X^2R: COUNTER-'COUNTER-RECONNAISSANCE'

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ABSTRACT

Degrading enemy surveillance while raising their uncertainty through deception is an overarching Force Design Imperative highlighted in the 2022 CNO (Chief of Naval Operations) Navigation Plan. The goal is to leverage deception measures such as electronic warfare, concealment, and maneuvers to control situations in contested battlespaces. However, it should be obvious to expect our adversaries to study and implement similar strategies in order to win the confrontation. In anticipation of our adversary's efforts in counter-surveillance, this project aimed to identify an effective approach that can defeat a certain counter-surveillance tactic, technique, or procedure(TTP). Specifically, we wished to apply an existing artificial intelligence/machine learning method to detect the presence of camouflaged objects. Within the limits of time and budget, we were able to study, implement, and modify the open-source Search Identification Network (SINet) model for testing and evaluation on visible images of animal and human subjects. Our experiments validated the usefulness of SINet and yielded some promising results. More surprisingly, the model was able to perform well even on targets that were absent from the training set, without additional cross-domain or transfer learning techniques. Our future research plan includes further assessment of the camouflaged object detection (COD) algorithm in the EO/IR/RF (electro-optics/Infrared/radio-frequency) domain. Finally, rapid evaluation of the method with a drone in real-time is being considered in a follow-on proposal.

1 INTRODUCTION

In the animal kingdom, both the hunter and the prey learn to use camouflage to increase their chances of survival. For a leopard, its spotted coat allows the predator to blend in with its surroundings and sneak up on its prey. On the other hand, the snowshoe hare takes advantage of its ability to change fur color in accordance with the season of the year, enabling the hare to hide itself from the predator. As a critical element of the kingdom, humans also learned to adopt camouflage as a defensive tactic through concealing themselves as part of their natural surroundings.

In military camouflage, visual deception techniques utilize materials, colors, and patterns to disrupt recognition and identification by the enemy. These means can be applied on soldiers/Marines, equipment, vehicles, and ships to disguise the object as something unimportant or to make it difficult to detect.

Recent advancements in computer vision and image processing have led to much research work and results in object detection. In (Perazzi et al., 2012), the authors developed an algorithm to decompose a given image into structurally representative basic elements. By computing the element contrast, the proposed approach then generates a saliency map with separated fore- and background, enabling the detection of target. Additionally, in order to measure the performance of object segmentation algorithms for salient object detection, researchers have also proposed various methods to quantify the similarity between a saliency map and a ground-truth map. In (Fan et al., 2017), the authors discussed an easy approach to compute structural similarities for evaluating non-binary fore-ground maps. To tackle the problem of camouflaged object detection, the authors of (Fan et al., 2020) compiled a dataset, COD10K, consisting of 10000 annotated images of camouflaged objects over 78 object categories. Furthermore, they developed a prediction model, SINet (Search Identification

Network), to solve camouflaged object detection problems. This is the model that we employed in this project. Lastly, we found that the image datasets presented in (Le et al., 2019) were more suitable for our experiments.

In this article, we first discuss the approach and methodology for testing and evaluating the chosen camouflaged object detection algorithm. This is followed by a description of the datasets selected and the experiments designed for model assessment. Then, we present our empirical results and some insights. Lastly, we conclude with our plans for future research.

2 Approach and Methodology

To begin, we searched and investigated existing open-source artificial intelligence/machine learning methods for camouflaged object detection (COD). Literature and on-line search led us to the 2020 CVPR (IEEE Computer Vision Pattern Recognition) paper authored by Fan et al. (Fan et al., 2020). The article provided the link to their GitHub site `https://github.com/DengPingFan/SINet/` with the PyTorch code for the SINet model.

With the COD algorithm identified, we proceeded to search for appropriate datasets for model assessment. The paper (Le et al., 2019) shared a link to the COD dataset used in the article. Another on-line search on military camouflage led us to the DEPSOC Mission Camouflage Effectiveness video found at `https://www.youtube.com/watch?v=14m3YFNg4YE`.

Next, we designed a series of experiments to test (1) the capability of SINet in detecting camouflaged objects, (2) the effectiveness of the model in detecting previously untrained and unseen objects, and (3) the model performance on distant objects.

