Laika: A 5uW programmable LSTM accelerator for always-on keyword spotting in 65nm CMOS

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Abstract—The ubiquitous importance of speech recognition for diverse applications in mobile devices, necessitates its low power embedded execution. Often, a Keyword Spotting System (KWS) is used to detect specific wake-up words spoken by a user, as a simple user interface, or front-end layer to a larger speech recognition system. Yet, such KWS must be always active, hence imposing strict power and latency constraints. While deep learning algorithms like Long Short-Term Memory (LSTM) demonstrated excellent KWS accuracies, current implementations fail to fit in the tight embedded memory and power budgets.

This paper presents Laika: the implementation of a KWS system using an LSTM accelerator designed in 65nm CMOS. For this application, an LSTM model is trained through a speech database and deployed on our custom, yet highly programmable LSTM accelerator. Approximate computing techniques further reduce power consumption, while maintaining high accuracy and reliability. Experimental results demonstrate a power consumption of less than 5 μ W for real-time KWS applications.

Index Terms—LSTM, Keyword Spotting, Deep Learning, Speech Recognition, Digital Accelerator.

I. INTRODUCTION

The rise of mobile devices has increased the importance of interactive human-machine interfaces to improve user experience. Voice command recognition, which allows a total hands-free experience for the user, has been subject of continuous research during the last years. For power consumption reasons, a large and more complex speech recognition engine is typically complemented with a more efficient keyword spotting (KWS) wake-up system. Since the KWS system must be always on, its total system power consumption is of utmost importance, required to be well below 100 μ W for continuous operation.

Along with this trend, Deep Learning has shown impressive results in terms of accuracy for different speech recognition tasks including keyword spotting [1]. These typically make use of recurrent neural networks, such as LSTMs, which allow to capture dynamic temporal behavior, yet pose a significant computational burden on the embedded device. To lower this burden, hardware accelerators have been developed targeting Keyword Spotting. [2] shows an ASIC with 8 execution engines for accelerating RNNs, showing its application for real-time KWS, consuming 6.6 mW at 20 MHz/0.8 V. A compact memory storage is presented in [3] through a programmable processor with 270 kB on-chip weight which executes real-time KWS with 300 μ W power consumption. In [4] a SIMD processor evaluates DNNs for automatic speech recognition tasks including a small vocabulary recognizer which achieves

172 μ W for real time power consumption. All these accelerators target the support of medium-to-large size deep learning models. They however fail to achieve real time operation with power budgets in the order of 10 μ W. For example, in [3] just leakage power accounts for more than 20 μ W of the total power consumption.

Yet, recent work [5] [1], indicates that a novel type of networks, Long Short-Term Memory networks (LSTMs), can attain acceptable KWS accuracies with only small sized networks. The customized acceleration of small but cheap LSTM models has remained unexplored, although its potential for reliable keyword spotting systems is eminent. Its realization is challenged by the careful balance needed between task accuracy and power consumption, necessitating cross-layer optimizations between the algorithm and hardware implementations, without giving up flexibility and programmability.

In this work we show such co-optimization together with the implementation of Laika (LSTM Accelerator IC for KWS Analysis), a low power, programmable LSTM accelerator in 65 nm optimized for Keyword Spotting. The chip can execute small-medium size LSTMs, with support for different network topologies, enabling to broaden the application to other domains. Power consumption is kept low through several cross-layer HW-algorithm co-optimizations, and by keeping the full model storage on-chip, avoiding any high speed I/O. Our contribution can be summarized as follows:

- Extensive HW-algorithm co-optimization for always-on LSTM operation jointly exploiting linear and non-linear quantization and activation function approximation.
- A flexible, programmable implementation with support for diverse LSTM networks and topologies, capable of storing complete models on chip.
- The first LSTM accelerator which can support always-on real-time keyword spotting, consuming less than 10 μ W.

In Section II the theoretical background for LSTMs is presented. Section III details the software/hardware co-design to reduce model size and computational complexity. In Section IV, the system architecture is discussed, highlighting the data flow and Laika's micro-architecture. The chip's measurement results are highlighted in Section V, and Section VI summarizes this work and compares it to the state-of-the-art.

