MITSUBISHI ELECTRIC RESEARCH LABORATORIES
http://www.merl.com

Overhead Reduction in Graph-Based Point Cloud Delivery

Fujihashi, Takuya; Koike-Akino, Toshiaki; Watanabe, Takashi; Orlik, Philip V.

TR2020-061 May 14, 2020

Abstract

Conventional point cloud delivery schemes use graph-based compression to stream three-dimensional (3D) points and the corresponding color attributes over wireless channels for 3D scene reconstructions. However, the graph-based compression requires a significant communication overhead for graph signal decoding, i.e., inverse graph Fourier transform (IGFT), and such large overhead causes a low 3D reconstruction quality due to power and rate losses. We propose a novel scheme of point cloud delivery to significantly reduce the amount of overhead while allowing a small degradation in the 3D reconstruction quality. Specifically, the proposed scheme exploits Givens rotation for the graph-based transform basis matrix to compress the basis matrix into quantized angle parameters. Even when the angle parameters are strongly quantized for compression, the receiver can reconstruct a clean point cloud by using the basis matrix obtained from the quantized angle parameters. Evaluation results show the Givens rotation in the proposed scheme achieves overhead reduction with a slight quality degradation. For example, the proposed scheme achieves 89.8% overhead reduction with 1.3 dB quality degradation compared with the conventional point cloud delivery scheme

IEEE International Conference on Communications (ICC)

Overhead Reduction in Graph-Based Point Cloud Delivery

Takuya Fujihashi†*, Toshiaki Koike-Akino†, Takashi Watanabe*, and Philip V. Orlik†
†Mitsubishi Electric Research Laboratories (MERL), Cambridge, MA 02139, USA
*Graduate School of Information and Science, Osaka University, Osaka, Japan

***Abstract*—Conventional point cloud delivery schemes use graph-based compression to stream three-dimensional (3D) points and the corresponding color attributes over wireless channels for 3D scene reconstructions. However, the graph-based compression requires a significant communication overhead for graph signal decoding, i.e., inverse graph Fourier transform (IGFT), and such large overhead causes a low 3D reconstruction quality due to power and rate losses. We propose a novel scheme of point cloud delivery to significantly reduce the amount of overhead while allowing a small degradation in the 3D reconstruction quality. Specifically, the proposed scheme exploits Givens rotation for the graph-based transform basis matrix to compress the basis matrix into quantized angle parameters. Even when the angle parameters are strongly quantized for compression, the receiver can reconstruct a clean point cloud by using the basis matrix obtained from the quantized angle parameters. Evaluation results show the Givens rotation in the proposed scheme achieves overhead reduction with a slight quality degradation. For example, the proposed scheme achieves 89.8% overhead reduction with 1.3 dB quality degradation compared with the conventional point cloud delivery scheme.**

I. Introduction

Point cloud [1] is one of data structures to reconstruct three-dimensional (3D) scenes and objects on holographic displays [2]. Point cloud typically consists of a set of 3D points, and each point is defined by 3D coordinates, i.e., (X, Y, Z), and color attributes, i.e., (R, G, B) or (Y, U, V).

In contrast to conventional two-dimensional (2D) images and videos, 3D point cloud data are not well-aligned in order and are not uniformly distributed in space. One of the major issues in the point cloud delivery is how to encode and send such numerous and irregular structure of 3D points while keeping high 3D reconstruction quality on displays. Hence, realizing wireless point cloud delivery faces a particular challenge as band-limited wireless channels are often unable to accommodate a large amount of traffic data required for 3D reconstructions.

For the conventional point cloud encoders, such as popular point cloud library (PCL) [3], [4], use octree decomposition, prediction, quantization, and entropy coding. Specifically, a sender first decomposes 3D points into 3D point subsets [5], i.e., octree blocks, and takes quantization and entropy coding for each octree block to generate the compressed bitstream for transmissions. However, such point cloud encoders have limited coding efficiency because the conventional schemes do not fully exploit the underlying correlations between the irregular structure of the 3D points. To realize better 3D reconstruction quality, recent studies consider the introduction of graph signal processing (GSP) [6] for point cloud delivery. HoloCast [7] is a pioneer work on graph-based point cloud delivery over wireless links. Specifically, HoloCast regards the 3D points as vertices in a graph $\mathcal{G}$ and take graph Fourier transform (GFT) [8] for the graph signals to exploit the correlations between the adjacent graph signals, and directly sends the GFT coefficients by using analog modulation [9]. The GFT-based coding realizes better energy compaction across the graph signals, and thus it offers better 3D reconstruction quality irrespective of wireless channel quality.

However, the graph-based coding needs to send the graph-based transform basis matrix in GFT as metadata for signal decoding. For example, the sender needs to inform N^2 real elements of the graph-based transform basis matrix as the metadata when the number of 3D points in an octree block is N. A large number of metadata transmissions causes a large communication overhead.

