FFNet: Frequency Fusion Network for Semantic Scene Completion

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Abstract

Semantic scene completion (SSC) requires the estimation of the 3D geometric occupancies of objects in the scene, along with the object categories. Currently, many methods employ RGB-D images to capture the geometric and semantic information of objects. These methods use simple but popular spatial- and channel-wise operations, which fuse the information of RGB and depth data. Yet, they ignore the large discrepancy of RGB-D data and the uncertainty measurements of depth data. To solve this problem, we propose the *Frequency Fusion Network* (FFNet), a novel method for boosting semantic scene completion by better utilizing RGB-D data. FFNet explicitly correlates the RGB-D data in the frequency domain, different from the features directly extracted by the convolution operation. Then, the network uses the correlated information to guide the feature learning from the RGB and depth images, respectively. Moreover, FFNet accounts for the properties of different frequency components of RGB-D features. It has a learnable elliptical mask to decompose the features learned from the RGB and depth images, attending to various frequencies to facilitate the correlation process of RGB-D data. We evaluate FFNet intensively on the public SSC benchmarks, where FFNet surpasses the state-of-the-art methods. The code package of FFNet is available at https://github.com/alanWXZ/FFNet.

Introduction

In recent years, the vision community has witnessed tremendous progress on semantic scene completion and its applications in diverse scenarios, e.g., grasping function of robots and obstacle avoidance of cars. The completion task aims to infer the 3D geometry occupancy of the voxelized scene and the semantic label of each voxel, simultaneously (Song et al. 2017; Liu et al. 2018a; Zhang et al. 2019).

It has proven that RGB and depth data are useful cues in semantic scene completion task (Wang et al. 2019; Li et al. 2020b,d; Liu et al. 2018a). RGB images provide semantic information for classifying different objects. And depth images provide the geometry information for inferring the 3D spatial structure and layout. In some challenging indoor scenes, depth significantly helps semantic scene completion, where the objects with various depth values are separated.

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Existing methods adopt the element-wise summation (Li et al. 2019, 2020b,d), the weighted summation (Liu et al. 2020a) or the channel-wise concatenation (Liu et al. 2018a) to fuse the multi-modality RGB-D data. However, these methods ignore the large discrepancy between the RGB and depth modalities. Note that there are many uncertainty measurements of the depth data, which is the challenge of RGB-D fusion (Chen et al. 2020c; Wang et al. 2020b; Valada, Mohan, and Burgard 2020; Piao et al. 2019). Thus, the current methods are ineffective when utilizing the RGB and depth data to boost semantic scene completion tasks.

The pair of RGB and depth data are various representations of the same scene. RGB data is the photometric representation, while depth data is the geometric representation. They have a strong structural similarity (Fu et al. 2020; Chen et al. 2020c; Chen and Fu 2020; Lin and Huang 2019; Lin et al. 2018, 2017). We aim at utilizing the correlation between RGB-D features for multi-modality fusion.

Motivated by the above analysis, we propose a novel and effective Frequency Fusion Network (FFNet) to achieve RGB-D fusion for semantic scene completion. FFNet adopts a correlation and assistance pipeline to tackle the challenges of RGB-D fusion. The key idea is to learn the frequency feature to capture the correlation of RGB and depth data. FFNet uses the correlated information to guide the computation of RGB and depth features. Our Frequency Fusion Module leads to the structure information enhancement of the RGB and depth features.

To achieve the correlation between the RGB and depth data for information enhancement, we propose a novel mechanism that facilitates one modality better fused with the other. We decompose the RGB and depth features by an elliptical mask, which is learned in a data-driven manner. The frequency describes the spatial changing of an image. High-frequency components correspond to the rapidly changing areas, like the edge and texture of an object. The low-frequency components represent the smooth areas (Li et al. 2020e). Intuitively, the similarity of different frequency components between RGB and depth features is discrepant. We find a more effective correlation between RGB-D features by emphasizing different frequency components.

There are two advantages of using frequency learning to correlate the RGB-D features. First, it can explicitly find the correlation of RGB-D data. Different from the features di-

