ENCODED HOURGLASS NETWORK FOR SEMANTIC SEGMENTATION OF HIGH RESOLUTION AERIAL IMAGERY

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ABSTRACT

Fully Convolutional Network (FCN) has been widely used in recent work for semantic segmentation of high resolution aerial imagery. However, FCN is poor at extracting multi-scale features and exploiting contextual information. In this paper, we explore stacked encoder-decoder structure which enables repeated bottom-up, top-down inference across various scales and consolidates global and local information of the image. Moreover, we utilize the Context Encoding Module to capture the global contextual semantics of scenes and selectively emphasize or de-emphasize class-dependent featuremaps. Our approach is further enhanced by intermediate supervision on the predictions of multiple decoders and has achieved 87.01% pixel accuracy and 69.78% mIoU on Potsdam test set, which surpasses various baseline models.

Index Terms— stacked encoder-decoder structure, contextual encoding module, high resolution aerial imagery

1. INTRODUCTION

Semantic segmentation becomes one of the most important problems in remotely sensed aerial imagery analysis. In particular, semantic segmentation can be applied to change detection, urban planning, or even automatic map mapping. Compared to the semantic segmentation on natural images, this task can be much more challenging for remotely sensed high resolution aerial imagery due to the high-spatial resolution and large volumes of pixels. Furthermore, aerial images are generally taken from the top side like drones, the viewing perspectives are different from natural images. To achieve good performance on semantic segmentation of high resolution aerial imagery, the segmentation models should have the following two characteristics:

- Extraction of rich features across multi-scales to capture relatively small objects.
- Utilization of contextual semantics which is significant for distinguishing ground objects from the top side view.

Recently, various deep neural networks structures have been utilized for semantic segmentation in aerial imagery. In [1,2,3], Fully Convolutional Networks (FCN) [4] have been used as the backbone of their networks. Audebert et al. [5] further utilizes SegNet [6] for the segmentation task which is an adaption of FCN by replacing the decoder with a series of pooling and convolutional layers. To overcome the loss of information from the initial layers and combine features from different scales, skip connection have been used in [7,8] for high resolution imagery segmentation. However, does utilization of skip layers is good enough for extracting rich multi-scale features? Recent work [9] shows that by stacking multiple encoder-decoder structures end-to-end, enabling repeated bottom-up, top-down inference across various scales, the network performance is greatly enhanced. In this paper, we adapt the Stacked Hourglass Architecture (SHG) proposed by [9] as the backbone of our network, which has the power to extract rich multi-scale features.

Despite multi-scale features, it is important to learn global contextual information for semantic segmentation of high resolution imagery. Recent work [10] leverages the classic computer vision encoders, Bag-of-Words (BoW) [11], with deep learning, and introduce the Encoding Layer [12], which captures global contextual semantics of the whole image. The proposed EncNet [10] based on the Encoding Layer achieved new state-of-the-art results on multiple semantic segmentation datasets [10]. However, EncNet is based on FCN, which does not exploit the stacked encoder-decoder structure. As a result, EncNet does not reuse the attended featuremaps by encoded semantics, and lacks intermediate supervision on the predictions of multiple encoders which has been demonstrated strong performance in prior work [9,13,14].

In this paper, we develop a novel Encoded Hourglass Network (EnHGNet). We utilize SHG as the backbone of our network, and after the class-dependent featuremaps being emphasized or de-emphasized by contextual semantics, we reuse the featuremaps for later stacks of Hourglass Modules, which adds more feedback loops for learning contextual semantics through intermediate supervision. Our EnHGNet has the abilities to both capturing rich multi-scale features and exploiting contextual information which tackles the difficulties of semantic segmentation of high resolution aerial imagery.

2. APPROACH

In this section, we will first review two related structures, namely Stacked Hourglass Architecture [9] and Context Encoding Module [10] and then introduce our EnHGNet.
2.1. Stacked Hourglass Architecture

Stacked Hourglass Architecture (SHG) \cite{9} is a sequence of modules each shaped like an hourglass. Each Hourglass Module firstly processes features down to a very low resolution by a set of convolutional and pooling layers, then continually bi-linear upsamples and combine features until reaching the final output resolution. The Stacked Hourglass Architecture connects multiple Hourglass Modules end-to-end consecutively, which enables repeated bottom-up, top-down inference across various scales and consolidate global and local information of the whole image. As a result, the performance of the network is greatly enhanced.

