MVSFormer: Learning Robust Image Representations via Transformers and Temperature-based Depth for Multi-View Stereo

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Abstract

Feature representation learning is the key recipe for learning-based Multi-View Stereo (MVS). As the common feature extractor of learning-based MVS, vanilla Feature Pyramid Networks (FPN) suffers from discouraged feature representations for reflection and texture-less areas, which limits the generalization of MVS. Even FPNs worked with pre-trained Convolutional Neural Networks (CNNs) fail to tackle these issues. On the other hand, Vision Transformers (ViTs) have achieved prominent success in many 2D vision tasks. Thus we ask whether ViTs can facilitate the feature learning in MVS? In this paper, we propose a pre-trained ViT enhanced MVS network called MVSFormer, which can learn more reliable feature representations benefited by informative priors from ViT. Then MVSFormer-P and MVSFormer-H are further proposed with fixed ViT weights and trainable ones respectively. MVSFormer-P is more efficient while MVSFormer-H can achieve superior performance. To make ViTs robust to arbitrary resolutions for MVS tasks, we propose to use an efficient multi-scale training with gradient accumulation. Moreover, we discuss the merits and drawbacks of classification and regression-based MVS methods, and further propose to unify them with a temperature-based strategy. MVSFormer achieves state-of-the-art performance on the DTU dataset. Particularly, our anonymous submission of MVSFormer is ranked in the Top-1 position on both intermediate and advanced sets of the highly competitive Tanks-and-Temple leaderboard on the day of submission compared with other published works. Codes and models will be released.

1 Introduction

Multi-View Stereo (MVS) aims to reconstruct highly detailed 3D representations with multi-view images, with the key step of estimating depth maps with known camera poses [13]. Many traditional methods [5, 19, 28, 43] have achieved good results by matching low-level features of images; unfortunately they may be negatively affected by various occlusions and different illumination conditions. To this end, learning-based methods enhanced by Deep Neural Networks (DNNs) [30, 60, 22, 21, 52] have developed recently. Typically, there are three steps for learning-based MVS methods, i.e., feature extraction, cost volume construction, and cost volume regularization [60, 21].

Many works devote to formulating better cost volumes with efficient multi-stage models [22, 58, 40] and visibility information [64, 54]. Meanwhile, learning a superior cost volume regularization with hybrid 3D U-Net structures [38, 45] or Recurrent Neural Networks (RNNs) [61, 52, 53] is also shown to improve performance. Generally, the cost volume regularization is designed to refine
Figure 1: Point Clouds of two real-world cases compared with CasMVSNet \cite{22}. These cases are challenging in complex structures (the first row), hairy, texture-less and reflective objects (the second row). MVSFormer-H enjoys better confidence to filter outliers and superior reconstructions.

Figure 2: Hard cases in DTU \cite{1} with reflection and texture-less regions. (c)(d) indicate Winner-Take-All (WTA) depth from the feature correlation (1/8 scale) achieved by the dot products among reference and source features (Eq. 4) before the 3D CNN cost volume regularization. WTA depth enhanced with pre-trained ViT (Twins-small \cite{11}) contains less noise compared with one without ViT priors. (f) can also get better final depth predictions compared with (d).

noise-contaminated cost volumes with non-Lambertian surfaces or object occlusions \cite{60} to smooth feature correlations as shown in Fig. 2(c)(e). Such regularization can not rectify ambiguous feature matching results from reflections or texture-less regions. Therefore, it is still of great significance to learn good representative features to improve the generalization of MVS in the first step.

As a common solution for feature extraction, Feature Pyramid Network (FPN) \cite{35} learns multi-scale image features in most MVS networks. Some works leverage deformation convolutions \cite{49,52,40,15}, attention mechanisms \cite{63,67,15}, and normal curvatures \cite{56,21} to learn more reliable features for FPNs. Nevertheless, these works still suffer from poor generalization in modeling the reflection and texture-less regions as visualized in Fig. 2(c)(d) and challenging real-world cases as in Fig. 1. On the other hand, there is a very limited exploration of utilizing features from the Convolutional Neural Networks (CNNs) pre-trained on extra image data, e.g., ResNet \cite{26}. However, such pre-trained CNNs also have to struggle with which CNN layer has good feature abstraction and priors, best for MVS learning: 1) low-level features of CNNs only consider limited receptive fields, which lack the holistic image understanding, and fail to tackle with reflections and texture-less areas; 2) high-level features of CNNs are of highly semantic abstract, thus best for the classification rather than the fine-grained visual feature matching. Empirically, pre-trained CNN models do not have significant performance improvement in MVS.

Recent Vision Transformers (ViTs) have achieved impressive performance on various image understanding tasks \cite{16,7,50,37,11,25}. Thus, a nature question is whether we can significantly strengthen the feature representation learning of MVS with pre-trained transformers from external 2D image dataset? For the issues of reflections and texture-less regions in MVS, ViTs equipped with long-range attention modules can provide global understanding for MVS models rather than the low-level textures. Moreover, the patch-wise feature encoding of ViTs works reasonably well for
feature matching. Since the depth prediction is intrinsically a 1D feature matching problem along epipolar lines, ViTs shall be the recipe for learning-based MVS. Unfortunately, to the best of our knowledge, there is no work explicitly exploiting pre-trained ViTs for MVS.

To this end, we systematically explore pre-trained models with transformers in boosting the MVS performance. As shown in Fig. 2(e)(f), the features from pre-trained ViT are complementary to those from FPN, and facilitate better modelling reflection and texture-less regions in MVS. Formally, we propose using the pre-trained ViTs to enhance FPN for feature extraction in MVS, and further formulate a novel MVS Transformer (MVSFormer). Specifically, by considering two typical ViT backbones – plain-ViT and hierarchical-ViT, we implement MVSFormer-P and MVSFormer-H as in Fig. 3(A). To reduce the computation cost for MVSFormer-P, we take the fixed off-the-shelf ViT backbone pre-trained by the no label self-supervised method – DINO with the good clustering property. We employ the hierarchical ViT Twins as the backbone of MVSFormer-H. Benefited by the pyramid architecture and the efficient attention mechanism, MVSFormer-H can be trained in high-resolution and typically achieve better results compared with MVSFormer-P.

Further, we present an efficient multi-scale strategy to train MVSFormer, as it is non-trivial to directly train ViTs for MVS. In MVS tasks, the models should be tested on various high-resolution images, while they have to be trained on low-resolution to save the training computations. It is thus not amenable to directly extending pre-trained ViTs to MVS tasks.

