A Multimodal Canonical-Correlated Graph Neural Network for Energy-Efficient Speech Enhancement

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Abstract

This paper proposes a novel multimodal self-supervised architecture for energy-efficient AV speech enhancement by integrating graph neural networks with canonical correlation analysis (CCA-GNN). This builds on a state-of-the-art CCA-GNN that aims to learn representative embeddings by maximizing the correlation between pairs of augmented views of the same input while decorrelating disconnected features. The key idea of the conventional CCA-GNN involves discarding augmentation-variant information and preserving augmentation-invariant information whilst preventing capturing of redundant information. Our proposed AV CCA-GNN model is designed to deal with the challenging multimodal representation learning context. Specifically, our model improves contextual AV speech processing by maximizing canonical correlation from augmented views of the same channel, as well as canonical correlation from audio and visual embeddings. In addition, we propose a positional encoding of the nodes that considers a prior-frame sequence distance instead of a feature-space representation while computing the node’s nearest neighbors. This serves to introduce temporal information in the embeddings through the neighborhood’s connectivity. Experiments conducted with the benchmark ChiME3 dataset show that our proposed prior frame-based AV CCA-GNN reinforces better feature learning in the temporal context, leading to more energy-efficient
speech reconstruction compared to state-of-the-art CCA-GNN and multi-layer perceptron models. The results demonstrate the potential of our proposed approach for exploitation in future assistive technology and energy-efficient multimodal devices.

Keywords: Canonical Correlation Analysis, Graph Neural Network, Multimodal Learning, Positional Encoding, Prior Frames Neighborhood

1. Introduction

Recent technological advances empowered computers to reason and perform activities once attributed to human beings only, such as writing, speaking, and even making some decisions. Nevertheless, such reasoning is limited to the domain upon which the algorithm was trained, i.e., the actions and decisions adopted by the algorithm are based on patterns somehow encoded in the dataset. This approach seems unnatural if we consider the learning process performed by the biological brain, in which stimuli are provided by a set of different sensors, e.g., vision and hearing, and this multimodal information is combined in such a way that redundant information is essential to reinforcing and improving noisy, ambiguous, and imperfect signals from distinct sources. In this context, Ngiam et al. showed that cross-modality learning approaches could be beneficial to improve one modality feature representation. To illustrate the idea, consider, for instance, a boisterous speech. If you have only the audio, your comprehension of the subject may be considerably impaired by the noise. On the other hand, if the images are also available, you can try to complement the corrupted information with insights provided by this secondary source, such as following the speaker’s hands and body movements or trying to read his lips. The approach was recently applied to a wide variety of applications, such as remote-sensing imagery classification and medicine, to cite a few. Regarding audio-visual (AV) data processing, Adeel et al. suggested an integration of Internet of Things (IoT) and 5G Cloud-Radio Access Network to create a chaotic encryption-based lightweight model for lip-reading driven hearing aids.
In further work \cite{5} the model was improved to transmit encrypted compressed audio-visual (AV) information and receive encrypted enhanced reconstructed speech in real-time. Recent works comprise a deep learning-based framework for speech enhancement that exploits AV cues concerning different operating conditions to estimate clean audio \cite{6}, as well as the CochleaNet \cite{7}, which integrates noisy audio and visual from distinct language speakers.

Despite the contextual information provided by different input signals, such tasks usually also rely on temporal information for reasoning. Revisiting the speech example, it is easy to infer that words being said at the present moment are probably strongly correlated with the last few pronounced words. Even though some works addressed the problem using recurrent networks \cite{8,9}, most of them perform supervised learning, which requires a considerable number of labeled samples for training and usually produce particular and target-driven representations.

In this context, unsupervised or self-supervised algorithms show themselves capable of extracting strongly correlated features, which are highly desired for two main reasons: (i) their representations are usually more general-purpose than target-driven features extracted with supervised algorithms, and (ii) they do not require labeled instances for training, which are usually limited and costly. Among such algorithms, one can refer to energy- \cite{10,11,12,13} and mutual information-based \cite{14,15} approaches. Regarding the latter, Velicković et al. \cite{16} proposed the Deep Graph Infomax, which rely on mutual information maximization and graph neural networks (GNN) for leveraging information propagation in a graph.

