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PERCEIVE AND PREDICT: SELF-SUPERVISED SPEECH REPRESENTATION BASED LOSS FUNCTIONS FOR SPEECH ENHANCEMENT

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ABSTRACT

Recent work in the domain of speech enhancement has explored the use of self-supervised speech representations to aid in the training of neural speech enhancement models. However, much of this work focuses on using the deepest or final outputs of self supervised speech representation models, rather than the earlier feature encodings. The use of self supervised representations in such a way is often not fully motivated. In this work it is shown that the distance between the feature encodings of clean and noisy speech correlate strongly with psychoacoustically motivated measures of speech quality and intelligibility, as well as with human Mean Opinion Score (MOS) ratings. Experiments using this distance as a loss function are performed and improved performance over the use of STFT spectrogram distance based loss as well as other common loss functions from speech enhancement literature is demonstrated using objective measures such as perceptual evaluation of speech quality (PESQ) and short-time objective intelligibility (STOI).

Index Terms— self-supervised representations, speech enhancement, loss functions, neural networks

1. INTRODUCTION

Speech enhancement remains an active area of speech research due to its applications in numerous downstream tasks [1]. Deep learning models have led to state-of-the-art results on numerous benchmarks for speech enhancement and related tasks [2–5]. A key area of research for these kinds of models has been the loss functions used [6]. Furthermore, metrics used to evaluate speech enhancement models have long been an active area of research; in many cases they can also be used as the loss function used to train the models themselves [7–10]. Self-supervised speech representations (SSSRs) are of increasing interest in a number of speech related tasks, including speech enhancement [11–13]. Generally, the strength of SSSR comes from their ability to predict the context of the speech content in the input audio, and thus model the patterns of spoken language. In this work, it is investigated whether SSSR distances between clean and noisy speech signals have a stronger correlation to perceptually motivated speech enhancement measures such as PESQ than the spectral distances of the signals. This analysis is also repeated for MOS. In the contribution here we consider both the output of SSSR encoder layers as well as the final output layer. It is demonstrated the encoder layers have a notably stronger correlation to the aforementioned evaluation measures than the output layers. Hidden unit BERT (HuBERT) [12] and XLSR [14] SSSRs are chosen as these

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have both been applied in related speech tasks previously but in different ways [15, 16]. Following from this, the distances between clean and noisy SSSR features are then evaluated for their usefulness as loss functions to train speech enhancement models. Their performance is compared to other standard loss functions including perceptually motivated loss functions such as STOI loss [17].

The remainder of this paper is structured as follows. In Section 2, SSSRs are introduced and the two specific models used in this work are detailed. In Section 3 the relationship between distance measures derived from these models with speech assessment metrics and human assessment is analysed, in order to obtain novel insight in to the use of SSSRs for perceptually motivated speech enhancement. Finally, in Section 4 simple signal enhancement networks are trained using loss functions derived from SSSR distances and are compared to baselines using conventional loss functions, analysing the distance measures usefulness as loss function for a single channel speech enhancement task.

2. SELF SUPERVISED SPEECH REPRESENTATION MODELS

SSSR models are neural models of speech which are trained in a self supervised way. This is typically done by ‘masking’ a portion of the input and then tasking the model with recreating the masked portion. At inference time, the network layers responsible for the recreation step are removed and the model instead returns a deep ‘context’ representation of the input time domain audio. At this point, additional task specific layers can be appended to the network, with the self supervised representation model either being fine-tuned or frozen as the task specific layers are trained. Generally speaking, SSSRs can be said to first *perceive* the input audio in a feature encoder step, and then *predict* the context of the content of the audio in the deeper layers.

HuBERT [12] (Hidden Unit BERT) is a SSSR model which utilises a BERT [18] style prediction loss in training. It consists of two main components; the first is a convolutional neural network (CNN) feature encoder block consisting of stacked 1 dimensional convolutional layers which transform the input time domain audio signal into a 512 channel feature representation. This is followed by a transformer [19] block which consists of several transformer layers to produce the final 768 channel output representation. The HuBERT model used in this work is trained on the 960h LibriSpeech [20] training set and is sourced from the fairseq Github repository¹.