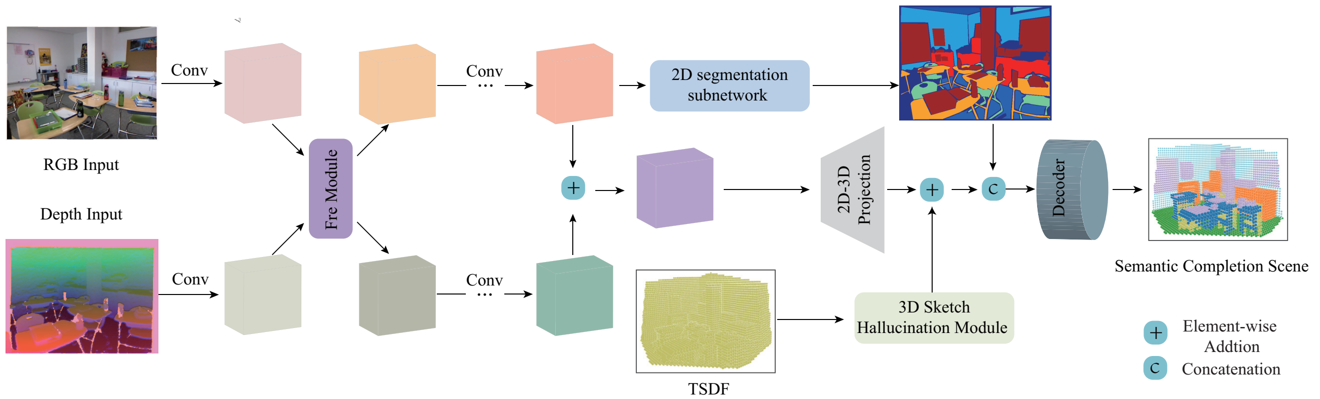


Figure 1: Overview of FFNet. We feed RGB-D data into the ResNet-50 backbone to extract RGB and depth features, which are fused by the Frequency Fusion Module. With the 2D-3D projection layer, we map the RGB-D features into the 3D space. We use the 2D segmentation subnetwork to predict the 2D semantic label from the RGB features extracted by the RGB branch. The semantic segmentation prediction is projected to 3D and concatenated with the RGB-D features. The concatenated features are fed into the decoder to predict the semantic scene completion results. "Fre Module" represents the proposed Frequency Fusion Module. The detail of the Frequency Fusion Module is illustrated in Figure 2.

rectly extracted by convolution operations, the proposed frequency correlation can be regarded as calculating the "patch similarity" between one modality and every position of the other modality. It thus obtains the relation between RGB-D data. Second, emphasizing different frequency components decomposed by the learned elliptical mask better helps to find the correlation of RGB-D data.

As illustrated in Figure 2 and 3, we propose three steps to fuse RGB-D data: 1) emphasizing different frequency components of RGB-D features by elliptical decomposition mask, 2) correlating the RGB-D features in the frequency domain, and 3) aggregating the correlation descriptor with RGB and depth features separately to generate the enhanced RGB and depth features.

As the overview shown in Figure 1, the framework of FFNet comprises four critical components: 1) a 2D feature extraction for computing the 2D multi-modality features boosted by Frequency Fusion Block, 2) a 2D segmentation subnetwork that uses the extracted RGB features to predict a 2D semantic segmentation mask and the 2D mask are concatenated with the fused RGB-D features, 3) a 2D-3D projection layer which projects the 2D feature to 3D volume and 4) 3D subnetwork for predicting the completion result.

Our contribution can be summarized as follows:

- We propose a novel FFNet to utilize the information of RGB-D data for semantic scene completion. FFNet fuses the RGB-D features by modeling the correlation between the RGB and the depth data in the frequency domain. The correlation enhances the RGB and depth features.
- We propose a frequency attention mechanism to boost the correlation of the RGB-D feature. The mechanism attends to different frequencies of each modality using the learnable elliptical mask.
- FFNet achieves state-of-the-art results on the public datasets for semantic scene completion.

Related Work

Semantic Scene Completion Song et al. (2017) initialize the task of semantic scene completion. They observe that occupancy patterns of the environment and the semantic labels of the objects are tightly intertwined. Therefore, they use 3D CNN to predict the semantic object categories and volumetric occupancy. Based on the data modality, we recognize the completion methods as the RGB- or depth-based methods.

For depth as input, most of the works encode depth as Signed Distance Function(SDF). It can directly represent the 2D observation into the same 3D physical and facilitate the network to learn geometry and scene representation. Zhang et al. (2018) speed up semantic scene completion by Spatial Group Convolution, which divides input voxels into different groups then carries out 3D sparse convolution on these separated groups. Zhang et al. (2019) propose a cascaded context pyramid network and a guided residual refinement module to integrate both local geometric details and multi-scale 3D contexts of the scene.

Another category is using RGB-D as input (Li et al. 2020d; Liu et al. 2018a; Chen et al. 2020b; Li et al. 2020b). Liu et al. (2018a) propose a CNN that sequentially accomplishes two subtasks, i.e., 2D semantic segmentation and 3D semantic scene completion. They extract the RGB-D features in a double-branch way. The extracted RGB-D features are concatenated. Chen et al. (2020b) present a novel anisotropic convolutional network that is much less computational demanding. Li et al. (2020d) propose the AMFNet that conducts 3D scene completion and semantic segmentation simultaneously via leveraging the experience of 2D segmentation and the reliable depth cues in the spatial dimension. The two tasks are multiplied in an element-wise manner. Yu et al. (2020a) propose a 3D gated recurrent fusion network to fuse the information from depth and RGB. Li et al. (2020b) propose to use a novel 3D Sketch Hallucination Module to guide the full 3D scene completion task.

