Quant-PIM: An Energy-efficient Processing-in-memory Accelerator for Layer-wise Quantized Neural Networks

Young Seo Lee, Eui-Young Chung, Young-Ho Gong*, and Sung Woo Chung*

***Abstract*—Layer-wise quantized neural networks (QNNs), which adopt different precisions for weights or activations in a layer-wise manner, have emerged as a promising approach for embedded systems. The layer-wise QNNs deploy only required number of data bits for the computation (e.g., convolution of weights and activations), which in turn reduces computation energy compared to the conventional QNNs. However, the layer-wise QNNs still cause a large amount of energy in the conventional memory systems, since memory accesses are not optimized for the required precision of each layer. To address this problem, we propose *Quant-PIM*, an energy-efficient processing-in-memory (PIM) accelerator for layer-wise QNNs. Quant-PIM selectively reads only required data bits within a data word depending on the precision, by deploying the modified I/O gating logics in a 3D stacked memory. Thus, Quant-PIM significantly reduces energy consumption for memory accesses. In addition, Quant-PIM improves the performance of layer-wise QNNs. When the required precision is half of the weight (or activation) size or less, Quant-PIM reads two data blocks in a single read operation by exploiting the saved memory bandwidth from the selective memory access, thus providing higher compute-throughput. Our simulation results show that Quant-PIM reduces system energy by 39.1~50.4% compared to the PIM system with 16-bit quantized precision, without accuracy loss.**

***Index Terms*—Processing-in-memory, accelerator, quantized neural network, layer-wise quantization, energy efficiency**

I. Introduction

RECENTLY, deep neural networks (DNNs) have been widely adopted in various applications such as image classification and speech recognition. In general, DNN applications cause high energy consumption, since it requires millions of multiply-accumulate (MAC) operations and high memory bandwidth, both. This high energy consumption makes it difficult to run the DNN applications on energy-constrained embedded systems. To address this problem, a quantized neural network (QNN) has emerged as a viable solution for embedded systems [2]. The QNN reduces computation energy by replacing floating-point MAC operations with fixed-point MAC operations. In addition, since the QNN exploits relatively low-precision weight (or activation) instead of high-precision one, it has lower memory bandwidth requirement than the DNN.

However, as the volume of the input data and the number of layers increase, QNNs still cause high energy consumption. Several studies have reduced energy consumption by adopting different precisions for weights or activations in a layer-wise manner [3][10], since the precision requirement varies across layers within a network. The layer-wise QNNs deploy only required number of data bits for the computation (e.g., convolution of weights and activations), which in turn reduces computation energy compared to the conventional QNNs. Though many researchers have focused on the computation energy reduction by adopting layer-wise QNNs [3][10], they did not consider the optimization of memory accesses for layer-wise QNNs. Even with low precision in the layer-wise QNNs, each single memory access still transfers a full data word (e.g., 64-bit or 32-bit); note, the conventional memory systems do not allow transferring data of which size is less than the data word size in a single memory access. Thus, the layer-wise QNNs cause a large amount of energy due to the non-optimized memory accesses, which is same as the conventional QNNs.

In this paper, we propose *Quant-PIM*, an energy-efficient processing-in-memory (PIM) accelerator for layer-wise QNNs. We adopt Quant-PIM to a high bandwidth memory (HBM), which is widely deployed for neural network (NN) hardware accelerators [7][8]; note HBM has recently been adopted to an embedded NN system [7]. Quant-PIM consists of two parts: i) I/O gating logics and ii) processing units for the gated I/O. In Quant-PIM, a single memory access selectively loads/stores only required data bits within a data word depending on the precision. To enable such selective memory accesses, we modify the I/O gating logics of the HBM. Quant-PIM controls the I/O gating logics depending on the required precision of a layer. In addition, to guarantee the MAC operations with any precision, we allocate multiple binary MAC units and accumulators into the base die of the HBM. Thus, Quant-PIM significantly reduces energy consumption for memory accesses depending on the required precision of a layer, while ensuring normal computation with any precision. Furthermore, Quant-PIM improves the performance of layer-wise QNNs. When the required precision is half of the weight (or activation) size or less, Quant-PIM reads two data blocks[1] in a single read operation by exploiting the saved memory bandwidth from the selective memory access, achieving higher compute-throughput.