The **Cross Lingual Speech Representation (XLSR)** [14] model is a variant of the Wav2Vec2 [11] SSSR model. It is trained on 436,000 hours of speech data from a number of different languages, including BABEL², which contains potentially noisy telephone conversations

¹<https://github.com/facebookresearch/fairseq>

²<https://catalog.ldc.upenn.edu/byyear>

in a number of languages. It is structured similarly to HuBERT, with a convolutional feature encoder block which outputs a 512 channel feature representation, followed by a transformer block which outputs a final representation with 1024 channels. In this work we make use of the smallest version of XLSR, sourced from the official HuggingFace repository³.

2.1. SSSRs in quality estimation and speech enhancement

In [16], a non intrusive human MOS predictor is proposed which makes use of pretrained XLSR representations as a feature extraction stage. With only a simple trained prediction network placed over these XLSR representations, the proposed model was able to achieve high performance in the Conferencing Speech 2022 [21] quality prediction challenge. This indicates that the XLSR SSSR model is able to capture quality information about the input signal, even without access to a reference. It’s training data differs to that of other SSSR models (such as HuBERT) in that it is trained in part on non-clean speech. In this work, we aim to analyse the behaviour of XLSR and HuBERT when exposed to noisy/low quality audio.

In [15], a number of techniques to incorporate SSSRs (namely HuBERT) into a single channel speech enhancement system are proposed. One of these techniques, called ‘supervision’ in [15] involves the use of the distance between the SSSR output representations of clean reference speech and the enhanced noisy speech output by the enhancement model as an additional loss term to train the model. This is in turn inspired by a prior work [22] in which the Wasserstein distance between clean and enhanced SSSR representations of the audio is used as a loss term. In [22] the relationship between the SSSR distances and perceptual measures is noted. However, both of these works are motivated by the phoneme level information encoded in later layers of the SSSR network and thus only consider the distance between the clean and noisy representations of the *final output layer* of SSSR models. Here, we aim to explore the use of distances derived from the intermediate *feature encoder layer* of the SSSR models. Moreover, we aim to directly compare SSSR derived distances with a standard distance used as a loss function for speech enhancement, by formulating the proposed distance measures similarly, i.e. as mean squared error (MSE) distances.

3. SSSR DERIVED DISTANCES IN RELATION TO SPEECH ASSESSMENT METRICS

In this work, first the mean squared error (MSE) distance between representations of some clean speech $s[n]$ and a corresponding noisy version of $s[n]$, $x[n]$

$$x[n] = s[n] + v[n], \quad (1)$$

is analysed, where n is the discrete time index and $v[n]$ is some additive noise caused by the recording environment. Specifically, we define these using either \mathbf{S}_{FE} , \mathbf{X}_{FE} or \mathbf{S}_{OL} , \mathbf{X}_{OL} where FE and OL denote the SSSR encoder representation and final output layer respectively:

$$\mathbf{S}_{FE} = \mathcal{G}_{FE}(s[n]) \quad (2)$$

$$\mathbf{S}_{OL} = \mathcal{G}_{OL}(\mathcal{G}_{FE}(s[n])) \quad (3)$$

with \mathcal{G}_{FE} , \mathcal{G}_{OL} denoting the encoder output and final layer in the SSSR mode respectively, and \mathbf{X}_{FE} , \mathbf{X}_{OL} defined similarly. \mathbf{S}_{FE} is the output of the SSSRs feature encoder layer, while \mathbf{S}_{OL} is the

output of its final layer. The MSE distances between these SSSR representations are defined as:

$$d_{FE}(\mathbf{S}_{FE}, \mathbf{X}_{FE}) = \sum_{t,f}^{T,F} (\mathbf{S}_{FE}[t, f] - \mathbf{X}_{FE}[t, f])^2 \quad (4)$$

$$d_{OL}(\mathbf{S}_{OL}, \mathbf{X}_{OL}) = \sum_{t,f}^{T,F} (\mathbf{S}_{OL}[t, f] - \mathbf{X}_{OL}[t, f])^2 \quad (5)$$

where T and F denote time and feature dimensions of the representation.

