Quantization for Maximin ARE in Distributed Estimation

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Abstract— We consider the design of optimal quantizers for the distributed estimation of a deterministic parameter. In particular, we design deterministic scalar quantizers to maximize the minimum Asymptotic Relative Efficiency (ARE) between quantized and unquantized ML estimators. We first design identical quantizers using the class of Score-Function Quantizers (SFQ). We show that the structure of SFQs generally depend on the parameter value, but can be expressed as thresholds on the sufficient statistic for a large class of distributions. We provide a convergent iterative algorithm to obtain the best SFQ that maximizes the minimum ARE for distributions of that class. We compare the performance of the optimal SFQ with a general quantizer designed without making any restrictions on the structure. This general quantizer is hard to implement due to lack of structure, but is optimal if the iterative design algorithm does not encounter local minima. Through numerical simulations, we illustrate that the two quantizers designed are identical. In other words, the optimal quantizer structure is that of an SFQ. For a distributed estimation setup, designing identical quantizers is shown to be suboptimal. We therefore, propose a joint multiple quantizer design algorithm based on a Person-by-Person Optimization technique employing the SFQ structure. Using numerical examples, we illustrate the gain in performance due to designing non-identical quantizers.

Index Terms— Distributed Estimation, Quantization, Asymptotic Relative Efficiency, Score-Function quantizer.

I. INTRODUCTION

A. Motivation

Distributed statistical inference is a classical problem in signal processing where a fusion center receives data from several distributed nodes and infers the parameter of the underlying process. One of the key differences of this problem from classical point estimation is that the fusion center cannot have complete access to every observed measurement. The data transmission from nodes to fusion center is restricted due to energy and bandwidth constraints. It is therefore imperative that the observations are quantized before transmission. This spawns two fundamental problems: design of quantizer at the node, and the estimator at the fusion center. The key metrics that need to be optimized are the quantizer size (number of quantization bits) and the estimation error at the fusion center.

The basic distributed estimation setup is shown in Fig. 1. The distribution of the observations $X_1, \cdots, X_n$ depends on an underlying parameter $\theta$. Node $i$ implements quantizer $\gamma_i$ on the observation $X_i$ and transmits the quantized value $\gamma_i(X_i)$ to the fusion center which then estimates the value of $\theta$. When the quantized values are perfectly available at the fusion center, the estimation error of $\hat{\theta}$ is only dependent on the quantizers $\{\gamma_i\}$ and the estimator $\hat{\theta}$. In this work, we are interested in the optimal design of quantizers that minimize estimation error when $\theta$ is a Maximum-Likelihood estimator.

The crucial hurdle in designing quantizers for parameter estimation is the unavailability of information about the parameter. One class of approaches to this problem has been from an information-theoretic perspective, initially proposed by Zhang and Berger [?]. In the information-theoretic setup, each node is assumed to observe a long sequence of measurements which is then compressed before transmission to the fusion center, and the key design metric was the asymptotic compression rate. For that problem, Han and Amari [?] obtained the best known achievable rate region and also provided a Maximum-Likelihood estimator for their encoders. The lack of knowledge about the parameter was circumvented in their solution by using the type of the long sequence as an alternative indexing of distributions.

In networks where nodes observe a few measurements, the type provides little or no information about the underlying parameter. In such situations, if the parameter is random, the known statistics of the parameter can be utilized to design quantizers that minimize the average estimation error. Optimal scalar quantizers for random parameter estimation have been designed for different types of estimators. Lam and Reibman [?] provided an iterative algorithm to obtain a quantizer that maximizes the Bayesian Fisher Information of a random parameter. For some special classes of linear estimators, Gubner [?] and Zhang and
Li [?] obtained the optimal quantizer that minimizes MSE at the fusion center.

For a deterministic parameter, the estimation performance varies with the parameter, and it is impossible to design a single scalar quantizer that achieves the optimum performance for all values of the parameter. It is therefore necessary to formulate an appropriate metric that represents the overall estimation performance. In some recent works, quantizers for deterministic parameter estimation have been designed under some restrictions on quantizer structure and underlying distributions. The idea of the maximin metric based on Fisher Information was considered by Fowler and Chen [?]. They proposed a transform coding based quantizer to minimize the maximum difference between Fisher Information of quantized and unquantized observations. When the observation is a parameter in additive noise, Ribiero and Giannakis [?] characterized the best possible Fisher Information. They also showed that when the range of the parameter is small, the performance of the optimal threshold quantizer is within a constant of the unquantized estimator. For non i.i.d. additive noise observations, Luo [?] optimized the allocation of total bits among binary quantizers to maximize estimation performance when the noise is bounded. In an earlier work [?], we had proposed the idea of Score-Function Quantization to maximize the Fisher Information for a given value of the parameter thereby providing an upper bound for quantizer performance.

In this work, we consider the design of fixed size scalar quantizers for networks, where the number of nodes is large, but each node measures a few observations. The observations are identically distributed according to some deterministic parameter. The fusion center estimates the underlying parameter using a Maximum-Likelihood (ML) estimator. For a fixed distribution of quantized observations, it is known that the ML estimator is asymptotically efficient. Furthermore, the asymptotic performance can be analytically characterized by the Fisher Information of the distribution of quantized values.

