Speech recognition from raw waveform involves learning the spectral decomposition of the signal in the first layer of the neural acoustic model using a convolution layer. In this work, we propose a raw waveform convolutional filter learning approach using soft self-attention. The acoustic filter bank in the proposed model is implemented using a parametric cosine-modulated Gaussian filter bank whose parameters are learned. A network-in-network architecture provides self-attention to generate attention weights over the sub-band filters. The attention weighted log filter bank energies are fed to the acoustic model for the task of speech recognition. Experiments are conducted on Aurora-4 (additive noise with channel artifact), and CHiME-3 (additive noise with reverberation) databases. In these experiments, the attention based filter learning approach provides considerable improvements in ASR performance over the baseline mel filter-bank features and other robust front-ends (average relative improvement of 5% in word error rate over baseline features on Aurora-4 dataset, and 5% on CHiME-3 database). Using the self-attention weights, we also present an analysis on the interpretability of the filters for the ASR task.

Index Terms— Speech representation learning, soft self-attention, raw speech waveform, cosine-modulated Gaussian filterbank, speech recognition.

1. INTRODUCTION

Even with several advancements in automatic speech recognition (ASR) systems using deep learning [1] and sequence modeling [2], there is significant performance degradation in noisy and reverberant environments. For most of the speech recognition systems, the first processing step is the extraction of features like mel filter-bank or gamma-tone filter-bank features [3,4]. This feature extraction step approximates the early part of human hearing. Recently, with the advent of neural networks, feature learning from data has been actively pursued from raw waveform [5,7].

In a supervised data-driven approach, the underlying model can automatically discover features needed for the objective at hand from the raw signals, e.g., detection or classification. Several works like [6,8,10] have specifically incorporated the learning of acoustic mel-like filters with convolution operations in the first layer of network. Many of these approaches also use mel filter initialization for the first filter-bank layer and the final learned filters have a close similarity to the mel-filters. While the approaches have yielded insights into the data driven filters, the interpretability is limited. There has been some early attempts to explore interpretability of filters recently [10].

In sequence-to-sequence modeling tasks like machine translation [11] and speech recognition [12], the use of network-in-network (NIN) architecture to derive attention weights has provided a significant boost in interpretability of such models [13]. For example, the analysis of attention in machine translation can tell if the translation is accurate at a word level in addition to being accurate at a sentence level. In these bidirectional recurrent neural network architectures, the attention network is provided with a feedback from the output prediction. The modification to self-attention which requires no feedback from the output [14] allows the extension of attention framework to all types of neural architectures [13]. For example, in tasks like language recognition, self-attention reveals features that are more relevant to the task [16]. The self-attention was also introduced for speech recognition in [17,18]. The self-attention networks have the ability to establish direct dependencies between any layer in the network with the targets [17].

In this paper, we hypothesize that representation learning can be efficiently performed with self-attention based filter-bank weighting approach. This work proposes a soft self-attention weighting approach applied on the output of the first layer of a deep model. The first layer performs acoustic filter-bank learning from the raw waveform using a convolutional layer. The acoustic filters are parametric cosine-modulated Gaussian filters [19] whose parameters are learned within the acoustic model. The convolution is carried out in time domain, and the output of the layer is pooled and log transformed to obtain time-frequency representation. The output is also fed to the NIN module to obtain self-attention weights for the filter-bank outputs. The weighted filter-bank representation is fed to the neural network architecture for the task of speech recognition. All the model parameters including the acoustic filter learning layer and the self-attention weights are learned in a supervised learning paradigm. The filter weights are initialized using the unsupervised learning framework [19].

The ASR experiments are conducted on Aurora-4 (additive noise with channel artifact) and CHiME-3 (additive noise with reverberation) databases. The experiments show that the learned representations from the proposed framework of filter learning with self-attention provides considerable improvements in ASR results over the baseline mel filter-bank features and other robust front-ends. We analyze the attention weights provided by the self-attention layer in the trained deep model. We also investigate the performance of the proposed framework in a semi-supervised setting where availability of labeled data is limited. The rest of the paper is organized as follows. Sec. 3 describes the proposed representation learning approach. Sec. 4 describes the ASR experiments with the various front-ends followed by the results and analysis. We conclude the work with summary in Sec. 5.
2. ATTENTION BASED ACOUSTIC FILTER LEARNING

The block schematic of the proposed soft self-attention based acoustic filter learning model is shown in Fig. 1.

