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Selectively Dilated Convolution for Accuracy-Preserving Sparse Pillar-based Embedded 3D Object Detection

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Abstract

Pillar-based 3D object detection has gained traction in self-driving technology due to its speed and accuracy facilitated by the artificial densification of pillars for GPUfriendly processing. However, dense pillar processing fundamentally wastes computation since it ignores the inherent sparsity of pillars derived from scattered point cloud data. Motivated by recent embedded accelerators with native sparsity support, sparse pillar convolution methods like submanifold convolution (SubM-Conv) aimed to reduce these redundant computations by applying convolution only on active pillars but suffered considerable accuracy loss.

Our research identifies that this accuracy loss is due to the restricted fine-grained spatial information flow (f-SIF) of SubM-Conv in sparse pillar networks. To overcome this restriction, we propose a **selectively dilated** (SD-Conv) convolution that evaluates the importance of encoded pillars and selectively dilates the convolution output, enhancing the receptive field for critical pillars and improving object detection accuracy. To facilitate actual acceleration with this novel convolution approach, we designed SPADE+ as a cost-efficient augmentation to existing embedded sparse convolution accelerators. This design supports the SD-Conv without significant demands in area and SRAM size, realizing superior trade-off between the speedup and model accuracy. This strategic enhancement allows our method to achieve extreme pillar sparsity, leading to up to $18.1 \times$ computational savings and $16.2 \times$ speedup on the embedded accelerators, without compromising object detection accuracy.

1. Introduction

With the shift of priorities in autonomous driving from convenience to safety, there is a growing need for robust perception systems that can accurately interpret time-critical semantic information in real-time, such as identifying and locating ²Seoul National University Seoul, South korea junwchoi@snu.ac.kr

road users [1]. At the heart of these systems is *3D object detection* that leverages LiDAR-generated point cloud data, providing comprehensive depth information and obstacle detection [1, 16]. In pursuit of real-time 3D object detection, research has gravitated towards grid-based methods that convert point clouds into 3D voxels or 2D pillars. One prime example is PointPillars [11], which utilizes a bird's-eye-view encoding technique, aggregating 3D point cloud features into sparse 2D pillars and transforming them into a dense pseudo-image for GPU-friendly 2D convolution (Conv2D). Thanks to this improved GPU efficiency, PointPillars has emerged as a leading solution for time-critical 3D object detection [13, 19, 20, 22, 24, 26].

However, emphasizing the fundamental inefficiency in dense pillar processing, which disregards the inherent sparsity of pillars stemming from dispersed point cloud data, the emergence of dedicated embedded accelerators with native support for sparse point cloud data imposes significant opportunities for sparse pillar-based object detection toward further speedup [6, 7, 12, 14]. A notable attempt is Sparse-PointPillars [21], which introduces submanifold convolution (SubM-Conv [10]) to sparsify pillar representation and significantly reduces the number of computations. Although SubM-Conv effectively preserves point cloud's original sparsity by limiting convolution dilation, the improved sparsity comes at the cost of significant degradation in 3D object detection accuracy; as shown in Fig. 1, Sparse PointPillars, which employs SubM-Conv, results in significant accuracy loss, especially for the complex mode (Hard). Therefore, a comprehensive understanding of the trade-off between sparsity and accuracy on sparse pillar convolution is lacking.

In this work, we identify that the key cause of the accuracy loss of previous sparse pillar convolutions is the sparsification structure that limits the *fine-grained spatial information flow* (f-SIF) from the increase of receptive field via dilation. Note that prior works on voxel-based methods [3, 5, 15] have noticed a similar issue on the SIF, but they primarily have



Figure 1. The accuracy and computation trade-off of 3D object detection. The pillar-based baseline, PointPillars [11], delivers high accuracy but uses redundant computation. Sparse PointPillars [21] employs SubM-Conv, reducing computation but losing considerable accuracy. In contrast to FS-Conv [3]'s inferior trade-off, our selectively dilated convolution (SD-Conv) retains accuracy while cutting computations by 18.1×, promising for embedded 3D object detection.