The metric we propose is a measure of relative performance between quantized and unquantized estimators known as the Asymptotic Relative Efficiency (ARE). The ARE represents the ratio of sample sizes required by the quantized and unquantized estimators to achieve the same asymptotic performance and it can be expressed as a ratio of Fisher Information between quantized and unquantized distributions. Due to its dependence on the value of $\theta$, the ARE cannot be maximized universally for all values of $\theta$. We, therefore, consider maximizing the minimum ARE across the parameter set as a criterion for quantizer design. The minimum ARE over $\theta$ corresponds to the least percentage of additional samples required by the quantizer to perform asymptotically as well as the unquantized estimator. Further, it can be shown that for a certain class of distributions, the maximin ARE quantizer requires the least sample size amongst all deterministic quantizers that achieve the same asymptotic error variance.

**B. Main Contributions**

In this work, we design quantizers that maximize the minimum ARE over the parameter set between quantized and unquantized observations. Assuming identical quantizers for the nodes, we first consider the quantizer structure that belongs to the class of Score-Function Quantizers (SFQ). Although SFQs are dependent on parameter $\theta$, we show that for a certain class of distributions that satisfy a monotonicity property, the SFQs are expressible as a set of thresholds on the sufficient statistic. For these distributions, we provide a convergent algorithm to obtain the best SFQ that maximizes the minimum ARE.

In order to compare the performance loss due to the restriction on structure, we propose an alternative algorithm to design the maximin ARE quantizer with no assumptions on quantizer structure or nature of distribution. This iterative algorithm, although optimal in the absence of local minima, does not provide any structural representation for the quantizer and is computationally intensive. However, through numerical simulations we illustrate that, for distributions that satisfy the monotonicity property, the two algorithms result in identical quantizers. In other words, the optimal quantizer structure is that of an SFQ.

Assuming identical quantizers for the nodes is restrictive and in general, suboptimal for distributed estimation. Hence, we utilize the optimality of SFQs and propose a Person-by-Person Optimization (PBPO) technique to design multiple non-identical quantizers that maximize the metric. Through numerical examples, we demonstrate a significant improvement in performance due to designing non-identical quantizers especially at low noise levels.

The basic organization of this paper is as follows. In Section II, we describe the maximin ARE criterion for quantizer design and the relations to sample size of estimators. In Section III, we discuss the optimality of Score-Function Quantizers and also present an algorithm to obtain the best SFQ for the maximin criterion assuming identical quantizers. In Section IV, we discuss the alternate approach to maximin quantizer design that does not make assumptions on structure. The comparison of the two quantizers and the optimality through numerical simulations are given in Section V. The design of multiple non-identical quantizers for maximin ARE and supplementary numerical results are presented in Section ???. Some concluding remarks and possible future extensions are mentioned in Section ???.

**II. System Model**

Consider the distributed estimation setup as shown in Figure 1. Let $X$ be some set endowed with a $\sigma$-field $G$. The observations $X_i \in X$ are independent and identically distributed. The probability measure of $X_i$ belongs to a family of probability measures $\{P_\theta; \theta \in \Theta\}$ on $(X,G)$ indexed by parameter $\theta$ lying in a set $\Theta$. Throughout this paper, we assume that $\theta$ is real-valued and $\Theta \subset \mathbb{R}$ is a bounded set. Node $i$ implements deterministic quantizer $\gamma_i$ and transmits the quantized version $\gamma_i(X_i)$ to the fusion center. For the remainder of this section and two subse-
quent sections, we shall focus on designing identical quantizers for the nodes, in other words, $\gamma_i = \gamma, \forall i$.

A deterministic quantizer can be formally defined as a $\mathcal{G}$-measurable mapping $\gamma : \mathcal{X} \mapsto \{1, \cdots, D\}$, where $D$, a fixed constant integer, is the size of the quantizer. In other words, a deterministic quantizer uniquely maps each observation to a positive integer $k \leq D$, which we refer to as the partition index of the observation. Since the observation space is uncountable, the structural representation of a quantizer can be very complex.

When nodes implement identical quantizers, the quantized variable $\gamma(X_i)$ at the nodes are i.i.d according to a probability mass function (p.m.f) $q_\theta$ indexed by $\theta$, where

$$q_\theta = (q_\theta(1), \cdots, q_\theta(D)),$$

$$q_\theta(i) = P_\theta(\gamma(X) = i).$$

The estimation is performed using only the quantized observations which are received perfectly at the fusion center. Therefore, for a fixed estimator $\hat{\theta}_{\text{ML}}$, the mean squared error can be expressed as a function of the distribution $q_\theta$. In this work, we assume that a Maximum-likelihood (ML) estimator $\hat{\theta}_{\text{ML}}$ based on $q_\theta$ is implemented at the fusion center and our goal is to minimize the loss in MSE performance due to quantization. For ML estimators, MSE performance is analytically characterizable using the Fisher Information, and the relative performance with respect to an unquantized estimator can be expressed using the Asymptotic Relative Efficiency. These concepts are discussed in the following section.

A. Cramer-Rao Bound and Asymptotic Relative Efficiency

It is well known that the MSE of any unbiased estimator is lower bounded by the Cramer-Rao Lower Bound (CRLB). Specifically, under some regularity conditions (see [7], pp. 169) on $\{P_\theta; \theta \in \Theta\}$, the MSE satisfies:

$$\mathbb{E}[|\theta - \hat{\theta}|^2] \geq \frac{1}{nI_\theta},$$

(1)

where

$$I_\theta = \sum_{i=1}^{D} q_\theta(i) \left( \frac{d}{d\theta} \log q_\theta(i) \right)^2$$

(2)

is the Fisher Information of the quantized observation and $n$ is the number of measurements. Although the CRLB may not be achievable for any finite $n$, under more regularity conditions (see [7], pp. 183), the MSE of an ML estimator converges to the bound asymptotically. Specifically, as $n \to \infty$,

$$\sqrt{n}(\hat{\theta}_{\text{ML}} - \theta) \xrightarrow{d} \mathcal{N}(0, \frac{1}{I_\theta}).$$

As a result, when an ML estimator is implemented at the fusion center, the Fisher Information (FI) of the quantized variable $\gamma(X_i)$ measures the asymptotic performance.

