Adaptive Instance Distillation for Object Detection in Autonomous Driving

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Abstract—In recent years, knowledge distillation (KD) has been widely used to derive efficient models. Through imitating a large teacher model, a lightweight student model can achieve comparable performance with more efficiency. However, most existing knowledge distillation methods are focused on classification tasks. Only a limited number of studies have applied knowledge distillation to object detection, especially in time-sensitive autonomous driving scenarios. In this paper, we propose Adaptive Instance Distillation (AID) to selectively impart teacher’s knowledge to the student to improve the performance of knowledge distillation. Unlike previous KD methods that treat all instances equally, our AID can attentively adjust the distillation weights of instances based on the teacher model’s prediction loss. We verified the effectiveness of our AID method through experiments on the KITTI and the COCO traffic datasets. The results show that our method improves the performance of state-of-the-art attention-guided and non-local distillation methods and achieves better distillation results on both single-stage and two-stage detectors. Compared to the baseline, our AID led to an average of 2.7% and 2.1% mAP increases for single-stage and two-stage detectors, respectively. Furthermore, our AID is also shown to be useful for self-distillation to improve the teacher model’s performance.

I. INTRODUCTION

Knowledge Distillation (KD) [1], [2] has been introduced to derive a high-performance and lightweight student model by mimicking the knowledge from a large, powerful, and computationally intensive teacher model. Many KD methods have been explored so far and have achieved promising results in classification problems. However, only a limited number of studies have applied KD to the more challenging object detection task. Most KD in object detection methods investigate what types of knowledge should be mimicked, e.g., feature maps [3], head soft prediction [4], attention-based feature map [5] or relation between instances [6]. They usually treat all instances equally when transferring the location and category knowledge from the teacher to the student. However, teachers do not learn the instances equally well. We argue that the distillation process should adaptively change focus based on different instances. In other words, knowledge distillation should not only pay attention to what kind of knowledge to imitate, but also to which instances are more valuable. Specifically, knowledge from instances that the teacher can accurately predict should be recognized and transferred to the student, and the student should avoid paying too much attention to the “unsure” instances from the teacher’s perspective.

Instance reweighting has been used to improve models’ performance in object detection by assigning larger weights to important instances [7]–[9]. However, Zhang et al. [10] have shown that the hard mining methods for object detection are not suitable for knowledge distillation. Zhang et al. [10] added an auxiliary task branch to the student model, and the variance of the features from that auxiliary branch, which they called data uncertainty, is utilized for distillation reweighting.

In this paper, we propose a new method called Adaptive Instance Distillation (AID) that reweights distilled instances based on teacher-judged difficulty. In contrast to Zhang et al. [10], our AID does not employ an uncertainty estimation method based on auxiliary tasks because the variance of auxiliary features may not always represent the task uncertainty and it results in additional computation. More importantly, we argue that the importance of instances should not be determined by the feature statistics of the student network but rather by the teacher’s prediction. Our AID reweights an instance based on the teacher’s original loss, which reflects the reliability of the teacher on that instance. Specifically, an instance with larger teacher’s prediction losses will receive small distillation weights and thus less attention from the student model. In other words, our AID allows the student to learn more from the teacher on instances that the teacher performs well, while giving the student more freedom to learn “teacher-uncertain” instances on their own. It is worth mentioning that most state-of-the-art object detectors adopt Feature Pyramid Networks (FPN) [11] in their detection pipeline. Our AID can be applied to each scale of the FPN output with the potential to improve the detection ability of multi-scale objects.

In summary, this paper has the following contributions:

1) For the first time in KD, we propose that students should selectively learn from their teachers on a per-instance basis according to teacher’s performance rather than blindly learning from all instances equally.
2) We propose Adaptive Instance Distillation (AID) to allow students to discern the reliability of the teacher’s knowledge regarding a particular instance based on the teacher’s predictions losses.
3) Our AID re-weighing method can be applied to each layer of FPN to achieve scale-wise selection in knowledge distillation.
4) Our AID is suitable for both single-stage and two-stage detectors, and it can improve the distilled model’s ability to detect difficult instances compared to several baseline networks.

