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Cluster-Based Quantization and Estimation for Distributed Systems

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Abstract

We consider a design of a combined quantizer and estimator for distributed systems wherein each node quantizes its measurement without any communication among the nodes and transmits it to a fusion node for estimation. Noting that the quantization partitions minimizing the estimation error are not independently encoded at nodes, we focus on the parameter regions created by the partitions and propose a cluster-based quantization algorithm that iteratively finds a given number of clusters of parameter regions with each region being closer to the corresponding codeword than to the other codewords. We introduce a new metric to determine the distance between codewords and parameter regions. We also discuss that the fusion node can perform an efficient estimation by finding the intersection of the clusters sent from the nodes. We demonstrate through experiments that the proposed design achieves a significant performance gain with a low complexity as compared to the previous designs.

Index Terms: Clustering, Distributed estimation, Distributed quantization, Sensor networks, Source localization

I. INTRODUCTION

Distributed systems such as sensor networks are used for many applications such as environmental monitoring, healthcare monitoring, and target positioning applications. In these systems, battery-powered sensor nodes are deployed in a sensor field to collect measurements for the parameter of interest. Each node quantizes its measurement before transmission to a fusion node that conducts the estimation on the basis of the received quantized data. Much effort has been made to improve the estimation performance by developing efficient design algorithms for quantizers at nodes or estimation techniques at the fusion node.

The generalized Lloyd algorithm known as a standard design framework has been used for designing independently operating quantizers at nodes for distributed systems wherein the sensor nodes transmit their local measurements directly to a fusion node via reliable communication links without exchanging data with the other sensor nodes. Since the Lloyd design was developed to minimize a local metric (i.e., reconstruction error), it should be properly modified so as to minimize a system-wide metric such as the estimation error. A direct replacement of the local metric by a global one typically causes a design difficulty. In other words, the global metric should be reduced at each iteration, while local measurements can be *independently* encoded or mapped into the corresponding partitions or codewords. However, the independent encoding of the quantization

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partitions constructed to optimize the global metric (i.e., a cost function of all the local measurements) would be impossible without the computation of the global metric that requires measurements at the other nodes.

Various novel design techniques have been presented to tackle the abovementioned difficulty. First, instead of directly using the global metric, new related cost functions have been suggested to ensure that the design algorithm guarantees both the non-increasing global metric and the independent encoding [1-5]. For distributed detection systems, the probabilistic distance between the distributions under two hypotheses was used for quantizer design to have a manageable design flow [1]. The weighted metric (i.e., local + weight × global) was introduced to design local quantizers for acoustic sensor networks [2, 3]. In [4], a functional quantizer design method was proposed for the Lloyd framework and an efficient technique for updating codewords was presented to accelerate the design process.

Second, efficient encoding techniques have been proposed to directly handle the optimized quantization partitions. The construction of the quantization partitions and the necessary conditions have been considered for distributed estimation systems [6]. An iterative quantizer design algorithm was presented for the Lloyd framework to show that the resulting scalar quantizers should operate in a *non-regular* manner to reduce the distortion, implying that several disjoint partitions are assigned to the same codeword [7]. A systematic transformation technique from regular quantizers to non-regular ones was proposed and applied for source localization, showing a noteworthy improvement in localization performance through experiments [8]. The non-regularity was systematically incorporated into the Lloyd design in [5]. In this approach, fine quantization partitions (e.g., fine intervals in scalar quantizers) are initially constructed and the non-regular mapping from multiple partitions to a single codeword that minimizes the estimation error is searched for in an iterative manner. As expected, the non-regular design showed an obvious advantage in performance over the regular design at the cost of increased complexity. Recently, novel approaches to quantization have been introduced. A set of multiple codewords corresponding to each quantization partition is allowed to enable the independent encoding [9] and a probabilistic distance based on the Kullback–Leibler (KL) divergence is minimized to construct the independent encoding for a distributed estimation [10].

