# Data Compression Trade-Offs for Multiple Inferences in Sensor Networks

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*Abstract* – **Sensor networks collect data upon which multiple inferences (estimations and decisions) will be based. The optimizing compression with respect to one inference may lead to suboptimal compression with respect to the others. Furthermore, not all of these inferences have the same level of importance to the end users of the network's data. To address this, a framework is developed that uses specific distortion measures to assess the impact of compression on the multiple inferences: Fisher information is used to assess the impact on estimation accuracy while Chernoff and Kullback-Liebler distances are used to assess the impact on decision accuracy. This framework is applied to two examples: (i) multiple estimations and (ii) single estimation and a binary decision. Simulation results are provided that show that there is indeed a trade-off between these multiple inferences and that with proper a priori information the proposed data compression framework can enact trade-offs between them.**

***Keywords*: Data Compression, Estimation/Detection, Sensor Networks**

## I. INTRODUCTION

Because the primary task of sensor networks is to make statistical inferences based on the data collected throughout the network, it is important to design compression methods that cause minimal degradation of the accuracy of these inferences. Data compression for distributed multi-sensor systems has been previously considered to some degree but they have not considered the issue that sensor networks may have multiple inference tasks to accomplish [5][6]. Notably, multiple inferences will likely have conflicting compression requirements and finding the right way to balance these conflicts is crucial. Thus, compression for sensor networks must consider the case of multiple inferences. This work also has importance in sensor applications other than sensor networks – an example is the use of RF sensors on aircraft for the purpose of detecting and then locating enemy RF emitters [2].

One of the keys to addressing compression for multiple inference tasks is to use distortion measures that accurately reflect the ultimate performance on the tasks. To design compression algorithms suitable for use under conflicting inference goals it is essential to have appropriate, useable metrics that measure the impact of reducing the rate on the inference performance. For estimation tasks, the impact of compression should be assessed by its impact on the variance of the estimation error (at least in the unbiased estimate case). For decision tasks (e.g., detection, recognition, identification, etc.) the impact of compression should be assessed by its impact on the probability of an error in the decision. In addition, there may be the need for an end-user to view image data collected in a sensor network – the distortion measure for high-fidelity reconstruction is often a version of the mean-square error (MSE) measure, modified to incorporate some appropriate perceptual criteria. We have proposed using the Fisher information to derive estimation-appropriate distortion measures, while others [3] have proposed using the Chernoff and Kullback-Liebler distances to derive decision-appropriate distortion measures. In this paper we show how to develop compression algorithms that trade-off between Fisher Information, Chernoff and Kullback-Liebler distances, and MSE in a setting where there are various conflicting goals in a multiple inference setting.

This paper is organized as follows: Section II discusses the reason for using Fisher Information, Chernoff and Kullback-Liebler distances, and MSE as the theoretical framework to derive the distortion measures for multiple inferences. Section III provides details on how these criteria are used to derive specific distortion criteria that can be use to optimize a specified data compression framework. Two specific cases are considered and numerical simulations are given. The conclusions and future work are presented in Section IV.

## II. DISTORTION MEASURES FOR MULTIPLE INFERENCES

This section will discuss the motivation for using Fisher Information, Chernoff and Kullback-Liebler distances, and MSE as the general theoretical framework to derive the distortion measures for multiple inferences. Let noisy measurement $\mathbf{x}$ be the set of data collected at one of the sensor node to support multiple inferences and reconstruction: estimation of the parameters $\theta_i$, $i = 1, 2, \ldots, p$, decision between hypotheses $H_0$ and $H_1$, and reconstruction of the data $\mathbf{x}$. In order to save energy and reduce transmission latency, the noisy measurement $\mathbf{x}$ will be lossy compressed before they are sent to other sensor nodes. The vector $\mathbf{x}$ can be represented as

$$\mathbf{x} = \mathbf{s}_\theta + \mathbf{n}\,, \tag{1}$$

where vector $\mathbf{s}$ stands for the unknown signal, its presence to be determined, $\theta$ is the unknown parameter vector to be estimated, and $\mathbf{n}$ is the noise, independent from the signal.

