Weighted Intersection over Union (wIoU) for Evaluating Image Segmentation

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Abstract

In recent years, many semantic segmentation methods have been proposed to predict label of pixels in the scene. In general, we measure area prediction errors or boundary prediction errors for comparing methods. However, there is no intuitive evaluation metric that evaluates both aspects. In this work, we propose a new evaluation measure called weighted Intersection over Union (wIoU) for semantic segmentation. First, it builds a weight map generated from a boundary distance map, allowing weighted evaluation for each pixel based on a boundary importance factor. The proposed wIoU can evaluate both contour and region by setting a boundary importance factor. We validated the effectiveness of wIoU on a dataset of 33 scenes and demonstrated its flexibility. Using the proposed metric, we expect more flexible and intuitive evaluation in semantic segmentation field are possible.

1. Introduction

In recent years, many studies have tried to train pixel-level classifiers on large-scale image datasets to perform accurate semantic image segmentation [27, 31]. The goal of the image segmentation is to assign a class label of each pixel in the scene. It is one of the most basic problems in computer vision fields and has various potential applications e.g., autonomous driving systems [8], scene understanding [21] and medical image diagnostics [15, 17]. Recently, significant advances in deep learning techniques are driving high-performance of semantic segmentation in various benchmark datasets [6, 9, 13]. Figure 1 shows a result of the semantic segmentation [31] and its error map in the KITTI dataset [13].

Although the method performs the best compared to other state-of-the-art methods, it still experiences classification errors. Most of the errors (i.e., false negatives and positives) occur around object boundaries due to high classification ambiguities around the boundaries as shown in Fig. 1 (b). That is because at least two classes are adjacent around the objects’ boundaries making class predic-

![Segmentation result with an original image](image1)

![Error map. Color of each pixel denotes: (green) True positive, (red) False negative, (yellow) False positive, (black) No label.](image2)

![Proposed weight map for the segmentation evaluation](image3)

Figure 1. Challenges in semantic segmentation and the proposed weight map. (a–b) It is difficult to predict pixel labels around object boundaries. (c) The proposed weight map emphasizes the importance of boundaries.
all classification performance. To evaluate semantic segmentation results, most methods [27,31] rank their methods by measuring intersection-over-union (IoU) score described in Section 3.2.

Unfortunately, IoU evaluates all pixels equally, so the performance scores of many newly proposed methods improve very subtly according to the evaluation criterion. To directly evaluate the boundary estimation results, several evaluation metrics such as BF score [7] and Boundary Jaccard (BJ) [12] were proposed; however, they do not evaluate internal areas of the objects. In addition, those methods are highly dependent on the setting of distance tolerance parameter $\theta$. As we mentioned above, both evaluations of internal and boundaries of objects are important, without relying on certain tuning parameters.

In this work, we propose a novel evaluation measure for semantic segmentation called weighted Intersection over Union (wIoU). It generates a weight map based on the boundary distance map, as shown in Figure 1 (c). The weight map is adjustable based on a boundary importance factor $\alpha$, as shown in Figure 5. Using the weight map enables weighted evaluation for each pixel. Setting the value of $\alpha$ is intuitive. Furthermore, it effectively evaluates both boundary and internal regions simultaneously. Our work makes significant contributions to the field of image segmentation by introducing the following advancements:

- We introduce a novel segmentation evaluation metric called Weighted Intersection over Union (wIoU), which provides a more comprehensive evaluation by integrating both the contour and region of the segments.

- Our proposed metric utilizes simple evaluation criteria, enabling it to assess segmentation performance effectively and intuitively.

- Unlike other metrics, wIoU relies on minimal hyperparameters, with only one intuitive parameter: the boundary importance factor.

- We have validated the effectiveness of our proposed metric across a diverse set of test images, demonstrating its robustness and reliability in real-world scenarios.

For comparing evaluation metrics, we construct a simple semantic segmentation dataset comprising 33 scenes. We have validated that the proposed wIoU can evaluate both contours and regions according to the boundary importance factor $\alpha$. When the $\alpha$ value is small, it functions similarly to region-based evaluation metrics, particularly IoU; otherwise it functions similar to boundary-based evaluation metrics. We anticipate that the proposed wIoU will be used not only for evaluating metric but also as a novel region-contour loss for training accurate semantic segmentation networks.

