Optimal Sensor Decision Rules for Quantized-but-Uncoded Distributed Detection

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***Abstract*—In conventional codeword-based distributed detection (CDD), sensors quantize their observations and report codewords to the fusion center (FC) where a final decision is made regarding the truthfulness of the hypotheses. Recently, quantized-but-uncoded DD (QDD) has been proposed, where sensors, after quantization, transmit summarized values instead of codewords to the FC. QDD can adapt well to the power constraint and offers better detection performance than CDD. However, the added degree of freedom in parameter selection in QDD comes with high complexity in optimal system design. The contribution of this letter is a proof showing that in QDD, the optimal sensor decision rules for binary decisions are likelihood-ratio-quantizers (LRQ), regardless of the reporting channel conditions, provided that the sensor observations are conditionally independent given the hypotheses. This property largely simplifies the design of QDD. Performance comparison is presented for CDD, QDD, and a benchmark system that reports original sensor observations, when both sensing and reporting channel noise exist.**

***Index Terms*—Codewords, distributed detection, likelihood-ratio-quantizer.**

I. Introduction

Distributed detection has broad applications in sensor networks and radar systems [1], [2], where a number of sensors gather information in a region of interest and report to a fusion center (FC) that makes a final decision regarding the presence of one of two possible signals. Fig. 1 shows a typical task to determine between two hypotheses, with signal strength $s = -\mu$ under H_0 and $s = \mu$ under H_1, respectively, via a parallel sensing structure with N sensors. The prior probabilities of the hypotheses are π_0 and π_1, where $\pi_0 + \pi_1 = 1$. We assume that observations at different sensors, i.e., $X_k,\ k = 1, \ldots, N$, are conditionally independent given either hypothesis, i.e., $p(X_1, \ldots, X_N|H_j) = \prod_{k=1}^{N} p(X_k|H_j),\ j = 0, 1$. When sensing involves additive white Gaussian noise (AWGN), we have $X_k \sim \mathcal{N}(-\mu, \sigma_s^2)$ under H_0 and $X_k \sim \mathcal{N}(\mu, \sigma_s^2)$ under H_1, where σ_s^2 is the noise variance. Each sensor either sends its observation X_k or sends $Y_k = \gamma_k(X_k)$, as a summarized representation, to the FC. $\gamma_k(X_k)$ is typically termed as the decision rule at sensor k. $\{Y_1, \ldots, Y_N\}$ are reported and arrive at the FC as $\{Z_1, \ldots, Z_M\}$ through channels represented by a conditional probability distribution $p(Z_1, \ldots, Z_M|Y_1, \ldots, Y_N)$. In general, M needs not be equal to N. If sensors use independent reporting channels, we have $M = N$ and $p(Z_1, \ldots, Z_M|Y_1, \ldots, Y_N) = \prod_{k=1}^{N} p(Z_k|Y_k)$.

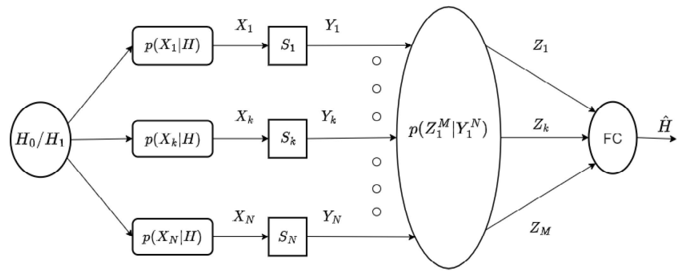

Fig. 1. Sensor networks with parallel topology.

