CIAN: Cross-Image Affinity Net for Weakly Supervised Semantic Segmentation

Junsong Fan    Zhaoxiang Zhang    Tieniu Tan
Chinese Academy of Sciences
{fanzhongsong2016@, zhaoxiang.zhang@, tnt@nlpr.ia.ac.cn}

Abstract

Weakly supervised semantic segmentation based on image-level labels aims for alleviating the data scarcity problem by training with coarse labels. State-of-the-art methods rely on image-level labels to generate proxy segmentation masks, then train the segmentation network on these masks with various constraints. These methods consider each image independently and lack the exploration of cross-image relationships. We argue the cross-image relationship is vital to weakly supervised learning. We propose an end-to-end affinity module for explicitly modeling the relationship among a group of images. By means of this, one image can benefit from the complementary information from other images, and the supervision guidance can be shared in the group. The proposed method improves over the baseline with a large margin. Our method achieves 64.1% mIOU score on Pascal VOC 2012 validation set, and 64.7% mIOU score on test set, which is a new state-of-the-art by only using image-level labels, demonstrating the effectiveness of the method.

1. Introduction

Semantic segmentation provides per pixel predictions for a given image. Recently, fully convolutional network (FCN) based segmentation methods [23, 5, 6] have achieved impressive performance. However, they need large scale dataset with per pixel annotations for training [9, 22], which limits its promotion of the practical usage. To alleviate the difficulty of collecting data for training, researchers proposed weakly supervised learning (WSL) [40] for semantic segmentation. It makes use of weak annotations for training, such as bounding boxes [8, 18], sparse scribbles [21, 30], image-level class labels [19, 33, 35, 1, 15]. In this paper, we focus on the image-level label based weakly supervised semantic segmentation, because they are the easiest to obtain.

Image label based WSL for semantic segmentation is very hard, since we have to find accurate positions and extensions for the target with only class tags. Existing works usually rely on attention to give a rough pixel-level segmentation mask for further training. Specifically, class activation map (CAM) [39] is the mostly adopted method. Though it can provide reliable information about the target’s position, CAM only activates to the most discriminative parts. Thus only sparse and incomplete segmentation masks (seeds) can be obtained from the CAM. Naively training a segmentation network with these sparse seeds usually leads to inferior results.

To make better use of the CAM, Wei et al. [33] adopt an iterative erasing strategy to mine complementary seeds, they also adopt multi-dilation convolution blocks to expand the seeds [35]. Ahn and Kwak [1] train additional pixel-
level affinity net to complete the seeds, Huang et al. [15] gradually confirm the undefined areas by region growing algorithm, Kolesnikov et al. [19] and Briq et al. [2] adopt additional constraints to regularize the predictions, and so on. A common character of these methods is that each sample is only considered independently. However, we argue that different images of the same class are of some similar characters. If we can model this similarity explicitly, information from a set of images can be integrated and then distributed to each sample to complement the vague areas. Thus the insufficient supervision problem caused by the weak labels can be alleviated.

Based on this motivation, we propose to explicitly model the cross-image affinity, and use it to bridge different images together to infer the predictions. In the embedded feature space, nodes (a node is a channel-vector takes up some spatial position of the feature map) are of high-level semantic information. Intuitively, the affinity between two nodes reflects their semantic similarity. Nodes with high affinity are more likely to belong to the same class, as shown in Fig.1. Though some nodes lack discriminative representations, they can retrieve supplementary information from other nodes by the affinities and then make correct predictions. Thus firstly the cross-image affinity can provide supplements for those weak regions. Secondly, by the affinity, each node holds the global context across multi-images. With this knowledge, nodes of the same class can learn a more consistent and robust representation. Thirdly, with connections by the affinity, a prediction is based on the whole group of images, and in turn its gradient can be back-propagated to every images in the group. By means of this, images in a group implicitly share the supervisions, thus can make up for the weakness of the supervisions to some extent.

