General-Purpose Speech Representation Learning through a Self-Supervised Multi-Granularity Framework

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Abstract

This paper presents a self-supervised learning framework, named MGF, for general-purpose speech representation learning. In the design of MGF, speech hierarchy is taken into consideration. Specifically, we propose to use generative learning approaches to capture fine-grained information at small time scales and use discriminative learning approaches to distill coarse-grained or semantic information at large time scales. For phoneme-scale learning, we borrow idea from the masked language model but tailor it for the continuous speech signal by replacing classification loss with a contrastive loss. We corroborate our design by evaluating MGF representation on various downstream tasks, including phoneme classification, speaker classification, speech recognition, and emotion classification. Experiments verify that training at different time scales needs different training targets and loss functions, which in general complement each other and lead to a better performance.

1 Introduction

Unsupervised pre-training, or representation learning, has drawn wide interests in both academia and industry. The BERT model [Devlin et al., 2019] has become a universal feature extractor for solving a wide range of natural language processing (NLP) tasks. Recently, it is reported that the image embedding learned in an unsupervised manner achieves comparable performance to its supervised counterparts in the image classification task [He et al., 2020; Chen et al., 2020]. Actually, most contemporary unsupervised pre-training methods adopt the self-supervised learning approach. We use these two terms interchangeably in this paper to refer to methods that do not need human annotation.

In the speech domain, pre-training is not a new concept. The speaker recognition task depends heavily on the supervised pre-training step to obtain a good feature embedding. Recently, self-supervised learning is also used to pre-train dedicated models for automatic speech recognition (ASR) [Schneider et al., 2019; Baevski et al., 2020a; Baevski et al., 2020b; Ling et al., 2020]. In this work, however, we are not focusing on these task-oriented pre-training.

Instead, we aim to pre-train a general-purpose feature extractor which embeds a speech signal into a feature representation that could be used for a variety of downstream speech tasks, in a way similar to how pre-trained language and image representations are used in their respective domains.

The main difficulty in learning a general-purpose speech representation is that speech carries complex hierarchical structure (samples, phonemes, and sentences) which contains relevant information at different time scales [Pascual et al., 2019]. In this work, we propose a Multi-Granularity Framework, named MGF, to train the model at multiple time scales. A key innovation in MGF is to adopt different learning approaches for the learning at different time scales. In particular, we use generative approaches to capture fine-grained information for small time scales on the order of a few milliseconds, and we adopt discriminative approaches to distill semantic information for large time scales which correspond to a phoneme and a sentence. In order to realize phoneme-level contrastive learning, we extend the token-oriented masked language model (MLM) model [Devlin et al., 2019] to continuous masked language model (cMLM) to accommodate the continuous speech signals without token boundaries. MGF is implemented by a deep bidirectional Transformer [Vaswani et al., 2017; Devlin et al., 2019].

We evaluate the MGF representation on multiple downstream tasks and benchmark datasets, which becomes the second main contribution of our work. The performance of MGF is first evaluated on phoneme classification and speaker clas-
sification tasks, following the other general-purpose speech representation learning work [van den Oord et al., 2018; Liu et al., 2020b]. We find that features learned by MGF is very powerful on these two orthogonal tasks. On the LibriSpeech dataset, MGF representation achieves a phoneme classification accuracy of 73.4% under linear evaluation, surpassing the existing unsupervised pre-training methods by a large margin. On the speaker classification task, MGF representation is the first to achieve an accuracy of 100%.

We further evaluate MGF in other three downstream tasks. First, in view of the saturated performance in speaker classification, we propose a new and harder task named one-shot speaker classification, where only one utterance per speaker is provided in the fine-tuning stage. In this task, MGF is evaluated against the well-known x-vector and d-vector and is shown to achieve better performance. Second, we compare MGF with a task-specific pre-training model wav2vec in the ASR task. Third, we test MGF representation on the IEMOCAP emotion classification task. Surprisingly, simply appending a fully-connected layer after MGF achieves the top performance among all existing audio-based approaches.