Graph theory describe strong architectures capable of modelling complex relationships, with applications ranging from small world design \cite{17} to data classification \cite{18} and oversampling \cite{19}. With the advent of deep learning, GNNs emerged as an elegant solution to extract in-depth dependencies from such intricate relationships. Moreover, it also presents itself as a powerful alternative to convolutional neural networks suitable for datasets composed of non-imagery data. Despite the success obtained by \cite{16} in this context, Zhang et al. \cite{20} point
a set of drawbacks in the model: (i) reliance on negative samples - corrupting
the graph structure by selecting arbitrary negative examples may lead to large
variance for stochastic gradients and slow training convergence; (ii) require a
parameterized estimator to approximate mutual information between two views;
and (iii) it contrasts node embeddings with graph embedding, which would re-
quire $O(N)$ space cost, where $N$ denotes the number of nodes. To tackle such
problems, they propose the GNNs with Canonical Correlation Analysis (CCA-
GNN), which aims at maximizing the correlation between two augmented views
of the same input while decorrelating different dimensions of such views. Their
approach does not rely on negative pairs, does not require learning parameters
of additional components such as an estimator, and requires $O(D^2)$ space cost,
where $D$ denotes the feature space size. Besides, Dwivedi et al. exposed an-
other shortcoming regarding GNNs message-passing mechanism, which builds
node representation by aggregating feature space-based local neighborhood in-
formation and leads representations dependants on the local structure of the
graph and proposed using positional encoding to solve the problem.

Therefore, this paper aims to redesign the GNNs with Canonical Correlation
Analysis (CCA-GNN) to deal with the challenging context of multimodal repre-
sentation learning. Specifically, we formulate a parallel CCA-GNN architecture
for each input channel, i.e., audio and visual. The new AV CCA-GNN model
minimizes both the canonical correlation between the augmented samples of the
same channel as well as between the augmented samples of the other mode. Ad-
ditionally, we introduce graph modeling that considers a time-frame sequence
distance positional encoding to compute the node’s neighborhood. The idea
is to introduce temporal information through the samples’ connectivity in the
embeddings.

Experiments conducted over the AV ChiME3 dataset compare the proposed
approach against a CCA-based multilayer perceptron (MLP). Results show that
(i) the multimodal CCA-GNNs produce more representative features than the
standard unimodal version, leading to lower errors over clean audio data recon-
struction; (ii) the proposed prior-frame approach for sequential-time modeling
in graphs outperform the standard feature-space distance-based neighborhood connections; and (iii) CCA-GNNs deliver better results than the CCA-MLP model in the context of feature extraction for data reconstruction, requiring a considerably reduced rate of firing neurons, indicating the new model is more suitable for energy-constrained environments, such as AV hearing aid devices. Therefore, the main contributions of this paper are fourfold:

1. To introduce a novel approach suitable for audio-visual processing that considers the fusion between different sources of information from the environment to improve sound quality.
2. To propose a multimodal CCA-GNN model for the task of correlated embeddings extraction.
3. To introduce a prior frame-based approach to model the nodes’ positional encoding considering a temporal relationship between the frames.
4. To provide a self-supervised energy-efficient multimodal approach to contextual AV feature learning and clean audio data reconstruction.

The remainder of this paper is described as follows. Section 3 provides a brief background regarding GNN-CCA and introduces the proposed approaches. Further, Section 4 provides the necessary information regarding the dataset and experimental setup. Finally, Sections 5 and 6 state the results and conclusions, respectively.

