

Learning Temporal Resolution in Spectrogram for Audio Classification

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Abstract

The audio spectrogram is a time-frequency representation that has been widely used for audio classification. One of the key attributes of the audio spectrogram is the temporal resolution, which depends on the hop size used in the Short-Time Fourier Transform (STFT). Previous works generally assume the hop size should be a constant value (e.g., 10 ms). However, a fixed temporal resolution is not always optimal for different types of sound. The temporal resolution affects not only classification accuracy but also computational cost. This paper proposes a novel method, **DiffRes**, that enables **differentiable temporal resolution modeling** for audio classification. Given a spectrogram calculated with a fixed hop size, DiffRes merges non-essential time frames while preserving important frames. DiffRes acts as a “drop-in” module between an audio spectrogram and a classifier and can be jointly optimized with the classification task. We evaluate DiffRes on five audio classification tasks, using mel-spectrograms as the acoustic features, followed by off-the-shelf classifier backbones. Compared with previous methods using the fixed temporal resolution, the DiffRes-based method can achieve the equivalent or better classification accuracy with at least 25% computational cost reduction. We further show that DiffRes can improve classification accuracy by increasing the temporal resolution of input acoustic features, without adding to the computational cost.

Introduction

Audio classification refers to a series of tasks that assign labels to an audio clip. Those tasks include audio tagging (Kong et al. 2020), speech keyword classification (Kim et al. 2021), and music genres classification (Castellon, Donahue, and Liang 2021). The input to an audio classification system is usually a one-dimensional audio waveform, which can be represented by discrete samples. Although there are methods using time-domain samples as features (Kong et al. 2020; Lee et al. 2017), the majority of studies on audio classification convert the waveform into a spectrogram as the input feature (Gong, Chung, and Glass 2021b,a). Spectrogram is usually calculated by the Fourier transform (Champeney and Champeney 1987), which is applied in short waveform chunks multiplied by a windowing function, resulting in a two-dimensional time-frequency representation. According

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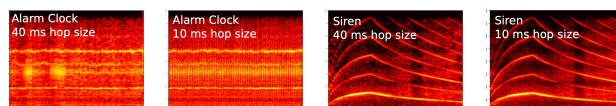


Figure 1: The spectrogram of *Alarm Clock* and *Siren* sound with 40 ms and 10 ms hop sizes. All with a 25 ms window size. The pattern of *Siren*, which is relatively stable, does not change significantly using a smaller hop size (i.e., larger temporal resolution), while *Alarm Clock* is the opposite.

to the Gabor’s uncertainty principle (Gabor 1946), there is always a trade-off between time and frequency resolutions. To achieve the desired resolution on the temporal dimension, it is a common practice (Kong et al. 2021a; Liu et al. 2022) to apply a fixed hop size between windows to capture the dynamics between adjacent frames. With the fixed hop size, the spectrogram has a fixed temporal resolution, which we will refer to simply as resolution in this work.

Using a fixed resolution is not necessarily optimal for an audio classification model. Intuitively, the resolution should depend on the temporal pattern: fast-changing signals are supposed to have high resolution, while relatively steady signals or blank signals may not need the same high resolution for the best accuracy (Huzaifah 2017). For example, Figure 1 shows that by increasing resolution, more details appear in the spectrogram of *Alarm Clock* while the pattern of *Siren* stays mostly the same. This indicates the finer details in high-resolution *Siren* may not essentially contribute to the classification accuracy. There are plenty of studies on learning a suitable frequency resolution with a similar spirit (Stevens, Volkman, and Newman 1937; Sainath et al. 2013; Ravanelli and Bengio 2018b; Zeghidour et al. 2021). Most previous studies focus on investigating the effect of different temporal resolutions (Kekre et al. 2012; Huzaifah 2017; Ilyashenko et al. 2019; Liu et al. 2023). Huzaifah (2017) observe the optimal temporal resolution for audio classification is class dependent. Ferraro et al. (2021) experiment on music tagging with coarse-resolution spectrograms, and observes a similar performance can be maintained while being much faster to compute. Kazakos et al. (2021) propose a two-stream architecture that processes both fine-grained and coarse-resolution spectrogram

and shows the state-of-the-art result on VGG-Sound (Chen et al. 2020). Recently, Liu et al. (2023) proposed a non-parametric spectrogram-pooling-based module that can improve classification efficiency with negligible performance degradation. However, these approaches are generally built on a fixed temporal resolution, which is not always optimal for diverse sounds in the world. Intuitively, it is natural to ask: can we dynamically learn the temporal resolution for audio classification?