These SSSR derived distances are compared with a distance which is commonly used as a loss function in speech enhancement tasks. The MSE distance between clean and noisy spectrogram representations is taken:

$$d_{SG}(\mathbf{S}_{SG}, \mathbf{X}_{SG}) = \sum_{t, f_{Hz}}^{T, F_{Hz}} (\mathbf{S}_{SG}[t, f_{Hz}] - \mathbf{X}_{SG}[t, f_{Hz}])^2 \quad (6)$$

where \mathbf{S}_{SG} and \mathbf{X}_{SG} are magnitude spectrogram representations of $s[n]$ and $x[n]$, respectively, and T and F_{Hz} are the time and frequency dimensions of the spectrograms.

In the following, d_{FE} and d_{OL} are computed using the XLSR and HuBERT models. As mentioned in the previous section, \mathbf{S}_{FE} , \mathbf{X}_{FE} and \mathbf{S}_{OL} , \mathbf{X}_{OL} of the XLSR model have feature dimensions F of 512 and 1024 respectively, while those of HuBERT have feature dimensions of 512 and 768, sharing a time dimension T , the size of which is dependent on the length in samples of the input time domain audio.

\mathbf{S}_{SG} and \mathbf{X}_{SG} are computed using a Fourier Transform with an FFT size of 512, window length of 32ms, and a hop length of 16ms (resulting in a 50% frame overlap) using a hamming window. This results in a spectrogram with a frequency dimension F_{Hz} of 257, and a time dimension T which is dependent on the length in samples of the input time domain audio.

3.1. Datasets

To express the relationship between the distance measures and psychoacoustically motivated metrics the VoiceBank-DEMAND [23], a popular and commonly used dataset for single channel speech enhancement, is used. Its training set consists of 11572 clean and noisy speech audio file pairs ($s[n]$, $x[n]$), mixed at four different signal-to-noise ratios (SNRs) {0, 5, 10, 15} dB. Eight noise files are sourced from the DEMAND [24] noise dataset; two others, a babble noise and a speech-shaped noise were also used. The training set contains speech from 28 different speakers (14 male, 14 female), with English or Scottish accents. The testset containing 824 utterances is mixed at SNRs of 2.5, 7.5, 12.5 and 17.5 dB, with five different noises which do not appear in the training set from the DEMAND corpus.

In order to assess the relationship between the distance measures and human MOS ratings, the NISQA [25] dataset is used. This is a dataset of variable length clean and noisy speech audio file pairs ($s[n]$, $x[n]$) with real human-annotated MOS labels, designed for the training and testing of neural MOS predictors. The two testsets used here contain 440 clean/noisy pairs in total.

The audio files in both datasets have a sample rate of 48 kHz and are down-sampled to 16 kHz such that $\mathcal{G}(\cdot)$ in (2), (3) can be computed.

³<https://huggingface.co/facebook/wav2vec2-xls-r-300m>

Distance	PESQ		STOI		Csig		Cbak		Covl		MOS	
	r	ρ	r	ρ	r	ρ	r	ρ	r	ρ	r	ρ
d_{SG}	-0.66	-0.53	-0.60	-0.68	-0.75	-0.70	-0.84	-0.69	-0.74	-0.64	0.35	-0.27
XLSR d_{FE}	-0.82	-0.78	-0.80	-0.81	-0.93	-0.92	-0.88	-0.85	-0.90	-0.87	-0.47	-0.43
XLSR d_{OL}	-0.66	-0.61	-0.69	-0.68	-0.76	-0.75	-0.74	-0.72	-0.74	-0.71	-0.44	-0.40
HuBERT d_{FE}	-0.83	-0.79	-0.75	-0.76	-0.95	-0.93	-0.90	-0.87	-0.91	-0.89	-0.48	-0.46
HuBERT d_{OL}	-0.44	-0.43	-0.40	-0.42	-0.52	-0.52	-0.45	-0.45	-0.50	-0.49	-0.42	-0.37

