

Semi-Supervised Semantic Segmentation Based on Pseudo-Labels: A Survey

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Abstract

Semantic segmentation is an important and popular research area in computer vision that focuses on classifying pixels in an image based on their semantics. However, supervised deep learning requires large amounts of data to train models and the process of labeling images pixel by pixel is time-consuming and laborious. This review aims to provide a first comprehensive and organized overview of the state-of-the-art research results on pseudo-label methods in the field of semi-supervised semantic segmentation, which we categorize from different perspectives and present specific methods for specific application areas. In addition, we explore the application of pseudo-label technology in medical and remote-sensing image segmentation. Finally, we also propose some feasible future research directions to address the existing challenges.

1 Introduction

Semantic segmentation is an important and well-received research area in the field of computer vision to classify every pixel in an image, and it has a wide range of applications in specific areas such as medical image segmentation [Li *et al.*, 2023a] and remote sensing image segmentation [Wang *et al.*, 2022a]. Over the past few years, many works have made significant progress in improving the effectiveness of semantic segmentation tasks. However, supervised deep learning requires large amounts of data to train models and the process of labeling images pixel by pixel is time-consuming and labor-intensive. Studies have pointed out that it takes hours to annotate just one finely labeled image from the Cityscapes dataset [Cordts *et al.*, 2016]. The performance of fully supervised models may not be able to be improved significantly due to the cost of training labels. In recent times, semi-supervised learning has been applied to semantic segmentation through numerous associated research studies.

The pseudo-label method is a well-known technique in the semi-supervised learning field that first appeared in [Lee and others, 2013] and has gained popularity in recent computer vision research, including domain adaptation [Li *et al.*, 2023b], semantic segmentation [Wu *et al.*, 2023], etc., which are favored for their simplicity and impressive performance.

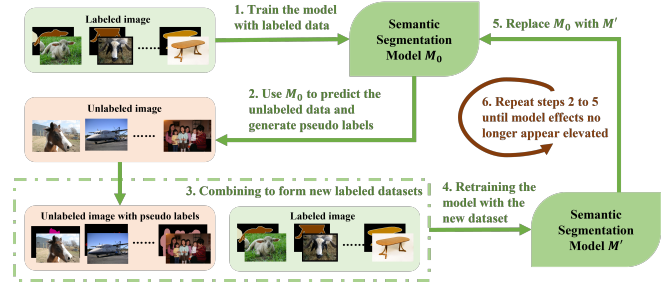


Figure 1: The plainest process of semi-supervised semantic segmentation with pseudo-label method. The acquisition and qualification of pseudo-labels are the main focus of the framework.

The process is depicted in Figure 1. In semantic segmentation, the pseudo-label method is considered to be a more dependable option than consistent regularization, which may be affected by different levels of data augmentation. Pseudo-label technology is renowned for its stability, interpretability, and ease of implementation, making it an area of research with increasing potential.

Extensive research has been conducted on the use of the pseudo-label method in semi-supervised domains. Nevertheless, a current survey [Peláez-Vegas *et al.*, 2023] merely classifies semi-supervised semantic segmentation techniques systematically, lacking detailed summaries and analyses of pseudo-label methods. This deficiency has motivated us to undertake a survey.

Our survey's primary objective is to offer a thorough and structured summary of recent research, categorizing the studies based on various perspectives, and presenting specific methods for specific application areas. Our main contributions are: 1. In this paper, we provide a comprehensive review of the recent advancements in the pseudo-label methods for semi-supervised semantic segmentation. 2. Specifically, we investigate three key aspects of the pseudo-label methods, which include the design of the model structure, refinement of pseudo-labels, and optimization techniques. 3. Furthermore, we discuss the existing challenges in this field that require attention and propose potential directions for future research.

2 Preliminary and Problem Formulation

Problem Definition

In the context of semi-supervised semantic segmentation, the objective is to minimize the loss by considering both labeled and unlabeled datasets. The labeled dataset, denoted as $D_l = \{(x_l, y_l)\}^p$, consists of p samples with corresponding labels. The unlabeled dataset, denoted as $D_u = \{x_u\}^q$, consists of q images, where q is significantly larger than p . The loss function L is defined as the sum of two terms: L^l which represents the loss on the labeled dataset, and L^u which represents the loss on the unlabeled dataset.

$$L = L^l + \lambda L^u, \quad (1)$$

where λ represents a hyper-parameter that balances the trade-off. This hyper-parameter can either be assigned a fixed value beforehand or adaptively adjusted during the training process. The supervised loss L^l typically refers to the cross-entropy loss computed between the predicted output and the corresponding y_l , while the unsupervised loss L^u can take on various forms depending on the specific method being used.