In this paper, we consider a design algorithm for combined quantization and estimation in distributed systems. Instead of formulating a new cost function (e.g., weighted sum [3] or functional metric [4]) for the quantizer design, we develop a novel encoding technique that allows each node to perform an independent encoding of the quantization partitions constructed to optimize the global metric. Motivated by the observation that once such partitions are constructed, the parameter space is divided into many regions, each corresponding to the intersection of the quantization partitions transmitted from the sensor nodes involved, we focus on encoding the parameter regions into codewords and not the quantization partitions, the encoding of which has been previously attempted. We propose a cluster-based encoding algorithm that seeks to build a given number of clusters of parameter regions, each region more similar to the corresponding codeword than to the others such that the average similarity at each node is maximized. Note that the fusion node can estimate a parameter by taking a centroid of the region obtained from the intersection of the parameter regions sent from the sensor nodes. While assessing the similarity between codewords and parameter regions, we introduce a new distance metric and create clusters by collecting the parameter regions closest to the corresponding codeword so as to minimize the average distance metric at each node. Note that the proposed algorithm deals with the parameter regions generated from the optimized quantization partitions, not a large number of local measurement samples, leading to a low-weight design. We demonstrate through extensive experiments that the proposed quantization–estimation algorithm achieves a significant performance improvement with a low design complexity as compared to the previously proposed novel designs.

The main contributions of this work are as follows: (a) we introduce a new distance metric between codewords (e.g., real value in scalar quantizers) and parameter regions (e.g., multidimensional space); (b) we propose a cluster-based quantization–estimation technique that performs well with respect to the previously proposed novel design techniques with a substantially reduced design complexity.

The rest of this paper is organized as follows: the problem formulation is presented in Section II. Motivation for our cluster-based algorithm is discussed in Section III, and the proposed design based on clusters is explained in Section IV. An application example for our design is introduced in Section V. Simulation results are presented in Section VI, and the conclusions are given in Section VII.

II. PROBLEM FORMULATION

We consider a distributed estimation system where M sensor nodes are deployed at known spatial locations, denoted by $\mathbf{x}_i \in \mathbf{R}^2$, $i = 1, \ldots, M$, and each node gathers sensor readings on the unknown parameter in a sensor field $S \subset \mathbf{R}^N$. The reading or the measurement, denoted by z_i at node i can be expressed as follows:

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

where $f_i(\theta)$ denotes the sensing model employed at node i and ω_i represents the measurement noise that is assumed to be approximated by the normal distribution $N(0, \sigma_i^2)$. It is also assumed that we use an R_i-bit quantizer with quantization level $L_i = 2^{R_i}$ at node i, which maps or encodes its local measurement z_i to one of the pre-computed quantization partitions Q_i^j $j = 1, \ldots, L_i$ if the mapping to the j-th partition satisfies a certain criterion. Note that the quantization partition may take various implications, depending on how the partitions are constructed during the design process. For example, in the standard quantizer design, the j-th partition typically indicates the codeword (or reconstruction value) $\hat{z}_i^j$, which is actually used for the estimation in the fusion node. However, if we define the partition as a set of M-tuple codewords $(\hat{z}_1, \ldots, \hat{z}_M)$ or a set of candidate parameter regions and construct them accordingly, then the fusion node would interpret it as such for the estimation. In this work, we first generate the quantization partitions optimized for a distributed estimation, and on the basis of these partitions, we propose an efficient encoding technique that can be independently conducted at each node.

III. MOTIVATION FOR CLUSER-BASED DESIGN APPROACH

Quantization is a process of data compression achieved by mapping an infinite number of measurements z_i to a finite number of codewords $\hat{z}_i^j$, $j = 1, \ldots, L_i$. The standard quantizer design is implemented by first constructing quantization partitions Q_i^j $j = 1, \ldots, L_i$, and then, computing the corresponding codeword for each partition so as to minimize a distortion such as the reconstruction error. Hence, the encoding of measurements into codewords is straightforward because measurements belonging to one of the quantization partitions will be automatically closer to the corresponding codeword than to the others. Formally,

$$Q_i^j = \left\{ z_i : \left| z_i - \hat{z}_i^j \right|^2 \le \left| z_i - \hat{z}_i^k \right|^2,\ \forall k \ne j \right\}. \quad (2)$$

For applying the standard quantization process to the design of quantizers at the nodes for a distributed estimation, various novel algorithms with appropriate distortions have been devised such that an efficient partitioning of the dynamic range could be accomplished in a way that the estimation error is iteratively reduced in the design process. Once the partitioning is completed, each codeword is updated as the centroid of the corresponding partition so as to further minimize the estimation error. Clearly, the codeword would be more optimized if it is obtained from better partitions.