Furthermore, we technically unify the advantages of both regressive depth (regression), and argmax depth (classification) for MVSFormer. Different from previous works, we find that optimizing the MVS network with cross-entropy loss can achieve much more reliable confidence maps but slightly worse depth predictions. Because the argmax operation can not provide exact depth results, which harms the depth performance. To address this issue, MVSFormer predicts the temperature-based depth expectation instead of the argmax during the inference and achieves smooth depth predictions and superior final point clouds.

Our contributions can be highlighted as: (1) To the best of our knowledge, it is the first work that systematically explores the influence of pre-trained ViTs on MVS. (2) We propose a novel ViT enhanced MVS network – MVSFormer that has the implementations of MVSFormer-P and MVSFormer-H, which are further trained with the efficient multi-scale training strategy to be generalized for various resolutions. (3) We analyze the merits and limitations of regression and classification-based MVS, and propose a simple but effective way to unify both. (4) The proposed methods can achieve the state-of-the-art performance in both DTU dataset and Tanks-and-Temple.

2 Related Works

Learning-based MVS methods. Learning-based MVS methods enhanced with DNNs have been extensively studied for MVS tasks. MVSNet proposes an end-to-end pipeline based on 2D CNN image feature extraction, cost volumes formulated by homography warping, and a cost volume regularization by 3D CNN. Many works are devoted to reducing the heavy computation of 3D CNN-based cost volume regularization with coarse-to-fine strategies and RNNs. Meanwhile, some researches formulate a more reliable cost volume, such as the visibility of ViS-MVSNet, and the epipolar aggregation of MVSTER. Besides, many works try to learn a better cost regularization by hybrid 3D U-Net, RNN-3DCNN, and epipolar attention. Although many efforts are paid to achieve better cost volumes, we advocate that learning superior feature representations are more effective for a generalized MVS method. Our method explores using pre-trained ViTs to improve MVS feature learning, which is orthogonal to these works based on cost volumes.

Feature learning in MVS. Since 2D image features are critical in MVS learning, powerful FPN is the common solution. FPN is designed as a U-Net to fuse multi-scale features. Deformation convolutions are widely used in MVS to improve the receptive fields flexibly. Furthermore, Xu et al. and Giang leverage fixed and learnable normal curvatures to dynamically select kernel sizes for FPN, which can learn robust features for various image resolutions. Besides, the attention mechanism is also utilized for MVS feature learning. Many works leverage

Intuitively Twins can also be pre-trained by DINO. However, it is non-trivial to implement and train it, due to technical difficulty and expensive running costs on ImageNet (taking 1 months on 2 V100 GPUs). Thus Twins pre-trained by DINO is beyond the scope of this paper.
Vision Transformers. Self-supervise pre-trained transformers have achieved prominent success in Natural Language Processing (NLP) [47, 14, 4]. Inspired by these achievements, transformers are also introduced into the computer vision [16, 7, 50, 37, 11, 25], which may include CNNs are all simplified as ViTs here. ViTs achieve state-of-the-art performance in many vision tasks, which include image classification [16, 37, 11, 25], detection and segmentation [11, 66, 34], optical flow [27], point cloud processing [23, 65] and so on. Compared with CNNs, ViTs enjoy much more long-range modelling capacity. Since ViTs lack some inductive biases inherent to CNNs, such as translation equivariance and locality, they are much more data-hungry to generalize to unseen data [17, 16, 55]. Therefore, pre-training is necessary for ViTs. For different pre-training tasks, ViTs can be categorized into self-supervised ones [2, 25, 7] and supervised ones [16, 50, 37, 11]. Supervised ViTs are usually pre-trained for the classification task, while self-supervised ones are implemented with masked prediction [25, 2] or contrastive learning [7, 9]. Furthermore, to reduce notorious computations and memory costs of the vanilla attention, many ViTs use multi-scale architectures [37, 50, 11] instead of single-scale backbones [16, 25]. Particularly, many works have tried to finetune pre-trained ViTs for various downstream tasks [7, 11, 25, 34, 27, 8]. Although pre-trained ViTs are appealing in many fields, releasing their potential in MVS is non-trivial, which will be discussed in the following sections.

3 Method

Overview. The architecture of MVSFormer is overviewed in Fig. 3 as the seminal MVS pipeline in [60]. Given a group of \( N \) images with different views which contain reference image \( I_0 \in \mathbb{R}^{H \times W \times 3} \) and source images \( \{ I_i \}_{i=1}^{N-1} \in \mathbb{R}^{H \times W \times 3} \), as well as the their camera intrinsics and extrinsics, MVSFormer learns feature representation in feature extraction (Sec. 3.1), enhanced by the plain ViT– DINO [7] (Fig. 3(a)) or the hierarchical ViT– Twins [11] (Fig. 3(b)) with several novel training strategies (Sec. 3.2). Then the multi-stage cost volume formulation and regularization are presented to compute the probabilities of coarse-to-fine depth hypotheses (Sec. 3.3). Finally, cross-entropy loss is employed to optimize the MVSFormer, while the inference is made on depth expectation (Sec. 3.4).

3.1 Feature Extraction

As many MVS works, we also use FPN [35] as the main feature extractor, which is enhanced with pre-trained ViTs. In MVSFormer, ViTs work to formulate global feature correlations, while FPN
is devoted to learning detailed ones. Before taking reference and source images to the ViT, we first downsample them into \((\frac{H}{4}, \frac{W}{4})\) to save the computation and memory costs. We resize the absolute position encoding of pre-trained ViTs with bicubic interpolation to fit different image scales \([16]\). Then plain-ViT output \(F^{(p)}\) or hierarchical-ViT output \(F^{(h)}\) is directly added to the highest level feature of the FPN encoder. Thus we can get coarse-to-fine features \(\{F^{(l)}\}_{l=1}^{L-1}\) from the FPN decoder scaled from \((\frac{H}{4}, \frac{W}{4})\) to \((H, W)\) of the origin resolution as shown in Fig. 3(A). These features contain priors from both ViT and CNN, and will be leveraged to formulate more reliable cost volumes.

**MVSFormer-P.** We use DINO \([7]\) as the backbone of MVSFormer-P. DINO is pre-trained with the self-distillation with no labels. The most prominent characteristic of DINO is that attention maps of its last layer can learn class-specific object segmentation as shown in Fig. 4. Thanks to the unsupervised training and the multi-crop \([6]\) strategy, DINO enjoys good generalizations for various environments, illuminations, and resolutions. Therefore, such beneficial property makes DINO suitable to solve MVS. Since MVS is a feature matching task essentially, the priors of object or scene segmentations are useful to avoid confused depth predictions of foreground and background.