We propose an end-to-end trainable cross-image affinity module (AM) and attach it with the segmentation network for training. The whole end-to-end network is named cross-image affinity net (CIAN). There are mainly two steps in the AM, firstly it computes the reliable cross-image affinity, and secondly it makes message passing based on the affinity. Original feature maps from the backbone can be enhanced by the passed messages, and then sent to the backend classifier. With a ResNet-101 [13], our method achieves new state-of-the-art for weakly supervised semantic segmentation with 64.1% mIOU score on Pascal VOC 2012 validation set [9], and 64.7% mIOU score on the test set. Solid experiments and ablation studies prove the method’s effectiveness. In summary, the main contributions are:

- We first propose to explicitly model the cross-image affinity for weakly supervised semantic segmentation. By means of this, the information in a group of images can be shared, and adopted to enhance each other.
- Solid experiments prove the proposed method is effective to mine useful supplementary information from a group of images, and the state-of-the-art results are obtained on VOC 2012 dataset.
- We further prove that our method is orthogonal to those state-of-the-art methods for generating high quality proxy seeds. Thus the performance can be further improved by combining these methods.

2. Related Work

In this section, we introduce related works about weakly supervised semantic segmentation and the proposed affinity module.

2.1. Weakly Supervised Semantic Segmentation

Existing weakly supervised semantic segmentation approaches mostly rely on initial pre-computed pixel-level proxy masks to train a normal segmentation network [5, 6, 23]. The class activation map (CAM) proposed by Zhou et al. [39] is widely used for generating the initial masks from image-level labels. CAM provides dense attention maps for each class. However, as it is trained by classification tasks, CAM only activates to the most discriminative areas, leading to sparse and incomplete masks (also called seeds).

To alleviate the incompleteness problem, Wei et al. [33] propose to adopt an iterative erasing strategy to mine and merge more complementary seeds. Further, Zhang et al. [37] extend this method into an end-to-end adversarial learning framework. MDC [35] expands the seeds by dilated convolutions. Besides, some methods dynamically enrich the initial seeds along the training process, such as region growing [15] and iterative mining [32]. Despite the effectiveness of these complicated methods, we use a simple CAM trained with a single dilated convolution block to generate our initial seeds.

There are also many other methods focus on the constraints specifically designed for weakly supervised semantic segmentation. For example, Pathak et al. [26] add linear constraints on the predictions, which is based on some latent probability distributions. Kolesnikov and Lampert [19] propose the global weighted rank pooling constrained by image labels and low level boundary constrained by CRF [20]. Briq et al. [2] normalize the prediction by the area constraint. As aforementioned, these constraints do not consider the relationship and potential common information across images. In contrast, our method fills this gap by explicitly modeling the affinity across images.

2.2. Densely Connected Affinity

Modeling the densely connected pair-wise relationship is very helpful for segmentation tasks. Early work [20] uses
Figure 2: The overall framework. The input batch is divided into groups. Images in a group have at least one common class label. After the backbone, two branches G-AM and S-AM (see Section 3.3 and Section 3.4) compute the messages according to cross-image affinity and intra-image affinity respectively. Then the original feature is augmented by these messages and sent to predict segmentation. All the parameters are shared between the two branches.

conditional random fields (CRF) for modeling the pair-wise relationships. CRF is also adopted as a post-processing stage in deep networks [5, 6, 23], and further extention as an end-to-end trainable layer in [38]. However, these CRF based methods only model intra-image relationships, lack the usage of cross-image similarities. While our method introduces cross-image affinity to highlight potential information in a group of images.

Recent work AffinityNet [1] samples sparse points by CAM seeds and then trains an additional affinity net by metric learning. It is different from our work that we focus on learning the online cross-image relationships and use it to extract sharable information. Our method is highly related to the non-local networks [31], since we use a similar strategy to model the affinity and make message passing based on the affinity. Besides, some recent works using non-local modules [11, 36] are also proposed for segmentation. However, these works focus on the long range intra-image (or video) contexts to discover the structures in an image, while we emphasize the cross-image relationships to highlight common parts and share complementary information to combat the weak label problem.

3. Approach

The whole weakly supervised pipeline can be divided into two parts. The first is to generate sparse but reliable initial proxy segmentation masks. The second is our proposed cross-image affinity module for training segmentation network (CIAN). We elaborate the details in the following.

