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### DOI

[10.1109/ISCAS46773.2023.10181602](https://doi.org/10.1109/ISCAS46773.2023.10181602)

### Publication date

2023

### Document Version

Final published version

### Published in

ISCAS 2023 - 56th IEEE International Symposium on Circuits and Systems, Proceedings

### Citation (APA)

Chen, Q., Chang, Y., Kim, K., Gao, C., & Liu, S. C. (2023). An Area-Efficient Ultra-Low-Power Time-Domain Feature Extractor for Edge Keyword Spotting. In *ISCAS 2023 - 56th IEEE International Symposium on Circuits and Systems, Proceedings* (Proceedings - IEEE International Symposium on Circuits and Systems; Vol. 2023-May). Institute of Electrical and Electronics Engineers (IEEE).  
<https://doi.org/10.1109/ISCAS46773.2023.10181602>

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# An Area-Efficient Ultra-Low-Power Time-Domain Feature Extractor for Edge Keyword Spotting

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**Abstract**—Keyword spotting (KWS) is an important task on edge low-power audio devices. A typical edge KWS system consists of a front-end feature extractor which outputs mel-scale frequency cepstral coefficients (MFCC) features followed by a back-end neural network classifier. KWS edge designs aim for the best power-performance-area metrics. This work proposes an area-efficient ultra-low-power time-domain infinite impulse response (IIR) filter-based feature extractor for a KWS system. It uses a serial architecture, and the architecture is further optimized for a low-cost computing structure and mixed-precision bit selection of the IIR coefficients while maintaining good KWS accuracy. Using a 65 nm process technology and a back-end neural network classifier, this simulated feature extractor has an area of 0.02 mm<sup>2</sup> and achieves 3.3 μW @ 1.2 V, and achieves 92.5% accuracy on a 10-keyword, 12-class KWS task using the GSCD dataset.

**Index Terms**—Keyword spotting (KWS), infinite impulse response (IIR), hardware acceleration, long short-term memory.

## I. INTRODUCTION

**K**EYWORD spotting (KWS) is an important task to reduce power consumption on consumer devices and smart assistants such as Apple Siri. It acts as a trigger for the system to perform the higher-computation and energy-consumption speech recognition tasks. Ideally, an edge KWS system should be always-on and for battery-powered devices, an ultra-low power design is needed.

A typical KWS design consists of a front-end feature extractor and a back-end neural network classifier [1]. Deep neural networks (DNNs) such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are usually used as the back-end classifier [2]–[4]. In recent years, a few dedicated KWS FPGA and ASIC designs have been designed with focus on reducing power consumption [5]–[12].

In addition to the back-end, the front-end feature extractor is another crucial module in speech recognition systems. The recent development of edge audio systems has heightened the need for area-power efficient feature extractors. Audio features can be categorized into two main types: 1) frequency-domain features such as the mel-scale frequency cepstral coefficients (MFCC) [8], [13], [14], and 2) time-domain features, such as ring-oscillator-based filters [7] or  $g_m C$  filters [15], [16]. MFCC features are typically used in state-of-the-art KWS digital systems [6], [8], [13], [17]–[19]. However, processing

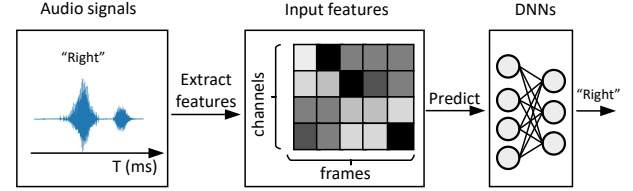


Fig. 1. Typical processing pipeline in a KWS system.

chains of MFCC mandates a large power consumption including pre-emphasis, windowing, fast Fourier transform (FFT), Mel-filtering, logarithmic computation, and discrete cosine transform (DCT). For example, in the 22nm 10.8 μW/15.1 μW dual computing modes KWS system [17], the MFCC feature extractor took up nearly one-third of the power consumption of the whole prototype system.

Infinite impulse response (IIR) filters are a class of widely-used recursive filters and have relatively simple computing chains thereby facilitating low memory and logic area costs [20]. In this work, we propose an area-efficient ultra-low-power digital serial IIR filter-based feature extractor as a front-end to a KWS system. The low-cost computing structure and mixed-precision implementation demonstrates a superior area-power efficiency. Designed in a 65 nm CMOS process, the feature extractor shows a 1.6x-to-54x lower power consumption than other designs while recording a 92.5% state-of-the-art KWS accuracy on the Google Speech Command Dataset (GSCD) [21].

