**An Energy-efficient Speech Classification Convolution Neural Network Accelerator Based on FPGA and Quantization**

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**Abstract**

Deep convolution neural networks (CNN) have been shown to own unique advantages in acoustic tasks over recurrent neural networks (RNN). However, activation data in convolution neural networks is often indicated in floating format, which is both time-consuming and power-consuming when be computed. Quantization method can turn activation into fix-point, replacing floating computing into faster and more energy-saving fix-point computing. Based on this method, this article provides a design space searching method to quantize a binary weight neural network. We then complete a specific accelerator on FPGA platform, which owns layer-by-layer pipeline design and is high-throughput and energy-efficient compared with CPU or RNN-based accelerators.

**[[1]](#footnote-1)**

**Keywords**: energy-efficient; reconfigurable computing; FPGA; quantization; sound classification

1. **Introduction**

Sound classification is a typical information analyzing task which is widely used in military and speech controlling. Since Deng, Yu et al introduced RNN and LSTM (Long-Short Stage Memory) acoustic model into speech recognition and sound classification, LSTM has reached series of excellent performance in this area (Geoffrey H, et al 2012; Wan H, et al 2019). However, deep neural networks based on RNN are hard to be trained and parallelized due to complex structure and recurrent computation. When applied in actual missions, RNN models usually demand high performance GPU and CPU to satisfy computing power need. Such hardware platforms have up to hundreds of watt power consumption, which cannot meet requirements for energy-sensitive circumstance. On the contrast, CNN has been found to get excellent performance on acoustic model (Tom S, et al 2016; Muckenhirn H, et al, 2018; Palaz D, et al, 2015). Audio files can be transferred into feature maps or feature matrixes by wave-filtering algorithms (such as Mel Frequency Cepstral Coefficients algorithm) (Pakyurek M,, et al, 2020), acoustic CNN models then run on these maps just like input images for computer vision models. With tiny 3x3 or 5x5 convolution kernels, CNNs can be trained and forward faster than RNN for convoluting operation is easier to be parallelized and accelerated than recurrent computation. This advantage makes it possible to accelerate an acoustic CNN model on specific power-efficiency hardware platforms.

Gradient descent algorithm (Jyrki Kivinen M K W, et al, 1997), which is sensitive to numerical fluctuation (Perkins S, et al, 2003), is widely applied to train deep neural networks (DNN). To pursue best DNN performance, it is necessary to store data in full-precision format during training process. However, floating data format needs longer word-length to store and more circuit parts to compute, leading to more energy consumption and bigger circuit designing area (Liu S, et al, 2011). Also, the computing complexity of floating-point data makes it difficult to reduce computing cycle counts. Floating computation, although can keep precision well, has become the bottleneck of power-efficiency high performance computing.

Fortunately, some works (Han S, et al, 2016; Dundar G, et al, 1995) have proven that floating-point data is unnecessary to CNNs’ forwarding tasks, low precision computing can achieve similar performance as well. These works provide quantization method, turning weight and activation data into fix-point data, integer data or even binary data with little accuracy loss. Based on kinds of quantized CNN models, there comes BNN (Binary Neural Network) accelerators (Guo P, et al, 2019; Liang S, et al, 2018; Conti F, et al, 2018) and GPUs supporting 8 bits integer data (Michael D, Ashish K, David R. Nvidia’s Xavier et al, 2018; Nvidia. 2018) etc. These designs reduce power consumption greatly and have up to hundreds of speedup ratios compared with CPU platforms. It turns out that hardware with corresponding quantized CNN models can achieve excellent computing performance as well as high energy efficiency.

Compared with CPU and GPU, ASIC and FPGA are more suitable to accelerate a specific task for their reconfigurable feature. These reconfigurable platforms can be customized by setting pipeline and expanding parallelism degree, lowering power consumption and raising computing performance. Although ASIC owns huge advantages over FPGA on power and speed, expensive designing and manufacturing cost limits it’s general application. On the contrast, FPGA keeps a good balance between performance, power, flexibility and expense due to programmable feature and mature industry design. Now, FPGA has been widely used in cloud computing and intelligence computing by Microsoft, Amazon and Alibaba (Gwennap L, et al, 2017; Turan F, et al, 2020), becoming an important part of high- performance computing.

