ENERGY EFFICIENT TRANSMISSION OF 3D MESHES OVER MMWAVE-BASED MASSIVE MIMO SYSTEMS

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ABSTRACT

Many mixed reality applications are based on the real-time compression and streaming of three-dimensional (3D) models. Thus, they demand very high-bandwidth and ultra-low latency from network specifications. The next-generation wireless networks will employ promising technologies to significantly improve the communication data rates. However, due to implementation complexity and thus increased energy consumption of these technologies, a trade-off between the quality-of-user-experience (QoE) and the hardware specifications is necessary. To overcome these limitations low-resolution quantizers have been of interest, which provide a trade-off between quality and complexity. In this paper, we propose a complexity-aware perceptual coding scheme that minimizes the reconstruction losses of the 3D models. Extensive simulations assuming different 3D models show that the proposed scheme achieves plausible reconstruction output offering significantly higher energy efficiency gains, as compared to a context unaware coding approaches.

1. INTRODUCTION

Augmented, virtual and extended reality applications for mobile users offer perceptually enriched experiences, bringing a range of benefits to business and society in various ways. At the same time, they introduce significant challenges, related to the acquisition and generation of reliable 3D models [1], the transmission data rate, the network latency, and the hardware complexity. Additionally, the scale of acquired data in real-time operation is growing very quickly, making communication and processing a very challenging task. Next-generation wireless networks are promising orders of magnitude increase in communication data rates. To achieve this goal, technologies such as large antenna arrays (massive MIMO) and millimeter wave (mmWave) frequencies will be employed. However, these technologies may consume significant power with excessive bit-rate due to the large signal bandwidth and the high number of bits/sample. Moreover, the implementation complexity of high-end components operating over high data rates is prohibitive.

One effective way to overcome these limitations is to reduce the high fidelity specifications considering the sampling resolution of the digital-to-analog converters (DACs) and analog-to-digital converters (ADCs) [2, 3]. Recently, designs with lower quantization resolution are being proposed [4]. Indeed, DACs/ADCs components have exponential power consumption, so lowering their resolution significantly reduces the overall system power consumption as well as the implementation complexity [5]. However, these designs introduce quality losses expressed as distortion to the transmitted/received signal which affect the quality-of user experience (QoE). In many mixed reality applications, the reconstruction does not necessarily have to be exactly equal to the input data [6]. This allows some loss of precision that is not easily distinguishable. To this end, perception-oriented techniques can employed to minimize the losses of the visual data and maximize QoE.

In this paper, we model this reduction in hardware complexity as an increase in the *energy efficiency* of the system (Fig. 1). First we consider that the 3D mesh can be decomposed into a number of layers representing different levels of details. Then, an optimal bit allocation strategy is proposed that assigns different quantization resolution to different levels. The optimality is based on joint maximization of the QoE and minimization of the quantization distortion. The proposed technique leads to a substantial increase of the energy efficiency for the transmission of the 3D object. This means that the visual errors at the receiver due to lower hardware specifications are not realizable. In summary, our contributions are:

- For the first time, a joint perceptual coding scheme with low hardware-complexity design is proposed for the mmWave massive MIMO transmitter.
- An integer optimization problem is formulated with a convex relaxation of the cost function. Its solution provides the allocation strategy for the transmitter's DAC resolution.

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- An extensive evaluation using a collection of 3D models with respect to different mmWave channel realizations that clearly shows the benefits of our method as compared to context unaware coding approaches.

The rest of this paper is organized as follows: In Section 2, we present the the spatial layer mesh decomposition. In Section 3, we provide the description of the complexity-aware mmWave massive MIMO transmitter. Section 4 presents the optimization problem and the algorithm for the bit allocation. Section 5 presents our experimental results. Section 6 draws the conclusions.