II. RELATED WORKS

This section reviews the most relevant works in the areas of Object Detection, Adaptive Sample Weighting, and Knowledge Distillation.

a) Object Detection: Some pioneers of object detectors include [12], [13]. Nowadays, object detection models are generally classified into two categories: Two-stage Detectors. Typical examples include Faster R-CNN [14], where in the first stage, the Region Proposal Network (RPN) is employed to generate a set of proposals for potential objects, then in the second stage, classification and localization are made on selected proposed regions. The other type of detector is One-stage Detectors. Some examples include [7], [15], [16]. They are well known for their high efficiency compared to two-stage detectors. They perform classification and localization prediction directly without proposals for regions of interest. Recently, single-stage detectors have been further divided into anchor-based and anchor-free detectors. Anchor-based detectors, such as [7], [17], need to traverse a large number of anchor boxes to ensure the accuracy of the entire detection task. The anchor-free methods [18], [19] directly predict the center point or key-points of an object from feature maps, which reduces the computational cost. The well-known method FPN [11] or its variant [20] has been adopted by many state-of-the-art detectors to improve the ability to detect objects of different scales.

b) Adaptive Instance Weighting: Adaptive instance weighting by adjusting the contribution of each instance can help with effective learning in object detection. “Hard example mining” is one reweighting technique that puts non-uniform attention to samples based on difficulty. In object detection works [7]–[9], hard-mining plays a critical role in improving model detection performance. Typically, hard mining gives larger weights to hard instances and forces the model to pay more attention to the complex instances during training. However, Zhang et al. [10] argue that hard-mining may not be appropriate for knowledge distillation. In contrast, down-weighting those hard samples or paying more attention to easy samples will allow the distillation model to achieve better performance. One important question to ask is: how should the example difficulty be measured? In object detection, He et al. [7] use modified cross-entropy loss (a.k.a. focal loss) to measure the difficulty of bounding boxes. Bounding boxes with high prediction probability of the correct class (e.g., most backgrounds) are considered to be easy and they receive even less attention compared to the unmodified cross entropy case. On the other hand, the modified loss directs more attention to the not-so-well-classified examples. GHM-C in [8] follows a similar idea to focal loss. Cao et al. [9] use Hierarchical Local Ranks to compute sample importance in mini-batches. In knowledge distillation, Zhang et al. [10] measure instance importance through feature variance of an auxiliary branch added to the student model. As in [10], our method applies instance reweighting during knowledge distillation. However, unlike previous approaches, we utilize the teacher network’s predictions to determine instance importance for the student.

c) Knowledge Distillation: Since its introduction by Hinton et al. [1], knowledge distillation (KD) has been widely applied in deep learning. The goal of KD is to train a new high-performance lighter-weight student network by transferring a powerful teacher network’s knowledge. In knowledge distillation, the knowledge comes in different forms: feature-based [5], [21]–[25], response-based [1], [4] and relation-based [6], [26], [27]. The main difference lies in the kind of the knowledge transferred. Unlike the distillation for classification problems, improving the efficiency and performance of an object detection model through knowledge distillation is a more challenging task. Relatively speaking, KD is less explored in object detection than in classification tasks. It was not until 2017 that Chen et al. [28] first proposed their KD method for object detection. To deal with the high imbalance between the background and foreground object regions of interest in object detection, Chen et al. [28] down-weighted the background distillation loss in the classification head. Zhang et al. [5] proposed to use an attention-based method to improve the distillation results. However, to the best of our knowledge, there is only one work [10] that attempts to apply the idea of instance-based reweighting to the domain of distillation. They used an auxiliary task branch to flatten the student’s feature map into a vector and that vector’s variance is utilized to adjust the distillation weights. They give larger weights to samples with low variances. However, there is no enough justification why auxiliary feature variance and sample importance are related. In contrast to Zhang et al. [10] that uses the student network’s information to measure instance weight, we leverage the teacher’s prediction for each instance to determine the reliability of the distilled knowledge.

