RFC-HyPGCN: A Runtime Sparse Feature Compress Accelerator for Skeleton-Based GCNs Action Recognition Model with Hybrid Pruning

1. Introduction

Action recognition based on deep learning has the great potential being applied in kindergartens, hospitals and stadiums to prevent danger motions. Skeleton-based graph convolutional networks (GCNs) methods have achieved state-of-the-art (SOTA) prediction accuracy in the field. Mature pose estimation algorithms extract human skeletons from video stream with real-time speed, for example Open pose and Alpha pose. GCNs action recognition models and pose estimation models thus can combine into an end-to-end system.

Despite skeleton-based GCNs having great advantages, several problems limit their applications in expected scenarios. Firstly, intensive computation and large network architectures are embedded in skeleton-based GCNs, causing great computing cost on GPU. Mobile pose can produce human skeletons on mobile platform Snapdragon 845 with 60 fps and 44.4 fps/Watt, while 2s-AGCN model merely has a performance of 28 fps and 0.11fps/Watt on Nvidia’s 2080Ti GPU. The computing speed and power-consumption’s gap indicates a great importance on accelerating GCNs action recognition algorithms. Secondly, the expected application environment of action recognition models poses stringent constraints on power-consumption and throughput. However, the high-performance GPU cannot meet the power-efficiency demand.

Pruning and sparsification are two effective methods to relieve model’s complexity. However, conventional pruning method on Convolutional Neural Networks (CNNs), or GCNs’ sparsification on large graphs methods are unsuitable for skeleton-based GCNs. There are two reasons. (i) *Dataflow is transformed:* Graph computation is introduced to raise prediction performance but changes the dataflow at the same time. When being conducted on different dataflows, traditional pruning methods for CNNs may not achieve the same computation-skipping efficiency. (ii) *Skeleton-relationship graph is unchangeable and sensitive.* Some works use pooling or graph sparsification to drop unimportant edges and points to decrease the scale of computation. However, the human skeleton graph cannot be modified from the view of Physiology for human bones and joints’ connection being unchangeable. Particularly, in some GCNs models there exist learnable hidden information graph, which lacks sparsity. The subtle elements in such graph are proved to be positively associated with prediction performance, for instance in 2s-AGCN model, the prediction accuracy decreases by 2.3% without learnable matrix.

Although there are many hardware accelerators for sparse CNNs and GCNs, previous works are not likely to be the best choice for high-throughput GCNs action recognition architecture. On the one hand, sparse CNNs accelerator is established on pruned models and computation reduction, but as is stated above, such pruning method cannot skip graph computation efficiently. Besides, zero-skipping dataflow is applied to ignore noneffective feature computation in sparse CNNs. However, when used in a layer-pipelined high-performance architecture, zero-skipping cannot reduce the useless on-chip storage. On the other hand, previous GCNs’ accelerators focus on utilizing the sparsity in target graph and on keeping a balancing workload dispatch. Meanwhile, data sparsity in action recognition GCNs is derived from feature and pruned weight, not the graph.

For these reasons, efficient pruning methods together with specific accelerator designs are urgently required to accelerate GCNs action recognition workloads. We therefore present RFC-HyPGCN: a runtime sparse feature compress accelerator for skeleton-based GCNs action recognition model with hybrid pruning in this paper.

A hybrid GCNs’ pruning method is proposed, which can reduce convolutional parameters as well as skipping graph computation efficiently. We reorganize dataflow by changing the multiply order of graph workloads and spatial convolution. Under new dataflow, a group of graph computation and spatial convolution is skipped if the parameter is pruned as zero. As to temporal convolution, multi-grained pruning method is elaborately designed. Fine-grained pruning operation can be dealt as whether to sample current data in time series, while coarse-grained pruning is decided by spatial convolution’s pruned dataflow. The experiments demonstrate that better prediction accuracy and hardware-friendly feature can be possessed by our pruned model compared with conventional pruning methods under the same compress ratio. Additionally, quantization and input-skipping are applied on software level.

