EXPLORING SPECTRO-TEMPORAL FEATURES IN END-TO-END CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Triangular, overlapping Mel-scaled filters ("f-banks") are the current standard input for acoustic models that exploit their input's time-frequency geometry, because they provide a psycho-acoustically motivated time-frequency geometry for a speech signal. F-bank coefficients are provably robust to small deformations in the scale. In this paper, we explore two ways in which filter banks can be adjusted for the purposes of speech recognition. First, triangular filters can be replaced with Gabor filters, a compactly supported filter that better localizes events in time, or Gammatone filters, a psychoacoustically-motivated filter. Second, by rearranging the order of operations in computing filter bank features, features can be integrated over smaller time scales while simultaneously providing better frequency resolution. We make all feature implementations available online through open-source repositories. Initial experimentation with a modern end-to-end CNN phone recognizer yielded no significant improvements to phone error rate due to either modification. The result, and its ramifications with respect to learned filter banks, is discussed.

1 Introduction

Time-frequency analyses of speech have long been the dominant feature representation for speech recognition. There have been many different transformations that attempt to localize an “event” in time and frequency, such as wavelets and Wigner-Ville distributions. A powerful and persistent form of analysis is the Short-Time Fourier Transform (STFT). It and its derivatives treat a speech signal as a series of windowed stationary processes. Even though neural architectures have proven capable of processing raw speech signals \cite{12, 28, 21}, they tend to require far more data, aggressive averaging across learned filters, and even then still benefit from some filter-based initialization. The best results on benchmark datasets, such as TIMIT, are still achieved with triangular, overlapping Mel-scaled log filters – “f-banks” \cite{33, 27}. F-banks post-process the STFT by isolating and integrating over different bands of the power spectrum. The stationary assumption of the STFT combined with cleverly spaced band-pass filters makes for a very robust time-frequency representation of the speech signal.

There remains the possibility that, at least in the case of neural architectures that do use the time-frequency geometry of the f-bank, what is needed is not necessarily a different representation, but an improvement upon this already time-tested representation, such as by improving its time-frequency resolution. As neural architectures become more sophisticated, a higher resolution may in fact become more desirable. We can incrementally improve the f-bank formula by optimizing the time-frequency trade-off while respecting the conventions of time-frequency features - namely, an audio signal produces a sequence of “frames” uniformly sampled in time.

There are many alternatives to the triangular filter that may have desirable properties for ASR. Two such filters are the Gabor and Gammatone. The former has a provably optimal time-bandwidth product \cite{18}, whereas the latter more closely resembles the stimulus response of the human auditory system \cite{23}. Both are much more efficient in terms of time and frequency resolution, but because the STFT pipeline integrates over a uniform window in time, much of that resolution is sacrificed \cite{18}. The information lost could be valuable, especially to acoustic models that treat the time-frequency representation as a 2-D geometry, such as those based upon Convolutional Neural Networks (CNNs).

\textsuperscript{1}The Uncertainty Principle, as applied to digital signal processing, states that one cannot have an arbitrarily fine resolution in both time and frequency \cite{18}. Filters with short temporal support will have wide bandwidths, and very narrowband filters will have longer temporal support.
A second potential improvement is to swap the order of integration in the STFT pipeline. This new order would more faithfully represent both the filters’ time and frequency bandwidths, and can integrate over shorter time scales, since it would avoid incurring a resolution penalty by directly windowing. Together, these two improvements would make a filter bank with better time and frequency resolution, though they could also be employed separately.

This paper’s contributions are twofold: first, we present the aforementioned modifications to speech features in detail. These modifications, alongside more traditional speech features, are made available in the accompanying open-source Python package\footnote{https://github.com/sdrobert/pydrobert-speech}, as well as through the open-source Matlab repository COVAREP\footnote{https://github.com/sdrobert/more-or-let}. Second, we separately evaluate these adaptations in the framework of an end-to-end speech recognition task. Constructing a CNN from the architecture described in\cite{39} for the TIMIT phone recognition task, we decode the phone sequence internally using Connectionist Temporal Classification (CTC)\cite{14}. We discuss the position of our results as it relates to current trend of learning filter banks from the raw waveform. The code developed for this experiment, including the trained weights, are also open-source and available online\footnote{https://github.com/sdrobert/more-or-let}.

