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Abstract

Communication of bioelectric signals, such as electroencephalography (EEG) signals, will be a key technology for smooth interaction between users and remote robots. The existing solutions use an orthogonal transform for EEG signal compression, such as Discrete Wavelet Transform (DWT) or Discrete Cosine Transform (DCT). This paper proposes a graph-based compression scheme for EEG signals to improve the quality at the given rate. The proposed scheme constructs a graph from the positions of the EEG sensors and adopts parameterized graph shift operators to obtain the graph basis functions for decorrelating the EEG signals. Graph Fourier Transform (GFT) based on the graph basis functions with the combination of quantization and entropy coding can send high quality EEG signals with fewer bits. Evaluations using the EEG signal dataset show that the proposed GFT-based compression can send better quality EEG signals than the existing DCT-based and DWT-based schemes at the same bit rates. In addition, an optimal parameter of the graph shift operator under the given rate is discussed to maximize the reconstruction quality of the graph-based scheme.

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Graph-Based EEG Signal Compression for Human-Machine Interaction

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ABSTRACT Communication of bioelectric signals, such as electroencephalography (EEG) signals, will be a key technology for smooth interaction between users and remote robots. The existing solutions use an orthogonal transform for EEG signal compression, such as Discrete Wavelet Transform (DWT) or Discrete Cosine Transform (DCT). This paper proposes a graph-based compression scheme for EEG signals to improve the quality at the given rate. The proposed scheme constructs a graph from the positions of the EEG sensors and adopts parameterized graph shift operators to obtain the graph basis functions for decorrelating the EEG signals. Graph Fourier Transform (GFT) based on the graph basis functions with the combination of quantization and entropy coding can send high quality EEG signals with fewer bits. Evaluations using the EEG signal dataset show that the proposed GFT-based compression can send better quality EEG signals than the existing DCT-based and DWT-based schemes at the same bit rates. In addition, an optimal parameter of the graph shift operator under the given rate is discussed to maximize the reconstruction quality of the graph-based scheme.

INDEX TERMS EEG, Graph signal processing, Parameterized graph shift operator

I. INTRODUCTION

Thanks to rapid advances in robotics, sensors, communications, and artificial intelligence (AI), human-machine interaction (HMI)-the interaction between users and remote robots over wireless channels-will be a key technology for realizing telework, remote operation, and epidemic care. Fig. 1 shows an example of an end-to-end HMI architecture. For a smooth interaction with the remote robots, the users in the HMI systems can send the physiological monitoring data of the users to the robots. Wearable sensors or monitors can measure the physiological data. The sensors can track continuous biosignals from the human body or other organic tissues such as the heart, brain, muscles, and blood as continuous bioelectric signals, including electrocardiography (ECG), intracranial/scalp electroencephalography (EEG), electromyography (EMG), magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and so on. Each robot can identify the user's vital signs, physiological data, and biometrics from the bioelectric signals by using signal processing solutions [1]–[4] to support the user's activity.

This paper aims to use EEG signals as bioelectric signals to send the tracked brain information to the remote robots. One of the key issues in HMI systems is to send high quality EEG signals for smooth interaction with remote robots. In other words, the accurate EEG signals should be reconstructed at the remote robots regardless of the available rate of the wireless channels. The existing solutions have successfully integrated source coding and transmission solutions for the EEG signals. The existing studies can be classified into signal processing based [5]–[9] and learning based solutions [10, 11]. For example, transform coding approaches have been proposed in signal processing-based solutions. The measured signals are transformed into frequency domain representations using discrete wavelet transform (DWT), discrete cosine transform (DCT), or other orthogonal transform techniques. Each representation is then quantized and/or entropy-coded prior to transmission.

This paper is the first attempt to introduce graph signal processing for EEG signal compression to improve the quality of EEG signals in band-limited networks. This paper proposes a compression scheme that integrates graph-based decorrela-

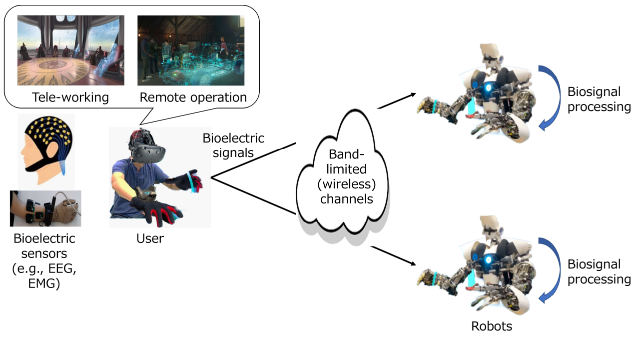


FIGURE 1: An example of an HMI system. A user unicasts/multicasts bioelectric signals to robots over band-limited networks, and each robot identifies the user's intelligence through biosignal processing.

tion, quantization, and entropy coding. Specifically, the 3D coordinates of the EEG sensors and the measured time-series signal at each sensor can be regarded as graph signals [12]. The proposed scheme can obtain the graph basis functions based on the constructed graph signals and performs Graph Fourier Transform (GFT) [13] with quantization and entropy coding for compression. Since the sensors are distributed unevenly in 3D space to measure brain signals, the GFT-based compression achieves better energy compaction than typical decorrelation techniques such as DCT and DWT. Evaluation results using the dataset of EEG signals show that the proposed scheme can reconstruct better quality EEG signals compared to the existing DCT-based and DWT-based schemes under the same amount of bandwidth.