We also design an application-specific architecture, where ten convolution blocks are mapped on a single chip for high throughput. Different from previous works, in our layer-pipelined architecture, challenges are not only reflected on four kinds of sparse tasks: graph computation, spatial convolution, temporal convolution and shortcut merging, but also on how to efficiently store sparse intermediate results on chip. Although CSC is the most common compact format, its irregular memory access and extra encoding/decoding cost are negative to circuits design. To address these challenges, our sparse-degree-based runtime sparse feature compress method is proposed, which splits data encoding/decoding and corresponding storage into fine-grained bank and mini-bank. Finally, dynamic data scheduling is applied intra process elements (PE) to decrease the utilization of DSPs.

The contribution of this paper is:

1. We propose a hybrid pruning method on 2s-AGCN model, which contains graph-convolution united pruning on spatial convolution task and multi-granularity on temporal convolution task. The experiments show that this method is better than structured and unstructured pruning on computation-skipping and prediction accuracy.
2. A co-designed architecture is implemented by us, including dynamic dataflow and a runtime sparse vector compress method. The proposed online data compressing and storage modules reduce the utilization of hardware resource, enabling our layer-pipelined architecture. Also, the DSP array’s size of each convolution layers can be adjusted to balance every segment of pipeline or fit in different scales of computing resource.
3. Our design is implemented on Xilinx XCKU-115 FPGA platforms with 172 MHz. It can achieve 9.59x accelerating ratio compared with Nvidia 2080Ti and 2.56x with Nvidia V100 with 10W power of consumption. It turns out to have the potential to apply in end-to-end and low-power real time environments.

This article is organized as follows: the 2s-AGCN model and related work is introduced in Background, the hybrid pruning method is illustrate in Methodology, the hardware design is interpretated in Architecture and the experiment results is shown in Experiment. In Conclusion section, we summarize our work and future improvement.

1. Background
2. *2s-AGCN model*

The skeleton-based action recognition GCN models depends human skeleton vectors as input, which can be generated by pose estimation algorithms. Several human skeleton datasets have been proposed, for example xx, xx and xx. There are ten convolutional blocks and one fully-connected layer (FC layer) in 2s-AGCN model. As shown in Fig. 1a (the structure in Fig.1, left), the computation in each block can be divided into five phases: graph computation, self-similarity computation, spatial convolution, temporal convolution and shortcut connection. Batch-normalization and ReLU activation follow behind each convolution operations. With network going deeper, more channels are stacked on feature. Fig. 1b (the structure in Fig.1, right) illustrates this tendency in data dimension.

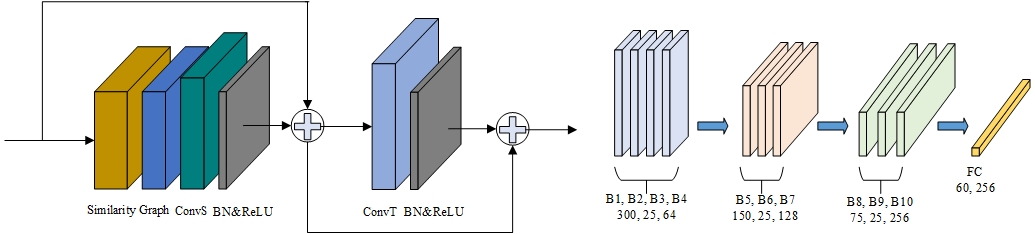


Figure 1. (a). Structure of the basic convolutional block. ConvS stands for spatial convolution and ConvT stands for temporal convolution. (b). Variance of the feature dimension. There are 25 key joints in human skeleton and 300 skeleton vectors in the original input feature.

In each layer’s graph computation, three different graphs are embedded: , and . The first part is the static human skeleton graph, the second part is a learnable skeleton connection graph and is a data-dependent graph generated from self-similarity process. Elements in are trained to indicate hidden relationships between joints and bones. Unlike static graph , is dense and sensitive to numerical changes. is produced via Eq. 1, where high-dimension tensors’ transposition and multiplication are conducted on input feature and represents similarity coefficient. To sum up, the computation of graph and spatial convolution can be described as Eq. 2. denotes the kernel size of the graph computation and is set to 3 in the 2s-AGCN model. The kernel size of spatial convolution’s weight, is set to 1.

