RGB-D Scene Labeling with Long Short-Term Memorized Fusion Model

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Abstract. Semantic labeling of RGB-D scenes is crucial to many intelligent applications including perceptual robotics. It generates pixel-wise and fine-grained label maps from simultaneously sensed photometric (RGB) and depth channels. This paper addresses this problem by i) developing a novel Long Short-Term Memorized Fusion (LSTM-F) Model that captures and fuses contextual information from multiple channels of photometric and depth data, and ii) incorporating this model into deep convolutional neural networks (CNNs) for end-to-end training. Specifically, global contexts in photometric and depth channels are, respectively, captured by stacking several convolutional layers and a long short-term memory layer; the memory layer encodes both short-range and long-range spatial dependencies in an image along the vertical direction. Another long short-term memorized fusion layer is set up to integrate the contexts along the vertical direction from different channels, and perform bi-directional propagation of the fused vertical contexts along the horizontal direction to obtain true 2D global contexts. At last, the fused contextual representation is concatenated with the convolutional features extracted from the photometric channels in order to improve the accuracy of fine-scale semantic labeling. Our proposed model has set a new state of the art, i.e., 48.1% average class accuracy over 37 categories (11.8% improvement), on the large-scale SUNRGBD dataset.

Keywords: RGB-D scene labeling, image context modeling, long short-term memory, depth and photometric data fusion

1 Introduction

Scene labeling, also known as semantic scene segmentation, is one of the most fundamental problems in computer vision. It refers to associating every pixel in an image with a semantic label, such as table, road and wall, as illustrated in Fig. 1. High-quality scene labeling can be beneficial to many intelligent tasks, including robot task planning [1], pose estimation [2], plane segmentation [3], context-based image retrieval [4], and automatic photo adjustment [5].

Previous work on scene labeling can be divided into two categories according to their target scenes: indoor and outdoor scenes. Compared with outdoor scene labeling [6-7], indoor scene labeling is more challenging due to a larger
set of semantic labels, more severe object occlusions, and more diverse object appearances. For example, indoor object classes, such as bathtubs, curtains, and bookshelves, are much harder to characterize than outdoor classes, such as road, building, and sky. Recently, utilizing depth sensors to augment RGB data have effectively improved the performance of indoor scene labeling because the depth channel complements RGB appearance data with structural information. Nonetheless, two key issues remain open in the literature of RGB-D scene labeling.

(I) **How to effectively represent and fuse the coexisting depth and photometric (RGB) data** For data representation, a batch of sophisticated hand-crafted features have been developed in previous methods. Such hand-crafted features are somewhat ad hoc and less discriminative than those RGB-D representations learned using convolutional neural networks (CNNs) [9][10][11][12][13]. However, in these CNN-related works, the fusion of depth and photometric data has often been oversimplified. For instance, in [12][13], two independent CNNs are leveraged to extract features from depth and photometric data separately, and such features are simply concatenated before used for final classification. Overlooking the strong correlation between depth and photometric channels could harm the performance of semantic labeling.

(II) **How to capture global scene contexts during feature learning** Current CNN-based scene labeling approaches can only capture local contextual information for every pixel due to their restricted receptive fields, resulting in suboptimal labeling results. In particular, long-range dependencies sometimes play a key role in distinguishing among different objects having similar appearances, e.g., labeling “ceiling” and “floor” in Fig. 1 according to the global scene context.

**Fig. 1.** An illustration of global context modeling and fusion for RGB-D images. Our LSTM-F model first captures vertical contexts through a memory network layer encoding short- and long-range spatial dependencies along the vertical direction. After a concatenation operation (denoted by “C”) over photometric and depth channels, our model utilizes another memory network layer to fuse vertical contexts from all channels and performs bi-directional propagation along the horizontal direction to obtain true 2D global contexts. Best viewed in color.
layout. To overcome this issue, graphical models, such as a conditional random field \([14,10]\) or a mean-field approximation \([15]\), have been applied to predicted feature maps in a post-processing step. These methods, however, separate context modeling from convolutional feature learning, which may give rise to suboptimal results on complex scenes. An alternative class of methods adopts cascaded recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM) networks, to explicitly strengthen context modeling \([16,17,18]\). In these methods, the long- and short-range dependencies can be well memorized by sequentially running the network over individual pixels.