In this paper, we propose a novel scheme for wireless graph-based point cloud delivery, motivated by HoloCast [7], to achieve better 3D reconstruction quality under a low communication overhead. For overhead reduction, the proposed scheme introduces the Givens rotation [10], [11] for the GFT basis matrix compression. The Givens rotation is used to represent any unitary basis matrices with the minimum number of angle parameters. Although the Givens rotation is studied in wireless communications systems to reduce the overhead of channel feedback [10], [11], there are no studies showing benefits of this technique in graph-based point cloud delivery systems. The angle parameters are quantized prior to metadata transmission and the receiver reconstructs the basis matrix by using the quantized angle parameters.

From the evaluation results, we demonstrate that the proposed scheme achieves 89.8% reduction on communication overhead compared with the conventional HoloCast while keeping high reconstruction quality.

II. Proposed Graph-based Point Cloud Delivery

The main objective of our study is to reduce the overhead of graph-based point cloud delivery, i.e., HoloCast [7], with a slight degradation of 3D reconstruction quality. Fig. 1 shows the overview of the proposed scheme. The proposed scheme uses octree decomposition to decompose graph signals into multiple octree blocks and then takes GFT for point attributes in octree blocks to compact the signal power, whose output

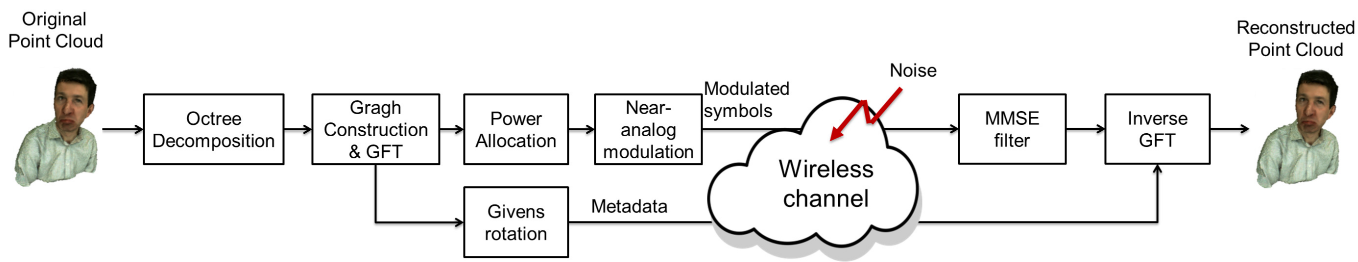


Fig. 1. Overview of the proposed point cloud delivery scheme, employing Givens rotation for the compression of graph-based transform basis matrix.

is then scaled and directly mapped to transmission signals using analog modulation. In addition, the proposed scheme exploits the Givens rotation to quantize the GFT basis matrix into angle parameters. The analog-modulated symbols and the quantized angle parameters are transmitted to the receiver. The receiver uses minimum mean-square error (MMSE) filter to denoise the received GFT coefficients and finally takes IGFT to reconstruct 3D coordinates and color components by using the basis matrix recovered from the received angle parameters.

1) Graph Construction: We assume that the 3D points have already been organized into octree blocks, where each octree block may contain N 3D points. The proposed scheme represents the 3D coordinates and color components in each octree block using a weighted and undirected graph $\mathcal{G} = (\boldsymbol{V}, \mathcal{E}, \boldsymbol{W})$ where $\boldsymbol{V}$ and $\mathcal{E}$ are the vertex and edge sets of $\mathcal{G}$, respectively. $\boldsymbol{W}$ is an adjacency matrix having positive edge weights and the (i, j)th entry $\boldsymbol{W}_{i,j}$ represents the weight of an edge connecting vertices i and j. We consider the attributes of the point cloud, i.e., the 3D coordinates $\boldsymbol{p} = [\mathsf{x}, \mathsf{y}, \mathsf{z}]^{\mathrm{T}} \in \mathbb{R}^{3\times N}$ and the color components $\boldsymbol{c} = [y, u, v]^{\mathrm{T}} \in \mathbb{R}^{3\times N}$ as signals that reside on the vertices in the graph where N is the number of vertices.

2) Graph Fourier Transform: From the attributes, each weight $\boldsymbol{W}_{i,j}$ can be calculated, e.g., by the bilateral Gaussian kernel [12] as follows:

$$\boldsymbol{W}_{i,j} = \exp\left(-\left(\frac{\|\boldsymbol{p}_i - \boldsymbol{p}_j\|_2^2}{\kappa_p} + \frac{\|\boldsymbol{c}_i - \boldsymbol{c}_j\|_2^2}{\kappa_c}\right)\right), \quad (1)$$