Based on the received information, the FC makes a final decision in favor of either H_0 or H_1. It is well known that the optimal FC decision rule is the likelihood ratio test (LRT). Denote $Z_1^M \triangleq \{Z_1, \ldots, Z_M\}$, and let $f(z_1^M|H_j)$ be the probability density of z_1^M under $H_j,\ j = 0, 1$. The LRT is,

$$\Lambda(z_1^M) = \frac{f(z_1^M|H_1)}{f(z_1^M|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta, \tag{1}$$

where $\eta = \frac{\pi_0}{\pi_1}$. Denote region $R_Z = \{z_1^M \in \mathbb{R}^M | \Lambda(z_1^M) > \eta\}$. Then, the false alarm probability and detection probability are $P_F = \int_{R_Z} f(z_1^M|H_0) dz_1^M$ and $P_D = \int_{R_Z} f(z_1^M|H_1) dz_1^M$, respectively. The Bayes' error is

$$P_e = \pi_1 + \pi_0 P_F - \pi_1 P_D. \tag{2}$$

A key research challenge in distributed detection is determining the sensor decision rules based on either the Bayesian criterion (i.e., minimizing P_e) or the Neyman-Pearson criterion (i.e., maximizing P_D, subject to a maximum value for P_F). The most popularly investigated DD framework is CDD where sensors quantize their observations and report codewords to the FC. That is, $Y_k = \gamma_k(X_k) = d, d \in \{0, \ldots, D-1\}$ where D is the number of distinct binary bit sequences. The codeword of d indicates a specific partition region in the observation space where the actual observation is observed. This framework was proposed in the 1980s by Tenney and Sandell [3] and quickly attracted significant attention.

While CDD has seen tremendous successes [4], [5], [6], [7], [8], some limitations exist. First, the digital modulation constellation may have to be adjusted, given the power constraint

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and the result of quantization. Second, when channel errors exist [7], [8], [9], [10], [11], [12], [13], the mapping between the codewords and symbols in the modulation constellation needs to be optimized to maximize the detection performance.

In [14], a concept of quantized-but-uncoded DD (QDD) has been proposed, where after quantization, sensors report summarized values, instead of codewords, to the FC using analog modulation. In other words, $Y_k = \gamma_k(X_k) = m_{kd} \in \mathbb{R}, d \in \{0, \ldots, D-1\}$, where m_{kd} are transmission values. Using analog communications, QDD bypasses the codeword mapping and adapts well to the power constraint. CDD can be viewed as a special choice within QDD, hence QDD offers better detection performance. However, the added degree of freedom in selecting m_{kd} values comes with high complexity in system design. The contributions of this paper is a theoretical proof of a key property of QDD. That is, the necessary condition for the optimality of sensor decision rules is a likelihood-ratio-quantizer (LRQ) for binary decisions. In other words, for $D = 2$, the optimal sensor decision is a binary quantizer that compares the likelihood ratio of sensor observation against a single threshold. This property can significantly reduce the design complexity of a QDD system.

The rest of this letter is organized as follows. Section II briefly describes the difference between CDD and QDD. Section III proves the optimality of using the LRQ as sensor decision rules in QDD. The property is then used in a simple process to search for the optimal parameters. Section IV provides some simulation results. Finally, Section V concludes the letter.

II. Properties of CDD and QDD

In CDD, $Y_k = \gamma_k(X_k) = d \in \{0, \ldots, D-1\}$. In QDD, $Y_k = \gamma_k(X_k) = m_{kd} \in \mathbb{R},\ d \in \{0, \ldots, D-1\}$. For the comparison purpose, we also consider another system where sensors report their original observations directly, i.e., $Y_k = \gamma_k(X_k) = X_k$. This system is termed as un-quantized distributed detection (UDD) in the sequel.

We assume that the transmission of either a codeword or an actual value is via one channel use, and hence consumes the same channel bandwidth as in [15]. We also assume that each sensor uses the same transmission power in all systems, which leads to the same symbol energy per channel use.

In UDD, for sensor $k, k = 1, \ldots, N$, we have

$$E_{u,k} = E[X_k^2]. \tag{3}$$

In QDD, we have

$$E_{q,k} = \sum_{d=0}^{D-1} m_{kd}^2 p_{m_{kd}} = \sum_{d=0}^{D-1} m_{kd}^2 (q_{0kd}\pi_0 + q_{1kd}\pi_1) \tag{4}$$

where $p_{m_{kd}}$ is the transmission probability of m_{kd}. q_{0kd} (or q_{1kd}) is the probability mass of the dth partition region under H_0 (or H_1) for sensor k. That is, $q_{jkd} = \int_{R_d} f(x_k|H_j)dx_k,\ j = 0, 1$, where R_d is the partition region such that when the observation falls within it, m_{kd} is reported. To maintain the same transmission power, we have $E_{u,k} = E_{q,k}$.