The plainest pseudo-label method would be: First, we train the initial model M_0 on the labeled dataset D_l using the cross-entropy loss L^l . This training process generates a pseudo-labeled dataset $\tilde{D}_u = \{(x_u, M_0(x_u))\}^q$ for the unlabeled dataset D_u , where $M_0(x_u)$ represents the pseudo-label of x_u . Next, we combine the labeled dataset D_l with the pseudo-labeled dataset \tilde{D}_u to form a comprehensive dataset $D = (D_l \cup \tilde{D}_u)$. Finally, we train a new model M using the complete dataset D . The aforementioned straightforward procedure can be iteratively performed to consistently improve the quality of the generated pseudo-labels.

The process can be significantly influenced by the generation, selection, and improvement of the pseudo-labels due to the unexpected distribution gap and the unsatisfactory performance of pre-trained models.

Datasets

Table 1 presents an overview of several commonly utilized datasets that find application in various scenarios. Typically, those fully annotated images are partially selected for semi-supervised learning using ratios such as 5%, 10%, and so on.

Category	Datasets
Natural Images	PASCAL VOC[Everingham <i>et al.</i> , 2015], MS-COCO[Lin <i>et al.</i> , 2014], ADE20K[Zhou <i>et al.</i> , 2017]
Street-view Images	KITTI[Geiger <i>et al.</i> , 2012], Cityscapes[Cordts <i>et al.</i> , 2016]
Medical Images	BRATS[Menze <i>et al.</i> , 2014], Kvasir-SEG[Jha <i>et al.</i> , 2020], LA[Xiong <i>et al.</i> , 2021]
Satellite Images	iSAID[Waqas Zamir <i>et al.</i> , 2019],xBD[Gupta <i>et al.</i> , 2019], GID[Tong <i>et al.</i> , 2020]

Table 1: A compilation of the frequently utilized datasets in the domain of semi-supervised semantic segmentation.

Performance Metrics

- **Pixel Accuracy** calculates the ratio of correctly classified pixels to the total number of pixels. Although this metric is simple and intuitive, it may not accurately reflect the model’s performance when there is an imbalance in the categories.
- **Mean Accuracy** takes into account the pixel precision for each category and calculates the average to address the issue of class imbalance.
- **Mean IoU** calculates the average Intersection over Union ($mIoU$) between the prediction and ground truth for all categories:

$$mIoU = \frac{1}{N} \sum_{i=1}^N \frac{N_{ii}}{\sum_{j=1}^N N_{ij} + \sum_{j=1}^N N_{ji} - N_{ii}} \quad (2)$$

where N is the number of categories, N_{ii} is of TP (True Positive) number for category i , N_{ij} is FP (False Positive) number for categories i as j , and N_{ji} is FN (False Negative) number for categories j as i .

- **Weighted IoU** is used as a modification to the $mIoU$ metric in situations where certain categories need to be given more importance.

3 Categorization

Drawing on the categorization of network structures for pseudo-label method in previous research [Peláez-Vegas *et al.*, 2023], as well as the innovative refinement of the Mean Teacher structure proposed by researchers [Tarvainen and Valpola, 2017], our investigation will focus on three main areas: the model-based perspective, pseudo-labels refinement, and optimization measures. Figure 2 presents a comprehensive overview of the various types of pseudo-label techniques.

Model perspective. Essentially, the various methods for generating pseudo-labels can be divided into two categories: the single-model family and the mutual-model family. Figure 2 (a) illustrates the single-model-based approach, where pseudo-labels generated by a single model are used for supervised subsequent training. For example, in the Mean-Teacher method, a single model is trained using pseudo-labels generated by the teacher model, which incorporates consistency regularization. On the other hand, multi-model mutual-training-based approaches aim to improve model performance by jointly training multiple models. Figure 2 (b) depicts this approach, where two different networks are initialized and one model supervises the training of the other model by providing pseudo-labels on unlabeled data. The cross-supervision of the two models helps localize and minimize errors in the pseudo-labels.

Refinement of pseudo-labels. We will discuss enhancements to the conventional architecture by focusing on refining pseudo-labels to generate specific labels. Furthermore, we will categorize these methods of refining pseudo-labels into two groups based on whether the pseudo-labels are changed: label updating and filtering only. The simplified architecture for pseudo-labels refinement is depicted in the blue areas of Figure 2 (a) and (b).

