Abstract

We present a novel method for multi-view depth estimation from a single video, which is a critical task in various applications, such as perception, reconstruction and robot navigation. Although previous learning-based methods have demonstrated compelling results, most works estimate depth maps of individual video frames independently, without taking into consideration the strong geometric and temporal coherence among the frames. Moreover, current state-of-the-art (SOTA) models mostly adopt a fully 3D convolution network for cost regularization and therefore require high computational cost, thus limiting their deployment in real-world applications. Our method achieves temporally coherent depth estimation results by using a novel Epipolar Spatio-Temporal (EST) transformer to explicitly associate geometric and temporal correlation with multiple estimated depth maps. Furthermore, to reduce the computational cost, inspired by recent Mixture-of-Experts models, we design a compact hybrid network consisting of a 2D context-aware network and a 3D matching network which learn 2D context information and 3D disparity cues separately. Extensive experiments demonstrate that our method achieves higher accuracy in depth estimation and significant speedup than the SOTA methods. Code is available: https://github.com/xxlong0/ESTDepth.

1. Introduction

Multi-view depth estimation aims to recover 3D geometry of given images with known camera parameters, which is one of fundamental problems in computer vision. Many applications benefit from the recovered depth, such as autonomous driving [36], augmented reality [18], 3D modeling [13], and image-based rendering [10].

Recently, learning based depth estimation methods, whether designed for images [9, 22, 17, 39] or videos [21, 43, 34, 26, 24], have achieved great improvements against their traditional counterparts [42, 28, 1, 15]; however, these methods, especially for videos, have significant room for improvement in terms of temporal coherence and computational efficiency.

Temporal coherence. Most of multi-view depth estimation methods [17, 39, 20, 23, 32] are designed for individual images so they are not suitable for temporally coherent videos. Directly extending the existing methods from images to video sequences causes flickering artifacts, i.e. inconsistent estimated depth maps across consecutive frames, because they do not take temporal coherence into consideration. As shown in Figure. 1, the independently estimated depth maps contain inconsistent values. Therefore, it is necessary to jointly estimate depth maps of a video sequence to produce temporally coherent results.

Existing works on video depth estimation can be divided into two categories: single-view methods [43, 6, 34, 26, 24] and multi-view methods [21], according to the input of the depth estimation network. Recurrent neural units are widely used in single-view video methods [43, 6, 34, 26] to encode temporal coherence implicitly. Although the inconsistency problem is alleviated by incorporating temporal coherence, these methods still suffer from the ambiguity of depth scale since depth estimation from a single image is an ill-posed problem.

Multi-view video methods are advantageous over single-view methods because epipolar geometry information pro-
vided by multiple images could be used to avoid depth scale ambiguity problem. To the best of our knowledge, there has been only one multi-view method [21] for video depth estimation based on the epipolar geometry information. This method produces compelling results but it is restricted by its specific network design that it can only make use of one preceding estimation to improve current estimation. We improve upon this multi-view method by proposing a novel Epipolar Spatio-Temporal (EST) network that is capable of utilizing temporal coherence of multiple preceding estimations, thus producing more accurate depth maps with better temporal coherence.

**Computational Efficiency.** Top-performing multi-view depth estimation models [17, 20, 21] are slow with low computational efficiency, because they adopt a single fully 3D convolution networks for cost regularization to learn both local feature matching information and global context information, which have been shown to be critical for accurate depth estimation [2, 19]. While the local feature information is necessary for matching texture-rich regions, the global context information is crucial for scenes with texture-less regions. The existing networks tend to use deeper and deeper networks to improve the ability of learning global context information, leading to increased computation cost. It should be pointed out that the global context information is essentially 2D, so learning it by deep 3D convolution layers will unnecessarily consume masses of computational resources.

Our insight is that for depth estimation the local feature information and global semantic information can be learned by two separate networks, as inspired by recent Mixture-of-Experts models [35, 44, 25]. Specifically, we propose a hybrid cost regularization network, consisting of two complementary expert sub-networks: a 2D ContextNet focusing on 2D global context information, and a shallow 3D MatchNet concentrating on 3D local matching information. By explicitly disentangles these two different types of information, our hybrid network consumes much less GPU computational resources and achieves faster running speed.