The sound classification model which focuses on specific speech instructions or acoustics signal, is a basic component of intelligent scenario analysis in both cloud and edge end. Such applying circumstance needs a low-power but high-performance computing platform especially. Typical deep convolution neural networks can do coarse sound classification work well. However, there still exists some space to accelerate CNN model and reduce computing platform’s energy consumption by quantization and customized hardware design. To implement this power-efficient sound classification computation platform, we choose a typical CNN-based speech classification model where weight value is +1 or -1 and activation data is in full precision floating-data format (Bo L, et al, 2018). We design an accelerator based on Xilinx XCKU-115 FPGA platform and run this BWN (Binary Weight Network) model. Compared with state-of-art CPU platform, our accelerator achieves 18-300x throughput speed up ratio and high energy efficiency. The main contributions of this work are as follows:

1. We turn float-type feature data into fix-point data in a rather common method. However, as to super parameter like batch-normalization arguments, we take a special bitwise allocation method and apply design space exploration means to find best quantization scheme. We also sperate middle result from feature data and take different quantization settings. Based on usual quantization method, we take these operations to help to decrease accuracy loss caused by quantization and achieve a closed model prediction accuracy compared with non-quantized model.

2. We design a novel layer-by-layer pipeline structure on our multi-PE BWN accelerator, which has shared weight storage, balanced pipeline partition and bitwise expansion. The performance, power consumption and energy efficiency of this accelerator are discussed in Section 5.

3. The target speech classification model is tested under single thread, multi-thread and multi-node environments to get sufficient performance baseline. Compared with these test results, our design has absolute advantage on performance per watt and throughput.

**2. Neural Network Forwarding Quantization**

When training a deep neural network, researchers usually choose full-precision data format to ensure best model accuracy. However, in inference task, these parameters will not be changed and therefore we can prune them in an offline method. (Bo L, et al, 2018) raises an algorithm to compress floating-point DNN parameters into binary data, which is consisted of +1 and -1. Compared with common DNN with floating-point weight and activation, this compression method not only sharply reduces parameter storage, but also replaces multiplication and division with add and minus. Less storage space and multiplication mean less memory-consuming energy and less computing cycles, leading to faster lower power consumption and faster working speed.

(Matthieu C, et al, 2016) brings out a method to turn activation into binary format. Unlike parameter in neural networks, activation data fluctuates numerically with different input (such like input image or input audio feature map). Although (Matthieu C, et al, 2016) still keeps a good model accuracy on very deep CNNs like VGGNet, great numerical precision loss would be brought out binary activation data, which may cause vital influence on some small-size CNNs (Jacob B, et al, 2017; Xu Y, et al, 2018). In this situation, turning floating data into fix-point format can keep a good balance between computing performance and model accuracy: fix-point data computation needs less computing cycles compared with floating data, and, fix-point can adapt to data’s numerical distribution by flexible allocation of integer bitwise and decimal bitwise.

When integer part is allocated with more bitwise, it can expand data-indication range; and when we give decimal part longer word-length, it can achieve better numerical precision correspondingly. For example, given a decimal number 10.06. With four-bit integer part and five-bit decimal part, this number can be indicated as 1010.00001 in binary format, which is 10.0625 when again translated into decimal number. Numerical precision loss here is generated by binary data’s discrete indicating method. With same integer part length and ten bit allocated to decimal part, the number 10.06 can then be reset as 1010.0000011111, which is 10.060546875 when translated into original format. This example shows that with longer decimal bit length, quantized can keep better numerical precision. However, increasing the length of fix-point data format will add cycle counts to computation or occupy more hardware’s resource on FPGA. Taking speed and computation precision into account, it is important to find the relatively best data format.

**3. Speech Classification Model**

**3.1 Model Architecture and Weight Binarization**

This CNN-based speech recognition model is trained on Tensorflow speech command dataset. It can recognize the six sort of short speech segment “up”, “down”, “yes”, “right”, “left” and “unknown words”. This model first uses MFCC algorithm turning an audio file into a float-type tensor, whose dimension is 20x49x1. Then this tensor will be sent into a convolution neural network, which is consisted of two convolution layers, three full-connected layers and binary weight parameters. The detail information of model architecture is shown in Fig 1. All convolution kernel size is 3 and convolution stride is 1. There is no padding and expansion operation in this network, which is convenient for us to accelerate. To be noticed that activation is still in float format at this stage. Via softmax function, this model outputs the possibility of six type of labels.