## II. INFINITE IMPULSE RESPONSE FILTER

IIR filters are defined by a set of coefficients of a rational transfer function, for which a stability criteria must be also satisfied. By doing a z-transform, the transfer function of the IIR filter is as follows:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{i=0}^{M-1} a_i z^{-i}}{1 + \sum_{i=1}^{N-1} b_i z^{-i}} \quad (1)$$

where  $a_i$  and  $b_i$  are coefficients in the numerator and denominator, respectively.  $M$  and  $N$  denote the number of poles and zeros in the filter function.

The most common IIR filter model is based on the decomposition of a higher-order filter into a cascade of second-order sections to ensure stability [22]. In this way, we can describe the transfer function of a higher order IIR filter as follows:

$$H(z) = \prod_{i=1}^L \frac{a_{0i} + a_{1i} z^{-1} + a_{2i} z^{-2}}{1 + b_{1i} z^{-1} + b_{2i} z^{-2}} \quad (2)$$

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This work was partially supported by the Swiss National Science Foundation CA-DNNEdge project (208227) and Bridge project VIPS (181010).

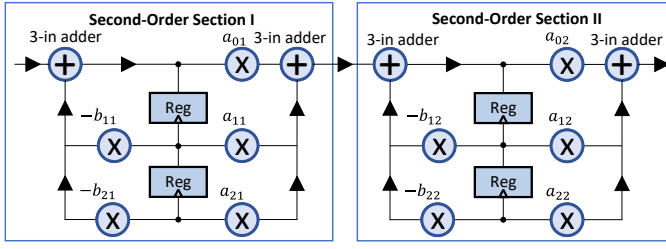


Fig. 2. Basic architecture of a 4<sup>th</sup> order IIR band-pass filter.

TABLE I  
COEFFICIENTS OF 16 IIR BAND-PASS FILTERS IN SECOND-ORDER  
SECTIONS REPRESENTATION

Ch	a <sub>01</sub>	a <sub>11</sub>	a <sub>21</sub>	b <sub>11</sub>	b <sub>21</sub>	a <sub>02</sub>	a <sub>12</sub>	a <sub>22</sub>	b <sub>12</sub>	b <sub>22</sub>	CF (Hz)
0	5.4-e04	1.1e-03	5.5e-04	-1.93	0.96	1	-2	1	-1.96	0.97	182
1	1.2e-03	2.4e-03	1.2e-03	-1.89	0.94	1	-2	1	-1.92	0.95	272
2	0.0022	0.0044	0.0022	-1.82	0.93	1	-2	1	-1.88	0.94	372
3	0.0036	0.0072	0.0036	-1.74	0.91	1	-2	1	-1.82	0.92	482
4	0.0056	0.011	0.0056	-1.63	0.88	1	-2	1	-1.74	0.90	603
5	0.0081	0.016	0.0081	-1.49	0.86	1	-2	1	-1.64	0.89	736
6	0.011	0.023	0.011	-1.31	0.84	1	-2	1	-1.53	0.86	884
7	0.016	0.031	0.016	-1.10	0.81	1	-2	1	-1.38	0.84	1046
8	0.021	0.042	0.021	-0.85	0.78	1	-2	1	-1.21	0.81	1225
9	0.027	0.054	0.027	-0.56	0.76	1	-2	1	-0.99	0.78	1422
10	0.035	0.070	0.035	-0.23	0.73	1	-2	1	-0.75	0.75	1639
11	0.044	0.089	0.044	0.14	0.70	1	-2	1	-0.46	0.71	1879
12	0.056	-0.11	0.056	-0.15	0.67	1	2	1	0.53	0.68	2143
13	0.069	-0.14	0.069	0.18	0.61	1	2	1	0.92	0.66	2435
14	0.085	-0.17	0.085	0.51	0.54	1	2	1	1.29	0.67	2756
15	0.10	-0.21	0.10	0.78	0.44	1	2	1	1.64	0.74	3110

where  $L$  is the number of second-order sections. Fig. 2 shows a basic architecture of a 4<sup>th</sup> order IIR band-pass filter implemented as a cascade of two second-order sections ( $L=2$ ). In this work, we design a 16-channel IIR-based feature extractor with 16 IIR filters. We use *signal.butter* function in the *Scipy* library to design *Butterworth* IIR band-pass filters. We chose *Butterworth* filter topology as it has a flat passband response, i.e., without passband ripple as it exists in Chebyshev/Elliptic filters, thereby leading to a easier and simpler design. The coefficients and central frequencies of the filter channels are given in Table I.