Let $\hat{\mathbf{x}}$ denote the $\mathbf{x}$ after passing through lossy compression codec. Then, the inferences' accuracy based on $\hat{\mathbf{x}}$ should be inferior to those based on $\mathbf{x}$ because some information relative to the inferences' accuracy is lost when $\mathbf{x}$ is processed by the lossy compression. Our goals here are to derive the distortion measures (besides MSE) to reflect the structure of data, and decrease the date rate significantly while minimizing the degradation relative to inference tasks.

**A. Fisher Information Matrix for Estimation:**

To estimate the unknown parameters $\theta$, Fisher information under uncompressed $\mathbf{x}$ is

$$[\mathrm{I}(\boldsymbol{\theta})]_{ij} = E\left[\frac{\partial \ln p(\mathbf{x};\boldsymbol{\theta})}{\partial \theta_i}\frac{\partial \ln p(\mathbf{x};\boldsymbol{\theta})}{\partial \theta_j}\right], \tag{2}$$

where $p(\mathbf{x};\ \theta)$ is the probability density function of $\mathbf{x}$ under the unknown parameter vector $\theta$. As is well-known, Fisher information is related to the Cramer-Rao Bound (CRB) in that the diagonal elements of its inverse provide lower bounds on the achievable estimation error variance, that is

$$\sigma^2(\hat{\theta}_i) \geq [\mathrm{I}^{-1}(\boldsymbol{\theta})]_{ii},\, i = 1,2,\ldots,p\ . \tag{3}$$

The Fisher information matrix $\mathbf{I}$ measures how much information is available from the observation $\mathbf{x}$ relevant to estimation of parameters $\theta_i$, $i$ = 1, 2, …, $p$., when the lossy compressed $\hat{\mathbf{x}}$ is used to do the estimation instead of $\mathbf{x}$, the Fisher information matrix becomes

$$[\hat{\mathrm{I}}(\boldsymbol{\theta})]_{ij} = E\left[\frac{\partial \ln p(\hat{\mathbf{x}};\boldsymbol{\theta})}{\partial \theta_i}\frac{\partial \ln p(\hat{\mathbf{x}};\boldsymbol{\theta})}{\partial \theta_j}\right]$$

and
$$[\hat{\mathrm{I}}(\boldsymbol{\theta})]_{ij} \leq [\mathrm{I}(\boldsymbol{\theta})]_{ij} \tag{4}$$

because lossy compression is equivalent to adding quantization noise to the data which causes the decrease of the Fisher information. The goals of compression design should be to minimize the decrease in the Fisher information under some set of constraints (e.g., on rate and energy in the more general R-E-A framework we have proposed in [1]). In other words, if $C(\cdot)$ denotes a compress algorithm, we have $\hat{\mathbf{x}} = C(\mathbf{x})$. The design of $C(\cdot)$ should maximize Fisher information that is given as follows:

$$\max_C E\left[\frac{\partial \ln p(C(\mathbf{x});\boldsymbol{\theta})}{\partial \theta_i}\frac{\partial \ln p(C(\mathbf{x});\boldsymbol{\theta})}{\partial \theta_j}\right] \tag{5}$$

Maximizing Fisher information minimizes the Cramer-Rao lower bound according to (3). The form (or structure) of the Fisher information for specific scenarios provides insight into how to allocate rate resources to satisfy trades among the accuracy of multiple estimations.

**B. Chernoff & Kullback-Liebler Distances for Decisions:**

Under the signal model as (1), detection of the signals $\mathbf{s}_\theta$ in the $\mathbf{x}$ can be formulated as a binary statistical hypothesis test,

$$\begin{cases} H_0: & \mathbf{x} = \mathbf{n} \\ H_1: & \mathbf{x} = \mathbf{s}_\theta + \mathbf{n} \end{cases} \tag{6}$$

Usually, the detection algorithm takes the form of a LRT,

$$L(\mathbf{x}) = \frac{p(\mathbf{x};H_1)}{p(\mathbf{x};H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \tau\ , \tag{7}$$