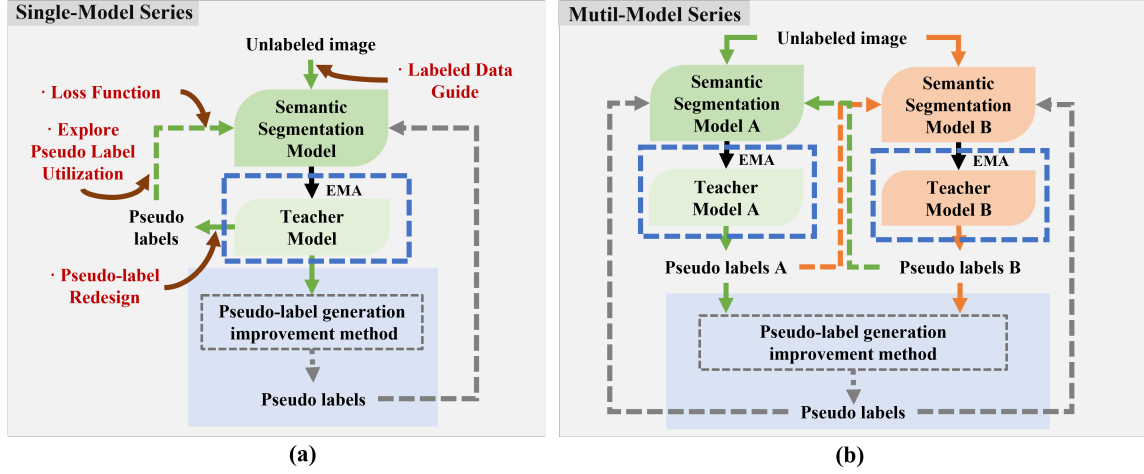


Figure 2: A summary of the primary classifications. Our review is organized into three primary categories: the model for generation (sub-figures a and b), the enhancement of pseudo-labels (blue boxed), and the perspective of optimization (dark red arrows). Within the category of the pseudo-labels generation, we investigate two approaches: single-model and multi-model series. Furthermore, various strategies are employed for the selection or refinement of pseudo-labels. Lastly, optimization methods are also becoming more prevalent in this field.

Optimization. Lastly, we also investigated a few emerging optimization techniques, which are depicted in dark red in Figure 2 (a). Further elaboration on these methods will be provided in the following sections.

4 Pseudo-Label for Semi-supervised Semantic Segmentation

In this section, we provide a summary of all the methods for semi-supervised semantic segmentation based on pseudo-labels mentioned in Table 2.

4.1 Model perspective

The significance of architecture in deep learning cannot be overstated as it establishes the framework and layout of the neural networks employed in these models. The architecture plays a crucial role in determining how input features are manipulated and analyzed by the network, thereby impacting the model’s capacity to learn and generate precise predictions. Selecting an appropriate architecture is a vital aspect of constructing a successful deep-learning model. In this subsection, we examine papers pertaining to single-model families and collaborative mutual-model families.

Single-Model-Based Methods

The initial proposal of the single-model self-training approach was made by Yarowsky [Yarowsky, 1995]. Later on, [Lee and others, 2013] suggested combining self-training with neural networks using pseudo-labels. Since the initial single-model self-training approach was straightforward, subsequent research has focused on enhancing different aspects of this network structure.

Self-training Iteration. GIST & RIST [Teh *et al.*, 2022], which can be explained as a greedy algorithmic strategy (GIST) and a follow-along iterative self-training strategy-based strategy (RIST) that alternates between ground truth

and pseudo-labels. Another approach proposed from a self-training iterative perspective is ST++ [Yang *et al.*, 2022], where the key step is selective retraining during the iteration process. Since segmentation performance is positively correlated with the evolutionary stability of the generated pseudo-labels during the supervised training phase, more reliable unlabeled images can be selected by evolution during the training process. The stability metric is based on the average IOU between each early pseudo-mask and the final mask:

$$s_i = \sum_{j=1}^{K-1} \text{mean IOU}(M_{ij}, M_{iK}) \quad (3)$$

The stability scores of all unlabeled images are then obtained and the entire unlabeled set is ranked accordingly, and the R images with the highest scores are selected for the first stage of retraining. ST++ predicts robustness based on asymptotic changes in reliability, thus eliminating the need to select confidence thresholds for pixel-by-pixel filtering manually.

