Yinghui Xing*, Dexuan Kong*, Shizhou Zhang[†], Geng Chen, Lingyan Ran, Peng Wang, Yanning Zhang. Abstract-Camouflaged object detection (COD), aiming to

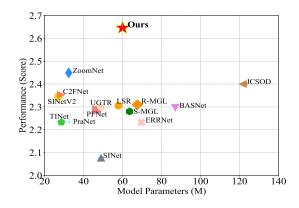
segment camouflaged objects which exhibit similar patterns with the background, is a challenging task. Most existing works are dedicated to establishing specialized modules to identify camouflaged objects with complete and fine details, while the boundary can not be well located for the lack of object-related semantics. In this paper, we propose a novel "pre-train, adapt and detect" paradigm to detect camouflaged objects. By introducing a large pre-trained model, abundant knowledge learned from massive multi-modal data can be directly transferred to COD. A lightweight parallel adapter is inserted to adjust the features suitable for the downstream COD task. Extensive experiments on four challenging benchmark datasets demonstrate that our method outperforms existing state-of-the-art COD models by large margins. Moreover, we design a multi-task learning scheme for tuning the adapter to exploit the shareable knowledge across different semantic classes. Comprehensive experimental results showed that the generalization ability of our model can be substantially improved with multi-task adapter initialization on source tasks and multi-task adaptation on target tasks.

Index Terms-Camouflaged Object Detection, Multi-Task Learning, Pre-Train, Adapt, Detect

I. INTRODUCTION

WILD animals have developed rich camouflage ability, which helps them protect themselves from their predators by blending in with their surroundings [1]-[3]. Camouflaged object detection (COD), typically defined as a binary segmentation task, is more difficult than traditional salient object detection or segmentation, due to the fact that camouflage strategy works by deceiving the visual perceptual system of the observer, found by sensory ecologists [4].

In recent years, COD has attracted increasing research interest from the computer vision community. Early works used low-level hand-crafted features, such as color, edge or texture to detect camouflaged objects [5]–[8], whose performances are limited for the lack of feature discrimination. Le *et al.* [9] provided a Camouflaged Object (CAMO) dataset to facilitate the application of deep neural networks to COD task. After that, many deep learning based COD methods were proposed. Existing research efforts either devoted to devising elaborate modules [3], [10] for accurate extraction of object structure or utilized auxiliary tasks to enhance the discriminative ability of the main segmentation stream for COD [11], [12].



Pre-train, Adapt and Detect: Multi-Task Adapter

Tuning for Camouflaged Object Detection

Fig. 1. The scatter relationship between the performance (Score) and parameters of competitors and our model on COD10K-Test [1]. (Score = $S_{\alpha} + E_{\phi} + F_{\beta}^w - M$).

The major difficulty in COD is how to accurately distinguish the subtle differences between the target object and the background in the image [13]. However, camouflaged objects have a large variety of object appearances, like object size and shape, which further aggravate the accurate detection of boundaries. We believe that it can be well addressed by learning context-aware and object-related semantic knowledge [14].

With the emergence of large-scale pre-trained models [15], [16], many researchers have developed to learn high-quality visual representations by a "Pre-training and Fine-tuning" paradigm [17], [18]. Benefiting from the pre-training, big foundation models with strong generalization ability can be learned with large-scale training data in supervised or selfsupervised ways. Then they can efficiently be adapted to many downstream tasks with lightweight feature adapters [19] or prompts [17]. Like a human that has been seeing and reading countless image samples, the large and deep models can learn and memorize rich general semantic knowledge [20], which we think is favorable to acquire subtle boundaries in COD through the learning of context-aware and object-related semantics.

In this paper, we propose to solve the COD task from a new perspective via pre-training a large-scale foundation model, then adapting it to COD task with a parameter efficient adapter module. Specifically, we detect the camouflaged objects within a "Pre-train, adapt and detect" paradigm. Large-scale multimodal data is used to pre-train the foundation model, ViT in our implementation, to learn rich meta knowledge. Then a lightweight adapter is appended to ViT to adapt the pre-trained model to downstream tasks. After obtaining a finer feature

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map, a COD head is used to precisely *detect* the pixel-wise camouflaged object.

Furthermore, it is observed that camouflaged objects have diverse semantic classes, varying from insects, birds, mammals to artificial camouflaged objects. Though the classes are diverse, they may have some similar camouflaged patterns, *i.e.* there may be some shareable knowledge among different classes. It is worth noting that shareable knowledge across different classes may be beneficial to the generalization of the proposed model. Therefore, we further propose to learn the adapter via a multi-task learning paradigm.

We conduct thorough experiments on four widely used benchmark datasets. The proposed framework outperforms 16 state-of-the-art methods by large margins with less or comparable model parameters, as can be seen from Figure 1. Additionally, to verify the effectiveness of the multitask adapter tuning, we partitioned the datasets according to the semantic classes of the camouflaged objects. Shareable knowledge across tasks can be learned by multi-task adapter initialization on source tasks and multi-task adaptation on target tasks to improve the generalization ability of our method.