2 Mel-scaled log filter banks

To illustrate what a coefficient of an f-bank captures in time and frequency, we adapt an argument from\cite{4}. In the continuous domain, a filter coefficient \( k \) for a given frame of length \( T \) centered at sample \( c \), is popularly calculated for signal \( f \) as\cite{35, 25}:

\[
\text{FBANK}_{T,f,w}(c, k) = \log \int_{-\infty}^{\infty} \hat{h}_k(\omega) |\hat{f}w_{c,T}(\omega)|^2 d\omega
\]  
(1)

Where \( \hat{x} \) is the Continuous Fourier Transform (CFT) of \( x \), \( h_k \) is the \( k \)th real filter in the filter bank, \( w_{c,T} \) is a windowing function of temporal support \( T \) centered at \( c \).

The \( h_k \) are triangular windows with vertices derived by linearly sampling the Mel scale\cite{31}. The Mel scale, based on psychoacoustic experimentation, is roughly linear with respect to frequency below 1000Hz and logarithmic above. Clearly, the frequencies captured by a coefficient of the f-bank are limited to the nonzero region of \( h_k \). Because the bandwidth of \( h_k \) scales with its central frequency, f-banks are robust to time warping\cite{4}. In contrast, acoustic models that operate directly on the normalized power spectrum\cite{8, 3} are sensitive to time-warping. Without log-scale spacing, power spectrum models must repeatedly learn the same patterns, transformed by small-scale dilations \((T_{\alpha}f(t) = f(\alpha t))\) that are commonly introduced by differences in vocal tract length\cite{15}.

Multiplying the signal with a window in time blurs the filtered frequency responses. By the convolution theorem, \( \hat{f}w_{c,T} = \hat{f} \ast \hat{w}_{c,T} \). For large \( T \), \( \hat{w}(\omega) \rightarrow \delta(\omega) \), the Dirac delta function \((\int_{0}^{\infty} \delta(\omega)d\omega = 1 \text{ and } \delta(\omega) = 0 \text{ for } \omega \neq 0)\). Nonetheless, \( \hat{w} \) will have a nonzero support. This functions similarly to a rolling average over \( \hat{f} \) and effectively increases the bandwidth of all \( h_k \). While not particularly detrimental to wideband filters, the bandwidth of the window can be similar or greater than that of the narrowband filters, which can drastically reduce their discriminative power.

The \( h_k \) are also entirely real in the Fourier domain. We can instead let \( \sqrt{h_k} \) represent a filter with a frequency response equal to the point-wise square root of \( h_k \)’s, and shift the filter into the modulus. By the convolution theorem and Parseval’s theorem, Equation (1) can be rearranged into an integration over the filtered response of the window:

\[
\text{FBANK}_{T,f,w}(c, k) = C + \log \int_{-\infty}^{\infty} \sqrt{h_k} \ast (f w_{c,T})^2 (t)dt
\]  
(2)

If \( w_{c,T} \) is distributed non-uniformly in time, even local transformations of \( f \) will affect the resulting coefficient. Popular choices of \( w_{c,T} \), such as Hann, Hamming, or triangular windows, attenuate values at the periphery of the window. In effect, signal transients smoothly transition between overlapping frames. However, a narrowband \( \sqrt{h_k} \) decays more slowly to zero in time and has a number of cusps in its envelope (side lobes). This makes the integration difficult to interpret temporally.

3 Filter types

Triangular or square-root filters are not the only types of filters that can be scaled in the Mel-domain. The first modification to the spectro-temporal recipe that we explore is to the type of filter employed. We experiment with two additional types of filter: the Gabor filter and the Gammatone filter.
3.1 Gabor filters

Gabor filters have been explored in a variety of contexts. 2-D Gabor filters are often applied to spectrograms (or log-spectrograms) for ASR as a collection of spectral-temporal features \[29, 5, 10\]. Their 2-D construction allows the bank to capture meaningful geometric structures, such as formant movement. Likewise, 2-D Gabor bases have been learned as convolutional layers \[6\]. The present paper focuses on the design and evaluation of spectrogram-like features, rather than high-level spectro-temporal features that sit atop a spectrogram. In \[9\], a Mel-scaled Gabor filter bank was designed much like the one presented here, but it was 1-D and employed in an HMM-based architecture, not a neural network. Recently, \[37\] trained end-to-end CNNs for phone recognition with weights initialized to a Gabor filter bank.

Gabor filters are simply Gaussian windows with a complex carrier. They are defined in time as

$$h_k(t) = Ce^{-t^2+i\xi_k t}$$

and frequency as

$$\hat{h}_k(\omega) = \sqrt{2\pi\sigma^{3/2}}Ce^{-i\xi_k \omega}$$

To design the filter bank, center frequencies \(\xi\) are sampled along the Mel-scale. Neighbouring filters’ frequency supports intersect at their -3dB bandwidths. Gabor banks (g-banks) are calculated the same way as in Equation (2), excluding the point-wise square root.