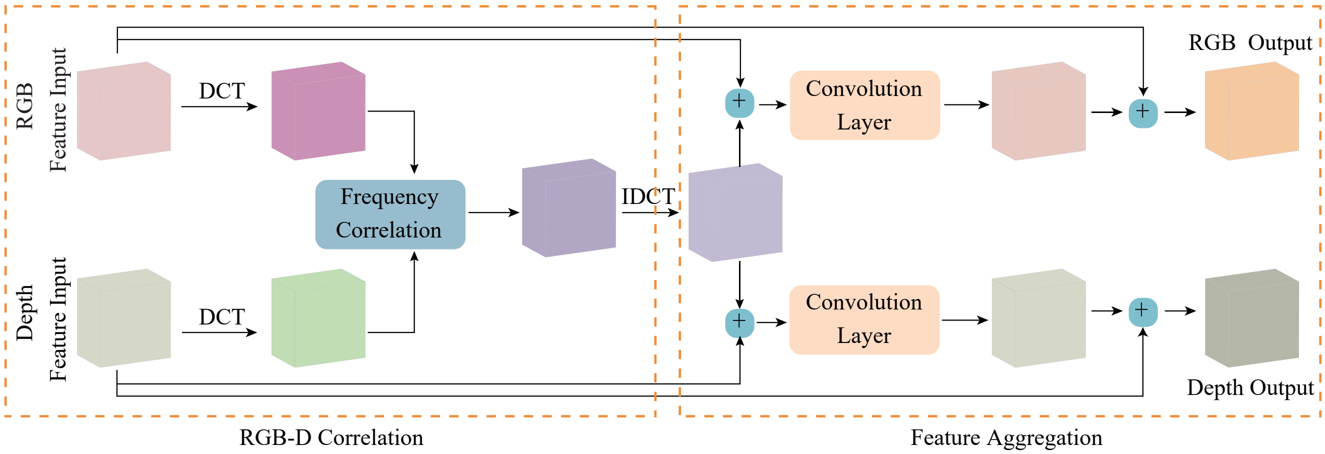


Figure 2: Overview of Frequency Fusion Module. It contains RGB-D Correlation and Feature Aggregation. More details of Frequency Correlation is provided in Figure 3.

Different from previous RGB-D SSC methods that combine RGB-D features by concatenation, element-wise summation, and weighted summation. We propose the Frequency Fusion Network to explicitly model the correlation of RGB-D and then use the correlation information to fuse RGB-D data for semantic scene completion.

Frequency Domain Learning Frequency analysis has been widely used in signal processing and computer vision. Recently, many works inspired by frequency analysis and aim at endowing neural network with powerful ability by frequency domain learning (Jin et al. 2020; Helou, Zhou, and Susstrunk 2020; Qian et al. 2020; Liu et al. 2018b; Li et al. 2020c; Bian et al. 2020; Li et al. 2020e). Most of these works focus on using the compressing ability of Discrete Cosine Transform(DCT), which can decompose the input signal and discover their redundancy in the frequency domain. Chen et al. (2020a) propose a frequency method for network pruning by converting filters into the frequency domain to investigate their redundancy. Xu et al. (2020) propose to reshape the high-resolution images in the DCT domain and feed the reshaped DCT coefficients to neural networks. Wang et al. (2020a) study the generalization of convolutional neural networks by frequency spectrum of image data.

In contrast, we obtain the correlation of the RGB-D data to guide RGB-D fusion in the frequency domain. And we propose the frequency attention by learned elliptical mask to facilitate modeling the correlation of RGB-D.

Method

In this section, we present the architecture of FFNet. Taking depth and its RGB counterpart as input, the network predicts the 3D voxel occupancy and the semantic categories of each voxel, as illustrated in Figure 1. Each voxel is mapped to one of the semantic labels $C = [c_0, c_1, ..., c_{N-1}]$, where c_0 represents the empty voxel and N is the number of semantic categories. Specifically, we feed RGB and depth data into a ResNet-50 to extract features. The RGB-D features are interacted and fused by the proposed Frequency Fusion Module. Then, we use the 2D-3D projection layer to map the fused RGB-D features 3D space. The 2D segmentation subnetwork is used to predict the 2D semantic label from the features extracted by the RGB branch. The semantic segmentation prediction is projected to 3D space. The prediction is concatenated with the projected RGB-D feature. Finally, the concatenated features are fed into the decoder to predict the semantic scene completion results.

Below, we introduce the details of FFNet from the following aspects: 1) Frequency Fusion Module, 2) RGB-D Semantic Scene Completion Framework, 3) Loss Function.

Frequency Fusion Module

Figure 2 and 3 show the framework of RGB-D Frequency Fusion and the frequency correlation process of Frequency Fusion, respectively. The key idea of Frequency Fusion is to obtain the explicit correlation of the RGB-D feature and then the correlation descriptor is used to guide the generation of RGB-assisted depth feature and depth-assisted RGB features. We propose three steps: 1) Frequency Attention, 2) RGB-D Frequency Correlation and 3) Feature Aggregation.