As inputs to ViT have been halved yet, after the patch-wise embedding with kernel and stride size 16, DINO performs the attention-based learning for feature maps with the resolution of \((\frac{H}{32}, \frac{W}{32})\). To better utilize the good segmentation property of DINO, we use a trainable Gated Linear Unit (GLU) \([44]\) to reduce the dimension of DINO features \(F_{\text{dino}}\) as shown in Fig. 3(a). We assume that \(A \in \mathbb{R}^{H \times W \times h}\) indicates attention maps of the \([\text{CLS}]\) token with \(h\) attention heads from the last layer of DINO. \(\hat{A} \in \mathbb{R}^{\frac{H}{16}, \frac{W}{16} \times 1}\) is averaged along \(h\) heads from \(A\). Thus GLU can be written as

\[
\hat{F}^{(p)} = \text{Swish}(\text{ConvBN}([F_{\text{dino}}; A]) \circ \text{Swish}(\text{ConvBN}_{r}([F_{\text{dino}} \circ \hat{A}])) \in \mathbb{R}^{\frac{H}{32}, \frac{W}{32} \times C_{P}}, \tag{1}
\]

where \(\text{Swish}(x) = x \cdot \text{sigmoid}(x)\) \([42]\); \(\circ\) means the element-wise multiplication; \([; ;]\) indicates the concat operation; \(C_{P}\) is the reduced channel of DINO. GLU helps to protect important features benefited from the class-specific attention maps during the dimension reduction, which can effectively improve the MVS performance. Then we use two transpose convolutions to upsample \(F^{(p)}\) to \(F^{(p)} \in \mathbb{R}^{\frac{H}{16}, \frac{W}{16} \times C}\) for the feature addition to the FPN encoder with channels \(C\). Although the plain-ViT based DINO suffers from heavy memory and computation costs, we find that MVSFormer-P can work well with even fixed DINO of trainable GLU and upsample convolutions. Therefore, MVSFormer-P only demands a little more memory cost compared with the vanilla MVS FPN training.

**MVSFormer-H.** The Twins \([11]\) is used as the backbone in MVSFormer-H. To finetune MVSFormer-H in various resolutions, the ViT backbone should meet two conditions, \(i.e.,\) the efficient attention mechanism and the robust position encoding for different scales, which are both solved by Twins elegantly. As a hierarchical ViT model, Twins consists of a multi-scale architecture as shown in Fig. 3(b). To further reduce the complexity, Twins proposes to use separable locally-grouped self-attention and global sub-sampled attention to construct each attention block. Such a global and local design outperforms the classic pyramid vision transformer \([50]\). Besides, Twins leverages Conditional Position Encoding (CPE) \([12]\) instead of absolute positional encodings in other ViTs \([16, 25, 37]\). CPE works as a residual 2D depthwise convolution added to the attention outputs, which is learned with positional cues from the zero-padding \([29]\). CPE breaks the permutation-equivalent of ViTs and introduces proper inductive biases from CNNs, which benefits the scale robustness of Twins.

As shown in Fig. 3(b), MVSFormer-H encodes 4 multi-scale features \(\{F^{(h,s)}\}_{s=1}^{4}\) with \((\frac{1}{8}, \frac{1}{16}, \frac{1}{32}, \frac{1}{64})\) of the origin resolution respectively. We use another FPN to upsample these multi-scale features as

\[
F^{(h)} = \text{FPN}(F^{(h,1)}, F^{(h,2)}, F^{(h,3)}, F^{(h,4)}) \in \mathbb{R}^{\frac{H}{8}, \frac{W}{8} \times C}. \tag{2}
\]

Benefited by the efficient design, we can finetune the pre-trained Twins during the training phase with a relatively low learning rate. MVSFormer-H costs a little more GPU memory compared with MVSFormer-P, and can achieve superior performance in MVS. More details are discussed in Sec. 4.

### 3.2 Efficient Multi-scale Training

Although ViTs have large capacity, missing translation equivariance and locality make them vulnerable to handling various input resolutions \([17, 16, 55]\). Unfortunately, most MVS tasks should be tested in different High-Resolution (HR) (from \(1200 \times 1600\) \([11]\) to \(1080 \times 1920\) \([33]\). CNN-based methods can largely solve this problem with dynamic kernels \([21]\) and random cropping \([40]\). Most
Figure 4: Mean attention maps of [CLS] token from DINO [7] with various resolutions. Note that 576×768 and 544×960 are max input sizes for DTU and Tank-and-Temples to our MVSFormer-P.

Algorithm 1 PyTorch pseudo code for efficient multi-scale training with gradient accumulation

```python
# B: maximal batch size
# scale_batch_dict: a mapping dict, key is resolution; value is related sub-batch size
# optimizer: Adam optimizer
for (x, y) in data_loader:  # load a batch consisted of inputs x and reference depth y
    b = scale_batch_dict[shape(x)]  # get related sub-batch size from the dict
    n = B // b  # get the step number n for accumulation
    for i in range(n):  # accumulate gradients for n steps
        y_pred = MVSFormer(x[i*b:(i+1)*b])  # model inference with a sub-batch
        loss = LossFunction(y_pred, y[i*b:(i+1)*b])  # calculate loss for sub-batch
        loss.backward()  # back-propagate and accumulate gradients
    optimizer.step()  # optimize model parameters
    optimizer.zero_grad()  # clear accumulated gradients
```

importantly, CNNs can process arbitrary input sizes benefited by their inductive biases, i.e., translation equivariance, and locality. For the trainable Twins in MVSFormer-H, training with the same resolution tends to overfit one input size, and fails to be generalized to HR cases. \(^3\)

Thus, we repurpose learning features with multi-scale training, which is originated from ViT-based segmentation tasks \([32,11,5]\). Particularly, for efficient multi-scale training, we have to ensure that 1) image sizes for each batch should be the same; 2) dynamically changing the batch size according to image sizes, which aims to make the full usage of limited memory. This algorithm is summarized as PyTorch pseudo-code in Alg. 1 We train our models with dynamic resolutions from 512 to 1280, while aspect ratios are randomly sampled from 0.8 to 0.67. Instead of the compromise that using a minimum batch size, we keep the multi-scale training with the largest batch size, assisted by the gradient accumulation. The gradient accumulation splits a batch into several sub-batches and accumulates their gradients to update the model. All instances are grouped into different pairs of resolution and sub-batch size at the start of each epoch randomly. Note that a larger image should have a smaller sub-batch to balance the memory cost and vice versa. Training with a larger batch size contributes to faster convergence with lower variances and better performance for BatchNorm layers \([28]\). Therefore, the gradient accumulation significantly improves the efficiency of the multi-scale training of MVSFormer. We find that dynamic training sizes from 512 to 1280 are sufficient to generalize MVSFormer to at least 2K resolution of Tanks-and-Temples \([33]\).