Figure 2. Example of an image and its predicted classes

2. Problem Definition

Image segmentation (also called semantic image segmentation) is a problem to find several sub-regions or partitions within the given image in the fields of computer vision and digital image processing. The sub-regions consist of sets of pixels belonging to objects. The goal of image segmentation is to predict the class labels $C$ of pixels in the given image $I$. An image can be represented as a set of pixels as follows,

$$I = \{i_p | p = (p_x, p_y), 1 \leq p_x \leq W, 1 \leq p_y \leq H\},$$

where $i_p$ denotes the value of pixel $p$. $W$ and $H$ represent the width and height of the image, respectively. In general, an image consists of 3-channel (e.g., R,G,B), but for convenience, we do not consider the channel index.

Using the given image pixels $i_p$, the probability distribution of class for each pixel is predicted as $p(c | i_p)$. To predict the probability distribution, we can employ various semantic segmentation approaches [27,31]. Next, we select the class label for each pixel based on the distributions as follows,

$$c_p^* = \arg\max_{c \in \mathcal{C}} p(c | i_p),$$

where $\mathcal{C}$ is a set of class (e.g., car, tree, road and Etc). Finally, we build a predicted class map of the given image as

$$\mathcal{C} = \{c_p^* | p = (p_x, p_y), 1 \leq p_x \leq W, 1 \leq p_y \leq H\}.$$

Then, $\mathcal{C}(p)$ denotes the class label $c$ at the point $p = (p_x, p_y)$. Figure 2 shows an example of a semantic segmentation result with predicted classes. As a result of semantic segmentation, each pixel corresponds to a distinct class label.

3. Related Works

3.1. Semantic Image Segmentation Methods

Semantic image segmentation is one of the most important problems in the field of computer vision research. With the recent development of deep learning, many attempts to
Table 1. Confusion matrix for classification. Blue color indicates correct estimation and red color indicates failure estimation.

| Actual class | Positive | Negative |
|--------------|----------|----------|
| Positive     | TP       | FP       |
| Negative     | FN       | TN       |

apply deep learning to semantic segmentation applications have been presented. R. Girshick et al. [14] proposed region proposal convolutional neural networks called R-CNN for object detection and semantic image segmentation. In addition, J. Long et al. [20] also proposed a semantic segmentation method via fully convolutional networks (FCN) which is an end-to-end framework performing pixelwise prediction. Thanks to the large model capacity of deep neural networks, they significantly improved the prediction performance compared to many popular traditional methods [4, 11, 18, 25, 26] reviewed in [28].

Recently, many methods [3, 5, 19, 22, 27, 29] have focused on the importance of boundary information in the scene to achieve accurate semantic segmentation. They added additional network branches and optimized the boundary loss to capture the boundary information. Then, the estimated boundary cues in the scene are effectively used for semantic segmentation. Many authors have argued that the boundary cue alleviates the problem of boundary blur and leads to edge-preserving results. Various benchmark datasets such as PASCAL VOC [9], Cityscapes [6], ADE20K [30], ISPRS2D [1] and KITTI [2, 13] are commonly used to train and evaluate the methods.

3.2. Evaluation Metrics

- **Basic notations for classification results.** To evaluate the results of classification, there are four basic notations according to the actual class and predicted class: (1) True Positive (TP); (2) True Negative (TN); (3) False Positive (FP); (4) False Negative (FN). Each notation is summarized in Table 1. TP and TN are correct estimations. FP and FN are false alarms, which are called Type I error and Type II error, respectively.

