



中国科学院大学  
University of Chinese Academy of Sciences

# 硕士学位论文

中国科学院大学学位论文L<sup>A</sup>T<sub>E</sub>X模板  $\pi\pi\pi$

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学位类别： 理学硕士

学科专业： 流体力学

培养单位： 中国科学院力学研究所

2014 年 6 月



**L<sup>A</sup>T<sub>E</sub>X Thesis Template**  
**of**  
**The University of Chinese Academy of Sciences  $\pi\pi$**

**A thesis submitted to the**  
**University of Chinese Academy of Sciences**  
**in partial fulfillment of the requirement**  
**for the degree of**  
**Master of Natural Science**  
**in Fluid Mechanics**

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**June, 2014**



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## 摘 要

本文是中国科学院大学学位论文模板`ucasthesis`的使用说明文档。主要内容为介绍 $\text{\LaTeX}$ 文档类`ucasthesis`的用法，以及如何使用 $\text{\LaTeX}$ 快速高效地撰写学位论文。

**关键词：** 中国科学院大学，学位论文， $\text{\LaTeX}$ 模板





## Abstract

This paper is a help documentation for the  $\text{\LaTeX}$  class ucasthesis, which is a thesis template for the University of Chinese Academy of Sciences. The main content is about how to use the ucasthesis, as well as how to write thesis efficiently by using  $\text{\LaTeX}$ .

**Keywords:** University of Chinese Academy of Sciences (UCAS), Thesis,  $\text{\LaTeX}$  Template



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## 符号列表

## 字符

Symbol	Description	Unit
$R$	the gas constant	$\text{m}^2 \cdot \text{s}^{-2} \cdot \text{K}^{-1}$
$C_v$	specific heat capacity at constant volume	$\text{m}^2 \cdot \text{s}^{-2} \cdot \text{K}^{-1}$
$C_p$	specific heat capacity at constant pressure	$\text{m}^2 \cdot \text{s}^{-2} \cdot \text{K}^{-1}$
$E$	specific total energy	$\text{m}^2 \cdot \text{s}^{-2}$
$e$	specific internal energy	$\text{m}^2 \cdot \text{s}^{-2}$
$h_T$	specific total enthalpy	$\text{m}^2 \cdot \text{s}^{-2}$
$h$	specific enthalpy	$\text{m}^2 \cdot \text{s}^{-2}$
$k$	thermal conductivity	$\text{kg} \cdot \text{m} \cdot \text{s}^{-3} \cdot \text{K}^{-1}$
$S_{ij}$	deviatoric stress tensor	$\text{kg} \cdot \text{m}^{-1} \cdot \text{s}^{-2}$
$\tau_{ij}$	viscous stress tensor	$\text{kg} \cdot \text{m}^{-1} \cdot \text{s}^{-2}$
$\delta_{ij}$	Kronecker tensor	1
$I_{ij}$	identity tensor	1

## 算子

Symbol	Description
$\Delta$	difference
$\nabla$	gradient operator
$\delta^\pm$	upwind-biased interpolation scheme

## 缩写

CFD	Computational Fluid Dynamics
CFL	Courant-Friedrichs-Lewy
EOS	Equation of State

JWL	Jones-Wilkins-Lee
WENO	Weighted Essentially Non-oscillatory
ZND	Zel'dovich-von Neumann-Doering

## 第1章 END-TO-END TEMPORAL FEATURE AGGREGATION FOR SIAMESE TRACKERS

### 1.1 Abstract

While siamese networks have demonstrated the significant improvement on object tracking performances, how to utilize the temporal information in siamese trackers has not been widely studied yet. In this paper, we introduce a novel siamese tracking architecture equipped with a temporal aggregation module, which improves the per-frame features by aggregating temporal information from adjacent frames. This temporal fusion strategy enables the siamese trackers to handle poor object appearance like motion blur, occlusion, *etc.* Furthermore, we incorporate the adversarial dropout module in the siamese network for computing discriminative target features in an end-to-end-fashion. Comprehensive experiments demonstrate that the proposed tracker performs favorably against state-of-the-art trackers.