A measure of relative performance between two estimators is Asymptotic relative efficiency (ARE), which is defined as follows [7].

**Definition 1:** If two estimators $W_n$ and $V_n$ satisfy

$$\sqrt{n}[W_n - \theta] \xrightarrow{d} \mathcal{N}(0, \sigma_W^2),$$

$$\sqrt{n}[V_n - \theta] \xrightarrow{d} \mathcal{N}(0, \sigma_V^2),$$

then, the Asymptotic Relative Efficiency (ARE) of $V_n$ with respect to $W_n$ is

$$\text{ARE}(V_n, W_n) = \frac{\sigma_W^2}{\sigma_V^2}.$$  (3)

Since any ML estimator satisfies the convergence criterion as stated in Definition 1, the ARE can be used as a relative measure of performance between ML estimators based on quantized and unquantized observations. If $p_\theta$ is the pdf of unquantized observations, then the ARE is equivalently expressed as the ratio of Fisher Informations $I_\theta$ where

$$J_\theta = \int_{\mathcal{X}} p_\theta(x) \left( \frac{d}{d\theta} \log p_\theta(x) \right)^2 dx$$

(4)

is the Fisher Information based on the unquantized observations. Since the FI $J_\theta$ is fixed for a given prior distribution, the ARE between quantized and unquantized ML estimators represents a measure of the asymptotic performance of the quantizer.

It is easily seen that, for every value of $\theta$, the performance of the quantized estimator is worse than that of the unquantized observations, or in other words, the ARE is less than 1 for all $\theta$. Furthermore, the ARE is also related to the ratio of sample sizes required for the same asymptotic performance. This relation can be derived using the notion of asymptotic effective variance [7]. The effective standard deviation of an estimator $\hat{\theta}^{(n)}$ can be defined as the solution $\tau(n, \epsilon)$ of the equation

$$\Pr(|\hat{\theta}^{(n)} - \theta| \geq \epsilon) = \Pr(|N| \geq \epsilon/\tau),$$

where $N$ is the standard normal variable. It was shown in [7] that, for an ML estimator,

$$\lim_{n \to \infty, \epsilon \to 0} n\tau^2(n, \epsilon) = \frac{1}{J_\theta}.$$  (5)

Therefore, if $\tau_u(n_1, \epsilon)$ and $\tau_a(n_2, \epsilon)$ represent the effective standard deviations of the quantized and unquantized estimators respectively, then the ARE between the two ML estimators is equivalent to

$$\text{ARE} = \frac{I_\theta}{J_\theta} = \lim_{n_1, n_2 \to \infty, \epsilon \to 0} \frac{n_2 \tau_u^2(n_2, \epsilon)}{n_1 \tau_a^2(n_1, \epsilon)}.$$  

If $\alpha$ is the ratio of sample sizes between the quantized and unquantized estimators such that their effective variances are asymptotically equal, then $\frac{I_\theta}{J_\theta} = \alpha$ implies

$$\lim_{n \to \infty, \epsilon \to 0} \frac{\tau_u^2(\alpha n, \epsilon)}{\tau_a^2(n, \epsilon)} = 1.$$  (5)

In other words, the ARE is equivalent to the ratio of sample sizes between the unquantized and quantized ML estimators such that their effective variances are asymptotically equal.
B. Maximin ARE Criterion

At any fixed value of $\theta$, the ARE between ML estimators for quantized and unquantized observations is a measure of decrease in performance due to quantization. Since a quantizer is designed without any knowledge of the parameter, it is not possible to design a single quantizer that has the best ARE at every value of $\theta$. We therefore consider the design of a quantizer that maximizes the minimum ARE over $\Theta$. In other words, if $\hat{\gamma}$ is the sign of a quantizer that maximizes the minimum ARE over $\Theta$, we consider the design of a quantizer that maximizes minimum ARE at every value of $\theta$. We therefore consider the design of a quantizer that maximizes the minimum ARE over $\Theta$. In other words, if $\hat{\gamma}$ and $\hat{\theta}$ are the ML estimators that use unquantized observations and quantized observations (using $\gamma$) respectively, then we wish to design quantizer $\gamma^*$ such that:

$$
\gamma^* = \arg\max_{\gamma \in \Gamma_D} \min_\theta \text{ARE}(\hat{\theta}_u, \hat{\theta}_u) = \arg\max_{\gamma \in \Gamma_D} \min_\theta \frac{I_0}{\gamma} J_0,
$$

where $\Gamma_D$ represents the set of all deterministic quantizers of size $D$. If $\frac{n_u}{n_\gamma}$ represents the ratio of sample sizes such that the ML estimators have asymptotically equal effective variances, then from (5), we know that

$$
\gamma^* = \arg\max_{\gamma \in \Gamma_D} \frac{n_u}{n_\gamma}.
$$

The optimal quantizer $\gamma^*$ thus minimizes the maximum percentage of additional samples $(\frac{n_u}{n_\gamma})$ required by the ML estimator due to quantization. Furthermore, if the observations can be expressed as $X = \theta + W$, where $W$ is a random variable with infinite support, it is easily shown that $J_0$ is a constant for all $\theta$. The optimal quantizer $\gamma^*$ for such distributions requires the least sample size amongst all deterministic quantizers of size $D$.