focused on the extension of the receptive field by strided sparse convolution only at each stage of 3D object detection backbone. This approach only enhances the *coarse-grained* SIF, thus showing a limited improvement in accuracy. In contrast, we reveal that the increase of the receptive field via *fine-grained* selective dilation at every convolution layer within the same stage plays a crucial role in constructing necessary receptive fields for identifying 3D objects in the scene. Therefore, we propose a simple yet effective operation called *selectively dilated convolution* (SD-Conv) that can identify important pillars at every convolution layer, based on their magnitude for selective dilation.

To achieve actual speedup, we have designed a specialized sparse point cloud accelerator architecture that operates in a streaming manner to support SD-Conv for acceleration. We evaluate the proposed method on various state-of-the-art pillar-based 3D object detection networks, including Point-Pillars [11], CenterPoint [24], and PillarNet [19], as well as popular benchmarks like KITTI [8] and Nuscene [2]. The experimental results consistently demonstrate that the proposed SD-Conv can simply replace SubM-Conv to recover accuracy while achieving higher sparsity. The achieved accuracies are on par with or even surpass the accuracy of the dense baseline models, while reducing the number of computations by 94.5%, 72.3%, 41.3% for PointPillars, CenterPoint, and PillarNet, respectively. With in-depth ablation study, we further demonstrate that our SD-Conv achieve superior accuracy-sparsity trade-offs compared to the prior sparse convolution approaches [3, 5, 15]. Moreover, when simulated on SPADE+, the method exhibited significant sparsity-proportional speedup of $16.2 \times, 3.1 \times, 1.7 \times,$ respectively. These findings emphasize the effectiveness of our approach and its potential to enable real-time 3D object detection, making it suitable for time-critical applications such as autonomous driving.

2. Background and Challenges

2.1. Pillar-based 3D Object Detection

Essential for autonomous driving, 3D object detection can be implemented through a variety of approaches, including point-based, voxel-based, and pillar-based techniques. Pointbased methods, such as PointNet [17] and PointNet++[18], deal directly with point cloud data, but they can encounter complexity issues due to sampling and sorting processes. Conversely, voxel-based methods like VoxelNet [25] partition space into 3D grids, but the inherent sparsity of 3D voxels can pose difficulties in GPU utilization. Pillar-based methods, such as PointPillars [11] as seen in Fig. 2(a), which segment space into 2D grids and utilize bird-eye-view (BEV) encoding, have risen in popularity for real-time 3D object detection [13, 19, 20, 22, 24, 26]. However, densify sparse BEV-based 2D convolution can lead to redundant computation, suggesting that improvements can be made in PointPillars' current implementation.

Fig. 2(b) illustrates the details of this feature extraction consisting of a backbone, neck, and head. The backbone consists of multiple stages of convolutions led by sparse down-sample convolution layers for the increased receptive fields. The outcome of all these stages is deconvoluted and then concatenated in the neck for box, class, and direction prediction in the head. Note that variations exist; Center-Point [24] incorporates center-based prediction heads while PillarNet [19] strengthens pillar encoding with additional SubM-Conv layers in front.

To achieve real-time speed, the key challenge in pillarbased methods is to reduce computations while extracting sufficient features for accurate object detection. To this end, the sparsification of pillars and utilizing sparse convolutions are getting significant attention for embedded 3D object detection since dedicated point cloud accelerators with native sparse convolution support have emerged as attractive alternatives for GPU [6, 7, 12, 14].

2.2. Sparse Convolution

Given the intrinsic sparsity of point cloud data, 3D object detection methods employ sparse 3D convolution [9] for efficiency. While conventional sparse convolution uses only non-zero elements in the input feature map, reducing the number of floating point operations (FLOPs) and memory demands, its dilation property can compromise overall sparsity.