Gabor filters have a provably optimal time-frequency trade-off \[18\]. Their regions of effective support in both time and frequency are bounded above by a Gaussian window.

One downside to the Gabor filter is its symmetric frequency response. Log-linear scales of speech perception, such as the Mel scale, are decidedly asymmetric. The Gammatone filter helps mitigate this trade-off.

3.2 Gammatone

Gammatone filters were derived in \[2\]. Their skewed frequency response lend themselves nicely to existing models of speech perception \[23\]. Gammatones have been employed in ASR directly \[26, 34\] or used as a starting point in learned feature representations \[38, 28\].

The complex Gammatone filter is defined in time as

$$h_k(t) = Ct^{n-1}e^{-\alpha t+i\xi_k t}u(t)$$

Where \(n\) is the order of the Gammatone, usually set to 4, which controls the skewness of the envelope of \(h\). The filter is defined in frequency as

$$\hat{h}_k(\omega) = \frac{C(n-1)!}{(\alpha+i(\omega-\xi_k))^n}$$

The same strategy for designing g-banks can be applied to Gammatone filter banks (tone-banks).

The Gammatone does not have an optimal time-frequency trade-off like the Gabor filter. It is a first-order approximation of the Gammachirp filter, which is time-scale optimal \[32\]. Incorporating the Gammachirp into the standard time-frequency pipeline is difficult, however, because the Gammachirp is not a linear-time invariant system.

4 Short integration

As is shown in Section 2, windowing widens the bandwidth of the narrowband filters in the f-bank, a form of spectral leakage. Increasing the width of the window will decrease the magnitude of the spectral leakage. However, a wider window will capture more of the signal in time, decreasing its temporal resolution. By taking inspiration from scattering transforms \[17, 14\], we can modify f-bank computations to better capture low-frequency information.

A sample of a first-order 1-D scattering transform is:

$$\text{SCAT}_{T,f,\psi,\phi}((\lambda_1), u) = \frac{1}{T} \int_{-\infty}^{\infty} |f * \psi_{\lambda_1}|(t) \phi(c-t) dt$$

for some family of wavelets \(\psi\) with \(\psi_{\lambda}(t) = \lambda^{-1}\psi(\lambda^{-1} t)\), and \(\phi\) a low-pass filter. Second-order scattering transforms are all paths of length 2 of the form \(|f * \psi_{\lambda_1} * \psi_{\lambda_2}|t\), and so on. The key observation is that the low-pass window has been shifted out of the nonlinear region. Note that

$$|f * \psi|^2(t) = (f * \psi) \overline{(f * \psi)}(t) \rightarrow (\hat{f} \hat{\psi} \overline{\hat{f} \hat{\psi}})$$
For real-valued $f$ and $\psi$, this is an autocorrelation in frequency. In general, the modulus pushes high-frequency information towards zero, where it can be captured by the low-pass $\phi$.

Existing work that uses scattering in speech has focused on wide $\phi$ and high-order (greater than first) paths \[24, 4, 36\]. Furthermore, though a scattering path is a contractive operation with a normed space as its image, the modulus is nonlinear. The nonlinearity makes it difficult to patch together a cohesive 2-D geometry along higher-order paths. Thus, scattering transforms are most useful in classifying stationary processes \[19\].

Instead of using a cascade of filters to capture high-frequency information, we can simply repeat the process in Equation (7), but with a shorter window. The following is the Short-Integration Filter Bank (sif-bank):

$$SIF_{\text{BANK}}_{f,w}(k,c) = \log \int_{-\infty}^{\infty} |f \ast \sqrt{h_k}|^2 w_{c,T}(t) dt$$

(8)

Windowing still performs a rolling average in the frequency domain, but, crucially, it is performed after the convolution. All energy within the modulus originated from the bandwidth of interest (dictated by $\sqrt{h_k}$). Hence, the sif-bank produces a more accurate representation of the frequency domain.