Self-cross Supervision. [Zhang *et al.*, 2022] proposes a method called uncertainty-guided self-cross-supervision (USCS) for semi-supervised semantic segmentation. This approach utilizes the results of a multiple-input multiple-output (MIMO) segmentation model to perform self-cross-supervision, resulting in significant reductions in parameter and computation costs.

Auxiliary Tasks Framework. Since another key to the pseudo-label approach is to set up auxiliary task frame supervision, some approaches have been proposed from this perspective. Earlier, [Li and Zheng, 2021] introduced residual networks to extend the self-training structure. The labeled data is fed into an auxiliary residual network to predict the residuals from the original segmentation results. While the later proposed ELN [Kwon and Kwak, 2022] is mainly to assist in locating errors, the auxiliary module is trained to identify the pixel points that may be incorrect by taking

Category		Method	Publication	Main contributions		
Model perspective	Single Model	Self-cross Sup.	USCS[Zhang <i>et al.</i> , 2022]	ACCV	Uncertainty leads self-cross Sup.	
		Self-training Iteration	GIST& RIST[2022]	CRV	Greedy and Randomized Iterative Self-Training	
			ST++[Yang <i>et al.</i> , 2022]	CVPR	Select reliable images for retraining	
		Auxiliary Tasks or Network	[Li and Zheng, 2021]	PRCV	Residual correction approach	
			ELN[Kwon and Kwak, 2022]	CVPR	Auxiliary Modules:Error localization network, ELN training with constrained loss function	
	Mutual Model	Cross Pseudo Sup.	EPS++[Lee <i>et al.</i> , 2023]	TPMAI	Explicit pseudo-pixel supervision, Using saliency as pseudo-pixel supervision	
			CPS[Chen <i>et al.</i> , 2021]	CVPR	Cross-pseudo-supervision	
			n-CPS[Filipiak <i>et al.</i> , 2021]	ArXiv	N networks cross-pseudo supervision	
			UCC[Fan <i>et al.</i> , 2022]	CVPR	Uncertainty-guided cross-head co-training	
		Dynamic Muti-train	CCVC[Wang <i>et al.</i> , 2023]	CVPR	Conflict cross-view consistency, Co-training two network branches	
			DMT [Feng <i>et al.</i> , 2022]	PR	Dynamic mutual training	
	Pseudo-label Refinement	Label Update	Pseudo-label Corrections	DMT-PLE [Ke <i>et al.</i> , 2022]	Access	Pseudo-label enhancement strategy
				[Yi <i>et al.</i> , 2021]	TIP	Graph-based noise labels correction
				CARD[Wang <i>et al.</i> , 2022b]	IJCAI	Semantic linking to correct noisy labels
ThreeStageSelftraining [2022]				TIP	Multi-task count and update pseudo-labels	
De-biasing			CISC-R[Wu <i>et al.</i> , 2023]	TPAMI	Labeled images correct inaccurate pseudo-label	
			DARS[He <i>et al.</i> , 2021]	ICCV	Redistribute biased pseudo-labels, aligned with the true distribution	
Filter-only		Confidence Filtering	DST[Chen <i>et al.</i> , 2022]	NeurIPS	De-biased self-training	
			C3-SemiSeg[2021]	ICCV	Dynamic Confidence Region Selection Strategy	
			CAFS[Ju <i>et al.</i> , 2023]	ArXiv	Adaptive classification confidence thresholds	
		Confidence Refinement	TorchSemiSeg2[2023]	ICME	Local Pseudo Label Filtering Module	
			PGCL[Kong <i>et al.</i> , 2023]	WACV	Network Pruning Refinement Confidence Score	
Optimization		Loss Function	GTA-Seg[Jin <i>et al.</i> , 2022]	NeurIPS	Assistants Teacher sift useful information	
			[Wang <i>et al.</i> , 2022c]	PR	Class-aware Cross-entropy loss	
		Labeled data Utilization	PS-MT[Liu <i>et al.</i> , 2022]	CVPR	Confidence-weighted Cross-entropy(Conf-CE)	
	GuidedMix-Net[2022]		AAAI	Label information guide unlabeled learning		
	Pseudo-label Redesign	PseudoSeg[2020]	ICLR	Structuring and quality redesign pseudo-label		
Pseudo-label Tradeoffs	CPCL[Fan <i>et al.</i> , 2023]	TIP	Conservative&progressive explore pseudo-label			