To address the aforementioned challenges, this paper proposes a novel Long Short-Term Memorized Fusion (LSTM-F) model and demonstrates its superiority in RGB-D scene labeling over existing state-of-the-art methods. Fig. 1 illustrates the idea of using memory networks for context modeling and fusion of different channels. Our model captures 2D dependencies within an image by exploiting the cascaded bi-directional vertical and horizontal RNN models introduced in \([19]\).

Our method constructs HHA images (images with three channels representing horizontal disparity, height above ground and angle with gravity respectively) \([12]\) for the depth channel through geometric encoding, and uses several convolutional layers for extracting features. Inspired by \([19]\), these convolutional layers are followed by a memorized context layer to model both short-range and long-range spatial dependencies along the vertical direction. For photometric channels, we generate convolutional features using the Deeplab network \([11]\), which is also followed by a memorized context layer for context modeling along the vertical direction. Afterwards, a memorized fusion layer is set up to integrate the contexts along the vertical direction from both photometric and depth channels, and perform bi-directional propagation of the fused vertical contexts along the horizontal direction to obtain true 2D global contexts. Instead of simply concatenating different feature vectors, this fusion layer facilitates deep integration of contextual information from multiple channels in a data-driven manner. Since photometric channels usually contain finer details in comparison to the depth channel, we further enhance the network with cross-layer connections that append the convolutional features of the photometric channels to the fused global contexts before the final convolutional layer, which predicts pixel-wise semantic labels. Various layers in our LSTM-F model are tightly integrated, and the entire network is amenable to end-to-end training and testing.

In summary, this paper has the following contributions to the literature of RGB-D scene labeling.

- It proposes a novel Long Short-Term Memorized Fusion (LSTM-F) Model, which is capable of capturing image contexts from a global perspective and deeply fusing contextual information from multiple sources (i.e., depth and photometric channels).
- It proposes to jointly optimize LSTM layers and convolutional layers for achieving better performance in semantic scene labeling. Context modeling and fusion are incorporated into the deep network architecture to enhance
the discriminative power of feature representation. This architecture can also be extended to other similar tasks such as object/part parsing.

– It is demonstrated on the large-scale SUNRGBD benchmark (10355 RGB-D images) that our method outperforms existing state-of-the-art methods by a large margin. In addition, it is found that our scene labeling results can be leveraged to improve the groundtruth annotations in 3943 newly captured RGB-D images.

2 Related work

Scene Labeling: Scene labeling problem has been approached with various research works [6,10,11,16,17,18,20] in recent years. Different from previously extracting features from over segmentation parts of image, recent methods usually utilize powerful CNN layers as feature extractor, especially taking advantage of proposed fully convolutional network (FCN) [9] and its variants to obtain pixel-wise dense feature. Another main challenging problem for scene labeling is the fusion of local and global context, i.e., taking advantage of global context to refine local decision. For instance, [6] exploits families of segmentations or trees to generate segments candidates. [21] utilizes inference method based on graph cut to achieve image labeling. [10,11] use pixel-wise Conditional Random Forest (CRF) to directly optimize a deep CNN-driven cost function. The above methods are almost use graphic model to do post-processing of obtained feature to refine labeling performance. The topological structure of Recurrent Neural Network (RNN) is used to solve the short- and long-range dependencies problem in [16,18]. In [17], multi-directional RNN is leveraged to extract local and global context without leveraging CNN, which is just suitable for low-resolution and relative simple scene labeling problem. In contrast, our model can jointly optimize the LSTM layers with the CNNs to explicitly improve the discriminative features learning for local and global context and fusion.

Scene Labeling in RGB-D images: With more and more convenient access of affordable depth sensor, scene labeling in RGB-D images [14,22,23,12,13,24] enables a rapid progress of scene understanding. Various sophisticated hand-crafted features are utilized in previous state-of-the-art methods. Specifically, kernel descriptions based on traditional multi-channel features, such as color, depth gradient, surface normal, are used as photometric and depth features correspondingly [22]. A rich feature set containing various traditional features, e.g., SIFT, HOG, LBP and plane orientation are acted as local appearance features and plan appearance features in [14]. HOG features of RGB images and HOG+HH (histogram of height) features of depth images are extracted as representations in [23] for training successive classifiers. Besides, unsupervised joint feature learning encoding model is proposed for scene labeling [24]. However, due to quantity limitation of RGB-D images, deep learning of scene labeling in RGB-D images is not as appealing as that in RGB images. Until the release of SUBRGBD dataset including most previous popular datasets, e.g., NYU-Depth v2 [25], Berkeley B3DO [26], SUN3D [27] and newly captured 3943 RGB-D im-
ages [28], it is appealing to leverage deep learning, especially various CNN based models, for scene labeling and object detection in RGB-D images [12,13].