II. Related Works

There have been many studies on the accelerators for layer-wise QNNs [3][10][13]. Judd et al. introduced an accelerator which provides the bit-serial execution of the MAC operation with any precision [3]. The accelerator serially executes a bit operation per clock cycle with high parallelism, which significantly reduces computation energy. Umuroglu et al. also presented a vectorized bit-serial matrix multiplication

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[1]In this paper, a data block indicates the data accessed from the main memory with a single read operation, whose size is typically determined by the product of data bus width and burst length.

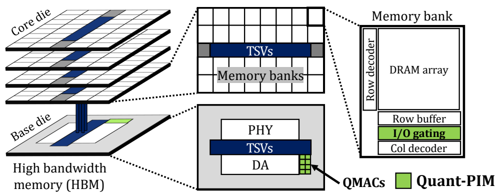

Fig. 1. Overview of the proposed Quant-PIM.

technique with high parallelism [13]. In addition, Sharma et al. proposed an accelerator with a bit-decomposition technique [10]. They divided a MAC operation into multiple sub-MAC operations to support variable precision, which reduces the amount of the required resources for the MAC operation. However, all the above studies focused on reducing computation energy for MAC operations, assuming that all the weights and activations are already prepared in on-chip buffers. They did not consider the optimization of memory accesses for layer-wise QNNs, thus causing a large amount of energy reading the data from the main memory. Different from the previous studies, our proposed technique selectively accesses only required data bits within the data word depending on the required precision of a layer, which significantly reduces energy consumption for memory accesses. To the best of our knowledge, this paper is the first study to optimize the memory accesses with any precision in the layer-wise QNNs.

III. QUANT-PIM

We propose a PIM accelerator for layer-wise QNNs called Quant-PIM. Quant-PIM significantly reduces system energy, since 1) it reduces memory power consumption by selectively accessing only required data bits at a bit-level granularity, and 2) it improves performance by reading two data blocks in a single read operation when the required precision is half of the weight (or activation) size or less.

A. Overall Architecture

As shown in Fig. 1, we adopt Quant-PIM to the HBM. The HBM has two different parts: base die and core dies. Since the base die is a logic die (not a memory die), it has been widely deployed for implementing small accelerators [5][11]. We implement processing units of Quant-PIM into the base die of the HBM, which is called quantized MAC units (QMACs); we allocate eight QMACs (i.e., one QMAC per memory channel), since each memory channel is independently accessed. More importantly, we modify the I/O gating logics in the memory banks of the core dies. In the original HBM, the I/O gating logic accesses the columns in the row buffer at a word-level granularity, depending on the result of the column decoder. Accordingly, a single memory access in the original HBM transfers the full data word even with low precision. On the other hand, Quant-PIM allows memory accesses at a finer granularity than the original HBM. Depending on the required precision of a layer, Quant-PIM controls the I/O gating logics to access the columns in the row buffer at a bit-level granularity.

B. Processing Flow

Fig. 2 describes the detailed design of Quant-PIM and the procedures for Quant-PIM in a single memory channel. The procedures for Quant-PIM are as follows (① to ⑦ in Fig. 2).

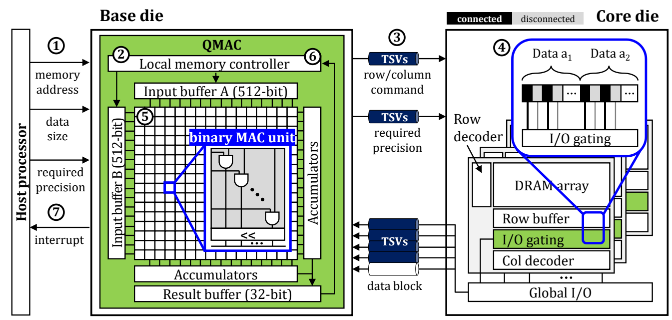

Fig. 2. Detailed design of Quant-PIM and procedures for Quant-PIM in a single memory channel.