Table 2: An overview of pseudo-label techniques in the field of semi-supervised semantic segmentation.

the images and segmentation results as inputs. The specific ELN structure contains the main segmentation network (encoder and decoder) and the auxiliary decoder (D_1, D_2, \dots, D_K). The main segmentation network is trained by standard cross-entropy loss, while the auxiliary decoder is trained by restricted cross-entropy loss:

$$\mathcal{L}_{aux} = \frac{1}{|D_L|} \sum_{X \in D_L} \sum_{k=1}^K \{L_{ce}(P^k, Y) > \alpha^k \cdot L_{ce}(P, Y)\} \cdot L_{ce}(P^k, Y) \quad (4)$$

As a result, the auxiliary decoder will perform much worse than the primary decoder because it contains various errors, which are then used as inputs to the ELN to train the ELN

to locate the labeling errors, similar to manually creating some error data for training. EPS++[Lee *et al.*, 2023] provides rich boundaries through the saliency map generated by the saliency detection model, which is combined with image-level labeling information for joint training, assisting the model in being trained from pixel-level feedback.

Mutil-model-based Methods

Several semi-supervised learning methods rely on pseudo-supervision, particularly self-training methods that generate pseudo-labels. However, the pseudo-labels generated by a single model in self-training can often be unreliable. This is because it is common to use only a single model's prediction confidence to filter out low-confidence pseudo-labels, which can leave behind high-confidence errors and waste many low-

confidence correct labels. The dual-model mutual-training method aims at the problems inherent in the single-model self-training method, i.e., a single model is unable to detect and correct its errors, which may result in the accumulation of bias and ultimately affect the training and segmentation effects, mutual-training [Zhang *et al.*, 2018] by which two or more models train each other according to their differences, localize their errors, and correct each other is proposed,

Cross-Pseudo-Supervision. A classical inter-training perspective is dual-model cross-supervision, such as CPS [Chen *et al.*, 2021] approach uses different initialization methods for two networks, where the pseudo-labels output by one network supervise the other segmentation network. The subsequently proposed n-CPS [Filipiak *et al.*, 2021] is the result of extending the CPS to n sub-networks, and experiments demonstrate that network integration significantly improves performance. Based on cross-supervision, [Fan *et al.*, 2022] introduces uncertainty-guided supervision and proposes UCC (Uncertainty-guided Cross-head Co-training of cross-heads), which further improves the generalization ability by sharing encoders. [Wang *et al.*, 2023] design a conflict-based cross-try consistency (CCVC) to force two subnets to learn knowledge from unrelated views. They propose a new cross-view consistency strategy to encourage two subnets, which are structurally similar but do not share parameters, to learn different features from the same input image. They introduce a feature difference loss to achieve this. For unlabeled data, they make the two subnets use each other’s pseudo-labels for model learning.

Dynamic Multi-training. In addition to cross-supervision for synchronous training, other researchers have proposed dynamic mutual training based on a two-network structure, where two networks are trained asynchronously. DMT [Feng *et al.*, 2022] points out that it is difficult for a single model to overcome its own errors. Therefore, they use two models with different initializations, one of which generates offline pseudo-labels for the other proposed. To effectively train machine learning models, it is important to identify labeling errors. This they do by comparing the predictions of two different models and quantifying the differences between them, so that they can dynamically adjust the weight loss during training to improve the accuracy of the model. Dynamic loss weight ω_u is defined as follows:

$$\omega_u = \begin{cases} p_B^{\gamma_1}, & y_A = y_B \\ p_B^{\gamma_2}, & y_A \neq y_B, c_A \geq c_B \\ 0, & y_A \neq y_B, c_A < c_B \end{cases} \quad (5)$$

Regarding the issue of noise in the pseudo-label technology, the DMT method proposes assigning different weights to the samples, rather than discarding them. This approach is intended to preserve low-confidence data, but it may not be effective in addressing the problem of high noise rates in the pseudo-label method. Additionally, the ”catastrophic forgetting problem” in neural networks cannot be fully resolved, since the basic components of these networks consist of fixed structures and parameters. However, the severity of this problem can be reduced through various mitigation techniques. The DMT-PLE[Zhou *et al.*, 2022]method extends the

pseudo-label enhancement strategy from the previous DMT method, mainly for the purpose mentioned above. They mention that it’s challenging for a model to retain the knowledge it has learned when processing input with multiple pixels of varying types. To prevent the model from developing a bias towards the last learned category, they use a strategy called Pseudo-Label Enhancement (PLE). This technique utilizes the pseudo-labels generated by the model in the previous stage to refine pseudo-labels generated by the current model.