II. LSTMS FOR KEYWORD SPOTTING

A. LSTMs

LSTMs, which stands for Long Short-Term Memory, are a more complex type of recurrent neural network that show state-of-the-art accuracy for sequence tasks like speech recognition and natural language processing. Every layer of an LSTM consists of a set of neurons, each computing 4 intermediate results called 'gates' (forget f_t , input i_t , output o_t and candidate gate g_t), from an internally stored hidden vector h_{t-1} and the current input vector x_t :

$$f_t = \sigma_s(W_f x_t + U_f h_{t-1} + b_f) \quad (1)$$

$$i_t = \sigma_s(W_i x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma_s(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

$$g_t = \sigma_h(W_g x_t + U_g h_{t-1} + b_g) \quad (4)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ g_t \quad (5)$$

$$h_t = o_t \circ \sigma_h(c_t) \quad (6)$$

where W_* , U_* and b_* are trained model coefficients for each gate, and σ_* are nonlinear activation functions $\tanh$ σ_h and sigmoid σ_s . The result of these gates (1)-(4) is subsequently used to compute the next memory cell c_t and hidden vector h_t through a series of element-wise multiplications, denoted by $\circ$ in (5)-(6).

LSTM models typically consist out of one to multiple of such LSTM layers, followed by one or more fully connected layers, operating on the outputs h_t of the last LSTM layer:

$$z_t = W_{fc} h_t \quad (7)$$

where W_{fc} are weights for the fully connected layer. As LSTMs are capable of achieving good accuracies on problems with dynamic temporal behavior with relatively smaller model sizes compared with other feed-forward neural networks such as CNNs, it makes them excellent candidates for KWS systems.

B. Keyword Spotting

Keyword Spotting typically relies on a pipeline of a feature extraction module, followed by a keyword classifier. Commonly used features for speech recognition applications are Mel Frequency Cepstral Coefficients (MFCC). These features are extracted from windows of audio samples, typically 25-32 ms windows, with a 10-16 ms overlap between subsequent windows. For every window, the extracted set of MFCC coefficients is subsequently sent to the classifier to detect target keywords.

In this work, we rely on such MFCC features, and further optimize the classification stage. Recent work has shown that it is possible to implement accurate, yet compact KWS using small-scale LSTMs [5] showing good results with a single LSTM layer with up to 64 neurons [1]. It is however important to realize that research to further balance accuracy and complexity is still in progress. As such, any hardware implementation hence has to maintain good programmability regarding the number of LSTM and fully connected layers.

TABLE I
IMPACT APPROXIMATE COMPUTING ON KWS ACCURACY

Numerical Precision	Precision	Recall	F1-score
FP	0.920	0.890	0.904
FxP without PLA	0.904	0.888	0.896
FP with PLA	0.920	0.889	0.904
FxP with PLA	0.918	0.882	0.900
NLQ without fine-tuning	0.910	0.805	0.853
NLQ with fine-tuning	0.917	0.883	0.900

III. ALGORITHM-HARDWARE CO-OPTIMIZATION

A hardware accelerator for real-time execution of such LSTMs should be able to consume a new feature vector every 16 ms, at low power consumption, without giving up programmability. Several algorithm-hardware co-optimizations have been performed with the goal of 1.) reducing the memory footprint of the network model, enabling efficient on-chip storage of the full model; 2.) reducing the computational complexity of the required model execution, enabling low power datapath operation.

All optimizations were assessed on a keyword spotting system consisting of a 56 neuron LSTM layer followed by one fully connected (FC) layer similar to [5]. The network was first trained in floating point, using the TIMIT database and a segmentation of 500 ms for labeling. The network is fed with 39 MFCC features per 32 ms window with 16 ms overlap. The four most common words of the dataset (water, greasy, wash and dark) were chosen as KWS targets and a binary classifier was trained for each of them, resulting in the floating point (FP) baseline accuracy for the test set shown in Table I. The Table presents the average precision, recall and F1 score (harmonic mean between precision and recall).

a) Network quantization: The use of low precision operations and model coefficients significantly reduces computational complexity and memory bandwidth with marginal loss in accuracy. The obtained 32-bits floating point parameters and inputs can be quantized to a low-resolution fixed point representation. Table I shows that accuracy is nearly unaltered when scaling down to 8-bit fixed point operation (FxP without Piecewise Linear Approximation) for inputs and weights, with internal 16-bit multiplication results, summed in 32-bit accumulators before being stored back into 8-bit registers capturing the outputs of the LSTM layer.

b) Function approximation: LSTMs require several non-linear activation functions $\tanh$ σ_h and sigmoid σ_s , which are expensive to compute exactly. They can however be approximated through a piecewise linear function relying on hardware LUTs storing the coefficients m and b of each segment of the linear approximations $mx+b$. Yet, the number of segments has to be selected carefully to balance hardware cost vs. accuracy implications. As can be seen in the aforementioned table (FP, resp. FxP with PLA), 8 linear segments still allow to obtain good accuracy, while enabling very small LUTs.