The contributions of our study are as follows:

- Our study is the first to realize graph-based compression for bioelectric signals, i.e., EEG signals, to support HMI systems.
- The parameterized graph shift operators are introduced for EEG signal decorrelation. The proposed scheme can adopt the appropriate graph shift operators to reconstruct high-quality EEG signals at the given rates.
- From the investigation of the graph shift operators, the optimized parameters for the graph shift operators perform well in band-limited networks and channels, while the gap between the optimized and known graph shift operators becomes negligible in broadband environments.

II. RELATED WORK

This study relates to bioelectric signal compression and graph-based compression and delivery studies.

A. BIOELECTRIC SIGNAL COMPRESSION

Lossless, near-lossless, and lossy compression techniques have been developed for bioelectric signals such as EEG and EMG signals. Lossless compression [14]–[18] guarantees no degradation between the original and reconstructed bioelectric signals. In contrast to lossless compression, near-lossless compression [15, 19]–[22] uses quantization, i.e. lossy operation, for efficient compression. However, it limits the quantization distortion according to the given error values. The lossless and near-lossless compression schemes can be divided into predictive coding [15, 17]–[19, 22]–[24] and transform coding [14, 21, 25]. Predictive coding first fits the measured bioelectric signals to the past signals using a predictor such as Markov chains, linear prediction, or artificial neural networks (ANN). The discrepancy between the measured and fitted signals is then obtained and coded with a variable length code (e.g., the Huffman code). Transform coding uses frequency conversion techniques for the bioelectric signals and discards some frequency representations from all frequency representations for compression. Finally, it encodes the difference between the original and reconstructed bioelectric signals from the limited frequency representations using Huffman coding. However, the lossless and near-lossless compression schemes do not achieve high compression ratios and are not well suited for band-limited wireless channels.

Lossy compression techniques [5, 6, 26]–[29] have been proposed for EEG signals. The lossy compression techniques introduce a relatively large distortion compared to the lossless and near-lossless compression techniques. However, they can achieve much higher compression ratios than the lossless and near-lossless compression techniques and are therefore preferable for band-limited channels. For example, Fourier-based [28], DCT-based [30], DWT-based [5, 6, 26], and discrete Tchebichef moment based lossy compression [29] have been proposed for EEG signals. The EEG signals are transformed into frequency representations using a certain orthogonal transformation, and the frequency representations are quantized and entropy-coded for compression.

This paper proposes a novel compression scheme for bioelectric signal communication. Unlike the lossy compression studies, the proposed scheme introduces graph signal processing for bioelectric signal compression. It utilizes EEG sensor correlations to compress the energy of EEG signals. The graph-based proposed scheme achieves better reconstruction quality than the typical DCT-based and DWT-based schemes under the same amount of traffic.

B. GRAPH-BASED COMPRESSION AND DELIVERY

Some recent studies have used Graph Signal Processing (GSP) for lossy compression and communication. In particular, GSP-based compression and communication is designed for point cloud content, i.e., holographic-type content. Recent work has used GFT and Graph Wavelet Transform [31] for energy compression of 3D coordinates and color components of point clouds [32]–[35]. A new paradigm of Graph Convolutional Neural Networks (GCNN) [36] has also been adopted for the energy compression of the graph signals [37]. Specifically, the graph signals are compressed into some latent variables using a series of GCNNs, and the latent variables are delivered over networks. The graph

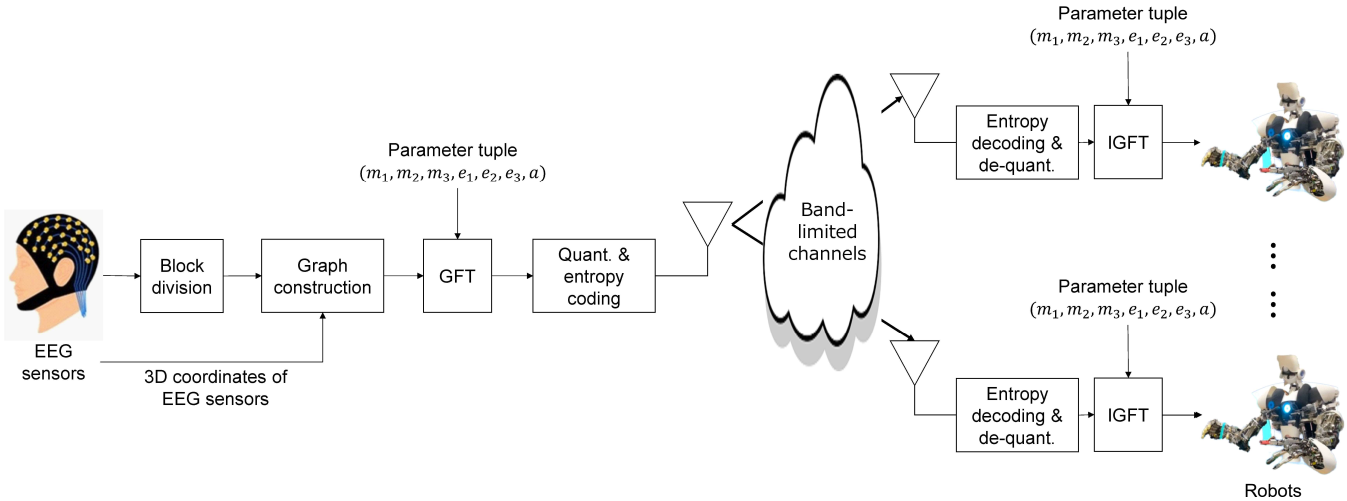


FIGURE 2: Overview of the proposed scheme. The proposed scheme decorrelates the EEG signals using the parameterized GFT followed by quantization and entropy coding.

signals can be decoded from the received latent variables using the multi-layer perceptron decoder.