### III. LOW-POWER AND COMPACT SERIAL IIR-BASED FEATURE EXTRACTOR

#### A. Serial Architecture and Computational Flow

Fig. 3 shows the top view of the proposed IIR-based feature extractor. It consists of a computing unit which includes a cascade of second-order section modules, a post-processing module, buffers and a control unit. The input audio signals are processed sequentially by the two second-order section modules and the post-processing module to generate the 16-dimensional feature vectors. The serial architecture allows the reuse of the computing units across the 16 channels and thereby, significantly reducing both the area and leakage power of the design. Fig. 4 shows the computation flow of the serial IIR-based feature extractor. The audio samples are

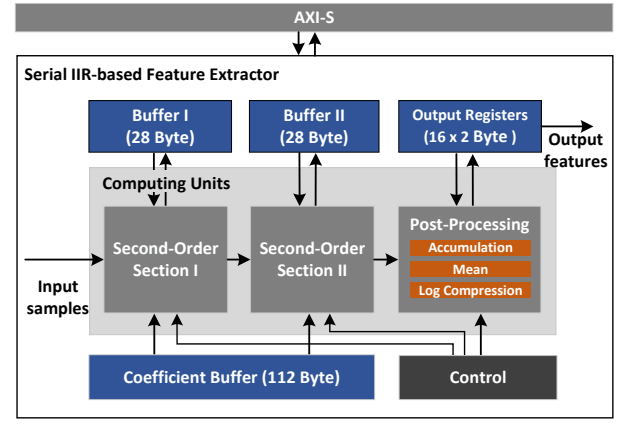


Fig. 3. Hardware architecture of a serial IIR-based feature extractor (within the outlined box).

partitioned into 16 ms frames without overlap. Each input frame contains 128 samples at the sampling rate of 8 kHz. Each audio sample is processed by the 16 IIR band-pass filters in a sequential manner by the same computation units. The computation units are divided into three pipeline stages to reduce the combinational logic area and power consumption. After each of the 128 audio samples is filtered and the outputs accumulated in the output registers, their values are divided by 128 (realized by a bit right shift) to obtain the mean of a frame, then it is followed by a log compression. Finally, the values in the output registers are streamed out as a 16-dimensional feature vector.

#### B. Low-Cost Computing Structure of the IIR Band-pass Filter

According to Fig. 2, which demonstrates the basic architecture of a 4<sup>th</sup> order IIR band-pass filter, 10 multipliers and 8 adders are required. If we look closer at the coefficients  $a$  and  $b$  across the 16 IIR filters as shown in Table I, we see hardware-friendly properties such as symmetries and constant value representations, e.g.:

$$a_{11} = 2a_{01} = 2a_{21}, \quad (3)$$

$$|a_{12}| = 2a_{02} = 2a_{22} = 2, \quad (4)$$

Shown in Fig. 5, a low-complexity architecture for the 4<sup>th</sup>-order IIR filter is designed by exploiting these properties. The number of multipliers are reduced to 5 by the replacement with shift operations and combining like terms, thus reducing both the power consumption and area.

#### C. Mixed-Precision Selection of Filter Coefficients

Due to potential numerical stability issues, a fixed-point analysis is required during the IIR filter implementation. The resource and power reduction strongly depends on the coefficient values of the filters. In this case, the selection of coefficient precision is essential. Previous works always adopt the unified bit precision for coefficients and focus on the goodness of fitting degree during the fixed-point analysis. In fact, thanks to the error resilience of neural networks, we



TABLE II  
COMPARISON WITH PREVIOUS WORKS

Metric	JSSC'20 [8]	TCAS-II'22 [13]	TCAS-I'20 [17]	VLSI'19 [23]	JSSC'22 [7]	This work
Technology (nm)	65	40	22	65	65	65
Sample rate (kHz)	16	8	16	4-16	-	8
Frequency (kHz)	250	400	250	250	0.11-10.4	128
Voltage (V)	0.6	0.6	0.6	0.6	0.5	1.2
Precision (bits)	-	-	8@Input 16@Output	10@Input 4,8@Output	-	12@Input, 12@Output $b_a=12, b_b=8$
Latency (ms)	48	16	40	16	-	16.11
Feature extractor type	Digital MFCC	Digital MFCC	Digital MFCC	Digital MFCC	Analog ring-oscillator	Digital IIR-based
Power ( $\mu$ W)	7	<b>0.67</b>	2.8	7.14	9.3	3.3
Area ( $\text{mm}^2$ )	-	-	<0.1	-	1.6	<b>0.02</b>
#Keywords / #Classes	10/-	10/12	10/12	10/12	10/12	10/12
Model <sup>1</sup>	LSTM	LSTM	BCNN	LSTM	GRU	LSTM
Accuracy <sup>2</sup>	90.87% <sup>m</sup>	92.40% <sup>s</sup>	87.90% <sup>s</sup>	90.87% <sup>m</sup>	86.03% <sup>m</sup>	<b>92.50%</b> <sup>s</sup>

<sup>1</sup> All LSTMs have one 64-unit hidden layer structure; BCNN – binary convolutional neural network; GRU – gated recurrent unit network.