In the following two sections, we provide techniques to design a single quantizer that maximizes minimum ARE and thereby propose the optimal structure for the quantizer. In Section 2, we use the proposed structure and design multiple non-identical quantizers for maximin ARE estimation.

III. SCORE FUNCTION QUANTIZERS

A deterministic quantizer is represented by a mapping from the observation space into a finite set. Unless some restrictions are imposed on the structure of the quantizer, this representation could be highly complex. To this extent, we propose the use of Score-Function Quantizers to provide the structure for the ARE quantizer.

Score-Function quantizers, introduced in [7], are represented by $D - 1$ thresholds on the score-function of the observation, given by

$$
S_\theta(x) = \frac{d}{d\theta} \log p_\theta(x),
$$

where $p_\theta(x)$ represents the density of the unquantized variable $X$. The existence of the score-function is subject to some regularity conditions (see [7], pp. 183). Score-Function Quantizers are formally defined as follows.

Definition 2: Let $\mathcal{J}$ denote the set of all vectors $t = (t_1, ..., t_{D-1}) \in \mathbb{R}^{D-1}$ satisfying $-\infty \leq t_1 \leq \cdots \leq t_{D-1} \leq \infty$. For any $t \in \mathcal{J}$, the associated intervals $I_1, ..., I_D$ are defined by $I_1 = [-\infty, t_1], I_2 = [t_1, t_2], \ldots, I_D = [t_{D-1}, \infty]$. We say that a quantizer $\gamma$ is a monotone Score-Function quantizer (SFQ) at $\theta$ (see Fig. 2) with threshold vector $t \in \mathcal{J}$, if

$$
\gamma_\theta(x) = d \iff S_\theta(x) \in I_d, \quad \forall d.
$$

We say that a quantizer is an SFQ at $\theta$ if there exists a permutation mapping $\pi$ : $\{1, \ldots, D\} \mapsto \{1, \ldots, D\}$ such that $\pi \circ \gamma_\theta$ is a monotone SFQ at $\theta$.

Fig. 2. Monotone Score-Function Quantizer : $I_i = (t_{i-1}, t_i)$ represent the partition $i$.

The motivation to use SFQs to design the maximin ARE quantizer comes from [7] where it was shown that SFQs, when coupled with maximum-likelihood estimators, exhibit some optimal properties. In particular, our approach is based on the following result.

Theorem 1: (from [7]) At a given value of $\theta$, the Fisher Information $I_0$ is maximized by a Score-Function Quantizer at that value of $\theta$.

In other words, the optimal SFQ at any value of $\theta$ represents the maximum achievable Fisher Information at that value of $\theta$. Since $I_0$ is fixed for a given distribution, this quantizer also achieves the maximum ARE at that $\theta$. Therefore, by evaluating the best SFQ at every value of $\theta$, one can obtain an upper bound (genie bound) on quantizer performance for a given distribution of observations. The optimality of SFQs in estimation is analogous to the optimal properties of Likelihood-Ratio quantizers (LRQ) in detection [7].

Using this optimality as a heuristic, we restrict our criterion to the design of quantizer $\gamma^*$ that satisfies

$$
\gamma^* = \arg\max_{\gamma \in \varSigma_D} \min_\theta \text{ARE}(\hat{\theta}_u, \hat{\theta}_u),
$$

where $\varSigma_D$ represents the set of all SFQs of size $D$.

SFQs, owing to their dependence on the value of $\theta$, are not directly applicable to the quantizer design problem. However, under some conditions on the underlying family of distributions $\{p_\theta\}$, the class of SFQs at all parameter values can be shown to be identical. Furthermore, under those conditions, the SFQs have a simple structural representation in the observation space. This is evident from the following Lemma.

Lemma 1: Let $S_\theta$ represent the class of SFQs at the parameter value $\theta$, i.e.,

$$
S_\theta = \{\gamma_\theta : \gamma_\theta \text{ is an SFQ at } \theta\}.
$$

Let $T$ be a sufficient statistic for $p_\theta$. If the score function can be expressed as $S_\theta(x) = f_\theta[T(x)]$, such that $f_\theta$ is monotone increasing for all $\theta$, then
1. The class of SFQs $S_\theta$ at parameter $\theta$ is identical for all $\theta$.
2. Every SFQ $\gamma_\theta$ can be equivalently expressed as $D - 1$ thresholds on the sufficient statistic. In other words, there exists $(t_1, ..., t_{D-1}) \in \mathbb{R}^{D-1}$ such that $\forall k$,
\[
\gamma_\theta(x) = k \iff T(x) \in [t_{k-1}, t_k].
\]

Proof: Since the score-function is monotonic in the sufficient statistic, any sequence of thresholds on the score-function will retain the same order in the sufficient statistic domain as well. Hence, the class of SFQs are independent of $\theta$. □

Therefore, when the family of distributions satisfy the monotonicity property, any SFQ corresponds to a sequence of $D - 1$ thresholds on the sufficient statistic $T(x)$. An example of a class of distributions that satisfy the monotonicity property is the exponential family of distributions. Distributions like the asymmetric Gaussian mixture do not belong to this class.

