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Distributed Estimation Using Non-regular Quantized Data

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Abstract

We consider a distributed estimation where many nodes remotely placed at known locations collect the measurements of the parameter of interest, quantize these measurements, and transmit the quantized data to a fusion node; this fusion node performs the parameter estimation. Noting that quantizers at nodes should operate in a non-regular framework where multiple codewords or quantization partitions can be mapped from a single measurement to improve the system performance, we propose a low-weight estimation algorithm that finds the most feasible combination of codewords. This combination is found by computing the weighted sum of the possible combinations whose weights are obtained by counting their occurrence in a learning process. Otherwise, tremendous complexity will be inevitable due to multiple codewords or partitions interpreted from non-regular quantized data. We conduct extensive experiments to demonstrate that the proposed algorithm provides a statistically significant performance gain with low complexity as compared to typical estimation techniques.

Index Terms: Distributed estimation, Non-regular design, Quantizer design, Sensor networks, Source localization

I. INTRODUCTION

We consider distributed estimation systems where many sensor nodes located at known sites gather measurements of the parameter of interest and quantize them before sending the data to a fusion node that executes the parameter estimation on the basis of the received quantized data. For these systems, particularly for power-constrained systems such as sensor networks, the design of the quantizers at the local nodes has a critical impact on the estimation performance. Thus, efficient quantization techniques have been suggested to achieve a statistically significant performance gain as compared to typical designs [1-7]. For example, the probabilistic distance between two hypotheses was employed as a cost function to yield a manageable design flow for distributed detection [1]. Necessary conditions were examined for constructing quantization partitions for distributed estimation systems [2]. For source localization in acoustic sensor networks, a novel algorithm was proposed to design local quantizers that minimize the localization error while maintaining a regular design by searching for appropriate weights [3, 4].

Most of the previous designs were developed on the basis of a regular quantization framework in which an infinite number of measurements are mapped to a given finite number of codewords such that the cost function is minimized. This minimization is achieved by maintaining a regular mapping structure where a single measurement belonging to a quantization partition is mapped to a single codeword. However, the resulting local quantizers have

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been operated in a *non-regular* manner in order to improve the system performance, implying that the same codeword is mapped to multiple disjoint partitions [8]. Further, a merging technique to systematically transform regular quantizers into non-regular ones was proposed for achieving a substantial rate reduction without degrading the estimation accuracy [9]. In addition, an iterative algorithm for designing non-regular quantizers for a distributed estimation was devised in the Lloyd design framework [6], illustrating the structural advantage of non-regular designs. A novel encoding of quantization partitions into codewords was recently proposed to construct non-regular quantizers by allowing multiple codewords corresponding to each quantization partition [10].

Previous estimation techniques have been noted to assume a single codeword or quantization partition if a quantization index is received from a single node. However, when non-regular quantization is employed at the nodes, a fusion node should be able to interpret a single quantization index as multiple codewords or quantization partitions so as to achieve an efficient estimation on the basis of the received non-regular quantized data. In this study, we first assume non-regular quantizers at the nodes and seek to develop a practical estimation algorithm that obtains the most feasible combination by computing the weighted sum of the possible combinations generated from non-regular quantized measurements. Since the number of combinations from non-regular quantized data would significantly exceed that from regular ones, a huge computational complexity to compute the weights of these combinations would be inevitable. Thus, to obtain a low-complexity algorithm, we adopt a learning process using training samples and compute the feasibility or weight by counting the occurrence of each combination. Further, we discuss that the proposed algorithm achieves a substantial reduction in the complexity for computing the weights as compared to a direct computation of the probability of the combinations. We also evaluate the proposed algorithm by a comparison of typical estimation techniques, showing that a significant gain in the estimation accuracy can be attained by using the proposed estimation technique through extensive experiments where regular and non-regular quantized data are generated with the quantizers designed in [4], [6], respectively.

The rest of this paper is organized as follows: The problem formulation for the distributed estimation is given in Section II. Non-regular quantization and estimation are elaborated in Section III, and the proposed estimation algorithm is summarized in Section III-A. In Section IV, a source localization system in acoustic sensor networks is introduced for the application of the proposed algorithm. Experimental results are provided in Section V, and the conclusions are presented in Section VI.