The main contributions can be summarized as follows,

- We propose to detect camouflaged objects with a novel "pre-train, adapt and detect" framework. Benefiting from pre-training, the proposed method achieves superior performance by only tuning a small number of parameters without elaborate design. To the best of our knowledge, it is the first COD method based on a large-scale pre-trained foundation model.
- We further propose to learn the adapter in a multi-task learning scheme, including multi-task adapter initialization and multitask adapter adaptation. Experiments on zero-shot task transferability, multi-task adaption, and cross-task generalization demonstrate the efficacy of each component.
- Our method sets a new record on four widely used benchmark datasets and provides new evaluation protocols to explore multi-task learning on COD tasks.

II. RELATED WORK

A. Camouflaged Object Detection

Detecting/segmenting camouflaged objects is of great potential in many applications. Early works mainly rely on handcrafted features such as color [6], 3D convexity [7], and motion [8], etc. These methods work well in a few simple cases but often fail in complex cases, such as scenes with multiple or occluded objects. Recent works resort to deep learning to recognize camouflaged objects in more challenging scenarios [1], [14], [21], [22]. Some of them are based on feature fusion to improve multi-scale object detection performance by capturing rich context information and aggregating cross-level features [1], [14]. While others take advantage of the rotation invariant and anti-noise ability of texture features to amplify the difference between camouflaged objects and background [21], [22]. Although these methods improve the performance of camouflaged object detection, they still have limitations in the scenes where the camouflaged objects have

high similarity with their background. In order to obtain accurate boundary and refined structures, Zhai et al. [2] introduced graph convolution to capture camouflaged regions and used the Edge-Constricted Graph Reasoning module to explicitly merge edge information. Qin et al. developed a boundary-aware segmentation network (BASNet) [23], which learned three-level hierarchy representations through a hybrid loss. Due to the camouflage strategy essentially deceiving the visual perception system, edge-based detection still has difficulties to achieve excellent performance. To further mimic the behavior of predators in nature or human visual psychological patterns, bio-inspired methods have recently emerged, such as PFNet [24], MirrorNet [25] and ZoomNet [3]. However these methods imitated human visual systems in a simple manner, which limits their performance. Different from the above methods, our model has learned more extensive knowledge through various tasks (including multi-modal data), making it more "intelligent" to confront the deceits of camouflaged objects.

B. Parameter Efficient Tuning

Recently, large-scale pre-trained models, such as CLIP [26], BEIT [27] and Vision Transformer [16], demonstrate great potential in many natural language processing and computer vision tasks. To minimize training costs when adapting large pre-trained models for downstream tasks, parameter efficient tuning focuses on updating only a small subset of parameters for the target task [28]. Mainstream methods can be roughly divided into two groups: prompt tuning [17], [29]–[31] and adapter tuning [19], [32]–[34].

Adapter tuning [32] aims to adapt pre-trained models to downstream tasks by inserting a learnable lightweight module, *i.e.* adapter while keeping the pre-trained weights frozen. Chen *et al.* proposed AdaptFormer [34], which set two fully connected layers in parallel to the feed-forward network of ViT model to adapt it to downstream visual recognition tasks. To enhance the few-shot capability of vision-language pretrained model like CLIP, Gao *et al.* [19] proposed to append a lightweight two-layer MLP to the pre-trained fixed-weight CLIP model.

C. Multi-Task Learning

Learning multi-tasks jointly has been demonstrated as a useful scheme to enable the shared representation or task-specific model to gain more generalized cross-task knowledge [12], [35]. Some auxiliary tasks, such as image classification [9], salient object detection [36], edge extraction [2], localization and ranking [37], have been introduced into the multitask learning paradigm to improve the performance of camouflaged object detection. Le *et al.* [9] designed a classification branch to predict the probability of containing camouflaged objects in an image. Li *et al.* [36] presented an adversarial learning framework to conduct multi-task learning on the joint datasets of salient object detection and camouflage object detection. Zhai *et al.* [2] decoupled an image into two task-specific feature maps to respectively locate the target and capture boundary details. Moreover, Lv *et al.* [37] built their network

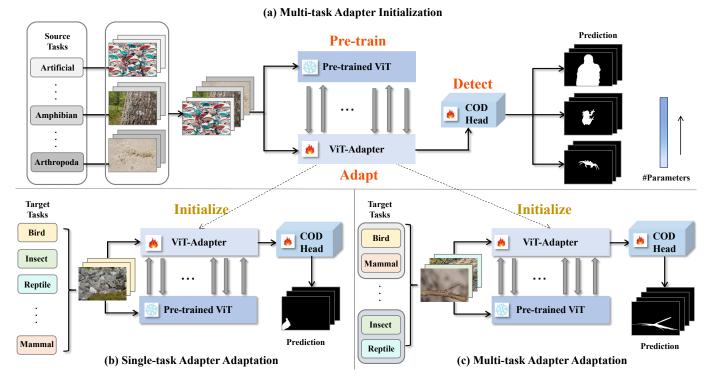


Fig. 2. Overall framework. (a) The architecture of the proposed "Pre-train, Adapt and Detect" paradigm and multi-task adapter initialization on source tasks. (b) Multi-task adaptation on single target task. (c) Multi-task adaptation on grouped target tasks.

in a triple-task learning framework to simultaneously localize, segment, and rank the camouflaged objects. Different from these methods that introduced auxiliary functional tasks to excavate extra cues from the shared features, we devoted to dividing the COD task into finer sub-tasks according to the semantic labels of the foreground objects, aiming to learn a generalized adapter through cross-task shared knowledge.