However, since quantization at each node should be conducted *independently*, the quantization partitions should be identifiable by using only the local measurement. Hence, instead of pursuing an optimal partitioning, most of the design algorithms for distributed systems focus on the construction of quantization partitions that are disjoint with each other and regular (i.e., there is a one-to-one correspondence between partitions and codewords) such that the encoding of measurements into partitions can be independently executed by simply choosing the codeword closest to the measurements [3, 4]. To further improve the performance, the structural constraint can be relieved to have a many-to-one correspondence, namely *non-regularity* at the cost of increased design complexity and higher memory requirement for the storage of mapping information for independent encoding [5].

In this work, we first consider the construction of the partitions and their codewords optimized for a distributed estimation that would be *jointly* encodable (i.e., on the basis of all the codewords from the nodes) and seek to find an efficient independent encoding technique that operates on these optimized partitions and codewords. Similar to the standard quantizer design, we construct the quantization partitions as follows:

$$V_i^j = \{ z_i(\theta) : E_{\theta|z_i} \left\| \theta(z_i) - \hat{\theta}(\hat{z}_i^j) \right\|^2 \le E_{\theta|z_i} \left\| \theta(z_i) - \hat{\theta}(\hat{z}_i^k) \right\|^2, \forall k \ne j \} , \quad (3)$$

where $\hat{\theta}(\hat{z}_i^j)$, the shortened form of $\hat{\theta}(\hat{z}_1, \ldots, \hat{z}_i^j, \ldots, \hat{z}_M)$ denotes the estimate obtained from M codewords and the partition V_i^j consists of the measurement samples that would be mapped to the j-th codeword if the estimation error is minimized with $\hat{z}_i$ replaced by $\hat{z}_i^j$. In this work, the notation V_i^j, and not Q_i^j, is used for indicating the partitions constructed to optimize the global metric. Note that the partitions are not identifiable from each node since the estimation error is not correctly computed without the other codewords, which are not available at node i in real applications. Clearly, any samples in the vicinity of $z_i \in V_i^j$ can belong to other partitions irrespective of their distances to $\hat{z}_i^j$, implying a failure of the Euclidean distance-based mapping in (2).

Here, we continue to compute the codeword by using the partitions V_i^j, $j = 1, \ldots, L_i$ as follows:

$$\hat{z}_i^{j*} = \arg\min_{\hat{z}_i} E\left[\left\| \theta(z_i) - \hat{\theta}(\hat{z}_i) \right\|^2 | z_i \in V_i^j \right] . \quad (4)$$

Note that the codewords computed using the partitions in (3) represent the measurements in an optimal way such that the global metric (i.e., estimation error) is minimized and the optimal codewords can be obtained perfectly as long as the joint encoding in (3) is permitted at each node.

Further, note that if each node seeks to find its codeword by using only the local measurement, the combination of M

codewords $(\hat{z}_1, \ldots, \hat{z}_M)$ transmitted from M nodes may result in the combinations with low probabilities because the encoding is conducted independently without taking into account the codewords at the other nodes. Thus, it would be desirable for the encoding at each node to generate only the feasible combinations of codewords rather than the corresponding codeword. This can be efficiently accomplished by grouping all the possible combinations into L_i clusters; each node will send the cluster of the combinations that are the most feasible given the local measurement. Then, the fusion node will decode the received M clusters by choosing one combination or multiple combinations that belong to the intersection of these clusters for the estimation. This consideration motivates us to propose a clustering-based encoding technique, which will be elaborated in the subsequent section.