(1)

(2)

Different from and which are determined before inference, relies on input feature, thus needs runtime computing for each prediction. Table. 1 demonstrates the computing cost of self-similarity workloads. The running performance of 2s-AGCN with and without are tested on Nvidia V100. At the cost of more computing complexity and longer time-delay, only elevates prediction accuracy by 0.3%. From the view of software-hardware co-design, dropping graph is a reasonable trade-off for workload reduction.

|  |  |  |  |
| --- | --- | --- | --- |
|  | accuracy | throughput | power efficiency |
| 2sAGCN+C | 93.70% | 69.38fps | 0.28fsp/watt |
| 2sAGCNwoC | 93.40% | 98.87fps | 0.40fps/watt |

Table 2. ’s influence on 2s-AGCN model. The throughput can be elevated by 29.83% without .

Following the spatial convolution, temporal convolutional layer is set at the end of each convolutional block. With kernel size of 9x1, temporal convolution extracts information from nine skeleton vectors in time order. Despite the insertion of the graph computation, temporal convolution layer in block can still be seen as the leading neighbour of spatial convolution layer in next block because graph computation does not change temporal convolutional result along its output-channel dimension, and spatial convolution operates indirectly on temporal convolution’s output. For above reasons, the connection between neighbours’ filters and channels can be kept, as shown in Fig. 2. When all spatial filters prune the same input channel, the effect can work on a reverse direction to invalidate the corresponding temporal filter of leading neighbour. Based on pruned spatial convolution layers, this code guides us to conduct coarse-grained pruning on temporal convolutional filters.

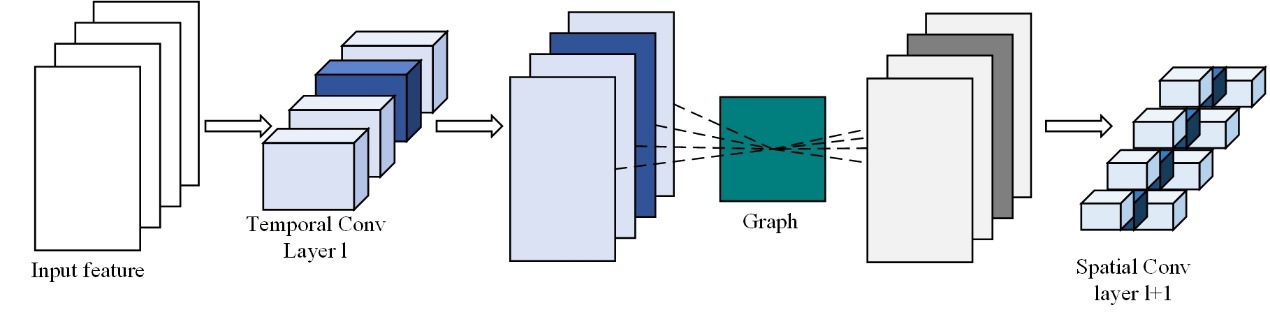


Figure 2. Temporal convolution’s output channel is the input channel of spatial convolution.

1. *Related Work*

**Sparse CNNs Accelerators on FPGA.** Works on FPGA-based acceleration of sparse CNNs can be categorized by different pruning granularity levels: (i) specific on structured pruned models, (ii) specific on unstructured pruned models, (iii) specific on mixed-grained pruned models. Zhu et al improve the ASIC-based SCNN and implement the hardware design on FPGA. This work presents a zero-skipping dataflow for feature, whose zero elements are generated by coarse-grained pruning. Although such method raises computing efficiency, zero elements in temporal result still occupy storage resource. Lu et al. propose a weight-oriented dataflow with tile look-up table on FPGA. By using element-matrix multiplication as the core operation, Lu et al. accelerates fine-grained pruned CNNs with little decoding cost. However, our 2s-AGCN model differs from above simple convolutional workloads in that each element in feature is generated by graph matrix multiplication. Despite this weight-oriented design ignores useless convolutional computation, it cannot skip corresponding graph computation. Li et al. work on PCONV, a mixed-grained pruning method where structure filter-dropping and unstructured pruning are combined. With weight-stationary dataflow designed on FPGA, Li et al. improve the computing efficiency by 14.7%~44%. However, this work still occupies storage space for huge scale of zero data like Lu et al, and its simple hardware structure cannot tackle four different workloads in our task.