Prior to conducting the experiments, we studied and tested the chosen SINet model on limited data samples to ensure proper model implementation. During the course of the project, we learned that proper fine-tuning and structural modifications were necessary to improve SINet's performance in camouflaged object detection.

2.1 Search Identification Network model

The SINet model is a complex framework designed for camouflaged object detection. Functionally it has the receptive field (RF) and partial decoder components (PDC). While the RF component resembles the human visual system for recognizing the differences between the target object and its background, the PDC component focuses on the search and identification tasks. Structurally, the model contains two main modules. The search module (SM) utilizes a ResNet-50 architecture to produce discriminative feature representations. On the other hand, the identification module (IM) leverages a combination of convolutional layers, batch normalization, and ReLU activation function to detect the camouflaged target. The general block diagram of an SINet is shown in Figure 1 .

2.2 Datasets

Two separate image datasets were used in our experiments.

<u>CAMO Data</u>

The first set was borrowed from `https://sites.google.com/view/ltnghia/research/camo`. The CAMO (Camouflaged Object) data was generated particularly to evaluate model performance for camouflaged object segmentation (Le et al., 2019; Lin et al., 2015). The images are categorized into two groups, naturally and artificially camouflaged animals and humans as well. There are in total 1250 images with a usual 80/20 training/test split for each group. Some examples are given below.

<u>DEPSOC Mission Camouflage Data</u>

The second set of images was captured from the video shown in `https://www.youtube.com/watch?v=14m3YFNg4YE`. The video was produced to assess the effectiveness of the DEPSOC Mission camouflage pattern in wooded environments during the fall/winter season. In it an individual wearing a uniform with camouflage pattern can be seen in either a stationary position or movement concealed in the environment. The size of the image of the individual and the degree of

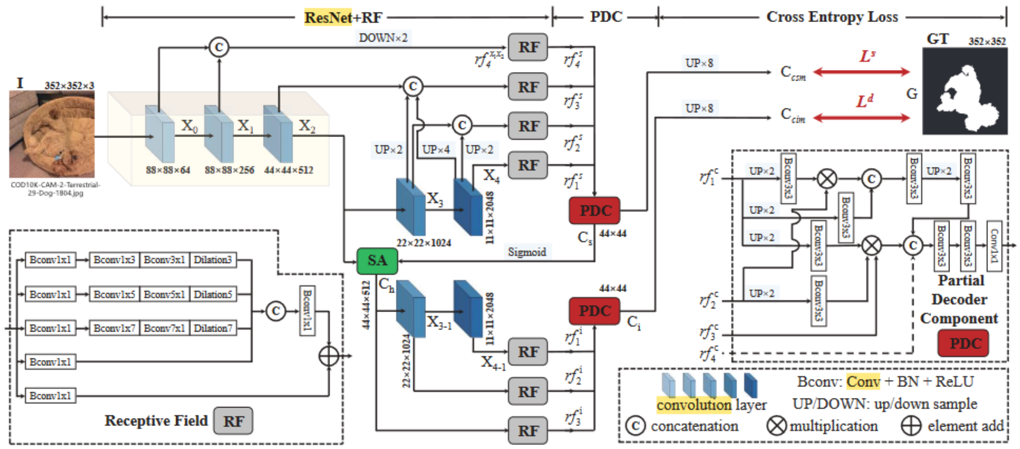

Figure 8: Overview of our *SINet* framework, which consists of two main components: the receptive field (RF) and partial decoder component (PDC). The RF is introduced to mimic the structure of RFs in the human visual system. The PDC reproduces the search and identification stages of animal predation. SA = search attention function described in [68]. See § 4 for details.

Figure 1: General block diagram of an SINet camouflaged object detection model.

Figure 2: The upper panel shows four cases of camouflaged objects blending into their background. The lower panel shows the detected objects.

body exposure vary in different scenes. Twenty two still images generated from the video were used in our experiments. Four example images are given below.

Figure 3: Still images captured from the DEPSOC Mission Camouflage Pattern video. The size of the target image and its level of exposure vary in different scenes. The orange arrow pinpoints the target location in each image.