3.1. Initial Seeds Generation

We adopt the CAM [39] to generate the initial seeds. CAM is obtained by training a classification network with global pooling layer. After training, it removes the global pooling layer, directly applies the backend classifier on the final feature maps, and obtains the so-called CAMs.

Following previous works, we use VGG16 [29] to train the CAM. Wei et al. [35] propose that dilated convolution blocks is beneficial to generate more complete seeds. Following this practice and the requirement to generate with larger resolutions, we adopt the DeepLab’s VGG16 segmentation backbone [5] with input size 321 and output stride 8. We attach a global average pooling layer and a classifier to the backbone, and train it with sigmoid cross-entropy loss by learning rate $1e^{-4}$. After training, we generate the CAMs, normalize them to $[0, 1]$, and use a thresh-
The affinity module (AM), takes in the two embedded feature maps, computes the affinity and then passes supplementary messages based on the affinity. The messages will be adopted to enhance the original input features.

**Affinity Matrix.** To compute the affinity, the first step is to embed the nodes into some space where affinity can be measured. Given two nodes \(x_i\) and \(x_j\), we use two embedding functions \(\phi\) and \(\varphi\) to act on them respectively. Where \(\phi\) is called the query function, and \(\varphi\) is called the key function. With a little abuse of the notation, we use abbreviation \(\phi_i\) to stand for \(\phi(x_i)\), and so does \(\varphi_j\). Then the affinity from \(x_i\) to \(x_j\) is computed by dot-production

\[
A_{ij}^{(k,h)} = \phi_i^{(k)} T \varphi_j^{(h)}
\]

Other distance measurements may also applicable, such as Gaussian kernel function, cosine distance, etc. Here we only choose dot-production because of its simplicity, since the embedding functions are learnable to adapt to the measurement.

Given \(\mathbf{x}^{(k)}\) and \(\mathbf{x}^{(h)}\), we apply query function to each node in the former, and key function to the latter. Then all the affinities from \(\mathbf{x}^{(k)}\) to \(\mathbf{x}^{(h)}\) form a matrix \(A^{(k,h)}\), where \([A^{(k,h)}]_{ij} = A_{ij}^{(k,h)}\). \(A^{(k,h)}\) reflects the so-called densely connected affinity across two images \(\mathbf{I}^{(k)}\) and \(\mathbf{I}^{(h)}\).

It should be noticed that because \(\phi\) and \(\varphi\) can be different functions, typically the affinity is not symmetric, i.e. \(A^{(k,h)} \neq A^{(h,k)^T}\).

**Message Passing.** The second step is to collect useful information from the key nodes and pass it to the query nodes. To increase the flexibility to choose the most informative messages, we use another embedding function \(g\) to abstract the information to be passed:

\[
g_j^{(h)} = g(x_j^{(h)})
\]

It is reasonable to keep the scale of the retrieved messages invariant to the number of the key nodes. Thus, we normalize each row of \(A^{(k,h)}\) by softmax:

\[
\bar{A}_{ij}^{(k,h)} = \frac{\exp(A_{ij}^{(k,h)})}{\sum_j \exp(A_{ij}^{(k,h)})}
\]

Then, the message for the query node is computed as a weight summarization over all the embeddings corresponding to the key nodes:

\[
q_i^{(k,h)} = \sum_j \bar{A}_{ij}^{(k,h)} \, g_j^{(h)}
\]

As the output of the AM, these messages will be adopted to augment the original query nodes’ corresponding feature maps:

\[
\hat{x}_i^{(k)} = \psi(q_i^{(k,h)}) + x_i^{(k)}
\]

where \(\psi\) is another embedding function to map the message to the original feature space. Fig.3 illustrates the above procedures.

### 3.3. Group Affinity Module

In this subsection, we extend the above AM between two images into a group affinity module (G-AM) relates to more images. It follows that if we have a group of images \(\{I^{(k)}\}\), we first compute affinity between any two images, then we merge the affinities and make message passings.

