Section 2). This degradation occurs because the problem becomes more difficult as the problem parameters - revisit rate and target mobility - are changed. However, it is important to identify a metric that characterizes problem difficulty in a concise and consistent manner because many permutations of the problem variables are possible. Chong's notion of the context metric provides this characterization by partitioning the problem parameter space into sets of parameter values that are equivalent under a particular performance metric [5]. In this paper, since we are interested in evaluating the performance of decentralized estimation algorithms under uncertain communications, we limit our attention to problem parameters that directly affect information flow.

State estimation performance of a fusion algorithm is influenced by both the quality of information it is provided with and the rate at which that information is made available. The quality of a received data set can be thought of (in an information theoretic sense) as being proportional to the reduction in uncertainty realized by updating the current state estimate with the new data set. The rate at which new information is received, or information rate, also affects algorithm performance. The information rate is a function of many factors, including the revisit rate of the sensors, the rate at which data sets are communicated and the quality of the link upon which information is transmitted. The context metric that we propose to characterize the rate and quality of information is the *Expected Information Rate*. A formal definition of this metric follows.

Consider an arbitrary network consisting of $n$ fusion nodes. Each node in the network contains a sensor that makes measurements according to the model in Equation 7. In addition, each node $i$ maintains a local estimate $p_i(x(k))$ of the state $x$, where $p_i(x(k)) \sim \mathcal{N}(\hat{x}_i(k), P_i(k))$. The amount that an observation $z_j(k)$ from node $j$ reduces the uncertainty of the state estimate at node $i$ can be described (as in Equation 6) by the Fisher information of that measurement $I_j(k) = H_j(k)^T \cdot R_j(k)^{-1} \cdot H_j(k)$ . So, if all $n$ information sources communicate their information updates at each time step, under ideal communication the amount of new information at node $i$ at time $k$ is:

$$I_i(k) = \sum_{j \in n} I_j(k)$$

However, due to bandwidth concerns, each node will generally not share information updates at each time step. In addition, the non-ideal nature of the underlying communication network implies that an update message transmitted from node $j$ will be received at node $i$ after some random delay. Using the total transmission event probability given in Equation 11 to account for communication uncertainty, the expected information rate is expressed as:

$$EIR(k) = \left| \sum_{j \in n} \mu^{ji}_{k_i,k_j} \cdot I_{ij}(k) \right| \qquad (15)$$

where $||$ is the matrix determinant. This metric captures both the quality of shared information and the expected rate at which this information is received and therefore characterizes problem difficulty in terms of the communication environment.

# 4 Results

The approach used to evaluate the performance of the DKF , CI and stochastic rules for decentralized data fusion was presented in Figure 1. In particular, a single target tracking problem was considered, where the object to be tracked moves according to the discrete time equation:

$$x(k+1) = Fx(k) + Aw(k+1) \qquad (16)$$

where target state is a 4-dimensional vector containing position and velocity, $x = [x, y, \dot{x}, \dot{y}]$, the process noise is a zero mean white noise sequence, $w \sim \mathcal{N}(0, Q)$ , and

$$F = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A = \begin{bmatrix} \frac{1}{2}T^2 & 0 \\ 0 & \frac{1}{2}T^2 \\ T & 0 \\ 0 & T \end{bmatrix}$$

The object is observed by a network of four sensors with linear measurement models as given in Equation 7. The covariance on measurement error and update transmission rate of the four sensors are left as problem parameters in the performance comparison.

A Monte Carlo simulation was developed to generate ground truth trajectories and measurement sequences for a number of independent trials. The initial state for each trial was generated from $x(0) \sim \mathcal{N}(0, 1)$ and each trial was 25 time steps in duration. For all evaluated tracking algorithms, state initialization was performed using the two-point differencing method presented in [1]. In our analysis, $Q$ and $R$ are constant in time and, unless otherwise stated, $Q$ is assumed to be the 2x2 identity matrix. In addition, we assume that transmitted messages not received within one time step are ignored - i.e. we assume that $L = 1$ in the stochastic formulation given in Equation 12.

We started our analysis by evaluating the performance of the DKF, CI and stochastic formulation under a few specific cases. In particular, we considered a situation where: 1) The four sensor nodes are homogeneous, i.e. $R_j = R$ for all $j$; 2) Each of the sensors communicate their updates at the same mean rate, i.e. $\lambda_{ij} = \lambda$ and 3) All communication links have the same probability of successful transmission, i.e. $\mu^{ij} = \mu$. Under these assumptions, we assessed the state estimation performance of the DKF, CI and stochastic formulation in terms of the Root Mean Square (RMS) position error and the Normalized Estimation Error Squared (NEES) (see e.g., [1] for description). These performance metrics were collected under the specific cases in Table 1.