In our implementation, we replace the residual block \cite{15} used in the original architecture with wide-dropout residual block \cite{16}, which prevents overfitting during training and improves the network performance. We stack 4 Hourglass Modules in our network and the number of output features in each Hourglass Module is 128, 128, 256, and 256 at corresponding locations where the resolution drops.

2.2. Context Encoding Module

Despite pixel-level information, how to utilize contextual information is a key point for semantic labeling. Contextual relationships provide significant clues from neighborhood objects. For example, a pedestrian is likely to appear over a road and a book is likely to appear on a table. To learn the global semantic context, the Encoding Layer \cite{12} is used to capture the context statistics \cite{10}. The Encoding Layer includes a learnable inherent dictionary which stores the semantic context information and a set of scaling factors which attends featuremaps of different classes. The following part reviews the details of Encoding Layer.

The input of Encoding Layer is a featuremap of shape $H \times W \times C$ or $N \times C$, which corresponds to a set of C-dimensional input features $X = \{x_1, \ldots, x_N\}$, where $N$ is the total number of features and $N = H \times W$. The layer has a learnable inherent codebook $D = \{d_1, \ldots, d_K\}$ containing $K$ number of codewords (visual centers) and a set of smoothing factor of the visual centers $S = \{s_1, \ldots, s_K\}$. The output of Encoding Layer is the residual encoder $E = \{e_1, \ldots, e_K\}$ of shape $K \times C$, and $e_k = \sum_{i=1}^{N} e_{ik}$, where $e_{ik}$ aggregates the residuals with soft-assignment weights, namely

$$e_{ik} = \frac{\exp \left( -s_k \| r_{ik} \|^2 \right)}{\sum_{j=1}^{K} \exp \left( -s_j \| r_{ij} \|^2 \right)} r_{ik},$$

(1)

where the residuals are given by $r_{ik} = x_i - d_k$. The final
encoded semantics $e$ is summed up over $K$ residual encoders, namely $e = \sum_{k=1}^{K} \phi(e_k)$, where $\phi$ denotes ReLU activation.

Two further branches are applied upon the Encoding Layer. One stacks a fully connected layer on it with a sigmoid activation function and outputs the scaling factors $\gamma = \delta(W \cdot e)$, where $W$ denotes the weights of fully connected layer and $\delta$ is the sigmoid function. The output of the Encoding Module is then obtained by a channel-wise multiplication between input featuremaps $X$ and scaling factors $\gamma$, namely $Y = X \otimes \gamma$, which emphasizes or de-emphasizes class-dependent featuremaps. Another branch also stacks a fully connected layer with a sigmoid activation function on the Encoding Layer, which outputs individual predictions for the presences of object categories in an image and learns with a binary cross entropy loss, namely Semantic Encoding loss (SE-loss) \footnote{SE-loss}. Different from pixel-level softmax loss, SE-loss considers big and small objects equally due to the fact that it only cares about the existence but not the number or size. The SE-loss forces the network to understand the global semantic information and regularize the training of Context Encoding Module.

### 2.3. Encoded Hourglass Network (EnHGNet)

Combining the Stacked Hourglass Architecture and the Context Encoding Module, we build an Encoded Hourglass Network (EnHGNet), an overview of which is shown in Fig. 1. The Encoding Layers are placed when the feature maps reach the 1/8 size of the original input, shown as the red rhombus in Fig. 1. This resolution retains more details without increasing the number of parameters. Compared to EncNet \footnote{EncNet}, our EnHGNet has the following differences.

1) We utilize SHG as the backbone of our network, whereas EncNet is based on FCN. Compared with FCN, SHG enables repeated bottom-up, top-down inference across various scales and consolidate global and local information of the whole image.

2) EncNet stacks the Context Encoding Module on top of convolutional layers right before the final prediction, which does not reuse the attended featuremaps by encoded semantics. Here we have two Context Encoding Modules in one Hourglass Module and every Encoding Layer shares the same codebook $D$ and smoothing factors $S$. After the featuremaps being emphasized or de-emphasized, we will reuse the featuremaps for later stacks of Hourglass Modules, which adds more feedback loops for learning contextual semantics through intermediate supervision.

3) EncNet adds SE-loss to two stage of their base network, and here we calculate two SE-loss in each Hourglass Module and sum up SE-loss of all Hourglass Modules as the final SE-loss. This procedure also helps predict more accurate individual predictions for the presences of object categories.