<sup>2</sup> m denotes chip measurement results, s denotes simulation results.

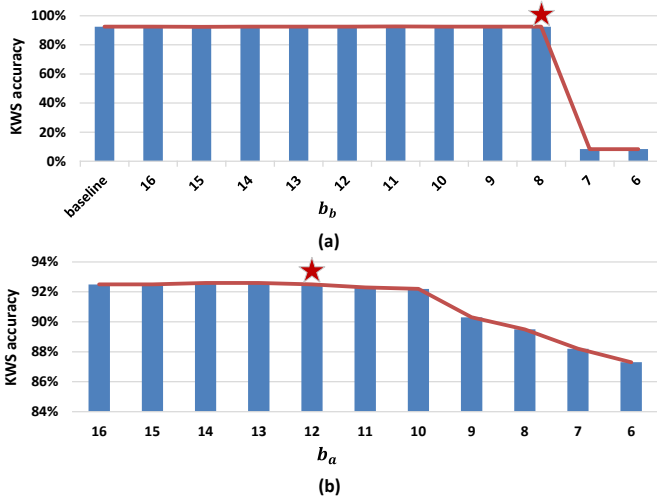


Fig. 6. Impact of bit precision on KWS accuracy: (a) KWS accuracy versus  $b_b$  ( $b_a = 32$  floating point, baseline), (b) KWS accuracy versus  $b_a$  ( $b_b = 8$ ).

Cadence Innovus for place and route using CMOS 65nm process. The pre-layout and post-layout functionalities are verified using ModelSim, and stimuli-based power consumption is analyzed from post-layout results. To offer real-time processing capability, the proposed design runs at a system clock of 128 kHz and a supply voltage of 1.2 V. Fig. 7 shows a final 5.5x power reduction with the breakdown across all the different optimization steps. The 16-channel IIR filter layout has an area of  $0.02 \text{ mm}^2$  as shown in Fig. 8(a) and the power breakdown of the different blocks is shown in Fig. 8(b). The second-order section modules are the most power-consuming blocks, followed by the buffers.

Table II compares our proposed digital IIR-based feature extractor with the state-of-the-art extractors including both digital implementations [8], [13], [17], [23] and analog implementations [7]. Unlike MFCC-based designs, the hardware resources and power consumption of the proposed IIR-based feature extractor is independent of the frame length (referred as

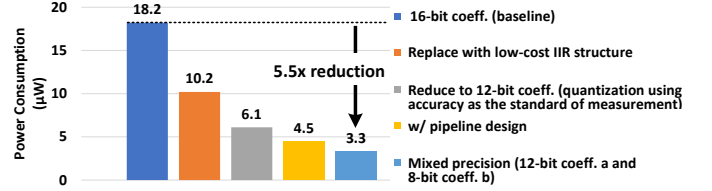


Fig. 7. Power reduction with each optimization operation.

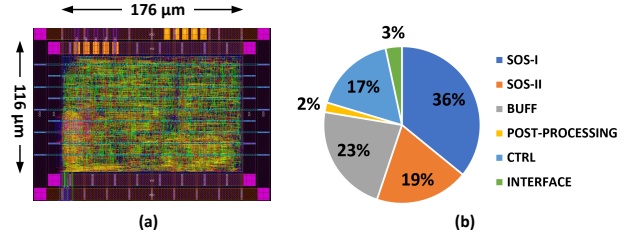


Fig. 8. (a) Layout and (b) power breakdown of the IIR-based feature extractor.

FFT size in MFCC). Our work achieves a competitive accuracy of 92.5% comparable to other works reporting accuracies on a 10-keyword, 12-class KWS task using the GSCD dataset. Simulations show that this feature extractor design consumes only  $3.3 \mu\text{W}$  @ 1.2 V.

## V. CONCLUSION

This work proposes an area-efficient ultra-low-power time-domain IIR-based feature extractor for edge keyword spotting. The implementation uses a serial architecture and is further optimized with a low-cost computing structure and mixed-precision selection to significantly reduce the power consumption while maintaining high KWS accuracy. It has an area of  $0.02 \text{ mm}^2$  and consumes only  $3.3 \mu\text{W}$  @ 1.2 V. The power of the entire KWS design including the IIR-based feature extractor and a network with an energy-efficient architecture [24] will be reported in future work.



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