2. Graph Neural Network with Canonical Correlation Analysis

Consider a single graph $G = (X, A)$ where $X \in \mathbb{R}^{N \times F}$ denotes the node’s feature vectors and $A \in \mathbb{R}^{N \times N}$ stands for the adjacency matrix, such that $N$ represents the number of nodes and $F$ is the dimension of the feature space. The CCA-GNN [20] is composed of three main parts: (i) a random graph generator $T$, (ii) a graph neural network encoder $f_\theta$, where $\theta$ stands for the learnable parameters, and (iii) a Canonical Correlation Analysis-based objective function. The idea is to present two augmented versions of the same graph to the network.
and maximize the canonical correlation between their outputs. Such an approach aims at preserving correlated components while discarding decorrelated ones, i.e., maintaining the relevant information present in both augmented versions and avoiding particular behaviors, such as anomalies and noise. Figure 1 depicts the Graph Neural Network with Canonical Correlation Analysis.

Figure 1: Graph Neural Network with Canonical Correlation Analysis. The dataset is converted into a graph where each sample represents a node, and the edges denote the nodes’ connection. Two augmented versions of this graph are generated and used to feed a GNN. Finally, the canonical correlation between the output of both versions is computed and used as the cost function to optimize the GNN parameters.

Regarding the graph augmentation, CCA-GNN employs the same approach used in [22, 23], which basically performs a random edge dropping and feature masking. Thus, each \( t \sim T \) stands for a transformed version of \( G \). Notice that those augmented versions are sampled at each iteration.

Concerning the encoder, the model employs a simple two-layered graph neural network, which can be easily replaced by more complex or sophisticated architectures.

Finally, the objective function aims at modeling the learning problem as a canonical correlation-based self-supervised approach in which the two randomly augmented versions of the graph yields two normalized views of the input data, \( Z_A \) and \( Z_B \), and their correlation is maximized. The objective function is described as follows:

\[
\mathcal{L}(Z_A, Z_B) = \|Z_A - Z_B\|_F^2 + \lambda(\|Z_A^T Z_A - I\|_F^2 + \|Z_B^T Z_B - I\|_F^2),
\]

where \( I \) is the identity matrix and \( \lambda \) is a non-negative trading-off hyperparam-
eter. The first term, namely the invariance term, is responsible for the minimization of the invariance between the two views, which is essentially the same as maximizing the correlation between them. The second is the decorrelation term, which seeks a regularization that encourages distinct features to capture different semantics.

Further, the authors provide a variance-covariance perspective of the objective function. Suppose \( s \) as an augmented version sampled from an input \( x \), and \( z_s \) is the representation of \( s \) obtained through a decoder. The invariance term can be minimized using expectation as follows:

\[
L_{\text{inv}} = \| Z_A - Z_B \|_F^2 = \sum_{i=1}^{N} \sum_{k=1}^{D} (z_{i,j}^A - z_{i,j}^B)^2 \\
\approx \mathbb{E}_x \left[ \sum_{k=1}^{D} \mathcal{V}_{s|x}[z_{s, k}] \right] * 2N,
\]  

(2)

where \( \mathcal{V} \) is the variance. In a similar fashion, the decorrelation term is written as follows:

\[
L_{\text{dec}} = \| Z_S^T Z_S - I \|_F^2 = \| \text{Cov}_s[z] - I \|_F^2 \\
\approx \sum_{i \neq j} (\rho_{i,j}^z)^2, \forall Z_S \in \{ Z_A, Z_B \},
\]  

(3)

where \( \text{Cov} \) is the covariance matrix and \( \rho \) is the Pearson correlation coefficient.

3. Proposed Approach

This section presents a multimodal extension for the Canonical Correlation Analysis Graph Neural Network. Further, it also introduces the idea of modeling the temporal information of sequence data as node relationships in a graph.

3.1. Multimodal Canonical Correlation Analysis Graph Neural Network for Audio-Visual Embedding Learning

The proposed extension of the Canonical Correlation Analysis Graph Neural Network for multimodal data comprises a pair of networks, each of them fed with
a modality of data, e.g., audio and visual, running in parallel. At the output layer, the canonical correlation analysis is performed considering both the intra-channel correlation, i.e., the two augmented versions of the same data modality, as well as inter-channels correlation. Figure 2 depicts the model.

