MelHubert: A Simplified Hubert on Mel Spectrograms

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Abstract

Self-supervised models have had great success in learning speech representations that can generalize to various downstream tasks. However, most self-supervised models require a large amount of compute and multiple GPUs to train, significantly hampering the development of self-supervised learning. In an attempt to reduce the computation of training, we revisit the training of HuBERT, a highly successful self-supervised model. We improve and simplify several key components, including the loss function, input representation, and training in multiple stages. Our model, MelHuBERT, is able to achieve favorable performance on phone recognition, speaker identification, and automatic speech recognition against HuBERT, while saving 31.2% of the pre-training time, or equivalently 33.5% MACs per one second of speech. The code and pre-trained models are available in https://github.com/nervjack2/MelHuBERT.

Index Terms — Self-Supervised Learning, Speech Representations, Automatic Speech Recognition, Speaker Recognition

1. Introduction

Self-supervised models have shown to be able to generalize across various downstream tasks, either as feature extractors or through fine-tuning [1 2 3 5 6 7]. To make use of large quantities of unlabeled data, self-supervised models are often large in terms of both the number of parameters and the amount of compute needed during inference [8]. One could argue that the amortized cost of training large models on large data sets is low, because the resulting models can be reused many times and across many downstream tasks. However, the ever increasing cost to train large self-supervised models on large data sets hinders the development of better training recipes. In fact, few can afford the cost to train their own self-supervised models from random initialization. In this work, we tackle this problem by studying and simplifying a training recipe of self-supervised models.

Our model of choice is HuBERT [5], a self-supervised model that performs well but also has a simpler training recipe than others. The training of HuBERT consists of stages. Each stage performs so-called masked prediction, a frame-wise prediction task with the input partially masked [3][5][6]. The stages differ in the targets used for pre-training. The targets of the first stage are cluster assignments of MFCCs frames (with k-means), while the targets of subsequent stages are cluster assignments of HuBERT hidden layers. Despite having a simple training recipe, some design decisions in HuBERT are derived from wav2vec 2.0 without much justification. It is also generally unclear how the design decisions impact the performance on downstream tasks. In this work, we identify and study several key components, such as the loss function, the number of target clusters, the impact of multiple states, the input frame rate, and the architectural choices.

A simple analysis shows that the first seven convolution layers in HuBERT constitute 33% of multiply-accumulation operations (MACs) of the entire forward computation (including the 12-layer Transformer). This result motivates us to replace convolution layers with commonly used speech features, such as Mel spectrograms. In fact, much prior work has been based on Mel spectrograms [1 9 10 11 12]. Since replacing convolution layers with Mel spectrograms is a significant change to HuBERT, we term our model MelHuBERT.

A fundamental question is how the choice of input representation impacts the learned representations. For many linguistic and paralinguistic properties, e.g., for the use of automatic speech recognition (ASR) and speaker identification (SID), Mel spectrograms should be sufficient [13 14]. Since replacing convolution layers with Mel spectrograms is a significant change to HuBERT, we term our model MelHuBERT.

In this work, we thoroughly compare speech representations learned by HuBERT and MelHuBERT on phonetic recognition, speaker identification, and automatic speech recognition. We will show that MelHuBERT performs favorably over HuBERT when pre-trained on the 360-hour subset of LibriSpeech, while saving 31.2% of the training time.

The fact that convolution layers can be replaced by Mel spectrograms does not imply that the two are equivalent in representation. We further conduct analyses with canonical correlation analysis (CCA) to show the degree of similarities between the convolution layers in HuBERT and Mel spectrograms. We are also able to identify the differences and strengths of the two.

We will begin with a review of HuBERT, discuss our changes to the original design, and present the experiments and analyses.
Mel spectrograms as input. Formally, we overload the sequence $x_1, \ldots, x_T$ to denote log Mel features at a 10-ms frame rate, and pass it directly to the Transformer. The targets are now quantized log Mel frames, or equivalently $c_t = \arg\min_{c=1, \ldots, k} \|x_t - v_c\|_2$, without depending on MFCC frames.