2 Related Work

There are two camps of self-supervised learning approaches, namely discriminative and generative approaches. We will first review these two approaches for speech pre-training, and then discuss other related work that motivates MGF.

2.1 Discriminative Approaches

Discriminative approaches acquire supervision signal from the contrastive distance between a selected positive sample and several negative samples. By carefully designing the training target and the data sampling procedure, samples can be automatically labelled.

Contrastive predictive coding (CPC) [van den Oord et al., 2018] is a contrastive learning method based on predicting the future in the latent space. The representations of temporally nearby segments are treated as positive samples while those of temporally distant segments are treated as negative samples. However, one could easily find a counter example in speech processing. For example, a word appears twice in an utterance with the same meaning. When the first appearance is the anchor, the second appearance should not be treated as a negative sample no matter how far it is. Previous work [Chung et al., 2019] also notices that the choice of negative samples in CPC has huge effect on its performance on the phoneme classification task.

While CPC itself is a general-purpose speech pre-training method, it can be leveraged in some task-specific pre-training models, such as wav2vec [Schneider et al., 2019], vq-wav2vec [Baevski et al., 2020a], and wav2vec 2.0 [Baevski et al., 2020b]. Vq-wav2vec proposes a quantization algorithm so that wav2vec (which adopts CPC) can be combined with the BERT model [Devlin et al., 2019] to achieve better performance. Wav2vec 2.0 improves vq-wav2vec by training the entire model end-to-end. It also uses a very large unlabelled dataset for pre-training. These task-specific pre-train models are very powerful in their target task, but perform poorly in other speech tasks.

2.2 Generative Approaches

Generative approaches learn to reconstruct signal in the input space or features in some latent spaces. Training is supervised by the reconstruction loss. Autoregressive predictive coding (APC) [Chung et al., 2019] uses an autoregressive model to encode the history and predict the future. A follow-up work [Chung and Glass, 2020] adds an auxiliary objective which encourages the model to additionally remember the past. DeCoAR [Ling et al., 2020] borrows the bidirectional learning idea from ELMo [Peters et al., 2018] so that it can learn deep contextualized acoustic representations for semi-supervised speech recognition.

Inspired by the MLM proposed in BERT [Devlin et al., 2019], recent works [Liu et al., 2020b; Liu et al., 2020a] have explored using BERT-style objective in speech pre-training. In Mockingjay [Liu et al., 2020b], part of input frames are masked to zeros and the pre-trained encoder is required to predict the masked frame from its neighborhood. TERA [Liu et al., 2020a] extends Mockingjay by introducing channel alteration and magnitude alteration.

2.3 Multi-Task Approaches

PASE [Pascual et al., 2019] uses multiple regressors and discriminators to learn a problem-agnostic speech encoder. Another work PASE+ [Ravanelli et al., 2020] improves PASE for robust speech recognition in noisy and reverberant environments by introducing data augmentation, more regression tasks, and a collection of architecture modification.

Our work and PASE both consider combinations of generative and discriminative objectives. However, PASE does not consider speech hierarchy. In our work, different objectives are used to handle signals at different time scales.

2.4 Self-Supervised Learning in Other Domains

Our work is inspired by some self-supervised learning methods in other domains. BERT [Devlin et al., 2019] is a milestone work for pre-training in NLP. The core of BERT is the MLM, where some input tokens are randomly masked out, and the training objective is to predict the vocabulary ID of the masked word based only on its context. SimCLR [Chen et al., 2020] proposes a simple contrastive learning framework for visual representation learning. It adopts the contrastive loss between augmented views of an image without relying on specialized architecture design or memory bank mechanism. BERT and SimCLR inspired our phoneme-scale and sentence-scale contrastive learning, respectively.

3 Multi-Granularity Framework

3.1 Overview

The main idea behind MGF is to extract the information attached to each speech hierarchy by multi-granularity objectives. At the finest granularity, we adopt generative approaches to reconstruct the original waveform and selected hand-crafted features to extract sample-scale and frame-scale information, respectively. At a coarser granularity, we design a novel continuous masked language model (cMLLM) which masks several consequent frames with the typical phoneme
length. The model is trained to estimate the feature embedding for one of the masked frames based on the context information. We do not expect the model to recover the exact feature, but we hope that the estimated feature for the masked frame is close to the ground truth feature and far away from features of other frames in different phonemes. At the sentence level, learning encourages segments within the same sentence to have close representations and segments across different sentences to have representations that are far apart.

