

Non-Intrusive Binaural Speech Intelligibility Prediction From Discrete Latent Representations

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Abstract—Non-intrusive speech intelligibility (SI) prediction from binaural signals is useful in many applications. However, most existing signal-based measures are designed to be applied to single-channel signals. Measures specifically designed to take into account the binaural properties of the signal are often intrusive – characterised by requiring access to a clean speech signal – and typically rely on combining both channels into a single-channel signal before making predictions. This paper proposes a non-intrusive SI measure that computes features from a binaural input signal using a combination of vector quantization (VQ) and contrastive predictive coding (CPC) methods. VQ-CPC feature extraction does not rely on any model of the auditory system and is instead trained to maximise the mutual information between the input signal and output features. The computed VQ-CPC features are input to a predicting function parameterized by a neural network. Two predicting functions are considered in this paper. Both feature extractor and predicting functions are trained on simulated binaural signals with isotropic noise. They are tested on simulated signals with isotropic and real noise. For all signals, the ground truth scores are the (intrusive) deterministic binaural STOI. Results are presented in terms of correlations and MSE and demonstrate that VQ-CPC features are able to capture information relevant to modelling SI and outperform all the considered benchmarks – even when evaluating on data comprising of different noise field types.

Index Terms—Non-intrusive speech intelligibility prediction; self-supervised representation learning; contrastive predictive coding.

I. INTRODUCTION

Speech intelligibility (SI) prediction aims to predict the ability of an average listener to comprehend speech within a signal – potentially corrupted by noise, reverberation or processing artefacts. SI is defined as the number of words or phonemes that can be correctly identified by assessors. It is often reported using the speech reception threshold (SRT) defined to be the level of degradation for which only 50% of the speech items are correctly identified [1]. Listening tests are typically considered the gold standard to measure SI. However, these tests are costly, time-consuming and cannot be applied in real-time, making the use of signal-based measures necessary. Signal-based measures of speech intelligibility can be categorized as either intrusive or non-intrusive. The computation of intrusive measures requires a clean reference signal

in addition to the test signal, whereas non-intrusive measures can be computed from the test signal only. Consequently, only non-intrusive measures can be applied in real-time settings. Additionally, SI largely depends on the presence of binaural cues [2] and so SI measures should be developed to incorporate them.

Most signal-based measures of SI were originally designed for telephony applications and applied only to single-channel signals. Among these measures the articulation index [3], the speech transmission index (STI) [4], the speech intelligibility index (SII) [5], the short-time objective intelligibility (STOI) [6] and mutual-information-based techniques, such as the algorithm proposed in [7], are intrusive. Non-intrusive measures include a non-intrusive extension of the STOI [8], [9], that relies on estimating the amplitude envelope of the clean speech from the input signal, and measures relying on machine learning techniques. Some measures use a trained speech recognizer as proposed in [10], [11] or a neural network trained to predict SI from a sequence of spectral features [12].

The aforementioned measures use a single-channel signal as input. Certain measures instead make predictions from binaural signals, aiming to take into account the relevance of binaural cues in modelling the intelligibility of speech signals. Notably, several binaural measures rely on simple equalization-cancellation (EC) models [13], often being combined with the SII [14], [15]. However, these measures do not take into account the impact that non-linear processing has on SI. The binaural STOI (BSTOI) uses an EC model to combine both channels of the binaural signal into a single-channel signal used as input to the STOI measure. BSTOI was later refined into the deterministic BSTOI (DBSTOI) that produces a deterministic output [16]. Both BSTOI and DBSTOI are intrusive. A non-intrusive measure has been proposed in [17], where the blind binaural preprocessing stage from [18] is used to process the binaural signal into a single-channel signal that is then input to an automatic speech recognizer (ASR). The SI is finally predicted by applying a trained mapping between the mean temporal distance (MTD) – a representation of the ASR error [19] – and the SRT.

Some measures do not rely on any model of the auditory system and input features to a predicting function that needs to be trained. Such methods include the use of both short- and long-term features input to a classification and regression tree [20] or the use of STOI like features as input to a convolutional neural network [21]. The measure proposed in this paper applies a similar approach but uses features that are computed as a latent representation of the input binaural signal using a combination of contrastive predictive coding (CPC) [22]

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and vector quantization (VQ) [23] methods. Previous uses of CPC in audio applications were limited to single-channel audio inputs [22], [24], [25] and images [22]. CPC models excel at representing “slow features” that span many time steps [22] which we believed would make it suited for speech intelligibility prediction (SIP). This is in contrast to other self-supervised methods such as autoencoders which attempt to represent all details because of their simple reconstruction loss. Additionally, CPC models do not need to reconstruct the input signal like autoencoder methods. This results in improved computational efficiency which is significant for high-dimensional signals such as raw waveforms.