3.3 Correlation Volume Construction

To achieve the multi-stage cost volume \([22]\), we first initialize a group of inverse depth ranges \({d_j}\}_{j=1}^G\) for each stage. Here we omit the superscript of \(l\)-th stage for the simplification. Features of source views are warped to the reference view. Given a 2D pixel \(p\) of the reference image \(I_0\) with known camera intrinsics \(K_0, K_i\) of reference and source views, as well as their rotation \(R_{0 \rightarrow i}\); and translation \(t_{0 \rightarrow i}\), warped \(p_j^i\) with the \(j\)-th depth hypothesis in source image \(I_i\) can be written as

\[
p_j^i = K_i \cdot R_{0 \rightarrow i} \cdot K_0^{-1} \cdot p \cdot d_j + t_{0 \rightarrow i}.
\]  

(3)

Then the group-wise pooling \([24]\) is leveraged to split features into \(G\) groups along the channel dimension. And the feature correlation \(C_i\) can be formulated by the inner production of group-wise reference features \(F_0^i\) and warped source features \(F_j^i\) as

\[
C_i(d_j, p, g) = \langle F_0^i(p), F_j^i(p_j^i) \rangle \in \mathbb{R}^\hat{C},
\]  

(4)

where \(\hat{C}\) is the channel of \(F_0^i\) and \(F_j^i\). Then the feature correlation from Eq. 4 is further averaged for each group to \(C_i(d_j, p) \in \mathbb{R}^\hat{C}\) for an efficient cost volume formulation. We also train a 2D CNN to
learn pixel-wise weight visibility \( \{ w_i \}_{i=1}^{N-1} \) for each source view through the entropy of normalized correlations [64][21]. Thus \( N - 1 \) source feature correlations can be fused with their visibility as

\[
C(d_j) = \frac{\sum_{i=1}^{N-1} w_i C_i(d_j)}{\sum_{i=1}^{N-1} w_i}
\]

which is the input for the 3D U-Net cost volume regularization. After being regularized by the 3D U-Net, we can achieve pixel-wise output 3D cost volume \( \hat{C} \in \mathbb{R}^{D \times H \times W} \) for each stage.

### 3.4 Temperature-based Depth Prediction

Given the cost volume \( \hat{C} \) from the 3D U-Net, the probability volume of depth hypotheses can be achieved by the \( \text{softmax} \) along the depth dimension as \( P = \text{softmax}(\hat{C}) \). REGression-based depth (REG) utilizes \( \text{soft-argmin} \) [32] to softly weighting for each depth hypothesis, i.e., the expectation of \( \{ d_j \}_{j=1}^{D} \) with probability \( P(d_j) \). For the CLAssification-based depth (CLA), the predicted depth \( D_{cla} \) is simply selected from all depth hypotheses with the maximum probability, i.e. the \( \text{argmax} \) depth hypothesis. Thus the regressive depth \( D_{reg} \) and the classification depth \( D_{cla} \) are

\[
D_{reg} = \sum_{j=1}^{D} d_j \cdot P(d_j), \quad D_{cla} = \underset{d_j \in \{ d_j \}_{j=1}^{D}}{\text{argmax}} P(d_j).
\]

\( D_{reg} \) is optimized with the \( L_1 \) loss with the ground-truth depth, while \( D_{cla} \) is optimized with the Cross-Entropy (CE) with the one-hot ground-truth depth volume.

**Remark.** Peng et al. [41] think that REGs suffer from the overfitting issue, as the ambiguous depth prediction and the weight distribution. And CLAs are more robust but fail to achieve exact depth results. Here we should hold the different opinion that confidence maps from CLAs are better than the REGs, which should not be neglected especially for the widely used multi-stage MVS models [22][58][50]. MVS networks can not ensure all predicted depth maps are correct, because of reflection, occlusion, or missing reliable source views. Therefore, providing solid confidence maps is also important for the MVS learning to reconstruct good point clouds. But as shown in Fig. 5(a), the REG maintains high-confidence values for out-of-range depth hypotheses in stage-2,3,4. It is difficult for REGs to filter outliers without hurting other correct depth predictions as shown in Fig. 5(b). Since CE can not tackle out-of-range depth labels, we mask all depth outliers during the training as [40]. We have tried to optimize the MVS with masked \( L_1 \) loss, but it performs worse than regular regression.

Although CLA has many good properties for MVS, REGs can achieve superior performance of depth and point cloud compared with CLAs in our early experiments. So we target on the issue mentioned in [41], i.e., inexact depth predictions. UniMVSNet [41] designs a Unified Focal Loss (UFL) to solve it, which regards CE as multiple Binary Cross-Entropy (BCE). And the focal loss [36] controlled by several hyper-parameters is used to solve the imbalance problem in BCE. Different from UFL, we propose a simple way to unify both REGs and CLAs, which only adjusts the inference process without re-training the model. We first multiply a temperature \( t \) to the cost volume \( \hat{C} \) before the
softmax, and rewrite \( D_{\text{reg}} \) to the temperature-based depth expectation \( D_{\text{tmp}} \) as

\[
D_{\text{tmp}} = \sum_{j=1}^{D} d_j \cdot \hat{P}(d_j), \quad \hat{P} = \text{softmax}(\hat{C} \cdot t). \tag{7}
\]

Obviously, when \( t = \infty \) or \( t = 1 \), \( D_{\text{tmp}} \) is equivalent to \( D_{\text{cla}} \) or \( D_{\text{reg}} \), respectively. The core idea is to adjust the temperature \( t \) during the inference to unify CLAs and REGs. For early stages with low-resolution, we set larger \( t \) to make the model work as a CLA for a better global distinguishing ability. And for later stages with high-resolution, our model tends to use lower \( t \) as a REG to smooth local details. In practice, we set \( \{t^1, t^2, t^3, t^4\} = \{5, 2.5, 1.5, 1\} \) and achieve better performance than classification (\( t = \infty \)), regression (\( t = 1 \)), and other consistent settings of \( t \). Note that \( D_{\text{tmp}} \) is only used during testing, as the masked CLA optimized with CE is robust enough for MVS learning. Thus, \( D_{\text{cla}} \) is adopted in MVSFormer for the training phase.