where κ_p and κ_c are hyperparameters for 3D coordinates and color components, respectively. In the proposed scheme, we use the sample variance across all the attributes for the hyperparameter κ_p and κ_c. A sender then transforms the graph signals into spectral representation using GFT. The GFT is defined through the graph Laplacian operator $\boldsymbol{L}$ using edge weight matrix $\boldsymbol{W}$ and degree matrix $\boldsymbol{D}$, where $\boldsymbol{D}$ is the diagonal degree matrix whose ith diagonal element is equal to the sum of the weights of all the edges incident to vertex i. Specifically, the diagonal matrix is represented as:

$$\boldsymbol{D}_{i,j} = \begin{cases} \sum_{n=1}^{N} \boldsymbol{W}_{i,n}, & \text{if } i = j, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Based on the degree matrix, we can calculate the graph Laplacian matrix [13]:

$$\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{W}. \quad (3)$$

Several other variants of Laplacian matrix such as random walk graph Laplacian [12] were also investigated in HoloCast [7].

In general, the graph Laplacian is a real symmetric matrix that has a complete set of orthonormal eigenvectors with corresponding nonnegative eigenvalues. To obtain the eigenvectors and eigenvalues, the eigenvalue decomposition of the Laplacian matrix is performed as:

$$\boldsymbol{L} = \boldsymbol{\Phi}\boldsymbol{\Delta}\boldsymbol{\Phi}^{-1}, \quad (4)$$

where $\boldsymbol{\Phi}$ is the eigenvectors matrix and $\boldsymbol{\Delta}$ is a diagonal matrix containing the eigenvalues. The multiplicity of the smaller eigenvalue indicates the number of connected components of the graph. The GFT coefficients of each attribute are obtained by multiplying the graph-based transform basis matrix by the corresponding attribute as follows:

$$\boldsymbol{s} = \boldsymbol{f}\,\boldsymbol{\Phi}, \quad (5)$$

where $\boldsymbol{s}$ is a vector of GFT coefficients corresponding to the attribute vector of $\boldsymbol{f}$ in an octree block. After power allocation for each GFT coefficient, the GFT coefficients are mapped to I (in-phase) and Q (quadrature-phase) components for analog wireless transmissions.

Let x_i denote the ith analog-modulated symbol, which is the ith GFT coefficient s_i of an attribute scaled by a factor of g_i for noise reduction as follows:

$$x_i = g_i \cdot s_i. \quad (6)$$

The optimal scale factor g_i is obtained by minimizing the MSE under the power constraint with a total power budget of P as follows:

$$\min_{\{g_i\}} \quad \mathsf{MSE} = \mathbb{E}\left[(s_i - \hat{s}_i)^2\right] = \sum_i^N \frac{\sigma^2\lambda_i}{g_i^2\lambda_i + \sigma^2}, \quad (7)$$
$$\text{s.t.} \quad \frac{1}{N}\sum_i^N g_i^2\lambda_i = P,$$

where $\mathbb{E}[\cdot]$ denotes expectation, $\hat{s}_i$ is a receiver estimate of the transmitted GFT coefficient, λ_i is the power of the ith GFT coefficient, N is the number of GFT coefficients, and σ^2 is a receiver noise variance. As shown in [9], the near-optimal solution is expressed as

$$g_i = \lambda_i^{-1/4}\sqrt{\frac{NP}{\sum_j^N \sqrt{\lambda_j}}}. \quad (8)$$

A. Decoder

Over the wireless links, the receiver obtains the received symbol, which is modeled as follows:

$$y_i = x_i + n_i, \quad (9)$$

where y_i is the ith received symbol and n_i is an effective AWGN with a variance of σ^2 (which is already normalized by wireless channel strength in the presence of fading attenuation). The GFT coefficients are extracted from I and Q components via an MMSE filter [9]:

$$\hat{s}_i = \frac{g_i\lambda_i}{g_i^2\lambda_i + \sigma^2}\cdot y_i. \quad (10)$$

The decoder then reconstructs corresponding graph signals $\hat{\boldsymbol{f}}$, i.e., attributes of 3D coordinates and color components in an octree block, by taking the inverse GFT for the filtered GFT coefficients in each attribute $\hat{\boldsymbol{s}}$ as follows:

$$\hat{\boldsymbol{f}} = \hat{\boldsymbol{s}}\,\boldsymbol{\Phi}^{-1}. \quad (11)$$

B. Overhead Reduction

In the conventional graph-based point cloud delivery schemes, the sender needs to inform the eigenvectors matrix, i.e., $\boldsymbol{\Phi}$, to the receiver for graph signal reconstruction. In this case, the sender transmits N^2 real elements to the receiver as the metadata in each octree block when the number of 3D points in an octree block is N.