① The host processor offloads the MAC operations for layer-wise QNNs by sending the memory address, data size, and required precision to the QMAC.

② The local memory controller of the QMAC generates row and column commands based on the memory address and data size.

③ The QMAC sends the row/column command and required precision to the target memory bank depending on the memory address.

④ Quant-PIM controls the I/O gating logics in the memory bank depending on the required precision, so that it selectively reads only required data bits within a data word.

⑤ The QMAC executes the MAC operations based on the data block loaded from the memory bank. Since one MAC operation with n-bit precision is replaced with n^2 1-bit MAC operations [13], the QMAC has multiple binary MAC units and accumulators. Considering the worst-case precision (i.e., 16-bit) of the weights or activations in the conventional QNNs, we allocate 256 (=16^2) binary MAC units and accumulators in the QMAC. Thus, the QMAC guarantees the MAC operations with 16-bit or less precision. The accumulated result of the MAC operations is stored in the result buffer.

⑥ The local memory controller of the QMAC stores the accumulated result to the memory bank. Similar to the read operation in step ④, Quant-PIM selectively stores the required data bits based on the precision.

⑦ Quant-PIM repeats the step ② to ⑥ until all the offloaded MAC operations are completed. Then, Quant-PIM notifies the host processor that all the offloaded MAC operations are completed through an interrupt signal.

Based on the procedures for Quant-PIM, Quant-PIM reduces I/O power when the required precision is lower than 16-bit, since it selectively accesses only required data bits within a data word. Thus, Quant-PIM reduces the total HBM power consumption, which results in the system energy reduction; I/O power occupies up to 70% of the total HBM power [12].

Furthermore, Quant-PIM improves the performance of layer-wise QNNs, when the required precision is half of the weight (or activation) size or less (i.e., 8-bit or less). In step ④, Quant-PIM reads two data blocks (data a_1 and a_2 in Fig. 2) in a single memory operation by exploiting the saved memory bandwidth from the selective memory access. Note Quant-PIM coalesces memory requests to two data block addresses. However, Quant-PIM is different from a memory coalescing

TABLE I
REQUIRED PRECISION PER LAYER WITH RELATIVE ACCURACY

Network	100% relative accuracy	99% relative accuracy
GoogLeNet	10-8-10-9-8-10-9-8-9-10-7	10-8-9-8-8-9-10-8-9-10-8
AlexNet	9-8-5-5-7	9-7-4-5-7
NiN	8-8-8-9-7-8-8-9-9-8-8-8	8-8-7-9-7-8-8-9-9-8-7-8

technique which is widely adopted in GPU; the memory coalescing technique only coalesces memory requests to the same data block address. In step 5, the QMAC executes the MAC operations for both data blocks a_1 and a_2 at the same time, by deploying the binary MAC units and accumulators; since the 8-bit MAC operations for a single data block requires only 64 binary MAC units among 256 binary MAC units, Quant-PIM is able to simultaneously execute the 8-bit MAC operations for two data blocks. Thus, Quant-PIM provides higher compute-throughput, resulting in the system energy reduction.

IV. EVALUATION

A. Methodology

Table I shows the required precision per layer with relative accuracy compared to the 16-bit quantized precision for three representative neural networks [3]. For quantization, a uniform quantization method is adopted, which replaces 32-bit floating-point data with 16-bit integer data by deploying the following equation (which is a general quantization method [8]).

$$quantized\ data = real\ data * scale \quad (1)$$

The required precision is obtained by repeatedly removing the least significant bit (LSB) of the 16-bit quantized weights and activations until the relative accuracy decreases; note removing the LSBs of the already quantized weights or activations is also the uniform quantization method. Based on Table I, we evaluate the execution time, power consumption, peak on-chip temperature, and system energy of Quant-PIM across neural networks. We consider a 16-bit PIM system as our baseline; the 16-bit PIM system reads 16-bit quantized weights and activations from the HBM and then execute the MAC operations with 16-bit precision. We first implement the QMAC (in the base die) in Fig. 2 with Verilog HDL using Design Compiler and IC Compiler based on Samsung System LSI 28nm process technology. We set the clock frequency of the QMAC to 1GHz, operating with the HBM synchronously. According to the implementation result, the QMAC is able to operate at 1GHz even in the worst-case precision (i.e., 16-bit). In addition, we obtain the dynamic power and leakage power of the QMAC by 1.0~12.7mW and 36.2µW, respectively; we extract dynamic power depending on the required precision. For the additional circuits in I/O gating logics (in the core die), we conservatively evaluate the power consumption based on logic process technology[2]. According to our implementation, we extract the dynamic power and leakage power of the additional circuits in I/O gating logics by 22.9mW and 14.7µW per memory channel, respectively.