III. METHODOLOGY

In this section, we first elaborate on the detailed architecture of the proposed method. Then we introduce a multi-task adapter tuning scheme to make the adapter learn shared knowledge among tasks.

A. Overall Architecture

We propose to solve the COD task with a three-step process, namely Pre-train, Adapt and Detect, which corresponds to a large pre-trained ViT model, a lightweight adapter module and a detection head respectively. The overall architecture is shown in Figure 2 (a).

Pre-train. Recent researchers come to a consensus to adopt pre-trained models as the backbone for downstream tasks rather than learning models from scratch [38]. Although there are many large-scale pre-trained models available, we adopt ViT [16] in our implementation as ViT pre-trained with large-scale multi-modal data [39] can make the obtained features include more semantics. During the pre-training phase, a large-scale ViT model is pre-trained with rich multi-modal data [39] and serves as a foundation model. Following [39], ViT backbone is pre-trained with multi-modal data in terms of image,

video and text, since transformer layers can indistinctively process patch embeddings, 3D patch embeddings and token embeddings. Concretely, all the embeddings are projected into D-dimensional vector representations and combined with the positional embeddings. Further, they are fed into L transformer encoder layers. Note that a learnable "CLS" token embedding is additionally prepended to extract the global feature representation gradually.

Adapt. After obtaining the foundation model, we need to adapt it for the downstream COD tasks. We introduce a lightweight pre-training-free vision-specific adapter, namely ViT-Adapter [40], which has only a small number of trainable parameters compared with the pre-trained ViT model, to act as a multi-scale feature extractor for COD task. Parallel to ViT, ViT-Adapter contains a convolution-based spatial prior module to model the local spatial contexts of input images, and two cross-attention-based modules named as injector and extractor, to make interactions between the adapter and the ViT backbone model. After N feature interactions, we obtain fine-grained hierarchical features of similar resolutions to ResNet [41], which can be used in COD. Note that ViT-Adapter includes *fewer than* 8% parameters of the large-scale pre-trained model.

Detect. We use UperNet [42] as our detection head. The pyramidal features obtained from the adapter are taken into UperNet [42]. In this process, Pyramid Pooling Module (PPM) [43] is applied on the lowest resolution feature to gain effective global prior representations, and Feature Pyramid Network (FPN) [44] is used to fuse high-level semantic information into middle and low levels via a top-down architecture

with lateral connections. It could be able to jointly infer and discover the rich visual knowledge underneath images by combining low-resolution, semantically strong features with high-resolution, semantically weak features.

Training Process. During training, the camouflaged images are fed into the backbone and the adapter simultaneously. We only optimize the parameters of the adapter module and the detection head while the parameters of the original pre-trained model remain frozen so that the power of the ViT foundation model can be efficiently transferred to the downstream COD task with little computational cost. Our entire training process is supervised by the combination of weighted binary cross-entropy loss (L_{BCE}^w) [45] and weighted intersection-over-union loss (L_{IOU}^w) [45], which can be formulated as $L = L_{BCE}^w + L_{IOU}^W$, forcing the model to pay more attention to hard pixels.

B. Multitask Adapter Tuning

Camouflaged objects have diverse semantic classes, varying from insects to mammals, from natural to artificial camouflage. To explore whether shareable knowledge across different semantic classes can be learned via a multi-task learning scheme, we divided the CAMO and COD10K datasets into nine nonoverlapped sub-datasets as nine different sub-tasks according to the object category. We found that compared with the independent learning on a single task, the joint learning across all tasks may improve the performance of the model on most tasks, but it performs poorly on some specific tasks possibly due to task interference/negative transfer issues (Table IV). In addition, it is extremely time-consuming to train on all tasks simultaneously. In order to improve the generalization performance of the model on each task and reduce resource consumption, we introduced a multi-task learning mechanism, which consists of two stages, multitask source adapter initialization and multitask target adapter adaptation.

Multitask Source Adapter Initialization. As shown in Figure 2 (a), the adaptation modules are trained jointly on all source tasks in this stage.

Multitask Target Adapter Adaptation. In this stage, we use the learned source adapter to initialize the target adapter. For single-task target adapter adaptation, we directly tune the adaptation modules on each target task separately, as demonstrated in Figure 2 (b). For multi-task target adapter adaptation shown in Fig. 2 (c), we first group several similar tasks together, then perform multitask adapter tuning within the selected groups. The grouping strategy is further discussed in Section IV-B. Finally, we test the model on each individual target task to evaluate the performance.

