# OpenStereo: A Comprehensive Benchmark for Stereo Matching and Strong Baseline

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# **Abstract**

Stereo matching, a pivotal technique in computer vision, plays a crucial role in robotics, autonomous navigation, and augmented reality. Despite the development of numerous impressive methods in recent years, replicating their results and determining the most suitable architecture for practical application remains challenging. Addressing this gap, our paper introduces a comprehensive benchmark focusing on practical applicability rather than solely on performance enhancement. Specifically, we develop a flexible and efficient stereo matching codebase, called OpenStereo. OpenStereo includes training and inference codes of more than 12 network models, making it, to our knowledge, the most complete stereo matching toolbox available. Based on OpenStereo, we conducted experiments on the Scene-Flow dataset and have achieved or surpassed the performance metrics reported in the original paper. Additionally, we conduct an in-depth revisitation of recent developments in stereo matching through ablative experiments. These investigations inspired the creation of StereoBase, a simple yet strong baseline model. Our extensive comparative analyses of StereoBase against numerous contemporary stereo matching methods on the SceneFlow dataset demonstrate its remarkably strong performance. The source code is available at https://github.com/XiandaGuo/ OpenStereo.

# 1. Introduction

Stereo matching, a core subject in computer vision, focuses on calculating the disparity between the left and right images. It is vital in a wide array of applications such as robotics [1], autonomous driving [2, 3], and augmented reality [4], as it enables depth perception and 3D reconstruction of the observed scene.

Traditional stereo matching algorithms typically rely on matching corresponding image regions between the left and right views based on their similarity measures. Several techniques have been proposed, including methods based on gray-level information [5–7], region-based approaches [8, 9], and energy optimization methods [10, 11]. Gray-levelbased methods [5–7] compute disparities by matching pixels or groups of pixels with similar intensities in the left and right images. Region-based approaches [8, 9] group pixels into larger regions and then compute correspondences between these regions. Energy optimization methods [10, 11] involve minimizing an energy function that represents the disparity between image pairs to improve the accuracy of 3D reconstruction from stereo images. While these approaches have made noteworthy progress, they suffer from certain limitations and challenges, such as occlusions, textureless regions, and computational complexity.

Recently, bolstered by extensive synthetic datasets [12– 16], CNNs-based stereo matching methods [17-24] has achieved impressive results. These methods have shown remarkable performance particularly in aspects of accuracy and efficiency. Unlike traditional methods, CNN-based stereo matching methods take left and right images as input and directly predict the disparity between them, which are end-to-end frameworks. In addition to the accuracy and efficiency benefits, CNN-based stereo matching methods have shown the potential for generalization to new environments and scenes beyond the training data. This is mainly due to the ability of CNNs to learn feature representations from raw data that are invariant to scale, rotation, and illumination changes. Furthermore, the emergence of large-scale datasets has paved the way for the integration of deep learning in stereo matching, allowing for more complex and sophisticated models to be trained.

Despite the considerable advancements made in CNN-based methods, the existing methods still face challenges in achieving both high accuracy and time efficiency. Encoder-decoder networks using 2D CNN methods [12, 24–28] offer efficiency but fall short in achieving extremely high precision, while the cost volume matching with 3D convolution

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methods [17–19, 29] deliver top-tier accuracy but pose challenges in deployment due to their substantial computational and memory requirements. However, choosing an appropriate architecture for stereo matching is still a challenging task, since the trade-off between accuracy and efficiency needs to be carefully balanced. In this context, recent studies have explored the potential of automated machine learning (AutoML) [23, 39, 42] on stereo matching, aiming to reduce the human effort required to design an efficient network structure. With the increasing number of new methods and datasets in stereo matching, there is a lack of a unified framework to support state-of-the-art models and datasets. To address these challenges, we propose OpenStereo, a platform for reproducing and comparing various stereo matching models on major datasets. By conducting extensive experiments, we aim to reproduce and assess the performance of various state-of-the-art models within a unified framework. Our platform also aims to facilitate the comparison of different models and provide a user-friendly environment for researchers to quickly reproduce and build new models.

In summary, this paper presents substantial contributions to the domain of stereo matching research, focusing on three key aspects. (1) **OpenStereo**, a unified and extensible platform, enables researchers to conduct comprehensive stereo matching studies. (2) With the support of OpenStereo, we deeply revisit the recent stereo matching methods and significantly influence future research in this field. (3) We introduce **StereoBase**, a model notable for its structural simplicity and powerful performance, offering a fresh perspective for the design of upcoming stereo matching algorithms. These contributions collectively advance the state-of-the-art in stereo matching, offering both theoretical insights and practical tools to the research community.