For scene labeling in RGB-D images, another main problem is the fusion of contextual representations of different sources (i.e., depth and photometric data). For instance, in [12,13], two independent CNNs are leveraged to extract features from the depth and photometric data separately, which are then simply concatenated for predicting classification. Ignoring the strong correlation between the depth and photometric channel usually harms the semantic labeling. In contrast, memorized fusion layer in our model facilitates integrate the contextual information of different sources in a data-driven manner, instead of simply concatenating the feature vectors.

**RNN on Image Processing:** Similar to CNNs, recurrent neural networks (RNNs) are another specific type of neural networks with loop connections [29]. They are designed to capture dependencies across a distance larger than the extent of local contexts. In previous work, RNN models are not widely used partially due to the difficulty to train such models, especially for sequential data with long dependency [30]. Fortunately, RNNs with gate and memory structures, including long short term memory (LSTM) [31] and gate recurrent unit (GRU) [32], can artificially learn to remember and forget information by using specific gates to control the information flow. Although RNN has outstanding capacity to capture short-range and long-range dependencies, there exists some problems for applying RNN on image processing due to the fact that the input in natural language processing (NLP) has nature sequential characteristics while image not. Thus, different methods are proposed for solving this problem. Specifically, in [19], cascaded bi-directional vertical and horizontal RNN layers are utilized for exploiting 2D dependency of images. multi-dimensional RNN with LSTM unit is applied to offline handwriting [33]. [34] proposes parallel multi-dimensional LSTM for image segmentation. In our work, we propose a LSTM-F model consisting memorized context layer and memorized fusion layer to exploite the image context from a global perspective and fusing the contextual representations of different sources.

### 3 LSTM-F Model

As illustrated in Fig. 2, our end-to-end LSTM-F model for RGB-D scene labeling consists of four components, layers for vertical depth context extraction, layers for vertical photometric context extraction, a memorized fusion layer for incorporating vertical photometric and depth contexts as true 2D global contexts, and a final layer for pixel-wise scene labeling given concatenated convolutional features and global contexts. The input to our model includes both photometric and depth images. The path for extracting global contexts from the photometric image consists of multiple convolutional layers and an extra memorized context layer. On the other hand, the depth image is first encoded as an HHA image, which is fed into three convolutional layers and an extra memorized context layer for global depth context extraction. The other component, a memorized
Fig. 2. Our end-to-end LSTM-F model for RGB-D scene labeling. The input consists of both color and depth images. Vertical contexts in color and depth images are computed in parallel using cascaded convolutional layers and a memorized context layer. Vertical photometric (color) and depth contexts are fused and bi-directionally propagated along the horizontal direction via another memorized fusion layer to obtain true 2D global contexts. The fused global contexts and the convolutional features of photometric channels are then concatenated together and fed into the final convolutional layer for pixel-wise scene labeling. “C” stands for the concatenation operation.

fusion layer, is responsible for fusing previously extracted global RGB and depth contexts in a data-driven manner. On top of the memorized fusion layer, the last convolutional features of color image and the fused global context are concatenated together and fed into the final convolutional layer, which performs pixel-wise scene labeling with the softmax activation function.

3.1 Memorized Vertical Depth Context

Given a depth image, we use the HHA representation proposed in [12] to encode geometric properties of the depth image in three channels, i.e., disparity, surface normal and height. Different from [12], the encoded HHA image in our pipeline is fed into three randomly initialized convolutional layers (to obtain a feature map with the same resolution as that in the RGB path) instead of layers taken from the model trained on the ILSVRC2012 dataset. This is because the color distribution of HHA images is different from that of natural images according to [28]. One top of the third convolutional layer (i.e., HHAConv3), there is an extra memorized context layer from Renet [19], which performs bi-directional propagation of local contextual features from the convolutional layers along the vertical direction. For better understanding, we denote the feature map HHAConv3 as $F = \{f_{i,j}\}$, where $F \in \mathbb{R}^{w \times h \times c}$ with $w$, $h$ and $c$ representing the width, height and the number of channels. Since we perform pixel-wise scene labeling, every patch in this Renet layer only contains a single pixel. Thus, vertical bi-directionally memorized context layer (here we choose LSTM as recurrent
unit) can be formulated as
\[ h_{i,j}^f = \text{LSTM}(h_{i,j-1}^f, f_{i,j}), \quad \text{for } j = 1, \ldots, h \]  \hfill (1)
\[ h_{i,j}^b = \text{LSTM}(h_{i,j+1}^b, f_{i,j}), \quad \text{for } j = h, \ldots, 1 \]  \hfill (2)
where \( h^f \) and \( h^b \) stand for the hidden states of the forward and backward LSTM.