where $p(\mathbf{x};\ H_0)$ and $p(\mathbf{x};\ H_1)$ are PDF under hypotheses $H_0$ and $H_1$ respectively, $\tau$ is an appropriate threshold which is chosen to minimize the probability of error $P_e$ or the probability of miss $P_{miss}$ for a given value of false alarm $P_f$. Since the ability to distinguish between two hypotheses depends on the respective data distributions and a larger distance leads to better decision performance, measures of distance between two distributions are a natural choice for the performance metrics. Therefore, instead of using intractable $P_e$ or $P_{miss}$ as the distortion measure, it is suggested in [3] that optimizing compression algorithm for detection could be based on Chernoff distance or Kullback-Leibler because they possess three attractive properties which are suitable for the compression algorithms: (i) they are invariant under application of invertible maps to the data; (2) they decrease under application of many-to-one maps such as quantization (causes of loss of information); (iii) they are very closely related to $P_e$ or $P_{miss}$. Letting $d(.)$ denote these two distances, we have the relationship between the distances under the $\mathbf{x}$ and its lossy compression processed version $\hat{\mathbf{x}}$ as

$$d(p(\hat{\mathbf{x}};H_0),p(\hat{\mathbf{x}};H_1)) \leq d(p(\mathbf{x};H_0),p(\mathbf{x};H_1)) \tag{8}$$

The explicit forms of Chernoff distance and Kullback-Liebler distance are

$$D_s(p(\mathbf{x};H_0),p(\mathbf{x};H_1)) = -\ln \int p(\mathbf{x};H_0)\left(\frac{p(\mathbf{x};H_1)}{p(\mathbf{x};H_0)}\right)^s d\mathbf{x}, \quad 0 < s < 1 \tag{9}$$

and

$$D(p(\mathbf{x};H_0)\,\|\,p(\mathbf{x};H_1)) = \int p(\mathbf{x};H_0)\ln\left(\frac{p(\mathbf{x};H_0)}{p(\mathbf{x};H_1)}\right)d\mathbf{x}\ , \tag{10}$$

respectively. Chernoff distance gives an upper bound on both $P_e$ or $P_{miss}$:

$$P_f = P_0[L(\mathbf{x}) > \tau] \leq \tau^{-s} e^{-D_s(p(\mathbf{x};H_0),p(\mathbf{x};H_1))} \tag{11}$$

$$P_{miss} = P_1[L(\mathbf{x}) < \tau] \leq \tau^{1-s} e^{-D_s(p(\mathbf{x};H_0),p(\mathbf{x};H_1))} \tag{12}$$

where $\tau$ is the threshold in the LRT in (7). Under some conditions, the relationship exists between the asymptotic probability of a miss and the Kullback-Leibler distance for a fixed small probability of false alarm as

$$P_{miss} \sim e^{-D(p(\mathbf{x};H_0)\|p(\mathbf{x};H_1))} \tag{13}$$

Multiple hypotheses can be handled in a similar way. Therefore, the goal of compression design should be to minimize the decrease in the distance measure under some set of constraints (e.g., on rate and energy in the more general R-E-A framework [1]). Similar to the Fisher information, the design of $C(\cdot)$ should maximize Chernoff distance or Kullback-Leibler distance which are given as follows:

$$\max_{C}\{D_s(p(C(\mathbf{x})\,;H_0),p(C(\mathbf{x})\,;H_1))\}\ , \tag{14}$$

or

$$\max_{C}\{D(p(C(\mathbf{x})\,;H_0)\parallel p(C(\mathbf{x})\,;H_1))\}\ . \tag{15}$$

**C. MSE for Reconstruction:**

As is well known, MSE is to minimize

$$\|\mathbf{x}-\hat{\mathbf{x}}\|^2 \tag{16}$$

where $\hat{\mathbf{x}}$ is the reconstructed data after compression and transmission and ||.|| denotes the Euclidean norm. The goal of compression design should be to minimize the increase in the MSE under some set of constraints (e.g., on rate and energy in the more general R-E-A framework [1]).

## III. TRADE-OFFS IN DATA COMPRESSION FOR MULTIPLE INFERENCES

The framework we consider here is not intended to be the most general scenario, but rather merely a vehicle by which we can explore the notion of designing compression methods that address multiple inferences. Thus, we consider one sensor sending its collected data to a central sensor where multiple inferences are made and reconstruction is performed. (Obviously this scenario will need to be broadened before application to sensor networks can be made; nonetheless, the scenario considered still provides applicable insight into the sensor network arena.) The set-up is shown in Figure 1, where the collected data samples **x** are compressed using transform-based coding with transform **T** and quantizers $Q_i$; at the processing sensor the compressed data is decoded (not explicitly shown) and inverted using $\mathbf{T}^{-1}$ to recover the data that is used for deciding between $M$ hypotheses, estimation of a vector of parameters, and visualization/reconstruction of the data.