### 1.2 Introduction

Visual object tracking is the task of estimating the state of an arbitrary target in each frame of a video sequence. Recently, siamese networks have demonstrated the significant improvement on object tracking performances. However, the learned generic representation may be less discriminative because of the deteriorated object appearances in videos (Fig. 1.1), such as motion blur, occlusion, *etc.* Researchers try different ways to improve the feature representation. For example, SA-Siam ? separately trains two branches to keep the heterogeneity of semantic/appearance features. In DaSiamRPN ?, a novel distractor-aware incremental learning module is designed, which can effectively transfer the general embedding to the current video domain and incrementally catch the target appearance variations during inference. SiamRPN++ ? introduces a simple yet effective sampling strategy to drive the siamese tracker with more powerful deep architectures. These efforts have produced some impact and improved state-of-the-art accuracy. However, all above siamese algorithms perform tracking based on features cropped from only the current frame, which limits the power of siamese trackers.



图 1.1 A comparison of our method with SiamMask and SiamFCv2. The example frames are from the GOT-10k testing set. Our approach effectively handles poor object appearance compared to existing approaches.

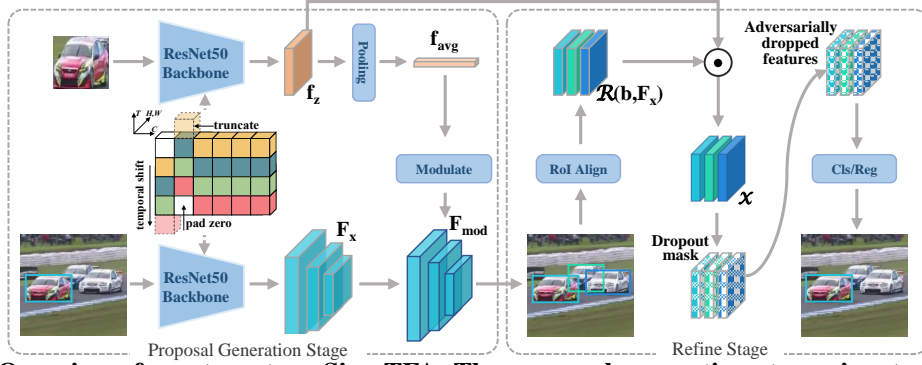


图 1.2 Overview of our two-stage SiamTFA. The proposal generation stage aims to generate proposals that are visually similar to the given template target. The refine stage aims to select the target from candidate proposals.

Actually, the video has rich information about the target and such temporal information is an important basis for video understanding and tracking. For example, in video object detection, FGFA ? leverages temporal coherence on feature level. It improves the per-frame features by aggregation of nearby features along the motion paths, and thus improves the video recognition accuracy. In video object segmentation, STCNN ? introduces a temporal coherence module, which focuses on capturing the dynamic appearance and motion cues to provide the guidance of object segmentation. In discriminative correlation filter-based object tracking, FlowTrack ? focuses on making use of the rich flow information in consecutive frames to improve the feature representation and the tracking accuracy. However, how to utilize the temporal information in siamese trackers has not been widely studied yet.

In this paper, we aim to take full advantage of temporal information in siamese trackers. We introduce a novel siamese tracking architecture equipped with a temporal aggregation module, which improves the per-frame features by aggregating features

from adjacent frames. This temporal fusion strategy enables the siamese tracker to handle poor object appearance like motion blur, occlusion, *etc.* To achieve this, we shift the channels along the temporal dimension ? in the backbone of the siamese network. Note that features of the same object are usually not spatially aligned across frames due to video motion ?, so the temporal shift is only performed on the residual layers ? to preserve the spatial feature learning capability of the siamese tracker. Different from other temporal fusion methods ??, the proposed method is able to be trained end-to-end on large-scale datasets. Additionally, our temporal fusion method is easy to implement, without changing the siamese tracking architecture or using optical flow ?.

To improve the robustness of target features, we further incorporate an adversarial dropout ? module in the siamese tracking network. Specifically, we first predict adversarial dropout masks based on divergence maximum. Then, we aim to minimize the divergence between the randomly dropped features and the adversarially dropped features. This module has both the advantages of dropout and adversarial training: the dropout makes our siamese network randomly disconnects neural units during training to prevent the co-adaptation of target features and the adversarial training enforces our tracker to learn difficult cases.

### 1.3 The proposed Method

In this section, we will introduce the proposed siamese architecture-based tracking method, namely SiamTFA (Fig. 1.2), which is inspired by the great success of siamese trackers ??. Specifically, SiamTFA takes an image pair as input, comprising a template image and a search image. The template image is the image patch cropped from the initial frame according to ground truth bounding box. The search image is one whole frame in the remaining of the video. Both inputs share the same feature extractor and parameters. Inspired by the success of the two stage detection paradigm ?, our siamese tracker is also a two stage method. The first stage aims to generate proposals that are visually similar to the given template target. In this stage, we introduce a temporal aggregation module to enhance the temporal information (Sec. 1.3.1). The second stage aims to identify the target from candidate proposals. In this stage, we insert an

adversarial dropout module to learn more robust features (Sec. 1.3.2).