### 3.2 Learning Objectives and Loss Design

Learning of sample-scale and frame-scale information adopts reconstruction loss, while learning of phoneme-scale and sentence-scale information adopts contrastive loss.

#### Sample-Scale Loss

As Fig.2 shows, a decoder is appended to the base module to reconstruct the original signal from the feature embedding. Let $\hat{x}$ denote the original signal and $\bar{x}$ denote the reconstructed signal. The sample-scale loss is implemented by the scale-invariant signal-to-distortion ratio (SI-SDR) [Roux et al., 2019] loss which is formulated as:

$$L_{\text{sample}} = -10 \log_{10}\left(\frac{\|\alpha x\|^2}{\|\alpha x - \bar{x}\|^2}\right) \text{ for } \alpha = \frac{\bar{x}^T x}{|x|^2}.$$  

(1)

SI-SDR loss is widely used in speech separation [Zhao et al., 2020] and we empirically find it works better than L1 loss.

#### Frame-Scale Loss

Several heads composed of two convolutional (conv) layers are appended to the base model to generate selected hand-crafted features frame by frame. These features, including log power spectrum (LPS), mel-frequency cepstral coefficient (MFCC), and maximum likelihood linear regression (fMLLR), have been proven effective in speech-related tasks. Following PASE+, we set the context window for LPS and MFCC allocations to a long time scale. We adopt SimCLR frame-based contrastive learning, to implement the idea. We make some modifications to SimCLR. First, since cropping is useful only in computing sentence-scale loss, we crop two segments of a sentence before applying other data augmentations. Then, one segment is treated as the original crop for the scale-invariant signal-to-distortion ratio (SI-SDR) [Roux et al., 2019].

#### Phoneme-Scale Loss

A speech segment that is tens to hundreds of milliseconds long contains distinguishable phonemes. We believe that learning distinguishable high-level semantic information is more important than waveform or feature reconstruction on this time scale.

Phoneme-scale information is learned by our proposed continuous MLM model and the discriminative learning objective. In the vanilla MLM, discrete tokens from a finite dictionary are masked in the language input and then predicted in the output based on their context. However, speech is a continuous signal without token boundaries. It is not possible to precisely mask some pre-defined phonemes. To address this challenge, we randomly mask a fixed-length speech segment, and use InfoNCE [van den Oord et al., 2018] loss to evaluate the quality of the estimated features of a masked frame. In our implementation, each masked segment has a length of 140ms, and the total length of all masked segments does not exceed 20% of the input speech crop. The masked segment is replaced by non-speech noise. We empirically find that it is a better choice than a segment of zeros or a random speech.

InfoNCE loss directly operates on real-valued feature vectors and is formulated as:

$$L_{\text{phoneme}} = -\mathbb{E}_{\hat{v} \in V} \log \frac{\exp(v^T \hat{v} / \tau_1)}{\sum_{k=1}^{K} \exp(v^T \hat{v}_k / \tau_1) + \exp(v^T \hat{v} / \tau_1)}$$

(3)

where $V$ is the set of masked frames, $v$ is the anchor sample, $\hat{v}$ is the positive sample, and $\hat{v}_k (k = 1, ..., K)$ are negative samples. $\tau_1$ is a temperature parameter.

Note that each sample is the feature representation of a single frame whose duration is 10ms. The anchor sample is drawn from the MGF representation of the masked crop, while the positive sample and negative samples are drawn from the feature representation of the original unmasked crop. In other words, the anchor sample is the estimated feature while positive and negative samples are ground-truth features at the same or different locations, respectively.