2.1. Acoustic Filter-bank learning

The first layer of the proposed ASR model performs acoustic filtering learnt from the raw waveforms using a convolutional layer. The input to the neural network are raw samples windowed into $s$ samples per frame with a contextual window of $t$ frames. This matrix of size $s \times t$ raw audio samples are processed with a 1-D convolution using $f$ kernels ($f$ also denotes the number of sub-bands in filter-bank decomposition) each of size $k$. The kernels are modeled as cosine-modulated Gaussian function \[ w_i(n) = \cos 2\pi \mu_i n \times \exp \left(-n^2 \mu_i^2 / 2\right) \] (1) where $w_i(n)$ is the $i$-th kernel ($i = 1, ..., f$) at time $n$, $\mu_i$ is the center frequency of the $i$th filter (in frequency domain), and variance of the Gaussian is tied to the mean as $\sigma_i = 1/\mu_i$. The number of filter taps is denoted as $k$. The parametric approach to FB learning generates filters with a smooth frequency response. We initialize the means $\mu_i$ through unsupervised pre-training using convolutional variational autoencoder (CVAE) \[19].

The convolution with the cosine-modulated Gaussian filters generates $f$ feature maps. These outputs are squared, average pooled within each frame and log transformed. This generates $x$ as $f$ dimensional features for each of the $t$ contextual frames, as shown in Fig. 1.

2.2. Soft Self-attention module

The attention paradigm is implemented using a network-in-network (NIN) module fed with the $f \times t$ output of the acoustic filter-bank layer from the previous step. The two layer DNN network with a softmax output generates weights $w$ as $f$ dimensional vector with weights corresponding to each filter.

The attention weights over the $f$ dimensional features tend to be small values for many sub-bands and results in hard suppression of sub-band features that are critical for phoneme separation. In order to overcome this issue, we propose a soft attention scheme applied on the attention weighted filter-bank outputs $y$. This is inspired by instance norm principle \[20][21]. Let $y_{i,j}$ denote the attention weighted filter-bank output for frame $j$ ($j = 1, ..., t$) of sub-band $i$ ($i = 1, ..., f$). The soft attention output $z_{j,i}$ is given as,

\[
z_{j,i} = \frac{y_{j,i} - m_i}{\sigma_i} + c \quad (2)
\]

where $m_i$ is the sample mean of $y_{j,i}$ over $j$ and $\sigma_i$ is the sample std. dev. of $y_{j,i}$ over $j$. The constant $c$ acts as a relevance factor. When the attention weight for sub-band $i$ is high, the std. dev. $\sigma_i$ is also high compared to $c$ and thus the soft attention output $z_{j,i}$ has a unit variance over $j$. When the attention weight for sub-band $i$ is low, the value of $\sigma_i$ is also relatively less compared to $c$ and this makes the variance of $z_{j,i}$ lower than 1. Thus, Eq. 2 modulates the attention mechanism and provides a soft version of the attention weights to be propagated for the acoustic modeling in ASR.

Following the acoustic filter-bank layer and the self-attention NIN module, the acoustic model consists of series of CNN and DNN layers. The configuration details are given in Fig. 1. In our experiments, we use $t = 101$ whose center frame is the triphone target for the acoustic model. We also use $f = 80$ sub-bands with $k = 129$. This value of $k$ corresponds to 8 ms in time for a 16 kHz sampled signal. The value of $s$ is 400 corresponding to 25 ms window length and the frames are generated at 10ms shifts. Thus, the input to the acoustic filter bank layer is about 1 sec. of audio. In our experiments, we also find that after the instance norm layer, the number of frames $t$ can be pruned to the center 21 frames alone for the acoustic model training without loss in performance. This has significant computational benefits and we prune the output of the soft-attention to keep only the 21 frames around the center frame (200 ms of context).

Fig. 2 shows the center frequency ($\mu_i$ values sorted in ascending order) of the acoustic filters obtained using multi-condition Aurora-4 and CHiME-3 datasets (details of the datasets are given in Sec. 3) and this is compared with the center frequency of the mel filterbank. As can be observed, the proposed filterbank has more number of filters in lower frequencies compared to the mel filterbank.

The soft self-attention weighted time-frequency representation $x$ obtained from the proposed approach is shown in Fig. 3(c) for an utterance with airport noise from Aurora-4 dataset (the waveform is plotted in Fig. 3(a)). The corresponding mel spectrogram with instance normalization (without attention) is also plotted in Fig. 3(b).
It can be observed that in the proposed approach, the formants appear to be shifted upwards because of the increased number of filters in the lower frequency region. Also, the attention weighting helps to reduce the effect of noise in higher sub-bands.