# 2. Related Work

## 2.1. Stereo Matching

With the rapid development of CNNs, there has been remarkable progress in the field of stereo matching. Based on the network pipeline of stereo matching, stereo matching methods can be roughly grouped into two categories [24], including the encoder-decoder network with 2D convolution (ED-Conv2D) and the cost volume matching with 3D convolution (CVM-Conv3D).

Stereo Matching with CVM-Conv3D The CVM-Conv3D methods are proposed to improve the performance of depth estimation [3, 17–20, 23, 29–37]. These techniques derive disparities from a 4D cost volume, primarily formed by concatenating left feature maps with their respective right analogs at each disparity level [18]. GCNet [17] firstly introduced a novel approach that combines 3D encoder-decoder architecture with a 2D convolutional network to obtain a dense feature representation, which is used to reg-

ularize a 4D concatenation volume. Following GCNet [17], PSMNet [18] proposes an approach for regularizing the concatenation volume by leveraging a stacked hourglass 3D convolutional neural network in tandem with intermediate supervision. To boost the expressiveness of the cost volume and thereby enhance performance in regions with ambiguity. GwcNet [19] proposes the group-wise correlation volume and ACVNet [37] proposes the attention concatenation volume. GANet [19] innovates with a semi-global aggregation layer and a local guided aggregation layer, designed to supplant the traditionally employed 3D convolutional layer. Based on GANet [19], DSMNet [30] constructs a robust "domain normalization" method to overcome the challenges in cross-domain generalization. CoEx [33] proposes a novel approach called Guided Cost volume Excitation (GCE), which leverages image guidance to construct a simple channel excitation of the cost volume. IGEV-Stereo [38] leverages an iterative geometry encoding volume to capture both local and non-local geometry information, which outperforms existing methods on KITTI benchmarks and achieves cross-dataset generalization and high inference efficiency. Besides, as a potential solution to reduce the need for humans to design a good volumetric method, Neural Architecture Search (NAS) [39–41] has been employed in stereo matching [23, 42].

However, these CVM-Conv3D methods continue to face challenges with time efficiency and substantial memory demands, hindering real-time inference, even on server-grade GPUs. Consequently, resolving these issues of accuracy and efficiency is crucial for their practical application in real-world scenarios.

Stereo Matching with ED-Conv2D The ED-Conv2D methods [3, 12, 21, 22, 24, 42-51], which adopt networks with 2D convolutions to predict disparity, has been driven by the need for improved accuracy, computational efficiency, and real-time performance. Subsequently, Mayer et al [12] present an end-to-end network, called DispNet, which is pure 2D CNN architectures. However, the model still faces challenges in capturing the matching features, resulting in poor estimation results. To overcome this challenge, the correlation layer is introduced in stereo matching [12, 26, 27, 52] to better capture the relationship between the stereo images. By incorporating this layer, the accuracy of the model is significantly improved. Furthermore, FADNet++ [24] proposes an innovative approach to efficient disparity refinement using residual learning [53] in a coarse-to-fine manner. AutoDispNet [42] applied neural architecture search to automatically design stereo matching network structures. AANet [21] leverages deformable convolution to enhance the standard convolution's ability to model geometric transformations. More recently, Croco-Stereo [54] demonstrates that large-scale pre-training, when aligned with appropriately chosen pretext tasks, can signif-

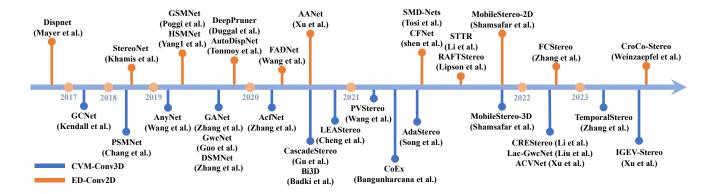


Figure 1. Timeline of Stereo Matching Models. This figure illustrates the timeline of various stereo matching models that have been proposed in the literature. The top part shows ED-conv2D-based models, while the bottom part shows CVM-conv3D-based models. Each model is labeled with its name and authors.

icantly enhance stereo matching performance.