Submanifold Sparse Convolution (SubM-Conv) [10] addresses this by forming a receptive field only around nonzero elements without dilation, further reducing computational requirements. However, this limited receptive field can lead to significant accuracy loss.

Spatial Pruned Sparse Convolution (SPS-Conv) [15] & Focal Sparse Convolution (FS-Conv) [3] both offering



Figure 2. (a) Pillar-based 3D object detection network structure. (b) Feature extraction steps: Backbone, Neck, and Head. (c) Comparison of the receptive field of various sparse convolution operations within a stage: Dense-Conv, SubM/SPS-Conv, FS-Conv, and SD-Conv.

coarse adaptive dilation based on voxel importance only once at each stage. SPS-Conv measures importance based on magnitude, whereas FS-Conv calculates the importance of each voxel through additional parameters learned during training. Furthermore, FS-Conv also learns the importance of dilation direction using extra parameters, enabling partial dilation.

Pruned Sparse Convolution (PS-Conv) [12] initially performs dilation on all non-zero values, akin to Dense-Conv as illustrated in Fig. 2(c), to then increase sparsity by applying pruning for computational reduction. However, employing high sparsity pruning during training can hinder stable learning, thereby imposing a limitation on accuracy.

Hardware for Sparse Convolution: To accelerate Sparse Convolution on Pillars, it's essential to operate only on non-zero values. This involves utilizing mapping information that represents the relationship between sparse input and sparse output [23]. One approach applicable to general-purpose processors like GPUs is employing hash tables. However, implementing hash tables introduces overhead from mapping that often outweighs the reduction in computation, thereby falling short of fully realizing the benefits of sparse convolution. Dedicated accelerators like PointAcc [14] or SPADE [12] address this by parallelizing the mapping process, reducing mapping overhead, and efficiently managing data to achieve speedup based on sparsity.

2.3. Challenges: Spatial Information Flow (SIF) within a Stage

To address SparsePointPillars' limitations and the challenges of existing sparse convolutions for pillars, we implemented SPS-Conv and FS-Conv into the pillar-based object detection backbone. As illustrated in Fig. 2(c), these methods aimed to balance computational savings and model accuracy through adaptive dilation but still failed to provide sufficient *spatial information flow* (SIF) [3] that constructs spatial expansion of features of important pillars to supply necessary cues for object detection. Both SubM-Conv and SPS-Conv do not increase receptive fields within a stage, while FS-Conv only allows one-time dilation towards deformable directions. This coarse dilation severely limits SIF, impeding the connection of sparse pillars inside the bounding box unless they proceed through downsampling layers in subsequent stages.

The main challenge lies in augmenting SIF by expanding the foreground pillar group, triggered by dilation and active pillars generated by point clouds. Previous convolution operations have not achieved this, either Dense-Conv facilitating the growth of foreground pillars without discerning background, or SubM-Conv suppressing both background and foreground pillar dilation together. SPS-Conv and FS-Conv enhance only the coarse-grained SIF, resulting in insufficient foreground information. Given that such SIF discrepancies, specifically the insufficient dilation of the foreground, hinder appropriate feature extraction for object detection, we propose a novel convolution method that selectively and effectively increases the receptive field for important pillars. As shown in Fig. 2(c), our proposed methods promote the fine-grained dilation of important pillars at every sparse convolution, achieving extreme sparsity while preserving model accuracy.

3. Method

To tackle the problem of granting SIF while preserving pillar sparsity, we introduce novel operations: selectively dilated convolution (SD-Conv).



Figure 3. An overview of Selective Dilated Convolution.