4.2 Pseudo-label Refinement Methods

Pseudo-label Update Methods

The pseudo-label method sometimes leads to incorrect predictions or inaccurate pseudo-labels being included in the training process, which can accumulate errors and make the learned pseudo-labels ineffective in guiding the subsequent learning, and ultimately affect the training results of the segmentation model. To solve this problem, some studies have proposed methods for updating pseudo-labels to alleviate the noise problem with good results.

Pseudo-label Corrections. In the beginning, some works formulated the task as a learning problem of pixel-level label noise. Yi *et al.* [2021] introduce a graph-based label noise detection and correction framework, which utilizes pixel-level labels generated by class activation maps (CAMs) as weakly annotated noise labels, trains a strongly annotated segmentation model to detect clean labels from the above noisy labels, and then corrects the noisy labels using a clean label supervised graph attention (GAT) network. The clean label supervised graph attention network is then used to correct the noise labels. Similarly, to address the problem of noisy label correction, [Wang *et al.*, 2022b] propose a category-independent relational network to correct labels based on reliable semantic associations between image features. They obtained relational estimates by augmenting the relationships between features. The predictions with weak correlations are discarded for effective noise label correction.

Unlike the perspectives of the above approaches, some of the improvement methods start with the training phase. Ke *et al.*[2022] advance a ThreeStageSelftraining method, where they attempted to extract initial pseudo-labels information on unlabeled data through three stages of self-training while enforcing segmentation consistency in a multitasking manner to generate higher quality pseudo-labels. In addition to the traditional remedies described above, [Wu *et al.*, 2023] raise the CISC-R method using labeled images to correct noisy pseudo-labels, considering that samples of the same kind have a high pixel-level correspondence. Inspired by ST++ [Yang *et al.*, 2022], they used a CISC-based image selection method that takes into account inter-class feature differences and the difficulty of correcting noisy pseudo-labels at the beginning of training. First, for each class k , an initial model is used to extract the anchor vector a_l^k for that class from the set of labeled images:

$$a_l^k = \frac{1}{n_l^k} \sum_i^{n_l^k} v_l^k = \frac{1}{n_l^k} \sum_i^{n_l^k} F_l^k \odot m_l^k. \quad (6)$$

Through this average generation, a_l^k is generated to represent the categorized anchor points of the labeled images. Specifically, a CISC mapping m' is generated by cosine similarity between a_l^k of the labeled image x and the high-level feature.

De-biasing Bias in training comes both from the network itself and from improper training of potentially incorrect pseudo-labels, which accumulate errors throughout iterations. [He *et al.*, 2021] propose Distributed Alignment and Random Sampling (DARS), a simple and effective method to redistribute biased pseudo-labels, to align pseudo-labels with the ground truth, and to improve the effect of noisy labels on training. Aligning their distribution with the true distribution improves semi-supervised semantic segmentation. Subsequently, to minimize the bias, Chen *et al.*[2022] suggest the debiased self-training (DST). The key of this method is that two parameter-independent classifier headers decouple the process of generating and utilizing pseudo-labels, and only clean labels are used for training, which improves the quality of pseudo-labels.

Pseudo-label Filtering-only Methodons

In addition, some researchers have proposed to enhance the segmentation effect by filtering the noisy pseudo-labels, and such methods do not perform the update of the noisy labels.

Confidence Filtering. Zhou *et al.*[2021] propose C3-SemiSeg, which presents a dynamic confidence region selection strategy to focus on high-confidence regions for loss computation. In addition, cross-set contrast learning is also integrated to improve feature representation. However, to address the problem that existing high-confidence-based pseudo-label methods lose most of the information, Ju *et al.*[2023] propose a class-adaptive semi-supervised framework (CAFS) for semi-supervised semantic segmentation, which allows the construction of a validation set on the labeled dataset to take advantage of the calibration performance of each class. This includes a core operation: adaptive class-by-class confidence thresholding (ACT), which de-emphasizes the use of calibration scores to adaptively adjust reliability confidence thresholds. Recently, TorchSemiSeg2[Chen *et al.*, 2023] introduces a localized pseudo-labels filtering module to assess the reliability of region-level pseudo-labels using a discriminator network. They also propose a dynamic region loss correction to further assess the reliability of pseudo-labels using network diversity and to evaluate the direction of convergence of the network.