Now, assume we use \(x^{(k)}\) as the query, then the affinity matrices from it to all the other keys in the group form a set \(\{A^{(k,h)}\}_{h \in N(k)}\), where \(N(k)\) denotes the set of image indices for the keys, and \(|N(k)|\) is the length of the set. Now we can either first normalize each affinity, then pass messages and merge the messages, or first merge the affinities, normalize and then pass the messages. Three different merging designs are studied:

- **Average:** We normalize each affinity and compute the corresponding message \(q_i^{(k,h)}\), as stated in Eq. (3) and Eq. (4). Then, we merge the messages by average pooling:
\[ q_i^{(k)} = \frac{1}{|N(k)|} \sum_{h \in N(k)} q_i^{(k,h)} \quad (6) \]

- Maximum: The same as average, but we merge the messages by maximum pooling:

\[ q_{i(m)}^{(k)} = \max_{h \in N(k)} \left\{ q_i^{(k,h)} \right\} \quad (7) \]

where, subscript \((m)\) denotes the \(m\)-th scalar value in the vector.

- Concatenation: We first concatenate all the affinity matrices horizontally, obtaining a big affinity matrix \(A^{(k)}\). The embeddings \(\{g_i^{(h)}| h \in N(k)\}\) are also put together for message passing, and denoted by \(\hat{g}^{(k)}\).

\[ A^{(k)}_i = \text{concat} \left\{ A_i^{(k,h)} | h \in N(k) \right\} \quad (8) \]

Then, the message is computed as weighted sum over the big matrix:

\[ \hat{q}_i^{(k)} = \sum_{j} A^{(k)}_{ij} \hat{g}_j^{(k)} \quad (9) \]

Finally, the message \(\hat{q}_i^{(k)}\) is used to enhance \(x_i^{(k)}\), as in Eq. (5). To ensure there are always sharable information in a group, images of at least on common class label are sampled to formalize a group. The number of images in a group is called group size.

### 3.4. Self Affinity Module

It is important to ensure each node can find at least one partner of the same class. As a counterexample, assume there is a maverick query node with no partners of the same class. Because of the normalization of the affinity matrix, there are always non-zero messages passed to it. However, these messages are optimized to enhance the discrimination of some classes different from the query node’s class. Thus these messages act as disturbance for the query node.

To cancel out the disturbance, we introduce the so-called self affinity module (S-AM). S-AM simply replaces the key image with the query image itself, thus it builds intra-image dense connections. It works because with identical image one query node can always find key nodes of the same class, at the worst case, the node matches to itself. Thus correct messages are always provided and can alleviate the disturbance.

There is another advantage to use S-MA. When testing we can not make image groups, neither does the affinity matrix or message passing from G-AM. Without S-MA the formulation of AM has to be canceled, and this gap may lead to depreciated performance.

### 3.5. The Overall Framework

The overall framework of the network is illustrated in Fig. 2, which is called cross image affinity net (CIAN). After extracting feature maps by the backbone, it splits into two branches. One enhances the feature maps by the proposed G-AM, another enhances it by S-AM. The two enhanced features are sent to a shared classifier to predict the segmentations. The two branches share all the same parameters. Let \(f(x_i) \in \mathbb{R}^c\) denote the predicted class probability at spatial location \(i\) (\(c\) is number of classes including background, we ignore image index \(k\) for simplicity), and let \(P_i \in \mathbb{R}^c\) denote the corresponding ground truth, we use the standard per pixel cross entropy loss for each image:

\[ L_1 = -\frac{1}{|N|} \sum_{i \in N} P_i^T \log f(x_i) \quad (10) \]

Besides, to further enhance the robustness of the training, we also use the network’s online prediction to derive another segmentation mask for training, as denoted by \(P_i'\), and use it to guide the training:

\[ L_2 = -\frac{1}{|N'|} \sum_{i \in N'} P_i'^T \log f(x_i) \quad (11) \]

where \(N\) and \(N'\) are the sets of indices corresponding to non-ignored positions in the corresponding proxy segmentation masks. The total loss for each branch is the summarization of \(L_1\) and \(L_2\).

### 4. Experiments

#### 4.1. Settings

**Dataset.** We evaluate our proposed method on Pascal VOC 2012 segmentation benchmark [9]. This dataset has 20 foreground classes and one background class, totally 21 classes. Each image contains one or multiple classes. Following the common practice [33, 35, 15], we use the images in the expanded extra set collected by Hariharan et al. [12] for training. Thus totally there are 10582 training images, 1449 validation images, and 1456 testing images. The performance is evaluated by mIOU across 21 classes.