After model parameters being fixed in the training process, we can transfer float weight value into (-1, 1). Fig 2 shows how we processing weight data. We assume the distribution of primitive parameter is normal distribution, the numerical distributing range is then modified by tanh function and a series of scale methods. Finally, all parameters are discretized to -1 or +1. This stage’s BWN model (activation data is still in floating format) can provide the accuracy no less than 85%.

**Fig. 1** Convolution Neural Network Architecture



**Fig. 2** Weight Binarization Process

**3.2 Quantizing Feature Data and Middle Results**

Once we change floating input feature into fix-point format, middle result, activation and other hyper-parameter (such as bias and batch-normalization parameter) will be in fix-point format naturally. The data computed in each layer can be divided to two parts: middle results after MAC (Multiply-Accumulate) operations and the batch-normalized output data. The batch-normalized output data is feature data which will be transferred to next layer of neural network. In some cases, absolute value and variance value of middle results can be huge, in another word, the data distribution of middle result is rather fluctuant, which brings difficulty to quantization. These middle results will then be normalized, where both absolute value and variance is narrowed down. Unlike middle result data, the feature data follows normal distribution and easy to be quantized. To turn middle result and batch-normalized data into fix-point format, the approximate data range of these two kinds of data needs to be determined first for numerical distribution range deciding data’s integer part bitwise. Middle result’s quantization thus demands longer integer indication for fluctuant data distribution.

On integrated development environment such as Matlab, their quantization functions library usually cannot reflect the real condition of middle results for CPU platforms doing float computation first and then converting result into fix-point format when running quantization operations. However, on FPGA platforms, hardware design and resource utilization will be influenced by middle result’s demand for longer word length. As a result, FPGA has to use more LUT to complete such fix-point computation and more register to store middle result.

When quantize feature data, we usually use eight bits for integer part (one for sign and seven for indicating value) and eight bits for decimal part in saturation mode, some layers’ feature data may need more decimal bits to increase indication precision. But it is obvious that this quantization setting is not suitable for middle results whose absolute value can go far beyond 127, we need to find a quantization format for middle results separately. Once we determine the absolute value’s range and corresponding integer bits for middle result, it is necessary to decrease decimal parts to reduce resource utilization. We try serval bitwise schemes with design space search method and the experiment result is discussed in section 5.1.

**3.3 Quantizing Batch-normalization’s Parameters**

Batch-normalization operation, which improves data distribution greatly among neural network layers, has been proven to be vital to model’s final prediction accuracy (Santurkar S, et al, 2018; Liu M, et al, 2017). However, the multiplication and division in this process not only depend on middle results, but also are sensitive to parameters’ numerical precision (Giri E P, et al, 2016). The experiment in section 5.1 shows the decimal bitwise of normalization parameters, which reflects numerical precision, influence model’s prediction performance greatly.

Despite taking occupy of more hardware resource, experiment result indicates that it is still important to allocate more decimal bits for batch-normalization parameters. Considering the module size of batch-normalization is not that large, our FPGA platform affords raising the computing precision in this process.

Based on original quantization idea, we separately raise three quantization formats for feature data, middle results and normalization parameters. We focus on keeping balance between hardware performance and numerical computing precision and apply search method to find best solution for middle results’ quantization. In the Experiment section, we will discuss detail quantization experiment results.

**4. Accelerator Architecture**

The target model is small, shallow and weight-binarized, so the main methods we focus are setting shared parameters storage on chip, accelerating neural network layer by layer and designing pipeline between layers. The general architecture of the accelerator is shown is Fig.3. Our accelerator contacts with DDR via input-data FIFO, output-data FIFO and series of address signal wires. Inside each process element, there comes different modules that mapped to different neural network’s layers, we can deploy layer-by-layer pipeline acceleration naturally by this design method. Also, shared parameter storage element is settled between each PE, reducing resource utilization on FPGA.



**Fig.3** Hardware Architecture

**4.1 Parameter Storage**

Unlike some neural network accelerators having to use DRAM instead of on-chip memory to store parameters (Cheung K, et al, 2012; Alessandro A, et al, 2018; Chen T, et al, 2015), our accelerator can store all parameters on chip due to small-sized network architecture. With whole parameters stored on chip, we can save time cost caused by communication with DRAM. The detail information of parameters is shown in Table 1.