These works represent the significant progress that has been made in stereo matching, highlighting the diverse range of methods and architectures that have been proposed to address the challenges associated with this problem.

### 2.2. Codebase

Numerous infrastructure code platforms have been developed in the deep learning research community, with the aim of facilitating research in specific fields. One such platform is OpenGait [55], a gait recognition library. OpenGait thoroughly examines the latest advancements in gait recognition, providing novel perspectives for subsequent research in this domain. In object detection, MMDetection [56] and Detectron [57] have emerged as an all-encompassing resource for several favored detection techniques. In Pose Estimation, OpenPose [58] has developed the first opensource system that operates in real-time for detecting the 2D pose of multiple individuals, including the detection of key points for the body, feet, hands, and face. With the rapid development of stereo matching, the prominence of an infrastructure code platform has risen markedly, underscoring the pressing demand for such a system.

# 3. OpenStereo

In recent times, the field of stereo matching has seen a surge in the development of new frameworks and evaluation datasets. Despite this growth, the absence of a unified and impartial evaluation platform in this domain stands out as a critical concern that warrants attention. To address this challenge and promote academic research and practical application we have developed **OpenStereo**, a PyTorchbased [59] toolbox that provides a reliable and standardized evaluation framework for stereo matching.

# 3.1. Design Principles of OpenStereo

As illustrated in Figure 2, OpenStereo covers the following standout features.

Compatibility with various frameworks. Currently, an increasing number of novel stereo matching methods are emerging in the field, such as Concatenatation-based [18], Correlation-based [21, 24, 60], Interlaced-based [3], Group-wise-correlation-based [38], Difference-based [44], and Combine-based methods [20]. As previously noted, many open-source methods are narrowly tailored to their specific models, making it challenging to extend to multiple frameworks. However, OpenStereo provides a solution to this problem by supporting all of the aforementioned frameworks. With OpenStereo, researchers and practitioners can easily compare and evaluate different stereo matching models under a standardized evaluation protocol.

**Support for various evaluation datasets.** OpenStereo serves as an all-encompassing tool, incorporating datasets frequently utilized by researchers in the field of stereo matching. OpenStereo not only supports synthetic stereo datasets such as SceneFlow [12], but also five real-world datasets: KITTI12 [15], KITTI15 [16], Middlebury [13], ETH3D [14], and DrivingStereo [61]. We introduce a suite of bespoke functions, meticulously crafted for each dataset, encompassing everything from initial data preprocessing to the final stages of evaluation.

**Support for state-of-the-arts.** OpenStereo successfully replicated various state-of-the-art stereo matching methods, including PSMNet [18], GwcNet [20], AANet [21], FAD-Net++ [24], CFNet [49], STTR [50], ACVNet [37], RAFT-Stereo [22], CoEx [33], CascadeStereo [31], MobileStere-oNet [3] and IGEV [38]. Notably, the performance metrics we achieved, in most cases, surpass those reported in their original publications. This comprehensive replication effort provides a valuable resource for novices in the field, offer-

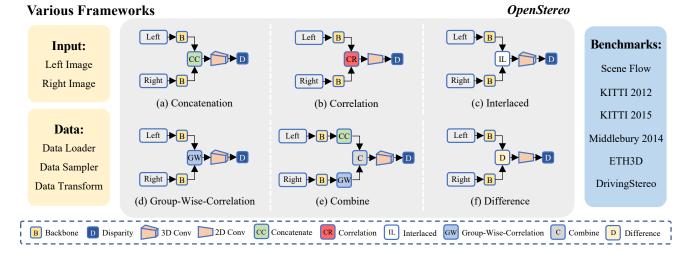


Figure 2. The design principles of proposed codebase OpenStereo.

ing a rich array of official examples to facilitate an effective and efficient start in stereo matching research.

#### 3.2. Main Modules

Technically, we align with the structure commonly found in PyTorch-based deep learning projects, organizing Open-Stereo into three modules, *data*, *modeling*, and *evaluation*.

Data module includes three key components: data loader, which is responsible for loading and preprocessing the data; data sampler, which is used to select a subset of data for each iteration; and data transform, which applies various transformations to the data to increase the diversity and complexity of the training set.

Modeling module is built upon the BaseModel base class, which predefines many behaviors of the stereo matching during both training and testing phases. This module consists of four essential components, namely the Feature Extraction, Cost Calculation, Cost Aggregation, and Disparity Processor, which are critical to current stereo matching algorithms.