IV. PROPOSED QUANTIZATION AND ESTIMATION TECHNIQUE BASED ON CLUSTERING

In this section, we consider the generation of L_i clusters at each node where only the local measurement is available. As in the standard encoding procedure that produces the codeword closer to the measurement of the Euclidean distance than the other codewords, we adopt the minimum distance rule in the parameter domain: that is, assuming the K combinations $\hat{\mathbf{z}}^k = (\hat{z}_1, \ldots, \hat{z}_M),\ k = 1, \ldots, K \gg L_i$ with $\sum_{k=1}^{K} P(\hat{\mathbf{z}}^k) \approx 1$, we introduce the distance metric between the local measurement z_i and the k-th combination $\hat{\mathbf{z}}^k$, which is defined as follows:

$$\left\|z_i - \hat{\mathbf{z}}^k\right\|^2 \equiv \left[\!\left[A_\theta(z_i) - \hat{\theta}^k\right]\!\right]^2 \equiv \min_{\theta \in A_\theta(z_i)} \left\|\theta - \hat{\theta}^k\right\|^2, \quad (5)$$

where $A_\theta(z_i)$ denotes a set of parameters with $P(\theta \in A_\theta(z_i)|z_i) \approx 1$ and $\hat{\theta}^k$ is obtained by taking the centroid of the parameter region A_θ^k constructed from the k-th combination $\hat{\mathbf{z}}^k$: formally, $P(\theta \in A_\theta^k|\hat{\mathbf{z}}^k) \approx 1$. This specifies the distance between the k-th combination $\hat{\mathbf{z}}^k$ and the local measurement z_i in the parameter domain. Note that the sets $A_\theta(z_i)$ and A_θ^k are constructed by using the training sets generated under the assumption of noiseless measurements (i.e., $\omega_i = 0$ in (1)) to avoid a computational burden. The performance of the proposed algorithm will be experimentally evaluated in the presence of the measurement noise in Section VI. When the parameter is directly accessible by each node (i.e., $z_i = \theta + \omega_i$), the distance metric is reduced to $\|z_i - \hat{\mathbf{z}}^k\|^2 \equiv \left\|\theta - \hat{\theta}^k\right\|^2$.

Now, we are in a position to describe the cluster-based independent encoding algorithm that seeks to minimize the average distance at each node given by $E_{z_i} = \left[\!\left[A_\theta(z_i) - \hat{\theta}^k\right]\!\right]^2$.

Algorithm: Cluster-based independent encoding algorithm at node i

Step 1: Initialize the codewords $\hat{z}_i^j, j = 1, \ldots, L_i$

Step 2: Group the combinations $\hat{\theta}^k, k = 1, \ldots, K$ into L_i clusters C_i^j, $j = 1, \ldots, L_i$ so as to minimize the average distance as follows:

$$C_i^j = \left\{\hat{\theta}^k : \left[\!\left[A_\theta(\hat{z}_i^j) - \hat{\theta}^k\right]\!\right]^2 \le \left[\!\left[A_\theta(\hat{z}_i^j) - \hat{\theta}^l\right]\!\right]^2, \forall l \neq k\right\}. \quad (6)$$

Step 3: Update the codeword that minimizes the average distance over each cluster:

$$\hat{z}_i^{j*} = \arg\min_{\hat{z}_i} E\left[\left\|A_\theta(\hat{z}_i) - \hat{\theta}\right\|^2 | \hat{\theta} \in C_i^j\right]. \quad (7)$$

Step 4: Repeat Steps 2 and 3 with $\hat{z}_i^j$ replaced by $\hat{z}_i^{j*}$ until there is no change in $\{\hat{z}_i^j\}, j = 1, \ldots, L_i$.

As opposed to the previously proposed design algorithms that deal with training measurement samples z_i for the design of quantizers, the proposed algorithm executes its iterative process over the K combinations $\hat{\theta}^k$ that are much smaller than the measurement samples, resulting in a low-weight design technique.

Clearly, the clusters C_i^j, $j = 1, \ldots, L_i$ can be identified at each node by finding the codeword closest to the local measurements. In particular, C_i^j is selected for the local measurement z_i at node i if $\left|z_i - \hat{z}_i^j\right|^2 \le \left|z_i - \hat{z}_i^k\right|^2, \forall_{k \neq j}$. Note that one of the clusters at each node is transmitted to a fusion node, which should be able to decode the received M clusters to obtain an estimate of the parameter $\hat{\theta}^*$. In this work, we suggest the following simple estimation technique:

$$C = \cap_{i=1}^{M} C_i, \qquad \hat{\theta}^* = E[\hat{\theta}|\hat{\theta} \in C], \quad (8)$$

where C_i denotes the selected cluster at node i. For the performance evaluation, our estimation technique in (8) is compared with the maximum likelihood estimation (MLE). Note that since the measurements are noise-corrupted in real situations, a few of these measurement samples may generate empty sets C at the fusion node. In our experiment, we apply the MLE technique to handle these samples for a fair comparison with MLE.