**GCN Accelerators on FPGA**. Many works on accelerating large graph’s GCNs based on FPGA are presented in recent time. AWB-GCN combines offline software averaging and runtime hardware workloads balancing on several large graph datasets. Zhang (ASAP GCN) et al. partition input data into smaller segments, then perform graph sparsification and node re-ordering for computation reduction and data locality. Hy-GCN splits GCNs workloads into *Aggregation* and *Combination* phases. Different hardware structures and dataflows are designed for two phases respectively. To sum up, above works focus on: (i) leveraging and expanding graph adjacency matrix’s sparsity, (ii) avoiding irregularity and randomness of data distribution in graph computation, (iii) keeping balanced workloads between PEs or computing phases, via offline and online ways. Unfortunately, graph in skeleton-based GCNs for action recognition models is dense and unchangeable. The data sparsity is embedded in temporal feature and pruned weights, not the graph. Moreover, action recognition GCNs behave not only like CNNs, but also like graph processing, leading to graph-specific hardware design requirements. Therefore, current specialized architectures on CNNs and GCNs cannot efficiently perform target algorithms since they just address one of the two sides.

While there exist many GCNs accelerators on large graph in social media and graph analytics, few works have been proposed to accelerate skeleton-based GCNs for action recognition. ST-GCN, a smaller GCNs model for action recognition, is accelerated by Ding et al. on FPGA. Their work falls short on more complex action recognition GCNs for: (i) they only apply quantization on model, does not prune or optimize ST-GCN from the view of software-hardware co-design; (ii) Ding et al. compress human skeleton graph into CSC format, while skeleton relationship matrix in some models is learnable and dense; (iii) their hardware design is established on sparse matrix-vector multiplication (SpMV) units, but only skeleton adjacent matrix is compressed. Data sparsity is not thoroughly utilized in their work; (iv) although the proposed single PE design improves DSP efficiency, its throughput performance does not meet the requirement of expected application scenario.

1. Methodology

This section introduces our hybrid pruning method for action recognition GCNs. The dataflow reorganization, coarse-grained and fine-grained pruning on temporal convolution are described respectively.

1. Dataflow Reorganization

After clipping self-similarity graph, the computing flow between graph and spatial convolutional filters can be further summarized as Eq. 3, where denotes from Eq.2. The computing order of this part is first high-dimensional matrix multiplication with , secondly the spatial convolution of and finally the result merging of three loops. In this dataflow, common pruning methods only functions on spatial second phase but cannot optimize the graph computation, which occupies 49.83% of total workloads in Eq.3.

(3)

To better analyse the dataflow, we simplify the cases by extracting first two phases and its output . A pixel can be described as , where represent height, width and output-channel coordinates respectively. Eq. 4.1 can then be deduced from Eq. 3 and is the acronym of input channel. Under the commutative law of multiplication, Eq. 4.1 therefore is transformed into Eq. 4.2. By reorganizing the computing order between graph phase and convolution phase, an opportunity for graph-skipping pruning is offered here. If the parameter element is pruned to zero, the graph matrix multiplication in current output channel can be ignored. Further, if we set all convolutional parameters in input channel as zero, then all graph computation can be skipped in current loops. The dataflow reorganization is then proposed when we apply above method to three loops in Eq. 3. Unlike conventional structure pruning method which drops different channels on filters, weights in specific input channels are all set as zero on every spatial filter in current convolutional blocks. In this way, not only the convolution workload is reduced, but also the graph computation is skipped.