We evaluate the execution time and power consumption of Quant-PIM across neural networks using gem5-aladdin [9] with a cycle-accurate DRAM simulator [6]. We reflect the clock frequency and power consumption for both the implemented QMAC and additional circuits in I/O gating logics to the simulator. We also reflect the performance and power of the HBM2 referring to the timing/current parameters [5][6][11]. Based on the power consumption, we evaluate the peak on-chip temperature of Quant-PIM using HotSpot 6.0 [14]. Since peak on-chip temperature is strongly affected by heat dissipated from power consuming units such as GPU, we assume that the HBM (including Quant-PIM) is integrated with a high-end GPU for a gaming console [15]. We also evaluate the system energy and area overhead of Quant-PIM.

[2] The logic implemented with memory process technology is more energy-efficient than that implemented with logic process technology [4].

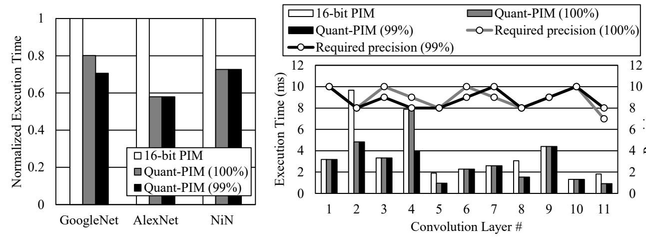

Fig. 3. Execution time across neural networks (left) and layer-wise execution time for GoogLeNet depending on the required precision (right).

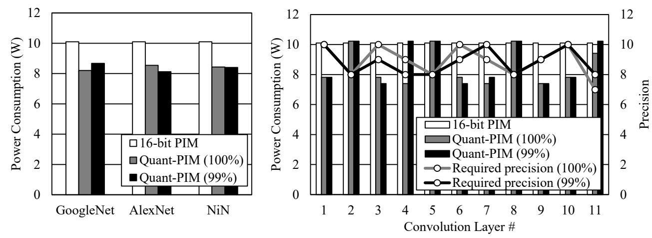

Fig. 4. Power consumption across neural networks (left) and layer-wise power consumption for GoogLeNet depending on the required precision (right).

B. Results

1) Execution time

Fig. 3 (left) shows the execution time of Quant-PIM across neural networks. Quant-PIM reduces execution time by 19.9~42.1% (27.4~42.1%) compared to the 16-bit PIM system, while maintaining 100% (99%) relative accuracy. We break down the execution time for GoogLeNet[3] into each layer, as shown in Fig. 3 (right). Quant-PIM (100%) significantly reduces execution time at the convolution layer 2, 5, 8, and 11 compared to 16-bit PIM. When 1% relative accuracy loss is tolerable, Quant-PIM (99%) additionally reduces execution time at the convolution layer 4. As explained in Section III, when the required precision is 8-bit or less, Quant-PIM simultaneously reads two data blocks and executes MAC operations for the two data blocks. Thus, Quant-PIM offers high compute-throughput, resulting in the short execution time for layer-wise QNNs.

2) Power consumption

Fig. 4 (left) shows the power consumption of Quant-PIM across neural networks. Quant-PIM reduces power consumption by 15.4~18.2% (14.2~19.6%) compared to the 16-bit PIM system, while maintaining 100% (99%) relative accuracy. We break down the power consumption for GoogLeNet into each layer, as shown in Fig. 4 (right). As explained in Section III, Quant-PIM reduces I/O power when the required precision is lower than 16-bit, since it selectively accesses only required data bits. However, Quant-PIM (100%) does not reduce the power (not energy) consumption at the convolution layer 2, 5,

[3] We present the layer-wise results only for GoogLeNet due to the page limit.