There are several reasons why Mel spectrograms are preferred. For speech tasks, such as automatic speech recognition and speaker recognition, the benefit of learning to process wave samples is marginal. In addition, training with Mel spectrograms can achieve state-of-the-art performance. Finally, despite that wave samples are taken as input in HuBERT, MFCC frames are still used during training. More importantly, the convolution network for extracting acoustic frames actually consumes 33% of the total MACs of HuBERT. We expect that removing the convolution layers not only saves a significant amount compute, but also has marginal impact on the learned representation.

3.3. Subsampling

If our model takes regular Mel spectrograms as input, the input and output frame rate would be 10 ms, as opposed to HuBERT’s 20 ms. To ensure that they have the same frame rate, we choose to subsample Mel spectrograms, concatenating every two contiguous frame to double the frame rate. As shown in Figure 1 we use the term MelHuBERT-10ms to refer to the model with a frame rate of 10, and MelHuBERT-20ms to refer to the variant with a frame rate of 20. Due to the difference in input sequence length, MelHuBERT-20ms
runs much slower than its 20ms variant. As we will show in Section 4.1, MelHuBERT-20ms has smaller MACs than MelHuBERT-10ms. In addition, MelHuBERT-20ms performs competitively or even better than MelHuBERT-10ms on downstream tasks.

4. EXPERIMENTS

Following prior work [11][19], we pre-train our models on subsets of LibriSpeech and evaluate downstream tasks on respective data sets.

For training MelHuBERT, we use a learning rate of $10^{-4}$ and do not apply any learning rate scheduling during pretraining. Similar to HuBERT, dropout with the probability of 10% is applied after most matrix multiplications, such as after query, key, and value multiplication, and after FC1 and FC2. We do not use LayerDrop [20] and mixed precision training, to match the setting of MelHuBERT. Training is otherwise exactly the same as the official release.

We follow the protocol of SUPERB [23] and S3PRL [1] computing a weighted sum of all hidden layers as the representation for downstream tasks. All self-supervised models are frozen, and the weights for each layer are learned for each task. We focus on phone recognition (PR), speaker identification (SID), and automatic speech recognition (ASR). Phone recognition and automatic speech recognition are conducted on the 100-hour subset of LibriSpeech, and phone error rate and word error rate are reported respectively. Speaker identification is conducted on Voxceleb1, and classification error rate is reported. We find that the default learning rates in SUPERB require tuning. For MelHuBERT, the learning rates for PR, SID and ASR are $10^{-4}$, $10^{-2}$, and $10^{-4}$, respectively, and for HuBERT, $10^{-3}$, $10^{-1}$, and $10^{-4}$.

4.1. Stage-1 initial results

We first present our initial experiments of training MelHuBERT by simply replacing the convolution layers with log Mel features and using cross entropy as the loss function. Detailed exploration will be discussed in the next section.

The input to MelHuBERT is 40-dimensional Mel spectrograms, normalized with global mean and variance. We quantize the same input Mel spectrograms as our targets, using $k$-means with 512 clusters. We concatenate every two contiguous frames to produce the input for MelHuBERT-20ms. The targets for training MelHuBERT-20ms are the cluster labels of the odd frames. The downstream performance and MACs are shown in Table 1.

Table 1. A comparison of MelHuBERT and HuBERT (pre-trained on the 360-hour subset of LibriSpeech) based on frame period (FP), MACs per one second speech, phone recognition (PR), and speaker identification (SID).

| Model          | FP  | MACs (G/sec) | PR (PER) | SID (ER) | ASR (WER) |
|----------------|-----|--------------|----------|----------|-----------|
| MelHuBERT-10ms | 10  | 10.76        | 15.1     | 35.2     | 11.6      |
| MelHuBERT-20ms | 20  | 4.93         | 13.0     | 33.7     | 11.9      |
| HuBERT         | 20  | 7.42         | 13.8     | 29.7     | 12.6      |

Table 2. Results of various design choices, including the number of $k$-means clusters, the number of Mel filters, and the number of targets during pre-training, and the loss functions, for training MelHuBERT-20ms (on 360-hour subset of LibriSpeech).