II. PROBLEM FORMULATION

In a sensor field $S \subset \mathbf{R}^N$, we assumed that M sensor nodes are spatially deployed at known locations, denoted by $\mathbf{x}_i \in \mathbf{R}^2$, $i = 1, \ldots, M$ and each node collects the measurements of the unknown parameter θ to be estimated. The measurement at node i, denoted by z_i, can be expressed as follows:

$$z_i(\theta) = f_i(\theta) + \omega_i, \quad i = 1, \ldots, M, \qquad (1)$$

where $f_i(\theta)$ indicates the sensing model employed at node i and the measurement is assumed to be contaminated with an additive noise ω_i approximated by the normal distribution $N(0, \sigma_i^2)$. The i-th node is assumed to quantize the measurement by using an R_i-bit quantizer before transmitting the quantization index j, where $j = 1, \ldots, L_i = 2^{R_i}$, to a fusion node. In particular, the quantizer at node i sends the quantization index j whenever z_i belongs to the j-th quantization partition. This partition can be defined as a single j-th codeword, a set of multiple codewords, or a union of disjoint partitions, depending on the quantization algorithms used at the node. Thus, a fusion node should produce the parameter estimate on the basis of the M-tuple quantization indices, each of which can be interpreted as a single codeword, multiple codewords, or union of quantization partitions, accordingly.

III. NON-REGULAR QUANTIZATION AND PROPOSED ESTIMATION ALGORITHM

In a typical parameter estimation, each node transmits the quantized measurement $\hat{z}_i$ to a fusion node that performs the parameter estimation on the basis of the received M-tuple$(\hat{z}_1, \ldots, \hat{z}_M)$. Note that the quantized measurement can be interpreted as a single region A_i where the parameter is found. In case of the minimum mean squared error (MMSE) estimation employed at the fusion node, the estimator is given as follows:

$$\hat{\theta} = E(\theta|\hat{z}_1, \ldots, \hat{z}_M) = E(\theta|A_1, \ldots, A_M), \qquad (2)$$

where $\hat{z}_i$ or A_i will be $\hat{z}_i^j$ or A_i^j if z_i is encoded to the j-th quantized measurement or quantization partition. However, to improve the rate distortion (RD) performance, non-regular encoding can be carried out in several ways: multiple disjoint quantization partitions or codewords can be mapped to a single measurement. Formally,

$$T_i : z_i \rightarrow V_i^j \ or \ C_i^j, j = 1, \ldots, L_i, \qquad (3)$$

where T_i defines the mapping at node i and V_i^j or C_i^j indicates a set of multiple disjoint quantization partitions or a set of multiple codewords, which can be constructed so as to minimize the cost functions such as the estimation error [6, 10].

First, the mapping between multiple partitions and measurements was proposed in [6] as follows:

$$V_i^j = \{Q_i^k : E_\theta[\|\theta(z_i) - \hat{\theta}(\hat{z}_i^j)\|^2 | z_i(\theta) \in Q_i^k] \\ \leq E_\theta[\|\theta(z_i) - \hat{\theta}(\hat{z}_i^l)\|^2 | z_i(\theta) \in Q_i^k], \forall l \neq j\}, \quad (4)$$

$$\hat{z}_i^j = arg\, min_{\hat{z}_i} E\left[\|\theta(z_i) - \hat{\theta}(\hat{z}_i)\|^2 | z_i \in V_i^j\right], \quad (5)$$

where K denotes the given number of quantization partitions $Q_i^k, k = 1, \dots, K \gg L_i$, which are initially constructed, and $\hat{\theta}(\hat{z}_i^j)$ is the abbreviated notation for $\hat{\theta}(\hat{z}_1, \dots, \hat{z}_i^j, \dots, , \hat{z}_M)$, which can be obtained using $\hat{z}_i^j$ for $\hat{z}_i$. Note that as K increases, the estimation performance improves at the cost of increased design complexity. Here, V_i^j represents the j-th set of multiple *possibly disjoint* quantization partitions that will be encoded to the j-th codeword $\hat{z}_i^j$ if such a mapping minimizes the distortion, producing a *non-regular* quantizer. Formally, the resultant set can be expressed as follows:

$$V_i^j = \{Q_i^j(1), \dots, Q_i^j(n_i^j)\}, j = 1, \dots, L_i, \quad (6)$$

where n_i^j denotes the partition index for the j-th set and if Q_i^j is assigned to the j-th set V_i^j by using (4), it will be the n_i^j-th element $Q_i^j(n_i^j)$ of the set. Clearly, $\sum_{j=1}^{L_i} n_i^j = K$. Therefore, we also use V_i^j to indicate a set of multiple codewords:

$$V_i^j = \{\hat{z}_i^j(1), \dots, \hat{z}_i^j(n_i^j)\},\ j = 1, \dots, L_i, \quad (7)$$

where $\hat{z}_i^j(n_i^j)$ denotes the centroid of the corresponding quantization partition $Q_i^j(n_i^j) \in V_i^j$. Notice from (4) that the encoding of multiple disjoint partitions into a single codeword is allowed so as to minimize the estimation error, whereas in a typical regular design framework, measurement samples belonging to a connected partition are assigned to a single codeword.

Secondly, the mapping between multiple codewords and measurements was recently published in [10]. First, quantization partitions $\hat{V}_i^j,\ j = 1, \dots, L_i$ that minimize the estimation error are generated as follows:

$$\hat{V}_i^j = \{z_i : E_{\theta|z_i}\|\theta(z_i) - \hat{\theta}(\hat{z}_i^j)\|^2 \\ \leq E_{\theta|z_i}\|\theta(z_i) - \hat{\theta}(\hat{z}_i^k)\|^2,\ \forall k \neq j\}, \quad (8)$$

$$\hat{z}_i^j = arg\, min_{\hat{z}_i} E\left[\|\theta(z_i) - \hat{\theta}(\hat{z}_i)\|^2 | z_i \in \hat{V}_i^j\right], \quad (9)$$

where $\hat{V}_i^j$ denotes the j-th quantization partition consisting of measurement samples and constructed to minimize the estimation error. Further, if z_i is encoded to $\hat{V}_i^j$ from (8), $\hat{\theta}(\hat{z}_i^j)$, the abbreviated form of $\hat{\theta}(\hat{z}_1, \dots, \hat{z}_i^j, \dots, \hat{z}_M)$ is computed by using $\hat{z}_i^j$ in place of $\hat{z}_i, \forall i$. Note that $\hat{V}_i^j$ in (8) is a single partition of the measurement samples and is thus different from V_i^j in (4). Considering $C_i^j,\ j = 1, \dots, L_i$, a set of codewords corresponding to $\hat{V}_i^j$, the set is constructed by appending the n_i^j-th element of the measurement z_i belonging to $\hat{V}_i^j$ but encoded to the other partitions $\hat{V}_i^k, k \neq j$:

$$C_i^j = \{\hat{z}_i^j(1), \dots, \hat{z}_i^j(n_i^j)\},\ j = 1, \dots, L_i, \quad (10)$$

where the codeword index n_i^j is increased to the cardinality of the set and z_i is regarded as $\hat{z}_i^j(n_i^j)$ if it is assigned to the j-th codeword set C_i^j.

Once the partition sets or codeword sets are constructed from (7) and (10), respectively, the independent encoding of the local measurement z_i into such sets at each node can be simply conducted as follows:

$$\hat{z}_i^j = arg \min_{j, n_i^j} |z_i - \hat{z}_i^j(n_i^j)|^2, \\ j = 1, \dots, L_i, n_i^j = 1, \dots, |V_i^j|. \quad (11)$$

Note that although efficient mappings between multiple partitions (or codewords) and measurements have been proposed to improve the estimation performance, estimation at the fusion node has been conducted by interpreting each non-regular quantization index transmitted from the nodes as a single codeword, not multiple partitions or codewords. In other words, the best single codeword $\hat{z}_i^j$ corresponding to V_i^j or C_i^j (see (5) and (9), respectively) is computed to represent the multiple partitions or codewords and used at the fusion node for the estimation, imposing a limited use of information of non-regular quantized data upon the estimation.