Our main contributions are summarized as follows:

- We proposed an Epipolar Spatio-Temporal (EST) transformer that propagates temporal coherence to perform joint depth estimation of multiple frames to make estimated depth maps more temporally coherent.
- We designed a hybrid network for cost regularization that consists of two expert networks to learn 3D local matching information and 2D global context information separately. This decoupling approach achieves faster speed and consumes less computational resources than using a single fully 3D network in prior works.
- Based on these two contributions we developed a new multi-view method for generating temporally coherent depth maps from videos. We conducted extensive experiments on several datasets to demonstrate that our method outperforms the SOTAs by a large margin in terms of accuracy and speed.

2. Related Work

**Depth estimation from single image** Learning based single-view depth estimation methods [9, 8, 3, 4, 33, 38, 5, ?, ?] have been extensively studied in recent years. Convolution neural network for depth estimation is first introduced by [9], which demonstrates the superior ability of CNN for depth regression. Later, [22] combines conditional random field (CRF) with CNN to further improve the quality of estimated depth. [11] proposed a seminal ordinal regression loss instead of metric l1/l2 loss, recasting depth regression as an ordinary regression problem. Some works [27, 40] introduce extra geometric constraints to improve depth estimation. However, these methods suffer from the scale ambiguity problem due to single-view depth estimation is an ill-posed problem.

**Multi-view stereo depth estimation** Recently, some learning based methods [39, 32, 17, 39] based plane-sweeping volume algorithm [12] have achieved promising improvements against their traditional counterparts [16, 14]. Some works [20, 23] introduce surface normal as extra constraint to further improve multi-view depth estimation. However, most of the methods are designed for individual images not suitable for videos, thus directly extending these methods from images to video sequence causes flickering artifacts. Moreover, these methods mostly adopt fully 3D convolution network for cost regularization, which is memory-consuming, expensive, and slow. Although one method [30] tries to avoid 3D convolution layers by replacing plane-sweeping construction by correspondence triangulation, singular value decomposition (SVD) operations used in its triangulation module lead to more time consumption than plane-sweeping methods.

**Temporal coherence in video depth estimation** To utilize temporal coherence to improve depth accuracy, some single image depth estimation methods [11, 34, 43, 26] exploit recurrent neural units to encode temporal correlation in latent space. However, these methods suffer from depth scale ambiguity problem and show poor generalization to frames with unseen camera motions. Another single depth estimation method [24] adopts an online training strategy, performing model re-training on testing videos with a geometric consistency loss function. However, the online training scheme costs more than 40 minutes for a video with 244 frames and might suffer from model degradation due to insufficient online training data. One multi-view method,
neuralrgbd [21] exploits temporal coherence by accumulating depth probability over time. However, it can only make use of one preceding estimation to improve the depth estimation of the current frame. In contrast, our method can take advantage of the temporal coherence of multiple preceding estimations for more accurate and temporally consistent depth maps.

3. Method

We propose an end-to-end pipeline for multi-view depth estimation as shown in Figure 2. In the training stage, our model takes a video clip with 5 images \{I_{t-2}, I_{t-1}, I_t, I_{t+1}, I_{t+2}\} as input, and estimate the depth maps of three target images \{I_{t-1}, I_t, I_{t+1}\} jointly with short-term temporal coherence. In the inference stage, our model could propagate long-term temporal coherence through the whole video by an Epipolar Spatio-Temporal Memory (ESTM) inference operation.

Briefly, our method has the following four parts, which will be discussed in detail in the subsequent sections:

i Hybrid cost volume generation (see Section 3.1). It obtains a regularized matching volume from each target image with its source images using MatchNet, and in parallel extracts context feature volume of the target image using ContextNet. Finally, it fuses the matching volume and context volume together to a hybrid cost volume.

ii Epipolar Spatio-Temporal Transformer (see Section 3.2). It is applied on the hybrid cost volumes of all the target images to enforce temporal coherence.

iii Depth extraction (see Section 3.3). In this part initial depth maps are first extracted from the transformed cost volumes and further refined by RefineNet.

iv Epipolar Spatio-Temporal Memory (ESTM) inference operation (see Section 3.4). In the inference stage, this operation propagates long-term temporal coherence through the whole video.

3.1. Hybrid cost volume generation

For computational efficiency, we utilize two expert sub-networks, MatchNet and ContextNet, to learn two types of cost volumes, 3D matching volume and 2D context volume, respectively.