In the forward LSTM, the unit at pixel \((i,j)\) takes \( h_{i,j-1} \in \mathbb{R}^d \) and \( f_{i,j} \in \mathbb{R}^c \) as input, and its output is calculated as follows according to [31]. The operations in the backward LSTM can be defined similarly.

\[
\begin{align*}
gate_i &= \delta(W_{if} f_{i,j} + W_{ih} h_{i,j-1} + b_i) \\
gate_f &= \delta(W_{ff} f_{i,j} + W_{fh} h_{i,j-1} + b_f) \\
gate_o &= \delta(W_{of} f_{i,j} + W_{oh} h_{i,j-1} + b_o) \\
gate_c &= \tanh(W_{cf} f_{i,j} + W_{ch} h_{i,j-1} + b_c) \\
c_{i,j} &= \gate_f \odot c_{i,j-1} + \gate_i \odot \gate_c \\
h_{i,j} &= \tanh(\gate_o \odot c_{i,j})
\end{align*}
\]  \hfill (3)

Finally, pixel-wise global depth contexts are collectively represented as a map, \( C_{\text{depth}} \in \mathbb{R}^{w \times h \times 2d} \), where \( 2d \) is the total number of output channels from the vertical bi-directionally memorized context layer.

### 3.2 Memorized Vertical Photometric Context

In the component for extracting global RGB contexts, we adapt the CNN architecture (Deeplab) proposed in [11]. Different from existing Deeplab variants, we concatenate features at three different scales to enrich the feature representation. Specifically, since there is hole operation in Deeplab convolutional layers, feature maps from Conv2_2, Conv3_3 and Conv5_3 have sufficient initial resolutions. They can be further elevated to the same resolution using interpolation and then concatenated together before being fed into the subsequent memorized fusion layer, which again performs bi-directional propagation to produce global photometric contexts. Here pixel-wise global photometric contexts can also be represented as a map, \( C_{\text{RGB}} \in \mathbb{R}^{w \times h \times 2d} \), which has the same dimensionalities as the map for global depth contexts.

### 3.3 Memorized Context Fusion

So far global depth and photometric contexts are computed independently in parallel. Instead of simply concatenating these two types of contexts, the memorized fusion layer, which performs horizontal bi-directional propagation from Renet, is exploited for adaptively fusing global depth and RGB contexts in a data-driven manner, and the output from this layer can be regarded as the fused representation of both types of contexts. Such fusion can generate more discriminative features through end-to-end training. The input and output dimensions of the fusion layer are set to \( \mathbb{R}^{w \times h \times 4d} \) and \( \mathbb{R}^{w \times h \times 2d} \), respectively.
Note that there are two separate memorized context layers in the photometric and depth paths of our architecture. Since the memorized context layer and the memorized fusion layer are two symmetric components of the original Renet [19], a more natural and symmetric alternative would have a single memorized context layer preceding the memorized fusion layer in our model and let the memorized fusion layer incorporate the features from the RGB and depth paths. Nonetheless, in our experiments, this alternative network architecture gave rise to slightly worse performance.

3.4 Scene Labeling

Between photometric and depth images, photometric images contain more details and semantic information that can help scene labeling in comparison with sparse and discontinuous depth images. Nonetheless, depth images can provide auxiliary information for improving scene labeling performance. Thus, we design a cross-layer combination that integrates pixel-wise convolutional features (i.e., Conv7 in Fig. 2) from the photometric image with fused global contexts from the memorized fusion layer as the final pixel-wise features, which are fed into the last convolutional layer with softmax activation to perform scene labeling at every pixel location.

4 Experimental Results

4.1 Experimental Setting

Dataset: We evaluate our proposed model for scene labeling on currently most intact SUNRGBD dataset [28], which consists of 10355 RGB-D images including most previous appealing datasets, e.g., NYU depth v2 [25], Berkeley B3DO [26], SUN3D [27] and new capturing 3943 RGB-D images [28]. For data splitting, there are 5285 images from four different sensors for training and remaining 5050 images constitute the testing set.