In this work, we demonstrate the first attempt to learn temporal resolution in the spectrogram for audio classification. We show that learning temporal resolution leads to efficiency and accuracy improvements over the fixed-resolution spectrogram. We propose a lightweight algorithm, DiffRes, that makes spectrogram resolution differentiable during model optimization. DiffRes can be used as a “drop-in” module after spectrogram calculation and optimized jointly with the downstream task. For the optimization of DiffRes, we propose a loss function, guide loss, to inform the model of the low importance of empty frames formed by SpecAug (Park et al. 2019). The output of DiffRes is a time-frequency representation with varying resolution, which is achieved by adaptively merging the time steps of a fixed-resolution spectrogram. The adaptive temporal resolution alleviates the spectrogram temporal redundancy and can speed up computation during training and inference. We perform experiments on five different audio tasks, including the largest audio dataset AudioSet (Gemmeke et al. 2017). DiffRes shows clear improvements on all tasks over the fixed-resolution mel-spectrogram baseline and other learnable front-ends (Zeghidour et al. 2021; Ravanelli and Bengio 2018b; Zeghidour et al. 2018). Compared with methods using fixed-resolution spectrogram, we show that using DiffRes-based models can achieve a computational cost reduction of at least 25% with the equivalent or better audio classification accuracy.

Besides, the potential of the high-resolution spectrogram, e.g., with a one-millisecond hop size, is still unclear. Some popular choices of hop size including 10 ms (Böck et al. 2012; Kong et al. 2020; Gong, Chung, and Glass 2021a) and 12.5 ms (Rybakov et al. 2022). Previous studies (Kong et al. 2020; Ferraro et al. 2021) show classification performance can be steadily improved with the increase of resolution. One remaining question is: can even finer resolution improve the performance? We conduct an ablation study for this question on a limited-vocabulary speech recognition task with hop sizes smaller than 10 ms. We noticed that accuracy can still be improved with smaller hop size, at a cost of increased computational complexity. By introducing DiffRes with high-resolution spectrograms, we observe that the classifier performance gains are maintained while the computational cost is significantly reduced.

Our contributions are summarized as follows:

- We present DiffRes, a differentiable approach for learning temporal resolution in the audio spectrogram, which improves classification accuracy and reduces the computational cost for off-the-shelf audio classification models.
- We extensively evaluate the effectiveness of DiffRes

on five audio classification tasks. We further show that DiffRes can improve classification accuracy by increasing the temporal resolution of input acoustic features, without adding to the computational cost.

- Our code is available at <https://github.com/haoheliu/diffres-python>.

Method

We provide an overview of DiffRes-based audio classification in Section . We introduce the detailed formulation and the optimization of DiffRes in Section , and .

Overview

Let $\mathbf{x} \in \mathbb{R}^L$ denote a one-dimensional audio time waveform, where L is the number of audio samples. An audio classification system can be decomposed into a feature extraction stage and a classification stage. In the feature extraction stage, the audio waveform will be processed by a function $Q_{l,h} : \mathbb{R}^L \rightarrow \mathbb{R}^{F \times T}$, which maps the time waveform into a two-dimensional time-frequency representation \mathbf{X} , such as a mel-spectrogram, where $\mathbf{X}_{:, \tau} = (\mathbf{X}_{1, \tau}, \dots, \mathbf{X}_{F, \tau})$ is the τ -th frame. Here, T and F stand for the time and frequency dimensions of the extracted representation. We also refer to the representation along the temporal dimensions as frames. We use l and h to denote window length and hop size, respectively. Usually $T \propto \frac{L}{h}$. We define the temporal resolution $\frac{1}{h}$ by frame per second (FPS), which denotes the number of frames in one second. In the classification stage, \mathbf{X} will be processed by a classification model \mathcal{G}_θ parameterized by θ . The output of \mathcal{G}_θ is the label predictions $\hat{\mathbf{y}}$, in which \hat{y}_i denotes the probability of class i . Given the paired training data $(\mathbf{x}, \mathbf{y}) \in \mathbb{D}$, where \mathbf{y} denotes the one-hot vector for ground-truth labels, the optimization of the classification system can be formulated as

$$\arg \min_{\theta} \mathbf{E}_{(\mathbf{x}, \mathbf{y}) \sim \mathbb{D}} \mathcal{L}(\mathcal{G}_\theta(\mathbf{X}), \mathbf{y}), \quad (1)$$

where \mathcal{L} is a loss function such as cross entropy (De Boer et al. 2005). Figure 2 show an overview of performing classification with DiffRes. DiffRes is a “drop-in” module between \mathbf{X} and \mathcal{G}_θ focusing on learning the optimal temporal resolution with a learnable function $\mathcal{F}_\phi : \mathbb{R}^{F \times T} \rightarrow \mathbb{R}^{F \times t}$, where t is the parameter denoting the target output time dimensions of DiffRes, and ϕ is the learnable parameters. DiffRes formulates \mathcal{F}_ϕ with two steps: i) estimating the importance of each time frame with a learnable model $\mathcal{H}_\phi : \mathbf{X} \rightarrow \mathbf{s}$, where \mathbf{s} is a $1 \times T$ shape row vector; and ii) warping frames based on a frame warping algorithm, the warping is performed along a single direction on the temporal dimension. We introduce the details of these two steps in Section . We define the *dimension reduction rate* δ of DiffRes by $\delta = (T - t)/T$. Usually, $\delta \leq 1$ and $t \leq T$ because the temporal resolution of the DiffRes output is either coarser or equal to that of \mathbf{X} . Given the same T , a larger δ means fewer temporal dimensions t in the output of DiffRes, and usually less computation is needed for \mathcal{G}_θ . Similar to Equation 1, \mathcal{F}_ϕ can be jointly optimized with \mathcal{G}_θ by

$$\arg \min_{\theta, \phi} \mathbf{E}_{(\mathbf{x}, \mathbf{y}) \sim \mathbb{D}} \mathcal{L}(\mathcal{G}_\theta(\mathcal{F}_\phi(\mathbf{X})), \mathbf{y}). \quad (2)$$