However, if multiple partitions or codewords in V_i^j or C_i^j are efficiently used for the estimation at the fusion node, the estimation accuracy will be significantly improved. Note that a direct use of multiple partitions or codewords in traditional estimation methods yields a huge computational complexity. In particular, the MMSE estimator denoted by $\hat{\theta}_{NR}$ on the basis of the non-regular quantization for the case of multiple partitions can be expressed as follows:

$$\hat{\theta}_{NR} = E[\theta | V_1, \dots, V_M] \\ = E[[\theta | Q_1^j(1), \dots, Q_1^j(n_i^j), \dots, Q_M^l(1), \dots, Q_M^l(n_i^l)] \\ = E[[\theta | \hat{z}_1^j(1), \dots, \hat{z}_1^j(n_i^j), \dots, \hat{z}_M^l(1), \dots, \hat{z}_M^l(n_i^l)], \quad (12)$$

where $V_1 = V_1^j$ and $V_M = V_1^l$ are assumed. As expected, the computation of (12) will be extremely costly and thus, will be efficient to first find the best combination of the *M*-tuple codewords from all the possible combinations that can be generated from the received *M*-tuple quantization partition sets $(V_1, \ldots, V_M)$. Note that this approach allows us to select one of the multiple codewords or partitions depending on measurements at the other nodes so as to minimize the estimation error when each measurement can be mapped to multiple partitions or codewords, whereas the typical estimation assumes a single partition or codeword, irrespective of the other quantized measurements.

A mathematical expression to find the best combination from the received *M*-tuple $(V_1, \ldots, V_M)$ can be provided as follows:

$$\hat{\boldsymbol{z}}_1^{M*} = arg\,min_{\hat{z}_1 \in V_1, \ldots, \hat{z}_M \in V_M} E\left[\left\|\theta(z_i) - \hat{\theta}(\hat{z}_i)\right\|^2 | V_1, \ldots, V_M\right], \quad (13)$$

where $\hat{\boldsymbol{z}}_1^{M*}$ indicates a vector of $(\hat{z}_1^*, \ldots, \hat{z}_M^*)$ and the *i*-th node is assumed to send V_i, which consists of multiple partitions (equivalently, multiple codewords), all of which are searched to find the best combination to minimize the estimation error. Obviously, the computational complexity of (13) is still beyond practical implementation because of the conditional expectation for a large number of possible combinations. To further reduce the complexity, the weighted sum of the combinations that are likely to occur given the received *M*-tuple $(V_1, \ldots, V_M)$ should be calculated:

$$\hat{\boldsymbol{z}}_1^{M*} = \sum_{\hat{z}_1 \in V_1, \ldots, \hat{z}_M \in V_M} \hat{z}_1^M \, P[(\hat{z}_1, \ldots, \hat{z}_M) \,|V_1, \ldots, V_M], \quad (14)$$

where $P[(\hat{z}_1, \ldots, \hat{z}_M) \,|V_1, \ldots, V_M]$ denotes the probability or feasibility of the combination $(\hat{z}_1, \ldots, \hat{z}_M)$ given the received *M*-tuple. Although a substantial reduction in the complexity of finding the best combination is provided by (14), a high computational cost to obtain the best combination may still be needed if the cardinality of $V_i, i = 1, \ldots, M$, is large. In this work, we further suggest a low-weight technique to compute the best combination by using training samples in a learning process.

A. Summary of Proposed Algorithm

Given the number of quantization levels, $L_i = 2^{R_i}$, the algorithm to compute the best combination for the partition sets $V_i^j, \forall i, j$ is summarized as follows: Note that the algorithm can be applied to the case of codeword sets $C_i^j, \forall i$, with V_i^j and $\hat{z}_i^j(n_i^j)$ replaced with C_i^j and $\hat{z}_i^j(n_i^j)$, respectively.

Algorithm: Proposed algorithm to find the best combination for non-regular quantized data

Step 1: Set frequency index $p(l, k_l) = 0, l = 1, \ldots, L = \prod_{i=1}^M L_i$, where l denotes the increase in the number of all possible combinations of *M*-tuple $(V_1, \ldots, V_M)$ and k_l indicates the k_l-th combination belonging to the *l*-th *M*-tuple $(V_1, \ldots, V_M)$. Note that k_l is increased to the number of all possible combinations of the *M*-tuple codewords $(\hat{z}_1(n_i), \ldots, \hat{z}_M(n_i))$, where $\hat{z}_i(n_i) \in V_i, n_i = 1, \ldots, |V_i|$.

Step 2: For each training sample $\boldsymbol{z}_1^M(\theta) = (z_1, \ldots z_M)$, find the codewords $\hat{z}_i, i = 1, \ldots, M$ by using (11).