III. METHODOLOGY

Object detection involves multiple tasks, e.g., bounding box regression, category classification, and objectness prediction. Therefore, knowledge distillation for object detection is more complex than for classification. In an image to be detected, the background instances are often more persuasive than the foreground object instances. To deal with the imbalance problem, many adaptive instance weighting strategies, such as hard sample mining [7], have been proposed. However, Zhang et al. [10] show that hard sample mining does not work well in knowledge distillation. Instead, they used an auxiliary task branch to estimate uncertainty in the data and make students pay more attention to the ‘stable’ samples. However, the variety of the auxiliary features is not necessarily a reliable indicator for instance importance, and it does not represent the importance of the knowledge from the teacher. In contrast to their approach, we propose to measure the value of the teacher’s knowledge on a per-instance basis by calculating the gap between the ground truth and the teacher’s prediction. In
other words, if the teacher model cannot predict an example well, it implies that the teacher’s knowledge about that instance is less trustworthy. On the other hand, valuable knowledge comes from those instances that can be accurately predicted by the teacher model. The student network should pay more attention to such instances.

**A. Adaptive Instance Knowledge Distillation**

In general, knowledge distillation tasks have two kinds of losses. One is the distillation loss $L_{\text{distill}}$ which measures the knowledge (or prediction) difference between the student and the teacher model. The other one is the task loss, which is used to guide the student to learn the original task. In this paper, we propose Adaptive Instance distillation (AID) to adaptively distill the knowledge of the teacher model on a per-instance basis for object detection tasks. The idea is that the student model should pay more attention to instances in which the teacher has more authority/trustworthiness rather than learn all instances equally from the teacher model. Fig. 1 illustrates how AID guides the student model to better learn the most valuable and reliable knowledge from the teacher model. We define the overall loss for student learning as:

$$L_i^S = L_{\text{task},i}^S + \lambda L_{AID,i}^{S,T},$$

where $i$ indicates the $i$-th instance. The superscripts $S$ and $T$ imply that a corresponding loss term depends on the student and/or the teacher prediction. $\lambda$ is a weighting factor balancing the contribution between the task loss $L_{\text{task}}$ and our instance adaptive distillation loss $L_{AID}$. The latter is defined as follows:

$$L_{AID,i}^{S,T} = \exp^{-\alpha D_i^T} L_{\text{distill},i}^{S,T},$$

where

$$D_i^T = L_{\text{task},i}^T$$

is the teacher’s object detection task loss, i.e., the distance between the ground truth and the prediction, on the $i$-th instance. $\alpha$ is a hyper-parameter that needs to be tuned empirically (we set it to 0.1 in all our experiments). As we can see from Eq. 2, the adaptive weight of the instance $i$ has a negative exponential correlation with the teacher’s prediction loss. The larger the teacher’s error on a certain instance $i$ (i.e., $D_i^T$ is), the smaller weight or less attention the instance $i$ will receive from the student model during the knowledge distillation process. On the other hand, instances where the teacher predicts accurately (i.e., with smaller $D_i^T$ values) deserve more of the student’s attention in the knowledge transfer process. The instance weight degrades exponentially with the increase of the teacher’s prediction error. The exponential function sets an appropriate range of the punishment. Take the extreme cases for example. An instance where the teacher’s loss is extremely large will receive approximately zero attention while there will be no knowledge transfer degradation for instances where the teacher model makes ‘perfect’ prediction (zero task loss).

Putting all things together, we get the final loss for our instance-adaptive student learning:

$$L_i^S = L_{\text{task},i}^S + \lambda \exp^{-\alpha L_{\text{task},i}} L_{\text{distill},i}^{S,T}.$$ (4)

Feature Pyramid Networks (FPN) [11] have been widely adopted by state-of-the-art object detectors. To improve knowledge transfer for objects of different scales, we apply our AID strategy to each output layer of the FPN. In this case, our AID adaptively weights not only the instance-wise knowledge but also scale-wise feature knowledge during the knowledge distillation process. The student will rely more on the teacher for scales where the teacher feels more confident. For scales where the teacher performs badly, the student will rely on itself to learn instead of being misled by the teacher. Such scale-adaptive knowledge distillation contributes to better object detection on different scales. More details will follow in the experiment section.