FC-1 layer occupies most of the parameter size, while other layers’ data is rather tiny and can be directly stored on chip. Considering the scale of FC-1 parameter, it is natural to share them between several PEs. In order to simplify the design, we set all PEs working synchronously and fetching exactly the same pretrained data at FC-1 computing step. Shared memory structure is consisted of 32 block memory generators, each for one kernel in FC-1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Layer | Filter | Kernel | Parameter | Parameter Size |
| conv1 | 32 | 3\*3\*1 | 288 | 36B |
| conv2 | 32 | 3\*3\*32 | 9216 | 1152B |
| fc1 | 32 | 16\*45\*32 | 737280 | 92160B |
| fc2 | — | — | 1024 | 128B |
| fc3 | — | — | 192 | 24B |

**Table.1 The Detail Information of Parameter**

The design detail of shared storage is demonstrated in Fig.4. PEs send target parameters’ loaf addresses to shared storage structure. These addresses are line addresses of BRAM blocks so BRAM blocks can access data with no delay. Parameters are stored along the third dimension in BRAM, which is consistent to the input data’s organization method of FC-1 layer. Shared-parameter data is sent to all PEs by broadcasting.



**Fig.4** FC-1’s Parameter Sharing Structure

As to other layers’ binary weight, we store them directly inside modules that mapped to corresponding layers. Similar to the shared parameter structure, each BRAM block is responsible for one filter. When the vector processing unit in Fig.5 starts computing, BRAM blocks directly send related parameters to the unit and these binary data then compute with activation. The vector unit will either keep original activation value or reverse it due to the input binary weight (indicating +1 or -1), each channel will have 32 temporary results. All temporary data will then be put through parallel adder tree to compute for result, each channel will get one valid data every computation and 32 valid data for 32 channels.

Prior batch-normalization parameters also need to be storage on chip. To pursue quantization accuracy, these data bitwise varies and thus it is better to storage batch-normalization parameter in flexible register.

**4.2 Bitwise Expansion**

Inside one convolution or full-connected layer, the input fix-point feature data is usually under normal distribution and varies in relatively small range, however, after MAC, the data’s variance can be huge and irregular (Wei Z, et al, 2017). Batch-normalization relies on these middle results’ mean and variance to improve data distribution, which is vital to final accuracy. If we simply apply the same data format as the input feature to middle results data in batch-normalization step, it will lead unnecessary loss to final prediction.

To handle this situation, we introduce bitwise expansion method which gives extra decimal bitwise to both feature data and normalization parameter when computing. After DSP outputting multiply results, these extra decimal bits will be cut and the data will return to original input format.

The batch-normalization operations can be divided into four steps: subtracting mean value, multiplying offset, dividing the square root of variance (which is substituted by multiplying the reciprocal of variance’s square root on our hardware design) and adding bias. We implement these four parts of normalization in pipeline way, as explained in Fig.6, to reduce the negative impact of multiply computation on FPGA.



**Fig.5** Vector Processing Unit



**Fig.6** Batch-Normalization Unit

Similarly, middle results of MAC process have same needs for bitwise expansion. The different point is MAC results usually need more bitwise in integer part instead of decimal number. We apply expansion to both normalization step and accumulator in adder tree of MAC, it turns out that this method ensures computing accuracy on hardware.

**4.3 Layer-by-layer Pipeline**

In deep convolution neural networks such as VGG-16 and AlexNet (Simonyan K, et al, 2014; Krizhevsky A. et al, 2012), it is difficult to keep this balance due that as networks going deeper, deep layers will demand layers ahead to generate feature result at a faster speed, which is beyond current hardware’s computing power limit.

The target neural network is shallow and tiny, so it is possible to keep balance between different layers. The key point of layer-by-layer pipeline’s implementation is to balance running periods between different function layers in neural network. In convolution neural networks, computation involves convolution kernels and feature’s sub-map on specific position is the basic computing model. This operation is time-costing and need large amount of circuit resource, so it is difficult to design balanced pipeline on resource-limited FPGA if choose convoluting computation as the basic grid of our pipeline. To decrease the waiting time and starting cost of pipeline, we use the “loaf data” in Fig.7 as our basic data operation unit.