Table 1. Performance comparison for t% in top-k selection (BEV Hard mAP of PointPillars on KITTI *val* set.

t	baseline	5	4	3	2	1
$mAP\uparrow$	85.63	85.80	85.75	85.66	85.61	83.38
$FLOPs(G) \downarrow$	63.14	5.23	4.58	4.10	3.48	3.06

3.1. Selectively Dilated Convolution

Addressing the issue of discontinued SIF, we introduce a novel module, *selectively dilated convolution* (SD-Conv). The foundation of this method is the measurement of pillar importance (I_p) , defined as follows:

$$I_p = G_{i \in g_p}(M(f_i)), \tag{1}$$

where g_p denotes a group of pillars in the vicinity of a pillar p, while $M(\cdot)$ signifies an importance measure applied to a feature vector $f_i \in \mathbb{R}^C$. An overview of these proposed methods is depicted in Fig. 3. This module performs a regular convolution selectively dilating important pillars, determined by I_p , with $g_p = p$, $G(\cdot) = identity(\cdot)$ and $M(\cdot) = mean(|\cdot|)$. The intuition is to allow each pillar to expand its feature to its neighbor, provided the feature is strong enough. The ablation study for justification of the proposed importance measure is more discussed in Sec. 5.3.

For an efficient on-the-fly decision of important pillars, we propose a *dilation threshold* learned throughout training. The top-k method is employed during this training to identify the important pillars, choosing pillars with the top t% importance for dilation, and performing SubM-Conv for the remaining less significant pillars. To prevent unnecessary dilation and preserve sparsity, the selection ratio t is kept small. Through an ablation study in Table 1, we confirmed that t = 2 is sufficient for PointPillars [11] on KITTI [8], while t = 4 is preferred in other cases. After training, an importance threshold satisfying the selection ratio becomes the dilation threshold for efficient inference.



Figure 4. (a) Training curve for SparsePointPillars with SD-Conv employing magnitude-based and trainable-based importance in high sparsity. (b) Performance comparison of the car detection task in SparsePointPillars using different methods to determine the dilation directions of SD-Conv applied to the KITTI dataset.



Figure 5. Feature representation of a single *car* object based on sparse convolution type. "Input Pillars" represents the initial input of the backbone network, while the images corresponding to SubM-Conv, FS-Conv, and SD-Conv are the outputs of the last layer in Stage 2. The white rectangles indicate the boundaries of GT-boxes.

3.2. Convergent Selective Dilation

SD-Conv employs two intuitive design aspects: a magnitudebased importance measure and dilation in all directions. These choices contrast with previous studies that advocated for more flexible dilation using learnable parameters. However, our findings showed that this parameterized approach is not suitable for extreme pillar sparsity.

Fig. 4(a) presents the training curve of SD-Conv on KITTI for PointPillars with 14% sparsity, comparing importance measured by either pillar magnitude or learnable parameters. The graph shows that the loss associated with the learnable parameters is consistently higher than that of magnitudebased importance, indicating optimization challenges under significant sparsity. Furthermore, Fig. 4(b) contrasts 3D object detection accuracy and FLOPs for various dilation direction choices. Surprisingly, random direction dilation outperforms the learned dilation direction in both FLOPs and mAP, while our all-direction dilation yields the best performance. Consequently, we choose to measure importance based on magnitude and implement dilation in all directions, eliminating additional overhead associated with learnable pa-



Figure 6. An overview of SPADE+ (Minor modification for SD-Conv).

rameters and dilation choices. As a result, SD-Conv demonstrates higher performance compared to both random and learnable-based dilation directions, with the added benefit of lower FLOPs.

3.3. Fine-Grain Spatial Information Flow

Fig. 5 contrasts SIF of various sparse convolution methods by observing output features from Stage 2 of PointPillars on KITTI. Specifically, we examine a focused region corresponding to a car (indicated by the white ground truth bounding box). Note that the input pillars are sparsely distributed and disconnected along the bounding box. The SubM-Conv output feature illustrates a discontinuous SIF, failing to provide sufficient features for object detection. FS-Conv, on the other hand, offers a more connected, albeit deformed, SIF that doesn't adequately cover the bounding box. Conversely, our proposed SD-Conv extends the SIF to fill most features within the bounding box, demonstrating that selective dilation within a stage by employing SD-Conv enhances feature provision for object detection.