### 1.3.1 Temporal aggregation module

The proposal generation stage consists of 3 components: (1) feature extractor, (2) temporal aggregation module, and (3) feature modulation module. The feature extractor generates the search features and the template feature for the search image and the template image, respectively. The temporal aggregation module is integrated into the feature extractor to utilize the temporal information. The feature modulation module merge the search features and the template feature to recognize the candidate targets.

**Feature extractor** To deal with the scale change of the target, we use Res50-FPN as our feature extractor. Feature Pyramid Network (FPN) exploits the inherent multi-scale, pyramidal hierarchy of deep convolutional networks to construct feature pyramids with marginal extra cost. Our siamese FPN takes a template image and a search image as input. For the search image, the FPN outputs proportionally sized feature maps at multiple levels, in a fully convolutional fashion. We denote the output for the search image as  $F_x = \{f_x^i\}_{i=1:5}$ , and note that they have strides of  $\{4, 8, 16, 32, 64\}$  pixels with respect to the input search image. For the template image, we use the last stage of the FPN output as the template feature with a spatial size of  $7 \times 7$ .

**Temporal aggregation module** Most popular siamese trackers use the still image to make prediction. This limits the ability of these siamese trackers. On one hand, tracking on single frame generates unstable results and fails when appearance is poor (Fig. 1.1); on the other hand, temporal adjacent frames can provide more information about the target. So we aim to improve the per-frame features by aggregating features of adjacent frames. Specifically, we insert a temporal aggregation module into the last stage of the feature extractor. To model temporal information, the images in one batch are several adjacent frames in the same video and are sorted by time, so we can regard the batch dimension as the time dimension. Assume the feature map at the last stage of the feature extractor is  $f \in \mathbb{R}^{T \times C \times H \times W}$ . For each time  $t \leq T$ , we first split feature  $f^t \in \mathbb{R}^{C \times H \times W}$  into 3 parts along the channel dimension:  $f_{1:K}^t \in \mathbb{R}^{K \times H \times W}$ ,  $f_{(K+1):2K}^t \in \mathbb{R}^{K \times H \times W}$ , and  $f_{(2K+1):C}^t \in \mathbb{R}^{(C-2K) \times H \times W}$ . Then we shifts the channels along

the temporal dimension following ?:

$$f_{agg}^t = \mathcal{C}(f_{1:K}^{t-1}, f_{(K+1):2K}^{t+1}, f_{(2K+1):C}^t), \quad (1.1)$$

where  $\mathcal{C}(\cdot)$  is the concatenation operation. According to ?, the shift operation is only performed at the residual layer to preserve the spatial feature learning capability of the siamese tracker. Note that the aggregated feature  $f_{agg}^t$  has the same shape with  $f^t$ , so we can insert this module into the backbone directly, without the need to change other part of the network. What's more, this operation only needs to do data movement, so it is computationally free and can be trained end-to-end.

**Feature modulation module** After getting the template feature  $f_z$  and the search feature pyramid  $F_x = \{f_x^i\}_{i=1:5}$ , they are modulated to generate target-specific features. Specifically, The modulation vector  $f_{avg}$  is generated from  $f_z$  using global average pooling, which carries the target-specific appearance information. The modulated feature pyramid  $F_{mod} = \{f_{mod}^i\}_{i=1:5}$  is generated as follows:

$$f_{mod}^i = \mathcal{M}(f_{avg}, f_x^i), \quad (1.2)$$

where  $\mathcal{M}(\cdot)$  is the depth-wise correlation ?. Each modulated feature map is fed into two sibling fully-connected layers—a box-regression layer with channel dimension  $4k$ , and a box classification layer with channel dimension  $2k$ , where  $k$  is the number of maximum possible proposals for each location. The object/background criterion and bounding box regression are defined with respect to a set of anchors. Following ?, we assign anchors with the same scale to each of the different pyramid levels. For detail information of the anchor setting, please refer to ?. We use the top- $N$  ranked proposal regions for the refine stage.