3.1.1 Matching volume generation

To simplify the exposition, we take frame \(I_t\) as an example to construct its matching volume. Frame \(I_t\) and its neighboring frames \(I_{t-1}, I_{t+1}\) are taken as reference image and source images respectively, since they share the largest overlapping regions. Without loss of generality, here we only consider the reference image and one of its source images, denoted as \(I_r\) and \(I_s\) respectively.

Feature extraction We first pass \(I_r\) and \(I_s\) through a spatial pyramid pooling (SPP) feature extractor [2] to extract corresponding hierarchical feature maps \(F_r\) and \(F_s\). For computational efficiency, the feature maps are downsampled by four to the original image size with 32 channels.

Raw matching volume A raw matching volume for reference image \(I_r\) is constructed by backprojecting source feature map \(F_s\) into the coordinate system defined by \(I_r\) at a stack of fronto-parallel virtual planes. The virtual planes are
Following prior works [17, 23, 21, 20, 32], we set \( D = 64 \) in all experiments. The coordinate mapping from the source feature map \( F_s \) to the reference feature map \( F_r \), at each depth \( z_m \), is determined by a planar homography transformation:

\[
    u'_m \sim H_m u, \quad u'_m \sim K[R_s | t_s] \left[ \frac{(K^{-1} u)z_m}{1} \right]
\]

where the \( \sim \) denotes the projective equality, \( u \) is homogeneous coordinate of a pixel in the reference image, \( u'_m \) is the projected homogeneous coordinate of \( u \) on the paired source feature map. \( K \) denotes the intrinsic parameters of the camera, \( \{R_s, t_s\} \) are the rotation and the translation of the source image \( I_s \) relative to the reference image \( I_r \).

Based on the above mapping, we warp the source feature map into all the virtual planes to construct a feature volume with dimension \( C \times D \times H \times W \). Finally, we concatenate the feature volume with \( F_r \) at each virtual plane to increase the dimension to \( 2C \times D \times H \times W \). By concatenation operation, the network could receive necessary information to perform feature matching between \( F_r \) and \( F_s \) without decimating the feature dimension [32, 23]. With \( N \) source images, we will obtain \( N \) raw matching volumes.

**MatchNet** The \( N \) raw matching volumes are first processed by three 3D convolution layers to decrease their dimension to \( C \times D \times H \times W \). Then a view average pooling operation is performed on the volumes to aggregate information across different source images, yielding a single aggregated volume. Finally, the aggregated volume is further regularized by a series of 3D convolution layers. Note that our MatchNet is only responsible for learning local features for matching. We will use another network for learning global context information to complement MatchNet for more efficient depth estimation, as will be discussed in the next section.

### 3.1.2 Context volume generation

Prior methods [21, 17, 20] adopt a heavy 3D regularization networks to learn 2D context information together with 3D local matching clues in a mixed manner, and the network is made very deep for increased ability of learning the two types of information. We observe that the global context information is essentially 2D information, so it is unnecessary to use a 3D network to learn it. Hence, we decouple the global context information from the local matching information and use a 2D network, called ContextNet, to learn the former. This makes the network simpler and, consequently, more efficient to train and run.

Specifically, we use ResNet-50 as the ContextNet. The output of ContextNet is a learned feature volume with size \( C' \times H \times W \), where \( C' \) is the number of feature channels and \( H \) and \( W \) are the same as the number of virtual planes \( D \). To fuse 3D matching volume and the 2D context volume, we expand the dimensions of context volume to \( 1 \times D \times H \times W \). Finally we concatenate the regularized matching volume and the expanded context volume together to get a hybrid cost volume, with size \( (C + 1) \times D \times H \times W \). As shown in Figure 2, we repeatedly apply the hybrid cost volume generation operation for images \( I_{t-1}, I_t, I_{t+1} \) and obtain three corresponding hybrid cost volumes \( C_{t-1}, C_t, C_{t+1} \).

### 3.2 Epipolar Spatio-Temporal transformer

To associate temporal coherence with the three hybrid cost volumes \( C_{t-1}, C_t, C_{t+1} \), we propose a novel Epipolar Spatio-Temporal (EST) transformer.

**Consistency constraint** Our EST transformer is inspired by the photometric consistency assumption: a 3D point in world space will be projected into visible images \( I_{t-1}, I_t, I_{t+1} \), and the image textures near their projections should bear high similarity. We formulate depth estimation as an occupancy estimation problem: if a pixel \((u, v)\) of image \( I_t \) has depth value \( d \) then the voxel \((u, v, d)\) in \( C_t \) is occupied, that is, the learned features of \( C_t \) encode the probability of occupancy for each voxel. The hybrid cost volumes are treated as multiple occupancy measurements for the same 3D world space in different viewpoints, namely, for a 3D point in world space, its corresponding voxels of the volumes \( C_{t-1}, C_t, C_{t+1} \) should keep similar embedding vectors.