In CDD, a codeword with $\log_2 D$ bits is transmitted as a symbol via a digital modulation, such as M-ary QAM or M-ary PSK as shown in Fig. 2. Since each modulation constellation symbol

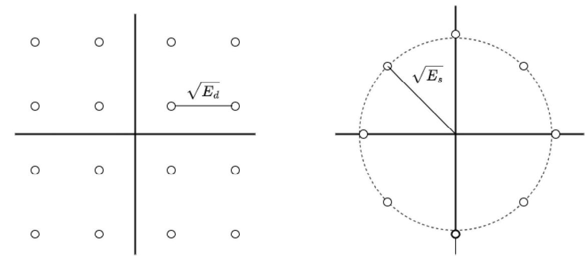

Fig. 2. Modulation types: 16-QAM and 8-PSK.

corresponds to one partition region in the observation space, the probability of using the dth constellation symbol is determined by the probability mass of the dth partition region. Consequently, different constellation symbols may have different probabilities of transmission. These probabilities vary as the partitions change in quantization. Therefore, to meet the power constraint (i.e., the average symbol energy per channel use), the constellation may need to be dynamically adjusted during the search for the optimal quantizer that maximizes detection performance. For example, in Fig. 2, $\sqrt{E_d}$ in the M-ary QAM constellation changes for different quantizers, whereas the constellation of M-PSK does not change because all symbols in M-PSK have the same energy for any quantization result. In addition, the mapping between the codewords and the symbols in the constellation also plays a crucial role because it determines how often one partition region (or codeword) is mistaken as another partition region (or codeword) at the FC. This is due to the occurrences of bit-flips in the codewords resulting from channel errors. In [11], the natural binary coding was used. In [13], the codeword mapping was formulated as a part of the optimization objective, and the result disapproved the use of Gray coding [12].

On the contrary, by adjusting the actual transmission values in (4), QDD can meet well the constraint of transmission power. In addition, by directly transmitting values via analog communications, there is no need to consider the mapping between the codewords and constellation points as in CDD. However, the difficulty in QDD system design is the selection of the transmission values. It can be noted that even for a given quantization, i.e., $\{p_{m_{kd}}, d = 0, \ldots, D-1\}$ probability values having been determined, the selection of m_{kd} satisfying a transmission power constraint is not unique. Therefore, determining the optimal sensor decision rules, i.e., $\gamma_k(X_k)$, in QDD could be highly complex. In the following, we prove through a person-by-person process that for QDD with $D = 2$, LRQ is a necessary condition for the optimality of sensor decision rules.

III. Optimal Sensor Decision Rules of QDD

A. Main Result

Theorem 1: For a QDD system where two possible values are used to report observations in each sensor, when $X_k, k = 0, \ldots, N-1$, are conditionally independent given the hypotheses, a necessary condition for the optimal decision rule of each sensor is an LRQ. This result is irrelevant to the reporting channel model, and the optimality holds under both the Neyman-Pearson (NP) and Bayesian criteria.

Proof: See Appendix A. □

The essence of this result is that the optimal sensor decision only involves a single threshold along the axis of the likelihood ratio of the sensor observations, eliminating the possibility that multiple disjointed intervals along the likelihood ratio lead to the same sensor decision. Therefore, the design of QDD is significantly simplified.

