ABSTRACT

The digital signal processing-based representations like the Mel-Frequency Cepstral Coefficient are well known to be a solid basis for various audio processing tasks. Alternatively, analog feature representations, relying on analog-electronics-feasible bandpass filtering, allow much lower system power consumption compared with the digital counterpart, while parity performance on traditional tasks like voice activity detection can be achieved. This work explores the possibility of using analog features on multiple speech processing tasks that vary in time dependencies: wake word detection, keyword spotting, and speaker identification. The results of this evaluation show that the analog features are still more power-efficient and competitive on simpler tasks than digital features but yield an increasing performance drop on more complex tasks when long-time correlations are present. We also introduce a novel theoretical framework based on information theory to understand this performance drop by quantifying information flow in feature calculation which helps identify the performance bottlenecks. The theoretical claims are experimentally validated, leading to a maximum of 6% increase of keyword spotting accuracy, even surpassing the digital baseline features. The proposed analog-feature-based systems could pave the way to achieving best-in-class accuracy and power consumption simultaneously.

Index Terms— Analog systems, audio classification, power efficiency, information theory

1. INTRODUCTION

With the new generation of intelligent devices in our daily lives, the user-device relation has drastically changed in the last decade. Gesture-free instant communication stands out as an appealing means of communication for users and manufacturers, especially when no touch interface is possible or restrictive. This kind of always-on listening platforms would benefit from on-device efficient inference, which could primarily alleviate the concerns for energy consumption from data transmission and data privacy. One promising method is to use analog processing for acoustic feature extraction [1][2]. The power consumption advantage of analog processing is twofold. One is that the analog processing itself is more efficient than the digital based on the mel-frequency cepstral coefficient (MFCC) [3] in the case of low-to-medium signal-to-noise ratio requirement [4]: The other is that the analog processing can directly interface with an analog MEMS microphone, without needing a power-consuming high-precision Analog-to-Digital Converter (ADC). A state-of-the-art 16-bit ADC [5] can consume ten times more power than the MFCC computation [3] itself.

Spiking neural network-based audio recognition has also been proved to be power efficient [6][7]. Unfortunately, missing chips postpone the usability of these methods. This work thus focuses on analog features with already fabricated chips. Recent works on analog features focus only on voice activity detection (VAD) with the power consumption in the range of nano to microwatts [1][2] and inference accuracy comparable to that of MFCC-based features. The missing performance of analog features on more complex classification problems would help discern its most appropriate application field. The chosen classification tasks in this paper with different complexity and time correlations are wake word detection [8], keyword spotting [9], and speaker identification [10]. Wake word detection is a simpler task with a relatively short-time correlation. Keyword spotting lies in the same time scale with increased difficulty. Speaker identification is a long-time correlation task.

Moreover, this paper devises an information theory-based analysis of compared feature representations to find the bottleneck operations in the computation of features. Both analog and MFCC representations are compared to LEAF [11], learnable feature extraction that outperforms the MFCC in multiple tasks while using a bandpass filter bank. Its processing pipeline is similar to the analog ones, and it allows to locate the information bottleneck in the system to help further improve the analog audio representation.

2. METHODS

We first compare analog features with conventionally digitally implemented features like MFCC for various audio classifications tasks to obtain the inference performance versus power...
efficiency. All the considered features are shown in Fig. 1 except for the log spectrogram since it corresponds to the first computation step in the MFCC. LEAF is a method that outperforms MFCC in multiple tasks, with a similar processing pipeline compared with the analog feature extraction.

![Feature Comparison Diagram](image)

**Fig. 1.** Scheme of all the compared features in this paper. STFT: Short Term Fourier Transform, DCT: Discrete Cosine Transform, PCEN: Per Channel Energy Normalisation, BPF: BandPass Filters, IAF: Integrate And Fire encoder.

### 2.1. Analog features

The schema of analog feature computation that roughly follows the human cochlea processing are shown in Fig. 1. The computation comprises three basic operations: 2nd-order bandpass filtering, an activation function, and spike generation based on Integrate-and-Fire (IAF) encoding. The IAF functions like a biological neuron, accumulating a certain amount of electrical charge and releasing a voltage spike after reaching a certain threshold. We call the analog feature extraction with a absolute value activation function “linear”, given its piece-wise linear nature and the linearity requirement on circuit implementation [1], and the one with a clipped exponential activation function “nonlinear”, which can be implemented with a limiting amplifier and a single voltage-to-current conversion transistor [2]. The output of the IAF encoder can be directly used for spiking neural networks [6] or counted in frames and used as a 2D feature like the MFCC. The MFCC feature has 20 frequency bands and ten coefficients [3], the analog linear one has 16 frequency bands, and the nonlinear analog one has 20 frequency bands.

