Data Augmentation based Consistency Contrastive Pre-training for Automatic Speech Recognition

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Abstract—Self-supervised acoustic pre-training has achieved amazing results on the automatic speech recognition (ASR) task. Most of the successful acoustic pre-training methods use contrastive learning to learn the acoustic representations by distinguishing the representations from different time steps, ignoring the speaker and environment robustness. As a result, the pre-trained model could show poor performance when meeting out-of-domain data during fine-tuning. In this letter, we design a novel consistency contrastive learning (CCL) method by utilizing data augmentation for acoustic pre-training. Different kinds of augmentation are applied on the original audios and then the augmented audios are fed into an encoder. The encoder should not only contrast the representations within one audio but also maximize the measurement of the representations across different augmented audios. By this way, the pre-trained model can learn a text-related representation method which is more robust with the change of the speaker or environment. Experiments show that by applying the CCL method on the Wav2Vec2.0, better results can be realized both on the in-domain data and the out-of-domain data. Especially for noisy out-of-domain data, more than 15% relative improvement can be obtained.

Index Terms—Speech recognition, self-supervised pre-training, contrastive learning, data augmentation.

I. INTRODUCTION

SELF-SUPERVISED pre-training has already shown amazing performance in the area of deep learning [1]–[4]. For the automatic speech recognition (ASR) task [5]–[8], a majority of the successful acoustic pre-training methods are based on the contrastive learning [9]. Contrastive learning aims to learn data representations which can distinguish a set of positive and negative samples through an InfoNCE loss [10]. The sampling method of the positives and negatives usually decides the performance of the pre-trained model.

In the ASR area, previous methods always sample the positives and the negatives from different time steps in the audios. For examples, researchers in [5], [11] contrast the acoustic representations with the true future audio sample and the representations from other audios Inspired by Bert [1]. researchers in [6], [7], [12] mask the input of the model and then ask the model to distinguish the representations at masked time steps from other time steps. By selecting samples on the timeline, the pre-trained model can learn the contextualized representations to represent the statistical properties of the speech sequence.

However, time steps based contrastive learning only concerns the sample relationship within one utterance, ignoring the speaker and environment robustness. For example, when same text is spoken by different speakers or spoken in different environments, the representations of these audios should also be similar enough. But current contrastive learning cannot guarantee this consistency. As a result, the pre-trained model could show lower performance on out-of-domain data than in-domain data.

To solve this problem, we design a novel consistency contrastive learning (CCL) method based on data augmentation. Different kinds of data augmentation are applied on one utterance to obtain different audios with same transcription. During contrasting, same time steps in every augmented audios can be regarded as the positive samples while others can be chosen as negatives. In addition, it should be noticed that the augmentation methods should not change the tempo of the audios to guarantee the waveform is synchronous. By this way, the encoder can learn a stable acoustic representation method which relies more on the transcription rather than the acoustic condition like speaker or environment.

Data augmentation based contrastive learning has been widely used in the image domain, researchers always apply different data augmentation on one image to obtain a series of augmented views [3], [4], [13]. The pre-trained network needs to learn representations by maximizing the agreement between different augmented views of the same image via the contrastive loss. And for ASR area, there are also several previous works [14]–[16] using data augmentation to create comparison pairs. However, these methods always compute the contrastive loss at the utterance level, ignoring the time relationship within one audio. Different from them, the CCL method proposed in this letter can calculate the contrastive loss on frames, both within and across audios. As a result, the encoder can learn the statistical properties of the speech sequence and the consistency between the different augmented audios at same time.

For experiments, we use the CCL method to pre-train the Wav2Vec2.0 model on Librispeech and fine-tune on in-domain and out-of-domain data. Results show that the CCL pre-trained model can outperform the traditional contrastive learning pre-trained model, both on in-domain and out-of-domain data. Especially for out-of-domain data, more than 15% relative improvement can be realized.

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is the temperature factor and is set to 0.1.

$X(10, 3, 3, 3, 3, 2, 2)$ describes the waveform, which has 512 channels with strides $(5, 2, 2, 2, 2, 2, 2)$ and kernel widths $(10, 3, 3, 3, 3, 2, 2)$. It will convert the waveform into compressed latent representation $Z$. And then, random mask will be applied on $Z$. $p = 0.065$ of all time steps are chosen as the starting indices and then the next $M = 10$ consecutive time steps will be masked. After masking, the Transformer based context network will build contextualized representations $C$ from masked $Z$ to capture high level content. In addition, a quantization module is used to convert $Z$ into discrete representation $Q$.