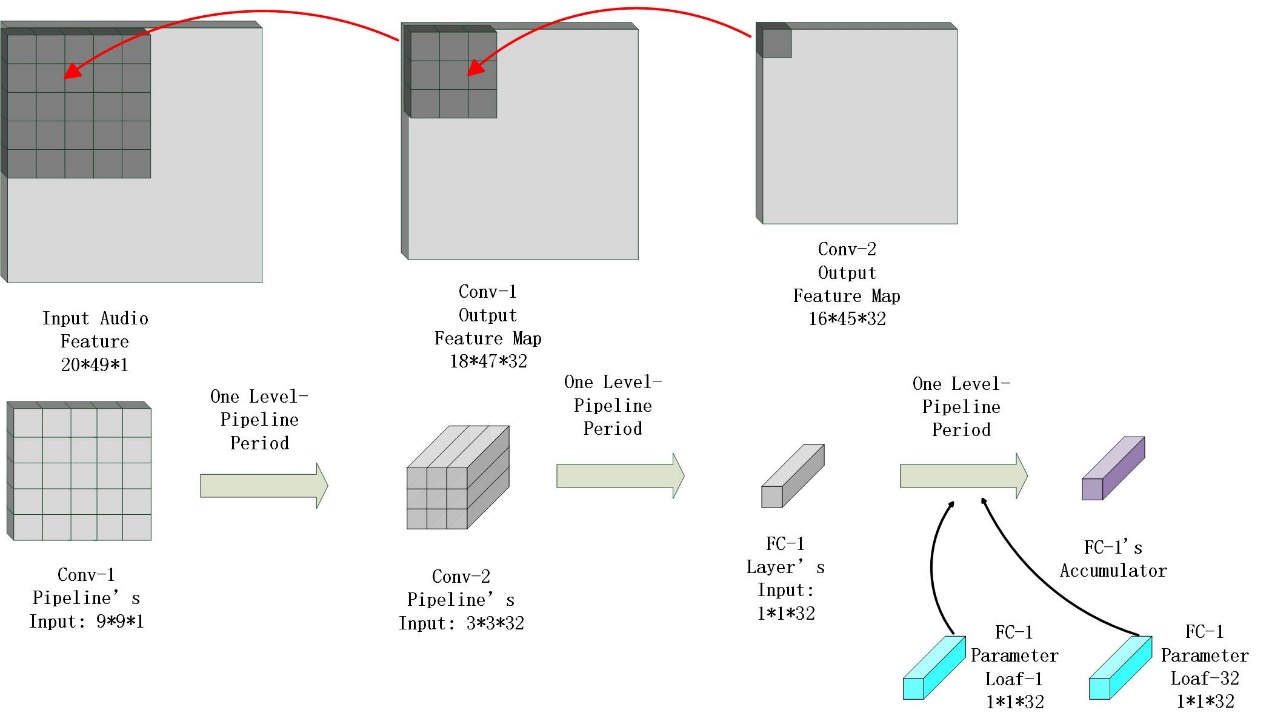
Fig.7 shows the cost of keeping balance between each network layer. To produce one unit of result in Conv-2 layers (which can just meets the need of starting full-connect layer’s pipeline) , this neural network has to compute one 3x3 slide window on Conv-1’s output map and compute nine 3x3 slide windows from a 5x5 area on input audio feature. Adjusting to this computation pattern, we expand the scale of Conv-1’s computing array to make it can generate nine 32x1 vectors in one macro pipeline period, and in next period these vectors will be sent to Conv-2 and generate one 32x1 vector for FC-1 layer’s input. In this way, Conv-1 layer, Conv-2 layer and FC-1 layer of the neural network can work in a pipeline mode, which in practice consists the “layer-by-layer” pipeline design.

In our neural network model, FC-1 layer occupies huge size of parameter and relatively small size of computation, and more importantly, FC-1 layer starts after convolution layers finishing computing corresponding data. It brings unbearable cost if FC-1 layer will wait until Conv-2’s computation is done, for it demanding lots of on-chip storage resource to keep middle result and increase pipeline’s waiting time. To eliminate the bottleneck of whole pipeline, we set “loaf data” as FC-1layer’s activating condition: every macro-period, FC-1 layer will get one vector (one load data) as input, fetch 32 groups of parameter from shared storage and compute them in one macro-period as well. The middle results only need one register which also functions as an accumulator. With the method shown in Fig.7, we finally get a balanced and high-performance layer-by-layer pipeline design.