Results from a subset of these cases are shown in Figures 4-6.

| Parameter | Values |
|---|---|
| $\mu^{ij} = \mu$ | 0.5, 0.6, 0.7, 0.8, 0.9, 1.0 |
| $\lambda_{ij} = \lambda$ | 1, 2, 4, 8 |
| $R_j = R$ | 1.0 |

Table 1: Parameter Values for Initial Analysis

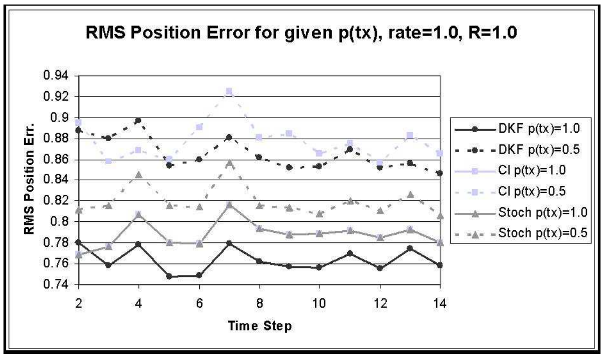


Figure 4: RMS Position Error for DKF, CI and Stochastic formulation with $\mu = 1.0$ & 0.5

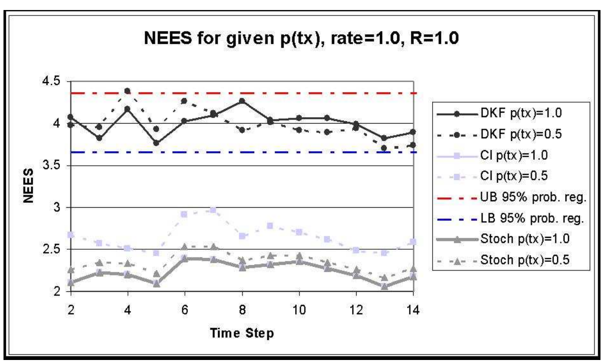


Figure 5: Average NEES for DKF, CI and Stochastic formulation with $\mu = 1.0$ & 0.5

Figure 4 and Figure 5 show the RMS position error and average NEES for two specific message transmission probabilities - $\mu = 1.0$ and $\mu = 0.5$. Not surprisingly, the RMS position error over the 1000 trials increases for all three algorithms as the probability of successfully transmitting updates decreases. As expected, the RMS position error for the CI algorithm and Stochastic formulation is the same when $\mu = 1.0$. Also of note is the fact that both the CI algorithm and Stochastic formulation are pessimistic in that their filter-calculated covariance is greater than the actual mean square error - i.e. $P(k|k) > E\left[\left(x(k) - \hat{x}(k|k) \cdot (x(k) - \hat{x}(k|k))^T\right)\right]$. This is shown in Figure 5 by the fact that the average NEES for both of these algorithms falls outside of the 95% probability region for the state estimation errors over the 1000 trials.

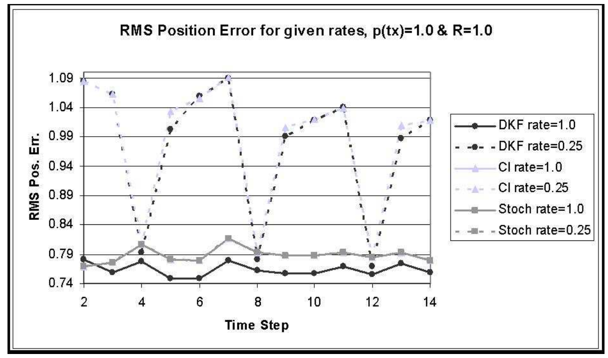


Figure 6: RMS Position Error for DKF, CI and Stochastic formulation with $\lambda = 1, 4$

| Parameters | Values |
|---|---|
| $\mu^{ij}$ | 0.5 - 1.0 |
| $\lambda_{ij}$ | 0.5 - 1.0 |
| $R_j$ | 1.0, 2.0, 4.0, 5.0, 7.0, 10.0 |

Table 2: Problem Parameters for Performance Comparison

Figure 6 shows the RMS position error for a mean rate of transmission of 1.0 and 0.25 (NOTE: a mean rate of 0.25 corresponds to $\lambda = 4$ time steps). The RMS position error for both the DKF and CI exhibit a saw tooth pattern with period of four time steps. This occurs because each fusion node, on average, receives new information to reduce state estimate uncertainty every 4th time step.