In bioelectrical signals, GSP-based solutions have been proposed for bioelectrical signal analysis [38, 39]. This paper is the first study on GFT-based compression for EEG signal communication. According to the positions of the bioelectric sensors, the proposed scheme constructs the graph basis functions from the parameterized graph shift operators for signal decorrelation. From the investigation of the parameterized graph shift operators, the regular graph shift operator achieves almost the same quality as the optimized graph shift operator regardless of the subjects.

III. PROPOSED SCHEME

A. OVERVIEW

Fig. 2 shows an overview of the proposed scheme. The proposed scheme first divides the measured EEG signals over EEG sensors into signal blocks of T length. In this paper, the length of each signal block is fixed to be 1024. The proposed scheme compresses the measured EEG signals using GFT for each signal block. To realize the GFT for the signals, an undirected graph is constructed from the positions of the EEG sensors. The GFT basis functions are then derived from the parameterized graph shift operator based on the undirected graph. The measured EEG signals are converted to frequency domain representations, i.e., GFT coefficients, using the GFT basis functions. The GFT coefficients are then binarized for transmission using quantization and entropy coding, which is the same operation in existing lossy compression techniques. The compressed bit stream is transmitted over wireless channels to the remote robot. Each robot reconstructs the EEG signals in each block by performing the inverse operation at the transmitter side and can recognize the user's intelligence from the reconstructed EEG signals.

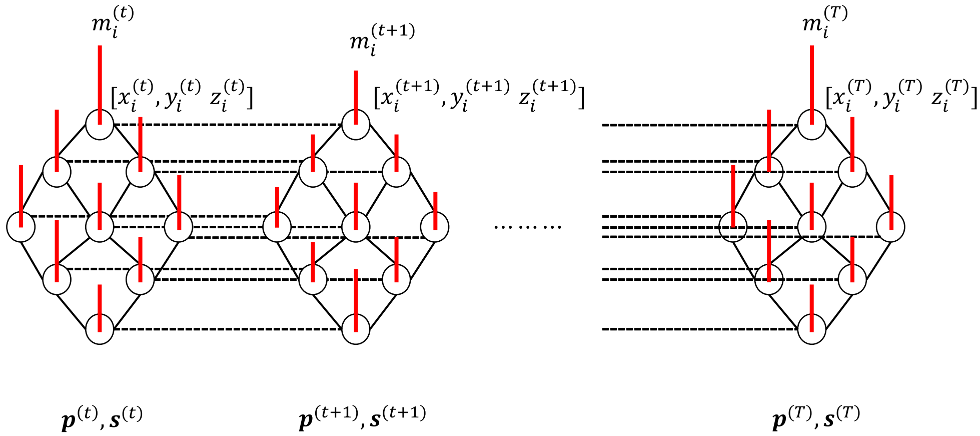
B. GRAPH-BASED EEG COMPRESSION

EEG sensors are placed on the user's head in 3D space, and each sensor measures a time series of EEG signals. The GFT can be used to decorrelate the EEG signals across the sensors. There are several definitions of the GFT depending on the directed/undirected graph, edge weight, and graph shift operators [12, 13]. In this paper, a weighted and undirected graph is defined from the 3D coordinates of the deployed EEG sensors. Specifically, the graph is defined as $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{W})$, where $\boldsymbol{V}$, $\boldsymbol{E}$, and $\boldsymbol{W}$ are the vertex set, edge set, and adjacency matrix, respectively. Here, each vertex has two attributes of the 3D coordinates of N EEG sensors $\boldsymbol{p}^{(t)} = [\mathrm{x}_i, \mathrm{y}_i, \mathrm{z}_i]^{\mathrm{T}} \in \mathbb{R}^{3\times N}$ and the measured EEG signal from N EEG sensors $\boldsymbol{s}^{(t)} = [\mathrm{m}_i] \in \mathbb{R}^{1\times N}$ at each time t.