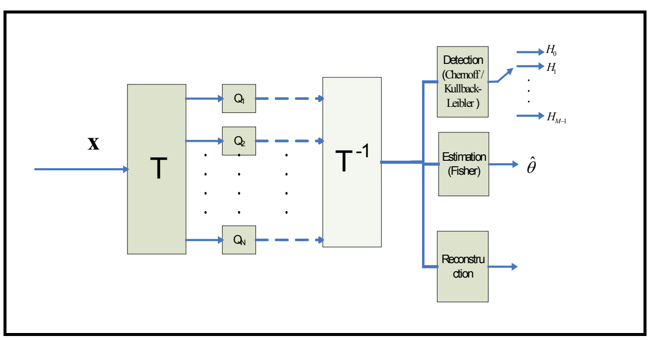


**Figure 1: Scenario considered for study of data compression for multiple inference tasks**

We have studied several specific problems using this framework, two of which will be discussed in the paper:

1. Estimation of multiple parameters without detection or reconstruction.
2. Estimation of a single parameter and a binary detection without reconstruction.

**A. Multiple Parameters Without Detection or Reconstruction**

The scenario considered in this case is estimating time-difference-of-arrival (TDOA) and frequency-difference-of-arrival (FDOA) between a pair of sensors to estimate the X-Y position of an RF emitter.

The noisy signal to be compressed at one of the sensor nodes in the continuous form is given by

$$x(t)=s(t)+n(t) \tag{17}$$

If we assume the other sensor has much higher SNR (Signal to Noise Ratio) than the one to be compressed and $n(t)$ is independent additive white Gaussian noise (AWGN), the Cramer-Rao Lower Bounds (CRLB) for TDOA and FDOA are

$$\sigma^2_{TDOA}\geq\left(\frac{1}{2\pi B_{rms}\sqrt{2SNR}}\right)^2=\frac{1}{8\pi^2\dfrac{\int f^2|S(f)|^2\,df}{P_n}} \tag{18}$$

$$\sigma^2_{FDOA}\geq\left(\frac{1}{2\pi D_{rms}\sqrt{2SNR}}\right)^2=\frac{1}{8\pi^2\dfrac{\int t^2|s(t)|^2\,dt}{P_n}} \tag{19}$$

where $P_n$ is the noise power, $S(f)$ is the Fourier transform of $s(t)$, $B_{rms}$ and $D_{rms}$ are the so-called RMS bandwidth and RMS duration, respectively [2]. Thus, the TDOA and FDOA Fisher information carried by $x(t)$ are

$$FI(TDOA)=8\pi^2\frac{\int f^2|S(f)|^2\,df}{P_n} \tag{20}$$

and

$$FI(FDOA)=8\pi^2\frac{\int t^2|s(t)|^2\,dt}{P_n} \tag{21}$$

respectively. If the signal $s(t)$ is confined to an appropriate interior range within (-T/2, T/2), we can see that for TDOA estimation, the high frequency components are more important than the low frequency components, whereas for FDOA estimation, the early/late components are more important than the middle components. Both $FI(TDOA)$ and $FI(FDOA)$ properly capture the impact of compression on TDOA accuracy and FDOA accuracy, so an operational R-D method can be developed based on maximizing these two Fisher information.

The design of our compression method can be expressed as transform coding with maximizing $FI(TDOA)$ and $FI(FDOA)$ simultaneously. Given some orthogonal signal decomposition (e.g., wavelet transform, DFT, etc.)

$$s(k)=\sum_{i=1}^{N}c_i\psi_i(k) \tag{22}$$

of the signal to be compressed, we wish to select a subset $\widetilde{\Omega}$ of coefficient indices and an allocation of bits $B = \{b_i \mid i \in \widetilde{\Omega}\}$ to those selected coefficients such that the signal given by

$$\widetilde{s}(k) = \sum_{i \in \Omega} \widetilde{c}_i \psi_i(k) \qquad (23)$$

where $\{\widetilde{c}_i \mid i \in \widetilde{\Omega}\}$ are the quantized version of the selected coefficients, maximizing *FI*(*TDOA*) and *FI*(*FDOA*) while meeting the rate constraint given by

$$\sum_{i \in \Omega} b_i \le R, \quad b_i \text{ is nonnegative integer.} \qquad (24)$$