Frequency Attention The pipeline of frequency attention is shown in Figure 3. It emphasizes different frequency components to boost RGB-D correlation by the mask of elliptical decomposition. Frequency is global information. The high-frequency components are related to the object edges, while the low-frequency components are related to the object body. The RGB data and depth data are the photometric and geometrical representations of the same scene, respectively. The main idea of frequency attention is that we can facilitate the correlation between RGB-D by emphasizing different frequency components. Note that the 2D low-pass filter passes the frequencies within a circle of radius D in signal processing. We propose the learned elliptical mask to decompose the frequency signal.

We denote $r_i \in \mathbb{R}^{H\times W}$ as the i-th channel of RGB features and denote $d_i \in \mathbb{R}^{H\times W}$ as the i-th channel of depth

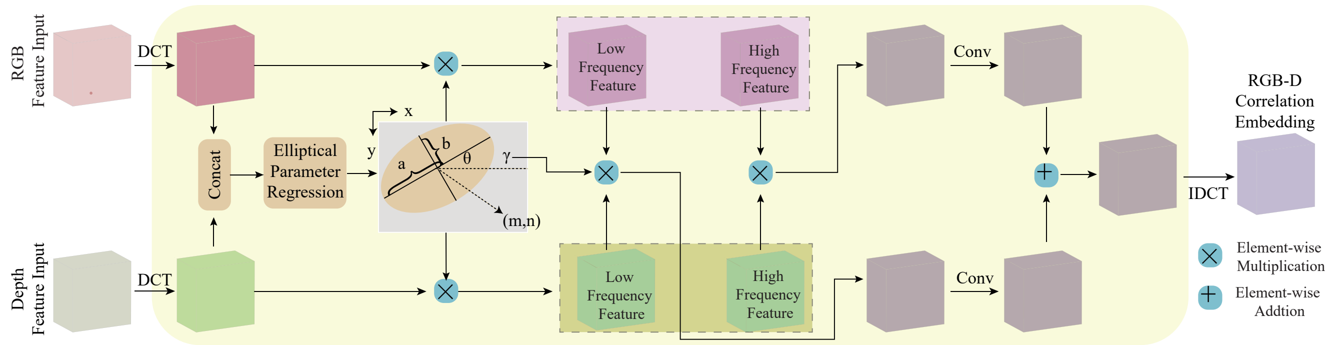


Figure 3: Overall architecture of frequency correlation boosted by frequency attention. Note that γ is the weight to emphasize the masked frequency component by elliptical decomposition.

feature. We transform the RGB and depth features into frequency domain by:

$$R_i = DCT(r_i), \;\; D_i = DCT(d_i), \tag{1}$$

where R_i and D_i represent the RGB feature and the depth feature in the frequency domain. $DCT(\cdot)$ represents the discrete cosine transform that transforms a feature in the spatial domain to the frequency domain.

Then, we use the elliptical mask to decompose each channel of RGB-D features in the frequency domain into separate frequency components. The elliptical mask is learned by a parameter prediction network which regresses the five parameters of the elliptical mask and a parameter of frequency attention. The frequency attention parameter is used to emphasize different frequency components. The detail of the parameter prediction network can be found in the supplementary material.

The elliptical mask of i-th channel is defined as:

$$M_i = \begin{cases} 1, \frac{((x-m)cos\theta-(y-m)sin\theta)^2}{a^2} - \frac{((x-n)cos\theta-(y-n)sin\theta)^2}{b^2} < 1 \\ 0, otherwise \end{cases} \tag{2}$$

Here, we denote M_i as the elliptical mask of the i-th channel. (m, n) represents the center of the elliptical mask. a, b, and θ represent the semi-major axis, semi-minor axis, and rotation angle.

Next, we use the mask weight γ to emphasize or suppress the masked frequency component. γ is learned by the parameter prediction network. The output of frequency attention is formulated as:

$$R^{'} = Conv(\sigma(\gamma \cdot M \cdot R)) + Conv(\sigma(\overline{M} \cdot R)), \tag{3}$$

$$D^{'} = Conv(\sigma(\gamma \cdot M \cdot D)) + Conv(\sigma(\overline{M} \cdot D)), \tag{4}$$

where R is the frequecy information transfromed from RGB features by DCT. D is the frequency information transformed from depth features by DCT. We denote $R^{'}$ as the frequency enhanced RGB features in DCT domain. $D^{'}$ is the frequency enhanced depth features in DCT domain, $\overline{M}$ = $1 - M$, $M = [M_1, M_2, \cdots, M_C]$. γ is the weight of low frequency component.