Step 3: Increase the frequency index $p(l, k_l) = p(l, k_l) + 1$ if $(V_1, \ldots, V_M)$ denotes the *l*-th combination and $(\hat{z}_1, \ldots, \hat{z}_M)$ obtained in Step 2 represents the k_l-th combination.

Step 4: Repeat Steps 2 and 3 for all the training samples.

Once the frequency indices $p(l, k_l)$ are computed, the best combination $(\hat{z}_1^*, \ldots, \hat{z}_M^*)$ corresponding to the *l*-th *M*-tuple $(V_1, \ldots, V_M)$ is chosen as the weighted sum given by $\sum_{k_l} \hat{\boldsymbol{z}}_1^M p(l, k_l)$. Thus, the proposed estimation technique based on non-regular data can be expressed as follows:

$$\hat{\theta} = E[\theta | V_1, \ldots, V_M] \approx E[\theta | \hat{z}_1^*, \ldots, \hat{z}_M^*] \;. \quad (15)$$

IV. APPLICATION OF DESIGN ALGORITHM

For the evaluation, we apply the proposed estimation algorithm to a source localization system in acoustic sensor networks, which is briefly introduced in this section. Each sensor node is assumed to obtain the source signal energy by using an energy decay model proposed and verified by the field experiment in [11]. Note that the sensor model was widely used for an energy-based source location [12-14]. Formally, the signal energy measurement at sensor *i*, denoted by z_i, can be expressed as follows:

$$z_i(\theta) = g_i \frac{a}{\|\theta - x_i\|^\alpha} + \omega_i \;, \quad (16)$$

where θ indicates the source location to be estimated and $f_i(\theta)$ represents an acoustic sensor model with the gain factor of the *i*-th sensor g_i and an energy decay factor α approximately equal to 2. The additive noise w_i is assumed to be approximated by using a normal distribution, $N(0, \sigma_i^2)$. In this work, we also assumed that the source signal energy a is known for the estimation in our evaluation of the proposed algorithm. Note that the signal energy is typically unknown and can be jointly estimated with the source location [14].

V. SIMULATION RESULTS

In this section, by assuming the model parameters in (16) given by $\sigma_i^2 = \sigma^2 = 0$ and $a = 50$, $\alpha = 2$, and $g_i = 1$, we collect training samples from the assumption of a uniform distribution of source locations and design regular and non-regular quantizers denoted by the localization-specific quantizer [4] and the distributed optimized quantizer [6], respectively. Once the non-regular quantizers are designed, we generate non-regular training samples in the simulation condition assumed during the quantizer design process. By using the algorithm proposed in Section III-A, we find the most feasible combination for each of the possible M-tuple quantization indices and calculate the average localization error $E\|\theta-\hat{\theta}\|^2$ by using the maximum likelihood (ML) estimation for fast computation. In the experiments, we gather training and test samples from 100 different configurations of M = 5 sensor nodes deployed in a 10 m × 10 m sensor field.

A. Performance Comparison with Typical Estimation Algorithm based on Regular and Non-regular Quantization

In this experiment, we compare the proposed estimation technique with the ML estimator, one of the typical estimation methods. For a typical estimation, we use the combination that represents the received M-tuple quantization indices, whereas we compute the weighted sum of the combinations for our estimation that are likely to occur given the M-tuple indices. Note that once the combination is found, the combination-based estimation is performed using the ML estimator for a fair comparison. In Fig. 1, the RD curves are plotted for regular and non-regular quantized data, and as expected, the proposed estimation technique produces a substantially improved estimation performance with respect to the typical estimation method. Note that the proposed algorithm operates considerably faster to find the best combination than directly calculating the probabilities of all the combinations. In testing the estimation algorithms, we generate test samples of 1,000 source locations for each configuration with σ_i = 0 and gather regular and non-regular quantized data by varying R_i = 2, 3, 4 bits.