4 Experiments

Settings. Our methods are evaluated on DTU [11] and Tanks-and-Temples [33]. Since DTU data is collected in an indoor environment with fixed camera poses, our model is finetuned on the BlendedMVS dataset [62] with various scenes and objects to generalize more complex environments in Tanks-and-Temples, as standard practice in [21, 15]. MVSFormer is trained by the view number \( N = 5 \) of 4 coarse-to-fine stages of 32-16-8-4 depth hypotheses. CNN parts in MVSFormer are trained by Adam with a learning rate of 1e-3. DINO-small is fixed in MVSFormer-P during the training phase, while Twins-small in MVSFormer-H is trained with learning rate 3e-5 and 0.01 weights decay. Our models are trained by 10 epochs on DTU and finetuned with another 10 epochs on BlendedMVS. The learning rate is warmed up with 500 steps and then decayed with the cosine scheduler. For the multi-scale training, we dynamically change the sub-batch from 8 to 2 according to the scales from 512 to 1280, with a maximum batch size of 8. We use mixed precision, and train the model with batch size 8 on two 32GB NVIDIA V100 GPUs. More details are in Appendix.

4.1 Results on DTU

Our MVSFormer is evaluated on DTU [11] with the official evaluation metrics of point clouds, \textit{i.e.}, accuracy, completeness, and the overall error. The testing resolution is fixed in 1152 \( \times \) 1536 and the view number \( N = 5 \). We use the depth fusion of Gipuma [20] with a consistent confidence threshold 0.5 for the point clouds. Quantitative results of DTU are shown in Tab. 1, and qualitative ones are shown in Appendix. Note that the post-processing hyper-parameters of all scans are fixed for learning-based methods. Traditional methods [20, 43] fail to get good completeness, which means that they have missed many points with sparse results. For learning-based methods, Our MVSFormer-H can achieve the best completeness and overall error. MVSFormer-P is the second-best in overall error which enjoys faster efficiency. Therefore, our methods can get more complete point clouds compared with other competitors. Note that results reported in GBiNet [40] need to use different hyper-parameters for the post-processing. Our methods can outperform GBiNet with fixed hyper-parameter settings for all scans. With the impressive improvements achieved by MVSFormer, we think that pre-trained ViTs have the potential to push the limits of MVS.

\begin{table}[h]
\centering
\begin{tabular}{llll}
\hline
Methods & Acc. & Cop. & Ovl. \\
\hline
Gipuma [20] & 0.283 & 0.873 & 0.578 \\
COLMAP [33] & 0.400 & 0.664 & 0.532 \\
R-MVSNet [61] & 0.385 & 0.459 & 0.422 \\
AA-RMVSNet [52] & 0.376 & 0.339 & 0.357 \\
CasMVSNet [22] & 0.325 & 0.385 & 0.355 \\
CDS-MVSNet [21] & 0.352 & 0.280 & 0.316 \\
UniMVSNet [41] & 0.352 & 0.278 & 0.315 \\
TransMVSNet [15] & 0.321 & 0.289 & 0.305 \\
GBiNet* [40] & 0.312 & 0.293 & 0.303 \\
MVSFormer-P & 0.327 & 0.265 & 0.296 \\
MVSFormer-H & 0.327 & 0.251 & 0.289 \\
\hline
\end{tabular}
\caption{Quantitative point cloud results (mm) with Accuracy (Acc.), Completeness (Cop.), and Overall (Ovl.) on DTU [11] (lower is better). Best results are in bold, and second ones are underlined. * means that GBiNet [40] is re-tested with the same post-processing threshold to all scans for fair comparisons with other methods.}
\end{table}
Figure 6: Qualitative results compared with our baseline worked with different pre-trained models.

4.2 Results on Tanks-and-Temples

Our anonymous submission of MVSFormer-H ranks Top-1 on both intermediate and advanced sets of the official Tanks-and-Temples leaderboard compared with other published works. We show the quantitative results on both intermediate set and advanced set in Tab. 2. All instances are inferred with the original $1088 \times 1920$ image size and view number $N = 10$. The metric is officially evaluated by the F-score based on precision and recall of submitted point clouds. [23]. MVSFormer-H outperforms all other state-of-the-art methods with mean F-scores of 66.37 and 40.87 for intermediate and advanced sets respectively. As shown in Tab. 2, our method can achieve best or second-best results in almost all cases except ‘Francis’ and ‘Auditorium’, which demonstrates its good generalization and impressive performance. Furthermore, confidence maps from CLA can filter outliers and get more precise point clouds. Besides, the proposed multi-scale strategy can generalize MVSFormer to fit larger resolutions, such as 2K. More qualitative results and analysis are in Appendix.

Table 2: Quantitative results of F-score on Tanks-and-Temples. Higher F-score means a better reconstruction quality. Best results are in bold, while the second ones are underlined.

| Methods       | Intermediate | Advanced |
|---------------|--------------|----------|
|               | Mean | Fam. | Fra. | Hor. | Lig. | M60 | Pan. | Pla. | Tra. | Mean | Aud. | Bal. | Cou. | Mus. | Pal. | Tem. |
| COLMAP        | 42.14 | 50.41 | 22.25 | 26.63 | 56.43 | 44.83 | 46.97 | 48.53 | 42.04 | 27.24 | 16.02 | 25.23 | 34.70 | 41.51 | 18.05 | 27.94 |
| CasMVSNet     | 56.84 | 76.37 | 58.45 | 46.26 | 55.81 | 56.11 | 54.06 | 58.18 | 49.51 | 31.12 | 19.81 | 38.46 | 29.10 | 43.87 | 27.36 | 28.11 |
| CDS-MVSNet    | 61.58 | 78.85 | 63.17 | 53.04 | 61.34 | 62.63 | 59.06 | 62.28 | 52.30 | –     | –     | –     | –     | –     | –     | –     |
| TransMVSNet   | 63.52 | 80.92 | 65.83 | 56.94 | 62.54 | 63.06 | 60.00 | 60.20 | 58.67 | 37.00 | 24.84 | 46.49 | 34.69 | 36.62 |
| UniMVSNet     | 64.36 | 81.20 | 66.43 | 53.11 | 63.46 | 64.84 | 62.23 | 62.28 | 52.30 | 38.96 | 23.83 | 39.74 | 32.80 | 34.63 |
| GBiNet        | 61.42 | 79.77 | 67.69 | 51.81 | 61.25 | 60.37 | 55.87 | 60.67 | 53.89 | 37.32 | 29.77 | 42.12 | 36.30 | 36.93 |
| MVSFormer-H   | 66.37 | 82.06 | 69.34 | 60.49 | 68.61 | 65.67 | 64.08 | 61.23 | 59.53 | 40.87 | 28.22 | 46.75 | 39.30 | 52.88 | 35.16 | 42.95 |

4.3 Ablation studies

Different pre-trained models. We have tested different pre-trained models for MVS in Tab. 3 which include ResNet50 [26], DINO [7], MAE [25], and Twins [11]. Our baseline method is a 4-stage MVS model with visibility modules [64] and the random cropping [40]. From Tab. 3, ResNet50 improves the depth but fails to reduce the overall error of point clouds. Because CNN-based pre-training can not learn proper features from reflection and texture-less areas, which causes discouraged metrics for