Evaluation module is employed to meticulously assess and measure the performance of the developed model. Recognizing that different datasets require distinct evaluation protocols, we have incorporated these varied protocols directly into OpenStereo, significantly simplifying the evaluation process.

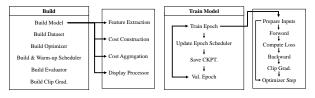


Figure 3. Training pipeline

# 3.3. Training Pipeline

We propose a unified training pipeline with a hooking mechanism that can be customized to suit different training processes. Our pipeline is based on a common workflow that includes iterative training epochs and optional validation epochs. In each epoch, we forward and backward the model through multiple iterations. To increase flexibility and customization, we define a minimal pipeline that repeatedly forwards the model, and additional behaviors are implemented through a hooking mechanism. This mechanism allows users to define custom operations to be executed before or after specific steps in the training process. The pipeline defines several time points where users can register executable methods or hooks, such as before and after training epochs, before and after training iterations, and before and after validation epochs. These hooks are triggered at the specified time points according to their priority level, enabling users to customize their training processes in a more granular way. A typical training pipeline in Open-Stereo is shown in Figure 3.

## 4. Benchmarks

OpenStereo contains high-quality implementations of popular stereo matching methods.

# 4.1. Supported Methods

PSMNet [18] is one of the most crucial and frequently cited networks in stereo matching. The official implementation code is available at https://github.com/JiaRenChang/PSMNet.

GwcNet [20] employs a Group-wise Correlation Stereo Network to exploit both local and global matching cost volumes. https://github.com/xy-guo/GwcNet.

AANet [21] focuses on adaptively fusing multi-scale fea-

tures through a lightweight and efficient adaptive aggregation module. https://github.com/haofeixu/aanet.

FADNet++ [24] employs a two-stage architecture, consisting of a feature-metric aggregation stage and a disparity refinement stage. https://github.com/HKBU-HPML/FADNet.

CFNet [49] utilizes a collaborative feature learning strategy to enhance the representation capacity of features in the matching cost computation. https://github.com/gallenszl/CFNet.

STTR [50] focuses on geometric correspondence problems, including stereo matching, by employing transformers to capture long-range spatial and temporal context information. https://github.com/mli0603/stereo-transformer.

ACVNet [37] addresses the issue of constructing accurate and efficient cost volumes by adopting an asymmetric strategy. https://github.com/gangweiX/ACVNet.

RAFT-Stereo [22] builds upon the RAFT[62] architecture, originally designed for optical flow estimation. https://github.com/princeton-vl/RAFT-Stereo.

CoEx [33] focuses on context-aware features and cost volume aggregation. https://github.com/antabangun/coex.

CascadeStereo [31] adopts a cascaded architecture for accurate and efficient disparity estimation. https://github.com/alibaba/cascade-stereo.

MobileStereoNet [3] builds upon the StereoNet [44], which proposes Interlacing Cost Volume Construction. https://github.com/cogsys-tuebingen/mobilestereonet.

IGEV [38] builds a combined geometry encoding volume that not only encodes both geometric and contextual information but also intricately captures fine-grained details of local matching. https://github.com/gangweiX/IGEV.

# 4.2. Benchmarking Results

**Implementation Details** All experiments are conducted using the PyTorch [59] version 1.13(or higher) on a cluster of 8 NVIDIA 3090 GPUs (more details in the Supplementary Material).

For benchmarking, it is critical to ensure that the results are reliable and trustworthy. To achieve this, we conducted our experiments using SceneFlow [12] and KITTI15 [16] datasets. As shown in Table 1, in most cases, the reproduced performances of OpenStero are better than the results reported by the original papers. Regarding the KITTI 2015 dataset, submission constraints led us to limit our leaderboard contributions to reproductions of the widely recognized PSMNet [18] and the latest state-of-the-art IGEV [38], as demonstrated in Table 2. We stand by the integrity of our benchmark, asserting its role in providing a reliable and valid evaluation of stereo matching models. OpenStereo is designed to offer the research community in stereo matching a standardized, comprehensive platform for method assessment. This facility enables meaningful and

Table 1. Quantitative evaluation on the Sceneflow [12] test. For each model, the specific category on the Sceneflow used is consistent with the original paper. The model without † refers to the results of the original paper. The model with † refers to the implementation of OpenStereo. Underline refers to evaluation in the non-occluded regions only [50]. Bold: Best