**Implementation Details.** We choose Deeplab-v2 [5] framework with ResNet101-LargeFoV as the segmentation backbone. \(\phi\), \(\varphi\) and \(g\) are by default implemented by \(1 \times 1\) convolutional layers with 1024 kernels. \(\psi\) is implemented by a \(1 \times 1\) convolution with zero-initialized batch normalization (BN) layer [16]. For computation efficiency, we downsample \(\varphi\) and \(g\) with stride 2. Standard data augmentation is adopted to train the segmentation network, i.e. random crop, random horizontal mirror, and random scale in \(\{0.5, 0.75, 1, 1.25, 1.5\}\). The training image is cropped to \(321 \times 321\). We use learning rate \(5e^{-4}\), weight decay \(5e^{-4}\) and momentum 0.9 with the SGD optimizer. The learning
rate is poly-decayed with power 0.9. ImageNet pretrained parameters are used, and all the learning rates of newly initialized parameters are timed by 10. We use batch size 16, and train the segmentation network with 20 epochs, which roughly equals the number of iterations in fully supervised settings. CRF [20] with default parameters is used to further refine the predictions as a post-processing. All the codes are implemented with MXNet [7].

4.2. Comparison with State-of-the-arts

It should be careful to make comparisons with other methods, since the additional supervisions, backbones, and other details may be different. We summarize the state-of-the-arts and our results in Table 1. Our CIAN-g2 and CIAN-g4 (group size 2 and 4 respectively) outperform the state-of-the-arts with a large margin. Among all the state-of-the-art weakly supervised segmentation methods, Fan et al. [10] achieve the best performance. However, they use a pre-trained instance saliency model to give the potential candidates, which is trained by much stronger pixel-level instance saliency annotations. Even though, our result is still competitive with it. With the more popular setting by only using image labels and weak class-agnostic saliency, Hou et al.’s [14] and Huang et al.’s [15] works achieve the best performance, our result outperforms them by 1% - 2% mIOU score on val or test set, leading to a new state-of-the-art using only image-level labels.

4.3. Ablation Study

We make various ablation studies to further prove the effectiveness of the proposed modules. The results are summarized in Table 2.

We first show results of the plain baseline, which is the original DeepLab network trained by the weak seeds with loss $L_1 + L_2$. Thanks to the better strategy for generating the CAM seeds, our baseline achieves decent results.

The next two rows in Table 2 show the results of only using S-AM or G-AM respectively. By only using S-AM, there is no boost compared to the baseline, proving that the cross image relationship is vital. By only using G-AM, the improvement is subtle, thus incorporating intra-image affinity is indeed necessary to cope with the no-match problem, as elaborated in Section 3.4.

The fourth row shows the result of CIAN with randomly sampled pairs, i.e. without the common class constraint in a group. The fifth row shows the result of our full CIAN with common class constraint. Comparing these two lines together with the baseline, it proves the effectiveness of the cross-image affinity learning and the common class group strategy. Our CIAN outperforms the baseline both with and without the CRF post-processing.

Following [15], the last row shows the result after a round of retraining. That is, we use the trained CIAN to generate predicted segmentation masks on the training set, then use the predictions to train the corresponding CIAN with another round. With this retraining strategy, the performance is further improved, especially when evaluated without CRF post-processing. This is because when generating predictions, low level cues are incorporated by CRF refining, which plays a similar role to the boundary constraint in SEC [19].

4.4. Qualitative Visualizations

We visualize some of the predictions of baseline and CIAN-g2 to qualitatively analyze the results. As shown in Fig.4, compared with the baseline, CIAN produces more complete predictions. Meanwhile, some of the wrong predictions are corrected, leading to more satisfactory results.

To further inspect what is learned by the affinity, we visu-
| Method            | mIOU w/o CRF | mIOU w/ CRF |
|-------------------|--------------|-------------|
| Baseline          | 56.2         | 61.1        |
| Only S-AM         | 57.6         | 60.3        |
| Only G-AM         | 56.5         | 61.4        |
| CIAN (random)     | 56.6         | 61.2        |
| CIAN              | 57.7         | 62.0        |
| CIAN + retrain    | 62.9         | 63.8        |

Table 2: Ablation studies on VOC 2012 val set. Group size 2 is adopted for CIAN.