**Epipolar warping** To associate temporal coherence with the hybrid volumes, we should first perform epipolar warping (see Figure 3) to convert the hybrid volumes into the same camera coordinate space. Assuming a 3D point \((X_w, Y_w, Z_w)\) in the world coordinate is observed by target images \( I_t \) and \( I_{t+1} \), that is, the voxel \((u, v, d)\) of \( C_t \) and \((u', v', d')\) of \( C_{t+1} \) are occupied. The coordinate mapping from \((u, v, d)\) to \((u', v', d')\) can be easily derived from Equation 1. Using this mapping, we warp \( C_{t-1} \) and \( C_{t+1} \) into the camera coordinate space of \( C_t \) and obtain two warped hybrid volumes \( C_{t-1}^{\text{warp}}, C_{t+1}^{\text{warp}} \). After converted
into the same camera coordinate, the two warped volumes and \( C_t \) should contain similar features in voxels for overlapped regions.

**EST transformer** As depicted in Figure 4, we denote the hybrid volume to be transformed \( C_t \) as query volume and others (\( C_{t−1} \) and \( C_{t+1} \)) as memory volumes. For computational efficiency, instead of applying EST transformer on the hybrid volumes, we first feed the query volume and memory volumes into two parallel and identical convolution layers to generate two new squeezed feature maps keys \( k \in \mathbb{R}^{C/2 \times D \times H \times W} \) and values \( v \in \mathbb{R}^{C/2 \times D \times H \times W} \). The memory keys and memory values denoted as \( k_m \) and \( v_m \), are first epipolar warped into the camera space of \( C_t \), obtaining warped keys and values denoted as \( k_w \) and \( v_w \). Then we calculate the correlation between the query key \( k_q \) and the warped keys \( k_w \), yielding a correlation volume, which measures the similarity of \( k_q \) and \( k_w \). Finally we apply a softmax layer to get an attention volume \( X \in \mathbb{R}^{1 \times N \times D \times H \times W} \):

\[
x_i = \frac{\exp(k_q \cdot k_w^i)}{\sum_{i=1}^{N} \exp(k_q \cdot k_w^i)} \tag{2}
\]

where \( x_i \in \mathbb{R}^{1 \times D \times H \times W} \) measures the similarity of query to the warped key of \( i^{th} \) memory volume, \( N \) is the number of memory volumes, and \( \cdot \) means dot product.

The attention map \( X \) is used to retrieve relevant values from all warped memory values \( v_w^i, i = 1, \ldots, N \). Finally we fuse the query value and retrieved values together to obtain the final output \( \bar{C}_q \):

\[
\bar{C}_q = f(v_q, \sum_{i=1}^{N} x_i v_w^i) \tag{3}
\]

where \( v_w^i \) is the \( i^{th} \) warped memory value, and \( f(\cdot, \cdot) \) denotes a fusion function.

We explore two types of fusion function: concatenation fusion and adaptive fusion. For concatenation fusion, we just simply concatenate query value and the retrieved values together, which is straightforward and introduces no trainable parameters. However, due to occlusion or surface reflection, there might exist incorrect information in retrieved values but the concatenation operation integrates all information equally. To avoid propagating wrong information to current estimation, we propose an adaptive fusion operation to fuse the query value and the retrieved values:

\[
f(v_q, y) = w \odot g + (1 - w) \odot f(v_q, r \odot g), y = \sum_{i=1}^{N} x_i v_w^i \tag{4}
\]

where \( \odot \) means Hadamard product, \( w, r \in \mathbb{R}^{D \times H \times W} \) are two learned weight volumes which measure the reliability of the retrieved values, \( g(\cdot, \cdot) \) is a convolution layer. Unless otherwise specified, EST transformer refers to the adaptive transformer. As shown in Table 1, the adaptive fusion outperforms the simple concatenation fusion.