Implementation Details: In our experiments, we adapt slightly modified CNN architecture (Deeplab) proposed in [11] as our basic structure for extracting convolutional feature maps due to its high performance, which is initialized with publicly available VGG-16 model pre-trained on ImageNet. For the purpose of pixel-wise scene labeling, this architecture transforms the last two fully connected layers of standard VGG-16 to fully-convolutional layers. For parallel depth path, three randomly initialized CNN layers with max-pooling are leveraged as depth feature extractor. On top of cascaded CNN layers, vertical bi-directionally memorized context layers exploiting LSTM as recurrent unit encode short-range and long-range spatial dependencies of depth and color images in parallel. Then, memorized fusion layer is built to adaptively integrate the global contexts of the two channels along horizontal bi-directions, which also leverages LSTM as recurrent unit. Besides, there is a cross-layer combination of last convolutional features (i.e., Conv7) and global representation of RGB-D images.
Table 1. A comparison of scene labeling on SUNRGBD with class-wise accuracy and mean accuracy. We compare our model with benchmark result reported in [28, 36] and previous state-of-the-art result [22]. Boldface numbers mean best performance.

| Wall | floor | door | cabinet | bed | chair | sofa | table | door | window | bookshelf | picture | counter | blinds | desk | shelves | curtain | dresser | pillow | mirror |
|------|-------|------|---------|-----|-------|------|-------|------|--------|-----------|---------|---------|--------|------|---------|---------|---------|--------|-------|
| 37.8 | 45.0 | 17.4 | 21.8 | 16.9 | 12.8 | 18.5 | 6.1 | 9.0 | 9.4 | 4.6 | 2.2 | 2.4 | 7.3 | 1.0 | 3.3 | 2.2 | 2.3 | 6.9 |
| 52.1 | 42.6 | 2.9 | 2.4 | 22.5 | 2.1 | 12.5 | 1.4 | 1.0 | 3.3 | 1.7 | 14.8 | 2.0 | 3.4 | 2.9 | 1.4 | 1.2 | 9.5 |
| 39.4 | 35.8 | 15.4 | 24.3 | 24.9 | 9.6 | 19.3 | 6.0 | 7.9 | 12.8 | 8.6 | 5.2 | 2.2 | 7.0 | 1.7 | 4.4 | 1.4 | 3.1 | 6.0 |
| 48.9 | 47.2 | 18.8 | 21.5 | 17.2 | 18.3 | 20.4 | 8.6 | 11.5 | 9.0 | 6.1 | 2.8 | 3.6 | 7.3 | 1.2 | 2.9 | 2.4 | 2.6 | 6.2 |
| 53.3 | 45.8 | 1.0 | 6.3 | 22.3 | 3.7 | 12.9 | 3.8 | 1.6 | 0.9 | 3.6 | 2.2 | 32.6 | 2.0 | 10.1 | 6.6 | 1.8 | 1.0 |
| 57.8 | 48.3 | 11.2 | 20.6 | 20.8 | 12.1 | 20.9 | 8.8 | 9.5 | 13.1 | 11.1 | 6.2 | 2.1 | 9.8 | 1.1 | 4.3 | 1.1 | 1.1 | 1.4 |
| 51.0 | 46.6 | 12.7 | 18.6 | 14.3 | 13.2 | 16.5 | 13.1 | 9.7 | 57.2 | 15.8 | 12.3 | 12.1 | 15.4 | 0.1 | 11.4 | 24.5 | 24.8 |

Ours: 74.9 | 82.3 | 47.3 | 62.1 | 87.7 | 55.5 | 97.8 | 45.6 | 52.8 | 43.1 | 56.7 | 39.4 | 48.6 | 37.3 | 9.6 | 63.4 | 35.0 | 55.8 | 44.5 |

For hyper-parameters setting, considering SUNRGBD dataset is collected by four different depth sensors, the scale of input image is cropped to 426 x 426 (the smallest resolution of four sensors). During fine-tuning, the learning rate of newly added layers, i.e., HHACConv1 to HHACConv3, memorized context layer, memorized fusion layer and Conv8, is initialized as $10^{-2}$ and previously learned layers of VGG-16 is initialized as $10^{-4}$. All weights of newly added CNN layers are initialized with Gaussian distribution with standard deviation 0.001 and weights of LSTM layers are randomly initialized with a uniform distribution of $[-0.01, 0.01]$. The hidden cells and memory cells dimension $d$ of memorized context layer and memorized fusion layer are both set as 200. We train all the layers in our deep network simultaneously using the stochastic gradient descent with momentum of 0.9, batch size of 1 RGB-D image and weight decay of 0.0005. The entire deep network is implemented on the publicly available platform Caffe [35] and is trained on a single NVIDIA GeForce GTX TITAN X GPU with 12GB memory. It takes about 1 days to train our deep network. In the testing stage, one RGB-D image takes 0.15 second on average, which is significantly outperform pervious methods, i.e., in [22] their test time is around 1.5 s.