#### Sentence-Scale Loss

Sentence-scale loss focuses on capturing semantic information relevant to a long time scale. We adopt SimCLR framework [Chen et al., 2020], which was proposed for visual representation learning, to implement the model. We make some small modifications to SimCLR. First, since cropping is useful only in computing sentence-scale loss, we crop two segments of a sentence before applying other data augmentations. Then, one segment is treated as the original crop for all the other objectives. Second, we use data augmentations specific to speech signal. The augmentations include temporal mask and additive noise.

The sentence-scale loss is defined as:

$$L_{\text{sentence}} = -\log \frac{\exp(z_i^T z_j / \tau_2)}{\sum_{k=1}^{2N} \exp(z_i^T z_k / \tau_2)}$$

(4)

where $z_i$ is the anchor sample, $z_j$ is the positive sample, $z_k (k \neq j)$ are negative samples, $N$ is batch-size, and $\tau_2$ is a temperature parameter. Each sample is obtained by averaging the MGF representation of all frames within a 2s-long...
speech crop and passing the averaged feature through a head of two conv layers. The positive sample corresponds to a speech crop from the same sentence as the anchor crop, while negative samples correspond to crops from other sentences. Following SimCLR, we draw negatives from the mini-batch so that there are \(2N - 2\) negative samples for each anchor.

**Multi-Granularity Objectives**

We train the base encoder by combining multi-granularity objectives. The total loss function is defined as:

\[
L = \lambda_1 L_{\text{sample}} + \lambda_2 L_{\text{frame}} + \lambda_3 L_{\text{phoneme}} + \lambda_4 L_{\text{sentence}}
\]

where \(\lambda_i, i = 1, 2, 3, 4\) are weights of each loss. We tune each weight in \(\{0.03, 0.1, 0.3, 1\}\) independently.

### 3.3 Implementation

MGF is implemented in PyTorch. The base encoder is composed of three conv layers and six blocks of Transformer. The first conv layer has a kernel size of 320 and implements 512 filters with stride 160 and padding 80. The second conv layer has a kernel size of 1 followed by ReLU activation. These two conv layers serve as a stem which transforms the time-domain waveform to a compact feature vector, so that Transformer does not need to handle very long and low-level input. The third conv layer aligns the dimension with the subsequent Transformer. In addition to the base encoder, the decoder for sample-level reconstruction also uses four blocks of Transformer. All Transformers share the same parameters with hidden size \(d_{\text{model}} = 768\), feed-forward size \(d_{\text{ff}} = 3072\), and the number of attention heads \(h = 12\).

### 4 Experiments

#### 4.1 Experiment Setup

In most of our experiments, we use the train-clean-100 subset of the LibriSpeech corpus [Panayotov et al., 2015] as the pre-training dataset. It contains 100 hours of speech data. We use dev-clean subset as the validation dataset for model selection. In the pre-training stage, we use the raw signal only and ignore any human labels such as speaker ID or transcriptions. Some of the MGF objectives rely on data augmentation of additive noise. We use DNS challenge dataset [Reddy et al., 2008] for this task. This corpus consists of five sessions with two speakers in each session. Following the usage in [Wu et al., 2019], we evaluate the MGF representation on four emotions, namely Neutral, Angry, Happy and Sad. The IEMOCAP dataset contains scripted data and improvised data and we only use the latter. We report results of five-fold cross-validation using four sessions as training and the other session as validation and testing.

**Speech Recognition**: We use Wall Street Journal (WSJ [Garofolo et al., 1993]) dataset for the ASR task. This corpus comprises about 81 hours of transcribed audio data. We train on si284, validate on nov93dev and test on nov92. We use the lexicon-free [Likhomanenko et al., 2019] acoustic model and four-gram KenLM [Heafield et al., 2013] language model which are implemented by wav2letter++ [Pratap et al., 2019]. Word error rate (WER) and letter error rate (LER) are used as evaluation metrics. We use the training recipe provided by wav2letter++ and only modifies the input embedding.