4.5. The Influence of Embedding Methods

We make comparisons with different embedding methods for $\phi$ and $\varphi$. Four different settings are evaluated, 1) they use $1 \times 1$ convolution layers respectively, (the default setting in Section 4.1); 2) they share the same $1 \times 1$ convolution; 3) they use $1 \times 1$ convolution + BN + ReLU respectively; 4) they share the same $1 \times 1$ convolution + BN + ReLU. The number of kernels is always set as 1024. Results are summarized in Table 3. The performance differs with different embedding methods. Among them, shared versions are worse than the corresponding unshared versions. For convenience, in the following experiments, we only use the default setting.

| Method            | mIOU w/o CRF | mIOU w/ CRF |
|-------------------|--------------|-------------|
| Conv              | 57.66        | 61.99       |
| Conv (share)      | 56.22        | 60.91       |
| Conv+BN+ReLU      | 56.86        | 61.74       |
| Conv+BN+ReLU (share) | 56.58   | 61.26       |

Table 3: Comparison of different embedding methods on VOC 2012 val set with group size 2.

4.6. The Influence of Merging Methods

When the group size is greater than 2, the merging methods influence the results. To explore the influence of different merging methods (see Section 3.3), we make some
experiments with CIAN-g4 (group size 4). The results are summarized in Table 4. It shows the average pooling and maximum pooling give better results. Meanwhile, concatenation gives inferior results. Thus directly building a too large affinity graph may not an optimal choice.

| Method   | mIOU  | mIOU  |
|----------|-------|-------|
|          | w/o CRF | w/ CRF |
| Avg      | 58.07  | 62.04  |
| Max      | 58.34  | 62.07  |
| Concat   | 57.73  | 61.72  |

Table 4: Comparison of different merging methods on VOC 2012 val set with group size 4.

4.7. Larger Group Size

It should be beneficial by using a larger group size, since there are more shared information. We prove this by the results of CIAN with different group sizes. To make the comparison fair, the batch size is always set as 16 for all the group sizes. The batch size should be divisible by the group size, thus we experiment with group size 2, 4 and 8. It should be noticed that when enlarging the group size, the classes in a batch tends to be identical. Specifically, when the batch size equals to the group size, all the images are of a single common class. This will lead to biased estimation of the BN stats and disturb the training. To overcome this difficulty, we use an already trained CIAN with group size 2 to initialize the networks with group size 4 and 8, and freeze the BN parameters during training. Results are summarized in Table 5. It shows that with larger group size, the performance improves steadily.

| Method  | mIOU  | mIOU  |
|---------|-------|-------|
|          | w/o CRF | w/ CRF |
| CIAN-g2  | 57.66  | 61.99  |
| CIAN-g4  | 58.07  | 62.04  |
| CIAN-g8  | 58.38  | 62.64  |

Table 5: Comparison of different group sizes on VOC 2012 val set.

4.8. Effectiveness with Other Backbones

To demonstrate the proposed CIAN works with other backbones, we test it with a ResNet50, which is a relatively weaker backbone. As shown in Table 6, on VOC 2012 val set, CIANs outperform the baseline by 0.8% - 1.5% mIOU score without CRF post-processing, and 0.6% - 1.2% mIOU score with CRF post-processing. As expected, with a larger group size, the result tends to be better.

| Method     | mIOU  | mIOU  |
|------------|-------|-------|
| Baseline-res50 | 55.1  | 59.7  |
| CIAN-res50-g2  | 55.9  | 60.8  |
| CIAN-res50-g4  | 56.3  | 60.3  |
| CIAN-res50-g8  | 56.6  | 60.9  |

Table 6: ResNet50 results on VOC 2012 val set.