4. SPADE+

We adapted SPADE [12] to support not only Sparse Convolution, PS-Conv and SubM-Conv, but also SD-Conv, creating new one called SPADE+. SPADE effectively handles operations only for non-zero points but considers dilation for all active points. In contrast, SPADE+ supports the generation of mapping for SD-Conv, where only important active pillars are dilated, through four stages: Alignment (), Row Merge (2), Dilation Check Window (3), and Column-wise Dilation (4) by rule generation unit (RGU). While the mapping operation in the original SPADE only consists of Alignment, Row Merge, and Column-wise Dilation, SPADE+ adds a Dilation Check Window (3) between Row Merge and Column-wise Dilation. Additionally, information regarding dilation status is added to the FIFOs of each stage in SPADE+, facilitating the generation of mapping information based on dilation status.

In SPADE+, only important input pillars dilate to generate output, so output index calculation depends on whether the merged column index dilates, determined by neighboring columns within Dilation Check Window (3). For dilated merged columns, the SPADE+ behaves like SPADE. For nondilated ones, rule generation depends on nearby columns' information. As illustrated in the example of Fig. 6, when generating the mapping for the 4-th target output row, the Merge Row results in a total of three merged columns. Subsequently, in cycle 0, column-wise dilation is applied to the first merged column, followed by column-wise dilation for the second merged column in cycle 1. In cycle 1, since I_0 and I_3 are not dilated and there are no adjacent columns with merged columns, no output is generated for the merged column (C^3), resulting in the mapping for $W_{:,0}$ not being created. However, for $W_{:,-}$ and $W_{:,+}$, adjacent columns are expanded to generate mapping information. As a result, it can be observed that I_0 is shifted by $W_{-,+}$ to be computed with O_{10} , indicating that when the positions of all outputs are known, I_0 is indeed shifted to the O_{10} by $W_{-,+}$. With minor tweaks to the rule generation unit, the SPADE+ operates akin to SPADE, facilitating SD-Conv operations.

SPADE+ retains the rest of SPADE's components un-

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Method	Conv type	FLOPs	3D Detection (%)			
		(G)↓	Easy	Mod	Hard	
PointPillars	Dense	63.14	87.01	77.31	75.61	
Sparse PointPillars	SubM-Conv	2.65	87.35	74.91	72.45	
	PS-Conv	16.73	86.10	76.94	74.15	
	FS-Conv	5.99	87.09	76.82	75.09	
		4.60	87.16	76.85	72.64	
	SD-Conv	3.48	87.44	77.43	75.54	

Table 2. Performance comparison of PointPillars among various types of sparse convolution (KITTI *val* set).

Table 3. Hardware comparison between SPADE and SPADE+.

SPADE	SPADE+				
$64 \times 64 = 4096$					
65	54				
11.6	11.73				
6.27	22.12				
0.27	22.13				
Sparse Conv, PS-Conv,	Sparse Conv, PS-Conv,				
SubM-Conv	SubM-Conv, SD-Conv				
	SPADE 64 × 64 65 61 65 65 11.6 6.27 5 5 Sparse Conv, PS-Conv, SubM-Conv 5 5 5				

changed, except for the RGU, which is modified to generate mapping information for SD-Conv. To streamline mapping in SPADE [12], it simultaneously identifies output positions from convolution operations and generates relevant mapping details using a RGU. Additionally, a gather-scatter unit manages input, weight, and output to minimize data movement during convolutions, enhancing performance based on sparsity. Furthermore, in SPADE, PS-Conv was proposed to minimize computational overhead without sacrificing performance. However, as evident from the Table 2 results, PS-Conv fails to address the discontinued SIF issue properly, resulting in higher computational complexity compared to SD-Conv.

Since SPADE+ only modifies the RGU portion to support SD-Conv, the area overhead of SPADE+ is only about 1% compared with original SPADE [12] as shown in the Table 3. When comparing the effective TOP/W of SPADE for PS-Conv and SPADE+ for SD-Conv, the latter utilizing SD-Conv shows a $3.5 \times$ improvement thanks to the small hardware overhead and computation efficiency of SD-Conv.