### 3. EXPERIMENTS AND RESULTS

The speech recognition system is trained using PyTorch [22] while the Kaldi toolkit [23] is used for decoding and language modeling. The ASR is built on two datasets, Aurora-4 and CHiME-3 respectively. The models are discriminatively trained using the training data with cross entropy loss and Adam optimizer [24]. A hidden Markov model - Gaussian mixture model (HMM-GMM) system trained using MFCC features is used to generate the triphone alignments for training the CNN-DNN based model. The ASR results are reported with a language model re-scoring of the lattices, where the lattices generated with tri-gram language model are rescoring with recurrent neural network language model (RNN-LM) [25] for the final ASR decoding. The best language model weight is obtained from development set. For each dataset, we compare the ASR performance of the proposed approach of filter-bank learning with soft attention (Raw-Att) with traditional mel filterbank energy (MFB) features, power normalized filter-bank energy (PFB) features [26], RASTA features (RAS) [27], and mean Hilbert envelope (MHE) features [28]. All the features are processed with CMVN on a 1 sec running window. The architecture shown in Fig. 1 is used for the acoustic filterbank layer and the attention module is used for all the baseline features.

#### 3.1. Aurora-4 ASR

The WSJ Aurora-4 corpus is used for conducting ASR experiments. This database consists of continuous read speech recordings of 5000 words corpus, recorded under clean and noisy conditions (street, train, car, babble, restaurant, and airport) at 10 – 20 dB SNR. The training data has 7138 multi condition recordings (84 speakers) respectively. The validation data has 1206 recordings with various feature extraction schemes.

![Fig. 3.](a) Speech signal from Aurora-4 dataset with airport noise. (b) mel spectrogram representation without attention (c) acoustic filterbank representation with soft self-attention (z in Fig. 1).

The ASR performance of the proposed (Raw-Att) features (soft self-attention on acoustic filterbank representation as discussed in Sec. 2) is shown in Table 1 for each of the 14 test conditions. For Aurora-4 dataset, we also compare the ASR performance with the acoustic filterbank representation (Raw) without attention. In addition, we learn and apply the self-attention weights over MFB features (MFB-Att) for ASR.

#### Table 1. Word error rate (%) in Aurora-4 database for multi-condition training with various feature extraction schemes.

| Cond | MFB | PFB | RAS | MHE | Raw | MFB-Att | Raw-Att |
|------|-----|-----|-----|-----|-----|--------|--------|
| Clean | 3.4 | 3.4 | 4.2 | 3.1 | 3.2 | 3.5 | 2.9 |
| A. Clean with same Mic | | | | | | | |
| B: Noisy with same Mic | | | | | | | |
| Airport | 6.0 | 6.3 | 6.8 | 6.3 | 5.2 | 5.9 | 5.1 |
| Babble | 6.1 | 6.4 | 7.4 | 6.5 | 5.6 | 6.3 | 5.2 |
| Car | 3.5 | 4.0 | 4.2 | 3.8 | 3.6 | 3.6 | 3.4 |
| Rest. | 8.4 | 8.2 | 9.5 | 8.0 | 7.3 | 8.2 | 6.8 |
| Street | 6.8 | 7.1 | 8.3 | 7.0 | 6.9 | 7.0 | 6.1 |
| Train | 7.4 | 7.4 | 8.5 | 7.4 | 7.1 | 7.4 | 6.4 |
| Avg. | 6.4 | 6.8 | 7.4 | 6.3 | 5.9 | 6.4 | 5.8 |
| C: Clean with Diff. Mic | | | | | | | |
| Clean | 6.1 | 6.2 | 7.6 | 6.4 | 6.1 | 6.0 | 6.9 |
| D: Noisy with Diff. Mic | | | | | | | |
| Airport | 14.9 | 16.9 | 16.1 | 16.8 | 15.7 | 15.5 | 14.6 |
| Babble | 15.5 | 16.7 | 18.1 | 16.8 | 16.4 | 15.6 | 14.8 |
| Car | 7.7 | 9.8 | 9.0 | 8.2 | 7.9 | 7.4 | 8.3 |
| Rest. | 17.0 | 19.5 | 19.9 | 18.3 | 17.1 | 17.3 | 16.2 |
| Street | 16.0 | 17.9 | 17.6 | 17.6 | 16.7 | 16.6 | 15.8 |
| Train | 16.3 | 17.3 | 18.2 | 17.1 | 16.7 | 16.5 | 15.2 |
| Avg. | 14.6 | 16.3 | 16.5 | 15.6 | 15.1 | 14.8 | 14.1 |
| Avg. of all conditions | | | | | | | |
| Avg. | 9.7 | 10.5 | 11.1 | 10.2 | 9.7 | 9.8 | 9.1 |