In order to design the optimal SFQ that maximizes the minimum ARE, it suffices to obtain the optimal thresholds on $T(x)$. In general, an exhaustive search for optimal thresholds after finely discretizing the observation space would yield the required quantizer within a small margin of error. Such techniques would, however, be computationally intensive. We therefore, propose an iterative algorithm that evaluates the optimal quantizer efficiently.

A. Iterative Algorithm

The algorithm is initialized with arbitrary thresholds $-\infty < t_1 < \cdots < t_{D-1} < \infty$ on the sufficient statistic. At every iteration, the lowest threshold is chosen to maximize the metric while keeping the other thresholds fixed. This process is carried out for each subsequent threshold and the entire iteration is repeated until the change in thresholds is negligible. Since the minimum ARE cannot decrease at any iteration, the algorithm converges.

Let $M(\gamma)$ denote the minimum ARE of a quantizer $\gamma$, i.e.,
\[
M(\gamma) = \min_{\theta} \frac{I_\theta(\gamma)}{J_\theta}. \tag{6}
\]

1. Initialization: Let $t = \{t_1, ..., t_{D-1}\} \in T^{D-1}$ represent the threshold set of the quantizer. Set $t_0 = -\infty, t_D = \infty$ and initialize $t$ arbitrarily such that $t_i < t_{i+1}$. Evaluate the probability mass function of the quantized variable as
\[
q_\theta(i) = P_\theta(T(x) \in [t_{i-1}, t_i]).
\]
For this $q_\theta$, evaluate the Fisher Information $I_\theta$ (in (2)) and the metric $M(\gamma)$ (in (6)).

2. Iteration $n+1$: Let $t_i^n$ represent the value of threshold $j$ in iteration $n$. Each iteration is divided into $D - 1$ steps. At step $j$, the new values for thresholds $t_1, ..., t_{j-1}$ would have been obtained. Threshold $t_j$ is then picked as that value between the new $t_{j-1}$ and the old $t_{j+1}$ which maximizes the metric. The $j^{th}$ step therefore, corresponds to obtaining the optimal value for $t_j$ given the other thresholds. More formally,
\[
\gamma_j^*(x) = \begin{cases}
  i & T(x) \in [t_{j-1}^{i+1}, t_{j+1}^{i}], i < j \\
  i & T(x) \in [t_{j-1}^i, t_{j+1}^i], i > j + 1 \\
  j & T(x) \in [t_{j+1}^{i+1}, t] \\
  j + 1 & T(x) \in [t, t_{j+1}^{i+1}]
\end{cases}
\]

The optimal threshold is chosen as
\[
t_j^{n+1} = \arg\max_{t} M(\gamma_j^*).
\]
Let the optimal quantizer at the end of $D - 1$ steps be denoted as $\gamma^{n+1}$ and the corresponding value of the metric be $M(\gamma^{n+1})$.

3. Termination: Choose $\epsilon$ as close to zero as required. At iteration $n$, evaluate $M(\gamma^n)$. If $|M(\gamma^n) - M(\gamma^{n-1})| < \epsilon$, then the algorithm terminates. In other words, when the change in performance is very close to zero, we terminate the algorithm.

Theorem 2: At the $n^{th}$ iteration, let $R^{(n)} = \max_{\theta} J_\theta/I_\theta^{(n)}$. Then $R^{(n+1)} \leq R^{(n)}, \forall n$. For any $\epsilon > 0$, the algorithm converges in finite steps.

Proof : See Appendix.

At every step of the algorithm, a new set of thresholds on the sufficient statistic are evaluated. The quantizer at the end of every iteration is therefore an SFQ. From Theorem 2, we know that the algorithm converges in finite iterations. Furthermore, in the absence of local minima, the algorithm converges to the best SFQ that optimizes the minimax ARE,
\[
\gamma^* = \arg\max_{\gamma \in S_D} \min_{\theta} ARE(\hat{\theta}_\gamma, \hat{\theta}_\theta).
\]

Note that the algorithm is valid only for those distributions that satisfy the monotonicity property of Lemma 1. The iterative algorithm can also be used to optimize other metrics within the class of SFQs by appropriately modifying the quantity $M(\gamma)$ [7].

Since the use of SFQ to design the quantizer was based on a heuristic, it is not known if it is the optimal quantizer structure for the maximin ARE criterion. In the following section, we therefore consider an alternate approach to design the optimal quantizer, when no restrictions are placed on quantizer structure or nature of distribution.

IV. General Quantizer Design

In this section, we present an iterative algorithm to obtain the maximin ARE quantizer without any assumptions on partition structure in the observation space or nature of distribution. Such an algorithm is generally computationally intensive and may not be useful for practical implementation. However, we present this approach to estimate the loss in performance due to the SFQ assumption.