Figure 2: Multimodal Canonical Correlation Analysis Graph Neural Network for Audio-Visual Embedding Learning.

To accommodate the intra- and inter-channel computations of the canonical correlation analysis in the objective function, one can firstly consider two randomly augmented versions of normalized views for each channel, namely $Z_1$ and $Z_2$ for audio data, and $Z_3$ and $Z_4$ for visual data. The individual losses for both channels are computed using Equation 1:

$$L_{\text{Audio}} = L(Z_1, Z_2),$$
$$L_{\text{Visual}} = L(Z_3, Z_4).$$

Further, all the possible combinations of audio and visual data are computed, namely $\text{Audio1Visual1} \ (Z_1, Z_3)$, $\text{Audio1Visual2} \ (Z_1, Z_4)$, $\text{Audio2Visual1} \ (Z_2, Z_3)$, and $\text{Audio2Visual2} \ (Z_2, Z_4)$, as follows:
\[ L_{\text{Audio1Visual1}} = \mathcal{L}(Z_1, Z_3), \]
\[ L_{\text{Audio1Visual2}} = \mathcal{L}(Z_1, Z_4), \]
\[ L_{\text{Audio2Visual1}} = \mathcal{L}(Z_2, Z_3), \]
\[ L_{\text{Audio2Visual2}} = \mathcal{L}(Z_2, Z_4). \]  

Finally, the objective function of the multimodal Canonical Correlation Analysis Graph Neural Network is given by:

\[ \mathcal{L} = \alpha L_{\text{Audio}} + \beta L_{\text{Visual}} + \gamma (L_{\text{Audio1Visual1}} + L_{\text{Audio1Visual2}} + L_{\text{Audio2Visual1}} + L_{\text{Audio2Visual2}}), \]  

where \( \alpha, \beta, \) and \( \gamma \) are constants that control the influence of audio, video, and the combined canonical correlation, respectively.

3.2. Modelling Temporal Information as Graph Nodes Relationships

The usual approach for modeling a dataset into a graph structure consists of representing its samples as the graph’s nodes, whose edges connect the adjacent instances inserted into a \( D \)-dimensional feature space. A common approach is to connect each node to its \( k \) nearest neighbors only, where \( k \) is a hyperparameter, presenting two main advantages: (i) it reduces the computational burden since it considers only \( k \) operations per node instead of \( N \), and (ii) it enhances the influence of the neighborhood of the node, avoiding the effect of uncorrelated samples to the local process. Figure 3(a) depicts the idea.

This paper proposes a novel approach for modeling the nodes’ connectivity considering temporal information propagation instead of the distance in the feature space. The strategy is conducted a positional encoding of the instances by connecting each node to its \( k \) previous nodes, e.g., frames in a video sequence. Figure 3(b) illustrates the process.
Figure 3: Node neighborhood modeling considering (a) the standard feature-space-based $k$-nearest neighbors approach and (b) the proposed $k$ prior frames with $k = 2$.

Notice that the edges between each pair of connected nodes are weighted accordingly to their distances in this temporal representation, i.e., the first prior frame of a node is more strongly connected to it than the second prior, and so on consecutively. The edge weight $w_{ij}$ connecting a node $i$ to a previous $j$ is computed as follows:

$$w_{ij} = k + 1 - d_{ij},$$  \hspace{1cm} (7)

where $d_{ij}$ is the distance from $i$ to $j$ in prior frames steps, i.e., $d_{ij} = 1$ means $j$ is the first prior frame of $i$, while $d_{ij} = 2$ means $j$ is two prior frames away from $i$, and so on. Notice each node is also connected to itself through a self-reference edge $w_{ii} = k + 1$ since $d_{ii} = 0$. Moreover, the experiments also consider weighting self-reference connections $w_{ii} = 1$, increasing the influence of neighborhood in the GNN decision process. After defining the distance between each pair of connected samples, such values are stored in a distance matrix employed to compute nodes’ normalized positional encoding, replacing the adjacency matrix in the factorization of the graph Laplacian.