IV. EXPERIMENTS

We first conduct experiments following the conventional protocols for a fair comparison with current state-of-theart methods in Section IV-A. To explore whether shareable knowledge across different semantic classes can be learned via multi-task learning scheme, we then conduct thorough experiments within the multitask framework in Section IV-B.

A. Conventional COD Experiments

Datasets. Our experiments are based on four widely-used COD datasets: (1) CHAMELEON [46] collects 76 images with manually annotated object level ground-truths (GTs). The images were collected from the Internet via the Google search engine using "camouflaged animal" as a keyword. (2) CAMO [9] has 1,250 images (1,000 for training, 250 for testing), covering eight categories, and includes two types of camouflaged objects, namely, natural and artificial camouflage. (3) COD10K [1] is the largest COD dataset till now, consisting of COD10K-Train (3,040 images) and COD10K-Test (2,026 images). The images are downloaded from multiple free photography websites, covering 5 super-classes and 69 subclasses. (4) NC4K [47]. As the largest testing dataset, NC4K includes 4,121 samples, which are used to evaluate the generalization ability of models. Following previous studies [3], [47], [52], we train our model on the training sets of CAMO and COD10K, and evaluate the detection performance on the whole CHAMELEON and NC4K datasets, together with the test sets of CAMO and COD10K.

Evaluation Metrics. Following existing works [1], [9], we take four commonly used metrics for evaluation: Structure measure (S_{α}) [55], Mean enhanced-alignment measure (E_{ϕ}) [56], weighted F-measure (F_{β}^w) [57], and mean absolute error (M) [15].

Implementation Details. In the training phase, we use Vision Transformer [16] as the foundation model and Uper-Net [42] as the COD head. The Vision Transformer is pre-trained with large-scale multi-modal data as in Uni-Perceiver [39] and kept frozen once pre-trained. The parameters of adapter and the COD head are both randomly initialized. We employ an AdamW [58] optimizer with initial learning rate of 6×10^{-5} and a weight decay of 0.05. They are trained 200 epochs with a batch size of 2. For testing, the images are resized to 512 ×512 as the network's input, and the outputs are resized back to the original size.

Competitors. We compare our method with 16 recent stateof-the-art methods: SINet [1], PraNet [48], TINet [21], ERR-Net [49], PFNet [24], UGTR [50], C²FNet [51], SINetV2 [52], S-MGL [2], R-MGL [2], LSR [47], JCSOD [36], Zoom-Net [3], BASNet [23], HitNet [53] and SAM-Adapter [54]. For fair comparison, all results are either provided by the published paper or reproduced by an open-source model re-trained on the same training set with recommended settings.

Quantitative Evaluation. The quantitative results are illustrated in Table I. As can be seen that our method achieves competitive performance on CHAMELEON dataset and outperforms all other models on other three datasets under four evaluation metrics with large margins, despite only a few parameters are fine-tuned.

For the CAMO test set, our method significantly improves S_{α} by 5.2%, E_{ϕ} by 4.4%, F_{β}^{w} by 8.4% and lowers the MAE error by 36.8%, compared with second-best model HitNet [53], which sets a new performance milestone.

For the COD10K test set, our method is consistently better than other competitors. Specifically, compared with the second-best model HitNet [53], our model increases S_{α} , E_{ϕ} ,

 TABLE I

 QUANTITATIVE COMPARISON WITH 16 SOTA METHODS FOR COD ON 4 BENCHMARKS. \uparrow / \downarrow INDICATES THAT LARGER/SMALLER IS BETTER. RED AND

 BLUE REPRESENT THE FIRST AND SECOND BEST PERFORMING ALGORITHMS, RESPECTIVELY.