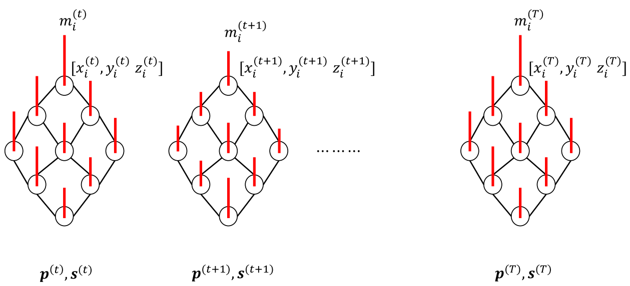
Fig. 3 shows an overview of the graph structure for the EEG signals. This graph structure consists of two subgraphs $\hat{\boldsymbol{G}}$ and $\bar{\boldsymbol{G}}$. One subgraph $\hat{\boldsymbol{G}}$ represents the graph structure for the EEG sensors at each time instant, and one subgraph $\bar{\boldsymbol{G}}$ represents the graph structure for the time series of the EEG signals at each sensor. Each vertex of the graph represents each bioelectric sensor. For the subgraph $\hat{\boldsymbol{G}}$, each element $\hat{W}_{i,j}^{(t)}$ in the adjacency matrix $\hat{\boldsymbol{W}}^{(t)}$ represents the edge weight between vertices i and j in the subgraph at time t. The edge weights are usually defined as the distance between the 3D coordinates of vertices i and j as follows:

$$\hat{W}_{i,j}^{(t)} = \exp\left(-\frac{\|\boldsymbol{p}_i^{(t)} - \boldsymbol{p}_j^{(t)}\|_2^2}{\epsilon_p}\right), \tag{1}$$

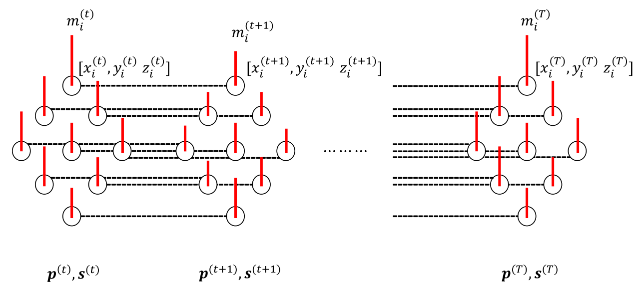
where ϵ_p is the standard deviation. In the following part, the operations are performed in each time instance. Therefore, the time index t is omitted for simplicity.



(a) Overall graph structure $\boldsymbol{G}$



(b) Subgraph $\hat{\boldsymbol{G}}$ for EEG sensors at each time instant



(c) Subgraph $\bar{\boldsymbol{G}}$ for the time series of the EEG signals at each EEG sensor

FIGURE 3: Graph structure of EEG sensors in the proposed scheme.

TABLE 1: Well-known graph shift operators based on parameter tuples

$\boldsymbol{M} = (m_1, m_2, m_3, e_1, e_2, e_3, a)$	Operator	Description
$(1, -1, 0, 1, 0, 0, 0)$	$D - W$	Regular
$(1, 1, 0, 1, 0, 0, 0)$	$D + W$	Signless
$(0, -1, 1, 0, -\frac{1}{2}, -\frac{1}{2}, 0)$	$I - D^{-\frac{1}{2}} W D^{-\frac{1}{2}}$	Combination
$(0, 1, 0, 0, -1, 0, 0)$	$D^{-1} W$	Transition
$(0, -1, 1, 0, -1, 0, 0)$	$I - D^{-1} W$	Random-walk

Based on the adjacency matrix, the diagonal degree matrix $\hat{\boldsymbol{D}}$ can be derived as follows:

$$\hat{\boldsymbol{D}} = \mathrm{diag}(\hat{D}_1, \ldots, \hat{D}_N), \ \hat{D}_i = \sum_{n=1}^{N} \hat{W}_{i,n}. \tag{2}$$

The graph shift operator that uniquely characterizes the graph topology is then derived from the graph shift operator L. Many graph shift operators have been discussed in the graph signal processing literature, and the parameterized graph shift operator $\boldsymbol{L}$ has been proposed in the recent literature [40]:

$$\boldsymbol{L} = m_1 \hat{\boldsymbol{D}}_a^{e_1} + m_2 \hat{\boldsymbol{D}}_a^{e_2} \hat{\boldsymbol{W}}_a \hat{\boldsymbol{D}}_a^{e_3} + m_3 \boldsymbol{I}, \tag{3}$$

where $\hat{\boldsymbol{W}}_a = \hat{\boldsymbol{W}} + a\boldsymbol{I}$, $\hat{\boldsymbol{D}}_a$ is the diagonal degree matrix of $\hat{\boldsymbol{W}}_a$, and $\boldsymbol{I}$ is the $N \times N$ identity matrix. In addition, m_1 through m_3 are scalar multiplicative parameters, e_1 through e_3 are scalar exponential parameters, and a is an additive parameter. Table 1 lists the known graph shift operators. The GFT basis functions are the right singular vectors of the graph shift operator. The right singular vectors $\boldsymbol{\Phi} \in \mathbb{R}^{N \times N}$ and the corresponding diagonal singular values $\boldsymbol{\Lambda}$ can be obtained from the singular value decomposition for the graph shift operator as follows:

$$\boldsymbol{L} = \boldsymbol{\Psi} \boldsymbol{\Lambda} \boldsymbol{\Phi}^{-1}. \tag{4}$$

where $\boldsymbol{\Psi}$ denotes the left singular vector matrix. Here, the associated frequencies of the singular vectors are the corresponding singular values. The GFT coefficients $\boldsymbol{f}$ of a given graph signal can be obtained by projecting the graph signal onto the GFT basis functions. The projection is derived by multiplying the singular vectors by the measured EEG signals over the EEG sensors $\boldsymbol{s}$ as follows:

$$\boldsymbol{f} = \boldsymbol{s}\,\boldsymbol{\Phi}. \tag{5}$$

The GFT coefficients corresponding to smaller singular values reflect the lower frequency of the graph signals, i.e., less variation in the graph.