### 1.3.2 Adversarial dropout module

The refine stage aims to select the target from candidate proposals. Features of these candidate proposals are cropped from the search feature pyramid  $F_x$  using RoIAlign ?, and then fused with the target feature  $f_z$ :

$$\mathcal{X} = \mathcal{R}(b, F_x) \odot f_z, \quad (1.3)$$

where  $\mathcal{R}$  represents the RoIAlign,  $\odot$  represents the element-wise multiplication,  $b$  represents an RoI in candidate proposals and  $\mathcal{X}$  represents the fused feature of  $b$ .

**Adversarial dropout** After the feature fusion, we use adversarial dropout ?? to increase the discriminative ability of  $\mathcal{X}$ . We first predict the adversarial dropout mask based on divergence maximum. The mask is applied to  $\mathcal{X}$  to get the adversarially dropped features. Then, we aim to minimize the divergence between the randomly dropped features and the adversarially dropped features. Specifically, let  $h^{cls}$  and  $h^{reg}$  denote the classification layer and the regression layer in stage 2, respectively. The adversarial dropout mask is calculated as follows according to ?:

$$\mathbf{m}^{adv} = \arg \max_{\mathbf{m}} D[h^{cls}(\mathcal{X} \odot \mathbf{m}^s), h^{cls}(\mathcal{X} \odot \mathbf{m})] \quad (1.4)$$

where  $\|\mathbf{m}^s - \mathbf{m}\| \leq \delta_e L$ ,

where  $L$  represents the dimension of  $\mathbf{m} \in \mathbb{R}^L$ ,  $\mathbf{m}^s$  represents the random mask and  $\mathbf{m}^{adv}$  represents the adversarial mask.  $\delta_e$  is a hyper parameter to control the perturbation magnitude with respect to  $\mathbf{m}^s$  ?.  $D[p, p'] \geq 0$  measures the divergence between two distributions  $p$  and  $p'$ .

To calculate  $\mathbf{m}^{adv}$ , ? optimizes a 0/1 knapsack problem with appropriate relaxations in the process. Please refer to ? for detail information. After generating  $\mathbf{m}^{adv}$ , we then aim to minimize the divergence between two predicted distribution regarding to  $\mathcal{X}$ : one with a random dropout mask  $\mathbf{m}^s$  and another with an adversarial dropout mask  $\mathbf{m}^{adv}$  ?.

$$\mathcal{L}_{adv} = \mathbb{E}[D_{KL}[h^{cls}(\mathcal{X} \odot \mathbf{m}^s) || h^{cls}(\mathcal{X} \odot \mathbf{m}^{adv})]], \quad (1.5)$$

where  $D_{KL}$  is the Kullback-Leibler divergence.

Finally, for each RoI, the classification layer produces softmax probability estimates over two classes (foreground or background) and the regression layer outputs four real-valued numbers for the foreground class. These four values encode the refined bounding-box position for the RoI. The loss of SiamTFA is:

$$\mathcal{L} = \mathcal{L}_{cls}^{stage1} + \mathcal{L}_{cls}^{stage2} + \mathcal{L}_{reg}^{stage1} + \mathcal{L}_{reg}^{stage2} + \lambda \mathcal{L}_{adv}, \quad (1.6)$$

where  $\lambda$  is a hyper-parameter to balance the adversarial loss and the classification/regression loss.  $\mathcal{L}_{cls}$  is the cross entropy loss and  $\mathcal{L}_{reg}$  is the standard smooth  $L1$  loss for



regression. During testing, the RoI with the top classification score is selected as the predicted target.

## 1.4 Experiments

In this section, we first present the implementation details. Then we evaluate our method on GOT-10K ? testing set and the UAV20L ? dataset.

### 1.4.1 Implementation details

The proposed network is trained on the training set of GOT-10k ? and the backbone is pretrained on ImageNet. We apply stochastic gradient descent with momentum of 0.9 and set the weight decay to 0.0005. The learning rate is decreased from  $10^{-2}$  to  $10^{-4}$ . The batch size is set to 2 and the network is trained for 90000 iterations. Our tracker is implemented in Python, using PyTorch.

### 1.4.2 Evaluation on GOT-10k dataset

In this subsection, we evaluate our method on GOT-10k ? dataset. GOT-10k is a recent large-scale high-diversity dataset consisting of over 10,000 video sequences with targets annotated by axis-aligned bounding boxes. The GOT-10k testing set includes 180 sequences with 84 different object classes and 32 motion patterns. As performance measure, we use the average overlap (AO) scores and success rate (SR) as proposed in ?. The AO denotes the average of overlaps between all groundtruth and estimated bounding boxes, while the SR measures the percentage of successfully tracked frames where the overlaps exceed 0.5/0.75.