2. SPATIAL LAYER MESH DECOMPOSITION USING TOPOLOGICAL INFORMATION

Let us assume that a 3D mesh $\mathcal{M} = (\mathcal{V}, \mathcal{F})$ is described by the set of n vertices $(\mathcal{V})$ and the set of the indexed faces $(\mathcal{F})$. Each vertex is represented using absolute Cartesian coordinates, denoted by $\mathbf{v}_i = [x_i, y_i, z_i]^T$. We assume that a neighborhood of a vertex $\mathbf{v}_i$ can be represented as the set $\mathcal{N}(i)$ of vertices connected to i by an edge $\mathcal{E}(i, j)$:

$$\mathcal{N}(i) = \{j | (i, j) \in \mathcal{E}\}. \quad (1)$$

More specifically, any vertex that belongs to the neighborhood $\mathcal{N}(i)$ is a neighbor of i, having each other topological distance equal to 1. The neighborhoods of undirected graphs, such as the graph of a mesh defined above are symmetric, meaning that if a vertex j is a neighbor of vertex i, then also i is a neighbor of j.

A spatial layer decomposition approach decimates vertices in a 3D mesh iteratively to obtain multiple layers. We decimate a single vertex at each layer and we denote with $\mathcal{M}_l = (\mathcal{V}_l, \mathcal{F})$ the mesh at layer l that consist of l active and $n - l$ inactive nodes. If therefore we assume that node $\mathbf{v}_l$ is decimated at $\mathcal{M}_l$ then we can write:

$$\mathcal{V}_l = \mathcal{V}_{l-1} \cup \{\mathbf{v}_l\}. \quad (2)$$

At each iteration we simply mark decimated vertices as inactive vertices. To accurately predict the position of each vertex $\mathbf{v}_i$, we define the neighboring vertices of $\mathbf{v}_i$ denoted by $N(\mathbf{v}_i, l, d_v)$, as the set of vertices $\mathbf{v}_j$ whose topological distance to $\mathbf{v}_i$, denoted by $t_d(\mathbf{v}_i, \mathbf{v}_j)$, are less than or equal to d_v:

$$\begin{aligned} \mathcal{N}(\mathbf{v}_i, l, d_v) &= \cup_{k=1}^{d_v} A_k(\mathbf{v}_i, l) \quad (3) \\ A_k(\mathbf{v}_i, l) &= \mathbf{w} \in \mathcal{M}_l : t_d(\mathbf{v}_i, \mathbf{w}) = k. \quad (4) \end{aligned}$$

The geometry information of the decimated vertices at higher levels is not available, while their connectivity information is maintained for estimating the topological distance in Eq. (4). The number of neighboring vertices should be also higher than a specific number (e.g., 3) in order to perform a prediction that introduces small errors on the surface that are not easily perceived. Therefore, we estimate d_v as the minimum value so that $\mathcal{N}(\mathbf{v}_i, l, d_v)$ includes at least three vertices:

$$\mathbf{d}_v = arg \min_d |\mathcal{N}(\mathbf{v}_i, l, d_v)| \; s.t. \; |\mathcal{N}(\mathbf{v}_i, l, d_v)| \geq 3, \quad (5)$$

where $|\cdot|$ operator returns the number of elements in a set.

After identifying the maximum topological distance between a vertex and its neighboring vertices we evaluate the decimation costs of all candidate vertices and the decimate the vertex $\mathbf{v}_l$ with the minimum cost $C(\mathbf{v}, l)$:

$$\mathbf{u}_l = arg \min_{\mathbf{v} \in \mathcal{M}_l} \{C_u(\mathbf{v}, l) + \lambda C_{d_u}(\mathbf{v}, l)\} \quad (6)$$

where $C_u(\mathbf{v}, l)$ is the prediction uncertainty cost, $C_{d_u}(\mathbf{v}, l)$ quantifies the uncertainty increase induced by the vertex decimation and λ is a weighting parameter. The prediction uncertainty index is calculated as a function of the number of i-ring neighbors $N_i(\mathbf{v})$ and the active neighbors $A_i(\mathbf{v}, l)$:

$$C_u(\mathbf{v}, l) = \sum_{i=1}^{d_u} \frac{|N_i(\mathbf{v})| - |A_i(\mathbf{v}, l)|}{|N_i(\mathbf{v})|} \rho^i \quad (7)$$

where $0 < \rho < 1$. The amount of uncertainty increase introduced by the vertex decimation, is calculated by:

$$C_{d_u}(\mathbf{v}, l) = \frac{1}{|\mathcal{M}_{l-1}|} \sum_{i \in \mathcal{M}_{l-1}} \{C_u(\mathbf{v}, l-1) - C_u(\mathbf{v}, l)\}. \quad (8)$$

3. LOW HARDWARE-COMPLEXITY TRANSMITTER

We consider that the input to the transmitter are N groups of 3D mesh coordinates. The output is forward to N DAC units, where depending on the modulation an k-bit uniform quantizer is applied. Afterwards, the quantized output is digitally modulated and transmitted via the mmWave wireless channel $\mathbf{Z} \in \mathbb{R}^{N \times N}$. The receiver applied the inverse procedure to the captured signal $\mathbf{y} \in \mathbb{C}^{N \times 1}$. Note that the number of the 3D groups and the size of the antenna array are equal to N.