As seen in the results, most of the noise robust front-ends do not improve over the baseline mel filterbank (MFB) performance. The Raw waveform features perform similar to MFB baseline features on average while performing better than the baseline for Cond. A and B. The MFB-Att features, which constitute the application of self-attention over filter-bank learning, also doesn’t improve over baseline MFB features. The proposed feature extraction scheme combines filter-bank learning with soft attention. These features provide considerable improvements in ASR performance over the baseline system with average relative improvements of 7% over MFB features. Furthermore, the improvements in ASR performance are consistently seen across all the noisy test conditions except condition C. In particular, the relative improvements in same microphone conditions (A and B) are about 15% relative compared to the baseline system.

#### 3.2. CHiME-3 ASR

The CHiMe-3 corpus for ASR contains multi-microphone tablet device recordings from everyday environments, released as a part of 3rd CHiMe challenge [29]. Four varied environments are present, cafe (CAF), street junction (STR), public transport (BUS) and pedestrian area (PED). For each environment, two types of noisy speech data are present, real and simulated. The real data consists of 6-channel recordings of sentences from the WSJ0 corpus spoken in the environments listed above. The simulated data was constructed.
by artificially mixing clean utterances with environment noises. The training data has 1600 (real) noisy recordings and 7138 simulated noisy utterances. We use the beamformed audio in our ASR training and testing. The development (dev) and evaluation (eval) data consists of 410 and 330 utterances respectively. For each set, the sentences are read by four different talkers in the four CHiME-3 environments. This results in 1640 (410 × 4) and 1320 (330 × 4) real development and evaluation utterances in total. Identically-sized, simulated dev and eval sets are made by mixing recordings captured in the recording booth with the environmental noise recordings.

The results for the CHiME-3 dataset are reported in Table 3. The proposed approach of raw waveform filter learning with soft attention provides considerable improvements over the baseline system as well as the other noise robust front-ends considered here. On the average, the proposed approach provides relative improvements of 5% over MFB features in the eval set. The detailed results on different noises in CHiME-3 are reported in Table 4. For most of the noise conditions in CHiME-3 in simulated and real environments, the proposed approach provides improvements over the baseline features.

### 3.3. Semi-supervised training

In this section, we test whether the filter-bank learning with soft attention is robust to the lack of supervised training data. We consider the case when only a fraction of the available training data is labeled. This is partly motivated by the fact that, while data collection in real noisy environments may be relatively easy, the labeling of noisy data is cumbersome and more expensive than in clean recording conditions. For semi-supervised ASR training, the Aurora-4 training set up is used with 70, 50 and 30% of the labeled training data. The performance comparison of ASR with semi-supervised training is shown in Fig. 5 for MFB and the proposed Raw-Att approach. As seen here, the proposed approach consistently performs better than the baseline MFB features even when the amount of labeled training data is small. These experiments show that the filter bank learning framework is not data hungry and the filter parameters can be learned effectively with limited supervised data.

### 3.4. Discussion

We analyze the soft self-attention weights for the Aurora-4 test data under various noise conditions. Fig. 4 shows the average attention weights of the sub-bands for an utterance of Aurora-4 dataset from 14 different test noise types in blue color. We also plot the corresponding sub-band energy profile of acoustic filterbank representation (averaged over all frames for an utterance) from all 14 test conditions in red color. Both the attention weights and the sub-band energies are unit length normalized in the plot.

From the plot, it can be observed that the obtained attention weights correlates with the sub-band energy profiles in most of the test conditions. The sub-band energies have more magnitude in the lower sub-band region (sub-bands 1 – 40) as compared to the higher sub-bands. The attention weights also follow similar trend for most of the test conditions, except for clean test condition, where we observe that the attention weights are almost flat. Thus, the attention weights provide information to the ASR to deweight the sub-band regions that are low in energy and vulnerable to noise.

### 4. SUMMARY

The major contribution of the work are as follows:

- Proposed an interpretable filter learning approach using soft self-attention from raw waveform.
- The acoustic filter bank in the first convolutional layer of the proposed model is implemented using a parametric cosine-modulated Gaussian filter bank whose parameters are learned.
- A network-in-network architecture provides self-attention to obtain attention weights over the sub-band filters.
- The proposed attention based feature learning for ASR gives considerable improvements in multiple datasets over baseline features. The performance improvements are consistent in semi-supervised ASR training as well.
- Analysis of the attention weights shows that it correlates well with the signal energy profile in the sub-bands.
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