Table 1. Spearman r and Pearson ρ correlation between distance measures and speech quality and intelligibility metrics in the VoiceBank-DEMAND testset, as well as MOS in the NISQA Challenge testset

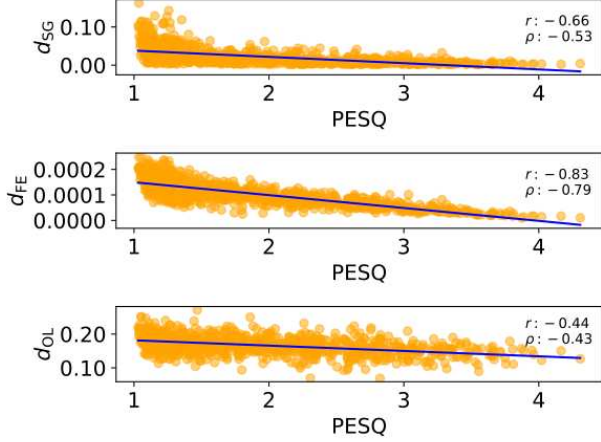


Fig. 1. Scatter plots showing the relationship between the PESQ metric and MSE Spectrogram distance d_{SG} as well as, HuBERT d_{FE} , HuBERT d_{OL} distances for the VoiceBank-DEMAND testset

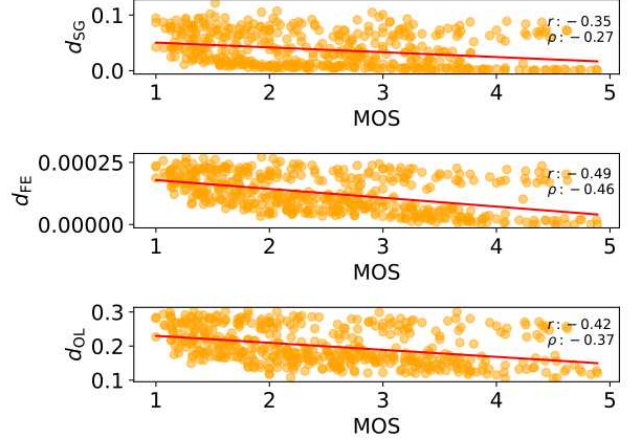


Fig. 2. Scatter plots showing the relationship between human MOS scores and MSE Spectrogram distance d_{SG} , HuBERT d_{FE} and HuBERT d_{OL} with in the NISQA Challenge testset

3.2. SSSR distances and psychoacustically motivated metrics

Fig. 1 shows the relationships between the distance measures and PESQ [7] scores computed using the $s[n]$, $x[n]$ pairs in the VoiceBank-DEMAND [23] testset using HuBERT SSSR. From these, it can be observed that both d_{FE} and d_{OL} correlate significantly more strongly than d_{SG} with quality metrics. Furthermore, the distance computed using the output of the 1D convolutional block d_{FE} correlates more strongly than the distance computed using the SSSR output d_{OL} . This suggests that the phonetic and linguistic processing which occurs in the deeper parts of the model are less sensitive to the noise in $x[n]$. The first 5 columns of Table 1 shows the Spearman r and Pearson correlations ρ between PESQ, STOI and the components of the Composite [26] measure. Like with PESQ, STOI and the Composite measure scores all correlate more strongly with the proposed SSSR distances than with d_{SG} . To our knowledge, this is the first time that the correlation between SSSR derived distances and the Composite measure have been analysed, and the high correlation displayed here shown.