5. Experiments

5.1. Experimental Setting

We employed three state-of-the-art pillar-based 3D object detection networks, PointPillars (PP) [11], CenterPoint (CP) [24], and PillarNet (PN) [19], for evaluation of the

proposed method on KITTI [8] (for PP) or nuScenes [2] (for CP and PN) benchmarks. We followed the baseline settings of SparsePointPillars [21] to replace the existing convolution operations (Conv2D and SubM-Conv) of PP, CP, and PN with SD-Conv. All the experimental settings are implemented with PyTorch-based frameworks, including OpenPCDet¹ for PP and the popular CenterPoint² code-base for PN and CP, and run on the NVIDIA A100 GPU.

5.2. Main Results

PointPillars (PP): We begin by comparing the performance of our proposed SD-Conv with other sparse convolution operations, SubM-Conv, PS-Conv and FS-Conv, on the Point-Pillars (PP) with the popular KITTI dataset. As shown in Table 2, SubM-Conv achieves a remarkable 95% reduction in computational operations (FLOPs). However, this comes at the cost of a significant decrease in accuracy, particularly evident in the Hard category (-3.16 mAP). This outcome underscores the adverse impact of constrained SIF caused by SubM-Conv on object detection. PS-Conv demonstrates a lesser accuracy degradation in the Hard category, with a -1.46 mAP decrease. While PS-Conv alleviates accuracy degradation to some extent, it offers a significantly lesser reduction in computational operations compared to the other methods. This highlights that merely applying pruning while concurrently training does not suffice to efficiently maintain SIF. To improve accuracy while saving computations, we systematically vary the target FLOPs for both FS-Conv and SD-Conv. Notably, FS-Conv demands 5.99 GFLOPs to maintain the original object detection accuracy. Any reduction in FLOPs below this threshold results in a substantial decline in accuracy, similar to what we observed with SubM-Conv. Conversely, SD-Conv achieves a remarkable 94.5% reduction in FLOPs while preserving the original accuracy. This demonstrates the effectiveness of our proposed fine-grained selective dilation in constructing essential SIF, thereby enabling accurate object identification.

CenterPoint (CP): We evaluate SD-Conv using Center-Point (CP), another popular pillar-based 3D object detection framework. The results in Table 4 show the FLOPs and 3D object detection accuracies in two categories, and errors in five categories, following the nuScenes *val* set convention. In the case of SubM-Conv, we observe a substantial 74.1% reduction in computations, but this comes at the cost of noticeable accuracy degradation across all categories. PS-Conv reduces computational load by 61.28%, which is smaller than the reduction achieved by SubM-Conv, but it demonstrates improved accuracy. In contrast, FS-Conv maintains original accuracy while achieving only up to a 66.7% reduction in computational load. SD-Conv, on the other hand, safely reduces computation by 72.3% while surpassing FS-

¹https://github.com/open-mmlab/OpenPCDet

²https://github.com/tianweiy/CenterPoint

Table 4. Performance comparison between CenterPoint and its variants on the nuScenes val set.

Model	Conv type	$\begin{array}{c} FLOPs \\ (G) \downarrow \end{array}$	mAP↑	NDS ↑	mATE	mASE	mAOE	mAVE	$mAAE\downarrow$
CenterPoint	Dense-Conv	70.01	50.79	60.55	31.77	25.97	35.94	34.77	19.97
	SubM-Conv	18.13	47.89	58.94	32.04	26.32	36.83	34.53	20.36
Sparse	PS-Conv	27.09	50.12	60.42	31.38	26.24	36.34	32.27	19.73
CenterPoint	FS-Conv	23.34	50.30	60.41	31.55	26.10	38.14	32.67	19.95
	SD-Conv	19.37	50.33	60.84	31.28	25.96	34.26	32.11	19.66

Table 5. Performance comparison between PillarNet and its variants on the nuScenes *val* set.