**B. Instance-adaptive Self Knowledge Distillation**

Although some effective self-knowledge-distillation approaches [29] exist for classification tasks, relatively few works have explored self-distillation on detection models. In addition to help better distill knowledge from a teacher model to a more compact student model, our AID strategy can also be used to distill useful knowledge into the original architecture itself. In this adaptive self-knowledge-distillation process, the knowledge from easy instances will be passed on to the new network with the same architecture, without much information loss. On the other hand, we pay less attention to or even discard the knowledge gained from difficult instances where the original model does not perform well. This provides an opportunity for the new network to re-learn those difficult examples given the knowledge from some easy instances. This instance-adaptive self-reflection process is expected to result in an improved detection model with the same architecture. Our AID-based self-distillation loss for object detection is defined as follows:

$$L_{\text{new}} = L_{\text{task},i}^\text{new} + \lambda \exp^{-\alpha L_{\text{task},i}} L_{\text{distill},i}^{\text{new,old}},$$ (5)

where $\text{new}$ represents the new model we want to train, $\text{old}$ indicates the previous pre-trained model. In our experiments, we conducted self-distillation experiments on both single-stage and two-stage detectors.

**IV. EXPERIMENTS AND RESULTS**

**A. Experimental Setup**

1) Datasets: To evaluate our method, we utilize two autonomous driving related datasets in our experiments. The first one is the KITTI 2D-object detection dataset [30], which includes three different types of road objects (i.e., car, cyclist, and pedestrian). The second one is the COCO traffic dataset,

\[^1\]here, confident is loosely defined as knowledgeable
which is obtained by selecting categories related to self-driving from MS COCO 2017 [31]. These categories include: person, stop sign, traffic light, fire hydrant, parking meter, bus, motorcycle, bicycle, car, train, truck.

2) Implementation Details: All the detection methods, including the baselines, are implemented within the MMDetection [32] framework. In our experiments, we chose Faster-RCNN [14] as an example of two-stage detectors and Generalized Focal Loss (GFL) [16] as an example of single-stage detectors. We experimented with two backbone architectures (i.e., ResNet101 and ResNet-50) on both the single-stage and two-stage detectors. The teacher model was directly trained with MMDetection’s default configuration (without any KD methods). We adopted one state-of-the-art KD method (Zhang et al. [5]) as the KD baseline and applied AID to verify our AID’s effectiveness. On the two datasets, we used the same experimental settings and hyperparameters. We do not perform much hyperparameter tweaking, and the default hyperparameters in the pre-configured file are adopted. In our implementation, the hyperparameters of Zhang et al. [5]’s method are set as \( \beta = 4 \times 10^{-3}, \gamma = \eta = 7 \times 10^{-5}, T = 0.5 \) for Faster R-CNN, \( \beta = 2 \times 10^{-2}, \gamma = \eta = 4 \times 10^{-4}, T = 0.1 \) for GFL. We set \( \alpha = 0.1 \) for all knowledge distillation. All models are sufficiently trained to convergence (i.e., 24 epochs for models with ResNet101 backbone, 12 epochs for ResNet50 backbone). All models are evaluated in terms of mean averaged precision (mAP) with 0.5 as the Intersection over Union (IoU) threshold.

Fig. 1. Illustration of the proposed adaptive instance distillation (AID) method. The losses associated with the multi-scale prediction of the teacher model will be transformed into weights to guide the knowledge distillation process.

B. Quantitative Analysis

We compare our Adaptive Instance Distillation (AID) method with the baseline and one state-of-the-art KD method. The baseline is trained with a certain backbone without any knowledge distillation. The compared KD method is an attention-guided knowledge distillation method of Zhang et al. [5]. We evaluate our AID method by applying it to Zhang et al. [5] to see whether our AID can improve the distillation results. In our experiments, all teacher models employ a ResNet-101 backbone. In addition to using ResNet-50 backbones for the students, we also employ students with ResNet-101 backbones to perform self-distillation and evaluate our AID-based self-distillation’s effectiveness.

Table I shows the comparison between our method and the baselines in different scenarios (e.g., different student backbones, one-stage vs. two stages detectors). It can be observed that the attention-based KD method (Zhang et al. [5]) can improve performance to a limited extent (for example, the mAP of the single-stage detector is increased by 1.3%). After we applied our method, those improvements became more significant (mAP got increased by 2.9%). In the self-distillation scenario, our approach can also improve the teacher model’s performance by 0.5% without any architecture changes or extra teachers.