Let the output of the compression block expressed by the vector $\mathbf{s} \in \mathbb{R}^{N \times 1}$. The effect of low-resolution quantization can be approximated by a linear additive quantization model

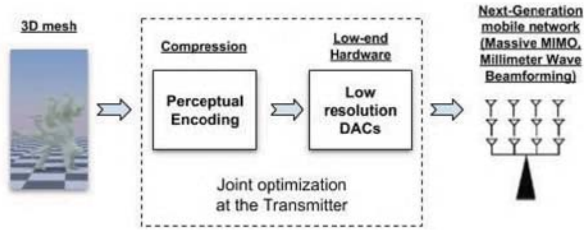

Fig. 1. MmWave massive MIMO transmitter with joint minimization of coding losses and hardware complexity.

[7, 3]. The output of the DAC block can be expressed in matrix form as follows:

$$\mathbf{x} = \mathbf{Q}\mathbf{s} + \epsilon \in \mathbb{R}^{N\times 1} \quad (9)$$

where is a diagonal matrix with $\mathbf{Q} \in \mathbb{R}^{N\times N}$ representing the multiplicative quantization distortion. Its k-diagonal entry is given as $[\mathbf{Q}]_l = \sqrt{1 - \frac{\pi\sqrt{3}}{2}2^{-2b_l}}$. The b_l defines the quantization resolution of the l-th entry; ϵ_l is the additive quantization noise (AWGN) with $\epsilon_l \sim \mathcal{CN}(0, \sigma_\epsilon^2)$ with $\sigma_\epsilon^2 = (1 - \frac{\pi\sqrt{3}}{2}2^{-2b_l})\frac{\pi\sqrt{3}}{2}2^{-2b_l}, \forall l$.

To measure the QoE we have to consider the signal $\mathbf{y} \in \mathbb{R}^{N\times 1}$, that is received after the effect of the mmWave channel. For simplicity we adopt similar modeling with [8]. Specifically, due to the special properties of the mmWave spectrum and massive MIMO, the interference noise due to the wireless transmission are minimized. So, the received signal can be expressed as:

$$\mathbf{y} = \mathbf{Z}\mathbf{x} + \mathbf{n} = \mathbf{Z}\mathbf{Q}\mathbf{s} + \mathbf{Z}\epsilon + \mathbf{n} \quad (10)$$

where $\mathbf{Z} \in \mathbb{R}^{N\times N}$ is a diagonal matrix and $\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma_n^2\mathbf{I})$ represents the additive white Gaussian noise $N \times 1$ vector.

4. COMPLEXITY-AWARE BIT ALLOCATION

To measure the introduced distortion of the low hardware-complexity transmitter we employ the mean-square-error cost function:

$$\mathcal{J}(b_l) = \mathcal{E}\{|s_l - y_l|^2\} \quad (11)$$

where s_l/y_l is the l-th transmitted/received layer and $\mathcal{E}\{\cdot\}$ denotes the statistical expectation. Based on (10) and the statistical independence of the terms, the cost function can be expressed as:

$$\mathcal{J}(b_l) = \left(1 - [\mathbf{Z}]_l[\mathbf{Q}]_l\right)^2\sigma_{s_l}^2 + [\mathbf{Z}]_l^2\sigma_\epsilon^2 + \sigma_n^2 \quad (12)$$

where $\sigma_{s_l} = \mathcal{E}\{s_l^2\}$. The first term of (12) is related with the *utility function* defined as a weighted average of the topological and geometrical cost of a group of vertices. More specifically the n vertices are classified into N groups according to their topological and geometrical cost. The second term represents the effect of the low-resolution DACs (via σ_ϵ^2 term) as well as the effect of the mmWave channel (via $[\mathbf{Z}]_l$ term). The third term is due to the AWGN.