Confidence-level Refinement. Since much of the previous work mentioned above evaluated pseudo-label data mostly based on confidence thresholds, the problem of confidence ambiguity that exists at the beginning of training may largely limit subsequent updates. Recently, Kong *et al.* introduced the PGCL [2023], which aims to solve the issue of fuzzy confidence scores in network pruning, by gradually teaching the network from easy to hard examples using a coarse strategy.

Assisted Net Filtering. In addition, some methods utilize auxiliary structures for filtering operations. For example, GTA-Seg[Jin *et al.*, 2022] selects an auxiliary structure known as the gentle Teaching Assistant. The GTA learns directly from the pseudo-labels generated by the teacher’s network, and only filtered, favorable information is passed on to

the student’s network to assist in supervising the training of the student’s network.

4.3 Optimization Methods

In addition to the above methods, some researchers have proposed unique optimization techniques to improve segmentation results. These techniques include loss function improvement, pseudo-labels redesign, etc.

Loss Function. Wang *et al.* [2022c] advise improving the quality of pseudo-labels through perceptual cross-entropy (CCE) and progressive cross-training (PCT). CCE can simplify the pseudo-label generation more than traditional cross-entropy. PCT gradually introduces high-quality predictions as additional supervision for network training. PS-MT[Liu *et al.*, 2022] uses a stricter confidence-weighted cross-entropy (Conf-CE) to address the problem that cross-entropy loss training can easily overfit prediction errors.

Labeled data Utilization. It’s worth noting that [Tu *et al.*, 2022] considers that dealing with labeled and unlabeled data separately usually results in discarding a large amount of a priori knowledge learned from labeled examples. So they proposed a method called GuidedMix-Net, which learns higher-quality pseudo-labels by using labeling information to guide the learning of unlabeled examples. Similarly, CISC-R[Wu *et al.*, 2023], which we mentioned earlier, corrects the pixel-level correction of pseudo-labels by estimating the pixel similarity between the unlabeled image and the queried labeled image and generating the CISC map.

Pseudo-label Utilization. Zou *et al.*[2020] focus on structured and qualitative design methods for pseudo-labels and proposed a single-stage consistency training framework, PseudoSeg, which generates pseudo-labels from two branches: the output of the segmentation model and the output of the class activation maps (CAM). They propose a pseudo-labels redesign strategy that combines pseudo-labels from two sources through a calibrated fusion strategy, i.e., given a batch of decoder outputs $\hat{p} = f_\theta(\omega(x))$ and SGC mappings computed based on the weakly augmented data $w(x)$, pseudo-labels \tilde{y} are generated:

$$\mathcal{F}(\hat{p}, \hat{m}) = \text{Sharpen}(\gamma \text{Softmax}\left(\frac{\hat{p}}{\text{Norm}(\hat{p}, \hat{m})}\right) + (1 - \gamma) \text{Softmax}\left(\frac{\hat{m}}{\text{Norm}(\hat{p}, \hat{m})}\right), T) \quad (7)$$

PseudoSeg generates well-calibrated, high-quality pseudo-labels by implementing a novel pseudo-labels redesign strategy that facilitates subsequent model training. With limited available labeled data, well-calibrated pseudo-labels can greatly improve segmentation. To further improve the calibration, they suggested exploring advanced techniques such as multimodal data fusion.

[Fan *et al.*, 2023] develop Conservative Progressive Collaborative Learning (CPCL) from the perspective of dual-model mutual training, where the conservative branch is cross-supervised using high-quality pseudo-labels to achieve conservative protocol-based evolution. The progressive branch is supervised by a union utilizing a large number of labels to achieve progressive exploration of divergence

5 Pseudo label Methods in Other Areas

Pseudo-label method is widely used in semantic segmentation because of its simplicity and effectiveness. The methods we summarized in the previous section are mainly focused on natural image segmentation, but there is no doubt that it is important to continue research and promotion of image segmentation in more fields. In this section, we focus on pseudo-label techniques applied to some specific domains, including medical images and remote sensing image segmentation.