- **Region-based evaluation.** Based on the types of classification results, many studies in fields such as machine learning and pattern recognition have evaluated their methods. For example, the evaluation metrics such as Precision and Recall are very widely used: 

\[
Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}
\]

Furthermore, \( F_1 \) score, which is the weighted average of \( Precision \) and \( Recall \), has been used as an evaluation metric:

\[
F_1 = \frac{2TP}{2TP + FN + FP}.
\]

It reflects two evaluation results (Precision and Recall) evenly. Another common metric for evaluating classification is a Jaccard index (JI):

\[
JI = \frac{TP}{TP + FN + FP}.
\]

For semantic image segmentation problem defined in Section 2, Intersection over Union (IoU) is equivalent to JI:

\[
IoU = JI = \frac{|C \cap C_{gt}|}{|C \cup C_{gt}|}
\]

where \( C \) denotes a predicted class map and \( C_{gt} \) denotes a ground-truth class label map. Most of the previous studies related to semantic segmentation [27, 31] have adopted IoU measure. It compares a similarity between two regions (\( C \) and \( C_{gt} \)) to evaluate all predicted pixels of the image.

- **Boundary-based evaluation.** Meanwhile, many studies [7, 24] have pointed out that the prediction performance on the boundaries of objects has a significant impact on the perceived segmentation quality. In fact, the object boundary has higher prediction difficulty than the internal area of the object – at least two classes are adjacent around the objects’ boundaries, which makes class prediction more difficult and ambiguous. However, IoU equally evaluates all pixels in the image, making it hard to evaluate performances around object boundaries.

A method [?] has adopted Hausdorff distance for edge evaluations. This distance measures the greatest of all the distances from a point in one set (i.e. ground-truth edge points set \( A \)) to the closest point in the other set (i.e. estimated edge points set \( B \)) by

\[
d_H(A, B) = \max \left\{ \sup_{a \in A} \inf_{b \in B} \|a - b\|, \sup_{b \in B} \inf_{a \in A} \|b - a\| \right\},
\]

where \( \sup \) and \( \inf \) are the supremum and infimum operators. This distance metric can measure similarity between two edge sets without any hyper-parameters, but it is highly sensitive to outliers or noise. In addition, it does not calculate a similarity but a distance which lies on \([0, \infty]\).
Some studies \cite{23, 24} evaluated the edge prediction results by measuring edge-based $F_1$ score as in Eq. 4 only around the objects’ edges via bipartite matching. To make the evaluation metric robust to small errors, they set the distance tolerance ($\theta$) for performing bipartite matching between predicted edge points and ground-truth edge points.

In addition, BF score \cite{7} and Boundary Jaccard (BJ) \cite{12} were also proposed to capture the edge prediction results.

The evaluation metrics can measure the boundary prediction performance; however they still require certain distance tolerance values ($\theta$), which determine the boundary region in the scene. Selecting a distance tolerance ($\theta$) leads an inflexibility in evaluation measures. Furthermore, region-based evaluation metrics and boundary-based evaluated metrics are separate, making it difficult to compare the image segmentation performances at a glance. In this work, we propose a single evaluation metric that can measure both evaluation factors (i.e., region- and boundary-based) in Section 4.

4. Proposed Evaluation Metric

4.1. Motivation and main ideas

We observed that it is more difficult to infer the label of the boundary of each object. This is because the inference probability of each label is mixed at the boundary. Unfortunately, the details of an object are usually at the boundary. Even if most of the object region is predicted correctly, if it fails to predict the boundary of the object, it looks qualitatively bad. In addition, missing object details can lead to poor results in applications of semantic segmentation.

To evaluate segmentation results while considering these issues, we first generate a weighted map based on a distance transform in Section 4.2. The weight map emphasizes the importance of the object’s boundaries. We then calculate the weighted intersection over union ($wIoU$) using the generated weight map in Section 4.3.

4.2. Weighted map generation

The problem of a distance transform is to compute the distance of each point from the boundary of foreground region \cite{10}. First, it assigns fore- and back-ground regions according to the class label $c$ as

$$\Omega^f_c = \{ p | C_{gt}(p) = c \}, \Omega^b_c = \{ q | C_{gt}(q) \neq c \}. \quad (8)$$

Each region consists of a set of points. Figure 3 shows predicted map (C) (Figure 3 (a)) and its corresponding fore- and back-ground regions ($\Omega^f_c, \Omega^b_c$) where $c = 1$ and $c = 4$ (Figure. 3 (b) and (c)). Solid blue lines are the boundaries of objects.

