WAV2VEC-S: SEMI-SUPERVISED PRE-TRAINING FOR SPEECH RECOGNITION

Han Zhu\textsuperscript{1,2}, Li Wang\textsuperscript{1}, Ying Hou\textsuperscript{3}, Jindong Wang\textsuperscript{4}, Gaofeng Cheng\textsuperscript{1}, Pengyuan Zhang\textsuperscript{1,2}, Yonghong Yan\textsuperscript{1,2}

\textsuperscript{1}Key Laboratory of Speech Acoustics and Content Understanding, Institute of Acoustics, China
\textsuperscript{2}University of Chinese Academy of Sciences, China
\textsuperscript{3}Department of Computer Science and Technology, Tsinghua University, China
\textsuperscript{4}Microsoft Research Asia, China

ABSTRACT

Self-supervised pre-training has dramatically improved the performance of automatic speech recognition (ASR). However, most existing self-supervised pre-training approaches are task-agnostic, i.e., could be applied to various downstream tasks. And there is a gap between the task-agnostic pre-training and the task-specific downstream fine-tuning, which may degrade the downstream performance. In this work, we propose a novel pre-training paradigm called wav2vec-S, where we use task-specific semi-supervised pre-training to bridge this gap. Specifically, the semi-supervised pre-training is conducted on the basis of self-supervised pre-training such as wav2vec 2.0, where we use task-specific semi-supervised pre-training to bridge this gap. Specifically, the semi-supervised pre-training is conducted on the basis of self-supervised pre-training such as wav2vec 2.0, wav2vec-S only requires marginal increment of pre-training time but could significantly improve ASR performance on in-domain, cross-domain and cross-lingual datasets. The average relative WER reductions are 26.3% and 6.3% for 1h and 10h fine-tuning, respectively.

Index Terms— Pre-training, self-supervised learning, semi-supervised learning, speech recognition, wav2vec 2.0

1. INTRODUCTION

The performance of automatic speech recognition (ASR) largely relies on the amount of labeled data, which is costly and not available in many scenarios. To alleviate this issue, conventional transfer learning approaches \cite{1, 2, 3, 4, 5} leverage labeled data in the high-resource domain to boost the performance on the low-resource domain. The typical practice is to first perform supervised pre-training on high-resource domain, and then fine-tune on low-resource domain. Unfortunately, these approaches still rely on large-scale labeled data and fail to utilize the knowledge contained in the unlabeled data. On the other hand, the self-supervised pre-training \cite{6, 7, 8, 9, 10, 11} is effective to learn representations from unlabeled data but does not use any labeled data.

Although effectively utilizing unlabeled data, the self-supervised pre-training is task-agnostic and it may not be optimal for a given downstream task since the mismatch between the task-agnostic pre-training and task-specific fine-tuning \cite{12}. On the other hand, conventional transfer learning could learn task-specific pre-trained model by utilizing labeled data and avoid this mismatch.

To utilize the benefits of both approaches, we propose a novel paradigm of pre-training: wav2vec-S, which learns the task-specific representation and uses both labeled and unlabeled data. Specifically, on the basis of the task-agnostic self-supervised pre-training, we further conduct task-specific semi-supervised pre-training to bridge the gap between pre-training and fine-tuning. During the semi-supervised pre-training, labeled data is used to guide the model to learn task-specific representations. And the unlabeled data is used via pseudo-labeling \cite{13, 14, 15, 16} to further improve performance since the amount of labeled data is limited. The semi-supervised setting is practical since it is less challenging to collect some labeled data in the source domain where we perform pre-training. Moreover, since self-supervised pre-training is known to be beneficial for the convergence speed of downstream tasks, the semi-supervised pre-training on the basis of self-supervised pre-training cost much less time than self-supervised pre-training or semi-supervised pre-training from scratch.

We specifically focus on ASR and this practice could also be applied to other speech processing tasks. Concretely, we adopt wav2vec 2.0 as the self-supervised pre-trained model. And semi-supervised training is conducted on the same unlabeled data for self-supervised pre-training with the aid of the labeled subset. Experiments show that wav2vec-S could consistently outperform wav2vec 2.0 and therefore could act as the alternative of vanilla wav2vec models as the pre-trained model for the downstream ASR task.