The resulting VQ-CPC features are input to a predicting function. Two predicting functions are considered in this paper to highlight the capacity of the proposed features to capture useful and accessible information and to show that our measure is competitive.

The remainder of this paper is structured as follows. The computation of the proposed features and the considered predicting functions are described in Section II. The experiments¹, including the used datasets of simulated data and considered benchmark, are described in Section III. The results are presented in Section IV and Section V concludes the paper.

II. PROPOSED METHOD

The proposed method aims at estimating the speech intelligibility from an M channel² signal $x_m(n)$, of length N and sampling frequency f_s , where m and n denote the channel index and sample index respectively. Such a signal can be modelled as:

$$x_m(n) = s(n) * h_m(n) + v_m(n), \quad (1)$$

where $s(n)$ denotes the anechoic speech signal, $h_m(n)$ denotes the room impulse response (RIR) between the speech source and the microphone and $v_m(n)$ denotes an additive noise signal. Aiming at non-intrusive prediction, the proposed method estimates the speech intelligibility from $x_m(n)$ only without knowledge of $s(n)$. This prediction relies on first computing a sequence of features to be input to the predicting function.

A. Feature computation

The microphone signal is divided into $T = \lceil N/H \rceil$ overlapping frames of length W , where H denotes the hop length. The samples in each t^{th} frame are used to construct a vector of length $M \cdot W$:

$$\begin{aligned} \mathbf{x}_t = [x_0(tH), x_0(tH+1), \dots, x_0(tH+W-1), \\ \dots \\ x_{M-1}(tH), x_{M-1}(tH+1), \dots, x_{M-1}(tH+W-1)]^T, \end{aligned} \quad (2)$$

resulting in the time-ordered sequence of T vectors:

$$\mathbf{x} = \{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_{T-1}\}. \quad (3)$$

¹Tools to generate the datasets and reproduce the experiments are made available online: <https://github.com/vvwm23/stoi-vqpc>

²Our method can be used on an arbitrary number of channels, but we simply use $M = 2$ throughout.

The feature computation results in the sequence:

$$\mathbf{c} = \{\mathbf{c}_0, \mathbf{c}_1, \dots, \mathbf{c}_{T-1}\}, \quad (4)$$

where each vector of length K is defined as:

$$\mathbf{c}_t = [c_t(0), c_t(1), \dots, c_t(K-1)]^T, \quad (5)$$

where $c_t(k)$ denotes the k^{th} feature coefficient extracted from the t^{th} frame. The feature extraction is typically designed such that $K < M \cdot W$ and learns to extract sequences \mathbf{c} that maximise the mutual information between the input and output sequences:

$$I(\mathbf{x}; \mathbf{c}) = \sum_{\mathbf{x}, \mathbf{c}} p(\mathbf{x}, \mathbf{c}) \log \left(\frac{p(\mathbf{x}|\mathbf{c})}{p(\mathbf{x})} \right). \quad (6)$$

To do so, VQ and CPC methods are used to compute the sequence \mathbf{c} as a latent representation of the input sequence \mathbf{x} . The computation of these VQ-CPC features consists of three main components: a non-linear encoder, a VQ codebook, and an autoregressive aggregator.

First, the non-linear encoder $f(\cdot)$ maps \mathbf{x} to an intermediate latent representation $\tilde{\mathbf{z}}$:

$$f(\mathbf{x}) = \tilde{\mathbf{z}} = \{\tilde{z}_0, \tilde{z}_1, \dots, \tilde{z}_{T-1}\}, \quad (7)$$

where \tilde{z}_ℓ denotes the ℓ^{th} vector, each of length E . VQ is applied to map each vector in $\tilde{\mathbf{z}}$ to an embedding vector from a finite codebook \mathcal{C} yielding the sequence:

$$\mathbf{z} = \{\mathbf{z}_0, \mathbf{z}_1, \dots, \mathbf{z}_{T-1}\}, \quad (8)$$

where each ℓ^{th} vector \mathbf{z}_ℓ is computed as:

$$\mathbf{z}_\ell = q(\tilde{\mathbf{z}}_\ell) = \arg \min_{\mathbf{e}_i \in \mathcal{C}} \|\tilde{\mathbf{z}}_\ell - \mathbf{e}_i\|_2 \quad (9)$$