4. Methodology

This section describes the dataset considered for the task of audio/visual correlated embedding learning for the task of clean sound reconstruction and the process employed for feature extraction. Further, it also exposes the setup considered in the experiments.
4.1. AV ChiME3 Dataset

This paper employs a dataset composed of pairs of image and noisy audio signals for input and clean audio signals for output, aiming to provide an efficient tool capable of enhancing and cleaning the relevant audio signal considering environmental information fusion. The dataset comprises a combination of clean videos from the Grid [26] dataset with noises (pedestrian area, public transport, street junction, cafe) with signal to noise ratios (SNR) ranging from -12 to 12dB extracted from ChiME3 [27], composing the AV ChiME3 [28] dataset. The preprocessing comprises sentence alignment, which is conducted to prevent the model from learning redundant or insignificant information and removing silent takes from data, as well as incorporating prior multiple visual frames used to include temporal data, thus improving the mapping between audio and visual characteristics. The dataset comprises 5 speakers (one black male, two white males, and two white females) selected from Grid corpus reciting 989 sentences each.

4.1.1. Audio feature extraction

The audio features are extracted using log-FB vectors, which are computed by sampling the input audio signal at 22,050kHz and segmented into $M$ 16ms frames with 800 samples per frame and 62.5% increment rate. Further, a hamming window and Fourier transformation are applied to produce a 2048-bin power spectrum. Finally, a logarithmic compression is applied to obtain a 22-dimensional log-FB signal. Notice similar approaches were conducted for creating both clean and noisy audio representations.

4.1.2. Visual feature extraction

The visual features were extracted from the Grid Corpus dataset through an encoder-decoder setup approach. After extracting a sequence of individual frames, the lip-regions are identified using Viola-Jones [29] and tracked across a sequence of frames using a method proposed in [30]. The sentences are manually inspected using a random approach to ensure good lip tracking and delete sen-
tences with misclassified lip regions. Finally, the encoder-decoder approach is employed to produce vectors of pixel intensities, whose first 50 components are vectorized in a zigzag order and then interpolated to match the equivalent audio sequence.

Finally, the dataset employed in this paper is composed of three subsets, i.e., clean audio, noisy audio, and visual features. Both clean and noisy audio subsets comprise 22 features each, while the visual features are represented by a 50-dimensional vector. The subsets contain 750 out of 989 sequences with 48 frames each, summing up to a total of 36,000 synchronized samples per subset. Figure 4 illustrates a simplified schema of the feature extraction process.

Figure 4: Simplified schema of the feature extraction process.

4.2. Experimental Setup

The experiments provided in the next section were conducted considering a graph neural network and a multilayer perceptron network as the backbone. Both networks share a similar architecture for comparison purposes, i.e., two
hidden layers with 512 neurons in each layer, using the Adam optimizer with a learning rate of 0.001. The models are trained with the objective of maximizing the canonical correlation for coherent features extraction during 5,000 epochs considering a trading-off parameter $\lambda = 0.0001$ in Equation 11 while Equation 6 is set with the values $\alpha = 0.5$, $\beta = 0.25$, and $\gamma = 0.0625$, which aims at giving more importance to the receptive input (noisy audio signal) than to the context provided by the visual information. The data augmentation step considers both an edge dropping rate and a feature masking rate of 0.5. Moreover, the graphs are generated considering three distinct neighborhood scenarios, i.e., with 3, 10, and 30 neighbors. Notice this neighborhood is defined in two manners, i.e., the standard feature-space-based approach and the proposed temporal-information-based relationship, as described in Section 3.2.

After training, the networks’ outputs are used to feed a dense layer, which is responsible for reconstructing the clean signal given the features extracted from noisy audio for the single modality and noisy audio and clean video for the proposed multimodal extension. The dense layer is optimized during 600 epochs using the Adam optimizer with a learning rate of 0.005 and a weight decay of 0.0004 using the minimization of the mean squared error as the objective function.