RGB-D Frequency Correlation We use RGB-D correlation to explicitly find the correlation of RGB-D features. To correlate RGB features with depth features, we define the operation in the frequency domain as:

$$I = R^{'} \cdot D^{'}, \tag{5}$$

where $\cdot$ represents pixel-wise multiplication and I is the RGB-D correlation information.

The correlation information of RGB-D features is normalized and learned as:

$$I^{'} = Conv(\sigma(I)), \tag{6}$$

where $\sigma(\cdot)$ is the element-wise sigmoid function. $Conv(\cdot)$ is the convolution layer. $I^{'}$ is the normalized and learned features of I and $I = [I_1, I_2, \cdots, I_C]$. C represents the channel dimension.

The $I^{'}$ is transformed into the spatial domain as:

$$F_i^{cor} = IDCT(I_i^{'}). \tag{7}$$

Here, $F_i^{cor} \in \mathbb{R}^{H \times W}$ represents the RGB-D correlation embedding in the spatial domain, $IDCT(\cdot)$ represents inverse discrete cosine transform that transforms a feature in the frequency domain to the spatial domain.

We further analyze the RGB-D frequency correlation as:

$$r_i * d_i = IDCT(DCT(r_i) \cdot DCT(d_i)), \tag{8}$$

where $*$ is convolution operation. r_i is the i-th channel of the RGB feature. d_i represents the i-th channel of depth feature. Notably, it is the well-known convolution theorem that point-wise multiplication in the frequency domain equals convolution in the spatial domain. Thus, the above operation in the frequency domain equals to convolve depth feature with RGB features in the spatial domain. In other words, we choose one of them as a convolution kernel and convolve with the other. Moreover, We add convolution operation to adjust and learn the features to facilitate RGB-D correlation. It thus obtains an explicit correlation of RGB-D features.

Feature Aggregation The feature aggregation process is illustrated in Figure 2. To make full use of the complementarity of RGB-D features, we take the correlation information of RGB-D features as guidance to compute the RGB-assisted depth feature and depth-assisted RGB feature.

To use complementarity of the RGB-D feature, we define below operation as:

$$r_{att} = Conv(F^{cor} + r), \ \ d_{att} = Conv(F^{cor} + d), \quad (9)$$

where r_{att} represents the attention score generated by RGB features and the correlation information of RGB-D. d_{att} represents the attention score generated by depth features and the correlation information of RGB-D and $Conv$ represents the convolution operation.

The final output of Frequency Fusion Module is:

$$r_{out} = r + r_{att}, \ \ d_{out} = d + d_{att}, \quad (10)$$

where r_{out} represents the depth-assisted RGB features, d_{out} represents the RGB-assisted depth features and $+$ denotes a residual connection, which allows us to insert our block into any network, without breaking its initial behavior.

Semantic Scene Completion Framework

We take the RGB-D images as input and predict the semantic labels of 3D scenes. The framework of semantic scene completion consists of 2D feature extraction, 2D semantic segmentation, 2D-3D projection, and 3D feature learning.

2D feature extraction To extract 2D features from the depth and RGB image, we use a ResNet-50 model which is pre-training on ImageNet to the RGB branch. The weight of the RGB branch is fixed and the weight of the depth branch is not fixed. The two branches are interacting and fusing by the proposed Frequency Fusion Module.

2D Semantic Segmentation 2D semantic segmentation acquires the pixel-wise semantic predictions to boost the semantic scene completion task. We use the RGB branch of the 2D feature extraction subnetwork as our encoder which is a pre-trained ResNet-50. We use the decoder as DeepLab v3+ (Chen et al. 2018). DeepLab v3+ is first pre-trained on the ADE-20k dataset (Zhou et al. 2017) and finetuned on the NYU dataset. The segmentation results are projected to the corresponding 3D space using the 2D-3D projection layer.

2D-3D projection To alleviate the gap between 2D and 3D, the fused 2D RGB-D features and 2D semantic segmentation results are projected into the corresponding 3D positions by 2D-3D projection layer according to the intrinsic camera matrix K_{camera}, the extrinsic camera matrix $[R|t]$ and the depth image I_{depth}.

3D feature learning We add the 3D features projected from the 2D fused RGB-D features and 3D sketch predicted by 3D Sketch Hallucination Module (Chen et al. 2020b). Then the added features are concatenated with the projected 2D semantic segmentation predictions. Below, the concatenated 3D features are fed into a stacked of AIC modules (Li et al. 2019), which is a lightweight 3D CNN module. Finally, we obtain the semantic scene completion results.