The basic idea for this technique comes from the fact that the Fisher Information at any fixed $\theta$ is the variance of the score-function at that $\theta$. Mathematically, if $\{S_\theta^p(x), z \in X\}$ and $\{S_\theta^p(i), i = 1 \cdots D\}$ represent the score-functions of the
unquantized and quantized observations respectively, then:

\[ S_{\theta}^{\gamma}(i) = \frac{d}{d \theta} \log q_\theta(i), \quad I_\theta = \sum_{i=1}^{D} q_\theta(i) (S_{\theta}^{\gamma}(i))^2, \]

\[ S_{\theta}^{\gamma}(x) = \frac{d}{d \theta} \log p_\theta(x), \quad J_\theta = \int_x p_\theta(x) (S_{\theta}^{\gamma}(x))^2 \, dx. \]

Furthermore, it is easily shown that the difference in Fisher Informations \( J_\theta \) and \( I_\theta \) can be expressed as MSE of the quantizer score-function \( S_{\theta}^{\gamma}(i) \) with respect to \( S_{\theta}^{\gamma}(x) \), i.e.

\[ J_\theta - I_\theta = \sum_{i=1}^{D} \int_{x: \gamma(x) = i} p_\theta(x) (S_{\theta}^{\gamma}(x) - S_{\theta}^{\gamma}(i))^2 \, dx. \tag{7} \]

We use (7) as the basis for iteration in the quantizer algorithm. The iterative algorithm is similar to the SFQ algorithm in Section III-A in principle. Instead of evaluating thresholds in each iteration, we compute the optimal partition index \( \gamma(X) \) for each observation\(^1 \) \( X \), keeping the others fixed. The algorithm converges because the minimum ARE cannot decrease at any iteration.

Let the partitions in \( \mathcal{X} \) in iteration \( n \) be represented by \( (L^{(n)}(1), \cdots, L^{(n)}(D)) \). If the quantizer at the iteration \( n \) is represented by \( \gamma^{(n)} \), then

\[ L^{(n)}(i) = \{ x : \gamma^{(n)}(x) = i \}. \]

The formal statement of the algorithm is as follows:

1. **Initialization:** Divide \( \mathcal{X} \) into \( D \) arbitrary non-overlapping partitions represented by \( (L^{(0)}(i)) \). Evaluate the score-function and Fisher Information as

\[ S_{\theta}^{(0)}(i) = \frac{d}{d \theta} \log q_\theta^{(0)}(i) = \frac{d}{d \theta} \log \Pr \{ x \in L^{(0)}(i) \}, \]

\[ I_{\theta}^{(0)} = \sum_{i=1}^{D} 1 \left( \frac{d q_\theta^{(0)}(i)}{d \theta} \right)^2. \]

2. **Iteration** \( n + 1 \): Let \( \theta^* = \arg \max_\theta \frac{J_\theta}{I_\theta} \).

For every \( x \in L^{(n)}(j) \), let

\[ M^{k}_{n}(x) = \begin{cases} \max_k M^{k}(x), & k = 1, \ldots, D, \\ \frac{p_\theta(x)}{J_\theta} (S_{\theta}(x) - S_{\theta}^{(n)}(k))^2, & k \neq j \\ \frac{p_\theta(x)}{J_\theta} (S_{\theta}(x) - S_{\theta}^{(n)}(k))^2, & k = j \end{cases}, \]

\[ x \in L^{(n+1)}(k). \]

3. **Termination:** Choose \( \epsilon \) close to zero. At each iteration, evaluate \( I_\theta^{(n)} \). If \( \max_\theta \left| I_\theta^{(n)} - I_\theta^{(n-1)} \right| < \epsilon \), then the algorithm terminates. In other words, when the change in Fisher Information is very close to zero, we terminate the algorithm.

**Theorem 3:** At the \( n \)th iteration, let \( R^{(n)} = \max_\theta J_\theta / I_\theta^{(n)} \). Then \( R^{(n+1)} \leq R^{(n)} \), \( \forall n \). For any \( \epsilon > 0 \), the algorithm converges in finite steps.

**Proof:** Refer to Appendix.

This algorithm, although computationally intensive, can be used for any underlying distribution (subject to regularity conditions) and, in the absence of local minima, provides the optimal quantizer

\[ \gamma^* = \arg \max_{\gamma \in \Gamma} \min ARE(\hat{\theta}_\gamma, \hat{\theta}_u). \]

As is evident from the description of the algorithm, the final quantizer is represented as an index for each observation and therefore does not specify a regular structure on the observation space. On the other hand, the quantizer resulting from the SFQ algorithm is Section III-A has a simple structure, but the optimization is over a subset of deterministic quantizers. It remains to be seen if there is a loss in performance due to the structural constraints.

In the following section, we present some numerical results and illustrate that for the distributions where the SFQ algorithm is valid, the two quantizers are identical.

**V. Numerical Results**

As mentioned in Section III, it is known that at any particular \( \theta \), the Fisher Information can be maximized \([?]\) by a Score-Function Quantizer (optimized at that \( \theta \)). The maximal Fisher Information thus obtained serves as a good upper bound to the performance of any quantizer.

In this section we consider the performance of the optimal quantizer for two different distributions: parameter in additive and multiplicative Gaussian noise. Since these distributions satisfy the monotonicity property of Lemma 1, the optimal Score-Function Quantizer was also evaluated through the algorithm in Section III. In both situations, the two algorithms resulted in identical quantizers. Although, in the examples considered in this section, the algorithms discussed did not result in a local minima, we do not have an analytical guarantee for their absence.

**A. Multiplicative Gaussian Noise**

The observation \( X_i \) is a faded version of the parameter \( \theta \), where the fading is assumed Gaussian.

\[ X = H \theta, \quad H \sim \mathcal{N}(0, \sigma_h^2), \quad \Theta \subset \mathbb{R}^+ \]

The Fisher Information in this case is a decreasing function of \( \theta \).