At this point it should be clear that evaluating the DKF, CI and stochastic formulation via direct comparison is intractable for more than a handful of cases. In order to evaluate performance on a range of problem parameter values, the Expected Information Rate context metric described in Section 3 is required. In particular, our analysis considered the problem parameter values shown in Table 2. Once again, we assume homogeneity of the four fusion nodes, in terms of the covariance on sensor measurements, mean rate of the message delay distribution and message transmission probability. The results for the performance comparison of the DKF, CI and stochastic formulation using the EIR context metric are shown in Figure 7 and Figure 8. The RMS position error values in these figures were computed as an average across the RMS position errors at each time step. The comparison indicates that for situations in which a linear dynamic target is observed by a set of homogeneous sensors, there is very little difference in the state estimation performance of the DKF and CI fusion techniques and that this is true across a wide variety of non-ideal communication environments. Figure 8 is a magnified view of Figure 7 in range $EIR \in [0, 10]$. It shows that there is indeed a difference in RMS accuracy between the DKF and CI algorithms.

However, such a difference is expected because the CI algorithm determines the convex combination of estimates with unknown cross-correlation, while the DKF combines information updates that are independent.

Figures 7 and 8 also show that the stochastic formulation outperforms both the DKF and CI techniques across most values of the EIR context metric. This performance gain is to be expected, however, because the stochastic formulation incorporates knowledge of the communication network not utilized by the DKF or CI algorithm. In other words, because the stochastic formulation requires a priori knowledge of the parameters of the communication model it can better weight the combination of the received estimates with the current estimate.

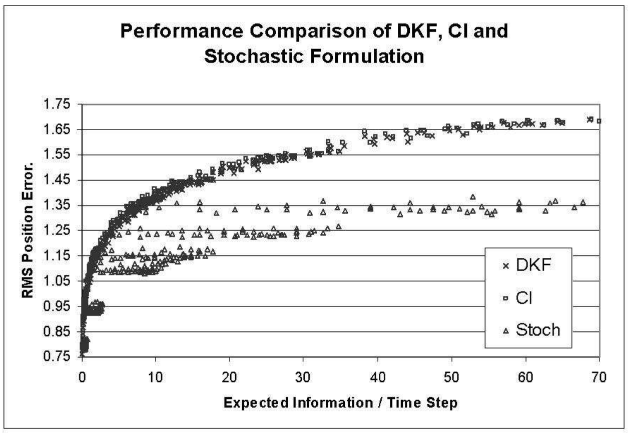


Figure 7: Performance Comparison of DKF, CI and Stochastic Formulation

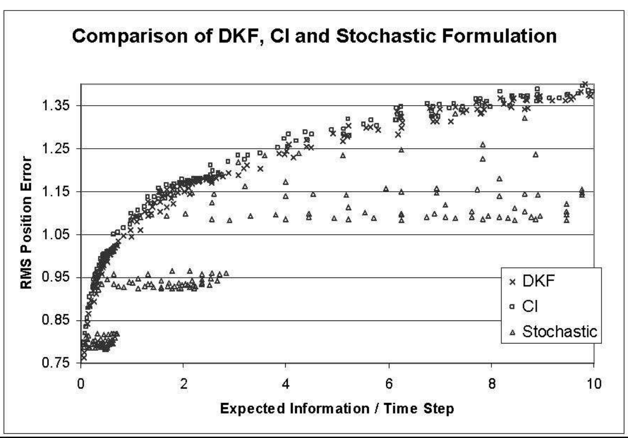


Figure 8: Performance Comparison of DKF, CI and Stochastic formulation on $EIR \in [0, 10]$

# 5 Summary

Recent studies have shown that wireless tactical networks experience significant numbers of transmission disruptions due to unpredictable changes in network conditions [2]. As shown in earlier work by Chang, these disruptions can and do have an effect on the performance of a decentralized estimation system [4]. Since fusion in a distributed architecture is dependent upon the characteristics of the underlying communication network, there is a need for robust methods of assessing the performance of decentralized estimation systems under communicational uncertainty.

This paper presented an approach for evaluating distributed fusion algorithms when information flow is governed by non-deterministic communication. A model was developed to describe the stochastic nature of inter-node communication in terms of the probability of successful transmission and the probability of delayed delivery. This model of non-ideal communication was then used as in [4] to develop a stochastic formulation of the fusion rule for linear Gaussian dynamic systems. And since algorithm performance in a distributed environment is directly influenced by the quality, rate and reliability of shared information, a context metric - the Expected Information Rate - was developed to characterize the difficulty of the fusion problem in terms of these stochastic communication factors.