For the subgraph $\bar{\boldsymbol{G}}$, a line graph with uniform edge weights is considered to represent the time series of EEG signals at each sensor. In this case, the GFT for the line graph with uniform edge weights is the same as the DCT, and thus 1D-DCT is performed on the time series of EEG signals

TABLE 2: Optimal graph shift operators at different bit rates

Bit rate (Kbps)	m_1	m_2	m_3	e_1	e_2	e_3	a
40	-1.0	-1.0	0.5	1.0	0.5	0.5	-0.5
80	0.5	-1.0	-0.5	0.5	0.5	-1.0	1.0
120	-1.0	-0.5	0	-1.0	-0.5	-1.0	0

at each EEG sensor. In summary, energy compaction in the graph $\boldsymbol{G}$ can be realized by integrating the GFT in Eq. (5) over the EEG sensors at each time instant and the DCT on the time series of EEG signals at each EEG sensor.

The GFT coefficients are uniformly quantized into symbols $\boldsymbol{c}$ using the quantization factor δ_i as $\boldsymbol{c} = \mathrm{round}(\boldsymbol{f}/\delta_i)$. After quantization, the symbols corresponding to the high-frequency GFT coefficients become zero. The proposed scheme integrates zero run-length coding with Huffman coding to compress the symbols into the bitstream. The integration is a well-known solution to represent the zero-value symbols with few bits.

The receiver side decodes the symbols from the received bitstream and obtains the quantized GFT coefficients as $\hat{\boldsymbol{f}} = \boldsymbol{c} \cdot \delta_i$. The receiver finally reconstructs the EEG signals by taking the inverse GFT for the quantized GFT coefficients.

IV. EVALUATION

A. EVALUATION SETTINGS

EEG Dataset

An EEG dataset from Motor-Imagery [41] is used for analysis. The dataset contains EEG signals from 52 subjects (19 females, mean age $\pm$ SD age $= 24.8 \pm 3.86$ years). The EEG signals are measured with 64 Ag/AgCl active electrodes at a sampling rate of 512 kHz. The 3D coordinates of the EEG electrodes are recorded in the data set. The hand movement experiments are performed for six seconds with 20 trials, and the EEG signals from the first trial are used for evaluation.

Metric

Two metrics are considered for the reconstruction quality of the EEG signals: Normalized MSE (NMSE) and Percentage Root Mean Square Difference (PRD). NMSE is defined as:

$$\mathrm{NMSE} = 10 \log_{10} \frac{\varepsilon_{\mathrm{MSE}}}{\sum_i^N s_i^2}, \tag{6}$$

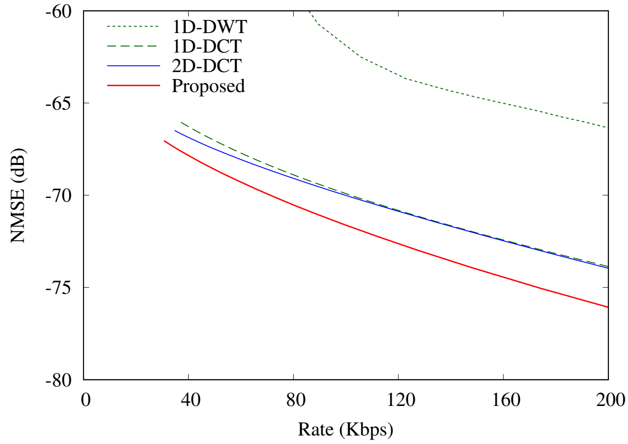
where $\varepsilon_{\mathrm{MSE}}$ is the MSE between the original and decoded EEG signals. PRD represents the normalized sum of squared errors as a percentage and is derived as follows:

$$\mathrm{PRD} = \sqrt{\mathrm{NMSE}} * 100. \tag{7}$$

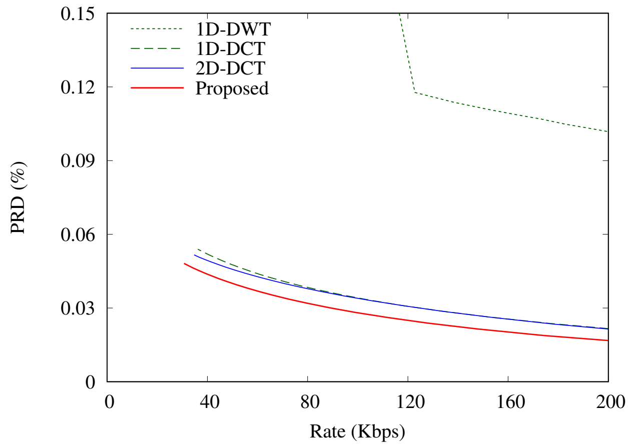
A lower PRD represents a better quality of the reconstructed EEG signal.

B. BASELINE PERFORMANCE

This section discusses the baseline performance of the proposed scheme against the existing schemes for EEG signal compression. 1D-DCT-based [30], 2D-DCT-based, and DWT-based [6] baselines are prepared for comparison. The



(a) NMSE



(b) PRD

FIGURE 4: Average reconstruction quality of EEG signals for 64 EEG sensors and 52 subjects as a function of bit rates.