		THAME	LEON [4	51	1	САМО	-Test [9]		1	COD10	K-Test [1]		1	NC4	K [47]	
Baseline Models	$\overline{S_{\alpha}\uparrow}$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$\frac{J}{M}$	$\overline{S_{\alpha}\uparrow}$	$E_{\phi}\uparrow$	$\frac{F_{\beta}^{w}}{F_{\beta}^{w}}\uparrow$	$M \downarrow$	$\overline{S_{\alpha}\uparrow}$	$E_{\phi}\uparrow$	$\frac{F_{\beta}^{w}\uparrow}{F_{\beta}^{w}\uparrow}$	$M \downarrow$	$\overline{S_{\alpha}\uparrow}$	$E_{\phi}\uparrow$	$F^w_\beta \uparrow$	$M \downarrow$
CDN-4 [1]	0.869	$\frac{D_{\phi}}{0.891}$	$\frac{1}{0.740}$	0.044	0.751	$\frac{D_{\phi}}{0.771}$	$\frac{1}{0.606}$	0.100	0.771	0.806	$\frac{1}{0.551}$	0.051	0.808	$\frac{D_{\phi}}{0.871}$	$\frac{1}{0.723}$	0.058
SINet [1]																
PraNet [48]	0.860	0.898	0.763	0.044	0.769	0.824	0.663	0.094	0.789	0.861	0.629	0.045	0.822	0.876	0.724	0.059
TINet [21]	0.874	0.916	0.783	0.038	0.781	0.847	0.678	0.087	0.793	0.848	0.635	0.043	0.829	0.879	0.734	0.055
ERRNet [49]	0.877	0.927	0.805	0.036	0.761	0.817	0.660	0.088	0.780	0.867	0.629	0.044	0.787	0.848	0.638	0.070
PFNet [24]	0.882	0.942	0.810	0.033	0.782	0.852	0.695	0.085	0.800	0.868	0.660	0.040	0.829	0.888	0.745	0.053
UGTR [50]	0.888	0.918	0.796	0.031	0.785	0.859	0.686	0.086	0.818	0.850	0.667	0.035	0.839	0.874	0.747	0.052
C ² FNet [51]	0.888	0.935	0.828	0.032	0.796	0.854	0.719	0.080	0.813	0.890	0.686	0.036	0.838	0.897	0.762	0.049
SINetV2 [52]	0.888	0.942	0.816	0.030	0.820	0.882	0.743	0.070	0.815	0.887	0.680	0.037	0.847	0.903	0.770	0.048
S-MGL [2]	0.892	0.921	0.803	0.032	0.772	0.850	0.664	0.089	0.811	0.851	0.655	0.037	0.829	0.863	0.731	0.055
R-MGL [2]	0.893	0.923	0.813	0.030	0.775	0.847	0.673	0.088	0.814	0.865	0.666	0.035	0.833	0.867	0.740	0.052
LSR [47]	0.893	0.938	0.839	0.033	0.793	0.826	0.725	0.085	0.793	0.868	0.685	0.041	0.839	0.883	0.779	0.053
JCSOD [36]	0.894	0.943	0.848	0.030	0.803	0.853	0.759	0.076	0.817	0.892	0.726	0.035	0.842	0.898	0.771	0.047
ZoomNet [3]	0.902	0.958	0.845	0.023	0.820	0.892	0.752	0.066	0.838	0.911	0.729	0.029	0.853	0.912	0.784	0.043
BASNet [23]	0.914	0.954	0.866	0.022	0.749	0.796	0.646	0.096	0.802	0.855	0.677	0.038	0.817	0.859	0.732	0.058
HitNet [53]	0.922	0.970	0.903	0.018	0.844	0.902	0.801	0.057	0.868	0.932	0.798	0.024	0.870	0.921	0.825	0.039
SAM-Adapter [54]	0.896	0.919	0.824	0.033	0.847	0.873	0.765	0.070	0.883	0.918	0.801	0.025	-	-	-	-
Ours	0.909	0.959	0.891	0.018	0.888	0.942	0.868	0.036	0.883	0.943	0.836	0.016	0.896	0.945	0.874	0.024

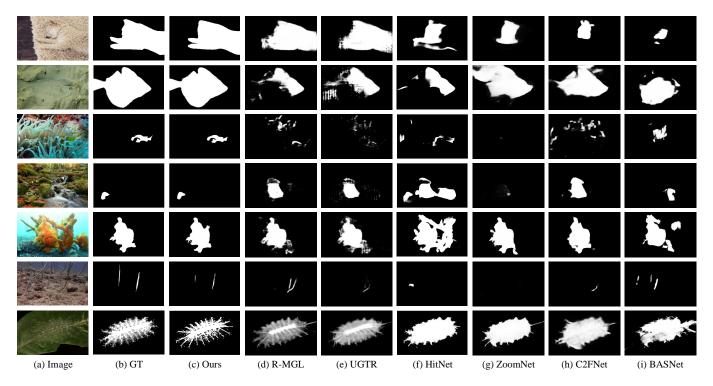


Fig. 3. Visual comparison of our method with other state-of-the-art COD methods. Our algorithm is capable of tackling challenging cases (*e.g.*, low contrast, occluded, small objects, confusing objects, multiple objects, and complex topological structures).

and F_{β}^{w} by 1.7%, 1.2%, and 4.8% respectively, and also lowers the MAE error by 33.3%.

We also evaluate the generalization ability of all models on NC4K dataset. It can be observed from the comparisons in Table I that our method sets a remarkable record to increase S_{α} , E_{ϕ} , and F_{β}^{w} by 3.0%, 2.6%, and 5.9% respectively, and decreases the MAE error by 38.5% than the second-best model HitNet [53].

Notably, compared to SAM-Adapter [54], which employs SAM [59] with strong generalization ability as the foundation model, our method still represent apparent superiority.