Our AID-based approach achieves promising results on the COCO traffic dataset as well (Table I). When using ResNet-50 as the student backbone, our AID method achieves 2.5% and 0.7% mAP improvement over the teacher baseline for the GFL and Faster R-CNN cases, respectively. In self-distillation scenarios, our AID approach also beats all other baselines.
TABLE I
RESULTS ON KITTI DATASET. STUDENT-BACKBONE AND TEACHER-BACKBONE REFER TO NON-DISTILLATION MODELS WITH RESNET-50 AND RESNET-101 BACKBONES, RESPECTIVELY. ZHANG ET AL. [5]: A STATE-OF-THE-ART DISTILLATION BASELINE WITHOUT ADAPTIVE WEIGHTING.

| Teacher-Backbone | Student-Backbone | Method          | mAP (GFL) | mAP (Faster R-CNN) |
|------------------|------------------|-----------------|-----------|--------------------|
| ResNet-101       | Student-Baseline | Zhang et al. [5]| 86.4      | 89.0               |
|                  | Ours (AID)       | **88.0**        | **89.6**  |                    |
| ResNet-101       | Teacher-Baseline | Zhang et al. [5]| 89.4      | 89.6               |
|                  | Ours (AID)       | **89.7**        | **89.8**  |                    |

Compared to the teacher baseline (also with a ResNet-101 backbone), our AID achieves 1.6% mAP improvement in the GFL case and 1.0% in the Faster R-CNN case.

In addition to mAP performance, we also compared different architectures’ efficiency in terms of FLOPs and parameters. The results are shown in Table III. It can be observed that our distilled models with the smaller ResNet-50 backbone are more efficient than the corresponding teacher baselines with ResNet-101 backbones. In addition to the previously mentioned higher mAPs, our distillation model enjoys an average of 34.4% reduction in number of parameters and an average of 20.4% savings in FLOPs.

C. Qualitative Analysis

Fig. 2 shows random qualitative results of our AID self-distilled GFL model and the two other GFL models with ResNet-101 as the backbone on the KITTI dataset. From top to bottom, the results are respectively generated by 1) the teacher baseline GFL model, 2) Zhang et al. [5]’s model, and 3) our AID-distilled model. For the readers’ convenience, we highlighted the prediction differences between our AID-based model and the other baseline models using green ovals. In the upper left image, the teacher baseline model incorrectly detected the fence as a car in the left part of the image. In the upper right image, the teacher baseline model generated a bunch of approximate bounding boxes to locate the pedestrian and the car that overlap each other in the right part of the image. According to the middle two images, Zhang et al. [5]’s attention-guided method’s distilled GFL model performed better than the non-distilled baseline GFL model. In the middle left image, the distilled baseline model (Zhang et al. [5]) did not make the same mistakes as the teacher baseline model. However, in the middle right image, the model derived by Zhang et al. [5]’s method still struggles to find the correct bounding boxes for the overlapping objects. Our AID-distilled model not only inherits the benefits of the existing KD approach but also has better detection capability for overlapping objects and small-scale objects. For example, in the down-left image, our AID distilled model did not make the same wrong prediction as the teacher baseline model and had higher confidence scores for small-scale objects at the far end of the street (marked with the smaller green oval). Moreover, in the down-right image, our model correctly detected the pedestrian and the car without generating any false positive prediction. In the same image, our AID-based model also successfully detected the small object behind the pole (as shown in the left green oval), something the previous two competing models failed to achieve.

Fig. 3 demonstrates another random example on the COCO traffic dataset. From left to right, the results are respectively generated from 1) the non-distilled student baseline GFL model, 2) Zhang et al. [5]’s distilled GFL model, and 3) our AID-distilled GFL model. All three models use ResNet-50 as the backbone for fair comparison. The two left images show that 1) and 2) incorrectly predicted the truck in the marked green ovals. The main reason for the detection failure is that the object is occluded, and the teacher model cannot impart trustworthy information to the student model in such scenarios. Zhang et al. [5]’s distilled model blindly trusted the teacher’s prediction and thus made a similar mistake. In contrast, our AID-distilled model relied more on itself when learned to predict for such instances and predicted correctly in the rightmost picture.