The dataset was divided into 15 folds to provide an in-depth statistical analysis. Each fold comprises 50 sequences of 48 frames each, summing up to a total of 2,400 samples per fold. As stated in Section 4.1, the dataset is formed by three subsets: (i) clean audio, (ii) noisy audio, and (iii) clean visual. The noisy audio is used to train the standard unimodal approach, while the proposed multimodal approach employs both the noisy audio and clean visual in the training process. The clean audio is used as a reconstruction target for both cases. Finally, each fold is split into train, validation, and test sets, following the proportions of 60%, 20%, and 20%, respectively. For statistical evaluation, the Wilcoxon signed-rank test with 5% of significance was considered.
5. Experiments

This section presents the experimental results considering three tasks: (i) feature extraction driven by canonical correlation analysis maximization, (ii) clean audio data reconstruction based only on noisy audio or noisy audio and clean visual data fusion, and (iii) energy efficiency analysis in terms of neuron activation rate.

5.1. Feature Extraction Analysis

The experiments presented in this section compare the performance of graph neural networks with canonical correlation analysis for the task of self-supervised relevant feature extraction in three distinct neighborhood scenarios, i.e., 3, 10, and 30 neighbors, namely GNN 3, GNN 10, and GNN 30, respectively. Moreover, two distinct neighborhood strategies are compared: (i) the standard (Std.) feature-space distance and (ii) the proposed prior frames-based connections for time-sequence (Seq.). Finally, a multilayer perceptron network with similar architecture (same number of layers, neurons per layer, optimizer, and learning rate) was trained using an identical self-supervised approach with the canonical correlation analysis maximization as the target function, denoted the baseline.

Figure 5(a) presents the convergence of the unimodal models considering the task of feature extraction through CCA maximization over noisy audio data. In this context, one can observe CCA-MLP obtained the highest results considering CCA maximization itself, even though such results do not necessarily imply better data representation for the specific task of clean audio reconstruction since the prior frames-based CCA-GNN (Seq. and Seq.\(^*\) for \(w_{ii} = k + 1\) and \(w_{ii} = 1\), respectively) obtained better reconstruction rates, as presented in Table 1. Notice CCA-GNN Seq.\(^*\) obtained similar results to CCA-GNN Seq. and thus is overlapped in the image.

Regarding the multimodal extension conducted over noisy audio and visual features, one can observe in Figure 5(b) that the proposed CCA-GNN Seq. obtained the best results overall considering a neighborhood (number of
prior frames) of 30. Such a behavior is expected since a more significant number of prior frames reinforces the coherent information shared between the two channels during a longer period of time, providing more robust and connected features. Such robustness is in fact propagated to the reconstruction task since CCA-GNN Seq. with $k = 30$ also provided the best results available in Table 1.

Figure 5: Feature extraction for (a) noisy audio only and (b) noisy audio and clean visual.

5.2. Clean Signal Reconstruction

Table 1 presents the clean audio data reconstruction error considering the unimodal approach given the noisy data signal as input. Notice Standard denotes the common approach using the feature space to represent the nodes adjacency, while Sequential and Sequential* stand for the proposed prior frame-based approach for the positional encoding using $w_{ii} = k + 1$ and $w_{ii} = 1$, respectively. From these results, one can observe that (i) a more significant number of nodes’ neighbors lead to better reconstruction errors; (ii) the proposed sequential approach with prior frame connections outperformed the standard feature space distance-based neighborhood modeling and the MLP, and (iii) Sequential and Sequential* did not present significative differences, showing that the influence of the node self-connection is not relevant for the task. Notice that the better results according to the Wilcoxon signed-rank test are presented in bold. In this context, none of the other approaches obtained statistically similar results to the proposed sequential CCA-GNN with $k = 30$. Further, Figure 6 shows that all techniques present similar convergence consid-
ering the reconstruction task, even though the MLP presents a slightly slower convergence, as depicted in the zoomed frame.