B. Optimization for QDD Design

Assume that $X_k \sim \mathcal{N}(-\mu, \sigma_{s_k})$ under H_0 and $X_k \sim \mathcal{N}(\mu, \sigma_{s_k})$ under H_1, $k = 1, \ldots, N$, are conditionally independent given either hypothesis. Let $D = 2$. The detection error P_e follows (2). Based on Theorem 1, the design of the QDD system becomes an optimization problem that considers only the set of LRQ sensor decision rules. That is, for sensor k, only one threshold t_k and two transmission values m_{k0}, m_{k1} are to be found.

$$
\begin{aligned}
P_1: \quad & \min_{\substack{t_k, m_{k0}, m_{k1} \\ k=1,\ldots,N}} \quad P_e \\
& \text{s.t.} \quad -\sqrt{\frac{E_{u,k}}{p_{m_{k0}}}} \leq m_{k0} \leq \sqrt{\frac{E_{u,k}}{p_{m_{k0}}}} \\
& \qquad p_{m_{k0}} m_{k0}^2 + p_{m_{k1}} m_{k1}^2 = E_{u,k} \\
& \qquad p_{m_{k1}} = \pi_0 Q\left(\frac{t_k + \mu}{\sigma_{s_k}}\right) + \pi_1 Q\left(\frac{t_k - \mu}{\sigma_{s_k}}\right) \\
& \qquad p_{m_{k0}} = 1 - p_{m_{k1}}
\end{aligned}
$$

The constraints include the range of transmission value of m_{k0} and the power constraint. $Q(x) = \int_x^{+\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-v^2}{2}} dv$ is the tail function of the standard Normal distribution. As t_k, m_{k0}, m_{k1} are linked by the power constraint, there are only two independent variables for each sensor. In a person-by-person process focusing on two independent unknowns each time, this optimization problem can be readily solved using many popular optimization solvers, such as those in the optimization toolbox of MatLab. It should be noted that the above optimization problem P_1 is formulated with the AWGN assumption in the sensor observations. It needs to be adjusted when other types of sensing noise are considered.

IV. Comparison and Numerical Results

We compare the detection performance of UDD, CDD, and QDD in terms of Bayes' error when both sensing and reporting channel noise exist. We assume the channel noise is zero mean additive Gaussian with variance of σ_c^2. Although reporting channels often involve fading, we assume that in practical systems, the multiplicative fading factors can often be reliably estimated. We set $\mu = 1, \pi_1 = 0.75$, $\sigma_s = 1.2$, and change σ_c. For QDD, the optimal sensor decision rules are obtained by solving the optimization problem P_1. For CDD, sensor k always transmits either $\sqrt{E_{u,k}}$ or $-\sqrt{E_{u,k}}$ using BPSK, but with the optimal LRQ value. This is equivalent to solving the optimization problem P_1 by fixing $m_{k0} = -\sqrt{E_{u,k}}$ and $m_{k1} = \sqrt{E_{u,k}}$, for $k = 1, \ldots, N$. As a result, QDD can be viewed as the generalization of CDD, in which the amplitude of the symbols can be optimally selected based on the power constraint and the noise level in sensing and transmission. At the FC, the LRT rule is used, and the Bayes' errors of different systems are calculated.

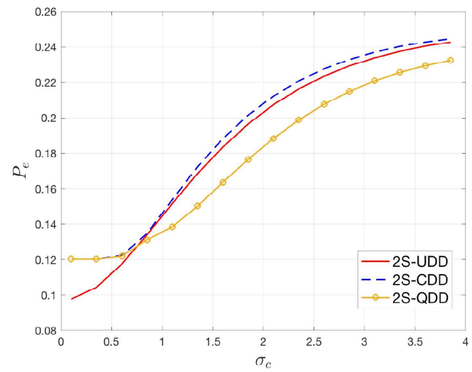

Fig. 3. Bayes error P_e. $\pi_1 = 0.75, \mu = 1, \sigma_s = 1.2$.

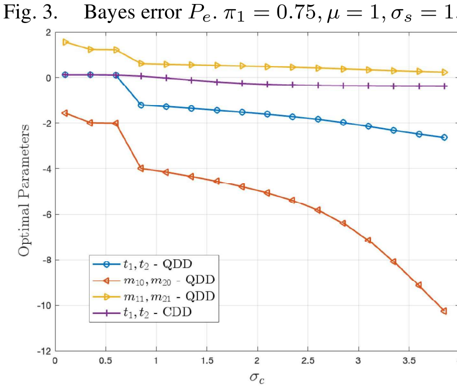

Fig. 4. Optimal sensor rules. $\pi_1 = 0.75, \mu = 1, \sigma_s = 1.2$.