**Fig. 3.** Maximin ARE quantizer for Multiplicative Noise: \( \theta \in [1, 4], \sigma_h^2 = 1, D = 2 \)
(a) Comparison of quantizer ARE b) Comparison of quantizer FI
Figure 3 plots the ARE and Fisher Information of the maximin ARE quantizer. The performance is compared to the genie bound obtained by evaluating the best SFQ at every value of \( \theta \) (Theorem 1). The figures also plot the performance of a quantizer which guesses the value of \( \theta \) to be the average value \((\theta_{\min} + \theta_{\max})/2\) in the parameter set. It can be seen that the shape of the maximin ARE quantizer curve follows that of the unquantized FI and the genie bound. Furthermore, the performance of the maximin ARE quantizer is significantly better than that obtained by just using the average value of the parameter.

B. Parameter in AWGN

The observation is of the form

\[
X = \theta + N, \quad N \sim \mathcal{N}(0, \sigma^2).
\]

The Fisher Information of the unquantized variable in this scenario is a constant for all values of \( \theta \).

\[
J_\theta = \frac{1}{\sigma^2}.
\]

Therefore, maximizing the minimum ARE is equivalent to maximizing the minimum Fisher Information across the parameter. Figure 5 plots the Fisher Information of the optimal quantizer for different values of \( D \).

It is interesting to observe that for \( D = 2 \), the maximin ARE quantizer and the optimal SFQ at \( \theta = (\theta_{\min} + \theta_{\max})/2 \) are identical. In other words, the quantizer designed by guessing the parameter value to be \((\theta_{\min} + \theta_{\max})/2\) is optimal. However, for \( D = 4 \), designing a quantizer by making a similar guess results in poor minimum ARE, although the quantizer has the best ARE at that guessed value of \( \theta \).

As number of quantization bins \( D \) increases, we see that the performance of the maximin quantizer tracks the genie bound more closely. It is also interesting to see that the maximin ARE quantizer for both distributions result in ARE curves where the extreme values of the parameter have nearly equal performance.

For the multiplicative noise distribution, the score-function \( S_\theta(x) = \frac{x^2}{\sigma^2} - \frac{1}{\theta} \) which is monotone in \( x^2 \). On the other hand, the score-function for the AWGN distribution is given by \( S_\theta(x) = x - \theta \) which is monotone in \( x \). The SFQs for the multiplicative and additive noise observations are, therefore, expressible as thresholds on the \( x^2 \) and \( x \) respectively. Figure 7 illustrates the partition information of the optimal quantizers for the two distributions when \( D = 4 \). The use of SFQs significantly simplifies the design of quantizer, especially when the observations are vectors. For example, if the observation at each node comprises multiple elements, each of which are independent and identically distributed as the parameter in AWGN, then, the SFQ corresponds to \( D - 1 \) thresholds on the sum of the elements of the vector observation.

VI. Multiple Quantizer Design

The material discussed so far dealt with optimal quantization assuming all sensors use identical quantizers. For a distributed detection setup with binary hypotheses, it has been shown [?] that use of identical quantizers is optimal. However, for a general \( M \)-ary hypothesis testing, the maximum number of quantizers required is given by \( M(M-1)/2 \). We, therefore, expect that for distributions that satisfy the monotonicity property, the maximin ARE quantizer is an SFQ.

Designing identical quantizers is generally suboptimal, as will be seen in the next Section. However, it provides some practical advantages especially in large scale networks like sensor networks where it is preferable for nodes to operate identically. Moreover, when quantizers are distinct, it would be necessary for the fusion center to obtain the quantizer information of each node as well which might lead to some overhead.
within the class of SFQs, identical quantizers are suboptimal.

Fig. 6. AWGN parameter with $\sigma^2 = 1$: Comparison between i) Fisher Information of optimal SFQ and ii) Average Fisher Information of two 1-bit SFQs with thresholds $t = 1$ and $t = 4$

In order to design multiple quantizers, the algorithm presented in Section III can be coupled with a Person-by-Person Optimization (PBPO) [?] across quantizers. Since the observations at multiple nodes are independently distributed, the Fisher Information of the total received data at the fusion center is the sum of Fisher Informations of the individual quantizers. In other words, let $\gamma_1, \cdots, \gamma_k$ represent the quantizers for $k$ nodes and $I_\theta(\gamma_i)$ be the Fisher Information for quantizer $\gamma_i$. Then, the ARE of the joint observation at the fusion center is given by

$$\text{ARE}(\gamma_1, \cdots, \gamma_k) = \frac{\sum_{i=1}^k I_\theta(\gamma_i)}{k J_\theta}.$$  

The algorithm in Section III is modified as follows. The metric $M(\gamma)$ is rewritten as

$$M(\gamma_1, \cdots, \gamma_k) = \min_\theta \sum \frac{I_\theta(\gamma_i)}{J_\theta}.$$  

Each iteration now involves optimizing $k(D - 1)$ thresholds. Each threshold of the first quantizer is optimized assuming all other thresholds and the remaining $k-1$ quantizers are fixed. This process is subsequently repeated for each quantizer in succession. The entire iteration is repeated until the change in $M(\cdot)$ is negligible. Since the basic iteration is identical to the algorithm in Section III, it is easily seen that the metric does not increase at any iteration. Furthermore, since the ARE is bounded, the algorithm converges in finite steps.

For a large scale network, the algorithm would be computationally intensive. However, as will be seen from numerical results, it may not be necessary to design as many quantizers as the number of nodes in the network.

A. Numerical Results

We consider the example of multiplicative Gaussian noise and implement the algorithm for multiple quantizer design. The modified ARE of non-identical quantizers is plotted in Figure ???. It can be seen that, by increasing the number of quantizers, the minimum ARE at the fusion center improves.