	I	SceneFlow		
Method				
COMPANY CANA	TrainSize	Categories	EPE(px)	
STTR [50]	$256 \times 512$	FinalPass	0.43	
STTR [50] <sup>†</sup>	$256 \times 512$	FinalPass	0.40	
RAFT-Stereo [22]	$256 \times 512$	FinalPass	-	
RAFT-Stereo [22] <sup>†</sup>	$256 \times 512$	FinalPass	1.18	
PSMNet [18]	$256 \times 512$	CleanPass	1.09	
PSMNet [18] <sup>†</sup>	$256 \times 512$	CleanPass	0.94	
CFNet [49]	$256 \times 512$	FinalPass	1.04	
CFNet [49] <sup>†</sup>	$256 \times 512$	FinalPass	0.89	
AANet [21]	$288 \times 576$	CleanPass	0.87	
AANet [21] <sup>†</sup>	$288 \times 576$	CleanPass	0.82	
Mobilestereo-2D [3]	$256 \times 512$	FinalPass	1.14	
Mobilestereo-2D [3] <sup>†</sup>	$256 \times 512$	FinalPass	1.03	
Mobilestereo-3D [3]	$256 \times 512$	FinalPass	0.80	
Mobilestereo-3D [3] <sup>†</sup>	$256 \times 512$	FinalPass	0.76	
GwcNet [20]	$256 \times 512$	FinalPass	0.76	
GwcNet [20] <sup>†</sup>	$256 \times 512$	FinalPass	0.74	
COEX [33]	$288 \times 576$	FinalPass	0.68	
COEX [33] <sup>†</sup>	$288 \times 576$	FinalPass	0.66	
FADNet++ [24]	$384 \times 768$	CleanPass	0.76	
FADNet++ $[24]^{\dagger}$	$384 \times 768$	CleanPass	0.65	
CascadeStereo [31]	$256 \times 512$	FinalPass	0.72	
CascadeStereo [31] <sup>†</sup>	$256 \times 512$	FinalPass	0.64	
ACVNet [37]	$288 \times 576$	FinalPass	0.48	
ACVNet [37] <sup>†</sup>	$288 \times 576$	FinalPass	0.59	
IGEV [38]	$320 \times 736$	FinalPass	0.47	
IGEV [38] <sup>†</sup>	$320 \times 736$	FinalPass	0.46	

Table 2. Quantitative evaluation on KITTI2015 test leadboard. The model without <sup>†</sup> indicates the results of the original paper. The model with <sup>†</sup> indicates the implementation of OpenStereo.

Method	KITTI2015				
Wictiou	D1-bg	D1-fg	D1-all		
PSMNet [18]	1.86	4.62	2.32		
PSMNet [18] <sup>†</sup>	1.80	4.58	2.26		
IGEV [38]	1.38	2.67	1.59		
IGEV [38] <sup>†</sup>	1.44	2.31	1.59		

comparative analyses across various models, thereby serving as an invaluable tool for the innovation and scrutiny of emerging algorithms.

# 5. Revisit Deep Stereo Matching

With the support of OpenStereo, we can conduct a comprehensive reevaluation of various stereo matching methods, including data augmentation, feature extraction, cost construction, disparity prediction and refinement.

**Setting** For all experiments in this section, each model was trained 90 epochs using a batch size of 64. AdamW is utilized as the optimizer. We implemented a one-cycle [63] learning rate schedule, setting the peak learning rate at 0.0008.

#### 5.1. Data Augmentation

Table 3. The model undergoes training and evaluation on the Finalpass of the SceneFlow [12] training and test sets. KITTI2015 [16] training set, consisting of 200 images, is only employed to evaluate the generalizability of models under various data augmentation conditions. RC stands for RandomCrop. CES represents ColorAug, Erase, and Scale. HFlip denotes both images of a stereo and disparity are horizontally flipped. HSFlip horizontally flips both images in the stereo pair and then swaps them. VFlip involves vertically flipping both images in the stereo pair along with the disparity, inverting their top-bottom orientation. † denotes the method proposed in this paper.