Fig. 3 shows the comparison of the detection errors for a 2-sensors case. It can be observed that UDD always performs better than CDD in this scenario. While QDD performs worse than UDD and very similarly to CDD when $\sigma_c < 0.75$, it consistently performs better than UDD and CDD as σ_c increases. Be noted that when σ_c reduces, UDD approaches the centralized detection. When $\sigma_c \to 0$, the FC using UDD has complete information observed at sensors and hence can make the most accurate detection. Fig. 4 shows the optimal sensor decision parameters for both CDD and QDD. The obtained optimal sensor decisions are the same for the two sensors, in both CDD and QDD.

It needs to be noted that problem P_1 is generally nonconvex. The complexity of solving it depends on the solver used. Using the global search algorithm in MatLab typically takes a few minutes to obtain a solution for QDD. In practice, these parameters can be computed offline and preset at sensors.

V. Conclusion

In this letter, we have proved the optimality of using LRQs as the sensor decision rules in QDD for $D = 2$, when the sensor observations are conditionally independent given the hypotheses. Therefore, with performance improvement over CDD, QDD may also retain low complexity in system design in certain cases. This work considers $D = 2$ only, the optimal sensor decision rules for $D > 2$ deserve more research efforts in the future.

Appendix A
Proof of Theorem 1

Considering a specific sensor while the decision rules of other sensors and the fusion rule are fixed, our approach is to show that for the sensor under consideration, the LRQ rule can perform at least as well as any non-LRQ rule, with less or equal power that is used by the non-LRQ rule. Consider two possible decision rules to be used in the sensor: one is a non-LRQ rule, in which the sensor reports either m_0 or m_1 to the FC, where m_0, m_1 satisfy the power constraint (4), and the other is an LRQ rule. Suppose that this LRQ rule also uses the same m_0 and m_1 as the non-LRQ rule used for reporting. Denote $P_f = P(m_1|H_0), P_d = P(m_1|H_1)$ as the false alarm and detection probabilities at the sensor for the non-LRQ rule, and P_f^*, P_d^* as the false alarm and detection probabilities for the LRQ rule. Based on Neyman-Pearson's Lemma, for any non-LRQ rule, we can always find an LRQ rule such that $P_d^* \geq P_d$ if $P_f^* = P_f$, or $P_f^* \leq P_f$ if $P_d^* = P_d$.

When H_0 is true, the average symbol energy of the systems using non-LRQ and LRQ rules are as follows:

$$\begin{aligned} E_T &= (1 - P_f)m_0^2 + P_f m_1^2, \\ E_T^* &= (1 - P_f^*)m_0^2 + P_f^* m_1^2. \end{aligned} \tag{5}$$

When H_1 is true, we have

$$\begin{aligned} E_T &= (1 - P_d)m_0^2 + P_d m_1^2, \\ E_T^* &= (1 - P_d^*)m_0^2 + P_d^* m_1^2. \end{aligned} \tag{6}$$

If $m_0^2 \leq m_1^2$, suppose that $P_d^* = P_d$, then we have $E_T = E_T^*$ under H_1 but $E_T^* \leq E_T$ under H_0. If $m_0^2 > m_1^2$, suppose $P_f^* = P_f$, we have $E_T = E_T^*$ under H_0 but $E_T^* \leq E_T$ under H_1. In other words, for any non-LRQ rule, we can always find an LRQ rule that uses the same m_0, m_1 but with less or equal transmission power compared to the non-LRQ rule. It must be noted that m_0, m_1 sent in the LRQ rule might not be the optimal values that lead to the best performance.