(4.1)

(4.2)

Since the graph-skipping strategy has been determined by dataflow reorganization, the next step is choosing the input channel to be pruned. Like other deep neural networks (DNN), features between convolutional layers are sparse and non-zero elements are unevenly distributed. Fig. 3 demonstrates the data sparsity and distribution of 2s-AGCN model. Based on the observation that unstructured pruning method drops weight-element with relatively small absolute value, we can cut off the input channels which have least averaging absolute data. To be more detailed, the number of dropped channels matching data sparsity will achieve best prediction accuracy, which is illustrated in Experiment section. Also, in order to pursue higher compress ratio, this method can prune more input channels with bearable accuracy loss. In this way, data reorganization prunes spatial convolutional weight and skips both graph and convolution computation.

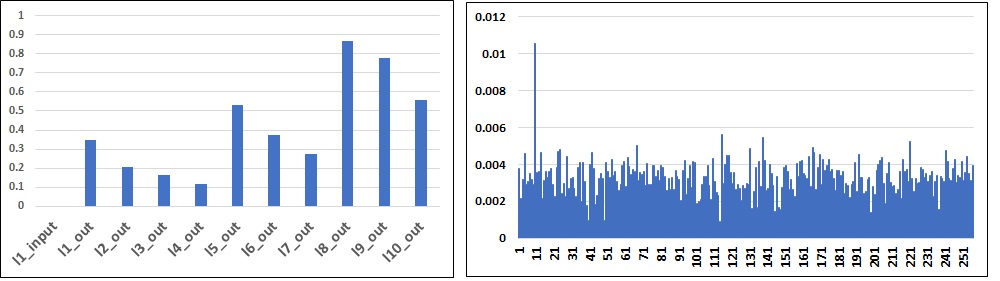


Figure 3. The demonstration of data sparsity and distribution of 2s-AGCN model. The left figure shows data sparsity of each block’s output feature. The right one is the averaging absolution of block 8’s output along channel, where x axis denotes channel and y axis denotes averaging absolute value.

1. Mixed-grained Pruning Method

Dataflow reorganization prunes same channels of spatial convolutional filters, which means features in specific channels are not computed. As shown in Fig. 2, the coarse-grained method prunes corresponding temporal filters via such connections with no extra accuracy loss. Moreover, this neighbour connection brings hardware-friendly advantages for that the number of pruned channels from spatial filters equals the pruned filters’ from temporal convolution. This feature supports an inherent balanced layer-pipelined architecture

Coarse-grained pruning can provide 49.83%~88.96% compression ratio on temporal filters, depends on the pruning scheme in data organization phase. To further prune temporal convolutional weights, fine-grained pruning is proposed. The key insight of fine-grained method is that in temporal convolution, zero weight means not sampling current vectors in time order. Fig.4 demonstrates details of sampling-like fine-grained pruning method. Two kinds of 1-interval, three kinds of 2-interval and three 3-interval pruning schemes with different shift conduct on every channel inside the filter recurrently. In this way, the pruning scheme design is turned into a sampling problem. By making cavity with different intervals and different offsets, we can simulate various sampling schemes on filters, with different sampling frequencies and phases. Experiments show that with proper pruning scheme, our fine-grained method can keep accuracy as well as discarding unimportant weight.