For the pre-training and classification downstream tasks, we use Adam optimizer with warm-up to update the model. We use learning rate of \(\{1e-3, 1e-3, 1e-3, 1e-3, 3e-4\}\), warm-up steps of \(\{10000, 5000, 5000, 5000, 2000\}\) and batch-size of \(\{120, 64, 32, 64, 3\}\) for pre-training, phoneme classification, speaker classification, speaker verification and emotion classification training, respectively. We also exponentially decay the learning rate with exponent of 0.3. We use 4 V100 GPU in both pre-training and downstream task finetuning. The total training epochs for pre-training is set to 300, and more epochs yield slight improvement. For all downstream task finetuning, we set total training epochs to 100 except the experiments in data efficiency.

#### 4.2 Ablation Study

We first present ablation study of MGF to show the effectiveness of multi-granularity objectives and cMLM. We report accuracies on phoneme classification and one-shot speaker classification tasks.

**Multi-Granularity Framework**

We study whether all four objectives at different time scales contribute to the final accuracy of MGF, and assess their respective importance on two target problems. We trained MGF four times, discarding one of the four loss objectives at a time. Results are presented in Table 1. The first row presents the results of the full model and the other rows present the results when a certain objective is discarded.

The first finding is that every objective matters. Discarding
any objective leads to notable accuracy drop in at least one task. Second, while some objectives have general impact on two tasks, others turn out to be more task-oriented. For example, sample-scale loss and frame-scale loss are generally helpful. This is consistent with our design as these two losses learn low-level problem-agnostic information. The frame-scale loss is specially important as it injects human prior knowledge into the model. The other two losses, however, are more task-dependent. Phoneme-scale loss has a remarkable impact on phoneme classification task (+27.4% in relative error) and sentence-scale loss only contribute to one-shot speaker classification task. It is worth noting that phoneme-scale loss also contributes a lot to the one-shot speaker classification task. This is caused by the sampling strategy used in cMLM, which will be described next.

cMLM

MGF uses cMLM and adopts InfoNCE loss for phoneme-scale target. Previous work [Liu et al., 2020b] has investigated a similar masking approach but has used a generative approach with reconstruction loss at a similar time scale. We believe that our proposed discriminative approach with InfoNCE loss is more suitable for this time scale. To validate this, we implemented a generative approach which calculates L1 loss between the predicted frame and the ground-truth frame in the masked segment. The two rows in Table 2 show the results of using discriminative (InfoNCE) loss and generative (L1) loss, respectively. The model trained with discriminative approach achieves 7.3% accuracy gain on phoneme classification and 1.4% accuracy gain on one-shot speaker classification, compared with the model trained with generative approach. Coincidentally, the speaker classification accuracy achieved by the generative approach (81.3%) is the same as MGF without phoneme-scale objective. In other words, using generative approach for phoneme-scale learning does not help the speaker classification task at all.

It is worth noting that the sample strategy in cMLM has notable impact on the performance of MGF representation. There are two options to choose negative samples in cMLM: from a different sentence or from the same sentence as the positive sample. Experimental results show that sampling from a different sentence leads to a better performance (1.2% and 0.9% accuracy gain on the two tasks, respectively). The reason is that a richer vocabulary is helpful for the model to learn more discriminative features. In addition, the different-sentence sample strategy allows the model to learn features that are able to discriminate speakers.

### 4.3 Comparison with General-Purpose Self-Supervised Speech Pre-Training Methods

We compare MGF with CPC [van den Oord et al., 2018], Mockingjay [Liu et al., 2020b], and TERA [Liu et al., 2020a] on phoneme classification and speaker classification tasks. All the systems use the same setup as specified in CPC. Results are shown in Table 3.

CPC [van den Oord et al., 2018] is a discriminative approach. We have pointed out earlier that it is not appropriate in CPC to distinguish positive and negative samples only based on the distance to the anchor. In contrast, MGF uses a masked model. When the input crop is masked or unmasked, features at the same location always form a positive pair. In addition, MGF is a multi-granularity framework and uses bidirectional model. These advances explain why MGF outperforms CPC by a large margin on both tasks. Note that the evaluated MGF model has 12G FLOPs, which is a bit heavier than CPC which has 9.7G FLOPs.