2. RELATED WORKS

The idea of semi-supervised speech pre-training is also explored in \cite{17, 18} to improve ASR. Unispeech \cite{17} uses multi-task learning to conduct semi-supervised pre-training, where contrastive loss is used on the unlabeled data and CTC
loss is used on the labeled data. XLST [18] uses supervised training as the initialization and then conducts self-training on the unlabeled data. In our work, CTC loss is used on both labeled and unlabeled data, where the ground-truth labels are used for labeled data and pseudo labels are used for unlabeled data. Moreover, previous work conducts semi-supervised from scratch thus requires substantial training time to converge. In this work, we treat semi-supervised pre-training as the refinement of the self-supervised pre-training. Therefore the semi-supervised pre-training could benefit from the initialization of self-supervised pre-training and require much less training time.

3. PROPOSED APPROACH

3.1. Problem Formulation

We denote the pre-training dataset as the source domain $S$ and the fine-tuning dataset as the target domain $T$. The two domains could be same (in-domain) or not (cross-domain and cross-lingual). Suppose we have large amount of speech data in source domain and labels are only partially available, i.e., an unlabeled dataset $U^S = \{x_1^S, \ldots, x_N^S\}$ and a relatively small labeled dataset $L^S = \{(x_1^S, y_1^S), \ldots, (x_M^S, y_M^S)\}$, where $M \leq N$ and $(x, y)$ denote a sample-label pair. The label type depend on the downstream task, e.g., transcriptions in ASR. The above datasets are used for pre-training and fine-tuning is performed on the target domain labeled dataset $L^T = \{(x_1^T, y_1^T), \ldots, (x_O^T, y_O^T)\}$

3.2. Preliminary: wav2vec 2.0

As shown in the first step of Fig. 1, wav2vec 2.0 model uses a convolutional feature encoder to maps the input raw audio $X$ to higher-level latent speech representations $Z$, which is then fed to the transformer context network to build context representations $C$. Furthermore, the mask module masked a proportion of the feature encoder outputs $Z$ to $Z'$. The masked time steps are denoted as gray color in Fig. 1. The quantization module will discretize the masked time steps of feature encoder outputs $Z$ to a finite set of quantized representations $Q$, which are used as targets in the self-supervised objective.

During pre-training, the main objective is a contrastive loss $L_c$, which encourage the model to identify the true quantized latent speech representation $q^*$ in a set of quantized candidate representations $\{q^*, q^-, \ldots, q^-\}$. Furthermore, the wav2vec 2.0 objective is augmented by a diversity loss $L_d$, which encourages the equal use of each quantized representation. We omit the details of $L_d$ for simplicity. Overall, the wav2vec 2.0 objective is

$$L_w = L_c + \alpha L_d,$$  \(1\)

where $\alpha$ is a tuned hyperparameter.

During fine-tuning, the quantization module is discarded and the mask module is optional for data augmentation. A random initialized linear layer is added after context representations to project the dimension to the vocabulary size. The resulting model is then optimized using task-specific loss.

3.3. Wav2vec-S

We illustrate the wav2vec-S procedure in Fig. 1. The pre-training consists of two steps. Firstly, self-supervised pre-training is performed on the unlabeled dataset $U^S$ using wav2vec 2.0 loss Eq. (1). Then, semi-supervised pre-training is applied on both labeled dataset $L^S$ and unlabeled dataset $U^S$. The total loss for semi-supervised learning is:

$$L_{semi} = L_{label} + \lambda L_{unlabel},$$  \(2\)

where $L_{label}$ and $L_{unlabel}$ denotes the loss for labeled and unlabeled data, respectively. $\lambda$ is the hyperparameter to be tuned.

After pre-training, we can use the task-specific loss $L_{task}$ to fine-tune the pre-trained model on the target domain labeled dataset $L^T$ or directly use the pre-trained model as the feature extractor for the downstream task [10].
Specifically, for ASR, during semi-supervised pre-training, both labeled and unlabeled loss are CTC loss. For labeled data, it is straightforward to compute the CTC loss as:

\[ L_{\text{label}} = -\mathbb{E}_{(x, y) \sim D} \log p(y | a(x)) \]  

(3)

where \((x, y)\) is the sample-label pair, \(p(x, y)\) is the distribution of samples from \(D\), \(\theta\) is the model parameter, and \(a(\cdot)\) is the augmentation function.