**5. Experiment and Discuss**

**5.1 Quantized Model’s Performance**

We use Matlab-2018a’s quantizer function to turn feature and batch-normalization parameters into fix-point format with saturate mode. In order to find the best bitwise allocation scheme, we run a couple of quantization experiments and compare their accuracy performance.



**Fig. 7** Balancing Conv-1 and Conv-2

Considering running neural networks on our specific hardware platform, the data format must fit the hardware design code. We set the bitwise of all data must range in 16 bits to 32 bits, which is hardware-friendly to our FPGA platform, as the boundary condition for design space searching. During actual experiments, we determine the approximate distribution range of feature data, middle results and normalization parameters, it shows that the integer bitwise of middle results usually needs 8~12 bits while normalization parameter needs 20~21 bits for integer part. This result can help us to determine the upper bound of decimal bitwise. In deep neural networks, activation and middle results are relatively unsensitive to numerical precision, so we do not have to devote too much work on these data’s decimal bitwise. On the other hand, normalization parameters need more data format accuracy than middle results, so in principle, we give them decimal bitwise no less than middle result.

**Fig.8** Accuracy Experiment Result

The horizontal axis (MRDB, NRDB) means different combination of Middle Result Decimal Bitwise and Normalization Result (Feature Data) Decimal Bitwise.

To find best quantization bitwise allocation scheme, we conduct serval experiments under the condition discussed ahead and experiments’ result is illustrated in Fig.8 and Fig.9. In Fig.8, vertical axis shows the corresponding model’s prediction accuracy with different combination of MRDB and NRDB. It turns out when middle data apply 8-bit decimal bitwise and normalization parameter apply 9-bit decimal bitwise, this model will achieve best accuracy. We also implement the experiment that middle result owns more decimal length than normalization data’s which violates our searching principle, the final result supports our idea effectively.

It is also noticeable that when (MRDB, NRDB) is over (8, 9), model’s final accuracy does not rise with better middle results and feature data’s indication precision. Some works have proven that neural networks have numerical robustness in low-precision data format (Zeng X, et al; Cheng G, et al), this feature is widely used by deep neural networks’ quantization and can keep model’s original prediction performance well. On the other hand, final accuracy can do be improved by better indication precision at initial stage of experiment. We consider that the point (MRDB, NRDB) equaling (8, 9) lies in a balance condition where both robustness and numerical precision can function well. When decimal bits are increased and model is over this balancing point, model’s robustness is weakened by better data indication performance and this boost on numerical precision cannot cover the loss of robustness, which we consider is the reason why model’s prediction effect cannot be enhanced in last couples of experiments.

The experiment results on normalization parameters' quantization scheme are demonstrated in Fig.9. We set (MRDB, NRDB) as (8, 9) and keep other variables unchanged. It is clearly shown that model’s prediction accuracy is improved by better normalization parameters indication precision. However, the word length of these parameters cannot exceed the upper boundary 32 bits, so it is suitable to allocate 12 decimal bits for batch-normalization parameters. There is one thing need to be noticed, hardware cannot handle division operation as easy as Matlab code, so we turn variance’s division in batch-normalization into reciprocal multiplication and expand decimal bit-width to ensure accuracy.

We run our non-quantization version of Matlab code on Intel core i7-8700K with and without multi-thread accelerating library. We divide whole program into several function segments and test their running time. Table.2 shows that when ignore the MFCC segment, the second convolution layer is performance bottleneck on CPU platforms and has vital effect to the model, which is corresponded to the largest computing scale of Conv-2 layer. Data in Table.2a also illustrates that although parallelism function library is used and running time is reduced sharply, Conv-2 is still the most time-costing layer on CPU.

Quantization version of code runs 9.85% slower than non-quantization version, detail is shown in Table.2b. As discussed in section 3.2, although we apply quantization functions and fix-point computing in the code, it is still executed in floating mode on CPU for CPU platforms cannot process fix-point data well. This procedure brings extra work converting data between floating format and fix-point format, which we think is responsible for worse performance of quantized code. For the similar reason, different quantization formats will not make noticeable impact on running time on CPU platforms. To truly reflect our accelerator’s performance, we do not choose quantization version’s running time but the non-quantization version’s as our performance baseline.