The EST transformer is applied to the other two hybrid cost volumes \( C_{t−1} \) and \( C_{t+1} \), yielding three transformed cost volumes \( \bar{C}_{t−1}, \bar{C}_t \) and \( \bar{C}_{t+1} \). We first apply two convolution layers on the transformed volumes to produce intermediate volumes with size \( D \times H \times W \), and then utilize the softmax operator over the depth dimension, so that we obtain probability volumes \( P \).

### 3.3. RefineNet and depth regression

We extract a depth map from probability volume \( P \) by soft argmax operation [19], which calculates the expected depth. We denote the depth map regressed from probability volume as initial depth map, since its size is downsized by four compared with original image size, whose fine grained features are lost and boundary edges are jagged. So we use a two-stage RefineNet to gradually upsample the initial depth maps and enhance fine-grained features, yielding a 1/2 resolution depth map and a full-resolution depth map. Besides, we also extract a depth map from hybrid cost volumes before being applied EST transformer. Consequently, we obtain estimated depth maps of four stages, and we denote the four types of depth map from hybrid cost volumes, transformed cost volumes, and two-stage RefineNet as \( D_s, s = 0, 1, 2, 3 \).

Unlike single-view depth loss used in prior works, we utilize multi-view depth loss to provide multiple supervision signals in different viewpoints:

\[
\text{loss} = \frac{1}{N} \sum_{s=0}^{3} \sum_{i=1}^{N} \lambda s^{-3} \left\| D^i_s - \hat{D}^i_s \right\|_1 \tag{5}
\]

where \( i \) is the the index of target image, \( N \) is the number.
of target images, $\hat{D}$ means ground truth depth map, and $\| \cdot \|_1$ means L1 norm. The weight $\lambda$ is set to 0.8 in all experiments.

### 3.4. Epipolar Spatio-Temporal Memory Inference

In the training stage, our model takes a short video sequence with 5 frames as input and jointly estimate the depth maps of three target images with short-term temporal coherence. To propagate long-term temporal coherence through the whole video, we propose an Epipolar Spatio-Temporal Memory (ESTM) inference operation. As depicted in Figure 6, we hold a sliding window containing one reference image and two source images to estimate the depth map of the current frame $I_t$. Using the EST transformer, we retrieve relevant values from a memory space storing the pairs of keys and values of $N$ past frames, thus useful information at different space-time locations can be utilized for estimating the depth map of the current frame. When the sliding window moves on, the memory space will be also updated accordingly, by which operation the long-term temporal coherence is propagated through the whole video.

### 4. Datasets and Implementation details

**Datasets** We use ScanNet dataset [7] for training our end-to-end pipeline. The whole dataset consists of more than 1600 indoor scenes, which provides color images, ground truth depth maps and camera poses. Some MVS methods, DPS [17] and MVDepth [32] are trained on DeMoN [31] dataset, but DeMoN dataset mainly consists of two-view image pairs, which is not appropriate for our setting. For a fair comparison, we finetune DPS and MVDepth on ScanNet, and evaluate all methods on the official test split of ScanNet.

Furthermore, we test our method on 7scenes [29] and SUN3D [37] datasets for cross-dataset evaluation. 7scenes and SUN3D datasets also provide color images, gt depth maps and camera poses. Unlike prior works [31, 17, 20] sample two-view image pairs from videos, we directly adopt whole videos for evaluation.

**Implementation** In the training stage, we use a video clip with 5 frames as input. The frames are sampled from 30fps video with an interval of 10. Our model is implemented by Pytorch with Adam optimizer ($lr = 0.00004$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $weight\_decay = 0.00001$). We train our model for 7 epochs (115k iterations) with batch size 4 on four GeForce RTX 2080 Ti GPUs, and the learning rate is downsampled by a factor of 2 every two epochs.

### 5. Experiments

We compare our method with SOTA models in two aspects: depth accuracy and computational efficiency.

#### 5.1. Evaluation metrics

To quantitatively evaluate the estimated depth, we use the standard metrics defined in [9]: i) inlier ratios ($\sigma < 1.25$ for $i \in \{1, 2, 3\}$); ii) Absolute error (Abs); iii) Absolute relative error (Abs Rel); iv) Square Relative error (Sq Rel); iv) Root Mean Square Error (RMSE); v) RMSE in log space (RMSE log).

To measure computational complexity of models, we adopt the following metrics: i) the number of trainable parameters; ii) the number of Multiply–Accumulate Operations (MACs); iii) inference memory usage; iv) inference time cost.