**Ablation Studies** From Table 1.1 (the 1<sup>st</sup> and 2<sup>nd</sup> row), we see that the AO perfor-

表 1.1 Performance of our algorithm with different components on GOT-10k test set.

Temporal aggregation	Adversarial dropout	AO	SR <sub>0.50</sub>	SR <sub>0.75</sub>
		0.542	0.607	0.456
✓		0.561	0.645	0.480
✓	✓	0.577	0.662	0.509

表 1.2 Comparing the results of our approach against other approaches over the GOT-10k test set.

Method	$AO$	$SR_{0.50}$	$SR_{0.75}$
Ours	<b>0.577<sup>1</sup></b>	<b>0.662<sup>1</sup></b>	<b>0.509<sup>1</sup></b>
SiamMask	0.459	0.560	0.205
SiamFCv2	0.374	0.404	0.144
SiamFC	0.348	0.353	0.098
GOTURN	0.347	0.375	0.124
CCOT	0.325	0.328	0.107
ECO	0.316	0.309	0.111
CF2	0.315	0.297	0.088
MDNet	0.299	0.303	0.099

mance increases by 1.9% by adding the temporal aggregation module. This is because the temporal aggregation module improves the per-frame features by aggregating temporal information from adjacent frames. From Table 1.1 (the 2<sup>nd</sup> and 3<sup>rd</sup> row), we see that with the adversarial dropout module, the AO increases by 1.6%. This is because the adversarial dropout module improves the discrimination power of our siamese tracking network.

**Overall Performance** We compare our proposed method with 8 trackers, including state-of-the-arts. The performances of the evaluated trackers is shown in Table 1.2. Compared to other listed approaches, our approach achieves a superior AO of 0.577. Compared with SiamMask, our tracker aims to make full use of the temporal information. As a result, our tracker outperforms SiamMask by 11.8% in terms of AO, which highlights the importance of the proposed temporal aggregation module.

#### 1.4.3 Evaluation on UAV20L dataset

In this subsection, we evaluate our tracker on the UAV20L ? long term tracking dataset. It contains 20 HD video sequences captured from a low-altitude aerial perspective with average sequence length of 2934 frames. In this experiment, all trackers are compared using two measures: precision and success. Precision is measured as

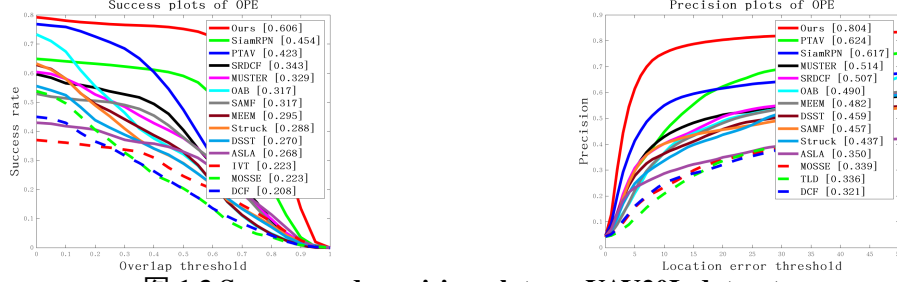


图 1.3 Success and precision plots on UAV20L dataset.

the distance between the centers of the predicted bounding box and the corresponding ground truth bounding box. Success is measured as the intersection over union of pixels in predicted bounding box and those in ground truth bounding box. In Fig. 1.3, we can find that the proposed algorithm achieves better tracking performance compared with some representative trackers. In the success plot, our tracker obtains an AUC score of 0.606. In the precision plot, the proposed algorithm obtains a score of 0.804. It shows that our tracker surpass other state-of-the-art algorithms, such as SiamRPN ? and PTAV ?. This demonstrates the effectiveness of our tracker in long-term tracking scenario.

## 1.5 Conclusion

In this paper, we introduce a novel siamese architecture for visual object tracking. Specifically, our proposed algorithm contains two main modules, *i.e.* temporal aggregation module and adversarial dropout module. The temporal aggregation module improves the per-frame features by aggregating features of adjacent frames. The adversarial dropout module improves the discrimination power of the siamese tracking network. Extensive experimental results show that the proposed algorithm performs favorably against the state-of-the-art algorithms.