Qualitative Evaluation. Figure 3 shows the visual comparison of several other recent models and ours. As can be seen, our method (the 3rd column) is able to handle different

types of challenging camouflaged cases. For objects with low contrast (the 1st and 2nd row), other models can vaguely identify a small part of them, while our method can completely and clearly detect the objects. For targets occluded by fine objects (the 3rd row), we can present more complete prediction than other methods. For small objects (the 4th row), extremely confusing objects (the 5th row) and multiple objects with low contrast (the 6th row), our method provides accurate camouflaged object predictions, while others are interfered more or less, resulting in wrong locations. For the examples that have complex topological structures with lots of dense edges or details (the 7th row), although they are difficult to be detected even by humans, our method is capable of segmenting clear edges and boundaries while all other methods failed. TABLE II Comparison of different pre-trained weights in the case of freezing the backbone. ↑ and ↓ indicate the higher score the better and the lower the score the better, respectively. L/B/S/T denotes Large/Base/Small/Tiny respectively.

Method	Pre_train	CHAMELEON [46]			CAMO-Test [9]				COD10K-Test [1]				NC4K [47]				
Methou		$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$
HitNet [53]	None	0.922	0.970	0.903	0.018	0.844	0.902	0.801	0.057	0.868	0.932	0.798	0.024	0.870	0.921	0.825	0.039
	BEiT-L [27]	0.895	0.951	0.869	0.022	0.866	0.922	0.841	0.047	0.866	0.921	0.810	0.018	0.884	0.931	0.858	0.026
	Uni-Per-L [39]	0.909	0.959	0.891	0.018	0.888	0.942	0.868	0.036	0.883	0.943	0.836	0.016	0.896	0.945	0.874	0.024
	AugReg-L [60]	0.869	0.931	0.820	0.027	0.831	0.889	0.789	0.056	0.830	0.881	0.750	0.024	0.859	0.905	0.817	0.033
Ours	AugReg-B [60]	0.860	0.922	0.807	0.031	0.843	0.911	0.806	0.053	0.837	0.904	0.757	0.024	0.869	0.926	0.829	0.032
Ours	DeiT-B [61]	0.858	0.915	0.812	0.032	0.823	0.886	0.783	0.057	0.819	0.871	0.731	0.026	0.850	0.901	0.804	0.036
	DeiT-S [61]	0.848	0.908	0.795	0.031	0.793	0.858	0.738	0.071	0.801	0.859	0.696	0.031	0.833	0.888	0.774	0.042
	AugReg-T [60]	0.809	0.893	0.730	0.042	0.751	0.816	0.673	0.085	0.776	0.847	0.654	0.036	0.817	0.875	0.751	0.048
	DeiT-T [61]	0.816	0.900	0.748	0.042	0.767	0.837	0.699	0.089	0.785	0.859	0.671	0.036	0.821	0.883	0.755	0.048

TABLE III Comparison of different pre-trained weights in the case of unfreezing the backbone. ↑ and ↓ indicate the higher score the better and the lower the score the better, respectively. L/B/S/T denotes Large/Base/Small/Tiny respectively.

Method	Pre_train	CHAMELEON [46]			CAMO-Test [9]				COD10K-Test [1]				NC4K [47]				
Wiethou		$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$	$S_{\alpha} \uparrow$	$E_{\phi} \uparrow$	$F^w_\beta \uparrow$	$M \downarrow$
HitNet [53]	None	0.922	0.970	0.903	0.018	0.844	0.902	0.801	0.057	0.868	0.932	0.798	0.024	0.870	0.921	0.825	0.039
	BEiT-L [27]	0.921	0.965	0.908	0.015	0.905	0.955	0.896	0.028	0.901	0.952	0.869	0.013	0.909	0.952	0.895	0.021
	Uni-Per-L [39]	0.917	0.969	0.907	0.015	0.880	0.936	0.860	0.038	0.883	0.936	0.836	0.016	0.894	0.936	0.869	0.025
	AugReg-L [60]	0.910	0.962	0.898	0.017	0.885	0.941	0.868	0.035	0.879	0.932	0.832	0.016	0.890	0.932	0.863	0.024
Ours	AugReg-B [60]	0.902	0.950	0.879	0.019	0.859	0.920	0.831	0.044	0.858	0.911	0.792	0.020	0.874	0.920	0.836	0.029
Ours	DeiT-B [61]	0.895	0.949	0.872	0.019	0.837	0.902	0.805	0.056	0.841	0.897	0.763	0.023	0.859	0.907	0.814	0.033
	DeiT-S [61]	0.885	0.938	0.851	0.022	0.817	0.884	0.776	0.061	0.825	0.883	0.735	0.026	0.850	0.898	0.798	0.037
	AugReg-T [60]	0.851	0.906	0.789	0.031	0.759	0.819	0.686	0.081	0.784	0.838	0.660	0.035	0.813	0.861	0.740	0.048
	DeiT-T [61]	0.859	0.916	0.804	0.027	0.757	0.821	0.684	0.081	0.776	0.843	0.647	0.039	0.805	0.859	0.730	0.052