However, for the unlabeled data, since the ground-truth labels are not available, pseudo labels are used instead:

\[ L_{\text{unlabel}} = -\mathbb{E}_{x \sim D} \log p(y' | a(x)) \]  

(4)

where \(\hat{y}\) denotes the pseudo label which is generated through:

\[ \hat{y} = \arg\max_y \log p(y | a(x)), \]  

(5)

where argmax denote the greedy decoding process, which first takes the maximum probability tokens in each frame and then post-processes by removing repeated and blank tokens. Note that the pseudo labels are generated using the up-to-date model \(\theta\) on-the-fly as in [13, 14, 15].

During fine-tuning, the task-specific loss is also CTC loss:

\[ L_{\text{task}} = -\mathbb{E}_{(x, y) \sim D} \log p(y | a(x)) \]  

(6)

4. EXPERIMENTS

4.1. Corpus

The pre-training (source domain) dataset is LibriSpeech [19] and the 100h clean subset is used as the labeled subset. As for fine-tuning (target domain) datasets, Wall Street Journal (WSJ) is used as the in-domain dataset. In order to verify the generalization ability, SwitchBoard (SWBD) [20] and AISHELL-1 [21] are used as cross-domain and cross-lingual dataset, respectively. We primarily consider the low resource scenario and randomly select 1h or 10h subset of the above datasets for fine-tuning.

4.2. Implementation Details

Our experiments are conducted using the fairseq [22] toolkit. In terms of self-supervised pre-training, we use the open-source wav2vec 2.0 base model pre-trained on Librispeech 960h\(^1\). For both semi-supervised pre-training and fine-tuning, we use gradient accumulation to achieve an effective batch size of 25.6m samples. The maximum learning rate is \(3 \times 10^{-5}\). Learning rate is warmed up for the first 10% of updates, held constant for the next 40% and then linearly decayed for the last 50%. The convolutional feature encoder is fixed during both semi-supervised pre-training and fine-tuning. For fine-tuning, the transformer context network is also fixed for the first 10k updates. The total training updates for 10h and 1h fine-tuning are 20k and 13k, respectively. As for data augmentation, we follow [6] to perform time and channel mask after the convolutional layers. Beam-search decoding with 4-gram language model is used for decoding. The hyperparameter \(\alpha\) in Eq. (1) is 0.1 and \(\lambda\) in Eq. (2) is 1.0.

4.3. Main Results

As shown in Table 1, for both 1h and 10h fine-tuning, wav2vec-S consistently outperforms the supervised pre-training and wav2vec 2.0 on in-domain (WSJ), cross-domain (SWBD) and cross-lingual (AISHELL-1) datasets. It shows that using both labeled and unlabeled data for pre-training is more effective than using only one of them. Note that in Table 1, only 100h labeled data is used in wav2vec-S, although more labeled data could provide better results (shown in subsection 4.4). Moreover, pre-training and fine-tuning both use charcter-level supervision and training updates is 20k. We will further discuss the impact of supervision level and training updates in subsection 4.5 and subsection 4.6. 10h fine-tuning is used in the following experiments.

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\(^1\)https://github.com/pytorch/fairseq/blob/master/examples/wav2vec

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### Table 1. 1h and 10h fine-tuning with different pre-training approaches.

| Method               | Pre-training Data | WER (%) |
|----------------------|-------------------|---------|
|                      | Labeled | Unlabeled | WSJ | SWBD | AISHELL-1 |
|                      | dev93 | eval92 | RT03 | H-SB | H-CH | dev | test | AVG |
| 1h fine-tune         |       |         |      |      |       |      |      |     |
| Supervised Pre-train | 100h x | 960h x | 18.7 | 13.0 | 50.2 | 38.6 | 56.0 | 76.4 | 77.4 | 47.2 |
| Wav2vec 2.0          | ×      | 960h x | 8.4  | 6.4  | 28.1 | 19.9 | 28.9 | 67.3 | 66.8 | 32.3 |
| Wav2vec-S            | 100h x | 860h x | 5.4  | 3.8  | 22.6 | 14.2 | 22.7 | 48.9 | 48.7 | 23.8 |
| 10h fine-tune        |       |         |      |      |       |      |      |     |
| Supervised Pre-train | 100h x | 960h x | 13.8 | 8.5  | 41.8 | 29.9 | 47.8 | 15.3 | 15   | 24.6 |
| Wav2vec 2.0          | ×      | 960h x | 6.2  | 3.6  | 25.8 | 15.6 | 29.7 | 27.0 | 27.8 | 19.4 |
| Wav2vec-S            | 100h x | 860h x | 4.4  | 2.9  | 18.7 | 10.8 | 18.8 | 13.6 | 14.0 | 11.9 |
4.4. Semi-supervised Pre-training data