## 第2章 Manipulating Template Pixels for Model Adaptation of Siamese Visual Tracking

### 2.1 Abstract

In this letter, we show that the challenging model adaptation task in visual object tracking can be handled by simply manipulating pixels of the template image in Siamese networks. For a target that is not included in the offline training set, a slight modification of the template image pixels will improve the prediction result of the offline trained Siamese network. The popular adversarial example generation methods can be used to perform template pixel manipulation for model adaptation. Different from current template update methods, which aim to combine the target features from previous frames, we focus on the initial adaptation using target ground-truth in the first frame. Our model adaptation method is pluggable, in the sense that it does not alter the overall architecture of its base tracker. To our knowledge, this work is the first attempt to directly manipulating template pixels for model adaptation in Siamese-based trackers. Extensive experiments on recent benchmarks demonstrate that our method achieves better performance than some other state-of-the-art trackers. Our code is available at <https://github.com/lizhenbang56/MTP>.

### 2.2 Introduction

Object tracking refers to the task of sequentially locating a specified moving object in a video, given only its initial state. Recently, Siamese networks ?? have demonstrated a significant improvement in object tracking performances. Siamese trackers formulate the visual object tracking problem as learning cross-correlation similarities between a target template and a search region. Tracking is then performed by finding the target object from the search image region by computing the highest visual similarity. Despite its recent success, the learned similarity measure of the Siamese network is not necessarily reliable for objects that are not included in the offline training set, leading to poor generalization ?. Several recent works aim to adapt the model to the current target appearance. For example, TADT ? identifies the importance of each convolutional

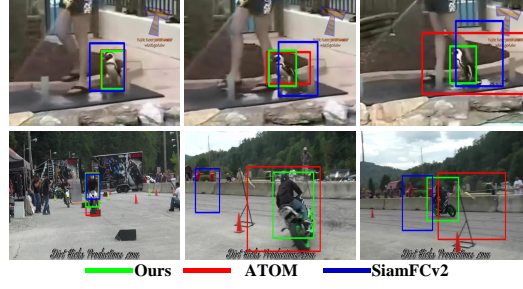


图 2.1 A comparison of our method with the state-of-the-art trackers ATOM ? and SiamFCv2 ? in challenging situations. The example frames are from the GOT-10k ? testing set.

filter according to the back-propagated gradients and selects the target-aware features based on activations for representing the targets. However, the feature extractor of TADT is pre-trained on ImageNet ?, not on large-scale visual tracking datasets. This limits the representation ability of its features on the object tracking task. GradNet ? exploits the discriminative information in gradients and updates the template in the Siamese network through feed-forward and backward operations. However, the extra sub-network increases the computational cost and is prone to overfitting. UpdateNet ? learns to combine the target features from previous frames. However, it does not use ground truth information to adaptively adjust the template features of the first frame.

In this work, we show that the challenging model adaptation task in visual object tracking can be handled by simply manipulating pixels of the template image in Siamese networks. Given an object tracker, our algorithm modifies template pixels in only a few gradient-descent iterations using the target ground-truth in the first frame. For a target that is not included in the offline training set, we believe that a slight modification of the template image pixels can improve the prediction result of the offline trained Siamese network. We use the adversarial example generation method to achieve this, because it is commonly used to slightly modify the input image, and thereby impose an impact on the prediction result of the network. We depart from the purpose of adversarial sample generating in that the latter is aimed to make the prediction of the network worse, while we hope the prediction of the Siamese network is better. The proposed model adaptation method can be integrated with varieties of Siamese trackers like SiamFC++ ?. Note that the parameters of the Siamese network remain intact to preserve the generative ability of offline-trained embedding space. We perform comprehensive experiments on

4 tracking benchmarks: VOT2018?, TrackingNet?, GOT-10k?, and OTB2015?. Our approach achieves state-of-the-art results while running at over 80 FPS (see Fig. 2.1).

### 2.3 Proposed Algorithm

In this section, we present a new model adaptation approach for Siamese trackers via directly manipulating template pixels. We start by revisiting the tracking process of popular template matching-based trackers, which is closely related to the proposed approach. Following ?, we formulate object tracking as a confidence-based regression problem, which learns a function  $s_\theta : \mathcal{Y} \times \mathcal{X} \rightarrow \mathbb{R}$ , and predicts a scalar confidence score  $s_\theta(y, x) \in \mathbb{R}$  given an output-input pair  $(y, x)$ . The final estimate  $f(x) = y^*$  is predicted as follows:

$$f(x) = \arg \max_{y \in \mathcal{Y}} s_\theta(y, x), \quad (2.1)$$

where  $x$  is an input image.  $y$  usually represents the center 2D image coordinate of the target object. Currently, there are two prevalent template matching-based paradigms: discriminative correlation filter (DCF) approaches and Siamese tracking methods.