### 2.2. Digital deep learning classification

We evaluate the different features on multiple classifiers for scaling analysis and robust results. The employed classifiers have different neural network architectures with growing classification capacities: A) a small version of EfficientNetV2 [12], B) LeNet-5 [13], C) depthwise separable CNN (DS-CNN) [14] and D) EfficientNetB0 [15]. A) is an efficient neural network, derived from an EfficientNetV2 architecture, using the same inverted residual bottleneck block, with reduced filter size and number, and only two residual blocks. Two more layers are added in classifiers A and B with the log spectrograms (due to their increased size) to match the number of parameters. All the classifiers are trained using ADAM as an optimizer with default learning rate, and SpecAugment [16] is used as data augmentation. A scheduler reduces the learning rate geometrically by e-0.01 after 100 epochs for the small neural networks (A,B) and 50 for the large ones (C,D).

### 2.3. Power consumption estimation

The power consumption of the analog feature extraction methods can be estimated from the fabricated chips [1 2]. The power consumption of the digital features MFCC and log spectrogram can be estimated from [3], adding the ADC’s contribution [5]. To estimate a lower bound for the power consumption of the classifiers, the energy efficiency from the state-of-the-art neural network processor 13.6TOPS/W is used [17]. Tab. 1 describes a summary of the power consumption of the employed neural networks. The power consumption is obtained with the number of multiply-and-accumulate (MAC) per classification in a neural network and assuming a 100 class/s inference rate.

| Classifier | MAC number | Power   |
|------------|------------|---------|
| A) Mini-EfficientNet | 5.8e4 | 0.43 µW |
| B) LeNet-5 | 2.1e5 | 1.5 µW |
| C) DS-CNN | 6.7e6 | 50 µW |
| D) EfficientNet | 7.6e7 | 0.56 mW |

### 2.4. Information theory

Information theory is used to compare the different features to identify the bottleneck operation in the feature computation. The tool used is the Shannon Entropy [18]:

\[
S_{\text{Shannon}} = - \sum_{i=0}^{N} p_i \log (p_i)
\]

with \( p_i \) the probability of the data distribution. The estimation of the data distribution in the features can be done in multiple ways. To retain the spatial information of the features this work encodes spatial information by giving each data point a unique identifier (an integer) in a second dimension. This two-dimensional object, with a "Data-Point value" and "spatial label" axis is then fit with a two-dimensional histogram to obtain the \( p_i \)’s. This methods should be seen as a test, there are currently no best way to extract entropy for matrices without probability priors. The histogram computation would also require more research, with the number of bins in the histogram greatly influencing results.
3. EXPERIMENTS

3.1. Wake word detection

We adopted the experimental setup from the Howl work [8] including the code provided in [19]. The dataset consisted of multiple positive wake words “Hey Firefox” and Common Voice dataset [20] prompts as background negative data. The noise was added from the MS-Noise dataset [21] at 10dB SNR. The final dataset contained 10% positive examples with a total of 30,000 audio samples of 2.5 seconds. The testing set was composed of 300 actual recordings of “Hey Firefox” and 1000 generated recordings given by [19]. 3500 background noise, and 3500 negative speech samples. Fig. 2 shows the energy efficiency of each result obtained. A 10 class/s inference rate was set for this task’s power estimate. The false alarm rate was set to 4 to compare it to Howl, when applicable. If not applicable, the lowest possible false alarm rate was used. The performance of the Howl system was estimated using the MACs of the used classifier (Res-8 small) [8], and the MFCC energy consumption estimate [3]. Howl’s result are extrapolated on our dataset using the ROC curve from [8].

The results thus demonstrate another potential usage of the analog features except for voice activity detection, with results close to digital features in general and possibly even better. The gain is also evident in energy efficiency for the analog features, with more than ten times better energy efficiency with the Mini-EfficientNet (A). The energy consumption of the classifier erases the difference when reaching the DS-CNN (C). Performance of existing Howl implementation lies between LeNet (B) and the DS-CNN (C), which is expected for a Res-8. Its power consumption is not competitive.