The EIR context metric was then used to compare the performance of the DKF, CI and stochastic formulation in terms of the RMS position error and NEES. The evaluations were made on a single target tracking problem that assumed homogeneity of the fusion nodes. The results of this comparison showed that the stochastic formulation outperformed both the DKF and CI techniques across a wide range of contexts. However, such a result was expected because the stochastic approach has the advantage of utilizing prior knowledge of the parameters of the uncertain communications model. In addition, the comparison showed that the DKF had smaller RMS position error than the CI algorithm over the range of EIR contexts. However, the improvement in state estimation performance was small, indicating that regardless of the stochastic communication effects, there is little difference between the algorithms in a single target tracking problem with linear process model and homogeneous linear measurement models.

The non-ideal communication model, stochastic fusion rule and EIR context metric presented in this paper provide the beginnings of a basis for robustly assessing the performance of alternative distributed estimation system designs. Clearly there is much room for improvement, as the current approach is limited to single target tracking problems with linear state and measurement models and assumes both homogeneity and stationarity of the parameters of the stochastic communication model. Additional context metrics will also be required to compare algorithmic performance in terms of other metrics, such as bandwidth utilization, node-to-node state estimation consistency and non-kinematic attribute estimation accuracy. Ultimately, the development of such context metrics will be crucial in evaluating the capabilities and performance of the decentralized systems required by the US Military's net-centric vision.

## References


[1] Bar-Shalom, Y. et al. Estimation with Applications to Tracking and Navigation: Theory, Algorithms and Software. John Wiley & Sons., 2001.

[2] Brown, W. et al., "Future Combat Systems - Scalable Mobile Network Demonstration Performance and Validation Results," IEEE Military Communications Conference (MILCOM), 2003, Vol. 2, pp:1286-1291.

[3] Bourgault, F. & Durrant-Whyte H.F. "Communication in General Decentralized Filter and the Coordinated Search Strategy," Proc. of the 6th Intl. Conf. on Information Fusion (FUSION), 2004.

[4] Chang, K.C. & Martin, T.W. "A Data Fusion Formulation for Decentralized Estimation Predictions under Communications Uncertainty." Intl. Conf. on Information Fusion, July 10-13 2006, pp:1-7.

[5] Chong, C., "Problem characterization in tracking/fusion algorithm evaluation," in Proc. of 3rd Intl. Conf. on Information Fusion (FUSION), 2000.

[6] Chong, C. et al., "Distributed Multi-Target Multi-Sensor Tracking." in Multitarget-Multisensor Tracking: Advanced Applications, Chapter 8, ed. Y. Bar-Shalom, Artech House, 1990.

[7] Durrant-Whyte, H.F. "A Beginner's Guide to Decentralised Data Fusion." Technical Report, Australian Centre for Field Robotics - University of Sydney. July 2000.

[8] Farina, A., D. Benvenuti, and B. Ristic, "A comparative study of the Benes filtering problem," IEEE Trans. on Signal Processing, Vol. 82 (2002), number 2, pp:133-147.

[9] Gan, Q. & Harris, C.J., "Comparison of two measurement fusion methods for Kalman-filter-based multisensor data fusion," IEEE Trans. on Aerospace and Electronic Systems, Vol. 37, Jan. 2001, pp:273-279.

[10] Julier, S.J. & Uhlmann, J. K. "General Decentralized Data Fusion with Covariance Intersection (CI)," In The Handbook for Data Fusion, eds. D. A. Hall and J. Llinas, Chapter 12, pp:12.1-12.18, 2001.

[11] Julier, S.J. & Uhlmann, J.K. "Using Covariance Intersection for SLAM," Robotics and Autonomous Systems, v.55 n.1, p.3-20, January, 2007.

[12] Kaplan, L.M., "Node selection for target tracking using bearing measurements from unattended ground sensors," In Proc. of IEEE Aerospace Conf., 2003. Vol. 5, pp:5-2137-2152.

[13] Liggins, M.E. et al. "Distributed Fusion Architectures and Algorithms for Target Tracking," Proc. of the IEEE, vol. 85, No. 1, January 1997, pp:95-107.

[14] Makarenko, A. & Durrant-Whyte H. "Decentralized Data Fusion and Control in Active Sensor Networks" Proc. of the 6th Intl. Conf. on Information Fusion (FUSION), 2004.

[15] Manyika J. & Durrant-Whyte, H.F. Data Fusion and Sensor Management: An Information-Theoretic Approach. Prentice Hall, 1994.

[16] Martin, T.W. & Chang, K.C. "A Distributed Data Fusion Approach for Mobile Ad Hoc Networks," Proc. of the 7th Intl. Conf. on Information Fusion (FUSION), 2005, pp:1062-1069.

[17] Mutambura, A.G.O. Decentralized Estimation and Control for Multisensor Systems. CRC Press, 1998.

[18] Utete, S. W. "Network Management in Decentralised Sensing Systems," PhD Dissertation, Robotics Research Group, Oxford, 1995.


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