4.9. Orthogonality with Other Methods

We prove that our method is orthogonal to the quality of the proxy seeds, which means it is also orthogonal to those state-of-the-art methods for generating better proxy masks [33, 14, 35]. We imitate higher quality proxy masks by randomly replace some of the proxy seeds with the ground truth. Specifically, 5% and 10% of the proxy seeds in training set are replaced respectively. As shown in Table 7, with a larger ratio of ground truth masks, the baseline’s performance improves quickly. Meanwhile, our CIAN always outperforms the baseline. It proves that our method consistently works with better proxy seeds. Thus we believe that by combining those state-of-the-art methods for generating better proxy masks, the CIAN’s performance can be further enhanced.

| Ratio | Baseline | CIAN |
|-------|----------|------|
|       | w/o CRF  | w/ CRF | w/o CRF  | w/ CRF |
| 0     | 56.21    | 61.09  | 57.66    | 61.99  |
| 0.05  | 59.69    | 64.03  | 60.39    | 65.42  |
| 0.10  | 61.86    | 65.62  | 63.13    | 65.91  |

Table 7: Comparison of the results with various initial seeds of different quality on VOC 2012 val set.

5. Conclusion

In this paper, we propose cross-image affinity net (CIAN) to mine the cross-image relationships for enhancing the weakly supervised semantic segmentation. By means of the CIAN, complementary information and the supervision can be shared across images. Our approach achieves the new state-of-the-art on VOC 2012 dataset for image-level label based semantic segmentation. Solid experiments prove the effectiveness of CIAN. Besides, we demonstrate that our method is orthogonal to the quality of the proxy seeds, thus can benefit from any advanced methods who generate better proxy seeds.
References

[1] J. Ahn and S. Kwak. Learning pixel-level semantic affinity with image-level supervision for weakly supervised semantic segmentation. arXiv preprint arXiv:1803.10464, 2018. 1, 3, 4, 6
[2] R. Bриq, M. Moeller, and J. Gall. Convolutional simplex projection network (cspn) for weakly supervised semantic segmentation. arXiv preprint arXiv:1807.09169, 2018. 2
[3] A. Chaudhry, P. K. Dokania, and P. H. Torr. Discovering class-specific pixels for weakly-supervised semantic segmentation. arXiv preprint arXiv:1707.05821, 2017. 6
[4] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Semantic image segmentation with deep convolutional nets and fully connected crfs. arXiv preprint arXiv:1412.7062, 2014. 6
[5] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence, 40(4):834–848, 2018. 1, 2, 3, 5
[6] L.-C. Chen, G. Papandreou, F. Schroff, and H. Adam. Re-thinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:1706.05587, 2017. 1, 2, 3
[7] T. Chen, M. Li, Y. Li, M. Lin, N. Wang, M. Wang, T. Xiao, B. Xu, C. Zhang, and Z. Zhang. Mxnet: A flexible and efficient machine learning library for heterogeneous distributed systems. arXiv preprint arXiv:1512.01274, 2015. 6
[8] J. Dai, K. He, and J. Sun. Boxsup: Exploiting bounding boxes to supervise convolutional networks for semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, pages 1635–1643, 2015. 1, 6
[9] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. International journal of computer vision, 88(2):303–338, 2010. 1, 2, 5
[10] R. Fan, Q. Hou, M.-M. Cheng, G. Yu, R. R. Martin, and S.-M. Hu. Associating inter-image salient instances for weakly supervised semantic segmentation. 2018. 6
[11] J. Fu, J. Liu, H. Tian, Z. Fang, and H. Lu. Dual attention network for scene segmentation. arXiv preprint arXiv:1809.02983, 2018. 3
[12] B. Hariharan, P. Arbeláez, L. Bourdev, S. Maji, and J. Malik. Semantic contours from inverse detectors. 2011. 5
[13] K. He, X. Zhang, S. Ren, and J. Sun. Identity mappings in deep residual networks. In European conference on computer vision, pages 630–645. Springer. 2016. 2
[14] Q. Hou, P.-T. Iiang, Y. Wei, and M.-M. Cheng. Self-erasing network for integral object attention. arXiv preprint arXiv:1810.09821, 2018. 6, 8
[15] Z. Huang, X. Wang, J. Wang, W. Liu, and J. Wang. Weakly-supervised semantic segmentation network with deep seeded region growing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7014–7023, 2018. 1, 2, 4, 5, 6
[16] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167, 2015. 5
[17] H. Jiang, J. Wang, Z. Yuan, Y. Wu, N. Zheng, and S. Li. Salient object detection: A discriminative regional feature integration approach. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2083–2090, 2013. 4
[18] A. Khoreva, R. Benenson, J. H. Hosang, M. Hein, and B. Schiele. Simple does it: Weakly supervised instance and semantic segmentation. In CVPR, volume 1, page 3, 2017. 1
[19] A. Kolesnikov and C. H. Lampert. Seed, expand and constrain: Three principles for weakly-supervised image segmentation. In European Conference on Computer Vision, pages 695–711, Springer, 2016. 1, 2, 4, 6
[20] P. Krähenbühl and V. Koltun. Efficient inference in fully connected crfs with gaussian edge potentials. In Advances in neural information processing systems, pages 109–117, 2011. 2, 6
[21] D. Lin, J. Dai, J. Jia, K. He, and J. Sun. Scribble-sup: Scribble-supervised convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3159–3167, 2016. 1, 6
[22] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014. 1
[23] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015. 1, 2, 3, 6
[24] S. J. Oh, R. Benenson, A. Khoreva, Z. Akata, M. Fritz, B. Schiele, et al. Exploiting saliency for object segmentation from image level labels. In IEEE Conf. Computer Vision and Pattern Recognition, 2017. 6
[25] G. Papandreou, L.-C. Chen, K. Murphy, and A. L. Yuille. Weakly-and semi-supervised learning of a dcnn for semantic image segmentation. arXiv preprint arXiv:1502.02734, 2015. 6
[26] D. Pathak, P. Krähenbühl, and T. Darrell. Constrained convolutional neural networks for weakly supervised segmentation. In Proceedings of the IEEE international conference on computer vision, pages 1796–1804, 2015. 2, 6
[27] X. Qi, Z. Liu, J. Shi, H. Zhao, and J. Jia. Augmented feedback in semantic segmentation under image level supervision. In European Conference on Computer Vision, pages 90–105. Springer, 2016. 6
[28] W. Shimoda and K. Yanai. Distinct class-specific saliency maps for weakly supervised semantic segmentation. In European Conference on Computer Vision, pages 218–234. Springer, 2016. 6
[29] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014. 3
[30] P. Vernaza and M. Chandraker. Learning random-walk label propagation for weakly-supervised semantic segmentation. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), volume 3, page 3, 2017. 1
[31] X. Wang, R. Girshick, A. Gupta, and K. He. Non-local neural networks. arXiv preprint arXiv:1711.07971, 10, 2017. 3
[32] X. Wang, S. You, X. Li, and H. Ma. Weakly-supervised semantic segmentation by iteratively mining common object features. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1354–1362, 2018.