|  |  |  |
| --- | --- | --- |
| 8700K without Parallelism | | |
| Function Segment | Time (Seconds) | Ration in Total Time |
| Data Loading & Pre-process | 9.413601 | 7.40% |
| Conv-1 | 3.084229 | 2.43% |
| Conv-2 | 114.582 | 90.14% |
| FC-1 | 0.023377 | <1% |
| FC-2 | 0.001659 | <1% |
| FC-3 | 0.001589 | <1% |
| Total | 127.1163 | 100% |
| 8700K with Parallelism | | |
| Function Segment | Time (Seconds) | Ration in Total Time |
| Data Loading & Pre-process | 9.804942 | 19.74% |
| Conv-1 | 1.803836 | 3.63% |
| Conv-2 | 38.02353 | 76.56% |
| FC-1 | 0.025257 | <1% |
| FC-2 | 0.001316 | <1% |
| FC-3 | 0.000981 | <1% |
| Total | 49.66721 | 100% |

**Table.2a** Running Time on CPU Platform (Non-quantization Version)

|  |  |  |
| --- | --- | --- |
| 8700K without Parallelism | | |
| Function Segment | Time (Seconds) | Ration in Total Time |
| Data Loading & Pre-process | 9.52507 | 6.82% |
| Conv-1 | 3.477169 | 2.49% |
| Conv-2 | 126.61824 | 90.67% |
| FC-1 | 0.02053 | <1% |
| FC-2 | 0.001604 | <1% |
| FC-3 | 0.0013259 | <1% |
| Total | 139.6440 | 100% |

**Table.2b** Running Time on CPU Platform (Quantization Version)

**Fig.9** The Relationship between Batch-Normalization Parameters’ Decimal Bits and Model’s Prediction Accuracy

**5.2 Accelerator’s Implement and Performance**

**Fig. 10** Performance Compared with Multiple CPU Platforms

To implement our layer-by-layer pipeline, it is necessary to expand Conv-1’s degree of parallelism to handle nine 3x3 slide windows on a 5x5 feature area. Not only the Conv-1 layer’s computing scale is expanded, but the data-address generating strategy is also modified to fetch input feature pixel in specific order.

By adapting pipeline on layers, target neural networks can be accelerated without putting between-layers results into DRAM and thus reducing memory accessing cost. In another word, we keep data stream in layer pipeline from input audio feature to final predict results without stop. The accelerator only communicates with DRAM in fetching and final writing back. Inside each layer’s pipeline, we also divide all computing into some function parts like vector computing unit, normalization unit in pipeline method, which can help to rise hardware running frequency.

We run this sound classification model on intel Core i7-8700K (3.7GHz, 6 cores, 95W) with single thread, intel Core i7-8700K with multi-thread and multi-node intel Xeon 5220 (2.2GHz, 18 cores, 125W) with Matlab distributed parallel library, the whole dataset contains 1512 audio files. We only test the running time of neural network’s forwarding part for we do not implement the MFCC and data pre-process on FPGA. Fig.10 shows that compared to state-of-art CPU platform, our single PE version accelerator achieves 18~300x throughput speed up ratio. Table.2 shows that Conv-2 layer is the most time-costing function, however, by using balanced layer-by-layer pipeline, our accelerator can eliminate bottlenecks on CPU platforms and achieve excellent accelerating performance. Also, the data stream inside the pipeline reduce the DDR bus communication tremendously, eliminate the DRAM limit on CPU platform.

The multi-PE version of our accelerator is implemented on Xilinx Vivado 2018.3 and KU-115 FPGA platforms. We conduct the test of computing accuracy, speed-up ratio and power performance validating hardware design. To ensure reliability, we conduct extensive pressure test for up to two hours. The implement results are shown in Table.3.

We compute the energy efficiency of state-of-art CPU platforms and ours. The results in Table.4 shows that by customized circuit design and replacing floating data with fix-point data, our accelerator has great energy efficiency improvement on this sound classification task.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| PE | LUT Utilization | FF Utilization | BRAM Utilization | DSP Utilization | Frequency |
| 1 | 25% | 14% | 9% | 12% | 150MHz |
| 2 | 47% | 26% | 10% | 23% | 150MHz |
| 3 | 66% | 38% | 11% | 36% | 150MHz |

**Table.3** Accelerator’s Implementation Results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 8700K | 5220-1Node | 5220-2 Node | 5220-4 Node | 1PE BWN | 2PE BWN |
| Perf. Per Watt (fps/W) | 0.23 | 0.47 | 0.43 | 0.4 | 471.63 | 753.41 |
| Board Power (W) | 95W | 125W | 250W | 500W | 7.794W | 9.758W |

**Table.4** Energy Efficiency on Different Platforms

In Table.5, we compare our accelerator with BWCNN-based (Binary Weight Convolution Neural Network) ASIC architectures, fully binarized CNN FPGA architectures and sparse RNN-based FPGA accelerators.