Table 1: Average Mean Squared Error and standard deviation over unimodal CCA-MLP and CCA-GNN considering clean audio reconstruction given noisy audio input.

| Model | Neighbors | Standard MSE ± Std | Sequential MSE ± Std | Sequential* MSE ± Std |
|-------|-----------|--------------------|----------------------|-----------------------|
| MLP   | -         | 0.0206 ± 0.0012    | -                    | -                     |
| GNN   | 3         | 0.0238 ± 0.0009    | 0.0220 ± 0.0025      | 0.0220 ± 0.0025       |
|       | 10        | 0.0235 ± 0.0008    | 0.0218 ± 0.0025      | 0.0218 ± 0.0025       |
|       | 30        | 0.0234 ± 0.0008    | 0.0187 ± 0.0026      | 0.0186 ± 0.0025       |

Figure 6: Clean audio reconstruction error convergence considering the unimodal architecture based on the noisy audio.

Figure 7 depicts a randomly selected clean audio sample reconstruction regarding the unimodal architecture trained over noisy audio data considering the standard approach and the proposed prior frame-based positional encoding for time sequence modeling. Regarding the standard approach, one can notice in Figure 7(a) that none of the models performed significantly well, especially for the first 8 features. On the other hand, the proposed approach for frame-based positional encoding obtained much better results in this context considering the sequential CCA-GNN with $k = 30$, as illustrated in Figure 7(b).

Table 2 present very similar results in the context of the multimodal archi-
Figure 7: Clean audio signal reconstruction regarding the unimodal architecture trained over noisy audio data considering the (a) standard approach and (b) the proposed prior frame-based positional encoding for time sequence modeling.

The proposed prior frame-based neighborhood outperformed the standard feature distance node’s connection and the CCA-GNN with $k = 30$ obtaining the better results overall considering the Wilcoxon signed-rank test. This table also shows that the multimodal approach is, in fact, capable of providing more representative features for clean audio reconstruction since all methods outperformed the respective unimodal versions. Figure 8, which depicts the reconstruction error convergence considering the multimodal architectures, also presents very similar results to Figure 6, in which all techniques perform similarly, with CCA-MLP showing a slower convergence in the first 50 iterations.

**Table 2:** Average Mean Squared Error and standard deviation over unimodal CCA-MLP and CCA-GNN considering clean audio reconstruction given noisy audio and visual inputs.

| Model | Neighbors | Standard       | Sequential | Sequential* |
|-------|-----------|----------------|------------|-------------|
| MLP   | -         | 0.0189 ± 0.0009| -          | -           |
| GNN   | 3         | 0.0233 ± 0.0009| 0.0220 ± 0.0025 | 0.0220 ± 0.0024 |
|       | 10        | 0.0233 ± 0.0009| 0.0216 ± 0.0025 | 0.0216 ± 0.0026 |
|       | 30        | 0.0225 ± 0.0009| 0.0179 ± 0.0025 | 0.0180 ± 0.0026 |

Similar to Figure 7, Figure 9 presents a randomly selected clean audio sample.
Figure 8: Clean audio reconstruction error convergence considering the proposed multimodal architecture based on the noisy audio and the clean visual data.

reconstruction regarding the multimodal architecture trained over noisy audio and clean visual data. Again, Figure 9(a) shows the standard approach did not performed significantly well for the first five or eight features, while the proposed approach with $k = 30$ provided much more accurate results, as depicted in Figure 9(b).

Figure 9: Clean audio signal reconstruction regarding the multimodal architecture trained over noisy audio and clean visual data considering the (a) standard approach and (b) the proposed prior frame-based positional encoding for time sequence modeling.