The minimization of (12) over b_l with $l = 1, \ldots, N$ describes an NP-hard *integer-based optimization problem.* So it does not have a solution with polynomial time. Moreover, the number N could be very large (i.e., the antenna array size), which also represents the number of the unknowns b_l. To overcome these difficulties, first we employ an additional constrain for our optimization problem. This will provide more information to the problem and will permit its solution even with a large number of unknowns. Then, we make a convex approximation for the values of b_l, and we provide an efficient algorithm to solve it.

The additional constraint can be expressed as an upper bound for the energy consumption. The energy consumption model depends on the structure we use, thus a general design should take into account the power of all the involved components, e.g., antenna elements, phases shifters, low power amplifiers, etc. Nevertheless, in this work the focus is on the optimization over the DACs energy consumption (which is one of the most energy consuming components), thus, we adopt the following exponential model for the energy losses [9],

$$P = \kappa 2^{b_l} \ (W) \quad (13)$$

where $\kappa = 1.5 \times 10^{-5}$ depends on the DAC hardware specifications and the sampling rate. Note that the energy losses can be expressed in terms of the introduced distortion, i.e., $[\mathbf{Q}]_l = \sqrt{1 - \frac{\pi\sqrt{3}}{2}P^{-2}}$.

Therefore, the constrained optimization problem is expressed as:

$$\min_{\mathbf{b}} \sum_{l=1}^{N} \mathcal{J}(b_l) \quad \text{subject to} \quad \sum_{l=1}^{N} P(b_l) \leq P \quad (14)$$

where $\mathcal{J}(b_l)$ is the cost function defined in Eq. (12). The constraint term in (14) sets an upper bound for the available energy budget for the entire antenna array.

However, the problem in Eq. (14) is an integer optimization one, hence is computationally intractable. To overcome this, we define the relaxed convex problem by minimizing (12) over $x_l \triangleq 2^{-b_l}$ and not over b_l. Afterwards, the mapping to an integer value is based on:

$$b_l = \max\left(0, \lceil -\log_2(x_l)\rceil\right) \in \mathbb{S}, \quad (15)$$

where $\lceil\cdot\rceil$ denotes the closest upper integer value and $\mathbb{S} = \{1, 2, \ldots, K\}$ is the set of all possible integer values for the quantization resolution.

To proceed, let us employ the first-order Taylor approximation two times to the first term of (12), i.e.,

$$\left(1 - [\mathbf{Z}]_l[\mathbf{Q}]_l\right)^2 \approx 1 - \frac{[\mathbf{Z}]_l}{2}[\mathbf{Q}]_l \approx \frac{\pi[\mathbf{Z}]_l\sqrt{3}}{4}x_l, \quad (16)$$

given that $|[\mathbf{Z}]_l[\mathbf{Q}]_l| \ll 1$. Then, the cost function can be approximated by:

$$\mathcal{J}(x_l) \approx \underbrace{\sigma_{s_l}^2\frac{\pi[\mathbf{Z}]_l\sqrt{3}}{4}}_{\alpha_l}x_l + \underbrace{\sigma_\epsilon^2\frac{[\mathbf{Z}]_l}{2}) + \sigma_n^2}_{\beta_l}. \quad (17)$$

Since β_l of Eq. (17) is independent of x_l, the minimization problem can be expressed as:

$$\begin{aligned} &\min_{\{x_l\}_{l=1}^N} && \sum_{l=1}^{N}\alpha_l x_l \\ &\text{subject to} && \kappa\sum_{l=1}^{N}x_l^{-1} \leq P_{\max}, \quad x_l > 0, \forall\, l \end{aligned} \quad (18)$$