V. APPLICATION TO SOURCE LOCALIZATION IN ACOUSTIC SENSOR NETWORKS

We consider an acoustic sensor network for source localization where M sensor nodes equipped with acoustic amplitude sensors collect the signal energy generated from a sound source and transmit their quantized energy readings to a fusion node. To generate the signal energy measured at each node, we employ an energy decay model that was proposed and verified by a field experiment in [11] and was also used in [12-14]. Formally, the signal energy measurement at sensor i, denoted by z_i, can be expressed as follows:

$$z_i(\theta) = g_i \frac{a}{\|\theta - x_i\|^\alpha} + \omega_i, \quad (9)$$

where the sensing model $f_i(\theta)$ in (1) consists of the source signal energy a, the gain factor of the i-th sensor g_i, and the energy decay factor α, which is approximately equal to 2. It is assumed that the measurement noise ω_i is approximated using a normal distribution, $N(0, \sigma_i^2)$. Note that the signal energy a is typically unknown in real applications, but in this experiment, it is assumed to be known to a fusion node for source localization. Thus, the source signal energy can be jointly estimated with its location (refer to [14] for further details).

VI. SIMULATION RESULTS

In this section, we first generate the training set from the model parameters $\alpha = 2$, $g_i = 1$, and $a = 50$ in (1) under the assumption of a uniform distribution of source locations and a noiseless condition, i.e., $\sigma_i^2 = \sigma^2 = 0$. We design our quantizers and estimators using the algorithms described in Section IV, denoted by the cluster-based quantizer and estimator (CQE). In the experiments, we consider an acoustic sensor network where M (=5) sensors are randomly placed in a sensor field measuring 10 m × 10 m. We generate 100 different sensor configurations, and for each of these configurations, we design uniform quantizers (Unif Q), Lloyd quantizers (Lloyd Q), and various novel quantizers by varying R_i = 2, 3, and 4. Using test sets of 1,000 source locations, we investigate different design algorithms with respect to the variation of the noise level. In the experiments, the performance of the design algorithms is evaluated by comparing their average localization errors $E\|\theta - \hat{\theta}\|^2$, which are obtained using the estimation technique proposed in (8) for our quantizer and using MLE for the other techniques.

A. Performance Comparison with Traditional Quantizers

The proposed quantizer is compared with typical designs such as uniform quantizers and Lloyd Q. The localization error (in meters) is averaged over 100 node configurations for each rate R_i. The overall rate–distortion (R–D) curves are depicted for the different designs in Fig. 1. As expected, CQE achieves a significant performance improvement in the localization accuracy since the proposed technique seeks to find the feasible combinations of codewords generated to minimize the localization error. Clearly, the approach to sending a cluster of the combinations yields a noteworthy performance gain when compared with the typical standard designs that quantize each of the local measurements into a single codeword for transmission to a fusion node.

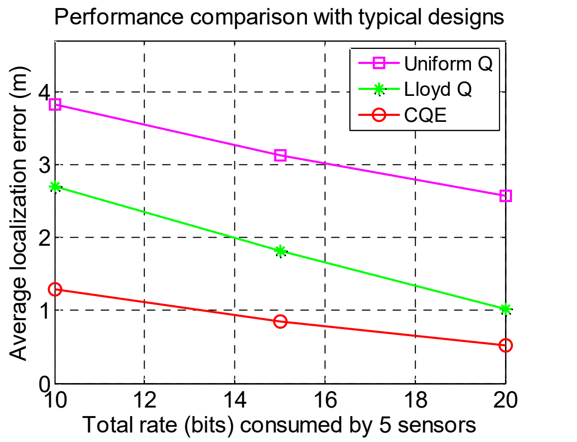

Fig. 1. Comparison of CQE with uniform quantizer and Lloyd quantizer: the average localization error (meters) is plotted vs. the rate R_i (bits) consumed by five nodes.