Next, it generates a distance map that consists of a distance value of each point $p$ by computing the smallest distance from the back-ground region $\Omega^b_c$. It is represented by

$$D_c(p) := \min \{ d(p, q) | p \in \Omega^f_c, q \in \Omega^b_c \}, \quad (9)$$

where $d(p, q)$ is the pixel distance between two points $p$ and $q$. To compute the distance, we can adopted $\rho$-norm (also called $l_\rho$ norm) defined by $d(p, q) = (|p_x - q_x|^\rho + |p_y - q_y|^\rho)^{1/\rho}$, where $\rho \geq 1$. $\rho$-norm generates various distance metrics such as Manhattan ($\rho = 1$), Euclidean ($\rho = 2$), and Chessboard ($\rho = \infty$) distances according to its value $\rho$. In this work, we set $\rho = 2$ to follow Euclidean distance for generating the weight map $D_c$. As it mentioned in Section 4.1, we aim to generate a weight map according to the distance from the object boundary. Calculating Euclidean distances can efficiently approximate to compute the normal distances from the boundaries. As a result, the distance maps for all categories $C$ can be simply calculated.

However, the distance map of each object has different distance range due to the difference in size between the objects. It causes unfair performance evaluation in many cases. To handle this, we designed the regularized distance as

$$\bar{D}_c(p) = \frac{D_c(p)}{\max(D_c(p))}, \quad (10)$$

Then it lies on $[0, 1]$ for all pixel points $p$ and classes $c$. Note that if a class $c$ has multiple instances, the regularization in Eq. 10 is performed for each instance. Figure. 4 shows examples of regularized distances. Considering all the class in the class map $C$, the distance maps $\bar{D}_c$ can be combined into one distance map as follows

$$\bar{D}(p) = \{ \bar{D}_c(p) | 1 \leq c \leq C \}, \quad (11)$$

Figure 4. Examples of distance maps. The ground-truth class map is illustrated in Figure 3 (a).
Algorithm 1: An algorithm of the propose wIoU

Input: Estimated class map $C$, Ground-truth class map $C_{gt}$
Output: Weighted intersection over union score $wIoU$

for each class label $c$ in $C_{gt}$ do
  for pixel index $p, q$ in $C_{gt}$ do
    $(\Omega_f^c, \Omega_b^c) =$ Get fore- and back-ground regions($c, C_{gt}$);
    for pixel index $p$ in $\Omega_f^c$, pixel index $q$ in $\Omega_b^c$ do
      $D_c(p) =$ Distance map generation($\Omega_f^c, \Omega_b^c$);
    for pixel index $p$ in $D_c(p)$ do
      $\bar{D}_c(p) = \frac{D_c(p)}{\max(D_c(p))}$;
    $\bar{D}(p) = \{D_c(p) | 1 \leq c \leq C\}$; % a combined distance map
    for pixel index $p$ in $\bar{D}(p)$ do
      $W(p) = \exp(-\alpha \bar{D}(p))$; % weight map calculation
    $wIoU = \frac{|C \cap (C_{gt} \circ W)|}{|C \cup (C_{gt} \circ W)|}$.

An example of the combined distance map is shown in Figure. 4 (e). Finally, we designed a weight map which is an exponential decay function with different $\alpha$ values by

$$W(p) = e^{-\alpha \bar{D}(p)}, \quad (12)$$

where $\alpha > 0$ is a boundary importance factor. As shown in Figure. 5, the value of $\alpha$ determines the importance of boundaries in the scene. When the boundary importance is small ($\alpha = 0.01$), the weight map is uniformly distributed (Figure. 5 (b)). It means that all areas have about the same weights. On the other hand, when the boundary importance is comparatively large ($\alpha = 100$), it emphasizes boundaries in the scene (Figure. 5 (f)). In this way, we can set the weight map very simply by manipulating only one parameter $\alpha$.