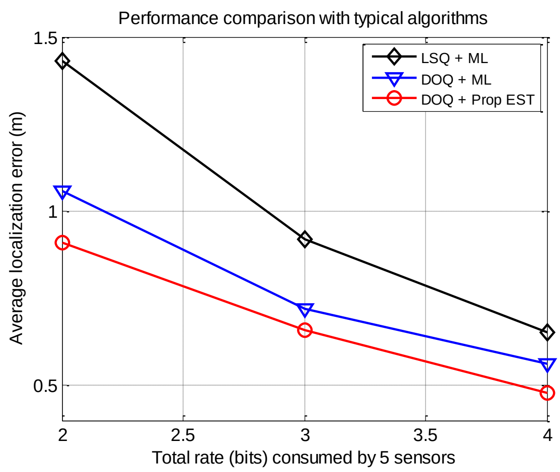

Fig. 1. Comparison of proposed estimation with typical ML estimation: average localization error is plotted vs. the rate R_i (bit). LSQ: localization-specific quantizer, ML: maximum likelihood, DOQ: distributed optimized quantizer, Prop EST: proposed estimation.

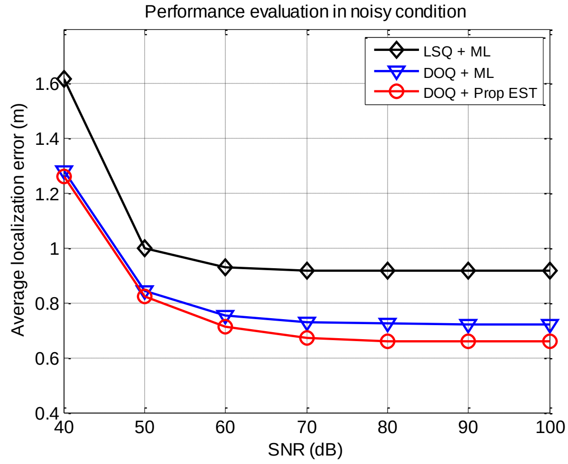

Fig. 2. Performance evaluation under a noisy condition: average localization error is plotted vs. the signal-to-noise ratio (SNR) with M = 5, R_i = 3, and a = 50. LSQ: localization-specific quantizer, ML: maximum likelihood, DOQ: distributed optimized quantizer, Prop EST: proposed estimation.

B. Performance Evaluation in Presence of Measurement Noise

We examine the sensitivity of the estimation algorithms with respect to the measurement noise by generating a test set of 1,000 source locations for each configuration with a = 50. For each of the test sets, we gather the noise-corrupted test samples by varying $\sigma_i = \sigma$, which can be expressed in terms of the signal-to-noise ratio (SNR) in the range of 40 dB to 100 dB. Note that the SNR is given by 10 log10 a^2/σ^2 measured at 1 m from the source location. Typical vehicles have been observed to generate a considerably higher noisy engine sound than 40 dB and the noise variance typically takes a value of σ^2 = 0.052 (=60 dB) [11, 13]. In Fig. 2, we demonstrate that the proposed estimation algorithm still operates robustly under noisy conditions as compared to the typical techniques, implying that finding the best combination should become an integral part of the estimation for distributed systems with non-regular quantization.

C. Sensitivity of Proposed Algorithm to Parameter Perturbation

We investigate the sensitivity of the proposed estimation to the parameter perturbation. In this experiment, we

Table 1. Localization error (LE) of the proposed estimation technique with R_i = 3 due to variations of the model parameters

Decay factor α	LE	Gain factor g_i	LE
1.8	1.2577	0.8	1.0559
1.9	0.9148	0.9	0.7731
2.0	0.6610	1.0	0.6610
2.1	0.9207	1.1	0.7619
2.2	1.2771	1.2	0.9247

LE is computed in meters by taking the average of 100 5-sensor configurations.

generate a test set of 1,000 source locations with a = 50 for each configuration by varying one of the model parameters. The experimental results presented in Table 1 show robustness to mismatch conditions where the parameters such as decay factor α and gain factor g_i are perturbed from the parameter values used in the quantizer design.

VI. CONCLUSION

In this paper, we have proposed a distributed estimation algorithm that makes full use of non-regular quantized data by finding the most feasible combination for each of the received quantized indices with a substantially reduced design complexity. We applied the proposed algorithm for source localization to acoustic sensor networks and demonstrated that a significant performance gain can be achieved by computing the weighted sum of the probable combinations given the received non-regular quantized data. Since non-regular quantization is expected to become attractive for distributed systems to improve system performance, we intend to develop a joint design methodology for non-regular quantization and estimation in the future.

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