4.2 Results and Comparisons

We evaluate our proposed model on three public datasets, e.g., SUNRGBD dataset, NYU-Depth v2 dataset and SUN3D dataset.

SUNRGBD dataset [28]: The performance and comparisons of our model and benchmark results are illustrated in Table 1. Our proposed architecture can outperform previous baseline with significant improvement: 11.8% over [22], 38.2% gains over [36] and 38.2% over results report in [28] in terms of 37 categories mean accuracy. Besides, improvements can be observed in 30 categories, including 19 large improvement over 10%. Furthermore, for better understanding, we illustrate confusion matrix for SUNRGBD dataset in Fig. 3(a). According to the statistics of semantic annotations report (Figure 4) in [28], we believe that the better performance is not only due to the power of neural networks we use, but
also owing to the power of memorized fusion of global context and incorporated global context and convolutional features. Specifically, due to the fact that our model with millions of parameters is a data-driven method with higher representation capacity, larger improvements of first 9 categories, i.e., from wall to bookshelf, are consistent with their high appearance frequency. Nevertheless, our model also performs better than previous models on low frequency categories (21 categories), which mainly owes to the integrated convolutional features of photometric image and fused global context of RGB-D image. It is worthy mentioning that our proposed architecture and most previous methods obtain 0 accuracy for two categories, i.e., floor and ceiling, which results from incorporated convolutional features such as floor and ceiling, which mainly results from incorporated convolutional features.

**NYU-Depth v2 dataset:** To further verify the superiority of our architecture and fulfill more comparisons with previous state-of-the-art baselines, we also conduct comparative experiments on NYU-Depth v2 dataset. The results are presented in Table 2. Besides, class frequencies and confusion matrix are also illustrated in Table 2 and Fig. 3(b) correspondingly for further performance analysis. According to the illustrated results, our proposed architecture gains 4.5% mean accuracy over most recent work [14] and more than 19% improvement over other strong baselines [25,22,23,24]. Considering the listed class frequencies, our proposed model significantly outperforms the baselines on high frequency classes and most low frequency categories. In terms of predicting categories with relative small complex region, e.g., pillow, chair, our method outputs a large improvement, which can be further verified in the following visualization part.

**SUN3D dataset:** Table 3 gives the comparison results on 1539 test images on SUN3D dataset. For fair comparison, 12-class accuracy is presented to be compared with recently reported state-of-the-art results in [14]. It is worthy mentioning that the 12-class accuracy is achieved through previous obtained model for 38-classes. Our model substantially outperforms [14] on large planar such as floor and ceiling, which results from incorporated convolutional features.

**Fig. 3.** Confusion matrix for SUNRGBD and NYU-Depth v2. Each category accuracy is shown on the diagonal. Best view in color.
Table 2. Comparison of scene labeling on NYU-Depth v2. We compare our proposed architecture with previous state-of-the-art baselines, i.e., Siberman et al. [25], Ren et al. [22], Gupta et al. [23, 24] and Kan et al. [14]. Class-wise accuracies and mean class accuracy of 37 classes are presented for comparison. Freq stands for class frequency in NYU-Depth v2 dataset. Boldface numbers mean best performance.