V. Future Work

In this paper, we have shown that by adjusting the weight of an instance according to its difficulty in the eyes of the teacher, our AID method can guide the student model to pay more attention to those instances where the teacher does well, enhancing the transfer of reliable and valuable knowledge. In addition to the baselines that we have experimented with, we believe that our AID approach can be generally applicable to other KD methods (e.g., [33], [34]) and detection models (e.g., YOLOs [35] and SSD [36]), and its generalization performance will be tested in our future experiments. We also plan to adopt even smaller backbones, such as ResNet18 and those obtained from pruning approaches [37]. Although some promising results have been achieved by our instance adaptive self-distillation method, we plan to make this process iterative. With more iterations, we expect that a detection model can be further refined. Last but not least, our AID can potentially help the student selectively learn from multiple teachers, each excels in a particular area (a certain set of instances).

VI. Conclusion

In this paper, we have proposed an adaptive instance distillation (AID) method to guide the student model to better learn from the teacher model. The method enables the student network to pay more attention to instances that the teacher model performs well on. By applying our AID to different scales of the FPN, we can also make the knowledge distillation process
**TABLE II**

**RESULTS ON COCO TRAFFIC DATASET. STUDENT-BASELINE AND TEACHER-BASELINE REFER TO NON-DISTILLATION MODELS WITH RESNET-50 AND RESNET-101 BACKBONES, RESPECTIVELY. ZHANG ET AL. [5]: A STATE-OF-THE-ART DISTILLATION BASELINE WITHOUT ADAPTIVE WEIGHTING.**

| Teacher-Backbone | Student-Backbone | Method            | mAP (GPL) | mAP (Faster R-CNN) |
|------------------|------------------|-------------------|-----------|-------------------|
| ResNet-101       | ResNet-50        | Student-Baseline  | 65.3      | 65.3              |
|                  |                  | Zhang et al. [5]  | 69.7      | 69.7              |
|                  |                  | Ours (AID)        | **70.1**  | **68.7**          |
| ResNet-101       | Teacher-Baseline | Zhang et al. [5]  | 71.0      | 67.1              |
|                  |                  | Ours (AID)        | **72.6**  | **68.1**          |

Fig. 2. **Qualitative Analysis on KITTI (best viewed when zoomed in)** – From top to bottom, the prediction results are respectively from 1) Teacher baseline model, 2) Zhang et al. [5]’s KD baseline model, and 3) our AID distilled model. We use green ovals to highlight some of the detection differences between our AID-based model and other baselines.

**TABLE III**

**MODEL COMPLEXITY (WITH 224×224 INPUT RESOLUTION)**

| Model     | Backbone | Parames(M) | GFLOPs |
|-----------|----------|------------|--------|
| RetinaNet+| ResNet-50| 32.06      | 10.07  |
|           | ResNet-101| 51.05      | 13.79  |
| Faster R-CNN| ResNet-50| 41.17      | 23.40  |
|           | ResNet-101| 60.17      | 27.13  |

scale-aware. Our instance/scale weighting method can potentially be combined with most if not all knowledge distillation methods while inheriting their advantages. In our experiment, we chose the state-of-the-art knowledge distillation approach (Zhang et al. [5]) as the baseline and tested our AID on both single-stage and two-stage detectors. Experimental results on the KITTI and COCO traffic datasets demonstrate our AID method’s efficacy. On average, 2.7% and 2.1% mAP increases can be achieved for the single-stage detectors and two-stage detectors, respectively.
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APPENDIX

To ensure the reproducibility of our work, we provide the random train/validation split of the KITTI dataset that we used in our experiments (the test data of KITTI has no ground truth annotations). The validation IDs are (other IDs form the training set): [000010 000022 000026 000061 000063 000067 000082 000083 000096 000105 000119 000124 000128]
The conference \cite{38} and journal versions \cite{39} of this preprint use the same train/validation split.