Since the filter bank need only be invariant to small transformations between frames, we can choose $T$ to be proportional to the frame shift. More complicated choices of $T$ based on the window type, however, can lead to improved time resolution without introducing significant aliasing. Treating $SIF_{\text{BANK}}(\cdot, c)$ as a discretely-sampled signal over sampling interval $i \rightarrow t \Delta c$. Applying this mapping and rearranging Equation (8), we can view a coefficient of the sif-bank as discretely sampling a continuous distribution:

$$SIF_{\text{BANK}}_{f,w,k}[i] = \left( \log |f \ast \sqrt{h_k}|^2 \ast w_T \right)[i]$$

For a fixed frame shift $\Delta$ seconds, the Nyquist-Shannon Sampling Theorem dictates that the sif-bank cannot represent frequencies higher than $1/(2\Delta)$ Hertz unambiguously. Frequencies above said limit will be subject to aliasing. The size of the window $T$ can be chosen to (approximately) enforce this limit. One may adjust $T$ until the zero-crossing or -3dB bandwidth of the main lobe of the window’s frequency response matches $1/(2\Delta)$ Hertz.

Decreasing the size of both the frame shift interval and window size can increase the temporal resolution of a short-integration filter coefficient when the bandwidth of the window is much smaller than the bandwidth of the modulus in Equation (8). A “downside” of short-integration is that decreasing the window size will not increase temporal resolution when the bandwidth of the modulus is smaller than that of the window already, as is the case for narrowband filters in the bank. For the low-frequency narrowband filters in a psychoacoustic filter bank, windowing has little effect, as the temporal support of these filters already far exceeds that of the frame shift. Thus, the coefficients corresponding to a narrowband filter in a sif-bank have poorer temporal resolution than those in an f-bank. This apparent downside is specious: the poor temporal resolution of narrowband filters is an inescapable property of the Uncertainty Principle, not the short-integration process. Any improved temporal resolution in STFT-based filter bank features is paid for with a less faithful frequency representation, discussed in Section 2.

It is worth noting that, due to the poor temporal resolution of narrowband filters, their coefficients will be more highly correlated across time than wideband filters. This makes the sampling along those bands highly redundant when the frame shift is small. Redundant representations are not necessarily a bad thing for classification; sequential frames of f-banks are overlapping in time, for example. Deltas and double deltas are merely convolutions of f-bank coefficients, which will clearly correlate the frames. Previously, f-banks were shown to be more effective than cepstral coefficients for deep learning precisely because the coefficients of the former are more strongly correlated \[20\].

Equation (8) generalizes to arbitrary choices of filter banks. Thus, we can combine the Gabor filters (Section 3.1) and Gammatone filters (Section 3.2) with short-integration to generate Short-Integration Gabor Banks (sig-banks) and Short-Integration Gammatone Banks (sitone-banks). The theoretical benefit of Gabor filters is their increased temporal resolution over f-banks, taking far less time to decay to near zero, whilst Gammatone filters are more faithful to human auditory perception.

Lastly, we address the computational efficiency of the short-integration filter bank. STFT-based computations have identical computational complexity with short-integration $O(N \log N)$. The short-integration implementations in are FFT-based, performing the overlap-save method of convolution. Because the FFT is not preceded by windowing, short-integration requires much larger FFTs to avoid the effects of circular convolution. This, and the required inverse FFT, increases computational time. Fortunately, a corresponding decrease in computational time comes from performing fewer FFTs in total. Traditional filter banks require an FFT for each frame of coefficients, since each frame windows the signal anew, whereas short integration can leverage coefficients from a single FFT-IFFT in multiple frames. Hence, overall computational times between the types of computation are quite comparable.
5 Experiment

In order to explore the efficacy of filter types and methods of computation in speech recognition, we tested them as drop-in replacements for f-banks in a deep end-to-end recognizer designed for f-banks. The TIMIT phone recognition task allows for fast experimental comparison and reduces the impact of language modeling on experimental results.

5.1 Data

We used Kaldi’s TIMIT recipe [25] to partition the audio data. TIMIT’s core test set is comprised of 192 utterances of 24 unique speakers. A 50 speaker set of 400 utterances is peeled from TIMIT’s complete test set for early stopping. 462 speakers and 3969 utterances comprise the training set. “Dialect sentences” (SA entries) were removed. The full set of 61 phone labels (including glottal closure) were used for training and decoding, but collapsed to the standard 39-phone set when calculating Phone Error Rate (PER), which includes the silence phone.

5.2 Model

The acoustic model, developed with Keras [7] and Tensorflow [1], mirrors the one described in [39]. The model comprises of mostly convolutional layers with maxout activations [13]. Connectionist Temporal Classification (CTC) [14] acts as the loss function for the network. CTC embeds the forward-backward algorithm into backpropagation to output phone labels directly, curtailing the need for external sequence modeling (e.g. Hidden Markov Models).