	SceneFlow	KITTI15		
Data Augmentation	EPE(px)	EPE(px)	D1_all	
RC(256×512)	0.5856	3.13	17.61	
RC(320×736)	0.5632	1.75	8.97	
BatchRandom <sup>†</sup>	0.5688	2.78	13.20	
RC(320×736)+HFlip	0.5955	2.84	13.05	
$RC(320\times736)+HSFlip$	0.8706	2.35	17.02	
RC(320×736)+VFlip	0.5629	2.24	12.87	
RC(320×736)+ColorAug	0.5861	1.61	7.81	
$RC(320\times736)+Scale$	0.6895	2.70	15.76	
$RC(320 \times 736) + Shift(10)^{\dagger}$	0.5702	2.66	14.95	
$RC(320\times736)$ +Erase	0.5606	2.83	15.03	
RC(320×736)+CE	0.5831	1.66	7.97	
RC(320×736)+CES	0.7132	1.75	8.97	

While five data augmentation techniques are prevalent in stereo matching [22, 38], including random crop, color augmentation, eraser transform, flip, and spatial transform, the empirical efficacy of each method specifically for stereo vision tasks remains an underexplored area in the field. Our work extends beyond these common practices, exploring not only these techniques but also experimenting with two additional methods: BatchRandom and Shift, to further understand their impact on stereo matching performance. BatchRandom denotes the technique applied during model training where the size of the random crop varies for each batch. The Shift involves randomly shifting the right image horizontally by a certain range and then cropping both images to a specified size. As shown in Table 3, most data augmentation strategies, except for the combined use of erase transform and random crop, lead to a decline in the model's performance metrics of SceneFlow. This is because stereo matching involves pixel-level matching, and these data augmentations (color augmentation, flip,

and spatial transform) can affect the alignment of pixels. The erase transform benefits stereo matching by enhancing the model's capacity to cope with occlusions, missing data, and diverse real-world scenarios. It encourages robust feature learning and generalization, ultimately improving model performance. Furthermore, the combination of RandomCrop (320×736) with color augmentation delivers the most striking improvements in KITTI15 dataset performance, achieving the lowest EPE of 1.61 px and the lowest D1\_all of 7.81. Such improvements highlight the critical role of color augmentation in boosting the model's resilience against the variability of color and lighting that naturally occurs in diverse driving environments.

Table 4. Ablation study of different backbones and pre-training methods on the Finalpass of SceneFlow test datasets [12]. Flops and Params represent the computational complexity and parameters within the whole model, respectively.

Backbone	Pre-train	Flops	Params	EPE
FadNet++ [24]	None	28.39G	1.77M	0.8633
MobilenetV2 100 [38]	None	31.83G	2.78M	0.8227
PSMNet [18]	None	130.87G	4.46M	0.8068
MobilenetV2 100 [38]	None	31.83G	2.78M	0.8227
MobilenetV2 100 [38]	Timm [64]	31.83G	2.78M	0.7132
MobilenetV2 120d [38]	Timm [64]	38.75G	5.21M	0.6603

## 5.2. Feature Extraction

In Table 4, we delve into an ablation study to examine the impact of different backbones and pre-training methods. Initially, we evaluate different backbones without any pre-training. The backbone of FadNet++ [24], despite its low parameter count of 1.77M, results in an EPE of 0.8633, indicating less precision in disparity estimation. Employing MobilenetV2 100 [38] as a backbone improves the EPE to 0.8227, with a slight increase in computational demand (31.83G FLOPs) and parameters (2.78M). The backbone of PSMNet [18], while the most computationally intensive (130.87G FLOPs) with the highest number of parameters (4.46M), achieves a further reduction in EPE to 0.8068, suggesting that the complexity of the network can contribute to the enhancement of stereo matching performance. Furthermore, we delve into the impact of pre-training on the MobilenetV2 100 backbone. Without pre-training, the EPE remains at 0.8227. However, when pre-trained, we observe a substantial improvement, as the EPE drops to 0.7132. This underscores the value of leveraging large-scale image datasets to enhance feature extraction capabilities before fine-tuning specific tasks like stereo matching. In conclusion, our ablation study highlights the critical role of both the architecture's complexity and pre-training in refining the stereo matching model's accuracy. It becomes evident that pre-training substantially enhances the model's capability to estimate disparities with higher precision.