Next, we follow the approach used in [10] to show the optimality of LRQ at sensors under both NP and Bayesian criteria at the FC. Let $U_0 = \gamma_0(Z_1^M)$ be the final decision at the FC, and $U_0 = j$ decides $H_j, j = 0, 1$. Let P_F and P_D be the false alarm and detection probabilities after the FC has made a final decision, respectively. When the non-LRQ rule is used for sensor k,

$$\begin{aligned} P_F &= P(U_0 = 1|H_0) = P(U_0 = 1, Y_k = m_0|H_0) \\ &\quad + P(U_0 = 1, Y_k = m_1|H_0) \\ &= P(U_0 = 1|Y_k = m_0, H_0) + a_k P(Y_k = m_1|H_0) \\ &= P(U_0 = 1|Y_k = m_0, H_0) + a_k P_f \end{aligned} \tag{7}$$

where

$$a_k = P(U_0 = 1|Y_k = m_1, H_0) - P(U_0 = 1|Y_k = m_0, H_0). \tag{8}$$

Similarly,

$$\begin{aligned} P_D &= P(U_0 = 1|H_1) = P(U_0 = 1, Y_k = m_0|H_1) \\ &\quad + P(U_0 = 1, Y_k = m_1|H_1) \\ &= P(U_0 = 1|Y_k = m_0, H_1) + b_k P(Y_k = m_1|H_1) \\ &= P(U_0 = 1|Y_k = m_0, H_1) + b_k P_d \end{aligned} \tag{9}$$

where

$$b_k = P(U_0 = 1|Y_k = m_1, H_1) - P(U_0 = 1|Y_k = m_0, H_1). \tag{10}$$

In the above, only P_f and P_d are related to the decision rule used in sensor k. Other terms, including $a_k, b_k, P(U_0 = 1|Y_k = m_0, H_0), P(U_0 = 1|Y_k = m_0, H_1)$, are only related to the channel features and the fusion decision. It is left to show that we can always find an LRQ rule for sensor k that improves the final performance at the FC, i.e., (P_F^*, P_D^*), over that of the non-LRQ rule.

1) When $a_k > 0, b_k > 0$, an LRQ rule can be found so that $P_f^* \leq P_f$ and $P_d^* \geq P_d$. Based on (7) and (9), we have $P_F^* \leq P_F$ and $P_D^* \geq P_D$.
2) When $a_k > 0, b_k < 0$, we can select an LRQ rule with a threshold of ∞, i.e., the sensor always sends m_0. Then $P_d^* = 0$ and $P_f^* = 0$. Returning to (7) and (9), it gives a performance of (P_F^*, P_D^*) that is better than or equal to (P_F, P_D).
3) When $a_k < 0, b_k > 0$, we can select an LRQ rule with a threshold of 0, i.e., the sensor always send m_1. Then $P_d^* = 1$ and $P_f^* = 1$. Returning to (7) and (9), it gives a performance of (P_F^*, P_D^*) that is better than or equal to (P_F, P_D).
4) When $a_k < 0, b_k < 0$, we may use the LRQ in "1." but switch the decision of U_0 from '0' to '1' and from '1' to '0', which is equivalent to minimizing (maximizing) the sensor detection probability (false alarm probability). Returning to (7) and (9), it gives a performance of (P_F^*, P_D^*) that is better than or equal to (P_F, P_D).

As a result, considering sensor k while other sensor decisions and fusion rules are fixed, for any non-LRQ decision rule, we can always find an LRQ rule that uses the same m_0, m_1 as the non-LRQ rule uses but gives the same or better detection performance with at most the same transmission power used by the non-LRQ rule. In addition, an LRQ rule with optimized m_0, m_1 under the power constraint cannot perform worse than the one simply adopting the m_0, m_1 values used by the non-LRQ rule. Therefore, the optimality of LRQ sensor rules has been established under Neyman-Pearson's criterion.

Under the Bayesian criterion, the detection error probability $P_e = \pi_0 P_F + \pi_1(1 - P_D)$. Using (7) and (9), we obtain

$$P_e = c_k + a_k \pi_0 P_f - b_k \pi_1 P_d \tag{11}$$

where $c_k = \pi_0 P(U_0 = 1|Y_k = m_0, H_0) + \pi_1(1 - P(U_0 = 1|Y_k = m_0, H_1))$ is a value irrelevant to the sensor decision rule. As a result, following the four cases of a_k and b_k and the proof for the NP criterion, it shows directly for any non-LRQ rule, we can always find an LRQ rule with the detection error probability $P_e^* \leq P_e$. □

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