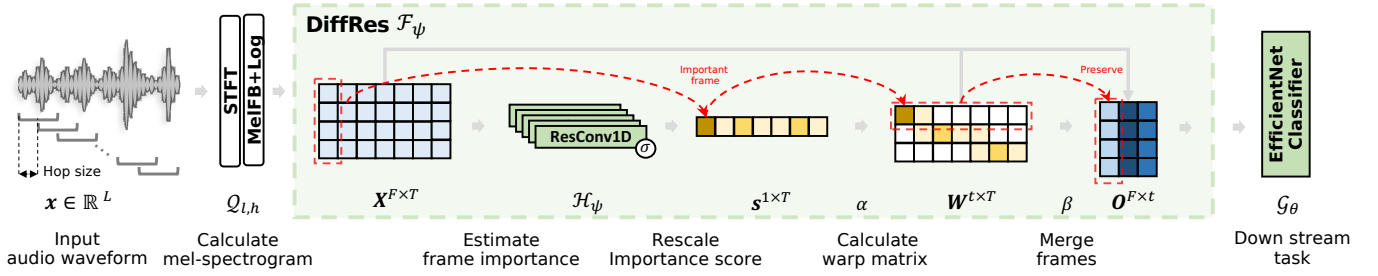


Figure 2: Audio classification with DiffRes and mel-spectrogram. Green blocks contain learnable parameters. DiffRes is a “drop-in” module between spectrogram calculation and the downstream task.

Differentiable Temporal Resolution Modeling

Frame Importance Estimation We design a frame importance estimation module \mathcal{H}_ϕ to decide the proportion of each frame that needs to be kept in the output, which is similar to the sample weighting operation (Zhang and Pfister 2021) in previous studies. The frame importance estimation module will output a row vector s' with shape $1 \times T$, where the element s'_τ is the importance score of the τ -th time frame $\mathbf{X}_{:, \tau}$. The frame importance estimation can be denoted as

$$s' = \sigma(\mathcal{H}_\phi(\mathbf{X})), \quad (3)$$

where s' is the row vector of importance scores, and σ is the sigmoid function. A higher value in s'_τ indicates the τ -th frame is important for classification. We apply the sigmoid function to stabilize training by limiting the values in s' between zero and one. We implement \mathcal{H}_ϕ with a stack of one-dimensional convolutional neural networks (CNNs) (Fukushima and Miyake 1982; LeCun et al. 1989). Specifically, \mathcal{H}_ϕ is a stack of five one-dimensional convolutional blocks (ResConv1D). We design the ResConv1D block following other CNN based methods (Shu et al. 2021; Liu et al. 2020; Kong et al. 2021b). Each ResConv1D has two layers of one-dimensional CNN with batch normalization (Ioffe and Szegedy 2015) and leaky rectified linear unit activation functions. We apply residual connection (He et al. 2016) for easier training of the deep architecture (Zaeemzadeh, Rahnavard, and Shah 2020). Each CNN layer is zero-padded to ensure the temporal dimension does not change (LeCun, Bengio, and Hinton 2015). We use exponentially decreasing channel numbers to reduce the computation. In the next frame warping step (Section), elements in the importance score will represent the proportion of each input frame that contributes to an output frame. Therefore, we perform rescale operation on s' , resulting in an s that satisfies $s \in [0, 1]^{1 \times T}$ and $\sum_{k=1}^T s_k \leq t$. The rescale operation can be denoted as $\tilde{s} = \frac{s'}{\sum_{i=1}^T s'_i} t$, $s = \frac{\tilde{s}}{\max(\tilde{s}, 1)}$, where \tilde{s} is an intermediate variable that may contain elements greater than one, \max denotes the maximum operation. To quantify how active \mathcal{H}_ϕ is trying to distinguish between important and less important frames, we also design a measurement, activeness ρ , which is calculated by the standard derivation of the non-

empty frames, given by

$$\rho = \frac{1}{1 - \delta} \sqrt{\frac{\sum_{i \in \mathbb{S}_{\text{active}}} (s_i - \bar{s}_i)^2}{|\mathbb{S}_{\text{active}}|}}, \quad (4)$$

$$\mathbb{S}_{\text{active}} = \{i \mid E(\mathbf{X}_{:, i}) > \min(E(\mathbf{X}_{:, i})) + \epsilon\}, \quad (5)$$

where $\mathbb{S}_{\text{active}}$ is the set of indices of non-empty frames, ϵ is a small value, $|\mathbb{S}|$ denotes the size of set \mathbb{S} , function $E(\cdot)$ calculates the root-mean-square energy (Law and Rennie 2015) of a frame in the spectrogram, and function $\min(\cdot)$ calculates the minimum value within a matrix. We use δ to unify the value of ρ for easier comparison between different δ settings. The activeness ρ can be used as an indicator of how DiffRes behaves during training. A higher ρ indicates the model is more active at learning the frame importance. A lower ρ such as zero indicates learning nothing. We will discuss the learning process of DiffRes with ρ in Section .