Loss Function

Given RGB-D images and ground truth semantic labels of the 3D scenes, our proposed method can be trained in an end-to-end manner. We jointly supervise the two parts, including L_{sm} and L_{sk} (Chen et al. 2020b). The total loss L is computed as:

$$L = L_{sm} + L_{sk}, \quad (11)$$

where L_{sm} represents the semantic loss, and L_{sk} (Chen et al. 2020b) represents the sketch loss. We adopt the voxel-wise cross-entropy loss function for the network training. The semantic loss function can be written as:

$$L_{sm} = \sum_{ijk} \omega_{ijk} L_{sm}(\hat{y}_{ijk}, y_{ijk}), \quad (12)$$

where $\hat{y}_{ijk}$ represents the predicted probability for the indexed voxel, y_{ijk} is the ground truth label, and ω_{ijk} represents the weight of each semantic category. We use the sketch loss (Chen et al. 2020b) to supervise the sketch of each scene. A sketch refers to the 3D boundary of a 3D scene.

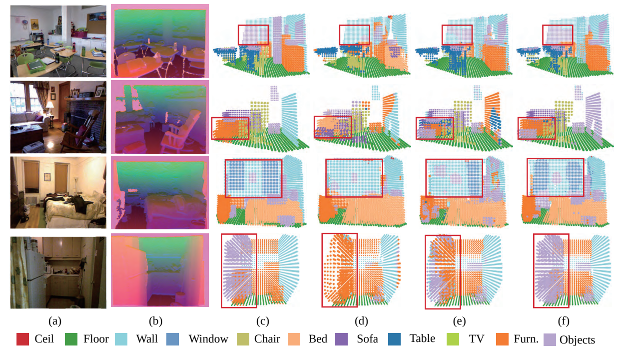


Figure 4: The results of different methods on the NYU dataset. (a) Input RGB; (b) Input Depth (HHA); (c) Ground truth; (d) SSCNet; (e) Our method without Frequency Fusion; (f) Our method with Frequency Fusion.

Experiments

Experimental Setup

Given the training data (i.e. the RGB image, the depth image, and the ground truth 3D labels), we train our network in an end-to-end manner. We implement our framework in PyTorch. We train our model with batch size 6 in 2 GeForce GTX 3090 Ti GPUs. We adopt mini-batch SGD with a momentum of 0.9 and weight decay of 0.0005. For both NYU and NYU CAD datasets, we train our network for 350 epochs with an initial learning rate of 0.1. We use a poly learning rate policy where the initial learning rate is updated by $(1 - \frac{iteration}{max\_iteration})^{0.9}$.

Comparisons with the State-of-the-art Methods

Quantitative Comparision We compare the proposed method on NYU and NYU CAD datasets with state-of-the-art methods. Table 1 shows the results on NYU dataset. Our method achieves the best performance in both SC and SSC tasks. Despite only taking the NYU dataset for training, our approach obtains higher IoUs than CCP. Note that CCP uses supplementing training data from the SUNCG dataset.

		Scene Completion			Semantic Scene Completion											
Method	Training Set	prec.	recall	IoU	ceil.	floor	wall	win.	chair	bed	sofa	table	tvs	furn.	objs.	avg.
Song et al. (2017)	NYU	57.0	**94.5**	55.1	15.1	94.7	24.4	0.0	12.6	32.1	35.0	13.0	7.8	27.1	10.1	24.7
Zhang et al. (2018)	NYU	71.9	71.9	56.2	17.5	75.4	25.8	6.7	15.3	53.8	42.4	11.2	0	33.4	11.8	26.7
Li et al. (2019)	NYU	71.5	80.8	61.0	21.1	92.2	33.5	6.8	14.8	48.3	42.3	13.2	13.9	35.3	13.2	30.4
Li et al. (2020b)	NYU	62.4	91.8	59.2	23.2	90.8	32.3	14.8	18.2	51.1	44.8	15.2	22.4	38.3	15.7	33.3
Liu et al. (2018a)	NYU	-	-	60.0	9.7	93.4	25.5	21.0	17.4	55.9	49.2	17.0	27.5	39.4	19.3	34.1
Liu et al. (2020b)	NYU	68.7	85.0	61.3	23.5	92.0	33.0	11.6	20.1	53.9	48.1	16.2	24.2	37.8	14.7	34.1
Li et al. (2020d)	NYU	66.3	80.5	57.2	20.0	78.7	27.3	20.5	21.8	56.5	53.9	19.5	18.8	40.1	19.5	34.2
Zhang et al. (2019)	NYU	74.2	90.8	63.5	23.5	96.3	35.7	20.2	25.8	61.4	56.1	18.1	28.1	37.8	20.1	38.5
Chen et al. (2020b)	NYU	85.0	81.6	71.3	43.1	93.6	40.5	24.3	30.0	57.1	49.3	**29.2**	14.3	42.4	28.6	41.1
Li et al. (2019)	NYU+SUNCG	78.8	94.3	67.1	25.5	**98.5**	38.8	27.1	27.3	**64.8**	**58.4**	21.5	**30.1**	38.4	23.8	41.3
Ours	NYU	**89.3**	78.5	**71.8**	**44.0**	93.7	**41.5**	**29.3**	**36.2**	59.0	51.1	28.9	26.5	**45.0**	**32.6**	**44.4**

Table 1: Results of different methods on NYU dataset.