5.3. Neuronal Activation Analysis

This section provides an energy-efficiency analysis based on neuronal activation behavior. Such an analysis is fundamental since using such models in
real-world applications, such as hearing devices embedded systems, for instance, is constrained to energy issues. Figure 10 describes the average rate of the first hidden layer’s neurons activation during the training of the unimodal approach, while Table 3 provides the area under the curve. Notice that some less relevant results were omitted from the plot for better visualization. In this context, one can observe that, even though GNNs and the MLP comprise the same architecture, i.e., two hidden layers with 512 neurons each, around 100 neurons in the MLP architecture fired 100% of the time, while the same pattern is observed over a range between 10 and 20 neurons concerning the GNNs. Moreover, although the best performing model for the clean audio reconstruction task, i.e., the sequential CCA-GNN with $k = 30$, is the most energy-consuming approach between all the CCA-GNN-based methods, it still presents a nominal neuron activation rate if compared to the MLP.

![Figure 10: Neuron activation rate considering the unimodal architecture.](image)

Figures 11(a) and 11(b) present the neural activation analysis considering the multimodal approach for the audio and the visual channels, respectively, whose values are reflected in Table 4. The figures present a similar behavior to the one observed in Figure 10 in which the MLP presents a neuron activation rate substantially larger than the MLP-based approaches. Moreover, one can also observe that the prior frame-based approach has different behaviors for each channel since their neuron activation conduct is more intense in the audio channel but produces a reduced fire rate considering the visual channel.
Table 3: Area under the curve considering the unimodal architecture neuron activation rate.

| Model | Neighbors | Standard | Sequential | Sequential* |
|-------|-----------|----------|------------|-------------|
| MLP   | -         | 147.27   | -          | -           |
| GNN   | 3         | 10.17    | 11.73      | 11.73       |
|       | 10        | 21.64    | 26.56      | 26.56       |
|       | 30        | 29.99    | 47.71      | 47.71       |

Figure 11: Neuron activation rate considering the multimodal architecture considering (a) audio and (b) visual channels.

Such behavior may suggest that using the prior frame-based approach implies a network inclined to extract more relevant features considering the temporal flow as a context, thus becoming less dependent on the visual context itself.

Table 4: Area under the curve considering the multimodal architecture neuron activation rate over.

| Model | Neighbors | Audio | Visual |
|-------|-----------|-------|--------|
|       | Standard  | Sequential | Sequential* |
|       | Standard  | Sequential | Sequential* |
| MLP   | -         | 142.07 | -       | 201.01 | -       |
| GNN   | 3         | 11.77  | 14.18  | 14.18  | 19.05  | 17.36  | 17.36  |
|       | 10        | 19.29  | 24.01  | 24.01  | 38.52  | 32.28  | 32.28  |
|       | 30        | 27.90  | 45.80  | 45.80  | 52.85  | 36.66  | 36.66  |
6. Conclusions

This paper proposes an intelligent and energy-efficient approach for improving and boosting sound signals through environmental information fusion. The model extends Graph Neural Networks with Canonical Correlation Analysis for multimodal data integration, and further incorporates a prior frame-based node’s positional encoding that considers the temporal sequence in data to establish the information similarity instead of the usual feature space distance. Experiments conducted over the AV ChiME3 Dataset considering the task of clean audio reconstruction based on the fusion of noisy audio and clean video data shows that the proposed approaches are capable of outperforming a baseline composed of a multilayer perceptron with similar architecture trained under the same conditions, i.e., in a self-supervised fashion using canonical correlation analysis maximization as the target function. Finally, it also shows that the proposed approaches provide a considerable gain regarding energy efficiency once the CCA-GNN neuron firing rates are dramatically lower.

The experiments also indicate that the multimodal approach can produce better results than the unimodal architecture, leading to minor reconstruction errors. Such behavior is expected since the visual data acts as a context to introduce some additional meaning and improve the noisy audio signal. Additionally, the prior frame-based approach provided better results than the standard model, showing the importance of the temporal information as an additional context to the noisy signal. Finally, one could notice by the neuron’s firing behavior that using prior frame node connection reinforces the information present in the noisy audio channel, making it less dependant on the visual data context for clean audio reconstruction.

Regarding future work, we aim to develop a more biologically realistic neuronal model, introduce the concept of memory, and improve communication mechanisms between the channels. We also aim at using Graph Neural Networks with Canonical Correlation Analysis to improve cross channels communication blocks within convolution neural networks.
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