Temporal Frame Warping We perform temporal frame warping based on s and \mathbf{X} to calculate an adaptive temporal resolution representation \mathbf{O} , which is similar to the idea of generating derived features (Pentreath 2015). Generally, the temporal frame warping algorithm can be denoted by $\mathbf{W} = \alpha(s)$ and $\mathbf{O} = \beta(\mathbf{X}, \mathbf{W})$, where $\alpha(\cdot)$ is a function that convert s into a warp matrix \mathbf{W} with shape $t \times T$, and $\beta(\cdot)$ is a function that applies \mathbf{W} to \mathbf{X} to calculate the warped feature \mathbf{O} . Elements in \mathbf{W} such as $\mathbf{W}_{i,j}$ denote the contribution of the j -th input frame $\mathbf{X}_{:, j}$ to the i -th output frame $\mathbf{O}_{:, i}$. We will introduce the realization of $\alpha(\cdot)$ and $\beta(\cdot)$ as follows.

Function $\alpha(\cdot)$ calculates the warp matrix \mathbf{W} with s by:

$$\mathbf{W}_{i,j} = \begin{cases} s_j, & \text{if } i < \sum_{k=1}^j s_k \leq i + 1 \\ 0, & \text{otherwise} \end{cases}, \quad (6)$$

where we calculate the cumulative sum of s to decide which output frame each input frame will be warped into. The warp matrix \mathbf{W} will be used for frame warping function $\beta(\cdot)$. Function $\beta(\cdot)$ performs frame warping based on the warp matrix \mathbf{W} . The i -th output frame is calculated with \mathbf{X} and the i -th row of \mathbf{W} , given by

$$\mathbf{O}_{i,j} = \mathcal{A}((\mathbf{X}_{j,:}) \odot (\mathbf{W}_{i,:})), \quad (7)$$

where $\mathcal{A} : \mathbb{R}^{1 \times T} \rightarrow \mathbb{R}$ stands for the frame aggregation function such as averaging, \mathbf{O} is the final output feature with shape $F \times t$.

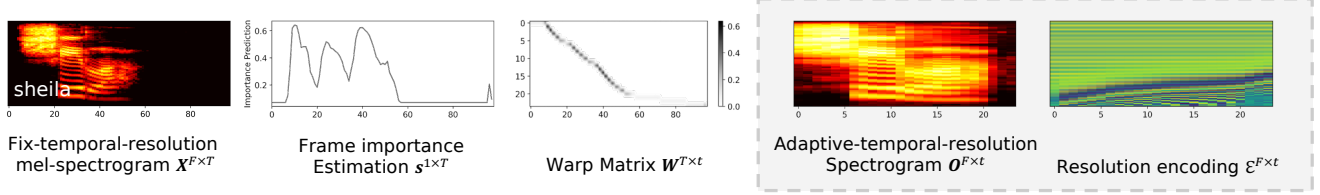


Figure 3: Visualizations of the DiffRes using the mel-spectrogram. The part with the shaded background is the input features.

Resolution Encoding. The final output O does not contain the resolution information at each time step, which is crucial information for the classifier. Since the temporal resolution can be represented with W , we construct a resolution encoding with W in parallel with frame warping. Firstly, we construct a positional encoding matrix E with shape $F \times T$, using the similar method described in Vaswani et al. (2017). Each column of E represents a positional encoding of a time step. Then we calculate the resolution encoding by $\mathcal{E} = EW^T$, where W^T stands for the transpose of W . The shape of the resolution encoding is $F \times t$. Both \mathcal{E} and O are concatenated on the channel dimension as the classifier input feature.

Optimization

We propose a guide loss to provide guidance for DiffRes on learning frame importance. Since we do not know the ground truth frame importance, we cannot directly optimize s . We introduce \mathcal{L}_{guide} as an inductive bias (Mitchell 1980) to the system based on the assumption that an empty frame should have a low importance score. Specifically, we propose the guide loss by

$$\mathcal{L}_{guide} = \frac{1}{|\mathcal{S}_{empty}|} \sum_{i \in \mathcal{S}_{empty}} \left(\frac{s_i}{1 - \delta} - \lambda \right)^+, \quad (8)$$

$$\mathcal{S}_{empty} = \{i \mid i \notin \mathcal{S}_{active} \text{ and } i \in \{1, 2, \dots, T\}\}, \quad (9)$$

where \mathcal{S}_{empty} is a set of time indexes that have low energy, and λ is a constant threshold. Given that the output of DiffRes has fewer temporal dimensions than X , the DiffRes layer forms an information bottleneck (Tishby, Pereira, and Bialek 2000; Shwartz-Ziv and Tishby 2017) that encourages DiffRes to assign a higher score to important frames. We analyze the information bottleneck effect of DiffRes in Section . The parameter λ is a threshold for the guide loss to take effect. This threshold can alleviate the modeling bias toward energy. For example, if $\lambda = 0$, the importance scores of empty frames are strongly regularized, and the model will also tend to predict low importance scores for lower energy frames, which may contain useful information. \mathcal{L}_{bce} is the standard binary cross entropy loss function (Shannon 2001) for classification, given by Equation 10, where \hat{y}_i is the label prediction and N is the total number of classes.