#### 5.2. Depth evaluation

**Depth accuracy** Since MVDepth [32] and DPS [17] are trained on DeMon dataset [31] not on ScanNet [7] dataset. For fair comparisons, we fine-tune MVDepthNet and DPSNet on ScanNet. As shown in Table 1, our model significantly outperforms all other methods over both ScanNet
### Table 1. Depth comparison over ScanNet [7] and 7scenes [29] datasets. Our method outperforms the other methods by a large margin. We report results in two depth ranges, since Neuralrgbd is trained in range 0 ~ 5m. Complete tables are in the supplementary materials.

| Range | Method       | Abs Rel | Abs Sq Rel | Rsq Rel | RMSE | σ < 1.25 |
|-------|--------------|---------|------------|---------|------|----------|
|       | ScanNet [7]  |         |            |         |      |          |
| 10m   | MVDepth [32] | 0.1167  | 0.2301     | 0.0596  | 0.3236| 84.53    |
|       | MVDepth-FT   | 0.1116  | 0.2087     | 0.0763  | 0.3143| 88.04    |
|       | DPS [17]     | 0.1200  | 0.2104     | 0.0688  | 0.3139| 86.40    |
|       | DPS-FT       | 0.0986  | 0.1998     | 0.0459  | 0.2840| 88.80    |
| 5m    | NAS [20]     | 0.0941  | 0.1928     | 0.0417  | 0.2703| 90.09    |
|       | CNM [23]     | 0.1102  | 0.2129     | 0.0513  | 0.3032| 86.88    |
|       | DELTAS [30]  | 0.0915  | 0.1710     | 0.0327  | 0.2390| 91.47    |
|       | Ours-EST(concat) | 0.0818 | 0.1536     | 0.0301  | 0.2234| 92.99    |
|       | Ours-EST(adaptive) | 0.0812 | 0.1505     | 0.0298  | 0.2199| 93.13    |

|       | 7scenes [29] |         |            |         |      |          |
| 10m   | MVDepth-FT   | 0.2554  | 0.0745     | 0.3435  | 79.82 |
|       | Neuralrgbd   | 0.2334  | 0.4060     | 0.2163  | 55.35 | 68.03    |
|       | Ours-EST(concat) | 0.2334 | 0.4060     | 0.2163  | 55.35 | 68.03    |
| 5m    | Neuralrgbd   | 0.1673  | 0.2970     | 0.1071  | 0.3905| 76.03    |
|       | Ours-EST(adaptive) | 0.1675 | 0.2970     | 0.1071  | 0.3905| 76.03    |

### Table 2. Comparison of temporal coherence over ScanNet dataset with depth evaluation range 0 ~ 5m.

| Metric   | DPS [17] | NAS [20] | Neuralrgbd [21] | DELTAS [30] | Ours |
|----------|----------|----------|-----------------|-------------|------|
| Abs      | 0.1887   | 0.1823   | 0.1642          | 0.1650      | 0.1432|
| Std      | 0.2243   | 0.2177   | 0.1848          | 0.1886      | 0.1673|

### 5.3. Analysis of computation complexity

To evaluate the computational efficiency of our model, we compare it with three plane-sweeping based methods, namely DPS, NAS, and neuralrgbd, plus the correspondences triangulation based method DELTAS. We run the models on one RTX 2080Ti GPU with the same setting: one reference image with two source images with a size of 320 × 256. We run our model using ESTM inference operation with 2 memory volumes.

Table 3 shows that DELTAS has the most trainable parameters but the lowest MACs, owing to the low computational cost of a fully 2D convolution network it uses. However, DELTAS consumes much more time than all the other plane-sweeping stereo methods because its correspondence triangulation module needs to perform time-consuming Singular Value Decomposition (SVD). Our method achieves significantly faster speed than the other methods. It takes about 40 milliseconds for our model to perform the adaptive ESTM operation, and 31 milliseconds to forward convolution layers, thus 71 milliseconds in total.

### 5.4. Ablation studies

In this section we evaluate the efficacy of our EST transformer and hybrid cost regularization network.

**Epipolar Spatio-Temporal transformer** We consider several variants of our method for ablation studies. We denote the depth estimated by the model without EST transformer as independent depth, the depth jointly estimated by the model with EST transformer as joint depth, and the depth sequentially estimated by the model using ESTM operation as ESTM depth. As shown in Table 4, when using the hybrid cost regularization network, both joint depth and
Our work was supported by the General Re-...
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