In fact, as the basis matrix is unitary, the minimum number of elements to represent the eigenvectors is $N(N-1)$ according to [11], where the Givens rotation was introduced to efficiently compress the eigenvectors. In our proposed scheme, we apply the same technique to reduce the amount of metadata transmissions via the Givens rotation. Specifically, the eigenvectors matrix $\boldsymbol{\Phi} \in \mathbb{R}^{N\times N}$ can be decomposed as follows:

$$\boldsymbol{\Phi} = \prod_{k=1}^{N}\Big[\boldsymbol{D}_k(\phi_{k,k},\ldots,\phi_{k,N})\prod_{l=1}^{N-k}\boldsymbol{G}_{N-l}(\psi_{k,l})\Big], \quad (12)$$

$$\boldsymbol{D}_k(\phi_{k,k},\ldots,\phi_{k,N}) = \mathrm{diag}(\mathbf{1}_{k-1}, \mathrm{e}^{\jmath\phi_{k,k}},\ldots,\mathrm{e}^{\jmath\phi_{k,N}}), \quad (13)$$

where $\mathbf{1}_{k-1}$ is an all-ones vector of size $k-1$, and $\boldsymbol{G}_{l-1}(\psi)$ is Givens rotation matrix in rows $l-1$ and l as follows:

$$\boldsymbol{G}_{l-1}(\psi) = \begin{bmatrix} \boldsymbol{I}_{l-2} & & & \\ & c & -s & \\ & s & c & \\ & & & \boldsymbol{I}_{N-l} \end{bmatrix}, \quad (14)$$

where $\boldsymbol{I}_l$ is $l\times l$ identity matrix, $c=\cos(\psi)$ and $s=\sin(\psi)$. Hence any basis matrix is represented with angle variables of $\phi_{k,l}$ and $\psi_{k,l}$.

We explain the parameterization procedure with a 3×3 eigenvectors matrix $\boldsymbol{\Phi}$ as follows:

$$\boldsymbol{\Phi} = \begin{bmatrix}\times&\times&\times\\\times&\times&\times\\\times&\times&\times\end{bmatrix} \xrightarrow{\boldsymbol{D}_1^\dagger} \begin{bmatrix}|\times|&\times&\times\\|\times|&\times&\times\\|\times|&\times&\times\end{bmatrix} \xrightarrow{\boldsymbol{G}_2^\dagger,\boldsymbol{G}_1^\dagger} \begin{bmatrix}1&0&0\\0&\times&\times\\0&\times&\times\end{bmatrix}$$
$$\xrightarrow{\boldsymbol{D}_2^\dagger} \begin{bmatrix}1&0&0\\0&|\times|&\times\\0&|\times|&\times\end{bmatrix} \xrightarrow{\boldsymbol{G}_2^\dagger} \begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix} = \boldsymbol{I}_N, \quad (15)$$

where $|\cdot|$ is the absolute value of the corresponding element. At the first step, the proposed scheme makes all the entries in the first column under the first component all zeros. To do so, we first extract the angle information from the first column by multiplying $\boldsymbol{\Phi}$ by $\boldsymbol{D}_1^\dagger$ to have an absolute-valued column, and then applying a series of Givens matrices with appropriate parameters to make all entries under $(1,1)$ element zeros. Since the Givens rotation has the length of vector, the $(1,1)$ element will be 1. At the same time, all the entries in the first row except the (1, 1) element also become zeros because of the orthogonality between the columns. We carry similar procedures on the remaining columns sequentially, and then finally we have an identity matrix $\boldsymbol{I}_N$. Since each Givens matrix is an orthogonal matrix, the matrix $\boldsymbol{\Phi}$ can be factored as:

$$\boldsymbol{\Phi} = \boldsymbol{D}_1(\phi_{1,1},\ldots,\phi_{1,3})\boldsymbol{G}_2(\psi_{1,1})\boldsymbol{G}_1(\psi_{1,2})\cdot$$
$$\boldsymbol{D}_2(\phi_{2,2},\ldots,\phi_{2,3})\boldsymbol{G}_2(\psi_{2,1}). \quad (16)$$

When we have a parameter set, i.e., the rotation angles $\{\phi_{k,l},\psi_{k,l}\}$, the proposed scheme exactly reconstructs the original matrix $\boldsymbol{\Phi}$. However, the transmission of the original parameter set still causes a large communication overhead. Therefore, the angle information of ϕ and ψ is quantized before transmission. Since the eigenvectors matrix consists of the real elements, the angles ϕ are quantized 0 or 2π by using 1 bit. On the other hand, the rotation angles $\{\psi_{k,l}\}$ are quantized between 0 and $\pi/2$ as given by the following equation:

$$\psi = \pi\cdot\frac{2k+1}{2^{b+2}}, \qquad k = 0,1,\ldots,2^b-1, \quad (17)$$

where b is the number of bits used to quantize ψ. As the probability density function of ϕ is not uniform according to [11], more efficient compression with modified quantization is also possible.