In our simulation, orthonormal wavelet transform is chosen to perform the transform coding because it gives us frequency resolution as well as time resolution, which make it possible to maximize *FI*(*TDOA*) and *FI*(*FDOA*) simultaneously. Wavelet transformed coefficients $c_i$ are divided into $M$ cells according to frequency resolution and time resolution, if we assume the quantization noise is additive noise to the signal, modifying (20) and (21), the optimal solution to the quantization of signal for TDOA and FDOA estimation is then to maximize the following two object functions under some rate constraint,

$$\sum_j^M \left( \frac{\sum_{j\,cell} f_i^2 |c_i|^2}{W_j \sigma^2 + \sum_{j\,cell} |c_i - \widetilde{c}_i|^2} \right) \qquad (25)$$

$$\sum_j^M \left( \frac{\sum_{j\,cell} t_i^2 |c_i|^2}{W_j \sigma^2 + \sum_{j\,cell} |c_i - \widetilde{c}_i|^2} \right), \qquad (26)$$

where $W_j$ is the number of coefficients in the $j^{th}$ cell and $\sigma^2$ is the variance of the noise.

If we weight (25) and (26) according to their relative importance and sum them we get a single objective function to be optimized:

$$D(\alpha) = \alpha \times \sum_j^M \left( \frac{\sum_{j\,cell} f_i^2 |c_i|^2}{W_j \sigma^2 + \sum_{j\,cell} |c_i - \widetilde{c}_i|^2} \right) + (1-\alpha) \times \sum_j^M \left( \frac{\sum_{j\,cell} t_i^2 |c_i|^2}{W_j \sigma^2 + \sum_{j\,cell} |c_i - \widetilde{c}_i|^2} \right) = \sum_j^M \left( \frac{\alpha \sum_{j\,cell} f_i^2 |c_i|^2 + (1-\alpha) \sum_{j\,cell} t_i^2 |c_i|^2}{W_j \sigma^2 + \sum_{j\,cell} |c_i - \widetilde{c}_i|^2} \right) \qquad (27)$$

where α is a parameter used to control the relative importance of TDOA accuracy and FDOA accuracy. This result now gives us the ability to compress in a way that allows a trade-off between the impacts on TDOA vs. FDOA. So in cases where one is less important we can compress to ensure the other has a small impact due to the compression. To demonstrate this we explore the range of solutions we get by compressing optimally with respect to *D*(α) as we let α vary over the interval [0,1]. The simulation results are shown in Figure 2, where results for two different SNR scenarios are shown. FM radar signal was generated and a time-delayed and doppler-shifted version was also created. White Gaussian noise was added to each to yield desired $SNR_1$ and $SNR_2$ on the two signals. To provide a reference case, these two noisy signals were cross-correlated without compression to estimate the TDOA and FDOA value of delay and doppler shift between the two signals. The wavelet coefficients are quantized at average rate 1.5 bits per sample, and no entropy coding is used. The two axes show the TDOA and FDOA estimation error standard deviation relative to that achieved with no compression. For each SNR scenario a square symbol (□) shows the single operating point achievable when optimizing the wavelet-based compression scheme relative to the standard MSE distortion criteria. The star symbols (*) show the points achieved in the simulation using our proposed Fisher-information-based distortion measure as the value of α is varied; the dashed line is a visually-fit curve to show the general trend as α is varied. In Figure 2, as α increases, the TDOA accuracy is increased while FDOA accuracy is decreased. Given certain a priori knowledge (likely coming from a user's query and request to the sensor network) it would be possible to know which value of α should be used. This simple example illustrates that the proposed framework can allow trading between simultaneous estimation tasks; in a more realistic scenario we can imagine multiple users exploiting the same set of network-collected data, which gets compressed based on a "central-command-determined" priority among these users' importance.

According to [7][8][9], besides Fisher information, the accuracy of location estimation also highly depends on geometry of target and the sensors. In some geometries of location scenario, either FDOA or TDOA accuracy contributes nothing to the overall location accuracy, however in other scenario, TDOA and FDOA are both important. Therefore, the relative importance of TDOA and FDOA can be determined by the geometry of target and sensors. This leads to an idea that we should first send a small amount of data – enough to roughly determine the geometry – and then choose the best suitable operating compression point in Figure 2.