		Scene Completion			Semantic Scene Completion											
Method	Training Set	prec.	recall	IoU	ceil.	floor	wall	win.	chair	bed	sofa	table	tvs	furn.	objs.	avg.
Song et al. (2017)	NYUCAD+SUNCG	75.4	96.3	73.2	32.5	92.6	40.2	8.9	33.9	57.0	59.5	28.3	8.1	44.8	25.1	40.0
Li et al. (2019)	NYUCAD	88.7	88.5	79.4	54.1	91.5	56.4	14.9	37.0	55.7	51.0	28.8	9.2	44.1	27.8	42.8
Li et al. (2019)	NYUCAD	88.2	90.3	80.5	53.0	91.2	57.2	20.2	44.6	58.4	56.2	36.2	9.7	47.1	30.4	45.8
Liu et al. (2018a)	NYUCAD	-	-	76.1	25.9	93.8	48.9	33.4	31.2	66.1	56.4	31.6	**38.5**	51.4	30.8	46.2
Liu et al. (2020b)	NYUCAD	87.2	91.7	80.8	54.8	92.8	60.3	15.3	43.1	60.7	59.9	37.6	8.1	48.6	31.7	46.6
Li et al. (2020d)	NYUCAD	60.6	89.1	56.3	81.3	68.5	54.1	61.8	30.2	45.9	50.7	34.3	42.7	41.9	28.4	49.1
Zhang et al. (2019)	NYUCAD	91.3	92.6	82.4	56.2	94.6	58.7	35.1	44.8	68.6	65.3	37.6	35.5	53.1	35.2	53.2
Chen et al. (2020b)	NYUCAD	90.6	92.2	84.2	59.7	94.3	64.3	32.6	51.7	72.0	68.7	45.9	19.0	60.5	**38.5**	55.2
Zhang et al. (2019)	NYUCAD+SUNCG	93.4	91.2	85.1	58.1	**95.1**	60.5	**36.8**	47.2	69.3	67.7	39.8	37.6	55.4	37.6	55.5
Ours	NYUCAD	**94.8**	90.3	**85.5**	**62.7**	94.9	**67.9**	35.2	**52.0**	**74.8**	**69.9**	**47.9**	27.9	**62.7**	35.1	**57.4**

Table 2: Results of different methods on NYU CAD dataset.

Method	mIoU
ResNet-50	42.1
ResNet-50+ cmFM +AFS (Li et al. 2020a)	42.8
ResNet-50+ SA-Gate (Chen et al. 2020c)	43.2
ResNet-50+Fre-Fusion	**44.4**

Table 3: Frequency Fusion v.s. other RGB-D fusion module.

We obtain an improvement of 4.7% SC IoU and 3.1% SS-C mIoU compared to the CCP method. It indicates that our method better exploits the complementary information from the RGB and depth data for semantic scene completion.

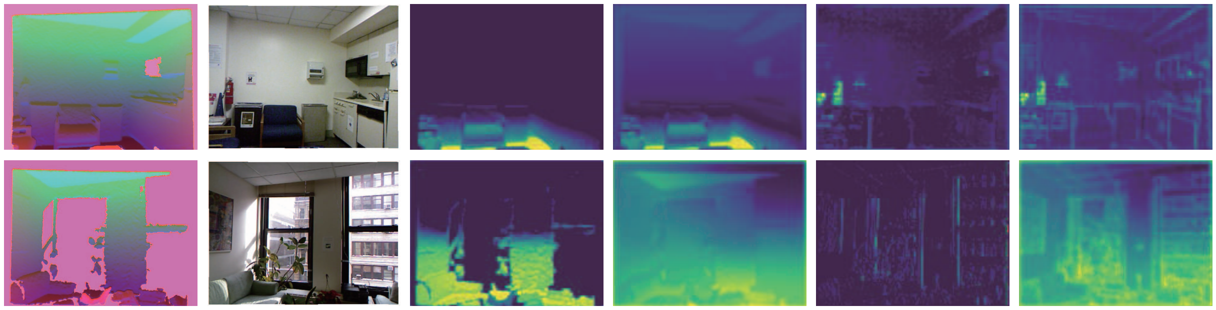
Table 2 shows the results on NYU CAD dataset. Our method achieves the best performance in both SC and SSC tasks. We obtain a improvement of 1.3% SC IoU and 2.2% SSC mIoU compared with (Chen et al. 2020b). Chen et al. only use NYU CAD as training data which is the same as us.