Table.5a illustrates comparison between BWCNN-based ASIC and ours. Two ASIC architecture own huge advantages on power-consuming and power-efficiency, however, our FPGA platform surpasses these ASIC design in expense, flexibility and perk performance.

The detail information of typical full-binary CNN-based FPGA accelerator is shown in Table.5b, together with ours. Our design performs better in peak performance, model’s accuracy loss and have larger throughput than two of targeted architectures. For fully-binarized accelerators taking less resource (which enables designer to set far more PEs than us) and bearing more prediction precision loss, it is considerable for some design can outperform ours in throughput.

Current state-of-art RNN-based (Recurrent Neural Network) usually use networks’ sparse feature to cut down useless computation thus accelerating original algorithm. For this reason, sparse accelerators have higher power-efficiency, however, our BWN-based convolution neural network accelerator still has least computing latency and relatively high computing performance.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Accelerator | Bo L, et al | Renzo A, et al | 1 PE BWN | 3 PE BWN |
| Platform | ASIC@28nm | ASIC@65nm | FPGA | FPGA |
| Frequency | 400MHz | N/A | 150MHz | 150MHz |
| Power | 0.054W | [15.54mW@0](mailto:15.54mW@0).6V | 7.794W | 13.136W |
| Peak Perf. | 25.6GOPS | 15GOPS@0.6V | 23.85GOPS | 71.55GOPS |
| GOPS/W | 474.07 | 965.25 | 2.37 | 5.45 |

**Table.5a** Comparison with Binary Weight Convolution Neural Network’s Architecture on ASIC

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Accelerator | Y. Umuroglu, et al | H. Alemdar, et al | Baicheng L, et al | 3 PE BWN |
| Platform | ZC706 | Kintex-7 160T | ZC706 | XCQU-115 |
| Frequency | 200MHz | 200MHz | 120MHz | 150MHz |
| Peak Perf. | 4.43GOPS | 56.09GOPS | 13.92GOPS | 71.55GOPS |
| Accuracy Loss | 0.64% | 0.75% | 0.41% | 0.35% |
| Throughput | 0.76K fps | 31.8Kfps | 1.4Kfps | 11Kfps |

**Table.5b** Comparison with Full-Binary Convolution Neural Network’s Architecture on FPGA. \*Peak Perf. And Throughput are equivalent to 16bit fixed.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Accelerator | Song H, et al | Shuo W, et al | Shijie C, et al | 3 PE BWN |
| Platform | XCKU060 | Virtex-7 | ZC706 | Arria 10 GX1150 |
| Frequency | 200MHz | 200MHz | 200MHz | 150MHz |
| Power | 41W | 22W | 19.1W | 13.136W |
| Perf. at Batch 1 | 8.8GOPS | 43.7GOPS | 304.1GOPS | 71.55GOPS |
| Latency | 15878.4us | 3206.4us | 460.8us | 218.4us |
| GOPS/W | 6.9 | 6.0 | 15.9 | 5.45 |

**Table.5c** Comparison with Sparse Recurrent Neural Network’s Architecture on FPGA. \*Latency is the time each accelerator needs to process whole audio frame.

**6. Conclusion**

To pursue power-efficiency, high-performance computing and prediction accuracy, we first optimize a sound classification algorithm based on deep convolution neural network. By quantization method, the activation size is reduced sharply and time-consuming floating computation is replaced by faster fix-point computation. Our accelerator design then focuses on parameter-shared storage structure, bitwise expansion and balanced layer-pipeline. With the combination of deep convolution neural network quantization and customized circuit design, we bring out a high-throughput, energy-efficient and high-performance sound classification computing platform based on FPGA. Compared with current state-of-art CPU platform, BWCNN-based ASIC architectures, fully binarized FPGA accelerators and sparse RNN accelerators, our hardware design has great advantages on computing performance, prediction accuracy, time-delay and power efficiency. We implement our design on Xilinx FPGA, it turns out this accelerator is a reliable and high-performance intelligent computing platform.

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**Compliance with ethical standards**

**Conflict of interest**

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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