Maxout activations take the per-unit maximum of the output of at least two weight matrices that have received the same input. This (at least) doubles the number of trainable weights in memory. After discussion with the first author of [39], we halved the weights listed therein to fit the 4.3 million parameter point listed with a size-2 maxout function.

Following [39], the bottom-most 10 layers of the network convolve intermediate representations with a $5 \times 3$ (time \times frequency) kernel with stride 1. There is only one pooling layer: a max pooling of size $1 \times 3$ after the bottom-most convolutional layer. The first four convolutional layers have 64 feature maps; the remainder have 128. Above the convolutional layers sit 3 time-distributed fully connected layers. The frequency axis is collapsed into the feature map axis with a max operator, and each such vector, indexed by time, is multiplied with the same fully-connected weight matrix. Each layer has 512 time-distributed hidden units. A final time-distributed weight matrix constructs the activation matrix over the 61 phone labels for CTC.

5.3 Training and decoding

In the first stage of training, optimization is performed with Adam [16] at a learning rate of $10^{-5}$. Dropout [30] of probability 0.3 is applied after the activation function of each layer. The stage ends when a model’s validation loss has not improved for 50 epochs. Afterwards, optimization continues using Stochastic Gradient Descent (SGD) at a learning rate of $10^{-8}$ and an L2 weight regularization penalty of $10^{-5}$. The early stopping regime is the same as in the first stage. Weights are saved after each epoch, and the weight set with the lowest validation loss from the second stage is used to decode. Initially, we tuned the beam width used in decoding on the development set. However, we quickly found that larger beam widths were almost always preferable, so we fixed the width to 100. Note that development of the CNN was always performed using f-banks; no architectural or optimization decisions were influenced by the experimental filters.

5.4 Features

The model is trained on four feature sets of identical shape. f-bank is our implementation of the standard log Mel-scaled triangular filter bank, g-bank refers to the log Mel-scaled Gabor filter bank proposed in Section 3.1 tone-bank refers to the log Mel-scaled Gammatone filter bank from Section 3.2 and sif-bank, sig-bank, and sitone-bank are the short-integration analogues (introduced in Section 4) of f-bank, g-bank, and tone-bank, respectively.

For the standard STFT pipeline features (f-bank, g-bank, and tone-bank), 40 log filters plus one energy coefficient are calculated every 10ms over a frame of 25ms. The short-integration filters’ window size was chosen to be 20ms, i.e., double the frame shift, in order to avoid aliasing. Filters are spaced uniformly on the Mel-scale between 20Hz and 8000Hz. Deltas and double deltas are concatenated to the end of each frame vector, totalling 123 dimensions. Pre-emphasis, dithering, and compression were enabled at their standard Kaldi values. An additional baseline, kaldfb, was included to test Kaldi’s built-in f-bank implementation as a sanity check.
| Filter   | Test PER (std) |
|----------|----------------|
| kaldifb  | 18.82 (0.14)   |
| f-bank   | 18.60 (0.22)   |
| g-bank   | 18.77 (0.26)   |
| tone-bank| 18.71 (0.27)   |
| sif-bank | 18.74 (0.26)   |
| sig-bank | 18.68 (0.36)   |
| sitone-bank | 18.75 (0.30) |

Table 1: Mean and standard deviation Phone Error Rate (PER) on the TIMIT test set.

### 5.5 Evaluation

To evaluate the performance of the filters and computations, we performed a hybrid non-parametric statistical analysis. First, we performed a Friedman test over the four filter types: kaldifb, f-bank, g-bank, and tone-bank. The Friedman test is appropriate for repeated measures of ranked data with more than two levels when the distribution of the dependent variable (in this case PER) is not assumed to be Gaussian. For the filter bank with the lowest mean PER, we performed a Wilcoxon signed-rank test between PERs derived from regular computations versus those derived from short-integration computation. 10 trials were performed with different seeds for each combination of filter and computation, for a total of 70 trained models. One seed - the same seed for each combination of filters and computations - failed to converge, with PERs around 70%. Those trials were removed from analysis, leaving 9 trials each.

### 6 Results and discussion

The Friedman test showed no significant differences between distributions of PER across kaldifb, f-bank, g-bank, and tone-bank features ($Q = 5.93, p = 0.12$). Table 1 shows that the f-bank condition lead to the lowest mean PER. A Wilcoxon signed-rank test found no significant difference between distributions of PER across f-bank and sif-bank features ($W = 13, p = 0.26$). Therefore we cannot conclude that one feature representation lead to better average PERs overall.