Qualitative Comparision Figure 4 shows the qualitative results on NYU dataset. We show the visualization results of our method, our method without Frequency Fusion Module and SSCNet. We find that the semantic scene completion result is more accurate with the proposed Frequency Fusion Module. Boosted by Frequency Fusion Module, our method shows an improvement in intra-class consistency and a sharper boundary between inter-class. Especially in the case, those different objects have a similar depth, RGB data can provide complementary semantic features to differentiate different objects. It can be seen in the first, third, and fourth rows that different objects have similar depth, RGB data provide complementary semantic features to differentiate different objects. We observe in the second row that the table in the bottom left corner has poor lighting conditions. It is difficult for the network to differentiate the table using only RGB images. By better utilizing the RGB-D data, our method can obtain a better semantic scene completion result.

Ablation Study

Effectiveness of Frequency Fusion Module We insert Frequency Fusion Module into our ResNet-50 backbone to fuse the RGB and depth data. Here, we insert the Frequency Fusion Module before the first bottleneck of ResNet-50. To verify the effectiveness of our Frequency Fusion Module, first, we conduct the baseline method that does not use Frequency Fusion Module. Then, we replace the Frequency Fusion Module with other state-of-the-art RGB-D fusion methods used in RGB-D segmentation (Chen et al. 2020c) and Saliency detection (Li et al. 2020a). The results shown in Table 3 indicate that our method is effective and outperform other state-of-the-art RGB-D fusion methods.

Effectiveness of Frequency Attention We use Frequency Correlation to correlate RGB-D features boosted by frequency attention. To verify the effectiveness of frequency attention, we replace Frequency Correlation with five differen-



(a) HHA input (b) RGB input (c) HHAin (d) HHAout (e) RGBin (f) RGBout

Figure 5: Visualization of depth and RGB features before and after the Frequency Fusion Module. From left to right: (a) Depth(HHA) input; (b) RGB input; (c) HHA input to Frequency Fusion Module; (d) HHA output to Frequency Fusion Module; (e) RGB input to Frequency Fusion Module; (f) RGB output to Frequency Fusion Module.

Method	Concat	Add	Prod	Channel	N-L	Ours
mIoU	41.4	43.2	43.3	43.5	43.7	**44.4**

Table 4: Ablation experiments on RGB-D Frequency Correlation part of Frequency Fusion Module on NYU dataset.

t architectures for comparison. 'Concat' represents that we concatenate the RGB and depth features and use convolution to transform the features into the channel size the same as a single modality. 'Add' means that we add RGB and depth feature to replace the frequency correlation information. 'Product' represents that we multiply RGB features by depth features. 'Channel' means that we use channel-wise attention (Hu, Shen, and Sun 2017) to fuse RGB-D features. 'N-L' means that we use the non-local operation (Chi et al. 2020; Wang et al. 2018) to replace the frequency correlation information. In the below list, the five architectures we use Feature Aggregation to obtain depth-assisted RGB features and RGB-assisted depth features. Table 4 shows that Frequency Correlation outperforms other architecture. The addition, production, channel-wise attention, and non-local architecture can only promote a little performance. Concatenation will lead to relatively worse performance.

Component Analysis on Frequency Fusion Module We evaluate the effectiveness of the three core components of Frequency Fusion Module. We ablate each design of Frequency Fusion Module in Table 5. 'Fre-Atten' represents that we use Frequency Attention to boost Frequency Correlation. 'Fre-Corr' represents that we correlate the RGB-D features in the frequency domain. 'Aggregation' represents that we aggregate the correlation information with RGB and depth features separately. Experiment results in Table 5 show the effectiveness of Frequency Attention, RGB-D Frequency Correlation, and Feature Aggregation operations.

How does Frequency Fusion help? We show several samples of the representative features without and with processed by Frequency Fusion Module. It shows how Frequency Fusion helps semantic scene completion.

We analyze the RGB features on the NYU dataset. In Figure 5, the structure is enhanced after the proposed module and thus reduce the background distraction (see the fifth and sixth column). Structure information contains more geometry information which is vital for semantic scene completion.

Fre-Corr	Fre-Atten	Aggregation	mIoU
×	×	×	42.1
✓	×	×	43.2
✓	✓	×	43.8
✓	✓	✓	**44.4**

Table 5: Ablation experiments on Frequency Correlation, Frequency Attention and Feature Aggregation.

Then, we analyze the HHA features on the NYU dataset. As shown in Figure 5, it can be seen that in the third and fourth columns the proposed module can recalibrate the depth features to fit for the RGB feature.

In conclusion, the proposed Frequency Fusion Network help to find the correlation of RGB-D features and make full use of RGB-D features to supplement each other.

Conclusion

RGB and depth data provide complementary information for semantic scene completion. To better utilize the RGB-D data for semantic scene completion, we propose a novel and effective method, the Frequency Fusion Network. The proposed method can explicitly model the correlation of RGB-D features and the correlation is used to guide the RGB-assisted depth features and the depth-assisted RGB features. Furthermore, we boost the correlation of RGB-D by frequency attention. It can thus alleviate the challenge of RGB-D fusion. Experimental results show that our method outperforms the state-of-the-art methods on NYU and NYU CAD datasets. Ablation study and visualization results also show the contribution of the proposed method.

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