1D-DCT-based schemes take 1D-DCT for the time series of EEG signals from each sensor and uniform quantization for the DCT coefficients. Finally, the quantized DCT coefficients are entropy coded using the combination of zero run length and Huffman coding, the same as the proposed scheme. The 2D-DCT based schemes perform 2D-DCT for EEG signals across sensors to exploit the correlations between the EEG sensors. The same operation of quantization and entropy coding is used for the 2D-DCT coefficients. The DWT-based scheme uses 1D DWT with level 6 for the EEG signals. The DWT coefficients are then compressed using set partitioning in hierarchical trees (SPIHT). Note that the recent discrete Tchebichef momentum-based scheme [29] requires even more traffic for sending EEG signals compared to other schemes, and thus this paper skips the comparison with the recent scheme [29].

Fig. 4 (a) and (b) show the average reconstruction quality of the baseline and proposed schemes over 64 sensors and 52 subjects as a function of bit rates. The proposed scheme

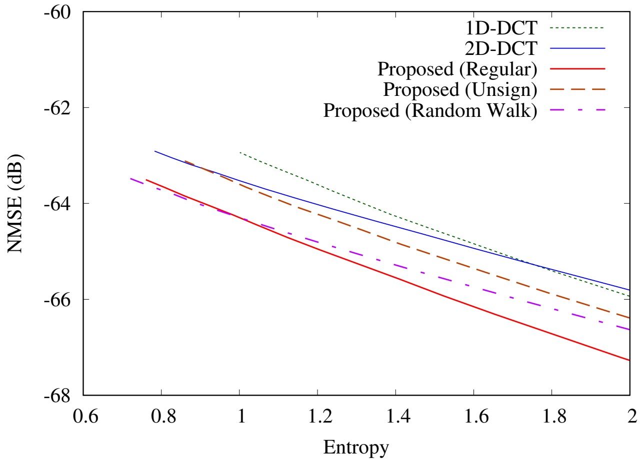


FIGURE 5: Average NMSE performance and entropy of quantized symbols from 64 EEG sensors for DCT-based and proposed schemes under different quantization factors δ_i. Here the subject ID is 1.

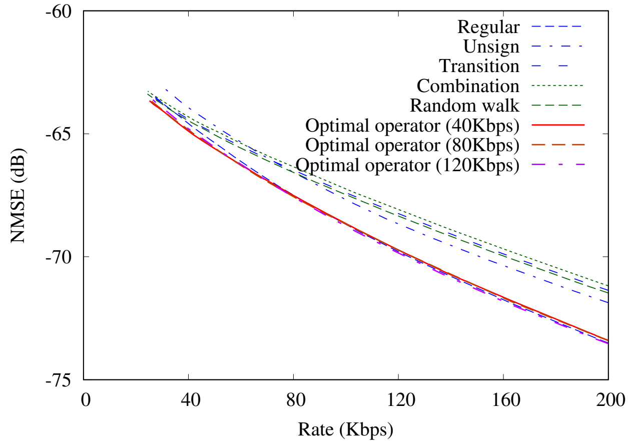
considers the regular graph shift operator for signal decorrelation. The evaluation results show that the reconstruction quality of the proposed graph-based scheme is higher than the existing DCT-based and DWT-based baselines at the same bit rates. Based on the results in Fig. 4 (a), we measure the Bjøntegaard delta (BD)-rate [42] between the NMSE of -67.0 dB and -80.0 dB to discuss the compression performance in detail. Note that a negative BD-rate indicates an improvement in performance over the baselines. The BD-rates between the proposed scheme and the 1D-DCT-based, 2D-DCT-based, and DWT-based baselines are -27.0%, -25.0%, and -82.0%, respectively. This means that the proposed scheme reduces the bit rate by at least 25% with the same reconstruction quality.

To clarify the reason for the performance gain of the proposed scheme, Fig. 5 shows the average NMSE performance and the entropy of the quantized signals of 64 EEG sensors for DCT-based baselines and the proposed schemes with other graph shift operators under different quantization factors δ_i. There are two findings from the evaluation results as follows:

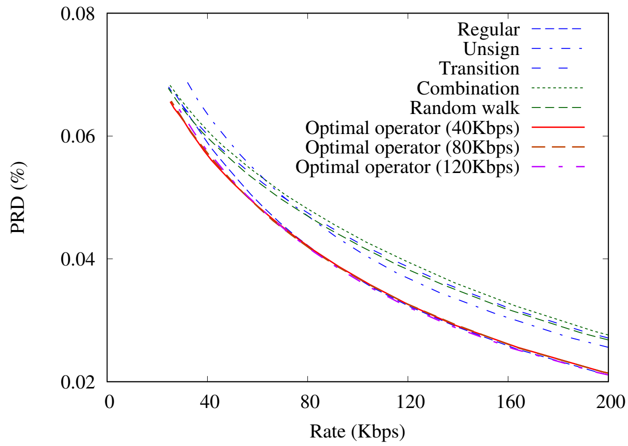
- The proposed graph-based schemes achieve lower entropy than the DCT-based baselines for the same NMSE performance. Such a lower entropy results in traffic reduction using the combination of quantization and entropy coding.
- The performance of the proposed scheme is highly dependent on the chosen graph shift operators.