Ablation Study. In this experiment, we study the effect on 4 different foundation models (ViT-Large/Base/Small/Tiny) pre-trained with 4 different ways, namely DeiT [61] which incorporates a data-efficient ViT pre-trained on ImageNet-1K, AugReg [60] which borrows lots of data augmentation and regularization technique and is trained on ImageNet-22K, BEiT [27] which is pre-trained with a self-supervised way on ImageNet-1K, and Uni-Perceiver [39] which is trained with large scale multi-modal data. In addition, we investigate the effect of adapter-tuning only and full fine-tuning with the frozen and unfrozen backbone parameters. The results are provided in Table II and Table III. We initialize ViT-Tiny/Small/Base with the DeiT [61] released weights, and ViT-Tiny/Base/Large with the ImageNet-22K weights from [60]. We also use the BEiT [27] pre-trained weights and Uni-Perceiver [39] to initialize the ViT-L separately.¹

In the case of frozen backbone, as shown in Table II, using Uni-Perceiver [39] initialization shows the best results that greatly outperform existing SOTA methods. While in the case of unfrozen backbone, as shown in Table III, it achieves astonishing full fine-tuning results when using BEiT [27] initialization, which greatly outperforms the existing counterparts. Specifically, our method boosts S_{α} by 7.2%, E_{ϕ} by 5.9%, F_{β}^{w} by 11.9% and lowers the MAE error by 50.9% on CAMO dataset; increases S_{α} by 3.8%, E_{ϕ} by 2.1%, F_{β}^{w} by 8.9% and lowers the MAE error by 45.8% on COD10K dataset; and improves S_{α} by 4.5%, E_{ϕ} by 3.4%, F_{β}^{w} by 8.5% and lowers the MAE error by 46.2% on NC4K dataset. We found that fully fine-tuning models significantly outperform the counterpart method when just tuning adapter in most cases. However, the latter is much more efficient with less than 8% parameters. Notably, in Section IV-B, we will try to close the

¹The pre-trained model weights with other settings are not released.

gap between adapter-tuning only and full fine-tuning through a multi-task learning mechanism.

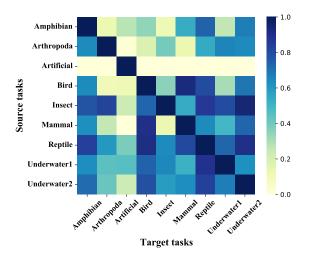


Fig. 4. A heatmap of our task transferability results. Each cell shows the relative performance on the target tasks of the transferred adapter from the associated source task (row) to the associated target task (column).

B. Multitask Learning Experiments

Multi-task learning mechanism is mainly evaluated in the following three problem settings: (1) Zero-shot task transferability; (2) Multitask adaptation, which shows the effectiveness of multitask adapter initialization and adaption; (3) Cross-task generalization, which measures the generalization ability of multitask adapter.

Datasets. We divided the entire COD10K datasets and the artificial camouflaged part of CAMO datasets into nine non-overlapped sub-datasets as nine different tasks according to

TABLE IV COMPARISON OF ADAPTER LEARNING METHODS ON 9 TARGET TASKS. (SCORE = $S_{\alpha} + E_{\phi} + F_{\beta}^{w}$ - M).

Method			Target Dataset											
		Amphibian	Arthropoda	Artificial	Bird	Insect	Mammal	Reptile	Underwater1	Underwater2	Avg			
	ST	2.731	2.497	2.498	2.728	2.640	2.543	2.598	2.579	2.618	2.604			
Adapter-tuning	MT	2.725	2.496	2.594	2.725	2.633	2.552	2.652	2.609	2.657	2.627			
Adapter-tuning	MS-ST	2.742	2.506	2.558	2.735	2.640	2.558	2.621	2.584	2.639	2.620			
	MS-MT	2.759	2.540	2.596	2.752	2.645	2.597	2.647	2.586	2.691	2.646			
	ST	2.753	2.574	2.643	2.744	2.681	2.595	2.645	2.598	2.636	2.652			
Model-tuning	MT	2.709	2.545	2.636	2.753	2.670	2.597	2.658	2.617	2.675	2.651			
mouei-luning	MS-ST	2.733	2.580	2.666	2.755	2.660	2.591	2.668	2.623	2.697	2.664			
	MS-MT	2.769	2.594	2.638	2.755	2.686	2.589	2.654	2.630	2.690	2.667			

TABLE V The results of five group experiments about cross-task generalization. Note that there is no overlap between source and target tasks, where "-" indicates source tasks. (Score = $S_{\alpha} + E_{\phi} + F_{\beta}^{w} - M$).