For a standard Wav2Vec2.0 model, the contrastive loss is calculated between the contextualized representations $C$ and discrete representation $Q$. For contextualized representation $c_t$ at time step $t$, the positive sample is the discrete representation $q_t$ at same time step, a negative samples set $Q_t$ are chosen from other time steps, the contrastive loss is calculated as follow:

$$L_c = - \log \frac{\exp(\text{sim}(c_t, q_t)/\kappa)}{\sum_{\tilde{q} \in Q_t} \exp(\text{sim}(c_t, \tilde{q})/\kappa)}$$  \hspace{1cm} (1)

$$\text{sim}(a, b) = \frac{a^T b}{\|a\| \|b\|}$$  \hspace{1cm} (2)

$\kappa$ is the temperature factor and is set to 0.1.

### II. Method

In this section, we demonstrate the framework of the proposed CCL method. The CCL method is applied on the structure of the Wav2vec2.0 model, which has shown great performance on many ASR tasks.

#### A. Model Structure

Wav2vec2.0 model [6] contains a CNN-based feature encoder and a Transformer [17] based context network. The CNN-based feature encoder consists of temporal convolution layers with GELU activation function. Each convolution layer has 512 channels with strides $(5, 2, 2, 2, 2, 2, 2)$ and kernel widths $(10, 3, 3, 3, 3, 2, 2)$. It will convert the waveform $X$ into compressed latent representation $Z$. Then, random mask will be applied on $Z$. $p = 0.065$ of all time steps are chosen as the starting indices and then the next $M = 10$ consecutive time steps will be masked. After masking, the Transformer based context network will build contextualized representations $C$ from masked $Z$ to capture high level content. In addition, a quantization module is used to convert $Z$ into discrete representation $Q$.

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### B. Consistency contrastive learning

The proposed CCL method aims to provide a consistency between different audios with same transcription. Borrow the idea in image domain, we apply different data augmentation on same audio to create more comparison pairs.

Given waveform $X$, we apply different kinds of augmentation on it to get a set of augmented waveform $\{X_i\}_{i=1}^K$. $K$ is the set size. Then, we feed $\{X_i\}_{i=1}^K$ into the Wav2Vec2.0 model to calculate the $\{Z_i\}_{i=1}^K$, $\{C_i\}_{i=1}^K$, $\{Q_i\}_{i=1}^K$.

There are two differences between this propose method and the stand Wav2Vec2.0. First, we use data augmentation to obtain the $\{X_i\}_{i=1}^K$, and the data augmentation methods should not change the tempo of the audios. Another difference is that when mask the latent representation $\{Z_i\}_{i=1}^K$, same time steps should be chosen for each $Z_t$. Both of the operations aim to guarantee the augmented audios are synchronous with each other.

We use the CCL loss to replace the contrastive loss in the stand Wav2Vec2.0. The CCL loss is calculated not only within one audio but also across audios with different augmentation methods. For each masked time step $t$ in the $i$-th waveform, the model needs to identify the true quantized latent speech representation $\tilde{q}_{j,t}$ in each augmented audios from the negative samples set $Q_t$. The loss function is defined by the InfoNEC loss as follow:

$$L_{ccl} = - \sum_{i,j} \log \frac{\exp(\text{sim}(c_{i,t}, q_{j,t})/\kappa)}{\sum_{\tilde{q} \in Q_t} \exp(\text{sim}(c_{i,t}, \tilde{q})/\kappa)}$$  \hspace{1cm} (3)

$i, j$ stand for the audio index.