In this section, we compare using different amounts of labeled and unlabeled data during semi-supervised pre-training.

| Pre-training Data | WSJ WER (%) | SWBD WER (%) | AISHELL-1 WER (%) |
|-------------------|-------------|--------------|------------------|
| Labeled | Unlabeled | dev93 | eval92 | RT03 | H-SB | H-CH | dev | test | AVG |
| 100h 0h | 4.6 2.7 | 19.1 11.2 | 18.8 | 14.1 14.2 12.1 |
| 960h 860h | 4.4 2.9 | 18.7 10.8 | 18.8 | 13.6 14.0 11.9 |

As shown in Table 2, the performance is the best when using all 960h labeled data and is the worst when using only 100h labeled data. Semi-supervised pre-training with 100h labeled data and 860h unlabeled data could effectively bridge the performance gap between them and achieve comparable performance with the 960h labeled pre-training.

4.5. Supervision Level

In this section, we discuss the optimal supervision level for semi-supervised pre-training. Specifically, we consider phone-level supervision and character-level supervision. The phoneme transcriptions are generated using phonemizer2

| Pre-train Fine-tune | WSJ WER (%) | SWBD WER (%) | AISHELL-1 WER (%) |
|---------------------|-------------|--------------|------------------|
| Phone | Phone | 5.9 4.7 | 20.2 13.1 | 20.2 | 15.8 15.3 13.6 |
| Char | Phone | 5.6 4.8 | 19.9 13.2 | 20.2 | 15.9 15.3 13.6 |
| Phone | Char | 4.8 3.3 | 19.3 11.3 | 19.1 | 14.7 15.5 12.6 |
| Char | Char | 4.4 2.9 | 18.7 10.8 | 18.8 | 13.6 14.0 11.9 |

As shown in Table 3, when phone-level fine-tuning is used, phone-level and character-level pre-training perform similarly. On the other hand, when character-level fine-tuning is used, character-level pre-training outperforms phone-level. It shows that the higher-level supervision (character) during pre-training could generalize well to the lower level (phone) but not vice versa. This conclusion also stands in the cross-lingual dataset (AISHELL-1), although the character-supervision during pre-training and fine-tuning are in different languages. Moreover, for a given pre-trained model, the character-level fine-tuning is always better than the phone-level. Based on the above results, character-level supervision is better for semi-supervised pre-training.

4.6. Training Updates

We illustrate the relation between the number of training updates and downstream performance in Table 4.

| Updates | WSJ WER (%) | SWBD WER (%) | AISHELL-1 WER (%) |
|---------|-------------|--------------|------------------|
| 10k | dev93 | 8.3 4.7 2.8 | 19.3 11.0 19.2 | 13.5 13.9 |
| 20k | eval92 | 7.7 4.4 2.9 | 18.7 10.8 18.8 | 13.6 14.0 |
| 40k | RT03 | 7.3 4.2 2.4 | 18.7 10.8 18.5 | 13.9 14.2 |

When training updates increasing, validation, in-domain (WSJ) and the cross-domain (SWBD) WER decreased. On the contrary, the cross-lingual (AISHELL-1) WER increased. This indicates the trade-off between performances of source language and other languages: with more training updates, the wav2vec-S model becomes more language-specific and the cross-lingual generalization ability is degraded.

4.7. Training Time

![Fig. 2. Comparison of training time.](image-url)

We conduct experiments using 8 V100 GPUs and as shown in Fig. 2, the semi-supervised pre-training in wav2vec-S requires much less training time than the wav2vec 2.0 self-supervised training. The reason is the self-supervised pre-training effectively speed up the convergence of the followed semi-supervised pre-training. Moreover, since the self-supervised pre-training is task-agnostic, it could be reused by all downstream tasks. Thus only semi-supervised pre-training is required to be conducted before fine-tuning for a new task.

5. CONCLUSIONS

In this work, we propose wav2vec-S to bridge the gap between self-supervised pre-training and downstream fine-tuning via semi-supervised pre-training. Experiments showed that wav2vec-S could consistently improve ASR performance on in-domain, cross-domain and cross-lingual datasets over wav2vec 2.0. In the future, we will explore the applications on other speech processing tasks.

2https://github.com/bootphon/phonemizer
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