III. Performance Evaluation

A. Simulation Settings

Performance Metric: We evaluate the 3D reconstruction quality of point cloud delivery in terms of the symmetric MSE based on [14] in each attribute of 3D coordinates $\boldsymbol{p}$ and color components $\boldsymbol{c}$. The symmetric MSE of the 3D coordinates, $\mathsf{sMSE}_{\mathsf{xyz}}$, can be obtained as follows:

$$\mathsf{sMSE}_{\mathsf{xyz}} = \frac{1}{2}\big(d(\boldsymbol{p}_{\mathrm{org}}\rightarrow\boldsymbol{p}_{\mathrm{dec}}) + d(\boldsymbol{p}_{\mathrm{dec}}\rightarrow\boldsymbol{p}_{\mathrm{org}})\big), \quad (18)$$

where $\boldsymbol{p}_{\text{org}}$ is the original 3D coordinates and $\boldsymbol{p}_{\text{dec}}$ is the decoded 3D coordinates. Here, each way of the asymmetric MSE in the 3D coordinates are defined as follows:

$$d(\boldsymbol{p}_{\text{org}} \rightarrow \boldsymbol{p}_{\text{dec}}) = \frac{1}{N} \sum_{\boldsymbol{p} \in \boldsymbol{p}_{\text{org}}} \left(\min_{\boldsymbol{p}' \in \boldsymbol{p}_{\text{dec}}} \left\| \boldsymbol{p} - \boldsymbol{p}' \right\|_2^2 \right), \quad (19)$$

$$d(\boldsymbol{p}_{\text{dec}} \rightarrow \boldsymbol{p}_{\text{org}}) = \frac{1}{N} \sum_{\boldsymbol{p} \in \boldsymbol{p}_{\text{dec}}} \left(\min_{\boldsymbol{p}' \in \boldsymbol{p}_{\text{org}}} \left\| \boldsymbol{p} - \boldsymbol{p}' \right\|_2^2 \right). \quad (20)$$

The symmetric MSE of the color components, sMSE_{yuv}, is derived analogously as follows:

$$\text{sMSE}_{\text{yuv}} = \frac{1}{2} \left(d(\boldsymbol{c}_{\text{org}} \rightarrow \boldsymbol{c}_{\text{dec}}) + d(\boldsymbol{c}_{\text{dec}} \rightarrow \boldsymbol{c}_{\text{org}}) \right), \quad (21)$$

where $\boldsymbol{c}_{\text{org}}$ and $\boldsymbol{c}_{\text{dec}}$ are the original and decoded color components, respectively. In this case, the asymmetric MSE of the color component is defined as follows:

$$d(\boldsymbol{c}_{\text{org}} \rightarrow \boldsymbol{c}_{\text{dec}}) = \frac{1}{N} \sum_{\boldsymbol{c} \in \boldsymbol{c}_{\text{org}}} \left\| \boldsymbol{c} - \boldsymbol{c}_{\text{dec}}(\boldsymbol{p}'_{\text{dec}}) \right\|_2^2, \quad \boldsymbol{p}'_{\text{dec}} = \arg\min_{\boldsymbol{p}' \in \boldsymbol{p}_{\text{dec}}} \left\| \boldsymbol{p}_{\text{org}} - \boldsymbol{p}' \right\|_2^2, \quad (22)$$

$$d(\boldsymbol{c}_{\text{dec}} \rightarrow \boldsymbol{c}_{\text{org}}) = \frac{1}{N} \sum_{\boldsymbol{c} \in \boldsymbol{c}_{\text{dec}}} \left\| \boldsymbol{c} - \boldsymbol{c}_{\text{org}}(\boldsymbol{p}'_{\text{org}}) \right\|_2^2, \quad \boldsymbol{p}'_{\text{org}} = \arg\min_{\boldsymbol{p}' \in \boldsymbol{p}_{\text{org}}} \left\| \boldsymbol{p}_{\text{dec}} - \boldsymbol{p}' \right\|_2^2, \quad (23)$$

where $\boldsymbol{c}_{\text{dec/org}}(\boldsymbol{p})$ represents the color components of the corresponding 3D coordinate $\boldsymbol{p}$.

Point Cloud Dataset: We use the reference point cloud, namely, *milk_color*, whose number of points is 13,704. We use octree decomposition to decompose 3D points into multiple octree blocks. In this case, the maximum number of 3D points in each block is N.

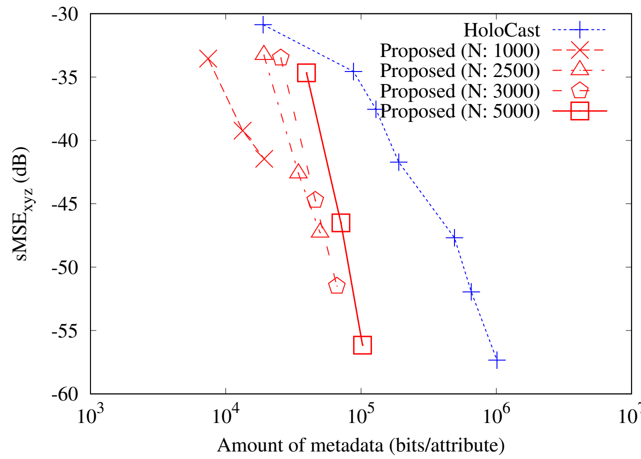
B. Overhead Reduction

We first evaluate the amount of communication overhead in the original HoloCast and the proposed schemes in terms of bits/attribute. Here, both schemes consider the different levels of N in octree decomposition to discuss the tradeoff between the overhead and reconstruction quality: N = 1,000, 2,500, 3,000, and 5,000. In addition, the proposed scheme uses the different number of bits b for the angle parameter ψ: $b = 4$, 8, and 12.