Table 5. Ablation study results of cost volume on the Finalpass of SceneFlow test datasets [12]. For these experiments, one-quarter features from stereo images are utilized to construct the cost volume. Gwc represents Group-wise correlation volume [20]. Cat stands for Concatenation volume [18]. G8-C16, G16-C24 and G32-C48 combine Group-wise correlation volume and Concatenation volume [20]. Channel represents the channel of cost volume. Dims refers to the dimensions of cost volume. Flops and Params represent the computational complexity and parameters within the whole model, respectively.

Cost Volume	Dims	Channel	Flops	Params	EPE
Difference	3D	-	17.44G	2.40M	1.02
Correlation	3D	-	24.80G	4.01M	0.81
Interlaced8	4D	8	126.87G	2.83M	0.70
Gwc8	4D	8	31.83G	2.78M	0.71
Gwc16	4D	16	75.28G	3.89M	0.66
Gwc24	4D	24	147.53G	5.75M	0.63
Gwc32	4D	32	248.60G	8.34M	0.62
Gwc48	4D	48	537.15G	15.73M	0.60
Cat24	4D	24	148.36G	5.78M	0.65
Cat48	4D	48	537.99G	15.76M	0.61
Cat64	4D	64	941.79G	26.09M	0.60
G8-C16	4D	24	148.36G	5.78M	0.62
G16-C24	4D	40	379.30G	11.69M	0.60
G32-C48	4D	80	1460.80G	39.37M	0.60

## 5.3. Cost Construction

In Table 5, an ablation study on various cost volume strategies for stereo matching is presented. The study begins with simpler 3D cost volume methods like Difference [44] and Correlation [24], yielding higher EPE of 1.02 and 0.81, respectively, at lower computational costs. This suggests that while efficient, these methods may lack the nuanced disparity capture necessary for complex scenes. The Interlaced8 model, introduced by MobileStereoNet [3], achieves the same EPE comparable to the Gwc8 model. However, its computational expense is substantially higher, with a FLOP count of 126.87G which is significantly larger than that of the Gwc8 model. The group-wise correlation models demonstrate a clear trend: as the channel depth increases, the EPE improves, dropping from 0.7132 to 0.6 as channels expand from 8 to 48. This suggests a richer feature capture with more channels, enhancing disparity estimations. Similarly, the concatenation volume shows improved performance with increased channel depth, with a notable decrease in EPE as channels expand from 24 to 64 channels. The combined volume (G8-C16) offers a more optimal balance between computational load and disparity estimation accuracy, which achieves an EPE of 0.62. G16-C24 and G32-C48 do not result in significant improvement in EPE, which stabilizes at 0.60, despite a dramatic increase in computational load, especially for G32-C48 which demands 1460.80 GFLOPs and has 39.37M parameters. These results highlight the delicate balance between accuracy and computational efficiency in designing cost volumes for disparity estimation. While deeper and combined volumes reduce the EPE, the gains might be marginal compared to the significant increase in computational requirements, raising questions about the practicality of these approaches in resource-constrained environments.

Table 6. Ablation study results of cost volume on the Finalpass of SceneFlow test datasets [12]. ArgMin refers to Differentiable ArMin. Context stands for ContextUpasmple. Flops and Params represent the computational complexity and parameters within the whole model, respectively.

Regression	Refinement	Flops	Params	EPE
ArgMin	None	26.37G	2.69M	0.7584
ArgMin	RGBRefine	53.15G	2.81M	0.7187
Context	None	31.83G	2.78M	0.7132
Context	RGBRefine	58.61G	2.89M	0.6895
Context	DRNetRefine	58.57G	2.89M	0.6860

# 5.4. Disparity Regression and Refinement

In stereo matching, two prevalent methods for disparity regression are predominantly employed: Differentiable ArgMin [3, 18-20, 24, 31, 37, 49, 65] and ContextUpsample [22, 38, 62]. The Differentiable ArgMin method, introduced by GCNet [65], calculates disparity by converting matching costs into probabilities via softmax and then computing a weighted sum of these probabilities across all disparity levels. In contrast, the ContextUpsample module, a concept from RAFT [62], focuses on aligning upsampled disparity maps coherently with the image content. This method shows an improvement in EPE to 0.7132, as shown in Table 6, albeit at slightly higher computational costs (31.83G Flops). Furthermore, RGBRefine, a technique involving the concatenation of the left image with the disparity map, further refines the disparity estimation. DR-NetRefine [21] slightly improves EPE to 0.6860, maintaining a similar level of computational complexity as RGBRefine.