Mockingjay [Liu et al., 2020b] and TERA [Liu et al., 2020a] are generative approaches which try to predict acoustic frames from its manipulated version. Mockingjay only uses temporal alteration and TERA extends it by adding channel alteration and magnitude alteration. In the previous section, we have tried similar generative loss and find that discriminative loss works better. Table 3 shows that MGF gets 9.1%/8.3% accuracy gain on phoneme classification and 3.9%/0.8% accuracy gain on speaker classification over Mockingjay and TERA, respectively.

### 4.4 Evaluation on More Tasks

#### One-Shot Speaker Classification

We additionally evaluate MGF representation against two well-known feature embeddings, namely d-vector [Wan et al., 2018] and x-vector [Snyder et al., 2018], in one-shot speaker classification task as well. The results are shown in Table 4.

| Method     | Phoneme Acc | Speaker Acc |
|------------|-------------|-------------|
| CPC        | 65.5        | 97.4        |
| Mockingjay | 64.3        | 96.1        |
| TERA-base (3xT) | 65.1 | 99.2 |
| TERA-medium (6xT) | 65.9 | - |
| MGF (6T)   | 73.4        | 100.0       |

Table 3: Comparison of self-supervised speech representation learning methods on Librispeech phoneme and speaker classification tasks under linear evaluation. nxT denotes n Transformer blocks.
Table 4: WSJ speech recognition results.

| Method     | nov93dev | nov92 |
|------------|----------|-------|
|            | LER     | WER   | LER     | WER   |
| Baseline   | 3.50    | 8.57  | 2.09    | 5.42  |
| wav2vec-large | 2.91    | 7.24  | 1.64    | 4.48  |
| MGF-960    | 3.07    | 7.58  | 1.78    | 4.87  |

Table 5: IEMOCAP emotion classification accuracies of different methods. A, V, T are shorts for audio, video and text, respectively.

| Method       | Modality | Emotion Acc |
|--------------|----------|-------------|
| M3ER         | AVT      | 82.7        |
| CNN LSTM     | A        | 68.8        |
| CNN GRU-SeqCap | A       | 72.7        |
| MGF-Scratch  | A        | 64.1        |
| MGF-Fixed    | A        | 71.2        |
| MGF-Finetune | A        | 73.1        |

classification task. d-vector is learned via a generalized end-to-end loss, which is similar to the triplet loss. x-vector is learned via a speaker recognition task using a time-delay DNN. In particular, x-vector is recognized as the state-of-the-art embedding for speaker classification tasks. d-vector and x-vector are both pre-trained on Switchboard [Godfrey et al., 1992] and NIST SRES [Doddington et al., 2000] datasets and x-vector is implemented officially via Kaldi’s V2 recipe [Povey et al., 2011].

We use the same linear evaluation protocol for all the methods to ensure a fair comparison. d-vector achieves 77.8% accuracy and x-vector achieves 79.6% accuracy. As a comparison, MGF achieves 82.7% accuracy which reduces the relative error by 15.2% compared with the best counterpart.

Speech Recognition

We evaluate the performance of an ASR system built on top of MGF representation. The baseline method uses 80 log-mel filterbank coefficients with a 25ms sliding window and 10ms stride. We also compare MGF with a well-known ASR-oriented self-supervised method wav2vec [Schneider et al., 2019]. We use their released wav2vec-large checkpoint. As wav2vec is pre-trained with the entire 960 hours of LibriSpeech training set, we train the model MGF-960 with the same amount of training data to ensure a fair comparison. MGF-960 has the same architecture and model size as our base model. As shown in Table 4, MGF-960 achieves significantly lower WER than the baseline and comparable WER as wav2vec-large. This means, without bells and whistles, our general-purpose speech representation can benefit the speech recognition task.

Emotion Classification

We present experimental results of emotion classification on IEMOCAP dataset. We want to use this task to evaluate the adaptation capability of MGF representation. Since this task is never evaluated by previous self-supervised representation learning methods, we compare MGF with state-of-the-art supervised methods instead. M3ER [Mittal et al., 2020] uses text, audio and video to predict speaker’s emotion. CNN GRU-SeqCap [Wu et al., 2019], CNN LSTM [Satt et al., 2017], and our MGF only use audio. We set three different settings for MGF. MGF-Scratch does not have pre-training stage while MGF-Fixed and MGF-Finetune are pre-trained. The base encoder of MGF is not trainable in fixed” and trainable in Finetune”. As shown in Table 5, MGF-Scratch does not work well but MGF-Fixed and MGF-Finetune both achieve high accuracy, showing that pre-training does do a lot help. MGF-Finetune even creates a new SOTA among audio-only methods.