Model	Backbone	Neck	Head	FLOPs	mΔP	NDS
wiodei	(Conv type	(G)	1112 11		
PilllarNet	SubM	Desne	Desne	276.26	59.58	66.95
Sparse	SubM	SubM	Desne	151.96	57.92	66.33
PillarNet	SubM	SD-Conv	Desne	162.29	59.45	67.40

Conv in terms of accuracy. This highlights the advantageous trade-off provided by SD-Conv between FLOPs and accuracy, primarily due to its fine-grained SIF construction.

PillarNet (PN): We further assessed SD-Conv's benefits in the context of PillarNet (PN), a cutting-edge pillar-based object detection method, where its backbone incorporates multiple layers of SubM-Conv to enhance feature extraction. Given that a significant portion of computation resides in its neck, our focus was on sparsifying it using both SubM-Conv and SD-Conv to reduce overall FLOPs while preserving accuracy. Table 5 reports key accuracy metrics, including mAP and NDS, using the nuScene val dataset, with consistent overall trends. Replacing the dense convolution in PN's neck with SubM-Conv results in substantial computational savings of 45.0% but noticeable mAP degradation. Conversely, transitioning from SubM-Conv to SD-Conv fully restores accuracy (its NDS even surpasses the baseline) with only a marginal increase in FLOPs compared to . These findings underscore SD-Conv's versatile applicability in maintaining or enhancing performance while simultaneously reducing computational overhead.

5.3. Ablation Study

In this section, we validate several design choices for our pillar-based 3D object detection: 1) the metric for measuring importance of SD-Conv, 2) types of sparse convolution for down-sampling, and 3) methods for enhancing SIF.

Importance Metric: Table 6 presents findings regarding various metrics related to I_p , as discussed in Sec. 3. We explore different metrics within a magnitude-based approach

Table 6. Ablation study of importance metric of SD-Conv (Sparse PointPillars with KITTI *val* set).

$M(\cdot)$	$G(\cdot)$	g_p	FLOPs	3D Detection (%)			
			(G)	Easy	Mod	Hard	
Mean	identity	p	3.48	87.44	77.43	75.54	
Max	identity	p	3.07	87.62	76.93	72.67	
Mean	Avg-Pool	SubM(p)	3.34	86.99	76.49	72.84	
Mean	Max-Pool	SubM(p)	3.43	87.14	77.12	74.73	

for I_p . Regarding the selection of important pillars, the mean across the channel consistently demonstrates the best performance. Conversely, the max metric tends to excessively emphasize outliers. Average pooling (Avg-Pool) faces challenges in making accurate assessments when neighboring values of a particular pillar were zero, diminishing its relevance. Meanwhile, max pooling (Max-Pool) underperforms as it places excessive emphasis on high-magnitude pillars.

Types of Down-Sample Sparse Convolution: As discussed in Sec. 2.1, down-sample sparse convolution at the beginning of stages increases the receptive field, affecting the pillar-based object detection's overall sparsity. Two down-sampling methods exist: sparse convolution with a 2x2 kernel used by SparsePointPillars [21] and spatial pruned regular sparse convolution (SPRS-Conv [15]). The former increases sparsity by shrinking the dilation window from 3x3 to 2x2. Meanwhile, SPRS-Conv dilates only vital features, risking pruning essential elements due to its pre-feature-importance stride mask. Table 7 shows that SPRS-Conv results in lower accuracy than the case with a 2x2 kernel window, thus we employed the 2x2 kernel approach in our work.