As mentioned at the beginning of Section ??, the design of multiple non-identical quantizers becomes imperative for low noise observations. Figure ?? plots the improvement in minimum ARE with design of additional quantizers for different noise levels of observations. As can be seen from the figure, as the noise level reduces, the improvement due to making quantizers non-identical increases.

Fig. 7. ARE for non-identical quantizers in Multiplicative Noise : $\theta \in [1, 4], \sigma^2 = 1$

Fig. 8. Minimum ARE for non-identical quantizers at different multiplicative noise levels : $\theta \in [1, 4]$.

It is interesting to note that the improvement in minimum ARE saturates with the increase in number of quantizers designed. For a large scale network, it would therefore be sufficient to design much fewer quantizers than the number of nodes in the network. The nodes can be divided into groups based on the number of quantizers designed, and each group implements one of the quantizers. This greatly simplifies node design and the communication overhead in large scale networks.

VII. CONCLUSION AND FUTURE EXTENSIONS

In this paper, we considered the performance criterion, Maximin ARE, to design quantizers for distributed estimation of a deterministic parameter. We proposed the use of Score-Function Quantizers to design the optimal quantizer for a certain class of distributions that satisfy a monotonicity property. Through numerical simulations, we illustrated that under those conditions, the SFQ provides the optimal structure. Furthermore, SFQs can be
expressed as a set of thresholds on the sufficient statistic which significantly reduces the complexity of implementation. SFQs also have some generic optimal properties [?] that strongly suggest the use of SFQs with ML estimation. 

The application of this metric is not restricted to distributed estimation. In practical situations of classical point estimation, the estimator may not be capable of handling several high resolution measurements to estimate the parameter, and it is necessary to compress the data into few bits to reduce complexity. Currently, the setup is simple and assumes identical distributions and quantizers. The extension of this idea to non-i.i.d distributions and noisy channels is an interesting direction to pursue. Improving the metric to handle vector parameters is also a non-trivial future extension.

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**References**


**Appendix**

**Proof of Theorem 2**

Let the quantizer have $D$ partitions. Since the quantizer is a monotone SFQ, we know that this corresponds to $D-1$ thresholds on the real line. Therefore, the Fisher Information can be expressed as the sum of expectations at each partition. i.e.

$$ I_\theta = \sum_i I_i^\theta $$

where $I_i^\theta = q_\theta(i) \left( \frac{d}{d\theta} \log q_\theta(i) \right)^2$

We know that, at every step threshold $t_i$ affects only the terms $I_i^\theta$ and $I_{i+1}^\theta$. Therefore, at iteration $n$, the new threshold $t_i^{(n)}$ is chosen such that

$$ \min_{\theta} \frac{I_i^{(n)}_\theta}{J_\theta} + \min_{\theta} \frac{I_{i+1}^{(n)}_\theta}{J_\theta} \geq \min_{\theta} \frac{I_i^{(n-1)}_\theta}{J_\theta} + \frac{I_{i+1}^{(n-1)}_\theta}{J_\theta} $$

Therefore, the new minimum ARE increases at every step. i.e.

$$ \min_{\theta} \frac{I_i^{(n)}_\theta}{J_\theta} \geq \min_{\theta} \frac{I_i^{(n-1)}_\theta}{J_\theta} $$

Since the ARE is upper bounded by 1, the algorithm converges in finite steps.

**Proof of Theorem 3**

Consider the minimax criterion:

$$ \arg \min_{\gamma} \max_{\theta} \frac{J_\theta}{I_\theta} = \arg \max_{\gamma} \min_{\theta} \frac{J_\theta}{I_\theta} $$

$$ = \arg \max_{\gamma} \min_{\theta} \left( 1 - \frac{I_\theta}{J_\theta} \right) $$

$$ = \arg \max_{\gamma} \min_{\theta} \frac{J_\theta - I_\theta}{J_\theta} $$

It is easily shown that

$$ \frac{J_\theta - I_\theta}{J_\theta} = \sum_i \int_{T_i} \frac{p_\theta(x)}{J_\theta} \left[ S_\theta(x) - S_\theta(i) \right]^2 dx $$

where $T_i = \{ x : \gamma(x) = i \}$. Using the steps of iteration, we get

$$ \max_{\theta} \frac{J_\theta - I_\theta^{(n)}_\theta}{J_\theta} = \max_{\theta} \sum_i \int_{T_i^{(n)}} \frac{p_\theta(x)}{J_\theta} \left[ S_\theta(x) - S_\theta^{(n)}(i) \right]^2 dx $$

$$ \leq \max_{\theta} \sum_i \int_{T_i^{(n-1)}} \frac{p_\theta(x)}{J_\theta} \left[ S_\theta(x) - S_\theta^{(n-1)}(i) \right]^2 dx $$

$$ \leq \sum_i \int_{T_i^{(n-1)}} \frac{p_\theta(x)}{J_\theta} \left[ S_\theta(x) - S_\theta^{(n-1)}(i) \right]^2 dx $$

$$ = \max_{\theta} \frac{J_\theta - I_\theta^{(n-1)}_\theta}{J_\theta} $$

We know that $I_\theta \leq J_\theta$ for every value of $\theta$. Therefore the metric is lower bounded by 0. Since, the algorithm cannot increase the metric at every iteration, in the absence of local minima, the inequalities are strict and hence the algorithm converges to the optimal quantizer in finite steps.