$$\mathcal{L}_{bce} = \frac{1}{N} \sum_{i=1}^N (\mathbf{y}_i \log(\hat{y}_i) + (1 - \mathbf{y}_i) \log(1 - \hat{y}_i)), \quad (10)$$

The loss function of the DiffRes-based audio classification system includes our proposed guide loss \mathcal{L}_{guide} and the binary cross entropy loss \mathcal{L}_{bce} , given by $\mathcal{L} = \mathcal{L}_{bce} + \mathcal{L}_{guide}$.

Experiments

We focus on evaluating DiffRes on the mel-spectrogram, which is one of the most popular features used by state-of-the-art systems (Chen et al. 2022; Gong et al. 2022; Koutini et al. 2021). We evaluate DiffRes on five different tasks and datasets including audio tagging on AudioSet (Gemmeke et al. 2017) and FSD50K (Fonseca et al. 2021), environmental sound classification on ESC50 (Piczak 2015), limited-vocabulary speech recognition on Speech-Commands (Warden 2018), and music instrument classification on NSynth (Engel et al. 2017). All the datasets are resampled at a sampling rate of 16 kHz. Following the evaluation protocol in the previous works (Zeghidour et al. 2021; Riad et al. 2021; Kong et al. 2020; Gong, Chung, and Glass 2021b), we report the mean average precision (mAP) as the main evaluation metric on AudioSet and FSD50K, and report classification accuracy (ACC) on other datasets. In all experiments, we use the same architecture as used by Gong, Chung, and Glass (2021b), which is an EfficientNet-B2 (Tan and Le 2019) with four attention heads (13.6 M parameters). We reload the ImageNet pretrained weights for EfficientNet-B2 in a similar way to (Gong, Chung, and Glass 2021a,b). For the training data, we apply random spec-augmentation (Park et al. 2019) and mixup augmentation (Zhang et al. 2017) following Gong, Chung, and Glass (2021b). All experiments are repeated three times with different seeds to reduce randomness. We also report the standard derivation of the repeated trials along with the averaged result. We train the DiffRes layer with $\lambda = 0.5$ and $\epsilon = 1 \times 10^{-4}$. For the frame aggregation function \mathcal{A} (see Equation 7), we use both the max and mean operations, whose outputs are concatenated with the resolution encoding \mathcal{E} on the channel dimension as the input feature to the classifier. The frame importance estimation module we used in this paper is a stack of five ResConv1D with around 82k parameters. We calculate the mel-spectrogram with a Hanning window, 25 ms window length, 10 ms hop size, and 128 mel-filterbanks by default. We list the implementation details and hyperparameters setting in the supplementary material.

Adaptive Temporal Dimension Compression

Compression of mel-spectrogram temporal dimension can lead to a considerable speed up on training and inference (Liu et al. 2023), which has significant promise in on-device scenarios. In this section, we evaluate the effectiveness of DiffRes in compressing temporal dimensions and classification performance. We compare DiffRes with three temporal dimension reduction methods: i) *Change hop*

size (CHSize) reduces the temporal dimension by enlarging the hop size. The output of CHSize has a fixed resolution and may lose information between output frames.; ii) *AvgPool* is a method that performs average pooling on a 100 FPS spectrogram to reduce the temporal dimensions. AvgPool also has a fixed resolution, but it can aggregate information between output frames by pooling; iii) *ConvAvgPool* is the setting that the 100 FPS mel-spectrogram will be processed by a stack of ResConv1D (mentioned in Section), followed by an average pooling for dimension reduction. ConvAvgPool has around 493k parameters. Based on a learnable network, ConvAvgPool has the potential of learning more suitable features and temporal resolution implicitly. We provide detailed implementations in the supplementary material.

Baseline Comparisons. Table 1 shows our experimental result. The baseline of this experiment is performed on mel-spectrogram without temporal compression (i.e., 100 FPS) and the baseline result is shown under each task name. When reducing 25% of the temporal dimension (i.e., 75 FPS), the proposed method can even considerably improve the baseline performance on most datasets, except on speech recognition tasks where we maintain the same performance. We assume the improvement comes from the data augmentation effect of DiffRes, which means divergent temporal compression on the same data at different training steps. With a 50 FPS, four out of five datasets can maintain comparable performance. With only 25 FPS, the proposed method can still improve the FSD50K tagging and music instrument classification tasks, which indicates the high temporal redundancy in these datasets. Our proposed method also significantly outperforms other temporal dimension reduction baselines. With fixed resolution and fewer FPS, the performance of CHSize degrades more notably. AvgPool can outperform CHSize by aggregating more information between output frames. Although ConvAvgPool has an extra learnable neural network, it does not show significant improvements compared with AvgPool. ConvAvgPool even has an inferior performance on FSD50K and environmental sound classification tasks. This indicates employing a simple learnable front-end for feature reduction is not always beneficial.