According to whether $i$ is equal to $j$, the CCL loss can be divided into self contrastive loss and cross contrastive loss as follow:

$$L_{ccl} = L_{self} + L_{cross}$$  \hspace{1cm} (4)

$$L_{self} = - \sum_i \log \frac{\exp(\text{sim}(c_{i,t}, q_{i,t})/\kappa)}{\sum_{\tilde{q} \in Q_t} \exp(\text{sim}(c_{i,t}, \tilde{q})/\kappa)}$$  \hspace{1cm} (5)

$$L_{cross} = - \sum_i \log \frac{\exp(\text{sim}(c_{i,t}, q_{j,t})/\kappa)}{\sum_{\tilde{q} \in Q_t} \exp(\text{sim}(c_{i,t}, \tilde{q})/\kappa)}$$  \hspace{1cm} (6)
\[ L_{\text{cross}} = - \sum_{i \neq j} \log \frac{\exp(\sin(c_{i,t}, q_{j,t})/\kappa)}{\sum_{q \in \mathcal{Q}_t} \exp(\sin(c_{i,t}, q)/\kappa)} \] (6)

According to Eq. (4) and (5), we can find that the CCL loss can be regarded as an expedition of the contrastive loss used by the previous works. The \( L_{\text{celf}} \) has the same format to the contrastive loss in Eq. (1). However, the negative samples set \( \mathcal{Q}_t \) can be sampled from all of the augmented audios, while traditional contrastive loss can only sample negatives from same utterance and other unrelated audios. This means that more deceptive distractors can be provided. The \( L_{\text{cross}} \) is an added part comparing to the contrastive loss. Optimizing the \( L_{\text{cross}} \) can maximize the measurement of the representations from different augmented waveform, however, at the same time step. This means that the CCL loss can provide a consistency between audios with same transcription. In a nutshell, by using data augmentation, the CCL loss can be calculated between more comparison samples.

C. Data augmentation

Data augmentation is one of the key component of our proposed CCL method. Especially, the augmentation should not change the audio tempo to guarantee same time step can be sampled during contrasting. We choose the traditional pitch shifting, reverberation and adding background noise as the augmentation methods. In addition, as the input of the Wav2Vec2.0 is raw waveform, we also design two extra augmentation methods to reduce the model’s sensitivity to the time domain characteristics, which is more easily disturbed by the environment. All of the augmentations are done by on-the-fly method. Details are shown as follow:

- Pitch shifting: randomly increase or decrease the pitch of the input audio. The number of semitones is random sampled from -3 to 3.
- Background noise: mix the input audio with other recording containing background sounds provided by [18]. The noise power is uniformly sample from -30dB to -10dB.
- Reverberation: generate far field simulated data by convoluting the audio with the room impulse responses provided by [18].
- Resampling: downsample the audio into 8kHz and then upsample it back to the original sample rate.
- Volume perturb: randomly increase or decrease the volume in parts of the audio from -5dB to 5dB.

We combine these data augmentation methods together to train a CCL model. For combination, the pitch shifting and volume perturb are applied with 50% probability while others are applied with 15% probability. So if none of them is applied on the audio, the audio will remain unchanged.

III. EXPERIMENT

A. Datasets

We consider the Librispeech [19], Switchboard [20] and CHiME-3 [21] 1ch track as the training corpus. These datasets can be divided into large scale unsupervised dataset for pre-training and in-domain or out-of-domain limited supervised dataset for fine-tuning. Details are shown as follow:

B. Experimental Settings

For experiments, we mainly follow the example project in the fairseq toolkits [23]. We pre-train two Wav2Vec2.0 base models on the augmented audios with contrastive loss or CCL loss to compare their performances, the only difference between them is the loss function. The official Wav2Vec2.0 base model pre-trained with only original audios is also evaluated in the experiments. To calculate the CCL loss, the size \( K \) of the augmented waveform set is 2, because larger \( K \) will consume too much cuda memory. We optimize the model with Adam for 400k training steps, warming up the learning rate for the first 32k updates to a peak of \( 5 \times 10^{-3} \). 8 GPUs are used for each experiment and the update frequency is set to 8. This configuration can guarantee a same batch size comparing to the official model. And for fine-tuning, we use 2 GPUs with update frequency 4. The learning rate is set to \( 5 \times 10^{-5} \) and the training steps are 20k. More details can be find in the fairseq toolkits.