C. DISCUSSION ON GRAPH SHIFT OPERATOR

As mentioned in the previous section, the performance of the proposed scheme depends on the graph shift operators of the graph basis matrix. To investigate the effect of the graph shift operators, we discuss the performance of the



(a) NMSE



(b) PRD

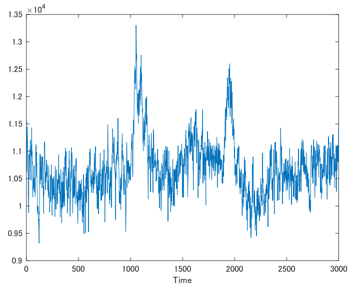
FIGURE 6: Average reconstruction quality of the proposed schemes over 64 EEG sensors under the different graph shift operators. Here, the subject ID is 1.

proposed scheme using the known and optimized graph shift operators for Subject 1. Here, the optimal graph shift operators were obtained by sweeping the parameter tuple of $\boldsymbol{M} = (m_1, m_2, m_3, e_1, e_2, e_3, a)$ in the range of [-1, 1] with an interval of 0.5. For each parameter tuple under the given quantization factor, we can measure the bit rate $f_{\mathrm{rate}}(\boldsymbol{M})$ (Kbps) and the PRD $g_{\mathrm{PRD}}(\boldsymbol{M})$ (%) of the proposed scheme. We define the cost function for each parameter tuple $C(\boldsymbol{M})$ as follows:

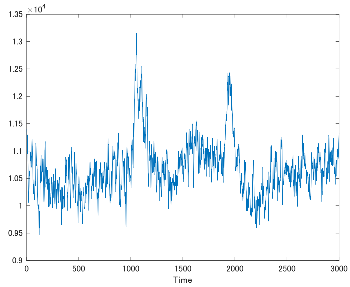
$$C(\boldsymbol{M}) = g_{\mathrm{PRD}}(\boldsymbol{M}) + \lambda f_{\mathrm{rate}}(\boldsymbol{M}), \tag{8}$$

where λ is a weight to adjust the range of bitrate and PRD values, and we set it to 0.001. We consider the parameter tuple with the lowest cost to be the optimized graph shift operator for the quantization factor. Table 2 shows the optimal parameter tuples at the bit rate of 40 Kbps, 80 Kbps, and 120 Kbps, respectively.

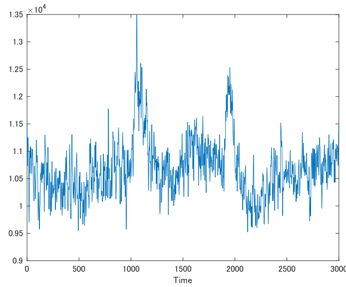
Figs. 6 (a) and (b) show the average reconstruction quality of the proposed schemes with different graph shift operators



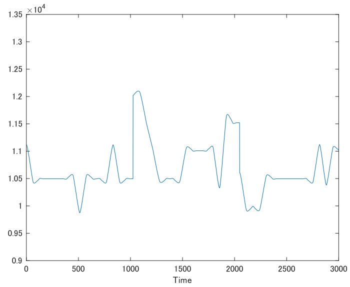
(a) Original



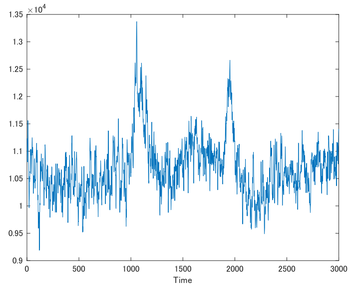
(b) 1D-DCT-based
NMSE:-36.0 dB, PRD:1.59%



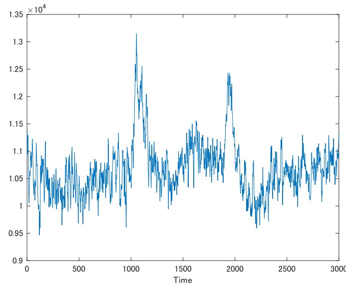
(c) 2D-DCT-based
NMSE:-35.4 dB, PRD:1.70%



(d) DWT-based
NMSE:-29.7 dB, PRD:3.27%



(e) Proposed (Regular)
NMSE:-36.3 dB, PRD:1.53%



(f) Proposed (Optimal graph shift operator at 40 Kbps)
NMSE:-36.9 dB, PRD:1.43%

FIGURE 7: Snapshots of the reconstructed EEG signals for baseline and proposed schemes at the bit rate of 40 Kbps. Here, the subject ID is 1 and the EEG sensor ID is 41.

in Tables 1 and 2 over 64 sensors for Subject 1 as a function of bit rates. We can see the following two observations:

- The proposed scheme with the graph shift operator optimized for 40 Kbps achieves the best reconstruction quality at low bit rates.
- Although the proposed schemes with the graph shift operators optimized for 80 Kbps and 120 Kbps achieve the best reconstruction quality at the bit rate, the reconstruction quality is almost the same as the proposed scheme with the regular graph shift operator.
- Among the known graph shift operators, the regular graph shift operator performs well.