#### 5.5. Analysis and Discussion

## 5.5.1 Necessity of Comprehensive Ablation Study

In the evolving landscape of deep stereo matching, comprehensive ablation studies play a pivotal role in deciphering the effectiveness of different components and strategies. A thorough ablation study goes beyond mere performance metrics; it uncovers the underlying mechanics of different algorithms, revealing their strengths and weaknesses in various scenarios. For instance, different data augmentation techniques may yield contrasting effects on the model's ability to match stereo images accurately. Similarly, the impact of varying backbones, cost volume configurations, and

Table 7. Quantitative evaluation on Scene Flow test set. Bold: Best.

Method	PSMNet [18]	MS3D [3]	GwcNet [20]	COEX [33]	FADNet++ [24]	CStereo [31]	ACVNet [37]	IGEV [38]	StereoBase
EPE(px)	1.09	0.80	0.76	0.68	0.76	0.72	0.48	0.46	0.43

disparity regression methods on the overall performance can be profound. Understanding the specific contributions of each component is crucial for building more efficient and effective stereo matching systems.

# 5.5.2 Necessity of A Strong baseline

A strong baseline in deep stereo matching research is critical for several key reasons. First, it serves as a vital reference point, enabling a clear assessment of new methods against an established standard. Second, a strong baseline allows for precise evaluation of the impact of specific changes, whether they are new data augmentation methods, different network architectures, or innovative disparity estimation techniques. This helps in isolating and understanding the contribution of each component to the overall performance. Additionally, a solid baseline ensures fair and meaningful comparisons across studies, providing a common ground for evaluating different research outcomes. This is crucial for maintaining consistency and validity in comparative analyses.

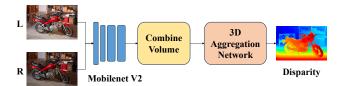


Figure 4. The architecture of StereoBase.

# 6. A Strong Pipeline: StereoBase

In light of our comprehensive analysis, the goal of this section is to establish a solid yet straightforward baseline model that not only matches but potentially surpasses existing standards in performance. StereoBase, our proposed solution, embodies this objective. It is crafted to be structurally streamlined yet experimentally potent and empirically resilient, setting a new benchmark for future explorations in the field.

#### **6.1. Pipeline**

As shown in Figure 4, we build a simple but strong baseline: StereoBase. StereoBase begins with a carefully curated data preprocessing step. Drawing from our ablation studies, we implement an optimized mix of data augmentation techniques, including RandomCrop, and Erase

Transform, proven to enhance model resilience and accuracy. This step ensures that the input data is not only varied and representative of real-world scenarios but also tailored to enhance stereo matching performance. Given the left and the right images, the pre-trained MobileNetV2 [64] networks are used as our foundational backbone, extracting features at a reduced scale of 1/4th the original size to form the cost volume. The cost volume utilizes a combined volume, which combines group-wise correlation volume with an 8-channel and concatenation volume with 16 channels, to ensure an optimal balance between computational load and disparity estimation accuracy. Hourglass networks [38] were implemented for cost aggregation, while context-upample [62] strategies were applied for the final disparity regression. DRNetRefine [21] module was used to refine the final disparity. Training is driven by the smooth L1 [18] loss function. We set the maximum disparity at 192.

## **6.2.** Comparison with State-of-the-art

In our comprehensive evaluation, we benchmarked StereoBase against current state-of-the-art methods on the Scene Flow test set. This assessment revealed that StereoBase sets a new benchmark in EPE, achieving an unprecedented low score of 0.43. This performance not only establishes a new state-of-the-art but also demonstrates a significant advancement over existing methods, including prominent approaches. The quantitative comparisons, as summarized in Table 7, clearly illustrate the edge of StereoBase in handling complex stereo matching scenarios with greater precision.

#### 7. Conclusion

This paper introduces OpenStereo, a codebase designed for stereo matching. Our initial endeavor involved the reimplementation of the most state-of-the-art methods within the OpenStereo framework. This comprehensive tool facilitates the extensive reevaluation of various aspects of stereo matching methodologies. Drawing on the insights gained from our exhaustive ablation studies, we proposed StereoBase. StereoBase not only demonstrates the capabilities of our platform but also sets a new standard in the field for future research and development. Through OpenStereo and StereoBase, we aim to contribute a substantial and versatile resource to the stereo matching community, fostering innovation and facilitating more effective and efficient research.

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