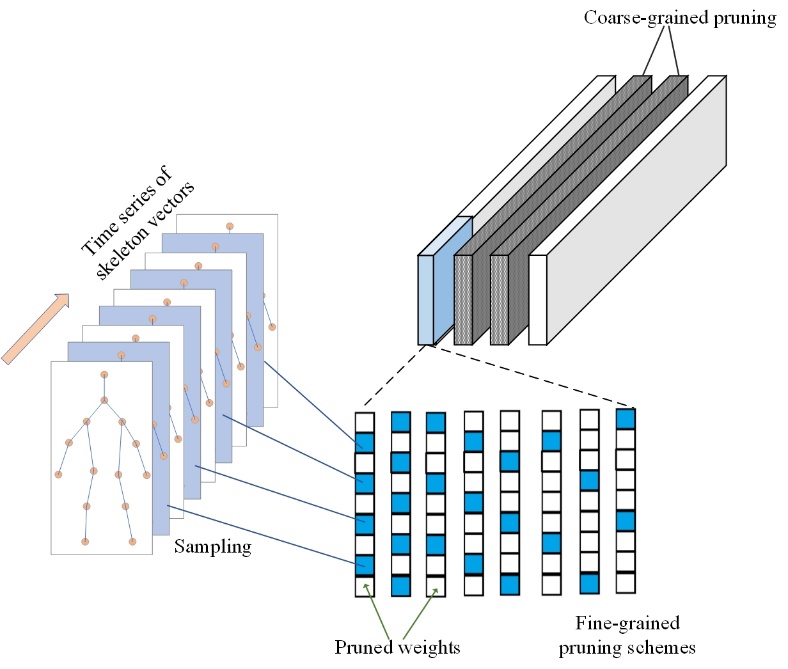


Figure 4. The illustration of fine-grained pruning on temporal convolution. White elements are pruned while blue ones are kept. Every 9x1 kernel performs on time series of skeleton vectors, and the blue vectors are sampled by first pruning scheme.

Conventional unstructured pruning methods randomly drop the weight elements with least absolute value, which are expensive and unbalanced on hardware. However, with determined cavity schemes, our fine-grained pruned model can be represented with structured weight and masks with negligible cost. Furthermore, we guarantee the balancing distribution of reserved weight by controlling start-points of different sampling patterns. Like fig. 4 shows, in a loop with eight different pruning modes, weight elements in every position of kernels are evenly kept by two or three times. Also, compression ratio can be adjusted via fine-grained pruning design.

1. Architecture

This section introduces the detailed architecture of our accelerator. Via specific tuning of 2s-AGCN model, all pruned convolutional blocks are mapped on chip.

Overview: Fig. 5 depicts the overall design of our layer-pipelined architecture. Based on our pruning method and layer-pipelined design, conv block module for each block constitutes the whole architecture. To be more detailed, one spatial conv module (SCM) and one temporal conv module (TCM) are included in conv block module. All convolutional parameters and graph are stored in ROM storages for proposed pruning method’s reduction on model size. Spatial convolutional computing units Mult-PEs are settled along output channel, while temporal convolutional computing units Dyn-MultPE works across input channel in parallel. Moreover, runtime sparse feature compression module (RFC) functions at the junctions of SCM and TCM or functions between different conv block modules to compact and store temporal results.

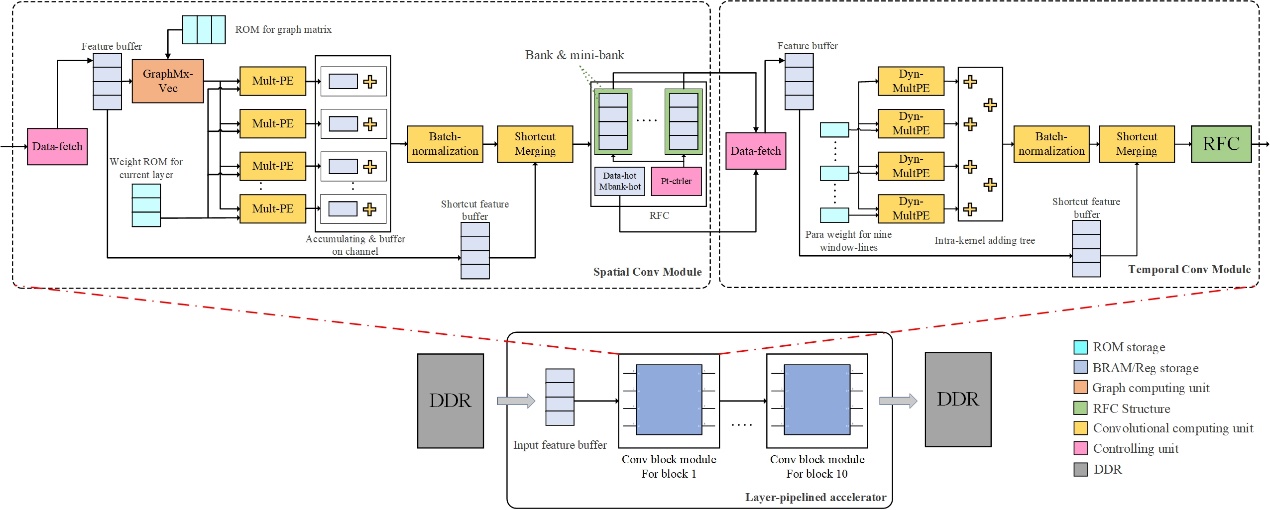


Figure 5. The demonstration of overall architecture.