Table 3: Ablations in DTU based on the baseline with different pre-trained models, prior attention based GLU of DINO, augmentation strategies, and loss types. Metrics are depth error ratios of 2mm ($e_2$), 4mm ($e_4$), 8mm ($e_8$) and the Overall error (Ovl.) of point clouds. The red line show results of our baseline; green and blue rows indicate our MVSFormer-P and MVSFormer-H respectively.

| Pre-trained | GLU | Augmentation | Loss | $e_2$↓ | $e_4$↓ | $e_8$↓ | Ovl.↓ |
|-------------|-----|--------------|------|--------|--------|--------|-------|
|             |     | Cropping     | HR-FT | Multi-scale | REG | CLA |       |
| –           | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| ResNet50    | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| DINO-small  | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| MAE-base    | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| Twins-small | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| Twins-small | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| Twins-small | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| Twins-small | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |
| Twins-small | ✓   | ✓            | ✓    | ✓      | ✓     | ✓     | ✓     |

9
these scans and leads to even worse results in point clouds as shown in Fig. 6. Our MVSFormers can improve the baseline even without the multi-scale training. For the comparisons among pre-trained ViTs with the multi-scale training strategy, both DINO-small and MAE-base are fixed during the training. But DINO-small achieves better performance with fewer parameters, which is benefited by the multi-crop \[6\] and our proposed global attention based GLU. Generally, MVSFormer-H achieves the best performance in point clouds, while MVSFormer-P gets better depth metrics.

**Multi-scale training.** We also analyze the effect of the multi-scale training in Tab. 3. Note that both MVSFormer-P and -H can achieve considerable improvements from it. We should claim that the high-resolution finetuning (HR-FT) can not get results as good as the multi-scale strategy.

**Temperature-based depth prediction.** Ablations about REG and CLA of MVSFormer-H are shown in Tab. 4. The vanilla CLA \( (t = \infty) \) based model can not achieve better results compared with the one trained with REG. As reducing the temperature \( t \), depth is smoothed and models tend to reconstruct more accurate point clouds. Because of the decrease in accuracy distance and the increase in completeness distance. Since the trade-off of the accuracy and completeness, \( t = 0.75 \) achieves a worse overall result. Simply reducing \( t \) for early stages causes over-smoothing results, which harms the completeness of point clouds. Our \( \{t^1, t^2, t^3, t^4\} = \{5, 2.5, 1.5, 1\} \) setting can get a good trade-off in both depth and point clouds, which is better than any consistent \( t \). Therefore, the idea of making early stages work as CLA and latter stages work as REG is reasonable.

## 5 Conclusion

In this paper, we discuss the influence of pre-trained models on MVS learning, and propose a ViT enhanced MVS architecture called MVSFormer. MVSFormer can achieve prominent improvements with pre-trained ViTs. Furthermore, MVSFormer can be divided into MVSFormer-P and MVSFormer-H with fixed plain-ViTs and trainable hierarchical-ViTs. And we also propose to use an efficient multi-scale training to generalize MVSFormer to various resolutions. Besides, a temperature-based depth prediction is proposed to simply unify both REG and CLA in the MVS learning. Our method can achieve state-of-the-art results in DTU, and rank top-1 on both intermediate and advanced Tanks-and-Temples.

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Appendix

6 More Implemented Details

Multi-scale training. The training scales are randomly selected from 25 patterns, whose height is ranged from 512 to 1024, while width is ranged from 640 to 1280. We also randomly crop images from [0.83,1.0] of the original scale. The relation of sub-batch size and resolution is shown in Tab. 5. Thanks for the mixed-precision, it only takes about 22 and 15 hours for our proposed MVSFormer to be trained with 10 epochs in DTU \[1\] and BlendedMVS \[62\] respectively with two V100 32GB NVIDIA Tesla GPUs.

Table 5: The relation of sub-batch size and resolution in the multi-scale training of MVSFormer-P and MVSFormer-H, which can be trained in two 32GB GPUs with maximum batch size 8.

| Resolution       | sub-batch size |
|------------------|----------------|
|                  | MVSFormer-P   | MVSFormer-H   |
| 512x640–768      | 8              | 8              |
| 576x704–832      | 8              | 8              |
| 640x832–960      | 8              | 8              |
| 704x896–1024     | 8              | 4              |
| 768x960–1088     | 4              | 4              |
| 896x1152–1280    | 4              | 4              |
| 960x1216–1344    | 4              | 2              |
| 1024x1280        | 4              | 2              |

Post-processing. For DTU, we get the final point clouds with the depth fusion tool from Gipuma \[20\] with consistent hyper-parameters, \textit{i.e.}, disparity threshold 0.1, number consistent 2, and probability threshold 0.5. For Tanks-and-Temples, to avoid adjusting hyper-parameters for each case, we follow the dynamic consistency checking proposed in \[57\].

7 Inference Memory and Time Costs

We test the inference memory and time costs with input resolution 1152 × 1536 in Tab. 6 compared with CNN-based pre-training and pure FPN. All comparisons are based on a V100 NVIDIA Tesla GPU. From Tab. 6, although the parameter scale is increased, ViT enhanced MVSFormers only cost a little more GPU memory and time compared with the baseline method. Except for parameters contained by ViT itself, most other trainable parameters are worked for the dimension reduction in MVSFormer. MVSFormer-H can infer faster compared with MVSFormer-P, which is benefited from the efficient multi-scale attention designed in Twins \[11\]. Note that the pre-trained CNN model –ResNet50 also costs a lot in GPU memory and inference time.
Table 6: Illustration of model parameters (Params.) and memory/time-cost during the inference phase of $1152 \times 1536$ images. Results in brackets are forwarded with 1 view at once, while ones outside are forwarded 5 views at once.

|                | Memory (MB) | Time (s/img) | Params. (all) | Params. (trainable) |
|----------------|-------------|--------------|---------------|---------------------|
| Baseline       | 4262(8997)  | 0.4125(0.4055)| 1.35M         | 1.35M               |
| Baseline+ResNet50 | 4882(9523)  | 0.4920(0.4704)| 37.27M        | 37.27M              |
| MVSFormer-P    | 4842(9251)  | 0.5530(0.5230)| 26.45M        | 4.79M               |
| MVSFormer-H    | 4970(9431)  | 0.4831(0.4398)| 28.01M        | 28.01M              |