4.3. Weighted intersection over union

Based on the calculated weight map in Section 4.2, we propose a new evaluation metric called Weighted Intersection over Union (wIoU) by

$$wIoU = \frac{|C \cap (C_{gt} \circ W)|}{|C \cup (C_{gt} \circ W)|}, \quad (13)$$

where $\circ$ is an element-wise product called Hadamard product [16]. In this step, we omit $p$ for convenience and all terms in the Eq. 13 have the same dimension (i.e., size of an input image). Comparing the proposed wIoU with conventional IoU (Eq. 6), it emphasizes the importance of each pixel based on the weight map $W$. The overall procedure of calculating wIoU score is described in Algorithm 1. In addition, the codes are available on https://github.com/engzenia/wIoU

Figure 5. Ground truth and its weight maps according to the boundary importance factor $\alpha$. The range of weight map is [0, 1]. White and black pixels denote weight values 1, 0, respectively. A small boundary importance factor leads a uniform weight map. On the other hand, a large boundary importance factor leads high weights around the boundaries of the objects and regions.
5. Experimental Results

5.1. Datasets

To compare evaluation metrics, we built a segment dataset as shown in Figure 6. We followed the KITTI [13] color assignments for classes. At the center of each scene, we placed an object (e.g., car, person). For each scene, we created test segments (Figure 7 (d)) that include prediction errors around boundaries, which commonly occur. To consider more possible situations, we applied morphological image processing to the objects in test images. We performed 5 different levels of erosion and dilation for each image. As a result, the total number of segment images is 33. These test images will be used to compare overall similarities between different evaluation metrics in Section 5.2.

Additionally, we created three test segment images that contain the same number of error pixels (FP+FN), but the positions of the error pixels are different, as illustrated in Figure 10. These test scenarios are quite unusual in semantic segmentation. However, we can precisely compare how each evaluation metric works under the same number of error pixels.

5.2. Comparisons of different metrics

In this section, we compare three different evaluation metrics: 1) Intersection over union (IoU), 2) Proposed weighted IoU (wIoU), 3) edge-based score $F_1$ [23]. For the proposed wIoU, we tested five different levels of boundary importance factors $\alpha$ as 0.01, 0.1, 1, 10 and 100. These values follow a simple logarithmic scale with a base of 10, but can create distinctive functions as shown in Fig. 8. The upper two values (10, 100) assign similar importance across the overall area ($0 \leq x \leq 1$), while the lower two values (0.01, 0.1) only emphasize the areas around the boundaries ($x \simeq 0$). Furthermore, as shown in Fig. 5, the five alpha values effectively highlight the importance of boundaries or areas with different criteria.

For the edge-based score $F_1$, we set the distance tolerance value $\theta$ as 3 pixels. To compare the evaluation results of the metrics, correlations $\rho_{X,Y}$ and sum of difference $D_{X,Y}$ are calculated as follows:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y},$$

$$D_{X,Y} = E[|X - Y|],$$

where $X, Y$ are sets of evaluation values calculated by each evaluation metric, $\text{cov}(X,Y) = \mathbb{E}[(X - \mu_X)(Y - \mu_Y)]$ is a covariance matrix between $X$ and $Y$. $\mu$ and $\sigma$ are mean and standard deviations of the evaluation values, respectively.

The correlation $\rho_{X,Y}$ measures strength of a relationship between two variable sets $X, Y$. Thus, although the absolute values between two variable sets are different, they have a correlation value when the tendency of value change is similar. The value of correlation lies on $[0, 1]$, and the value 1 indicates the high similarity. On the other hand, sum of difference $D_{X,Y}$ measures the absolute value difference between the two variable sets. It can lie on $[0, \infty]$, and the value 0 indicate the high similarity. Based on both evaluations, we can measure a relationship and differences between metrics.

Figure 9 illustrates correlations and summations of differences between IoU, wIoU, and edge-based $F_1$. wIoUs with low boundary importance factors ($\alpha = 0.01, 0.1$) are very similar with IoU in terms of both correlation and sum of differences. On the other hand, wIoUs with high boundary importance factors ($\alpha = 10, 100$) show the high similarity with edge-based $F_1$. The sum of differences between edge-based $F_1$ and wIoU series become lower as the boundary importance factor increases. In this way, the proposed wIoU combines both conventional region and boundary-based evaluation metrics depending on $\alpha$.