**B. Single Parameter With Detection**

The scenario considered in this case is detecting the presence of a signal and then estimating TDOA between a pair of sensors in the presence of AWGN. For the AWGN model, the Chernoff distance and Kullback-Liebler distance are[3]

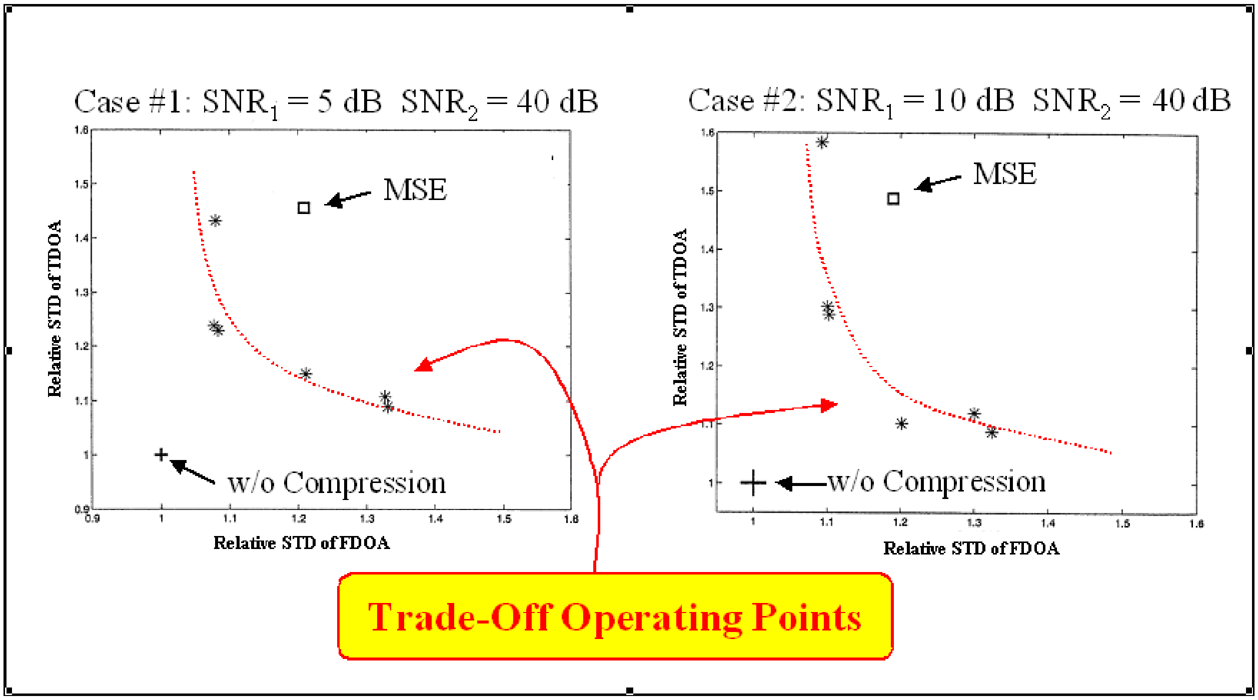


**Figure 2: Results showing trade-off in the two-parameter case.**

$$D_s(p(\mathbf{x};H_0),p(\mathbf{x};H_1)) = \frac{s(1-s)}{2}\frac{\sum|s(k)|^2}{N\sigma^2} = \frac{s(1-s)}{2}SNR \tag{28}$$

$$D(p(\mathbf{x};H_0)\parallel p(\mathbf{x};H_1)) = \frac{\sum|s(k)|^2}{2N\sigma^2} = \frac{1}{2}SNR, \tag{29}$$

which are both proportional to SNR. If the quantization noise is assumed to be AWGN, and still use the orthonormal wavelet transform as we did in the above example, we have the following objective functions to maximize

$$D_s(p(\hat{\mathbf{x}};H_0),p(\hat{\mathbf{x}};H_1)) = \frac{s(1-s)}{2}\sum_j^M\left(\frac{\sum_{j\,cell}|c_i|^2}{W_j\sigma^2+\sum_{j\,cell}|c_i-\tilde{c}_i|^2}\right) \tag{30}$$

$$D(p(\hat{\mathbf{x}};H_0)\parallel p(\hat{\mathbf{x}};H_1)) = \frac{1}{2}\sum_j^M\left(\frac{\sum_{j\,cell}|c_i|^2}{W_j\sigma^2+\sum_{j\,cell}|c_i-\tilde{c}_i|^2}\right), \tag{31}$$