C. Results on in-domain data

We fine-tune the pre-trained models on the Libri-light 10h dataset to compare their performances on in-domain data. We use both of the original audios and augmented audios to fine-tune the pre-trained models to explore whether the data

| Model       | Augment | dev clean | dev other | test clean | test other |
|-------------|---------|-----------|-----------|------------|------------|
| Wav2Vec2.0  | No      | 4.2       | 9.4       | 4.3        | 9.8        |
| Wav2Vec2.0  | No      | Yes       | 4.2       | 9.2        | 4.3        | 9.6        |
| Wav2Vec2.0  | Yes     | 4.3       | 9.5       | 4.5        | 9.7        |
| Wav2Vec2.0  | Yes     | Yes       | 4.3       | 9.3        | 4.4        | 9.6        |
| Wav2Vec-CCL | Yes     | No        | 4.3       | 9.0        | 4.3        | 9.5        |
| Wav2Vec-CCL | Yes     | Yes       | \textbf{4.2} | \textbf{8.8} | \textbf{4.2} | \textbf{9.3} |

1) Large Scale Unsupervised Dataset: We use all of the speech in Librispeech training corpus for pre-training. This training corpus contains 960 hours of 16kHz reading English speech with little background noise.

2) Limited Supervised Dataset: We fine-tune the pre-trained model on limited supervised data. Both of the in-domain data and the out-of-domain data are used to evaluate the effect of the pre-trained model.

- Libri-light 10h: a subset sampled from the Librispeech training corpus, which is a popular benchmark for limited or no supervision ASR [22].
- SwitchBoard 10h: out-of-domain data for the pre-trained model. SwitchBoard is a telephone corpus sampled with 8kHz. As the SwitchBoard does not have a standard small size split, we sort the audios with utterances id and then choose the first 10 hours. We up-sample the audios to 16kHz during fine-tuning.
- CHiME-3 tr05: out-of-domain data for the pre-trained model, which contains about 30 hours real and simulated speech under noisy backgrounds.
augmentation can be used during fine-tuning. Word Error Rate (WER) results on the dev clean/other and test clean/other sets are shown in Table I. According to the Table I, we can find that the CCL model can show better performance than most of the baseline. And the data augmentation based CCL pre-training is compatible with the data augmentation in fine-tuning. However, without CCL, only applying the data augmentation on the pre-training data shows little improvement, even bring harmful effects to the performance. This is reasonable because without CCL loss, the neural network will treat the audios with different augmentation independently. The encoder could be hindered by the augmented waveform during pre-training. But when CCL loss is used, the encoder can find the consistent representations for different augmented audios by the L_cross in Eq. (6). These experiments show that for in-domain data, the CCL is a crucial method to apply the data augmentation in self-supervised pre-training stage.

D. Result on out-of-domain data

We fine-tune the different pre-trained models on SwitchBoard and the CHiME-3 to evaluate their performances on out-of-domain data. Eval2000, dt05-real and et05-real are used for testing. WER results are shown in Table II. Results show that for out-of-domain data, the improvement of the CCL is more significant. On the dt05-real set, more than 15% relative word error rate reduction can be realized. Another difference from the results on in-domain data is that when directly using data augmentation without CCL in pre-training, the out-of-domain results can be better than the in-domain results. We analyze the reason is that, on the one hand, using data augmentation can simulate some out-of-domain data. (previous works [24] have shown that adding the unlabeled out-of-domain data during pre-training can improve the performance), on the other hand, the CCL loss can teach the model to learn a stable representation method, which will not change with the pitch shifting, background noise, reverberation and even sample rate.

E. Analysis

We use t-SNE [25] method to reduce the dimension of the output of the pre-trained model to visualize the acoustic representations. Both of the latent representations Z and contextualized representations C are visualized. The visible results are shown in Figure 2. The red plots are the representations of the original audio, and the blues are from augmented audio. For each subfigure, the left part is the result of the baseline Wav2Vec2.0 model and the right is the result of the Wav2Vec-CCL model.

IV. Conclusion

In this letter, we proposed a data augmentation based CCL method to pre-train the ASR model to improve the robustness. Comparing to the previous self-learning method, the CCL method can provide more positive and negative samples to do contrastive learning. As a result, more text-related and acoustic-stable representations can be learned. Experiments on Librispeech, Switchboard and CHiME-3 show that the CCL pre-training can realize better performance than the contrastive pre-learning, especially for the out-domain-data, more than 15% relative improvement can be realized. And the visible results also verify our assumption. For the further works, we will explore how to sample more effective positive and negative pairs to calculate the CCL loss.

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