Switching from Kaldi’s f-banks to any of our filter banks improved PER by approximately 0.1%, but otherwise the filters were quite similar in effect. Furthermore, the size of the variance between runs is large enough to discount any gains or losses.

The average PER across runs on the test set was 18.72%. This is higher than the percentage reported in [39] 18.2%, but the authors of said paper did not report an average over trials. One trial with sif-banks yielded a PER of 18.21%.

Experimentation excluding dithering tended to have lower overall PERs of around 18.5%, with the lowest observed rate from sif-banks at 17.89%. Dithering inserts random noise into the signal, which is intended to prevent systems from over-fitting on the signal. It is therefore possible to reduce the overall PER of the systems by removing dithering, but this is not recommended.

One must be careful about what is concluded from these results. They are consistent with the null hypothesis, which suggests that swapping features in end-to-end phone recognition has little effect on PER, we conjecture that this is indeed the case. Given the recent interest and success of learned filter bank representations, notably that of [37], one might extend this perspective and claim that exploring fixed filter banks is outdated and irrelevant. The difficulty comparing this work on fixed filter banks and previous work on learned filter banks (e.g. [57, 12, 28]) is that the latter class of paper tends to present a single error rate when discussing results, whereas we have presented a proper statistical analysis of the results over repeated trials. It is unclear whether those individual numbers are representative of a trend or a lucky setting of parameters. For example, as mentioned, we observed the PER of 17.89% (twice, in fact) from sif-banks. Had we only presented the best results, short-integration would have beaten out the best result (learned or otherwise) from [37]. We are not concluding here that sif-banks are better than learned filter banks or even traditional f-banks. The statistical analysis does not support that, nor does it seem likely. But neither can we come to understand more than what is merely possible from individual error rates.

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4We question, however, why learned filter banks tend to perform best when their weights are initialized with coefficients from a fixed filter bank, and why the learned banks tend to so strongly resemble a fixed filter bank in weight distribution, if what they learn is worth the additional effort and parameters.
7 Conclusions

We presented two distinct ways of modifying traditional f-bank features in order to produce a higher-resolution time-frequency representation of a speech signal. The first is to replace triangular filters with Gabor filters, which have a theoretically optimal time-bandwidth product, or Gammatone filters, which are more faithful to human speech perception. The second is to window over the filter response only after taking its power. This leverages the low-pass characteristic of the modulus to minimize information loss after windowing. Experimentation with a modern end-to-end CNN architecture with CTC [39] yielded no significant effect of filters or the modification to computation on PER. All filter bank and computation implementations are available as an open-source Python package as well as through the open-source Matlab repository COVAREP [11].

All of our results are predicated on swapping out STFT features for short-integration features without any adjustments to the model architecture. End-to-end neural ASR backpropagates through the decoding process. Even at the level of phone recognition, end-to-end models are responsible for modeling an entire sequence. Contrast this with an acoustic model in a hybrid DNN-HMM, which is only responsible for (and trained for) discriminatively classifying each frame of features. In the latter case, decisions are a function of only the features within a small context window, whereas an end-to-end system uses the entire utterance context. It is likely that an end-to-end system might spend more resources building a probability distribution over sequences of phones than it does focusing on any interval of speech features, nullifying the differences between filter types and resolution. In our experience, there is considerable variability in the outcome of the training process of end-to-end systems. More experimentation with traditional, hybrid architectures could prove illuminating in this respect.

Another interesting question is whether a neural architecture exists that is capable of processing shorter frame intervals. As was mentioned in Section 4 frame shift and window size can drastically affect the resolution in time of the feature representation. Where the support in time of the square root filters in a Mel-scaled f-bank range between about 90-400ms, Mel-scaled complex Gabor filters with roughly the same bandwidths in frequency range between about 3-24ms in support in time. Gabor filters are much more capable of representing information at much smaller time scales. Unfortunately, existing DNNs already suffer from vanishing and exploding gradients when dealing with long time series data [22]. The end-to-end CNN experimented on here relies on delta and double-delta features to transmit long-term dependency information. Increasing the total number of frames in an utterance would make it more difficult to transmit this data. Also, averaging over shorter time intervals means less spectral smoothing, which may prove difficult for architectures that are not noise robust. Such a feature set may nonetheless be a more user-friendly and robust alternative to backpropagating directly through the speech signal, without requiring the additional parameters.

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