We can see from (30) and (31), the distortion function derived from Chernoff distance and Kullback-Liebler distance in the AWGN mode is equivalent to MSE. Using the framework above we can derive the following Fisher-information-Kullback-Liebler-based distortion measure that should be maximized by the compression method under a rate constraint in a similar way.

$$\begin{aligned} D(\alpha) &= \alpha\times\sum_j^M\left(\frac{\sum_{j\,cell}f_i^2|c_i|^2}{W_j\sigma^2+\sum_{j\,cell}|c_i-\tilde{c}_i|^2}\right) + \\ &\quad (1-\alpha)\times\sum_j^M\left(\frac{\sum_{j\,cell}|c_i|^2}{W_j\sigma^2+\sum_{j\,cell}|c_i-\tilde{c}_i|^2}\right) \\ &= \sum_j^M\left(\frac{\alpha\sum_{j\,cell}f_i^2|c_i|^2+(1-\alpha)\sum_{j\,cell}|c_i|^2}{W_j\sigma^2+\sum_{j\,cell}|c_i-\tilde{c}_i|^2}\right) \end{aligned} \tag{32}$$

where α is a parameter used to control the relative importance of TDOA accuracy and binary decision accuracy. Similarly, (32) gives us the ability to compress in a way that allows us to trade-off between the impact on TDOA vs. Binary Decision. As above, to demonstrate this we explore the range of solutions we get by compressing optimally with respect to $D(\alpha)$ as we let αvary over the interval [0,1], the same FM radar signals used in the above example is used here, the quantization bit rate is still 1.5 bits per sample and probability of false alarm is 0.1. The simulation result is shown in Figure 3. The vertical axis shows the impact of compression on TDOA accuracy while the horizontal axis shows the impact on the probability of error. The star symbols (*) show points achieved in the simulation using our proposed Fisher-Kullback-Liebler-based distortion measure as the value of α is varied; the dotted line is a visually-fit curve to show the general trend as α is varied. We see that by varying the value of α we can accomplish a trade-off between the detection performance and estimation performance. As α increases, the TDOA accuracy is increased while probability of error is increased. As in the first example, a priori knowledge from user queries can be used to adjust the compression algorithm for optimal operation.

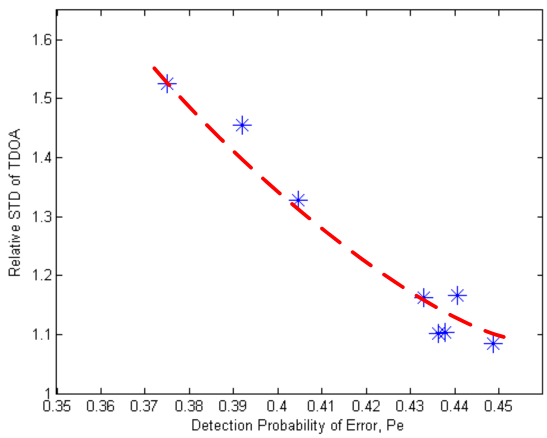


**Figure 2: Results showing trade-off in the one-parameter & binary detection case. ($SNR_1$ = 10 dB, $SNR_2$=40 dB)**

## IV. CONCLUSION

The major novel contributions of the paper are the following:

- Compression methods within sensor networks must take into account the fact that the data collected in a sensor network is likely to be used for multiple inference tasks – those multiple inferences may originate from a single user or from multiple users. Some inferences may have higher accuracy needs than others.
- To address this issue compression algorithms should be based on combinations of distortion measures that are chosen specifically for the inferences to be made. The Fisher information is the natural choice for estimations while the Chernoff and Kullback-Liebler distances are natural choices for decisions.
- A framework is developed under which these ideas can be addressed and explored. The framework is applied to examples that show that such trade-offs do indeed exist and can be addressed within this framework.
- Further work will focus on showing how these ideas can be used in realistic sensor network scenarios.

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