4.5 Data Efficiency

Last but not least, we show how pre-training could help in low-resource scenarios where human labels are scarce. We use LibriSpeech phoneme classification task and reduce the labeled data usage from 100% to 0.1%. The performance of MGF in different settings are plotted in Figure 3. To compare fairly with the model without pre-training, we open up the entire model for fine-tuning. We find that pre-trained MGF outperforms its train-from-scratch counterpart by a large margin when the length of labeled data is less than one hour. In an extreme low-resource scenario where only six minutes of labeled data are available, the pre-trained model still achieves a reasonably good performance of 72.3% phoneme accuracy while the train-from-scratch model is only able to achieve 34.9% phoneme accuracy.

5 Conclusion and Future Work

We have proposed a multi-granularity framework for self-supervised speech representation learning. By taking the speech hierarchy into consideration, MGF achieves top performance among existing speech pre-training methods on a collection of speech tasks. Comprehensive ablation studies have been carried out to demonstrate the effectiveness of our design in MGF. In the future, we plan to expand this multi-granularity self-supervised framework to the image domain, which may benefit tasks that demand multi-scale features.
References

[Baevski et al., 2020a] Alexei Baevski, Steffen Schneider, and Michael Auli. vq-wav2vec: Self-supervised learning of discrete speech representations. In ICLR, 2020.

[Baevski et al., 2020b] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. wav2vec 2.0: A framework for self-supervised learning of speech representations. In NeurIPS, 2020.

[Busso et al., 2008] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeanette N. Chang, Sungbok Lee, and Shrikanth S. Narayanan. IEMOCAP: interactive emotional dyadic motion capture database. Lang. Resour. Evaluation, 2008.

[Chen et al., 2020] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey E. Hinton. A simple framework for contrastive learning of visual representations. In ICML, 2020.

[Chung and Glass, 2020] Yu-An Chung and James R. Glass. Improved speech representations with multi-target autoregressive predictive coding. In ACL, 2020.

[Chung et al., 2019] Yu-An Chung, Wei-Ning Hsu, Hao Tang, and James R. Glass. An unsupervised autoregressive model for speech representation learning. In INTERSPEECH, 2019.

[Devlin et al., 2019] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In NAACL-HLT (1), 2019.

[Doddington et al., 2000] George R. Doddington, Mark A. Przybocki, Alvin F. Martin, and Douglas A. Reynolds. The NIST speaker recognition evaluation - overview, methodology, systems, results, perspective. Speech Commun., 2000.

[Garofolo et al., 1993] John Garofolo, David Graff, Doug Paul, and David Pallett. Csr-i (wsj0) complete ldc93s6a. \textit{Download Philadelphia: Linguistic Data Consortium}, 1993.

[Godfrey et al., 1992] John J. Godfrey, Edward Holliman, and Jane McDaniel. SWITCHBOARD: telephone speech corpus for research and development. In ICASSP, 1992.

[He et al., 2020] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross B. Girshick. Momentum contrast for unsupervised visual representation learning. In CVPR, 2020.

[Heafield et al., 2013] Kenneth Heafield, Ian Pouzyshevsky, Jonathan H. Clark, and Philipp Koehn. Scalable modified kneser-ney language model estimation. In ACL (2), 2013.

[Likhomanenko et al., 2019] Tatiana Likhomanenko, Gabriel Synnaeve, and Ronan Collobert. Who needs words? lexicon-free speech recognition. In INTERSPEECH, 2019.

[Ling et al., 2020] Shaoshi Ling, Yuzong Liu, Julian Salazar, and Katrin Kirchhoff. Deep contextualized acoustic representations for semi-supervised speech recognition. In ICASSP, 2020.