c) Non-linear quantization: To further reduce precision below 8-bit, without giving up accuracy, clustering techniques similar to Deep Compression [6] can be applied. By cluster-

ing 8-bit model weights into 2^M representative values, only M -bits instead of 8-bits are needed for coefficient storage. Online, each M -bit word is translated back to its 8-bit cluster center value using a small codebook look up table (LUT), before using it in the LSTM computation. This non-linear quantization of the model weights into 2^M clusters however reduces detection performance, as can be seen in Table I (NLQ without fine-tuning, $M=4$). Yet, the original accuracy can be recovered by retraining the cluster centers after clustering, showing good results for $M=4$ (NLQ with fine-tuning). The LSTM coefficients can now be stored in on-chip memory using only 4-bits each, and be converted back to their 8-bit cluster center value in a LUT when fetched for computation. All hardware-algorithm co-optimizations together as such reduce the memory footprint with up to 8x and simplify the computation of network gates and activation functions, while showing negligible loss compared to a 32-bits FP model.

IV. HARDWARE ARCHITECTURE

To exploit the discussed algorithmic optimizations, a custom yet highly-programmable hardware accelerator was developed for Laika.

a) *System architecture*: The system architecture is depicted in figure 1. The near-memory compute processor avoids any off-chip data communication besides the MFCC inputs and KWS detection outputs. A 32 kB on-chip memory stores the complete LSTM+FC model, while internal data buffers buffer data close to the Functional Units (FUs). Four processing elements (PE) each are responsible for one gate of an LSTM neuron (eqn. (1)-(4)). They are fed the required inputs from 3 possible storage locations: 1.) the 8-bits model coefficients W_* and U_* from the Model Memory; 2.) the MFCC input data x_t from the input buffer; and 3.) the hidden state h_{t-1} from the data buffers, with support for up to 2 LSTM layers (corresponding to the FIFOs $H1$ and $H2$ in the architecture).

Every PE performs the required 2 multiplications per gate, which is accumulated in a 32-bits value (see fig. 2). After cycling through the multiply-and-accumulate operations of each neuron (corresponding to a complete row of the gate matrices in eqn. (1)-(4)) the accumulation output is fed to the activation function (NL), implemented with the 8-segment LUT-based function approximation. Two LUT blocks per function (one saving the slope m and the other the offset b for each linear approximation $mx + b$) are shared by all 4 PE's. The output of the non-linear functions (NL OUT 1 - 4) is subsequently sent to the gate buffers, formed by 8-bit FIFOs implemented with registers: one for each of the gates (I, G, F, O).

After computing the gates, all the element-wise multiplications are carried out by one PE. This PE loads data from the gate buffers, the hidden state buffer ($H1$ or $H2$) and memory cell buffer ($C0$ or $C1$) to compute a new hidden state that is saved into the correspondent hidden state buffer (eqn(5)-(6)). In order to execute the FC layers, one PE loads the weights from the Model Memory and data from the hidden state buffers ($H1$ or $H2$), computing the multiply-and-accumulate

operations for each output neuron and saving the result into the output buffer as final products of the frame inference (eqn. (7)).

Fig. 1. Top level chip architecture

Fig. 2. Microarchitecture of the PEs and non-linear approximator NL.

b) *Clustering mode*: Laika supports nonlinear quantization, through programmable LUTs which can be activated between the model memory and the PEs. In this mode, 4-bit model weights are fetched from memory, doubling the amount of fetched weights per clock cycle. While the first half of the weights is subsequently sent to the LUT, decoding the 4-bit cluster values into the actual 8-bit weights, the other half is buffered to be used the next clock cycle. This effectively halves the memory bandwidth, positively impacting system level power consumption as will be shown in Section V. A different LUT is used for each gate, allowing to train cluster values for each gate independently.

c) *Accelerator programmability*: A control unit controls the operation of the PEs and memory fetches. It can be configured to execute various network topologies through a series of configuration registers (number of hidden LSTM layers, number of neurons per layers, clustering en/disabled), as well as the dimensions of the FC layer (dictating the number of targeted detection keywords). An SPI interfaces with these configuration data, the model memory, the input buffer, output buffer and the internal FIFO buffers. Reprogramming model memory and configuration registers allows support for a wide variety of applications and power-accuracy trade-off points.