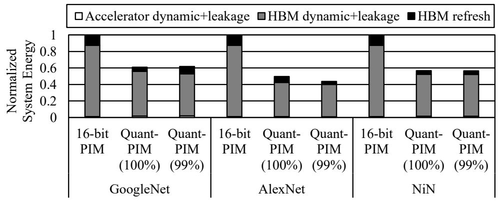

Fig. 5. System energy breakdown across neural networks.

and 8, since two weights or activations (16-bit, in total) in different data blocks are transferred together; the required precision is 8-bit. With 1% relative accuracy loss, Quant-PIM (99%) does not reduce power consumption at the convolution layer 4 and 11 as well; the required precision is 8-bit. Though Quant-PIM causes additional power from the additional circuits in I/O gating logics, this power overhead is only 2.2% of the total power consumption, which is much smaller than the I/O power reduction (up to 19.6%).

3) *Peak on-chip temperature*

Based on the power consumption for neural networks, we analyze the peak on-chip temperature, considering heat dissipated from the GPU. The peak on-chip temperature of the 16-bit PIM system is 88.2℃ for all the neural networks. On the other hand, the peak on-chip temperature of Quant-PIM is 84.8℃, 85.4℃, and 84.9℃ for GoogLeNet, AlexNet, and NiN, respectively. In all the neural networks, Quant-PIM has lower peak on-chip temperature than the 16-bit PIM system, since it reduces I/O power consumption.

4) *System energy*

Fig. 5 shows the system energy of Quant-PIM across neural networks. Quant-PIM reduces system energy by 39.1~50.4% (38.3~56.4%) compared to the 16-bit PIM system, while maintaining 100% (99%) relative accuracy. Since the accelerator itself causes negligible energy (< 1% of the total system energy) due to its extremely small power, the HBM (memory) energy accounts for most of the total system energy. Quant-PIM (both 100% and 99%) significantly reduces the dynamic and leakage energies of the HBM compared to the 16-bit PIM system due to the following reasons: 1) Quant-PIM reduces power consumption when the required precision is lower than 16-bit. 2) Quant-PIM provides higher compute-throughput when the required precision is 8-bit or less, which results in the short execution time for layer-wise QNNs. In addition, Quant-PIM (both 100% and 99%) has lower HBM refresh energy than the 16-bit PIM system. When peak on-chip temperature exceeds 85℃, the HBM requires frequent refresh operations to retain the data in the memory cells, which in turn increases refresh energy [1]. As explained earlier, Quant-PIM has peak on-chip temperature lower than 85℃ in most cases, which leads to lower refresh energy. Though the peak on-chip temperature of Quant-PIM exceeds 85℃, HBM refresh energy is reduced due to the short execution time.

5) *Area overhead*

According to the implementation results, the area is only 0.16mm^2 and 0.02mm^2 for all the QMACs and additional circuits in I/O gating logics, respectively. Since the area of the HBM base die is 96mm^2 [11], Quant-PIM causes negligible area overhead (< 0.2% of the HBM base die area).

V. Conclusion

We present a PIM accelerator for layer-wise QNNs called Quant-PIM. Quant-PIM significantly reduces system energy, since 1) it reduces memory power consumption by selectively accessing only required data bits at a bit-level granularity, and 2) it improves performance by reading two data blocks in a single read operation when the required precision is half of the weight (or activation) size or less. Our simulation results show that Quant-PIM reduces system energy by 39.1~50.4% without accuracy loss, compared to the 16-bit PIM system. Though we only consider the layer-wise QNNs maintaining 100% (99%) relative accuracy, Quant-PIM could further improve energy efficiency when tolerating moderate accuracy loss. For example, in the case of GoogLeNet with 4-bit quantization, Quant-PIM reduces system energy by 67.6% with 89.4% relative accuracy, compared to the 16-bit PIM system. We expect that Quant-PIM synergistically co-operates with the recent accelerators for energy-efficient layer-wise QNNs.

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