For further comparisons of evaluation metrics, we additionally tested three test images as illustrated in Figure 10. Those test images were generated from Scene #01 (Figure. 6 (a)) while they keeps the same numbers of error pixels (FP+FN). Therefore region-based IoU metric showed the same evaluation results (0.972) for all test images. On the other hand, other evaluation metrics (i.e., wIoU, edge-based $F_1$, edge-based recall) measure different aspects of performance evaluations. wIoU with small boundary importance factors ($\alpha = 0.01, 0.1$) are very relevant to IoU metric as they worked in common test images in Figure 9. When boundary importance factor was set large ($\alpha = 100$) for wIoU, it works almost the same with edge-based Recall ($\frac{TP}{TP + FN}$). This result indicates that wIoU with large boundary importance is difficult to measure false positive (FP) pixels which are not around ground-truth boundaries. wIoU with a boundary importance factor ($\alpha = 1$) makes difference between the test images compared to IoU. It gives more weight to the boundaries, but it can evaluate both the regions and the boundaries in a reasonable way.

An edge-based $F_1$ was highly dependent on the predicted boundary in the scene; it evaluated very different
Figure 7. Examples of generated test segments. (d) Generated test segments for each scene including prediction error. Based on morphological image processing (5 different levels of erosion (a–c) and dilation (e–g)), the test segments were augmented.

Figure 8. Weight values $e^{-\alpha x}$ with different $\alpha$ values. $\alpha$ follows logarithmic scale with a base of 10. When the $x$ value is close to 0 and 1, it indicates the boundary and the innermost area of the object, as described in Eq. 12.

values for each test image (0.5843, 0.936, 0.8603) despite of the same error pixels. We also tested the Hausdorff distance for these test scenarios. It computed distance values of (189.38, 158.09, 32.53), where smaller values indicate higher similarity. It ranked the third image as the best segmentation result, with a large gap unlike other edge-based measures. The distance highly focuses on measuring the localization error of the predicted boundaries. It calculates a large error if false positives are spatially far from the actual boundary. This means that the measure can be sensitive to outliers and noisy boundaries. Furthermore, it requires an additional scale factor to normalize the distance value from $[0, \infty]$ into a similarity value $[0, 1]$.

In real-world scenarios, Fig. 11 shows the comparison of evaluation metrics of different test frames. The test frames contain various objects and background classes which are much more complex and general than synthesized test scenarios in Fig. 7. The results demonstrate that the proposed $wIoU$ series effectively measures segmentation performance based on the importance of both boundary and region. When the boundary importance factor is high ($\alpha = 100$), $wIoU$ calculates a lower performance than the edge-based $F_1$ score. That is because, while the edge-based metric addresses a binary problem of determining whether a pixel is part of an edge or not, the proposed $wIoU$ also requires predicting the class of the edge, making it a much more difficult problem. A high alpha value in the $wIoU$ metric can result in a much stricter evaluation of edges compared to edge-based $F_1$.

6. Discussions and Future Works

$wIoU$ has several limitations and concerns. First, boundary importance factor $\alpha$ must be determined. We recommend setting $\alpha = 1$ to evaluate both region and edge of the segmentation results in a balanced manner. However, the organizer of the competition will determine $\alpha$ in advance, depending on which area (boundary or region) they consider important. Second, in cases where the shape complexity of an object is high, boundaries may have a greater impact on performance evaluation than regions. For example, if the ratio of the object’s boundary to its area is high (see a circle and a human in Fig. 6), the boundary occupies a higher proportion of the total evaluation pixels, and the boundary performance has a significant impact on the final score due to the $wIoU$’s policy. While this may be natural and reasonable, it is an issue that needs further consideration for a fairer evaluation. Based on our study, there are a few areas that could be explored for the future works. Beyond using it as an evaluation metric, we can adopt the proposed $wIoU$ as an optimization loss for deep neural networks. To demonstrate the efficiency of $wIoU$ in training networks, we have to design various structures of deep neural networks and experimentally demonstrate performance improvements in the next works.
flexibility and rationality of the proposed \( wIoU \) evaluation metric.

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Figure 11. Comparison of evaluation results based on different metrics in real scenes. First and second rows are ground-truth segments, and error map of predicted segmentation results. Third row images are weighted map of $wIoU(\alpha = 1)$. The last row illustrates evaluation results based on each metric.