On Variable-length Audio Data. We observe that the proposed method improves the mAP performance by 1.3% with only 25 FPS on the FSD50K dataset. We analyze it because the audio clip durations in the FSD50K have a high variance (i.e., from 0.3 to 30s). In previous studies (Gong, Chung, and Glass 2021a,b; Kong et al. 2020), a common practice is padding the audio data into the same duration in batched training and inference, which introduces a considerable amount of temporal redundancy in the data with a significantly slower speed. By comparison, DiffRes can unify the audio feature shape regardless of their durations. Model optimization becomes more efficient with DiffRes. As a result, the proposed method can maintain an mAP of 55.6 ± 0.2 on the FSD50K, which is comparable to the baseline, with only 15 FPS and 28% of the original training time. This result shows that DiffRes provides a new mind map for future work on classifying large-scale variable-length audio clips.

Learning With Higher Temporal Resolution

Previous studies have observed that a higher resolution spectrogram can improve audio classification accuracy (Kong et al. 2020; Ferraro et al. 2021). However, a hop size smaller than 10 ms has not been widely explored. This is partly because the computation becomes heavier for a smaller hop size. For example, with 1 ms hop size (i.e., 1000 FPS), the time and space complexity for an EfficientNet classifier will be 10 times heavier than with a common 10 ms hop size. Since DiffRes can control the temporal dimension size, namely FPS, working on a small hop size spectrogram becomes computationally friendly. Table 2 shows model performance can be considerably improved with smaller hop sizes. AudioSet and environment sound dataset achieve the best performance on 6 ms and 1 ms hop size, and other tasks benefit most from 3 ms hop sizes. In later experiments, we will use these best hop size settings on each dataset.

Comparing With Other Learnable Front-ends. The DiffRes is differentiable, so the Mel+DiffRes setting as a whole can be viewed as a learnable front-end. Table 3 compares our proposed method with SOTA learnable front-ends, our best setting is denoted as Mel+DiffRes (Best), which achieves the best result on all datasets. For a fair comparison, we control the experiment setup to be consistent with Zeghidour et al. (2021) in Mel+DiffRes. Specifically, we change the backbone to EfficientNet-B0 (5.3 M parameters) without ImageNet pretraining. We also remove spec-augment and mixup, except in AudioSet, and change our Mel bins from 128 to 40, except in the AudioSet experiment where we change to 64. The result shows Mel+DiffRes can outperform SOTA learnable front-end (Zeghidour et al. 2021; Ravanelli and Bengio 2018b; Zeghidour et al. 2018) by a large margin, demonstrating the effectiveness of DiffRes.

Computational Cost. We assess the one-second throughput of different front-ends on various FPS settings to compare their computational efficiency. We control the FPS of Mel and LEAF by average pooling. The computation time is measured between inputting waveform and outputting label prediction (with EfficientNet-B2). We use 128 filters in LEAF (Zeghidour et al. 2021) for a fair comparison with 128 mel-filterbanks in Mel and DiffRes. As shown in Figure 4, our proposed DiffRes only introduces marginal computational cost compared with Mel. The state-of-the-art learnable front-end, LEAF, is about four times slower than our proposed method. The majority of the cost in computation in LEAF comes from multiple complex-valued convolutions, which are computed in the time-domain with large kernels (e.g., 400) and a stride of one.

Analysis for the Learning of DiffRes

Learning Activeness. DiffRes does not explicitly learn the optimal frame importance score because the ground truth frame importance is not available. Instead, DiffRes is optimized with the guidance of guide loss \mathcal{L}_{guide} (Equation 8), which is a strong assumption we introduced to the model. Figure 5 shows the trajectories of the DiffRes learning activeness (defined in Section) during the optimization with different FPS settings on the speech recognition task in Table 1. According to the final converged value, DiffRes with a

Task name 100 FPS baseline (%)	Metric	FPS	Change hop size (%)	AvgPool (%)	ConvAvgPool (%)	Proposed (%)
AudioSet tagging 43.7 ± 0.1	mAP	25	38.6 ± 0.3	39.9 ± 0.2	40.1 ± 0.2	41.7 ± 0.1
		50	41.8 ± 0.2	42.4 ± 0.1	42.7 ± 0.2	43.6 ± 0.1
		75	42.7 ± 0.2	43.6 ± 0.0	43.5 ± 0.2	44.2 ± 0.1[†]
FSD50K tagging 55.6 ± 0.3	mAP	25	48.9 ± 0.4	51.4 ± 0.3	49.2 ± 0.4	56.9 ± 0.2[†]
		50	53.3 ± 0.4	54.5 ± 0.4	52.2 ± 0.8	57.2 ± 0.2[†]
		75	54.8 ± 0.4	55.3 ± 0.3	54.4 ± 0.2	57.1 ± 0.4[†]
Environmental sound 85.2 ± 0.5	ACC	25	74.6 ± 0.6	75.6 ± 0.3	72.4 ± 1.2	82.9 ± 0.5
		50	82.4 ± 0.5	83.2 ± 0.3	77.3 ± 0.8	85.5 ± 0.4[†]
		75	84.9 ± 0.3	85.2 ± 0.4 [†]	81.8 ± 0.6	86.8 ± 0.3[†]
Speech recognition 97.2 ± 0.1	ACC	25	93.5 ± 0.1	94.9 ± 0.4	95.8 ± 0.3	95.0 ± 0.3
		50	96.1 ± 0.1	96.0 ± 0.2	96.0 ± 0.1	96.7 ± 0.2
		75	96.8 ± 0.2	96.9 ± 0.1	97.0 ± 0.1	97.2 ± 0.0[†]
Music instrument 79.9 ± 0.2	ACC	25	79.7 ± 0.2	78.3 ± 0.7	78.0 ± 0.5	80.5 ± 0.2[†]
		50	79.9 ± 0.0 [†]	79.5 ± 0.3	79.4 ± 0.3	81.0 ± 0.5[†]
		75	79.8 ± 0.2	79.6 ± 0.3	79.7 ± 0.4	80.8 ± 0.2[†]