Algorithm 1 Proposed bit allocation algorithm

Input: $P_{\max}$
Output: $b_l \in \mathbb{S}$

```
Initialization: S = {1, 2, ..., K} and P = 0
for l = 1, 2, ..., N do
    Compute b̃_l with Eq. (20) and then use Eq. (15) to get
    the integer approximation of b_l
    if b_l = 0 then
        S = S − {l}
    else
        Compute the required power for the l-th layer and
        the total required as P = κ Σ_{i=1}^{l} x_l^{-1}
    end if
end for
if P > P_max then
    for i ∈ S do
        T_i = (2^{-⌊b̃_i⌋} − 2^{-b̃_i}) / (2^{-b_i} − 2^{-⌊b_i⌋}) u_i σ_l
    end for
    while P > P_max do
        i = arg min_{i∈S} T_i
        S = S − {i}
        Compute P = Σ_{i∈S} P(b_i)
    end while
end if
```

where $P_{\max}$ is the prefixed upper bound for the energy consumption. Problem in Eq. (18) has a closed-form solution given by:

$$x_l = \frac{1}{P_{\max}} \frac{\sum_{k=1}^{N} \sqrt{\alpha_k}}{\sqrt{\alpha_l}}. \tag{19}$$

Hence,

$$\tilde{b}_l = \log_2 P_{\max} + \log_2 \sum_{k=1} N\sqrt{\alpha_k} - \frac{1}{2}\log_2 \alpha_l. \tag{20}$$

These detailed steps for solving (17) are provided by Algorithm 1.

5. SIMULATION RESULTS

5.1. Mesh Encoding and Reconstruction

The differential or δ coordinates of a mesh are calculated as the difference between the coordinates of each vertex $\mathbf{v}_i$ and the barycenter of its neighbors, according to:

$$\boldsymbol{\delta}_i = [\delta_x,\ \delta_y,\ \delta_z]^T = \mathbf{v}_i - 1/d_i \sum_{j\in\mathcal{N}(i)} \mathbf{v}_j, \tag{21}$$

where d_i is the number of immediate neighbors of i, also known and as degree of vertex i. The differential coordinates correspond to the set of displacements that are produced by applying the Laplacian operator to the vertices of a mesh. Large $\boldsymbol{\delta}_i$ values indicate the existence of a small or large scale geometric features while small values correspond to vertices belonging in flat areas.

In the proposed bit allocation scheme, we are able to encode geometric features, like high curvature regions, e.g., corners and edges, with an increased number of bits resulting in reconstruction errors, which cannot be easily perceived, building on the same line of thought with the previous work presented in [10]. The bit allocation algorithm provides a k_j number of bit for encoding the vertices of the j group, $j = 1, \cdots, \lfloor n/N \rfloor$. The k_j bits are uniformly assigned to the vertices with the largest δ coordinates, ensuring that each δ coordinate is encoded with 12 bits. The rest delta coordinates are set to zero. Additionally, with the vector $\boldsymbol{\delta}_z$ we also quantize a set of known vertices (anchors), also known as control points, that are uniformly distributed on the model surface $\mathbf{v}_c = \mathcal{Q}([\mathbf{v}_{i_1}, \cdots, \mathbf{v}_{i_k}])$ where i_k is the vertex index and k correspond to the 1% of the total number of vertices n. Finally, the reconstruction of the 3D mesh vertices at the decoder side is performed by solving the following sparse linear system:

$$\begin{bmatrix} \mathbf{L} \\ \mathbf{I}_k \end{bmatrix} \mathbf{v} = \begin{bmatrix} \boldsymbol{\delta}_z \\ \mathbf{v}_c \end{bmatrix},\ \mathbf{L} = \mathbf{D} - \mathbf{C}, \tag{22}$$

where $\mathbf{I}_k \in \mathbb{R}^{k\times n}$ is a sparse matrix with ones at the i_k indices where the vertices $\mathbf{v}_c$ lie and zeros anywhere else, so that $\mathbf{v}_c = \mathbf{I}_k\mathbf{v}$, $\mathbf{L} \in \mathbb{R}^{n\times n}$ is the binary Laplacian matrix and $\mathbf{C} \in \mathbb{R}^{n\times n}$ is the connectivity matrix of the mesh with elements:

$$\mathbf{C}_{(i,j)} = \begin{cases} 1 & \text{if } (i,j) \in \mathcal{E} \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

$\mathbf{D}$ is the diagonal matrix with $\mathbf{D}_{(i,i)} = |\mathcal{N}(i)|$.