[33] Y. Wei, J. Feng, X. Liang, M.-M. Cheng, Y. Zhao, and S. Yan. Object region mining with adversarial erasing: A simple classification to semantic segmentation approach. In *IEEE CVPR*, volume 1, page 3, 2017.

[34] Y. Wei, X. Liang, Y. Chen, X. Shen, M.-M. Cheng, J. Feng, Y. Zhao, and S. Yan. Stc: A simple to complex framework for weakly-supervised semantic segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(11):2314–2320, 2017.

[35] Y. Wei, H. Xiao, H. Shi, Z. Jie, J. Feng, and T. S. Huang. Revisiting dilated convolution: A simple approach for weakly- and semi-supervised semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7268–7277, 2018.

[36] Y. Yuan and J. Wang. Ocnet: Object context network for scene parsing. *arXiv preprint arXiv:1809.00916*, 2018.

[37] X. Zhang, Y. Wei, J. Feng, Y. Yang, and T. Huang. Adversarial complementary learning for weakly supervised object localization. In *IEEE CVPR*, 2018.

[38] S. Zheng, S. Jayasumana, B. Romera-Paredes, V. Vineet, Z. Su, D. Du, C. Huang, and P. H. Torr. Conditional random fields as recurrent neural networks. In *Proceedings of the IEEE international conference on computer vision*, pages 1529–1537, 2015.

[39] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. Learning deep features for discriminative localization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2921–2929, 2016.

[40] Z.-H. Zhou. A brief introduction to weakly supervised learning. *National Science Review*, 5(1):44–53, 2017.