8 More Experiment Results

8.1 Pre-trained ViTs without FPNs

To explore the learning ability of ViTs, some quantitative results about ViTs (DINO-small [7], MAE-base [25], Twins-small [11]) trained without FPNs for MVS are shown in Tab. 7, which are also compared with CNN-based pre-trained ResNet34 and ResNet50 and the vanilla FPN. Note that these experiments are only based on low-resolution cases in DTU of $256 \times 320$, because we want to save computation with all trainable ViT weights. The learning rates of MAE and DINO are 1e-5; the learning rate of Twins is 3e-5, and the ones of all CNNs are 1e-3. From Tab. 7 ViTs cannot achieve as good details as CNNs (2mm, 4mm), but results from ViTs are more robust in large depth error metrics (8mm, 14mm). Therefore, we think that ViTs can tackle some serious mistakes caused by reflection and texture-less areas as mentioned in the main paper. Interestingly, FPN trained from scratch achieves better depth results in low-resolution cases compared with other pre-trained CNNs, which demonstrates the dilemma of using pre-trained CNNs in MVS again. Twins-small can get better depth than FPN except for the 2mm error benefited by its pyramid architecture. So ViTs can work complementarily with CNN-based FPNs for both global understanding and local details in MVS.

Table 7: Depth metrics for DTU ($256 \times 320$) compared with FPN, pre-trained CNNs and VITs [25, 7, 11]. Note that FPN is trained from scratch without pre-training.

|                | FPN | ResNet34 | ResNet50 | MAE-base | DINO-small | Twins-small |
|----------------|-----|----------|----------|----------|------------|-------------|
| Error(\%)      |     |          |          |          |            |             |
| 2mm            | 19.53 | 20.65    | 20.55    | 21.85    | 26.66      | 19.65       |
| 4mm            | 11.85 | 12.43    | 12.32    | 12.42    | 14.42      | 11.53       |
| 8mm            | 8.25  | 8.55     | 8.45     | 8.17     | 8.87       | 7.92        |
| 14mm           | 6.48  | 6.75     | 6.60     | 6.33     | 6.60       | 6.24        |
| mean           | 11.52 | 12.09    | 11.98    | 12.19    | 14.14      | 11.34       |

8.2 Different Feature Fusion Strategies of MVSFormer

We pay more attention to the essential improvements gained from pre-trained ViTs in this paper. Thus we tend to use simple feature fusion strategies in MVSFormer. Both the Direct Feature Addition (DFA) (used in the main paper) and the Multi-scale Feature Addition (MFA) is considered in Tab. 8. For the multi-scale addition, we use extra convolution blocks to further upsample ViT features to 1/4 and 1/2, and add them to related feature maps in FPN. Since inputs to ViTs are halved, we do not try to upsample ViT features to 1/1. From Tab. 8 MFA can achieve slightly better depth predictions but worse point cloud metrics. We think that ViT features are not suitable for high-resolution features, and adopt DFA as our solution.

Table 8: Ablations about different feature fusion strategies of Direct Feature Addition (DFA) and Multi-scale Feature Addition (MFA) in MVSFormer-H.

|            | $e_2$ | $e_4$ | $e_8$ | Acc. | Cop. | Ovl. |
|------------|-------|-------|-------|------|------|------|
| DFA        | 17.50 | 12.48 | 9.14  | 0.327| 0.251| 0.289|
| MFA        | 17.53 | 12.24 | 8.62  | 0.329| 0.253| 0.291|
8.3 Qualitative Results of Temperature-based Depth Prediction

We show additional qualitative results of CLA with different temperature $t$ in Fig. 7. $t = 100$ tends to output depth maps with jagged boundaries, while depth maps with $t = 1$ and based on regression suffer from uncertain and ambiguous predictions. Although the visual difference is not obvious between Fig. 7(e) and Fig. 7(f), our setting of $\{t_1, t_2, t_3, t_4 = 5, 2.5, 1.5, 1\}$ can get more exact depth predictions compared with $t = 100$ or $t = \infty$, which leads to better detailed depth and point clouds results as discussed in the main paper.

Figure 7: Qualitative depth comparisons among REG, and CLA with different $t$ settings.

8.4 Comparison of Different ViT Capacities

We further evaluate the performance of MVSFormer-P and MVSFormer-H with larger ViT backbones (base model) in Tab. 9. Interestingly, DINO-base achieves worse performance compared with DINO-small. We think that smaller DINO [7] used in MVSFormer-P enjoys better generalization, because the DINO backbone is fixed in MVSFormer-P due to the costly plain-ViT design. On the other hand, Twins-base can achieve full depth improvements compared with the small one, but improvements of point clouds are negligible. Obviously, point cloud metrics are more difficult to be improved. But we can still expect for good performance from larger trainable pre-trained ViTs. Besides, both DINO-base and Twins-base make training be converged faster compared with small ones.

Table 9: Ablations about different capacities of MVSFormer-P and MVSFormer-H.

|         | $e_2$ | $e_4$ | $e_8$ | Acc.↓ | Cop.↓ | Ovl.↓ |
|---------|-------|-------|-------|-------|-------|-------|
| DINO-small | 17.18 | 11.96 | 8.53  | 0.327 | 0.265 | 0.296 |
| DINO-base | 17.41 | 12.22 | 8.67  | 0.334 | 0.268 | 0.301 |
| Twins-small | 17.50 | 12.48 | 9.14  | 0.327 | 0.252 | 0.289 |
| Twins-base | 16.78 | 11.94 | 8.82  | 0.326 | 0.252 | 0.289 |

8.5 The Effect of Pre-training for ViTs

Although training a transformer (with CNN) for MVS is feasible [67], we think that the pre-training is still important for MVS learning, especially for the feature learning in our work. In particular, we train our MVSFormer-H with Twins-small from scratch as shown in Tab. 10. We increase the learning rate of no pre-trained Twins-small from 3e-5 to 1e-4, while all other settings are unchanged. Results from Tab. 10 show that pre-training is critical to our proposed MVSFormer. The Twins-small without pre-training is not as good as pre-trained one. Without the pre-training, our methods (without temperature based depth) are close to those attention-based MVS methods [15, 67] with only intra-view attention. Actually, no pre-trained MVSFormer-H performs similarly compared with TransMVSNet [15]. So the pre-training is important for ViTs to model proper feature representations to tackle the essential feature matching problem in MVS.
Table 10: The ablation study about pre-training of MVSFormer-H.

| Pre-trained | $e_2$↓ | $e_4$↓ | $e_8$↓ | Overall↓ |
|-------------|--------|--------|--------|---------|
| ✓           | 17.50  | 12.48  | 9.14   | 0.289   |
| ×           | 20.16  | 14.91  | 11.02  | 0.300   |

8.6 The Effect of GLU in MVSFormer-P

We compare GLU based attention map fusion with the simple concatenation and $\times2$ convolutions to balance the parameters in Tab. 11. GLU can achieve better depth with the same computation.