3.3. SSSR distances and human quality assessment

Fig. 2 and the last column of Table 1 show the relationship between the MSE distances and human MOSs in the ‘FOR’ and ‘P501’ testset $s[n]$, $x[n]$ pairs of the NISQA [25] dataset. While the overall correlations are lower here than those of the metrics analysed in the first 5 columns, the same pattern emerges with d_{FE} and d_{OL} correlating

more strongly with the MOS scores than d_{SG} . The HuBERT based distances again correlate more strongly than XLSR; this is possibly due to the language match between the training data of HuBERT and that of the data, both being English only.

4. SSSR BASED SIGNAL ENHANCEMENT EXPERIMENT

An experiment is carried out in order to assess the effectiveness of the SSSR derived distance measures as loss functions for speech enhancement tasks.

4.1. Experiment setup

Simple masking based speech enhancement models were trained using a number of different loss functions; d_{SG} , d_{FE} , d_{OL} as described in the previous sections, as well as Si-SDR loss [27] and STOI loss [17]. Each model was trained for 50 epochs on the VoiceBank-DEMAND [23] training set. d_{FE} , d_{OL} are computed for XLSR or HuBERT feature encoder and output representations. The Adam [28] optimiser is used with a learning rate of 0.001. At test time, the epoch obtaining the highest PESQ score on the validation set is loaded. The SpeechBrain [29] toolkit is used to implement the experiment.

4.2. Loss Functions

The distance measures defined in (4), (5) and (6) are modified to be used as loss terms for a speech enhancement neural model:

$$L_{FE}(\mathbf{S}_{FE}, \hat{\mathbf{S}}_{FE}) = \sum_{t,f} (\mathbf{S}_{FE}[t, f] - \hat{\mathbf{S}}_{FE}[t, f])^2 \quad (7)$$

$$L_{OL}(\mathbf{S}_{OL}, \hat{\mathbf{S}}_{OL}) = \sum_{t,f} (\mathbf{S}_{OL}[t, f] - \hat{\mathbf{S}}_{OL}[t, f])^2 \quad (8)$$

$$L_{SG}(\mathbf{S}_{SG}, \hat{\mathbf{S}}_{SG}) = \sum_{t, f_{Hz}} (\mathbf{S}_{SG}[t, f_{Hz}] - \hat{\mathbf{S}}_{SG}[t, f_{Hz}])^2 \quad (9)$$

where $\hat{s}[n]$ is the enhanced time domain audio signal output by the neural model when $x[n]$ is input and $\hat{\mathbf{S}}_{FE}$, $\hat{\mathbf{S}}_{OL}$ and $\hat{\mathbf{S}}_{SG}$ are the feature encoder output, output layer and spectrogram representations of $\hat{s}[n]$ respectively.

4.3. Enhancement Model Structure

The same model structure is used for all models. It consists of 2 bidirectional long short term memory (BLSTM) layers followed by two linear layers, with the first linear layer using a LeakyReLU activation and the second a Sigmoid. The input to the model is a magnitude spectrogram (\mathbf{X}_{SG}) and the model returns a ‘mask’ which is multiplied with the noisy input spectrogram to produce the enhanced spectrogram $\hat{\mathbf{S}}_{SG}$. From this, the enhanced time domain speech $\hat{s}[n]$ is then created via the overlap-add resynthesis method, using the original noisy phase of $x[n]$. This structure is selected because, despite being relatively simple and with a small parameter count, it is able to achieve state of the art performance in perceptually motivated speech enhancement [2, 5, 10].

4.4. Signal Enhancement Performance

Table 2 shows the experiment results. The proposed model using HuBERT L_{FE} as its loss function outperforms the baseline using the spectrogram distance L_{SG} in terms of PESQ and the Composite measure Csig, Cbak and Covl. Additionally, the best performing model by a significant margin in terms of Cbak uses the XLSR encoder distance loss function L_{FE} , and most SSSR based losses outperform the baseline systems in this measure. Those models which use SSSR encoder distance L_{FE} outperform those which use SSSR output layer distance L_{OL} ; this is consistent with the correlation values in Table 1 where d_{FE} distances correlate more strongly with the metrics than d_{OL} distances.