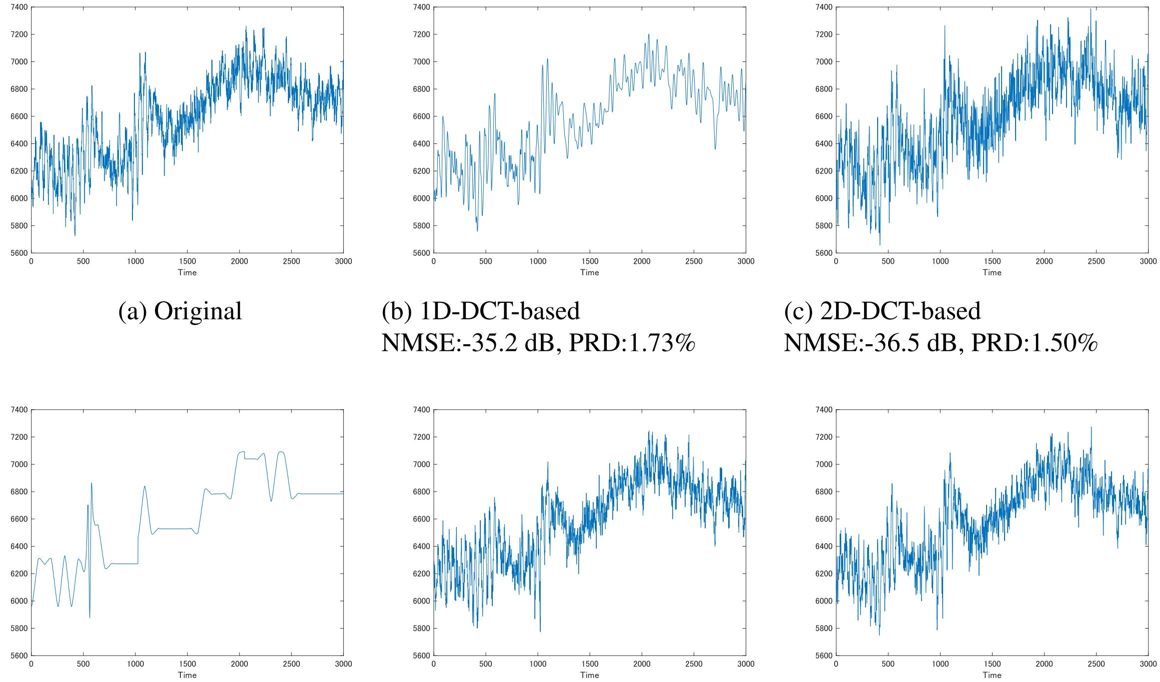
Although the optimized graph shift operator has the best quality, it needs to find the best parameter tuple from the $5^7 = 78125$ combinations. The regular graph shift operator is sufficient for decorrelating EEG signals with little computation.

D. VISUAL QUALITY

Finally, Fig. 7 (a)-(f) and Fig. 8 (a)-(f) show the snapshots of the reconstructed EEG signals in the baseline and proposed schemes under the bit rate of 40 Kbps. Here, the subject ID is 1, and we select sensor IDs 41 and 57 for comparison. Due to the low coding efficiency, the DWT-based scheme lacks the details of the EEG signals under the same bit rate. In sensor ID 41, the gap between the DCT-based scheme and the proposed scheme is not quite large, although the reconstruction quality of the proposed scheme is high. In sensor ID 57, the 1D-DCT-based scheme loses high frequency details and the 2D-DCT-based scheme causes large noise after compression. The proposed scheme can reconstruct clean EEG signals at the same bit rate even in both sensors. In addition, the visual gap between the proposed schemes with the regular and optimized graph shift operators is small.

V. CONCLUSION

This paper proposes a novel graph-based EEG signal compression scheme to transmit high-quality EEG signals to multiple robots over band-limited networks and channels. The proposed scheme constructs the graph structure based on the 3D coordinates of the deployed EEG sensors and performs the parameterized graph basis function based on the graph structure for signal decorrelation. Evaluations using the EEG signal dataset show that the proposed graph-based scheme achieves better reconstruction quality than the typical DCT-based and DWT-based schemes at the same bit rates. In addition, the effect of the graph shift operators on the reconstruction quality is discussed. It is found that the graph shift operators optimized for low bit rates perform well in band-limited environments, and the regular graph shift operator has almost the same performance as the optimized graph shift operators at high bit rates.



(a) Original

(b) 1D-DCT-based
NMSE:-35.2 dB, PRD:1.73%

(c) 2D-DCT-based
NMSE:-36.5 dB, PRD:1.50%

(d) DWT-based
NMSE:-33.0 dB, PRD:2.23%

(e) Proposed (Regular)
NMSE:-38.6 dB, PRD:1.18%

(f) Proposed (Optimal graph shift operator at 40 Kbps)
NMSE:-38.7 dB, PRD:1.16%

FIGURE 8: Snapshots of the reconstructed EEG signals for baseline and proposed schemes at the bit rate of 40 Kbps. Here, the subject ID is 1, and the EEG sensor ID is 57.

In future work, we will evaluate the effect of the reconstructed EEG signals on the recognition performance through biosignal processing. In addition, the discussion of the effect of EEG sensor distributions on the reconstruction quality and the fast finding of optimal graph shift operators are also left for future work.

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