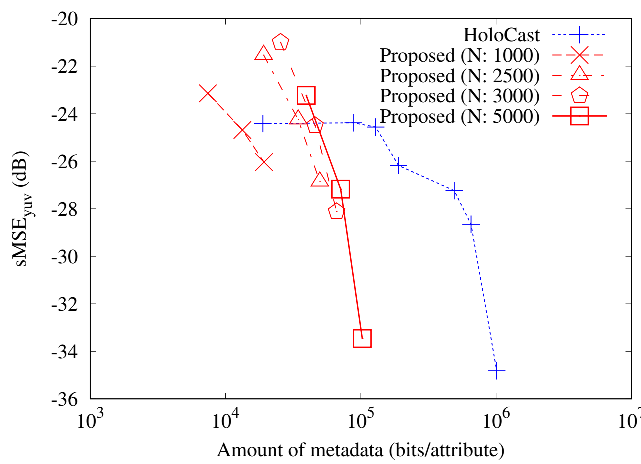
Figs. 2(a) and (b) show the reconstruction quality of the 3D coordinates and color components as a function of the communication overhead for graph-based transform basis matrix in both schemes at a wireless channel SNR of 20 dB. From the evaluation results, we have the following key observations:

- The proposed scheme improves the 3D reconstruction quality with an increase of N.
- The proposed scheme achieves the same 3D reconstruction quality as the original HoloCast with a lower communication overhead.

For example, the proposed scheme achieves 89.8% overhead reduction compared with HoloCast under 1.4 dB and 1.2 dB



(a) 3D coordinates $\boldsymbol{p}$



(b) Color components $\boldsymbol{c}$

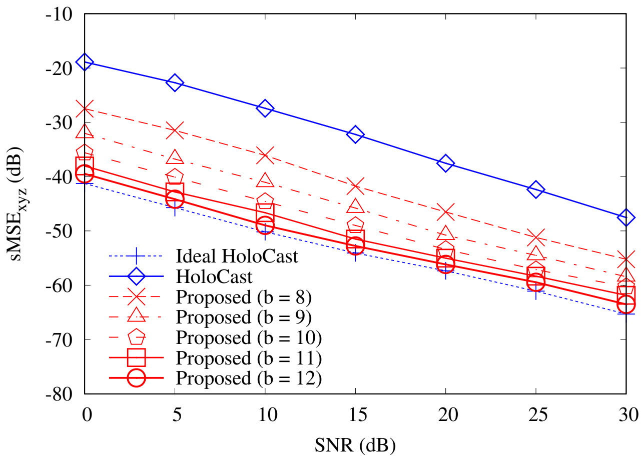
Fig. 2. MSE of 3D coordinates and color attributes as a function of overhead in original graph-based HoloCast and the proposed schemes at wireless channel SNR of 20 dB.

MSE degradation in the 3D coordinates and color components at the octree decomposition level N of 5,000.

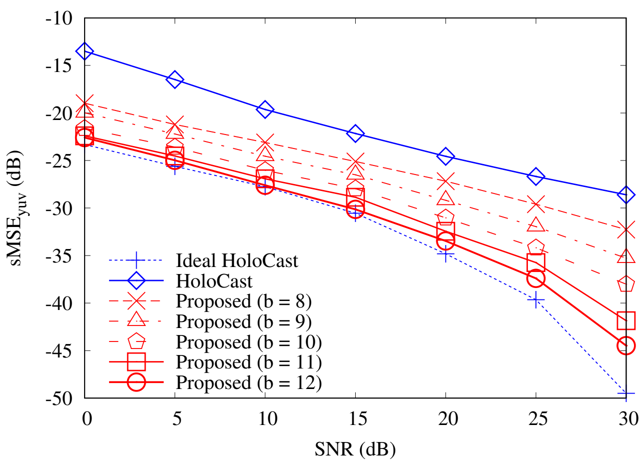
C. 3D Reconstruction Quality

The previous section demonstrated that the Givens rotation in the proposed scheme yields a large overhead reduction to achieve the same quality at a certain channel SNR. In this section, we discuss the 3D reconstruction quality of both schemes in different wireless channel quality environments. Here, we set a maximum number of 3D points in each octree block to 5,000 in the proposed scheme. In addition, we discuss the 3D reconstruction quality of the conventional HoloCast with/without overhead reduction, we also consider two types of HoloCast with N of 5,000 and 750, namely, ideal HoloCast and HoloCast. In this case, the ideal HoloCast and HoloCast schemes require 1,011,306 and 128,915 bits/attribute, respectively.