| Wall | floor | cabinet | bed | hair | sofa | table | door | bookshelf | acture | counter | blinds | desk | shelves | curtain | dresser | galley | mirror |
|------|-------|---------|-----|------|------|-------|------|-----------|--------|---------|--------|------|---------|---------|---------|--------|--------|
| Freq | 21.4  | 9.1     | 6.2 | 1.8  | 1.3  | 2.7   | 2.1  | 2.2       | 2.1    | 1.9     | 2.1    | 1.4  | 1.7     | 1.4     | 1.6     | 0.9    | 0.8    | 1.0    |
| Ours | 60.7  | 77.8    | 33.8 | 50.1 | 40.4 | 32.4  | 25.3 | 21.0      | 29.7   | 27.7    | 35.7   | 33.1 | 40.6    | 4.7     | 5.4     | 27.4   | 19.3   | 18.9   | 14.4   |
| Ours | 59.0  | 74.5    | 31.7 | 42.5 | 32.8 | 28.2  | 10.6 | 12.9      | 27.7   | 17.3    | 32.4   | 38.6 | 25.0    | 30.1    | 27.6    | 7.0    | 19.7   | 17.9   |
| Ours | 61.7  | 80.5    | 30.8 | 48.5 | 40.4 | 44.8  | 21.0 | 12.1      | 34.1   | 20.5    | 38.7   | 50.7 | 44.7    | 10.1    | 1.6     | 25.3   | 21.6   | 31.3   | 14.6   |
| Ours | 61.4  | 60.4    | 39.2 | 43.9 | 34.3 | 33.5  | 22.6 | 8.3       | 27.6   | 19.6    | 22.7   | 20.2 | 34.6    | 27.7    | 15.9    | 16.8   | 12.5   | 19.2   |
| Ours | 50.7  | 62.5    | 40.1 | 41.1 | 44.5 | 30.8  | 51.6 | 49.2      | 26.3   | 31.4    | 51.6   | 49.2 | 55.8    | 48.0    | 35.2    | 55.3   | 50.5   | 46.1   |
| Ours | 79.6  | 83.5    | 69.3 | 77.0 | 58.3 | 64.9  | 52.6 | 47.0      | 43.6   | 59.5    | 74.5   | 68.2 | 74.6    | 53.6    | 43.1    | 53.2   | 66.5   | 48.0   | 57.7   |
| Boormat | clothes | ceiling | books | fridge | tv | paper | pencil | over | floor | box | board | person | nightstand | toilet | sink | tank | bathtub | bag | mean |
| Ours | 50.7  | 62.5    | 40.1 | 41.1 | 44.5 | 30.8  | 51.6 | 49.2      | 26.3   | 31.4    | 51.6   | 49.2 | 55.8    | 48.0    | 35.2    | 55.3   | 50.5   | 46.1   |
| Ours | 79.6  | 83.5    | 69.3 | 77.0 | 58.3 | 64.9  | 52.6 | 47.0      | 43.6   | 59.5    | 74.5   | 68.2 | 74.6    | 53.6    | 43.1    | 53.2   | 66.5   | 48.0   | 57.7   |
| Ours | 50.7  | 62.5    | 40.1 | 41.1 | 44.5 | 30.8  | 51.6 | 49.2      | 26.3   | 31.4    | 51.6   | 49.2 | 55.8    | 48.0    | 35.2    | 55.3   | 50.5   | 46.1   |
| Ours | 79.6  | 83.5    | 69.3 | 77.0 | 58.3 | 64.9  | 52.6 | 47.0      | 43.6   | 59.5    | 74.5   | 68.2 | 74.6    | 53.6    | 43.1    | 53.2   | 66.5   | 48.0   | 57.7   |
| Ours | 50.7  | 62.5    | 40.1 | 41.1 | 44.5 | 30.8  | 51.6 | 49.2      | 26.3   | 31.4    | 51.6   | 49.2 | 55.8    | 48.0    | 35.2    | 55.3   | 50.5   | 46.1   |
| Ours | 79.6  | 83.5    | 69.3 | 77.0 | 58.3 | 64.9  | 52.6 | 47.0      | 43.6   | 59.5    | 74.5   | 68.2 | 74.6    | 53.6    | 43.1    | 53.2   | 66.5   | 48.0   | 57.7   |

Table 3. Class-wise accuracy and mean class accuracy on SUN3D dataset are illustrated with comparison with recent state-of-art performance report in [14].

| Wall | floor | bed | chair | table | counter | curtain | ceiling | tv | toilet | bathtub | bag | Mean |
|------|-------|-----|-------|-------|---------|---------|---------|-----|--------|----------|-----|------|
| Ours | 73    | 35  | 71    | 35    | 30      | 68      | 27      | 56  | 23     | 49       | 62  | 29   |
| Ours | 86    | 32  | 65    | 57    | 22      | 76      | 69      | 75  | 62     | 49       | 23  | 58.5 |

and fused global context. Furthermore, considering the mean average class accuracy, the superiority and generalization of our proposed model are further verified.