5.2. Evaluation Study

In Fig. 3, we present an example of the proposed bit allocation scheme. We use N = 128 channels and in each channel, we transmit a similar number of vertices $\sim (k/N)$. In this figure, two different ways for the transmission of the data are used: (i) The uniform transmission, in which we use 6 bits to encode each vertex at any of the existent channels. (ii) The modified transmission, in which the mean bits-per-vertex (bpv) for encoding is also equal to 6, however, depending on the channel's capability we assign different bpv for the vertices transmitted in different channels. Please note that a higher number of bits is assigned to group of vertices with large topological and geometrical values.

Next we identify the benefits of the proposed bit allocation algorithm as compared to and different allocation schemes that do not take into account different spatial and/or quantization resolutions, in terms of both energy efficiency and reconstruction quality. For the evaluation of the energy efficiency of the different approaches, we adopt the following metric, defined as:

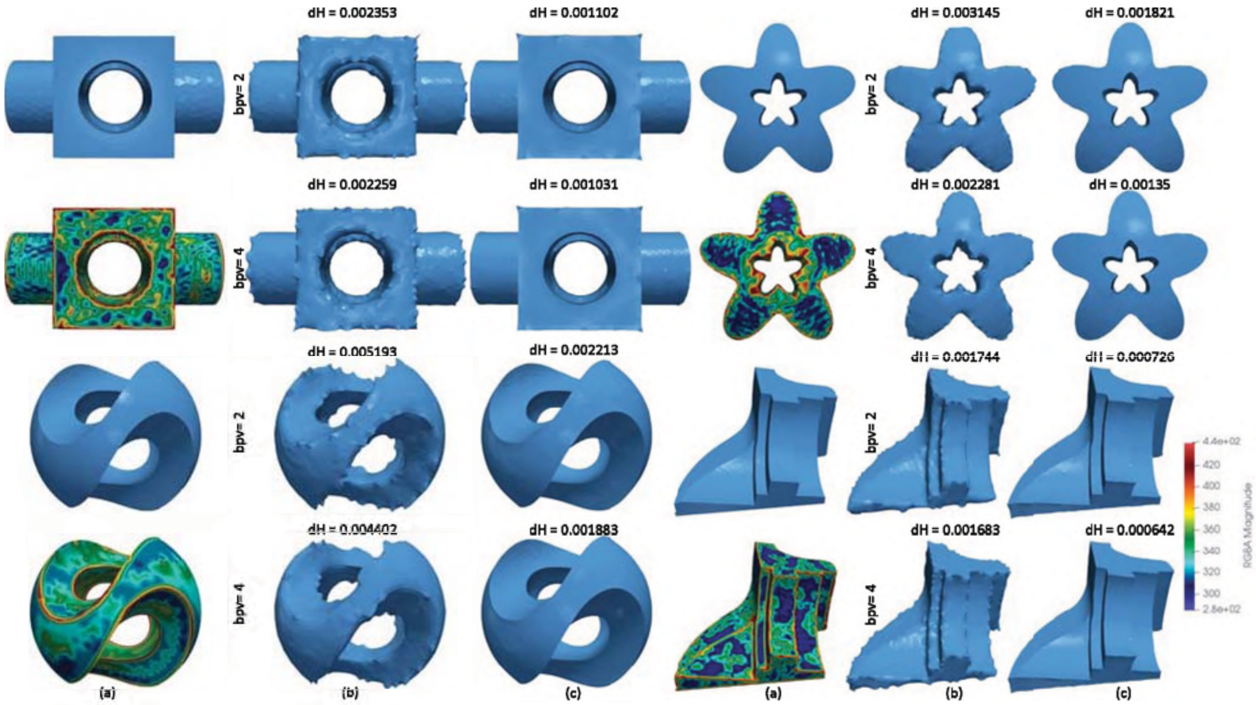

Fig. 2. *(a) [first]-[third] lines: original meshes of different 3D models (block, trim-star, sculpt, and fandisk), [second]-[fourth] lines: heatmap visualizing the importance of each vertex based on their corresponding δ coordinates, (b) reconstructed results using the uniform approach (c) reconstructed results using the modified approach.*