Where \mathbf{e}_i denotes the i^{th} in the \mathcal{C} embedding vectors of the codebook. Finally, an autoregressive aggregator $g(\cdot)$ is applied to compute each vector from the sequence in (4) as:

$$\mathbf{c}_t = g(\mathbf{z}_{\ell \leq t}). \quad (10)$$

B. VQ-CPC training

Training of $f(\cdot)$, $q(\cdot)$ and $g(\cdot)$ is conducted end-to-end to maximize the mutual information defined in (6). The proposed approach follows the method in [22] with additional loss terms to support the added VQ codebook [26]. To encourage shared information to be encoded, each vector \mathbf{c}_t is used to predict \mathbf{z}_{t+k} for up to k steps in the future. However, rather than modelling the distribution $p(\mathbf{x}_{t+k}|\mathbf{c}_t)$, the proposed method models the density ratio defined as:

$$\sigma_k(\mathbf{x}_{t+k}, \mathbf{c}_t) \propto \frac{p(\mathbf{x}_{t+k}|\mathbf{c}_t)}{p(\mathbf{x}_{t+k})}. \quad (11)$$

The density ratio $\sigma_k(\mathbf{x}_{t+k}, \mathbf{c}_t)$ may be unnormalized and, in this paper, is computed as:

$$\sigma_k(\mathbf{x}_{t+k}, \mathbf{c}_t) = \exp(\mathbf{z}_{t+k}^T \mathbf{W}_k \mathbf{c}_t), \quad (12)$$

where \mathbf{W}_k denotes a learned linear projection and \mathbf{z}_{t+k} is the output of the encoder corresponding to \mathbf{x}_{t+k} , used as a proxy for more efficient computation of the ratio. Using

this definition, the encoder and aggregator are trained by minimising the InfoNCE loss \mathcal{L} , based on noise-contrastive estimation and importance sampling:

$$\mathcal{L} = \beta \cdot \mathcal{L}_{\text{vq}} + \frac{1}{k} \sum_{i=1}^k \mathcal{L}_i, \quad (13)$$

where \mathcal{L}_{vq} denotes the weighted VQ commitment loss defined as:

$$\mathcal{L}_{\text{vq}} = \frac{1}{T} \sum_{\ell=0}^{T-1} \|\tilde{z}_\ell - \text{sg}[e_i]\|_2^2 \quad (14)$$

where e_i is the corresponding embedding vector of \tilde{z}_ℓ and $\text{sg}[\cdot]$ is the stop-gradient operator [26] and:

$$\mathcal{L}_k = -\mathbb{E}_X \left[\log \frac{\sigma_k(\mathbf{x}_{t+k}, \mathbf{c}_t)}{\sum_{\mathbf{x}_j \in X} \sigma_k(\mathbf{x}_j, \mathbf{c}_t)} \right], \quad (15)$$

where X is a set of many negative samples drawn from $p(\mathbf{x}_{t+k})$ and one positive sample drawn from $p(\mathbf{x}_{t+k}|\mathbf{c}_t)$ [22]. The codebook embedding vectors are updated using exponential moving averages (EMA) as described in [26].

C. Intelligibility score predictor

The computation of the VQ-CPC features does not rely on any assumptions about the downstream task for which these features are used. In this paper, the sequence \mathbf{c} is input to a predicting function for the purpose of SI prediction. Two different predicting functions are considered.

The first considered predicting function uses each vector \mathbf{c}_t as input to a single shared linear layer in order to compute a per-frame score. The score assigned to the complete sequence is the mean of the scores computed from each vector. This simple predicting function is used to demonstrate how easily accessible information about SI is when using the VQ-CPC features. This predicting function is referred to as “Small” in the remainder of the paper.

The second considered predicting function first builds a global representation using sequence pooling (SeqPool) methods originally used for the classification of images [27]. A global representation is computed by applying SeqPool to each vector in the sequence \mathbf{c} . In this case SeqPool inputs each vector \mathbf{c}_t to a linear layer that outputs a scalar before applying softmax to the computed scalars, forming weightings for each frame. The weighted sum of each vector is then computed, forming the global representation. This global representation is then input to a small multi-layer perceptron (MLP) to compute the estimated speech intelligibility score assigned to the sequence \mathbf{c} . This predicting function is referred to as “Pool” in the remainder of the paper.