| Loss cluster | Mel filters | targets | PR (PER) | SID (ER) | ASR (WER) |
|--------------|-------------|---------|----------|----------|-----------|
| 1. Eq (3)    | 512         | 40      | 1        | 13.3     | 34.6      | 12.3      |
| 2. CE        | 512         | 40      | 1        | 13.0     | 33.7      | 11.9      |
| 3. CE        | 100         | 40      | 1        | 12.4     | 31.7      | 11.7      |
| 4. CE        | 100         | 80      | 1        | 12.9     | 32.7      | 11.8      |
| 5. CE        | 512         | 40      | 2        | 12.4     | 32.7      | 11.5      |
| 6. CE        | 100         | 40      | 2        | 12.3     | 30.5      | 11.3      |

Similar to the findings in prior work [24], downsampling the input (by concatenation) does not suffer degradation on downstream tasks. Overall, MelHuBERT behaves similarly to HuBERT while saving 33.5% MACs per one second speed for MelHuBERT-20ms. The results align well with prior studies [25][26][27][28][29], showing that it is possible to prune convolution layers without much performance degradation. In favor of the faster runtime (in both training and inference), we will focus on MelHuBERT-20ms for the rest of the paper.

4.2. Stage-1 pre-training

The initial experiments MelHuBERT show promising results. In this section, we further study the individual choices of $k$-means clusters, the number of Mel bins, and the loss functions. Results are shown in the Table 2.

HuBERT’s loss function [5] is inherited from wav2vec [2] and wav2vec 2.0 [3]. We choose cross entropy for its simplicity, and compare the two in this section. Results are shown in the first two rows of Table 2. We see a slight improvement in PR, SID, and ASR when using the cross entropy.

The original study of HuBERT [5] experiments with 50, 100, and 500 clusters when quantizing MFCCs, and finds that using 100 clusters performs better than 500 clusters on ASR.

https://github.com/s3prl/s3prl
The number of clusters is also studied in [18] in the context of autoregressive predictive coding (APC) with LSTMs, and similar to the finding of [5], using 100 clusters performs better than 512 clusters on phone classification. On the contrary, 512 clusters works best in vector-quantized APC for phone classification [4]. The number of clusters has a different impact on speaker tasks, and is in general less explored [4]. We compare different numbers of clusters in training MelHuBERT. Results are shown in row 2 and 3 of Table 2. We find that using 100 clusters leads to better overall results, especially on speaker identification.

Next, we study the number of Mel filters used to extract Mel spectrograms. Various numbers of Mel bins have been used in prior work. For example, APC [1,18] uses 40 filters; Mockingjay [30], DeCoAR 2.0 [10], and TERA [31] use 80 filters; while SSAST [32] uses 128 filters. We explore this option for MelHuBERT, and the results are shown in row 3 and 4 of Table 2. We find that using more Mel filters does not lead to any improvement.

Instead of only using the cluster labels of the odd frames, we also explore predicting the cluster labels of both the odd and the even frames. Specifically, when the two frames at $t$ and $t+1$ are concatenated, we compare training MelHuBERT-20ms against only the cluster labels at $t$ to the one against both $t$ and $t+1$. We simply use two projection matrices when predicting two targets, a multitask approach. Results are shown in row 2 and 5 of Table 2 and we do find that using two targets is better than one.

Finally, combining all the previous findings, we use cross entropy as the loss function, 100 clusters as targets, 40 Mel filters, and predicting multiple both the odd and the even targets. The result of our final stage-1 model is presented in the last row of Table 2. The small adjustments lead to a sizeable improvement over our initial MelHuBERT. We will proceed with the best setting for the rest of the paper.

### 4.3. Stage-2 pre-training

After the first stage,[2] HuBERT includes multiple subsequent stages to train their models [5]. We limit ourselves to two stages. The second stage uses quantized hidden vectors as targets for training, and we need to decide which layer to quantize. In the original study, hidden vectors of each layer are clustered, and the phone purity and cluster purity are measured based on forced alignments. The layer with the highest purity is chosen for stage two, since it aligns most closely with the phone units. The effect of multi-stage training is reported in [5] with a focus on ASR. It is unclear how this decision might impact phone recognition and speaker identification. Following HuBERT, we first calculate the phone purity and

![Table 3. Results of stage-2 pre-training on PR, SID, and ASR. MelHuBERT-20ms (scratch) is trained from random initialization, while MelHuBERT-20ms (cont) continues pre-training from stage 1.](image)

| stage                  | PR   | SID | ASR  |
|------------------------|------|-----|------|
| MelHuBERT-20ms         | 12.3 | 30.5| 11.9 |
| HuBERT                 | 13.8 | 29.7| 12.6 |
| MelHuBERT-20ms (scratch) | 8.6  | 25.3| 9.7  |
| MelHuBERT-20ms (cont)  | 8.7  | 31.7| 9.8  |
| HuBERT                 | 8.1  | 26.6| 10.2 |

With the term *stages* instead of iterations, because the differences among multiple stages are quite significant.