Figs. 3 (a) and (b) show the MSE performance of 3D coordinates and color attributes in each reference scheme as a



(a) 3D coordinates $\boldsymbol{p}$



(b) Color components $\boldsymbol{c}$

Fig. 3. MSE of 3D coordinates and color attributes in HoloCast and the proposed schemes at $N = 5{,}000$ as a function of wireless channel SNRs.

function of wireless channel SNRs. In this case, the proposed scheme sets the number of bits for the angle parameter ψ from 8 to 12 to demonstrate the impact of overhead on the 3D reconstruction quality. Here, the overheads in the proposed schemes at $b = \{8, 9, \cdots, 12\}$ bits are 71,086, 78,984, 86,882, 94,780, and 102,678 bits/attribute, respectively.

We can see that the 3D reconstruction quality of the proposed scheme approaches to the ideal HoloCast with an increase of b. For example, when the number of bits b is 12, the degradation of reconstruction quality between ideal HoloCast and the proposed scheme in both 3D coordinates and color components is 1.5 dB on average across the wireless channel SNRs of 0 dB to 30 dB. As we will discuss the visual quality of the reference schemes in the following section, the degradation at a large number of b is small for human perception.

In addition, we can verify that the proposed scheme simultaneously realizes better 3D reconstruction quality and low overhead requirement compared with the original HoloCast irrespective of wireless channel quality. For example, the MSE performance of the proposed scheme in the 3D coordinates and color components is 19.4 dB and 9.9 dB higher than HoloCast, respectively, on average across the wireless channel SNRs of 0 dB to 30 dB at $b = 12$. In this case, the communication overhead of the proposed scheme is 20.3% lower than that of HoloCast. It suggests that the Given rotation in the proposed scheme can reconstruct graph-based transform basis matrix with a lower communication overhead and clean 3D point cloud can be obtained from the reconstructed basis matrix compared with the conventional graph-based point cloud delivery schemes.

D. Visual Quality

Finally, we discuss the visual quality of the conventional HoloCast and the proposed scheme to further clarify the effect of the Givens rotation on the reconstructed 3D point cloud. Figs. 4 (a)–(f) discuss the visual quality of the reference schemes at the wireless channel SNR of 30 dB. We consider the same N in each reference scheme as mentioned in Sec. III-C. The amount of metadata in each reference scheme is thus the same in Sec. III-C.

The key results from these figures are summarized as follows:

- The visual quality of HoloCast significantly degrades when the amount of metadata is restricted. Whereas, the proposed scheme achieves high quality in 3D reconstruction at a lower requirement of metadata overhead.
- The proposed scheme at $b = 12$ achieves almost comparable visual quality of the ideal HoloCast. The minor degradation does not impose a significant effect on the human perception.

IV. Conclusion

In this paper, we proposed a novel point cloud delivery scheme to maintain better 3D reconstruction quality under a low communication overhead requirement. Specifically, the Given rotation in the proposed scheme can compress the GFT basis matrix into quantized angle parameters. Based on the quantized angle parameters, the proposed scheme can reconstruct the basis matrix at the receiver under a low communication overhead. Evaluation results showed that the proposed scheme simultaneously yields better 3D reconstruction quality and lower communication overhead compared with the conventional HoloCast. In addition, the proposed scheme achieves a similar visual quality to the ideal HoloCast scheme with a significant reduction on communication overhead.

Acknowledgment

T. Fujihashi's work was partly supported by JSPS KAKENHI Grant Number 17K12672 and The Telecommunications Advancement Foundation.

References

[1] R. Mekuria and L. Bivolarsky, "Overview of the MPEG activity on point cloud compression," in *Data Compression Conference*, 2016, p. 620.

[2] P. Su, W. Cao, J. Ma, B. Cheng, X. Liang, L. Cao, and G. Jin, "Fast computer-generated hologram generation method for three-dimensional point cloud model," *Journal of Display Technology*, vol. 12, no. 12, pp. 1688–1694, 2016.

[3] J. Kammerl, N. Blodow, R. B. Rusu, S. Gedikli, M. Beetz, and E. Steinbach, "Real-time compression of point cloud streams," in *IEEE International Conference on Robotics and Automation*, 2012, pp. 778–785.

[4] K. Muller, H. Schwarz, D. Marpe, C. Bartnik, S. Bosse, H. Brust, T. Hinz, H. Lakshman, P. Merkle, F. H. Rhee, G. Tech, M. Winken, and T. Wiegand, "3D is here: Point cloud library (PCL)," in *IEEE International Conference on Robotics and Automation*, 2011, pp. 1–4.