4.3 Ablation Study

To discover the vital elements in the success of our proposed model, we conduct an ablation study to remove or replace specific individual components in our model. Specifically, we have tested the performance of models without depth information, multi-scale features of photometric image, memorized context layer and memorized fusion layer. In addition, we also conduct an experiment with a model that does not combine last convolutional features of photometric data (i.e., Conv7 in Fig. 2) with global context of RGB-D images to figure out the importance of different components. The results are present in Table 4. From the given results, we find that last convolutional features of photometric data is the most vital information, i.e., the cross-layer combination is the most effective component in our model as the performance drops to 15.2% without it, that is consistent with previous mentioned properties of depth and photometric data. In addition, multi-scale features of photometric image also plays a vital role on performance, which directly affect the global context of photometric data. Besides, it is obvious that performance would be inevitably harmed due to the lack of important depth channel information. In terms of memorized layer, memorized fusion layer is more important than memorized context layer in our pipeline as it accomplishes the fusion of different channels.
Table 4. Ablation study

| Model                                  | Mean Accuracy |
|----------------------------------------|---------------|
| Without depth                          | 43.7%         |
| Without multi-scale photometric        | 42.1%         |
| Without photometric convolutional features | 15.2%       |
| Without memorized fusion layer         | 44.7%         |
| Without memorized context layer        | 45.7%         |
| Without both memorized layer           | 45.0%         |

4.4 Visualized Comparisons

Visualization on SUNRGBD Dataset: For better understanding and more intuitive superiority demonstration, we present more visual results in different scene classifications in Fig. 4 e.g., bedroom, living room, study room, kitchen, toilet and so on. Here, we leverage the super-pixel average to smooth the visualization results as [14], in which the conventional segmentation algorithm [37] is exploited to obtain superpixel. As can be observed from these visualized results in Fig. 4, our proposed architecture outputs semantical and precise predictions, especially the large region and high frequency labels. For instance, wall in Fig. 4(e), bed in Fig. 4(a) and mirror in Fig. 4(i) is well labeled by our model considering taking advantage of global context. In terms of label with high frequency such as chair, our proposed model can precisely label almost chairs by exploiting combined information of photometric and depth, regardless of occlusion.

Comparison on NYU-Depth v2: Here we also conduct experiment on appealing NYU-Depth v2 dataset with more complicated indoor scene and well-labeled ground truth. For better understanding and comparison, we compare our obtained scene labeling results with released labeling results of [23]. From illustrated results, we can conclude that the classification of our model is much better than that in [23]. However, due to the fact that scene labeling in [23] is based on sophisticated segmentation, scene labeling of [23] is much better than ours as our model is built on pixel classification. However, our model also outperform previous state-of-the-art performance [23] regardless of the overall visualization performance and average class accuracy.

Refine newly labeled RGB-D images: During experiments, it is surprisingly that our model can intelligently refine some regions which are not correctly labeled in ground truths, especially in the newly captured 3943 RGB-D images, as illustrated in Fig. 6. Specifically, in Fig. 6(a), the cabinet is labeled as background in ground truth, pillow in Fig. 6(g) is labeled as bed, table in Fig. 6(n) is labeled as wall by mistakes. However, outputs from our model can novelty deal with these difficult regions as illustrated in the third row in Fig. 6. Specifically, pictures in Fig. 6(e), pillow in Fig. 6(g) are effectively improved. Thus, our model can be exploited to refine the ground truth of SUNRGBD dataset, which is also another contribution of our model.
Fig. 4. Examples of the semantic labeling results on the SUNRGBD dataset. The top row shows the photometric data, the bottom row are the scene labeling results obtained by our model and the middle row are ground truths. The semantic label and its corresponding color are shown in the figure legend in the bottom.

5 Conclusions

In this paper, we have developed a novel Long Short-Term Memorized Fusion (LSTM-F) model that captures image contexts from a global perspective and deeply fuses contextual representations from multiple sources (i.e., depth and photometric data). Our model can jointly optimize LSTM layers and convolutional layers for better performance of semantic scene labeling. Superiority of our model has been demonstrated with state-of-the-art performance on the large-scale SUNRGBD benchmark. In future, we plan to incorporate an attention mechanism into the memorized context layer and the memorized fusion layer, and refine the performance of our model on boundary labeling. Such extensions will give rise to more complex network architectures and achieve more accurate context learning, especially for small regions.
Fig. 5. Comparison experiments on NYU-Depth v2 dataset. The first and second rows are photometric data and corresponding ground truth. The third row is the released results of [23] and the last row is the output of our LSTM-F model.

Fig. 6. Refine ground truth results on the SUNRGBD dataset. The top row shows the photometric data, the middle row are ground truths and the bottom row are obtained scene labeling results from our model.
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