In DCF-based methods, a circular correlation filter  $w_\theta$  is trained during tracking to predict a target confidence score:

$$s_\theta(y, x) = (w_\theta * \phi(x))(y), \quad (2.2)$$

where  $\phi(x)$  is the features extracted from the search image  $x$ .

In contrast to DCF, Siamese trackers exploit a two-stream architecture. One stream extracts the target's features  $\phi_\theta(z)$  based on the template image  $z$  which is cropped from the first frame according to the ground truth bounding box. The other stream receives as input a large search image  $x$  and outputs the search features  $\phi_\theta(x)$ . The two outputs are cross-correlated to predict a target confidence score:

$$s_\theta(y, x) = (\phi_\theta(z) * \phi_\theta(x))(y). \quad (2.3)$$

DCF-based trackers and Siamese trackers both have the advantage of utilizing large-scale visual tracking datasets to train the feature extractor  $\phi(\cdot)$  or the embedding network  $\phi_\theta(\cdot)$  by their own right. This way the representation ability of features on the object tracking task can be enhanced.

In contrast to Siamese trackers, DCF learns the filter  $w_\theta$  from example patches of the target appearance to discriminate it from the background. Despite the improved tracking efficiency using the circular correlation operation, its boundary effect and sophisticated optimization prevent itself from making a good trade-off between computational speed and tracking performance. Siamese trackers do better in this aspect, although the learned similarity measure in the cross-correlation is not necessarily reliable for objects that are not included in the offline training set, leading to poor generalization.

In this letter, we aim to design a new Siamese tracking method that has the ability to make full use of the specific information of the current video for model adaptation like the DCF-based trackers, although the object in it is not included in the offline training set. This is achieved by utilizing the annotation information in the first frame to perform model adaptation.

Note that Equ. (2.2) and Equ. (2.3) bear some similarities with each other, and the main difference lies in the kernel term for correlation: the kernel of DCF is the online-learned  $w_\theta$ , and the kernel of the Siamese network is  $\phi_\theta(z)$ . In order for the Siamese network to have the model adaptation ability, we need to adapt  $\phi_\theta(z)$  using the first frame ground truth annotation of the current video. There are two design choices to adapt  $\phi_\theta(z)$ : changing  $\phi_\theta(\cdot)$  or changing  $z$ . However, changing  $\phi_\theta(\cdot)$  may cause too much tedious meta-learning settings to ensure the generative ability of offline-trained embedding space  $\mathcal{Z}$ . In contrast, our solution is in a simple way to perform model adaptation of Siamese trackers by changing  $z$ , i.e., modifying template pixels in only a few gradient-descent iterations using the target ground-truth at the first frame. Compared with current model adaptation methods of Siamese trackers, the proposed method has the following advantages. First, we never modify parameters of the Siamese network to preserve the representation ability of offline-trained embedding space. Second, different from current template update methods  $\mathcal{Z}$ , which aim to combine the target features from previous frames, we focus on the initial adaptation using target ground-truth at the first frame. Finally, our model adaptation method is pluggable, in the sense that it does not alter the overall architecture of the base tracker. In the next subsection, we will show how the popular adversarial example generation methods can be used to perform



template pixel manipulation for model adaptation.

### 2.3.1 Manipulating Template Pixels for Model Adaptation

At first glance, there may be a contradiction between the model adaptation task and the adversarial example generation task, because these two tasks have different purposes. An adversarial example ? is a sample of input data which has been modified very slightly in a way that is intended to perform an attack on machine learning systems, which means to cause a machine learning model to make wrong predictions. However, the purpose of model adaptation in our work is to make full use of the annotation information in the first frame to improve the tracking performance for the current video. We will point out in the following that there are some similarities between these two tasks and we can utilize adversarial example generation methods to perform the model adaptation task.