### 3. EXPERIMENTAL RESULTS

In this section, we first briefly introduce the dataset, then describe the implementation details and show our final results.

### 3.1. Data

The Potsdam 2D segmentation dataset is provided by Commission II of ISPRS \footnote{ISPRS}. The dataset includes 38 high resolution aerial images, where 24 images are used for training, and the rest 14 images are for testing. Each image has the resolution of $6,000 \times 6,000$ pixels and the ground sampling distance is 5 cm. The image data contains five channels, namely near-infrared (NIR), red (R), green (G), blue (B), and the normalized digital surface models (nDSMs).

We use a sliding window method to extract patches of size $256 \times 256$ from the original images without overlap, and pad 0s if needed. We further split the original training images to training and validation sets under the ratio of 9:1. Finally, in the dataset, there are 12,441 images for training, 1,383 images for validation and 8,064 images for test.

### 3.2. Implementation Details

We implement our network based on open-source toolbox Tensorflow \footnote{Tensorflow} and train it on 4 NVIDIA GTX 1080 Ti GPUs. Each GPU processes a batch of 4 images and the total batch size is 16. The training data are randomly shuffled and we drop the remainder of the last batch. We use the learning rate scheduling $lr = baselr \cdot (1 - \frac{iter}{total\_iter})^{\text{power}}$ following prior work \footnote{lr}. The Adam optimizer \footnote{Adam} is used for optimization, and we set the base learning rate as 0.0001, the power as 0.9. The image data in Potsdam dataset have 5 channels where pretrained weights are unavailable. We follow \footnote{lr} and use a similar way, namely first pretrain the network without Context Encoding Module for 100 epochs, then restore the pretrained weights and train our EnHGNet another 100 epochs.

For data augmentation, we randomly flip the image horizontally and vertically, then scale it between 0.5 to 2 and finally crop the image into fix size padding 0s if needed.

The ground truth for SE-loss is a binary vector of size number of categories, where each bin represents whether this category is present in the image or not. The final loss is a weighted sum of per-pixel softmax loss and SE-loss. For training EnHGNet, we follow prior work \footnote{lr} to use the number of codewords 32 in Encoding Layers and set the weight for SE-loss as 0.2.

### 3.3. Results on Potsdam Dataset

We train our EnHGNet on the training set and evaluate it on the test set using two standard metrics, namely pixAcc and mIoU. The validation set is used for adjusting hyperparameters in the network.
Fig. 2: Results on Potsdam test set. EnHGNet produces more accurate predictions. For example, in the 1st and 3rd images, EnHGNet captures the shallow red and white regions well and in the last two images, EnHGNet predicts more consistent results.

| Method         | Backbone     | pixAcc% | mIoU% |
|----------------|--------------|---------|-------|
| FCN [4]        | VGG-16       | 82.75   | 61.71 |
| SegNet [6]     | VGG-16       | 83.93   | 63.42 |
| SHG [9]        | Hourglass-104| 85.38   | 67.26 |
| EncNet [10]    | ResNet-101   | 86.37   | 69.04 |
| EnHGNet (ours) | Hourglass-104| 87.01   | 69.78 |
| EnHGNet* (ours)| Hourglass-104| 86.97   | 69.95 |

Table 1: Segmentation results on Potsdam test set. *: Dilated convolution [21] used in residual blocks.

We use FCN [4], SegNet [6], SHG [9] and EncNet [10] as our baseline models. FCN is the generally used framework for semantic segmentation, and SegNet is an adaptation of FCN by replacing the decoder with a series of pooling and convolution layers. SHG and EncNet are compared with our EnHGNet to show the effectiveness of Contextual Encoding Module and Stacked Hourglass Architecture, respectively.

EnHGNet achieves 87.01% pixAcc and 69.78% mIoU on the Potsdam test set, and EnHGNet* achieves 86.97% pixAcc and 69.95% mIoU, which outperforms all baseline models. The numerical results are shown in Table 1. We also show some visual examples of size 256 × 256 in Fig. 2.

4. CONCLUSION

We develop a novel Encoded Hourglass Network (EnHGNet) for semantic segmentation of high resolution aerial imagery. EnHGNet has the abilities to both extract rich multi-scale features of the image and learn the contextual semantics in scenes. This is achieved by repeated bottom-up, top-down inference across various scales and selectively highlighting the class-dependent featuremaps. Our EnHGNet also utilizes intermediate supervision to enhance the performance. The experimental results on Potsdam test set have demonstrated the superiority of our EnHGNet.

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