Table 1: Comparison of different temporal dimension reduction methods. The numbers under the task name show the baseline performance. Baseline methods use fix-temporal-resolution mel-spectrogram with 10 ms hop size. Numbers with [†] mean better or comparable performance compared with the 100 FPS baseline.

Hop size	10 ms	6 ms	3 ms	1 ms
AudioSet	43.7 ± 0.1	44.1 ± 0.1	43.8 ± 0.0	43.7 ± 0.1
ESC-50	85.2 ± 0.4	87.2 ± 0.3	88.0 ± 0.6	88.4 ± 0.5
SC	97.2 ± 0.1	97.6 ± 0.0	97.9 ± 0.1	97.8 ± 0.1
NSynth	79.9 ± 0.2	81.3 ± 0.3	81.8 ± 0.2	80.6 ± 0.4
Avg.	76.5 ± 0.2	77.6 ± 0.2	77.9 ± 0.1	77.5 ± 0.2

Table 2: Learning with high temporal resolution spectrograms. FPS is controlled at 100, so the computational complexity of the classifier is the same in all hop-size settings. Results are reported in the percentage format.

smaller FPS tends to be more active at learning frame importance. This is intuitive since smaller FPS leads to more information bottleneck effects (Saxe et al. 2019) in DiffRes. With a 25 FPS, the activeness even keeps increasing with more training steps, indicating the active learning of DiffRes. Figure 6 shows the guide loss curve during training with different FPS settings. Intuitively, when the FPS is small, a model needs to preserve more non-empty frames and fewer empty frames for better accuracy. This assumption is aligned with our experiment result, which shows the model tends to have a lower guide loss with a smaller FPS.

Data Augmentation and Regularization Effect. As reflected in the curve of ρ and \mathcal{L}_{guide} in Figure 5 and 6, DiffRes is optimized along with the classifier during training. Hence DiffRes produces different outputs for the same training data at different epochs. This is equivalent to performing data augmentation on the audio data. We suppose this is the main reason for the improved performance shown in Table 1. Also, DiffRes reduces the sparsity of the audio feature by adaptive temporal compression. This is equivalent

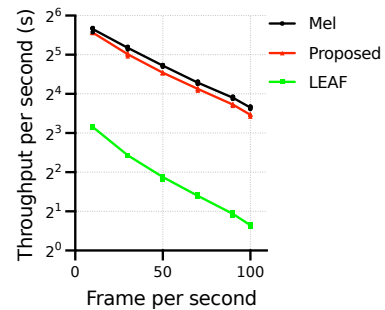


Figure 4: Audio throughput in one second. Evaluated on a 2.6 GHz Intel Core i7 CPU.

to performing an implicit regularization (Neyshabur 2017; Arora et al. 2019) on the feature level, which is beneficial for the system efficiency.

Ablation Studies. We further study the effect of hyperparameters used in the DiffRes method, including guide loss (e.g., activeness ρ , threshold λ), dimension reduction ratio δ , small value ϵ . We also experiment with different model architectures (Kong et al. 2020)). We perform the ablation studies on the SpeechCommands dataset since it has a reasonable amount of data and is computationally friendly on model training. We also study the potential of DiffRes in multimodal tasks such as audio captioning (Kim et al. 2019). Results and analysis of the ablation studies are shown in the supplementary materials.