Both Small and Pool are trained to minimise the mean-squared error (MSE) between the estimated and true speech intelligibility scores (see Section III).

III. EXPERIMENTAL SETUP

A. Generated datasets

For training of both the VQ-CPC model and the predicting functions, training and development datasets of binaural

signals are generated. All signals have a sampling frequency $f_s = 16$ kHz and are generated as per (1). The clean anechoic speech is extracted from either the 360 hour training set or the 5 hour development set from the LibriSpeech corpus [28]. Reverberant speech is generated by convolving each utterance of clean speech with a binaural RIR (BRIR) randomly selected from the Aachen Impulse Response Database [29]. For each reverberant utterance, two different noise segments of the same length are selected from the noise signals in the MUSAN database [30]. These two signals are used to generate the two-channel noise signal of a spherically isotropic noise field using the method from [31]. Finally, this generated noise signal is added to the reverberant signal after being scaled to a chosen signal-to-noise ratio (SNR), randomly selected between -10 dB and 30 dB, measured in the first channel according to [32]. In the training and development sets, this process is repeated three times for each clean speech utterance.

Additionally, two testing datasets are generated, hereafter denoted “Test_{iso}” and “Test_{real}”. The signals in Test_{iso} are generated using the same method, as well as noise and BRIR datasets, as for the training and development sets but using clean speech from the test split of the LibriSpeech corpus. The signals in Test_{real} are generated by convolving the speech signals used as target utterances in the first Clarity Challenge [33], [34] with BRIRs randomly selected from the BRIRs available in [35] recorded in either a cafeteria or a courtyard. In this case, two-channel noise signals recorded at the same location are used and added to the reverberant signals with an SNR randomly selected and measured.

A total of 1090.8, 16.2, 5.4 and 10.4 hours of data are generated in the training, development, Test_{iso} and Test_{real} dataset, respectively. Labelling this large amount of data in terms of intelligibility would be a daunting task and the experiments aim mostly at evaluating the use of the proposed features. Consequently, we labeled all signals with an intrusive measure known to highly correlate with intelligibility and the ground truth is here defined as the DBSTOI computed using the clean reverberant signal and the noisy reverberant signal as input [16].

B. Parameters of proposed method

For training, we use \mathbf{x} of length $T = 40960$ as input to the encoder $f(\cdot)$. The encoder has a frame length and hop size of 25 ms and 10 ms respectively. It is implemented as a series of five convolutional blocks, each consisting of a one-dimensional convolutional layer with 256 filters, a dropout layer [36], batch normalisation [37] and the rectified linear unit (ReLU) activation function. The strides for each block are [5, 4, 2, 2, 2] and the kernel sizes are [10, 8, 4, 4, 4]. VQ is applied using a codebook of 512 vectors of dimensionality 128, with the commitment loss defined as in (14). The aggregator $g(\cdot)$ is implemented as a two-layer gated recurrent neural network (GRU) [38] with 128 hidden channels. Hence, in our experiments, $K = E$. The InfoNCE loss is computed using 10 negative samples and $k = 12$ steps. Augmentation is applied as random channel and polarity swapping, additive noise and random audio gain. All resulting sequences \mathbf{c} (with $K = 128$)