V. IMPLEMENTATION AND MEASUREMENTS

a) *Physical implementation*: The chip, depicted in Fig. 3, is implemented in 65nm CMOS with a standard cell P&R flow. To further improve power efficiency while ensuring reliability, several back-end optimizations were implemented: Logic and SRAM power domains were separated to allow maximal voltage scaling for each domain. Aggressive clock

gating was applied through a global 'freeze' input signal, which gates the clock tree of the complete data path to stall the system when the accelerator completes an inference before the next real time feature vector arrives. Finally, high V_t standard cells were used for logic ensuring low leakage, with low V_t standard cells for clock distribution to allow more aggressive voltage scaling without generating hold violations.

b) Measurement setup: A ZedBoard Zynq-7000 ARM/FPGA interfaces over SPI with the configuration registers, model weights, input features and detection outputs. Since Laika supports the storage of a complete model on-chip, only feature vectors and detection outputs are actually communicated during real-time measurements.

c) Performance measurements: Fig 3 shows the measured minimum supply voltage for the accelerator logic at various operating frequencies, fixing SRAM voltage to 0.7 V. The system is able to work with voltages in the range of 0.575 V - 0.8 V at clock frequencies ranging 380 kHz - 8 MHz. The figure moreover shows the resulting measured energy consumption for a complete KWS inference on a 16msec frame. The energy of the complete system (including memories) is measured when deploying the 56-neuron KWS model of Section III, for both linear quantization (LQ) and nonlinear quantization (NLQ). The energy per inference improves with lower frequencies because of voltage scaling, with a floor due to leakage power. Nonlinear quantization reduces the energy per inference with 25%, due to reduced memory fetching.

Fig. 3. Left) Photo of chip. Right) Maximal Operating Frequency for different voltages and Energy Efficiency for several operating points.

d) Application and flexibility measurements: Power consumption was measured when deploying different network topologies in a real-time keyword spotting application. The features are fed to the accelerator at a constant rate of 16 ms. The clock frequency and supply voltage of the chip are adjusted to match the required computation speed for such real time operation. This information is summarized in Table II (with hl the number of hidden layers and n the number of neurons per layer, all followed by 1 FC layer). All deployed networks fit in the 32 kB SRAM. The power consumption lies between 2 - 7 μ W depending on the model topology. Using the model optimized in Section III, real-time KWS can be achieved with $<5 \mu$ W at 0.575 V/250 kHz by activating the nonlinear quantization mode.

VI. CONCLUSIONS

This paper presents Laika, an ultra-low power LSTM accelerator for Keyword Spotting. The chip supports full on-

TABLE II
REAL-TIME POWER CONSUMPTION FOR DIFFERENT NETWORK TOPOLOGIES

Model	Freq(kHz)	MACs	Leakage (μ W)	Total Power LQ (μ W)	Total Power NLQ (μ W)
1 hl, 40 n	148	12800	0.614	3.84	3.23
1 hl, 48 n	196	16896	0.614	4.80	4.08
1 hl 56 n	250	21504	0.614	5.85	4.97
1 hl, 64 n	309	26624	0.614	7.22	6.01
2 hl, 16 n	77	5888	0.614	2.27	2.05
2 hl, 24 n	147	11328	0.614	3.70	3.27
2 hl, 32 n	239	18432	0.614	5.65	4.91
2 hl, 40 n	352	27200	0.614	7.98	6.84

TABLE III
PERFORMANCE SUMMARY AND COMPARISON WITH STATE-OF-THE-ART

	This work	2017 ISSCC Price [4]	2017 ISSCC Bang [3]	2017 ESSCIRC Chen [2]
Technology	65nm	65nm	40nm	65nm
ML algorithm	LSTM	DNN	DNN	GRU
Area [mm ²]	1.15x0.9	3.1x3.1	2.5x2.85	2.9x3.5
On-chip memory	32kB	5.84Mb	270kB	64kB
Power for real-time KWS	5 μ W	172 μ W	321 μ W	6.6 mW
Clock	250kHz	3Mhz	3.9MHz	20Mhz
Voltage	0.575	0.6	0.65	0.8
Energy per inf.	60 nJ	4.5 μ J	2 μ J	NA

chip models through a 32 kB SRAM, allowing to execute small-medium size LSTM networks with a broad variety of programmable topologies. The accelerator is able to execute models using linear as well as nonlinear quantization. The support for clustered models allows to improve the energy efficiency of inference without impacting accuracy. The prototype achieves between 59 - 94 nJ/inference at 380 kHz - 8 Mhz. For a real-time Keyword Spotting application the accelerator consumes less than 5 μ W at 0.575 V.

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