Visualization. We visualize the compression results of DiffRes, as compared with the *ConvAvgPool* method. The visualization results are as shown in Figure 7. We observe that DiffRes learns to remove silent frames and compress the pattern in the mel-spectrogram. This observation shows

Front-end	Mel	TD-fbank	SincNet	LEAF	Mel+DiffRes	Mel+DiffRes (Best)
Parameters	0	51 k	256	448	82 k	82 k
AudioSet tagging	96.8 ± 0.1	96.5 ± 0.1	96.1 ± 0.0	96.8 ± 0.1	97.0 ± 0.0	97.5 ± 0.0
Speech recognition	93.6 ± 0.3	89.5 ± 0.4	91.4 ± 0.4	93.6 ± 0.3	95.4 ± 0.2	97.9 ± 0.1
Music instrument	70.7 ± 0.6	66.3 ± 0.6	67.4 ± 0.6	70.2 ± 0.6	78.5 ± 0.7	81.8 ± 0.2
Average	87.0 ± 0.3	84.1 ± 0.4	85.0 ± 0.3	86.9 ± 0.3	90.3 ± 0.3	92.4 ± 0.1

Table 3: Comparison with SOTA learnable front-ends. All the methods use 100 FPS. Results are reported in the percentage format. Mel+DiffRes controls the experimental settings mentioned in Section to be consistent with Mel, TD-fbank, SincNet, and LEAF. Mel+DiffRes (Best) use the best possible settings.

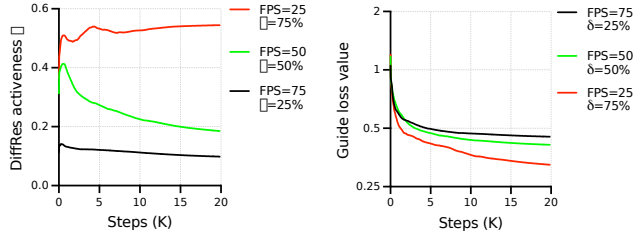


Figure 5: Trajectories of DiffRes learning activeness (ρ) on different training steps and FPS settings.

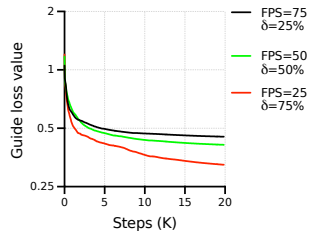


Figure 6: The training curve of guide loss (\mathcal{L}_{guide}) with different FPS settings.

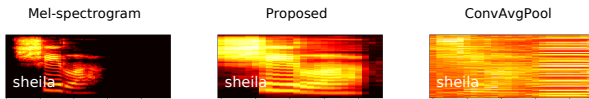


Figure 7: Comparison of mel-spectrogram, DiffRes feature, and ConvAvgPool learned feature. The DiffRes feature preserves more details in the original mel-spectrogram and is more interpretable than the ConvAvgPool feature.

the both effectiveness and interpretability of DiffRes.

Related Work

Neural-network based methods have been successfully applied to audio classification and achieved state-of-the-art performance, such as the pre-trained audio neural networks (PANNs) (Kong et al. 2020), pretraining, sampling, labeling, and aggregation-based audio tagging (PSLA) (Gong, Chung, and Glass 2021b), and audio spectrogram transformer (AST) (Gong, Chung, and Glass 2021a). We will cover two related topics on audio classification in the following sections.

Learnable Audio Front-ends. In recent years, learning acoustic features from waveform using trainable audio front-ends has attracted increasing interest from researchers. (Sainath et al. 2013) introduced one of the earliest works that propose to jointly learn the parameter of filter banks with a speech recognition model. Later, SincNet (Ravanelli and Bengio 2018b) proposes to learn a set of bandpass filters on the waveform and has shown success on speaker recognition (Ravanelli and Bengio 2018b,a). Most recently, (Zeghi-

dour et al. 2021) proposes to learn bandpass, and lowpass filtering as well as per-channel compression (Wang et al. 2017) simultaneously in the audio front-end and shows consistent improvement in audio classification. Different from existing work on learnable audio front-ends, which mostly focus on the frequency dimension, our objective is learning the optimal temporal resolution. We show that our method can outperform existing audio front-ends for audio classification on both accuracy and computation efficiency (see Table 3 and Figure 4). Note that our proposed method can also be applied after most learnable front-ends (Zeghidour et al. 2021), which will be our future direction.

Learning Feature Resolution. One recent work on learning feature resolution for audio classification is DiffStride (Riad et al. 2021), which learns stride in convolutional neural network (CNN) in a differentiable way and outperforms previous methods using fixed stride settings. By comparison, DiffStride needs to be applied in each CNN layer and can only learn a single fixed stride setting, while DiffRes is a one-layer lightweight algorithm and can personalize the best temporal resolution for each audio during inference. Recently, (Gazneli et al. 2022) proposed to use a stack of one-dimension-CNN blocks to downsample the audio waveform before the audio classification backbone network, e.g., Transformer, which can learn temporal resolution implicitly for audio classification. In contrast, DiffRes can explicitly learn temporal resolution on the feature level with similar interpretability as the mel-spectrogram.

Conclusions

In this paper, we introduce DiffRes, a “drop-in” differentiable temporal resolution learning module that can be applied between audio spectrogram and downstream tasks. For the training of DiffRes, our proposed guide loss is shown to be beneficial. We demonstrate over a large range of tasks that DiffRes can improve or maintain similar performance with 25% to 75% reduction on temporal dimensions, and can also efficiently utilize the information in high-resolution spectrograms to improve accuracy. In future work, we will move forward to evaluate DiffRes on different kinds of time-frequency representations with more sophisticated frame importance prediction models. Also, we will explore the potential of DiffRes in other time series data as well for learning optimal temporal resolutions.

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