[Liu et al., 2020a] Andy T. Liu, Shang-wen Li, and Hung-yi Lee. TERA: self-supervised learning of transformer encoder representation for speech. CoRR, abs/2007.06028, 2020.

[Liu et al., 2020b] Andy T. Liu, Shu-Wen Yang, Po-Han Chi, Po-chun Hsu, and Hung-yi Lee. Mockingjay: Unsupervised speech representation learning with deep bidirectional transformer encoders. In ICASSP, 2020.

[Mittal et al., 2020] Trisha Mittal, Uttaran Bhattacharya, Rohan Chandra, Aniket Bera, and Dinesh Manocha. M3ER: multiplicative multimodal emotion recognition using facial, textual, and speech cues. In AAAI, 2020.

[Panayotov et al., 2015] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. Librispeech: An ASR corpus based on public domain audio books. In ICASSP, 2015.

[Pascual et al., 2019] Santiago Pascual, Mirco Ravanelli, Joan Serrà, Antonio Bonafonte, and Yoshua Bengio. Learning problem-agnostic speech representations from multiple self-supervised tasks. In INTERSPEECH, 2019.

[Peters et al., 2018] Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. In NAACL-HLT, 2018.

[Povey et al., 2011] Daniel Povey, Arnab Ghoshal, Giles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al. The kaldi speech recognition toolkit. In WASRU, 2011.

[Pratap et al., 2019] Vineel Pratap, Awni Hannun, Qiantong Xu, Jeff Cai, Jacob Kahn, Gabriel Synnaeve, Vitaliy Liptchinsky, and Ronan Collobert. Wav2letter++: A fast open-source speech recognition system. In ICASSP, 2019.

[Ravanelli et al., 2020] Mirco Ravanelli, Jianyuan Zhong, Santiago Pascual, Pawel Swietojanski, Joao Monteiro, Jan Trmal, and Yoshua Bengio. Multi-task self-supervised learning for robust speech recognition. In ICASSP, 2020.

[Reddy et al., 2020] Chandan K. A. Reddy, Vishak Gopal, Ross Cutler, Ebrahim Beyrami, Roger Cheng, Harishchandra Dubey, Sergiy Matusevych, Robert Aichner, Ashkan Aazami, Sebastian Braun, Puneet Rana, Srima Srinivasan, and Johannes Gehrke. The INTERSPEECH 2020 deep noise suppression challenge: Datasets, subjective testing framework, and challenge results. CoRR, abs/2005.13981, 2020.

[Roux et al., 2019] Jonathan Le Roux, Scott Wisdom, Hakan Erdogan, and John R. Hershey. SDR - half-baked or well done? In ICASSP, 2019.

[Satt et al., 2017] Aharon Satt, Shai Rozenberg, and Ron Hoory. Efficient emotion recognition from speech using deep learning on spectrograms. In INTERSPEECH, 2017.

[Schneider et al., 2019] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli. wav2vec: Unsupervised pre-training for speech recognition. In INTERSPEECH, 2019.

[Snyder et al., 2018] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur. X-vectors: Robust DNN embeddings for speaker recognition. In ICASSP, 2018.

[van den Oord et al., 2018] A{"a}ron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. CoRR, abs/1807.03748, 2018.

[Vaswani et al., 2017] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In ICLR, 2017.

[Wan et al., 2018] Li Wan, Quan Wang, Alan Papir, and Ignacio Lopez-Moreno. Generalized end-to-end loss for speaker verification. In ICASSP, 2018.

[Wu et al., 2019] Xixin Wu, Songxiang Liu, Yuewen Cao, Xu Li, Jianwei Yu, Dongyang Dai, Xi Ma, Shoukang Hu, Zhiyong Wu, Xunying Liu, and Helen Meng. Speech emotion recognition using capsule networks. In ICASSP, 2019.

[Zhao et al., 2020] Yucheng Zhao, Chong Luo, Zheng-Jun Zha, and Wenjun Zeng. Multi-scale group transformer for long sequence modeling in speech separation. In IJCAI, 2020.