Medical Image Segmentation

Segmenting medical images, which involves identifying the pixels corresponding to organs or lesions in images like CT or MRI images, is a highly difficult task in medical image analysis due to a lack of sufficient labels. Numerous studies have proposed the use of pseudo-labels, yielding promising outcomes when applied to specific medical datasets. In their recent work, [Huo *et al.*, 2021] introduces a novel approach called asynchronous teacher-student optimization (ATSO) to challenge the conventional learning strategy. Instead of training two models alternately, they propose dividing the unlabeled training data into two subsets. This approach is particularly applied to 3D medical images, where each 3D body is divided into 2D slices representing coronal, sagittal, and axial views. A 2D network is then employed for segmentation, and the resulting output is stacked to form 3D bodies. A common issue in semi-supervised medical image segmentation is the discrepancy between the distribution of labeled and unlabeled data. Prior studies have primarily addressed labeled and unlabeled data in isolation or with inconsistency, which can result in disregarding the knowledge gained from the labeled data. In their research, [Bai *et al.*, 2023] propose a straightforward approach to alleviate this problem by incorporating labeled and unlabeled data in both directions using a Mean-Teacher model called BCP.

Remote Sensing Image Segmentation

The process of labeling high-resolution remote-sensing satellite images is a task that requires a significant amount of time and effort. This limitation affects the performance of segmentation models. To address this issue, certain reports propose the utilization of pseudo-label techniques that rely on semi-supervised learning. These methods aim to assist in the segmentation of remote-sensing images. In their paper, [Li *et al.*, 2023a] propose a technique for enhancing the segmentation accuracy of limited-sample high-resolution remote sensing images. They achieve this by utilizing two networks, namely UNet and DeepLabV3, to predict pseudo-labels and filter them effectively. In their recent work, [Cui *et al.*, 2023] propose a novel approach that utilizes bicommutative entropy consistency and a teacher-student structure. This task is challenging due to the presence of multiple classes, complex terrain, significant overlap between classes, and indistinct features. To address these challenges, the authors incorporate a channel attention (CA) mechanism into the teacher coding network. This CA module effectively filters the feature mapping and suppresses noise interference, thereby constraining feature extraction and reducing the information entropy generated by the coding network.

6 Challenges and Future Perspectives

Upon conducting a thorough examination, it is evident that pseudo-label techniques have ventured into various techniques for image segmentation, yielding remarkable outcomes. Nevertheless, this section will concentrate on the difficulties encountered in the pseudo-label method for semi-supervised semantic segmentation and emphasize potential research directions.

Quality enhancement using foundation models. Foundation models have transformed AI, powering prominent chatbots and generative AI. A cutting-edge interactive prompt-based model called Segment Anything Model (SAM) [Kirillov *et al.*, 2023] has recently been integrated into semantic segmentation tasks. It is anticipated that in the future, the prompt functionality of SAM will be leveraged to further improve the efficiency and effectiveness of the pseudo-label.

Utilization of additional information. At present, the use of low-quality pseudo-labels is limited to a single type of supervised signal, disregarding the valuable information present in other pixels. Hence, there is an opportunity to integrate alternative forms of supervisory signals into the model, enhancing its capacity to effectively utilize both coarse and fine-labeled data. We anticipate that future studies will enhance segmentation performance by adopting a more holistic approach to supervision.

Engage in the active selection and refine the process. Pseudo-label techniques struggle to effectively resolve the problem of noisy data. Instead of training the model on the entire dataset, strategies like active learning involve selecting a subset of the most informative data points to query for additional labels. This approach is more efficient and cost-effective because it allows the model to learn from the most informative examples without requiring the entire dataset to be labeled. The future looks promising when active selection and refinement strategies are incorporated.

Explore complex segmentation scenarios. Expanding the application of pseudo-label models to a wider range of real-world situations is essential. While there has been notable advancement in theoretical research, the current utilization of pseudo-label methods is limited to specific datasets such as PASCAL VOC 2012 [2015], which consists of only 20 commonly occurring categories. To advance this field, it is crucial to investigate datasets that better represent real-life scenarios. For example, ADE20K [Zhou *et al.*, 2017] contains over 150 classes of object information and could serve as a more representative dataset for future exploration.

7 Conclusion

We are the first to provide a comprehensive overview and categorization of pseudo-label techniques in the realm of semi-supervised semantic segmentation. Our categorization is based on the viewpoint of the model, methods for refining pseudo-labels, and innovative optimization approaches. Furthermore, we have examined various pseudo-label techniques employed in medical and remote-sensing image segmentation. Lastly, we have identified the current obstacles in this domain and proposed potential future directions. We have also put forth research avenues to tackle these challenges.

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