In our opinion, the pipeline seems to be unsupervised if it relies on forced alignments. We include the results and analyses for completeness.

### 5. ANALYSIS

Given that MelHuBERT and HuBERT perform similarly on downstream tasks, there are several questions remained open. Since MelHuBERT and HuBERT are self-supervised models for learning speech representations, the first and the most important question is whether the two learn different representations. If the two do learn different representations, the question becomes whether we can characterize the differences. Finally, if we can characterize the differences, what their strengths and weaknesses are is also worth studying. In this section, we conduct a set of experiments to answer these questions.
5.1. Layer-wise similarity to phones

Since we replace seven convolution layers with Mel spectrograms, the immediate question is how it impacts the representation learned. We will focus on the phonetic information, as it is important for phone recognition and ASR. The analysis comparing the first and the second stage of pre-training is also generally lacking in prior work. To answer both questions, we study how HuBERT differs from MelHuBERT with layer-wise analysis proposed by [34, 35] and compute the CCA similarity between one-hot vectors of phones and mean-pooled phone-level representations.

The analysis of phonetic information across layers is shown in the top plot of Figure 2. HuBERT and MelHuBERT behave similarly, and there is no significant difference from the first Transformer layer to the ninth. Compared to HuBERT, MelHuBERT has a more significant drop in phone similarity before the first and after the tenth Transformer layer. This can be attributed to the autoencoding behavior, and is consistent with the observation in [34].

Compared to stage 1, the phone similarity of stage 2 (for both HuBERT and MelHuBERT) is higher after the eighth Transformer layer and stays high. This can be attributed to the targets for stage 2 training, because the targets are from the sixth layer of stage 1 and are phonetically more prominent.

5.2. Layer-wise similarity to Mel spectrograms

The fact that HuBERT and MelHuBERT has similar down-stream performance does not necessarily imply that the convolution layers are computing features similar to Mel spectrograms. To study whether the two share anything in common, we compare similarity to Mel spectrograms for all layers in HuBERT and MelHuBERT.

The similarity to Mel spectrograms is shown in the bottom plot of Figure 2. Similar to the findings in [35], convolution layers in HuBERT have high similarity to Mel spectrograms. The similarity stays about the same throughout the Transformer layers in HuBERT, but in MelHuBERT, the similarity decreases until layer eleventh and increases again in the twelfth layer. This is again consistent with the autoencoding behavior of pre-training.

Compared to stage 1, similarity to Mel spectrograms is lower in stage 2. The decrease in similarity is more significant for MelHuBERT, especially in higher layers. We again attribute this to the targets (for stage-2 pre-training) being more phonetically prominent.

5.3. Strengths of HuBERT’s convolution layers

Based on the layer-wise analysis, convolution layers have a high similarity to Mel spectrograms. Since convolution layers are trained, we further study whether there is information more accessible for convolution layers than for Mel spectrograms. We probe phonetic information with ASR on both Mel spectrograms and the convolution layers following SUPERB (with a two-layer LSTM and CTC [36]). In addition, we probe the fundamental frequency ($F_0$), following SUPERB-prosody [37]. The reference pitch is computed with pY AAPT and we train linear regression models to predict the log of $F_0$.

The results of probing are shown in Table 4. Mel spectrograms perform slightly better than convolution layers on ASR, while convolution layers are better at extracting $F_0$. Interestingly, despite HuBERT using the sixth layer as targets in stage-2 pre-training, the ability to track $F_0$ improves over stage 1. Technically, it is possible to count the harmonics in Mel spectrograms to determine $F_0$, but $F_0$ is less linearly accessible due to the nonlinear Mel scale.

| Feature            | ASR (WER) | log $F_0$ (MSE) |
|--------------------|-----------|-----------------|
| Mel spectrograms   | 23.18     | 0.089           |
| stage-1 HuBERT-C7 | 24.97     | 0.024           |
| stage-2 HuBERT-C7 | 24.02     | **0.021**       |
Table 5. A comparison of MelHuBERT and HuBERT pre-trained on the 100-hour subset of LibriSpeech in terms of PR, SID, and ASR.

| Model            | PR (PER) | SID (ER) | ASR (WER) |
|------------------|----------|----------|-----------|
| MelHuBERT-20ms   | 19.2     | 38.9     | 17.4      |
| HuBERT           | 32.0     | 43.7     | 19.4      |

Fig. 3. Pre-training time required to epoch 50, 100, 150, and 200 on the 100-hour subset of LibriSpeech, and the respective downstream ASR performance.