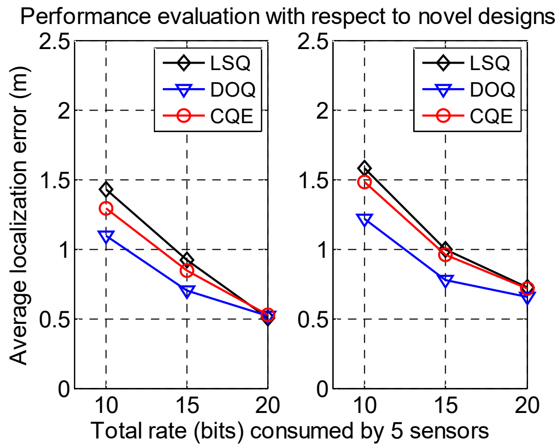

Fig. 2. Comparison of CQE with novel design techniques: the average localization error (meter) is plotted vs. the total rate (bits) consumed by five sensors with $\sigma^2 = 0$ (left) and $\sigma^2 = 0.15^2$ (right).

B. Performance Evaluation of Different Novel Designs

The performance of CQE is evaluated by comparing with several novel designs such as the localization-specific quantizer (LSQ) [3] and the distributed-optimized quantizer

(DOQ) [5]. Both of them have been previously proposed as design techniques for local quantizers in distributed estimation systems and tested for source localization in acoustic sensor networks. For each node configuration, two test sets are generated for evaluation with the measurement noise $\sigma_i = 0$ and $\sigma_i = 0.15$, respectively. The R–D curves for the design techniques are plotted in Fig. 2. Note that CQE performs well as compared to LSQ because the proposed algorithm directly handles the quantization partitions constructed to minimize the estimation error, whereas LSQ operates on the partitions generated to optimize the weighted metric, i.e., an indirect but related one. Furthermore, our quantizer achieves a considerable performance gain with respect to DOQ, which applies non-regularity to the design process at the cost of a huge design complexity. Note that our cluster-based technique executes much faster than LSQ and DOQ while maintaining a comparable estimation accuracy.

C. Performance Evaluation in the Presence of Measurement Noise

In this experiment, we test the design algorithms by varying the measurement noise σ_i. For each configuration, a test set of 1,000 source locations is generated with the SNR in the range of 40 dB to 100 dB. Note that the SNR is measured at 1 m from the source by using 10 log10 a^2/σ^2. For example, the SNR of 50 dB corresponds to $\sigma_i = 0.15$ with $a = 50$ and practical vehicle targets generate a noisy engine sound that is much higher than 40 dB [11, 12]. The localization errors with an increase in the SNR are plotted in Fig. 3. Obviously, CQE offers a competitive characteristic in noisy cases as compared to the other novel designs.

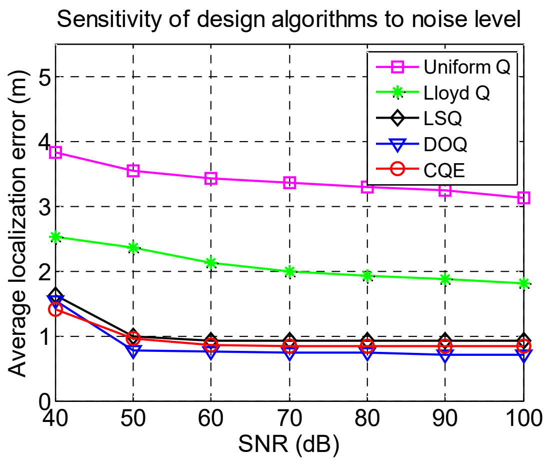

Fig. 3. Performance evaluation under a noisy condition: the average localization error is plotted vs. SNR (dB) with $M = 5$, $R_i = 3$, and $a = 50$.

VII. CONCLUSIONS

In this paper, we proposed an efficient design for a combined quantizer and estimator for distributed systems. Instead of generating a single codeword at the local quantizers as in the previous proposed designs, we introduced a new distance metric between the local measurements and the vector codewords and presented an iterative cluster-based design technique in the generalized Lloyd algorithm framework that produces clusters of vector codewords closest to the local measurements. We demonstrated through extensive experiments that the proposed algorithm achieves a substantial performance improvement over typical designs and different novel ones.

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