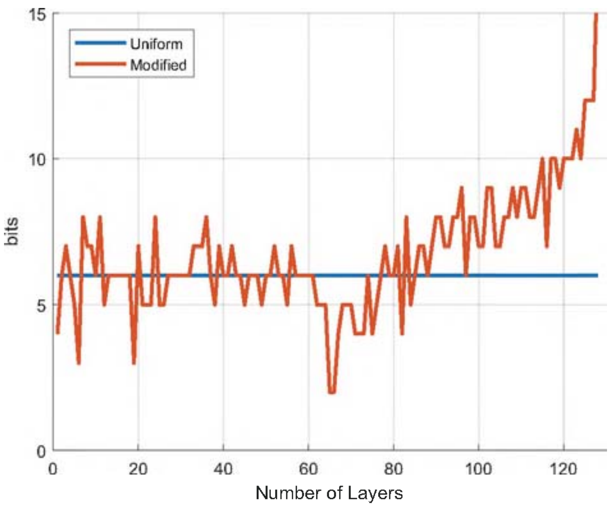

Fig. 3. *Bit allocation using two different approaches: (i) the uniform approach (6 bpv in every channel, and (ii) the modified approach assigning different bpv per each channel.*

1. The average one-sided Hausdorff distance d_H from the denoised mesh to the known ground-truth mesh.
2. The metric θ which represents the average angle difference between the normals of the ground truth and the reconstructed model.

In Fig. 2, we present the reconstructed results using two different approaches, namely uniform transmission and transmission using the proposed bit allocation algorithm. For the evaluation, we use different 3D meshes and different bits-per-vertex values. This figure highlights the benefits provided by the proposed scheme in comparison to the uniform transmission since its reconstructed 3D meshes outperform the results of the uniform case. The Hausdorff distance metric is also provided for easier comparison. Fig. 4 shows how the metric θ, of the reconstructed 3D models, changes while the P_{total} increases. As we expected, in both approaches, the reconstructed results are improved when more energy is used for the transmission. Nevertheless, the reconstructed results provided by the bit allocation scheme are much better even when low power is used for the transmission.

6. CONCLUSION

In this work, we presented a hardware aware 3D mesh coding scheme for a mmWave-based massive MIMO transmitter

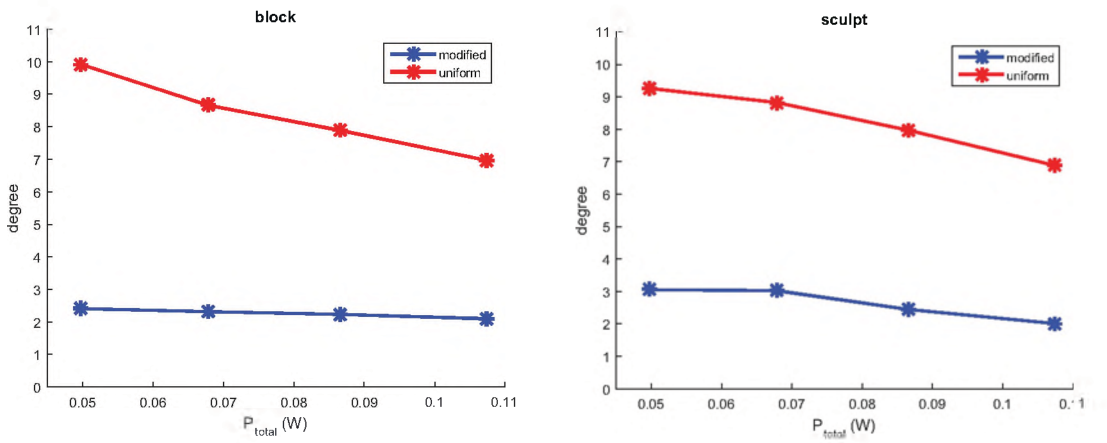

Fig. 4. *Metric θ (in degree) of the reconstructed results while the P increases. Higher P values also indicate higher hardware requirements (i.e., quantization resolution). The modified and the uniform approach is presented for different 3D models.*

with low-complexity hardware. The proposed technique minimizes the perceptual coding losses in static and dynamic 3D meshes. An optimal bit allocation strategy ideally suited for low-resolution quantizers, allocates a constrained number of bits to the perceptually coded vertices assigned to each antenna. The presented results show that the proposed scheme, achieves plausible reconstruction output offering significantly higher energy efficiency gains, as compared to a context unaware coding approaches.

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