2.3 Experiments and Results

We conducted our experiments in three phases. In the first phase, we implemented the SINet model, trained it and verified its detection capability on the CAMO dataset, following the 80/20 training/test split rule of thumb. In the second phase, we again trained the model over the original training dataset which does not contain any images of individuals wearing camouflaged uniform. We then applied the trained model on still images captured from the DEPSOC Mission Camouflage dataset. Even without having added any cross-domain adaptation or transfer learning techniques, the SINet model managed to detect the presence of the concealed target. After tuning the model several times, we were able to obtain much clearer results. In the final phase, we wished to determine if the algorithm was effective when the size of the target is small in comparison to the entire image. In other words, we wanted to find out if SINet would fail completely if the target image is too small. Our results showed that SINet was successful in some cases but ineffective in others, suggesting that the target size may not be as critical as expected when other factors are considered.

Some of our empirical results are shown in the following figures.

Phase 1: SINet trained and evaluated on selected CAMO images

Figure 4: Phase 1 results from trained SINet model applied on selected CAMO test images. In each paired image, the left panel shows the camouflaged object while the right panel reveals the outline of the detected target.

Phase 2: SINet trained with CAMO images but evaluated on previously untrained/unseen camouflaged Marine

Figure 5: Phase 2 results from trained SINet model applied on previously untrained/unseen camouflaged Marine. In each paired image, the left panel shows the camouflaged Marine while the right panel finds the location of the detected target.

Figure 6: After repeated fine-tuning, the SINet model generates much clearer detection of the target Marine. Upper panel: After fine-tuning, the model not only detects but also produces better-defined body segments. Lower panel: Camouflaged object detection results before model fine-tuning.

Phase 3: Measuring the effectiveness of SINet camouflaged object detection algorithm on distant objects

Figure 7: Phase 3 results from trained SINet model applied on distant targets. In each paired image, the left panel shows the camouflaged object while the right panel reveals the location of the detected target.

Success and Failure

We noticed that in many cases the SINet algorithm worked well after model tuning and structural modification. However, without appropriate training dataset that contains images of the expected target and corresponding surroundings, the model could reach its performance limit quickly. This is demonstrated below.

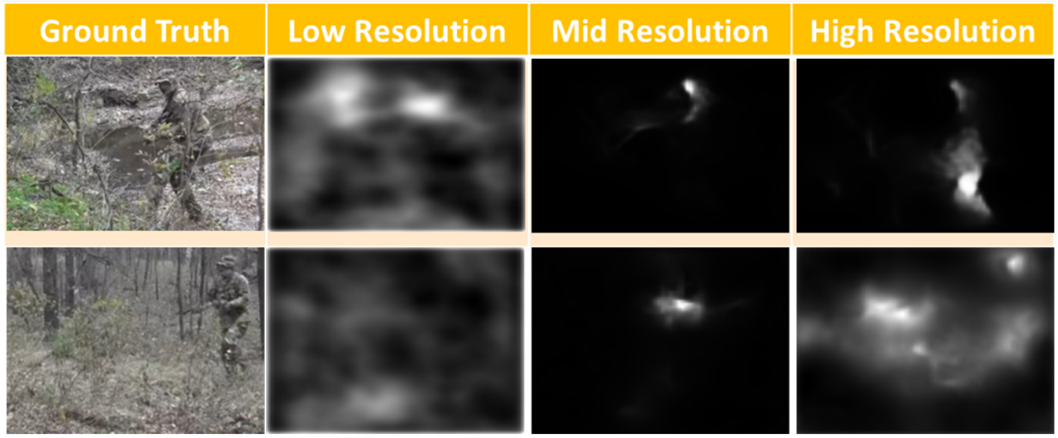

Figure 8: Success and Failure. Upper panel: The SINet model gradually improves its detection performance as additional tuning and layer modification. Lower panel: Model detection performance is not consistent or robust.

3 Conclusions and Future Work

In this work, we explored and implemented SINet, an open-source camouflaged object detection model. We tested and evaluated its algorithm on the CAMO camouflaged object dataset and still images captured from the DEPSOC Mission Camouflage video. Our empirical results showed that the model could perform well even on targets that were absent from the training set, without additional cross-domain or transfer learning techniques. However, without a training dataset that contains images of the expected target and corresponding surroundings, the model may not be able to detect the previously unseen target consistently.

Our future research will seek to accomplish three main tasks. First, we want to assess the SINet model on EO(electro-optics)/IR(infrared) images. In addition, we want to investigate the factors that limit the detection performance of the model. Finally, we plan to modify the model structure to conduct camouflaged signal detection experiments in real-time.

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