Table 11: The ablation study of GLU in MVSFormer-P without multi-scale training.

| GLU | Concat+Conv×2 | $e_2$↓ | $e_4$↓ | $e_8$↓ | Overall↓ |
|-----|---------------|--------|--------|--------|---------|
|     |               | 24.12  | 18.29  | 13.66  | 0.312   |
| ✓   |               | 22.78  | 17.25  | 13.30  | 0.310   |
| ✓   |               | 22.06  | 16.63  | 12.78  | 0.309   |

8.7 The Performance of Pre-trained ResNet50 with All Other Techniques

To further ensure the effectiveness of pre-trained ViTs for MVS, we provide more results in Tab. 12 about pre-trained ResNet50 with all other techniques used in our MVSFormer including the multi-scale training. Since CNNs enjoy good spatial invariance, the multi-scale training for ResNet50 is not as important as one for ViT based MVSFormers. The external experiment in Tab. 12 shows that multi-scale training can not improve ResNet50 a lot.

Table 12: Results of ResNet50 with all other proposed components. ‘T-CLA’ indicates temperature based depth with CLA.

| Pre-trained | Multi-scale | T-CLA | $e_2$↓ | $e_4$↓ | $e_8$↓ | Overall↓ |
|-------------|-------------|-------|--------|--------|--------|---------|
| ResNet50    | ✓           | ✓     | 20.09  | 15.11  | 11.78  | 0.323   |
| ResNet50    | ✓           | ✓     | 20.38  | 13.87  | 10.37  | 0.312   |
| DINO-small  | ✓           | ✓     | 17.18  | 11.96  | 8.53   | 0.296   |
| Twins-small | ✓           | ✓     | 17.50  | 12.48  | 9.14   | 0.289   |

8.8 Qualitative Results of DTU

We provide qualitative results of DTU compared with CDS-MVSNet [21] and GBiNet [40]. Qualitative depth and confidence comparisons are shown in Fig. 8 while point clouds are compared in Fig. 9. From Fig. 8, our MVSFormer-H can achieve more robust depth maps compared with others. Notably, depth maps from MVSFormer-H are as smooth as the regressive depth got from CDS-MVSNet. Besides, the $argmax$ operation used in GBiNet fails to achieve stable depth predictions, and relies heavily on confidence maps to filter invalid depth. But our MVSFormer can get not only good depth predictions but also reliable confidence maps, which is benefited from the proposed temperature-based depth prediction. From Fig. 9, our method can faithfully reconstruct some challenging point clouds, which are usually omitted by other competitors.

8.9 Qualitative Results of Tanks-and-Temples

Our qualitative depth results of Tanks-and-Temples are shown in Fig. 10. Benefited by the proposed temperature-based depth prediction, MVSFormer-H can achieve not only good depth predictions but also reliable confidence maps, which leads to high-quality filtered depth in Fig. 10(d).

We also provide qualitative results of Tanks-and-Temples compared with TransMVSNet [15] and UniMVSNet [41]. Fig. 11 shows qualitative results of ‘Horse’ and ‘Lighthouse’ in the Tanks-and-Temples intermediate set. From Fig. 11 our MVSFormer-H can reconstruct more details (better Recall) and generate point clouds with more accurate positions (better Precision). But TransMVSNet
Figure 8: Qualitative DTU depth and confidence compared with CDS-MVSNet \([21]\), GBiNet \([40]\), and our MVSFormer-H.

Figure 9: Qualitative DTU point clouds compared with CDS-MVSNet \([21]\), GBiNet \([40]\), and our MVSFormer-H. Please zoom-in for details.

misses some structures in ‘Horse’ and predicts biased points in ‘Lighthouse’. On the other hands, UniMVSNet suffers from many outliers in ‘Horse’, and fails to reconstruct a correct lighthouse.

9 More Point Cloud Results

We show all point clouds of DTU test set generated by our MVSFormer-H in Fig. [12]. And point clouds of both intermediate and advanced sets of Tanks-and-Temples are shown in Fig. [13].

10 Limitations and Future Works

We discuss the limitations and potential future works. In particular, 1) we utilize the recent ViTs pre-trained with self-supervised (MAE \([25]\), DINO \([7]\)) and supervised (Twins \([11]\)) tasks, while it is an interesting future work of exploring the influence of different pre-training tasks on MVS. The involved methods – MAE, DINO, and Twins are relatively representative. Specifically, MAE and DINO are based on the vanilla plain-ViT, while Twins is based on the hierarchical-ViT. Additionally, note that due to the memory cost limitation, we have to fix ViT weights in MVSFormer-P, which loses some advantages over another variant – MVSFormer-H. Therefore, these ViTs are not ensured to be pre-trained with the same architecture and training settings in our paper. So it is interesting to use the same ViT architecture for different pre-training tasks, and further explore how these pre-training tasks (supervised and self-supervised) affect MVS. However, re-training all of these ViTs with different
Figure 10: Depth prediction, depth confidence, and filtered depth of our MVSFormer-H on Tanks-and-Temples. Depth maps are filtered by confidence $> 0.5$ in (d).

Figure 11: Qualitative results of Tanks-and-Temples (Horse and Lighthouse), compared with TransMVSNet [15], UniMVSNet [41], and our MVSFormer-H. $\tau$ is the distance threshold provided officially. $\tau = 3$mm and $\tau = 5$mm for ‘Horse’ and ‘Lighthouse’ respectively.

Our methods can take the 3D reconstruction based on 2D images. Since learning-based MVS methods can be generalized to various real-world datasets, the proposed method may cause some societal pre-training tasks is very non-trivial, and demands extraordinary computing resources. Thus we take it as future work. Critically, the performance of our proposed models has already outperformed all existing methods; this demonstrates the efficacy of our models. 2) Despite being simple, the fusion method used in this paper is good enough to make our models competitive. Here, we only consider the single and multi-scale feature addition. On the other hand, more technical and informative fusion strategies would be much advisable, such as cross-attention [47] and GRU modules [10]. This however would also be a very interesting future work that may inspire the community.

11 Broader Impact

Our methods can take the 3D reconstruction based on 2D images. Since learning-based MVS methods can be generalized to various real-world datasets, the proposed method may cause some societal
Figure 12: Point Clouds of all test set in DTU [1] reconstructed by MVSFormer-H.

impacts with controversial 2D images. Note that we only provide technical methods in this paper, but the real-world practice with potential negative societal impacts should be further considered.
Figure 13: Point Clouds of Tanks-and-Temples [33] reconstructed by MVSFormer-H.