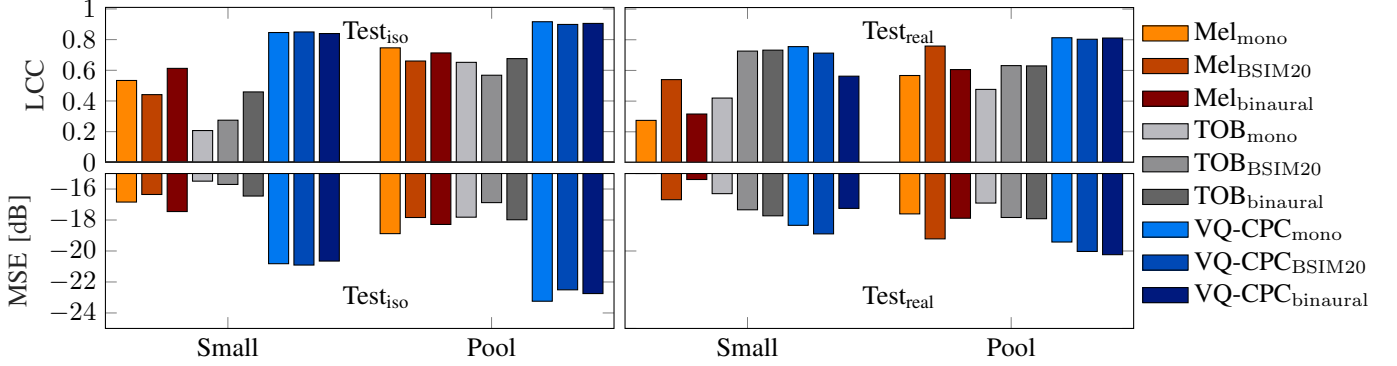


Fig. 1. Performance of the proposed VQ-CPC and considered benchmark features on the Test_{iso} (left) and $\text{Test}_{\text{real}}$ (right) datasets when using either the Small or Pool predicting function. All correlations appeared significant, with p-values inferior to 0.01.

in the training set are used to train the considered predicting functions. VQ-CPC features are extracted from Test_{iso} and $\text{Test}_{\text{real}}$ using the complete VQ-CPC model trained on the training set.

The Small predicting function consists of a single layer mapping each feature vector of length K to a single element followed by the sigmoid activation function. The Pool predictor is implemented as a single shared linear layer to compute the weighting and a MLP with one hidden layer of size $2K$. The hidden layer uses ReLU as its non-linearity and the output layer consists of a single element followed by the sigmoid activation function.

Training and testing of the VQ-CPC model and predicting functions were implemented in PyTorch [39]. The total number of trainable network weights in the VQ-CPC model is $\approx 1.74 \times 10^6$.

C. Benchmark and figures of merit

The performance of the proposed VQ-CPC is measured in terms of Pearson's correlation coefficient (LCC) and MSE between the ground truth and the output of the predicting functions. The experiments aim to quantify the ability of VQ-CPC features to represent information useful for speech intelligibility prediction. To this end, their performance is compared with the use of mel-spectrogram (Mel), with deltas and double-deltas, and with envelopes extracted in third-octave bands (TOB) similarly as used in [21]. All features are extracted from either the first channel (mono), concatenated from both channels (binaural) or extracted from the single-channel signal computed using a blind binaural preprocessing stage [18] (BSIM20). The type of signal is indicated in subscript in the following. All features are computed using the same frame length and hop size as the VQ-CPC. For all considered features, the predicting functions Small and Pool are trained using the same dataset as for VQ-CPC.

IV. RESULTS

All results are depicted in Fig. 1. On Test_{iso} , VQ-CPC features yield the best performance regardless of the type of signals from which they are computed, when using either the

Small or the Pool predicting function. Using Small and VQ-CPC features yields a LCC 0.84 and an MSE of -20.7 dB. Using Pool and VQ-CPC features yields a LCC of 0.94 and an MSE of -22.7 dB. In contrast with the other considered features, the difference in performance between the use of Small and Pool is rather modest. Success applying Small suggests that the VQ-CPC features contain easily accessible information about the intelligibility of speech.

On $\text{Test}_{\text{real}}$, the performance of all combinations of features and predicting functions decreases, as expected. It can however be noted that the TOB features, that performed the least satisfactorily on the less challenging Test_{iso} , outperform Mel on $\text{Test}_{\text{real}}$. This seems to confirm their suitability in realistic scenarios [21]. The proposed VQ-CPC features remain the best performing of the considered features. Using VQ-CPC features computed from binaural signals as input to the Pool predicting function yields LCC of 0.81 and an MSE of -20.2 dB.

A more powerful predictor such as STOI-Net [12] could be improve performance further, but we emphasize the purpose of our study is to show that good performance can be obtained with VQ-CPC features alone. Though the VQ-CPC were here proposed to predict intelligibility from binaural signals, the difference in performance between VQ-CPC_{mono}, VQ-CPC_{BSIM20} and VQ-CPC_{binaural} is modest. Further experimentation, e.g., using intelligibility scores as ground truth rather than an intrusive measures, are needed to determine if the VQ-CPC features do capture information such as binaural cues. Regardless, the difference in network size between the various VQ-CPC models is negligible.

V. CONCLUSION

This paper proposes to use VQ-CPC features as input to a trained neural network to non-intrusively predict intelligibility from binaural signals. The performance of the proposed measure is assessed in terms of correlation and MSE. Results show that the VQ-CPC features are effective in encoding readily accessible information relevant for SI prediction and the features outperform all considered benchmarks. This is despite VQ-CPC features not relying on any assumptions about the downstream task of SI prediction.

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