3.2. Keyword spotting

Keyword spotting was evaluated on the Speech Command dataset V2 [9], using all the 35 different classes with no added noise. The results are summarised in Fig. 3. The results indicate that the analog features perform worse by about 2 to 3% for all classifiers comparing to the digital features. For both large classifiers (C,D), the energy consumption of the classifier dominates the total power consumption, and there is no reason to chose analog preprocessing over MFCCs. The accuracy gap is the same for the smaller neural network (A,B). Power consumption is around two times better for both analog features with LeNet (B) and seven times greater for the Mini-EfficientNet (A). It is also interesting to note that the log spectrograms perform worse with the smaller neural networks. The log spectrogram also consume significantly more power.

3.3. Speaker identification

Speaker identification was evaluated with the VCTK dataset [10], restrained to 30 out of 110 speakers. A 10 class/s inference rate is used due to the size of the audio samples. The results are presented in Fig. 4. Overall, results are similar to keyword spotting except for the small neural networks (A,B). The analog feature seems to have an equal amount of information compared to the MFCC. However, the information appears harder to extract. There is a loss of 20 to 40 % in accuracy when comparing the different features with LeNet-5 (B) and the Mini-EfficientNet (A). Since the small classifiers (A,B) are required to take advantage of the energy efficiency of the analog preprocessing, this task is not suited for the analog features. The analog process is unsuitable for paralinguistic tasks and cannot capture the subtle formations required to discern different speakers talking.

4. FEATURE ANALYSIS AND IMPROVEMENTS

To improve the analog features, we first compared them to the MFCCs and LEAF features to understand where difference arise. The idea is to know the causes of the loss in accuracy of the analog features on keyword spotting. A thousand
samples with equal class repartition are used for this analysis. The features are separated into their computation steps, and the entropy is computed as described in section 2.4. The average of the entropy on all the samples is then plotted with its standard deviation in Fig. 5.

Analyzing Fig. 5 allows understanding of information bottlenecks. The pattern is similar for all the features; the first step extracts as much information as possible. The dimensionality of the features is then reduced, inducing a reduction in information. The MFCC loses a bit of information in the last step, indeed there are twenty Mel-Frequency bands and only 10 final coefficients after DCT. LEAF sees its information increase in mean and variance with the use of PCEN. The output entropy of the MFCC is higher than LEAF, with LEAF having a higher variance. Knowing that the MFCC and LEAF have the same performance on keyword spotting, it could be a testament on how the variance in entropy is primordial, or an issue with our experimental theoretical framework. The analog features lose the most information with the spikes computation in the IAF and when counting the spikes. To confirm these hypotheses, we tested adjustments in the analog feature computation by replacing them with LEAF’s counterparts. The IAF was replaced with the Gaussian low pass filters of LEAF. Then, we added PCEN as the last step of the computation. Finally, the BPF filters were replaced by LEAF’s Gabor filters. Since the coded framework allowed it, the BPF parameters of the analog extractor were also able to be optimized in conjunction with the classifier using gradient descent. The testing was done using the LeNet classifier and the keyword spotting task.

Table 2. Verification of the claims of the information theory framework using LeNet (B) on keyword spotting. For every row, one computation step of the analog extractor were replaced sequentially by the LEAF equivalent.

| Modification                       | Fixed BPF | Learned BPF |
|------------------------------------|-----------|-------------|
| Analog linear (baseline)           | 79.1%     | -           |
| IAF $\rightarrow$ Gaussian Low Pass | 81.7%     | 82.8%       |
| Adding sPCEN                       | 82.6%     | 85.1%       |
| BPF $\rightarrow$ Gabor filters    | -         | 85.0%       |
| MFCC                               | 84.8%     | -           |

Table 2 shows that the theoretic framework is valid for this specific task. All the tested replacements increase the accuracy by a significant amount, and the learning of the parameters of the BPF in the original analog extractor allows for significant and easy to implement improvement. The fully improved analog extractor gains 6% in accuracy, surpassing the MFCC. The optimized BPF parameters and the PCEN can be implemented directly, while the Gaussian low-pass requires more experimentation to integrate in an actual system.

5. CONCLUSIONS

This paper compared different feature extraction methods and showed the potential of the analog features. Easier tasks, especially those that do not require paralinguistic information, seem to be the most suitable for analog features. The wake word detection task showed that the analog feature extractor could outperform the digital ones, with an order of magnitude lower power consumption. We then identified the bottleneck in the analog feature extractor’s computation pipeline using an information theory framework, which was validated with a 6% accuracy improvement on keyword spotting by replacing the bottleneck stages with some building blocks from LEAF. Future works include adapting the processing in the modified stages to feasible integrated electronics implementation and exploring the possibility of directly using spiking neural networks as the classifier after IAF for accuracy improvement.
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