5.4. Strengths of using Mel spectrograms

Since MelHuBERT does not require to learn a feature extractor from wave samples, we suspect MelHuBERT would have a stronger edge over HuBERT when there is not that much data for pre-training. To study this, we pre-train HuBERT and MelHuBERT on the 100-hour subset of LibriSpeech (about a third of the pre-training data for the experiments before). The results are shown in Table 5. Indeed, MelHuBERT tops HuBERT in all PR, SID and ASR. We confirm that MelHuBERT has an advantage over HuBERT in low-resource settings, in terms both data and compute.

5.5. The pre-training speed-up of MelHuBERT

To show the speed-up of MelHuBERT against HuBERT, we measure the training time to epoch 50, 100, 150, and 200 when pre-training on the 100-hour subset of LibriSpeech and the respective downstream ASR performance. The experiment is conducted on a single NVIDIA RTX 3090 without mixed precision training. The results are shown in Figure 3. MelHuBERT-20ms takes about 14.7 minutes per epoch, while HuBERT takes about 21.4 minutes. The result shows that our training recipe saves 31.2% of the pre-training time. MelHuBERT is not only faster to train but also enjoys a lower WER.

6. RELATED WORK

MPC proposed by [9] is the first to learn speech representations with 12-layer Transformers and masked prediction on Mel spectrograms. Subsequent variants of MPC include DeCoAR 2.0 [10], Mockingjay [30], and Tera [31]. However, MelHuBERT outperforms all of them on the SUPERB benchmark, despite only pre-trained on a third of LibriSpeech.

BEST-RQ [38] also learns speech representations on Mel spectrograms, but it makes other changes to HuBERT, trading the initial k-means clustering with clever initialization. BEST-RQ is only evaluated on ASR with fine-tuning, and does not explore stage-2 pre-training.

Our motivation is similar to [39], with the goal of reducing the barrier of self-supervised learning under limited computational resources. However, they focus on reproducing HuBERT without altering the model architecture and training objective, while we study the impact of model architecture and several key components in pre-training. MelHuBERT not only runs faster but also requires less memory consumption, amenable to training on a single consumer-grade GPU (RTX 3090), while they use 8 high-end GPUs (A100).

Reducing computational cost by replacing convolution layers in wav2vec 2.0 is explored in [28]. Similar to BEST-RQ, they only evaluate their models on ASR with fine-tuning, while we include an analyses on the similarities and differences of convolution layers and Mel spectrograms. Their models are based on wav2vec 2.0 and do not include stage-2 pre-training, while we study stage-2 pre-training with layer-wise analysis and downstream tasks.

The experiment of replacing the convolution layers of pretrained HuBERT with Mel spectrograms by a front-end adapter has been explored in [29]. Their model yields a comparable WER when compared to the original HuBERT. Again, they only evaluate their model on ASR and do not train their model from scratch. Additionally, we have a more in-depth analysis between these two kinds of features.

7. CONCLUSION

In this paper, we propose MelHuBERT, a simplified version of HuBERT on both model architecture and training recipe. MelHuBERT achieves favorable performance against HuBERT and is more efficient on both pre-training and inference, with 31.2% reduction on pre-training time and 33.5% reduction on MACs per one second speech. A comprehensive analysis is conducted between HuBERT and MelHuBERT, including the differences of the learned representations, the strengths of each model, and the pre-training efficiency. There are still many open questions in self-supervised learning, and the simplified training recipe could facilitate studies on the interaction between self-supervised learning and speech representations, beyond performance on downstream tasks.

4The downstream performance of DeCoAR 2.0, Mockingjay, and Tera can be found at https://superbbenchmark.org/leaderboard.
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