1. Spatial conv module

The main task of SCM is performing graph computation and spatial convolution at the same time. Feature buffer stores the extended feature vectors, which are decoded in Data-fetch part. Data-fetch controls the address of data-loading and decodes compact feature into sparse form, which is convenient to compute. The decoding process will be explained later. Sparse feature will first multiply with graph vectors, and then conduct convolution with pruned weight in Mult-PE. Zero weights are skipped and multiplication results are summed up in accumulating buffer on output channel. After batch-normalization operation, dataflow merges with original input activation, which is stored in shortcut feature buffer. ReLU function is combined with encoding, where sparse data is compressed into compact format again.

In order to combine graph computation and pruned convolution workloads, dataflow is organized as Fig. 6 shows. A line in feature buffer caches 25 data from feature, and the depth of the buffer is varied to store all data in one row of feature tensor. Depth equals the number of input channels in different blocks. When computing, feature buffer offers one line of original feature data. After computation with one column vector of graph, this feature vector generates one valid element in Eq. 4. Afterwards, feature buffer provides data in next cache line, which continues to produce . Following this mode, when all output elements on current output channel are computed, feature buffer returns to the first line and graph ROM switches to the next column vectors to prepare for . When the workload of one row feature tensor is finished, feature buffer receives next row of tensor to start a new sub-loop. Algorithm 1 depicts the whole loop operation. In this way, feature is produced in a channel-first order. To be noticed that our dataflow reorganization method essentially abandons feature data on specific channels, so we skip corresponding workloads by not loading them to data-fetch module.

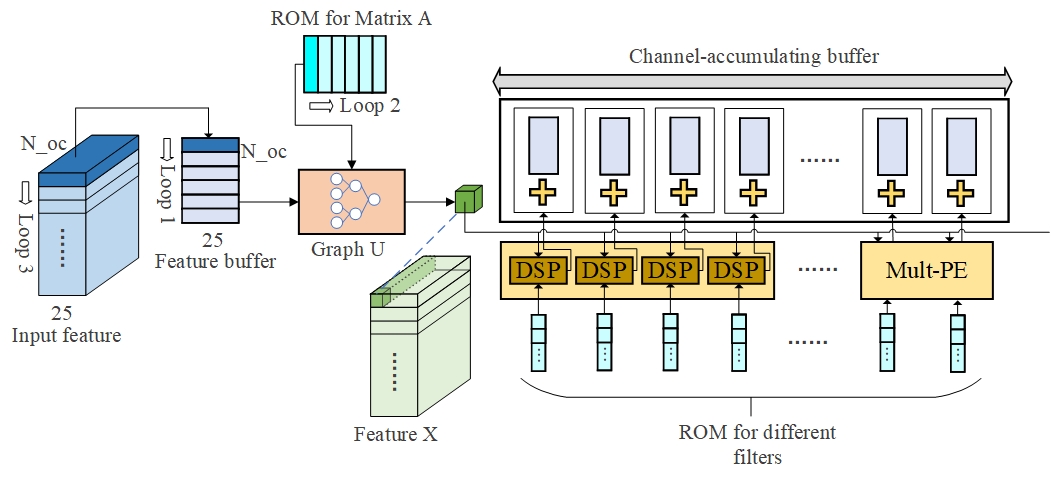


Figure 6. Illustration of SCM dataflow organization.

With feature element being broadcast to all Mult-PEs, weight ROM sends different filters’ parameters into different computing units, in the same channel-first order. To cooperate with the pruned model and feature-loading-skipping mechanism, only non-zero elements in filters are stored in ROM with original order. Each Mult-PEs includes four DSPs, and by adjusting the number of Mult-PE, our design can fit into different layers. Results from parallel Mult-PEs are accumulated and buffered on channel direction as well. When the sum counter reaches the number of valid channels, current data will be transferred into post-processing modules.

1. Temporal conv module