loss function	PESQ	STOI	Csig	Cbak	Covl	Si-SDR
<i>noisy</i>	1.97	0.92	3.35	2.44	2.63	8.98
d_{SG}	2.70	0.94	4.00	2.62	3.35	18.62
L_{SISDR} [27]	2.28	0.92	3.51	2.44	2.88	18.66
L_{STOI} [17]	2.12	0.93	3.46	2.16	2.77	13.31
HuBERT L_{FE}	2.79	0.94	4.10	2.68	3.44	18.47
HuBERT L_{OL}	2.55	0.92	3.66	2.42	3.08	14.92
XLSR L_{FE}	2.69	0.92	3.77	3.05	3.21	9.72
XLSR L_{OL}	2.43	0.91	3.21	2.64	2.79	13.00

Table 2. Signal Enhancement performance on the VoiceBank-DEMAND testset

4.5. Analysis

Fig. 3 shows an example of the feature representations of $s[n]$ and $x[n]$ used as inputs to d_{SG} and d_{FE} for both HuBERT and XLSR. Tonal noise introduced in $x[n]$, visible as a line spanning approximately the first 50 time frames in \mathbf{X}_{SG} , is well represented in the XLSR \mathbf{X}_{FE} but not in HuBERT \mathbf{X}_{FE} . This is a possible explanation for the increased Cbak score for the XLSR L_{FE} loss over the HuBERT based loss L_{FE} as XLSR \mathbf{X}_{FE} representations appear to be more sensitive to noise in non speech regions of the representation. The fact that XLSR is trained in part on noisy data is a potential explanation for this behaviour.

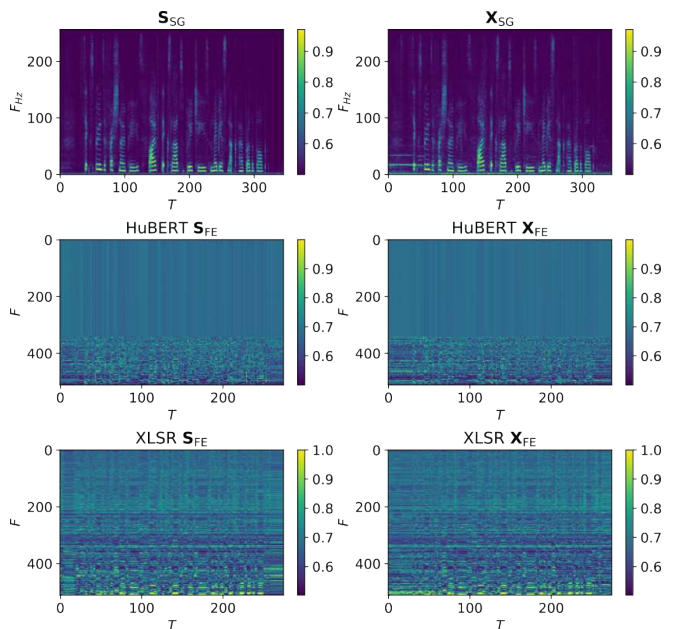


Fig. 3. Visualisation of inputs representations of $s[n]$, $x[n]$ to d_{SG} , HuBERT d_{FE} and XLSR d_{FE} . SSSR features are sorted according to depthwise euclidean distance following Algorithm 1 in [30] and a sigmoid function is applied to increase clarity.

5. CONCLUSION

In this work it is demonstrated that the earlier ‘perceive’ feature encoder layers of SSSRs preserve aspects of noise and distortion in speech to a greater degree than the deeper ‘predict’ layers. Moreover, we find that a simple distance measure between the encoder representations of clean and noisy speech correlates strongly with perceptually motivated metrics of speech quality, as well as with human speech quality assessment. This correlation is affected by the attributes of the data used to train the SSSR. This finding is validated by the use of these distance measures as loss functions for a speech enhancement task, where feature encoder distance outperforms both the deeper output layer and a standard spectrogram based loss. Future work will include the further tuning of SSSR encoders towards human perception, as well as investigating the effect of the training data on the SSSR encoder representations.

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