SD-Conv vs. Additional Down-Sampling for SIF: Computation savings from SubM-Conv restrict the SIF, compromising object detection accuracy. A recent method, VoxelNext [4], introduces an additional down-sampling (ADS) to enhance SIF in SubM-Conv. While ADS can boost SIF via a larger receptive field, it also increases the computational load. To compare SD-Conv with ADS, we adjusted

Modal	Down-Sample	FLOPs	3D Detection (%)		
Widder	Conv Type	(G)	Easy	Mod	Hard
PointPillars	2x2 kernel [21]	3.48	87.44	77.43	75.54
+ SD-Conv	SPRS-Conv [15]	3.57	87.39	76.92	74.16

Table 7. Comparison of down-sample sparse conv: 2x2 kernel vs. SPRS-Conv (Sparse PointPillars on KITTI *val* set).

Table 8. Comparison of additional down-sampling (ADS [4]) and SD-Conv (PointPillars on KITTI *val* set).

Method	FLOPs	3D Detection (%)				
Wiethou	(G)	Easy	Mod	Hard		
Dense	63.14	87.01	77.31	75.61		
SubM	2.65	87.35	74.91	72.45		
SubM + ADS	4.10	87.06	76.23	72.37		
SD-Conv	3.48	87.44	77.43	75.54		

Sparse PointPillars to include an extra down-sampling and SubM-Conv for ADS. Table 8 shows SubM+ADS's mixed impact on 3D object detection accuracy (a +1.32 increase on Moderate but drops of -0.29 on Easy and -0.08 on Hard) at the cost of additional 1.45G FLOPs of computation. In contrast, SD-Conv matches the dense baseline's accuracy but with fewer computations than SubM+ADS, underscoring SD-Conv's advantages.

5.4. Hardware Evaluation

Harnessing the sparsity of point cloud processing for runtime savings on conventional GPUs is ineffective due to architectural constraints. However, several point cloud-based sparse convolution accelerators, featuring dedicated logic for sparse data structures, have been introduced [6, 7, 12, 14]. These accelerators support sparse convolution by mapping active inputs to outputs, focusing only on non-zero value GEMM operations. To assess the proposed SD-Conv's feasibility and benefits, we created cycle-accurate simulators for recent point cloud accelerators [12, 14].

More specifically, mapping information calculates inputweight-output index tuples, indicating the output from each input with a specific kernel index. This allows for efficient storage of each weight's product with an active point, optimizing sparse convolution calculations. While GPUs often use hash tables to create this mapping, leading to collisions and increased overhead, PointAcc [14] employs merge sorting, and SPADE [12] uses a pipelined strategy with sorted inputs to reduce overhead. Unlike PointAcc, which uses a cache, deterministically processes the mapping details and employs scratch pads to minimize memory overhead. Due to these architectural enhancements, both PointAcc and SPADE achieve sparsity-related speedup, as verified in our cycle-accurate simulators.



Figure 7. Comparison of relative cycle with and without SD-Conv in embedded accelerators (SPADE+, PointAcc), using dense convolution accelerators as the baseline.

To assess the hardware speedup of SD-Conv, we implement SD-Conv's mapping algorithm into our PointAcc/SPADE simulators and tested it on three models (PP, CP, PN). These simulators also feature a baseline architecture for executing dense convolution in a systolic manner. Fig. 7 shows relative execution cycles compared to the baseline, with SD-Conv configurations as per Tables2-5. For PP, CP, and PN, SPADE+ attains a $16.2\times$, $3.1\times$, $1.7\times$ speedup, nearing the ideal $18.1\times$, $3.6\times$, $1.7\times$ speedup from computational savings, respectively. PointAcc lags behind SPADE+ in all tests due to cache misses but still significantly outperforms the baseline using sparsity.

6. Conclusion

This research demonstrated that pillar-based 3D object detection, an efficient approach in autonomous driving technology, outperforms point-based and voxel-based methods in speed and accuracy, despite the computational redundancy from densifying the intrinsically sparse pillar data. We discovered that the accuracy loss in recent submanifold convolution (SubM-Conv) methods is due to their limited receptive field. To address this, we introduced a selectively dilated convolution (SD-Conv) that enhance accuracy by focusing on key pillars and eliminating non-essential ones. Evaluation across several state-of-the-art models validated that our approach maintains superior sparsity without sacrificing mAP.

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