Method	Group	Target Dataset											
		Amphibian	Arthropoda	Artificial	Bird	Insect	Mammal	Reptile	Underwater1	Underwater2			
ST	None	2.731	2.497	2.498	2.728	2.640	2.543	2.598	2.579	2.618			
	1	-	-	-	-	2.653	-	2.619	2.585	2.627			
	2	2.749	-	-	2.737	-	2.561	2.599	-	-			
MS_ST	3	2.744	-	2.531	-	-	-	2.602	2.586	-			
	4	2.750	2.530	2.522	2.738	-	-	-	-	-			
	5	-	2.518	2.530	-	2.653	2.550	-	-	-			

the object category, which includes Amphibian, Arthropoda, Artificial, Bird, Insect, Mammal, Reptile, Underwater1 and Underwater2 (Underwater1 and Underwater2 have obvious differences). For the first two settings, we use all nine tasks as source tasks and target tasks. For the cross-task generalization setting, we randomly sample five tasks as source tasks and the remaining four non-overlapped tasks as targets.

Implementation Details. Throughout the multi-task experiments, we use ViT-Large as the backbone and initialize it with the Uni-Perceiver-L released weights [39]. We train the adaptation modules on source tasks for 100 epochs and on target tasks for 200 epochs with a batch size of 2. All the input images is resized to 512×512. We use AdamW [58] optimizer with an initial learning rate of 6×10^{-5} and a weight decay of 0.05.

Zero-shot Task Transferability. Which tasks should be learned together to help share information among tasks? To investigate this, we conduct a large-scale empirical study with 9 tasks in 81 combinations. We perform 200 epochs tuning on each source task to initialize adapter for different target tasks followed by zero-shot adaptation. We normalize the scores to the range of [0, 1] by dividing the transfer performance with the best one on that task and presented the results in Figure 4. It demonstrates that tasks with similar characteristics have better transferability, such as Bird, Mammal and Reptile. To determine the appropriate grouping strategy, we select the top-3 transferability tasks for each target task. Then we jointly train such groups in multitask adaptation stage to test each task respectively.

Multitask Adaptation. We present results for all 9 subtasks in Table IV. Single-Task (ST) refers to the results of independently trained adapter/model for each task. Multi-Task (MT) refers to the results of jointly trained adapter/model on all tasks. Multi-Source-Task-Single-Target-Task (MS-ST) shows the results of single-task target adapter/model adaptation using the initialization adapter on multi-source tasks. Multi-Source-Task-Multi-Target-Task (MS-MT) shows the results of multitask target adapter/model adaptation using the initialization adapter on multi-source tasks.

By comparing the performances of different fine-tuning approaches in the case of *adapter-tuning* in Table IV, we summarized four important findings: (1) Comparing ST and MT, MT boosts the averaged performance by 0.9%, which demonstrates that there are advantages in sharing knowledge cross tasks through multi-task learning. However, we also find that there are considerable performance drops for Amphibian and Insect using MT over ST, which indicates that learning a shareable adapter jointly can not guarantee the best results for all tasks. (2) By comparing ST and MS-ST, together with MT and MS-MT, we observe that multi-source-task initialization improves the detection accuracy, verifying the efficacy of multitask adapter initialization. Specifically, MS-ST outperforms ST on averaged score by 0.6% and increases the performance for 8/9 tasks. MS-MT boosts 0.7% on averaged score than MT, and improves the performance for 7/9 tasks, which shows that leveraging information from other tasks has favorable effects. (3) In contrast to MS-ST, MS-MT obtains better results on all tasks and improves the results 1.0% on average. It clearly demonstrates that multitask adapter adaptation variants exhibit better transferability than single target task adapter adaptation counterparts. (4) Furthermore, we can see that MS-MT under adapter-tuning almost achieves the performance of ST under full model-tuning, despite only a small number of parameters of the entire model are updated. It proves that our multi-task learning mechanism can reduce the gap with full model-tuning and even exceeds full model-tuning by a large margin on some tasks such as Reptile and Underwater2.

Cross-Task Generalization. We conduct five groups of

experiments in which the source tasks and target tasks are not overlapped. We perform multi-task learning on the source tasks to learn a shared adapter. Then the shared adapter is used as the adapter initialization for single-task adaptation on each target task. The results shown in Table V indicate that multi-task adapter initialization mostly outperform the baseline adapter learning counterparts by a significant margin. It concludes that using the adapter trained on the source tasks to initialize the adapter of the target task can help the target task better learn the knowledge transferred from the source tasks, and also help to improve the generalization ability of the model.

V. CONCLUSION

In this paper, a novel "pre-train, adapt and detect" paradigm is proposed to detect camouflaged objects. A large scale foundation model is pre-trained with massive multi-modal data, with the assumption that abundant knowledge can be learned through the pre-training step and can be efficiently transferred to benefit the downstream COD task. A lightweight adapter with much fewer tunnable parameters is devised to adjust the features of the foundation model to suit for dense prediction COD task. We conduct extensive experiments on four challenging benchmark datasets and the results demonstrate that our method outperforms existing state-of-the-art COD models by a large margin under four widely-used evaluation metrics. Moreover, we designed a multi-task learning scheme to explore whether the adapter can learn shareable knowledge across tasks. Comprehensive experimental results verified that multi-task adapter initialization on source tasks and adaptation on target tasks can further improve the generalization ability of the proposed model.

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