[5] R. schnabel and R. Klein, "Octree-based point-cloud compression," in *Eurographics Symposium on Point-Based Graphics*, 2006, pp. 111–121.

[6] A. Ortega, P. Frossard, J. Kovacevic, J. M. F. Moura, and P. Vandergheynst, "Graph signal processing: Overview, challenges, and applications," *Proceedings of the IEEE*, vol. 106, no. 5, pp. 808–828, 2018.

[7] T. Fujihashi, T. Koike-Akino, T. Watanabe, and P. Orlik, "HoloCast: Graph signal processing for graceful point cloud delivery," in *IEEE International Conference on Communications*, 2019, pp. 1–7.

[8] C. Zhang, D. Florêncio, and C. Loop, "Point cloud attribute compression with graph transform," in *2014 IEEE International Conference on Image Processing (ICIP)*, 2014, pp. 2066–2070.

[9] S. Jakubczak and D. Katabi, "A cross-layer design for scalable mobile video," in *ACM Annual International Conference on Mobile Computing and Networking*, Las Vegas, NV, sep 2011, pp. 289–300.

[10] M. A. Sadrabadi, A. Khandani, and F. Lahouti, "Channel feedback quantization for high data rate MIMO systems," *IEEE Transactions on Wireless Communications*, vol. 5, no. 12, pp. 3335–3338, 2006.

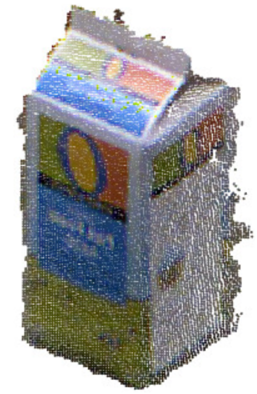
[11] J. C. Roh and B. D. Rao, "Efficient feedback methods for MIMO channels based on parameterization," *IEEE Transactions on Wireless Communications*, vol. 6, no. 1, pp. 282–292, 2007.

[12] X. Liu, G. Cheung, X. Wu, and D. Zhao, "Random walk graph Laplacian based smoothness prior for soft decoding of JPEG images," *IEEE Transactions on Image Processing*, vol. 26, no. 2, pp. 509–524, 2017.

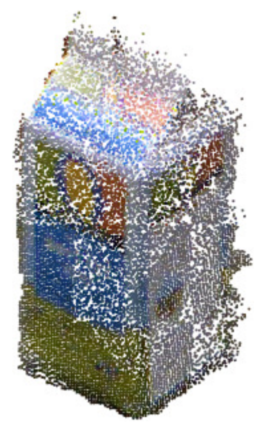
[13] R. Horaud, "A short tutorial on graph Laplacians, Laplacian embedding, and spectral clustering." [Online]. Available: http://csustan.csustan.edu/ tom/Lecture-Notes/Clustering/GraphLaplacian-tutorial.pdf

[14] P. A. Chou, E. Pavez, R. L. de Queiroz, and A. Ortega, "Dynamic polygon clouds: Representation and compression for VR/AR," Microsoft Research Technical Report, Tech. Rep., 2017.

(a) Original

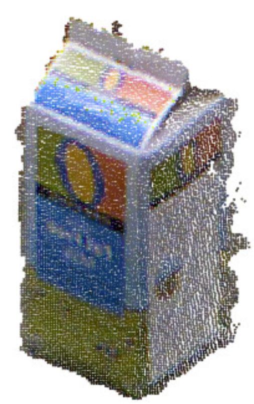


(b) Ideal HoloCast
$\mathsf{sMSE}_{\mathsf{xyz}}$: -65.3 dB
$\mathsf{sMSE}_{\mathsf{yuv}}$: -49.5 dB
Overhead: 1,011,306 bits



(c) HoloCast
$\mathsf{sMSE}_{\mathsf{xyz}}$: -47.5 dB
$\mathsf{sMSE}_{\mathsf{yuv}}$: -28.6 dB
Overhead: 128,915 bits

(d) Proposed ($b = 10$)
$\mathsf{sMSE}_{\mathsf{xyz}}$: -60.3 dB
$\mathsf{sMSE}_{\mathsf{yuv}}$: -38.0 dB
Overhead: 86,882 bits



(e) Proposed ($b = 11$)
$\mathsf{sMSE}_{\mathsf{xyz}}$: -61.9 dB
$\mathsf{sMSE}_{\mathsf{yuv}}$: -41.9 dB
Overhead: 94,780 bits

(f) Proposed ($b = 12$)
$\mathsf{sMSE}_{\mathsf{xyz}}$: -63.3 dB
$\mathsf{sMSE}_{\mathsf{yuv}}$: -44.5 dB
Overhead: 102,678 bits

Fig. 4. Snapshots in the reference schemes at wireless channel SNR of 30 dB under the different number of bits for the angle parameters.