Before introducing the proposed method, we first revisit the popular adversarial example generation methods. One of the simplest methods to generate adversarial images  $I^{adv}$  works by linearizing loss function in  $L_\infty$  neighbourhood of a clean image and finds exact maximum of linearized function using following closed-form equation ?:

$$I^{adv} = I + \epsilon \operatorname{sign}(\nabla_I L(I, y_{true})), \quad (2.4)$$

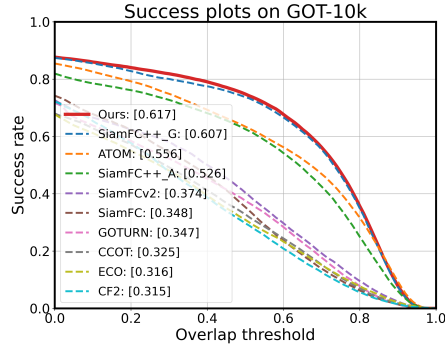
where  $I$  is the input image, and the values of the pixels are integer numbers in the range  $[0, 255]$ .  $y_{true}$  is the true label for the image  $I$ .  $L(I, y)$  is the cost function of the neural network for the attack purpose, given image  $I$  and label  $y$ .  $\epsilon$  is a hyper-parameter to be chosen. A straightforward way to extend the above method is applying it multiple times with small step size, and clipping pixel values of intermediate results after each step to ensure that they are in an  $\epsilon$ -neighbourhood of the original image. This leads to the Basic Iterative Method (BIM) introduced in ?:

$$\begin{aligned} I_0^{adv} &= I, \\ I_{N+1}^{adv} &= \operatorname{Clip}_{I, \epsilon} \{I_N^{adv} + \alpha \operatorname{sign}(\nabla_I L(I_N^{adv}, y_{true}))\}, \end{aligned} \quad (2.5)$$

where  $\operatorname{Clip}_{I, \epsilon} \{I'\}$  is the function which performs per-pixel clipping of the image  $I'$ , so that the result will be in  $L_\infty$   $\epsilon$ -neighbourhood of the source image  $I$ . The BIM can be

**表 2.1 State-of-the-art comparison on the popular tracking benchmark OTB2015 with the running speed. FPS: frame per second. Our speed is tested on an NVIDIA RTX 2080Ti GPU.**

Trackers	ECO	MDNet	SiamRPN++	ATOM	SiamFC++_G	Ours
Success	70.0	67.8	69.6	66.9	68.3	69.7
FPS	8	1	35	30	90	82



**图 2.2 Comparing the results of our approach against other approaches over the GOT-10k test set. The trackers are ranked by their average overlap scores.**

easily made into an attacker for a specific desired target class, called the Iterative Target Class Method ?:

$$I_0^{adv} = I, \quad (2.6)$$

$$I_{N+1}^{adv} = Clip_{I, \epsilon} \{I_N^{adv} - \alpha \text{sign}(\nabla_I L(I_N^{adv}, y_{target}))\}.$$

Equ. (2.6) shows that manipulating pixels of the input image in only a few gradient-descent iterations is able to change the network’s prediction to the target class  $y_{target}$ . Note that our purpose is manipulating pixels of the template image in the first frame, so that the prediction is closer to the ground truth bounding box. So we can perform model adaptation for Siamese networks using Equ. (2.6) with some modifications:

$$z_0 = z, \quad (2.7)$$

$$z_{N+1} = Clip_{z, \epsilon} \{z_N - \alpha \text{sign}(\nabla_z L(z_N, y_{bb}))\},$$

where  $z$  is the template image in the first frame, and  $y_{bb}$  is the label for Siamese trackers generated from the ground truth bounding box. In the next subsection, we will introduce the overall tracking process equipped with the proposed model adaptation module.

**表 2.2 state-of-the-art comparison on the TrackingNet test dataset in terms of precision, normalized precision and success.**

Method	Prec.	Norm. Prec.	Succ.
Ours	70.6	81.7	74.9
SiamFC++_G	70.5	80.0	75.4
SiamFC++_A	64.6	75.8	71.2
ATOM	64.8	77.1	70.3
SiamRPN++	69.4	80.0	73.3
MDNet	56.5	70.5	60.6
ECO	49.2	61.8	55.4
SiamFC	51.8	65.2	55.9

### 2.3.2 Tracking Framework

The proposed model adaptation method is integrated with the SiamFC++ tracker in a plug-and-play manner. SiamFC++ is based on SiamFC and progressively refined according to several guidelines proposed in [1]. The input of the original SiamFC++ network is composed of the template image  $z_0$  cropped from the first frame and search image  $x_i$  cropped from the  $i$ -th frame. However, we expect to perform template manipulating such that, after  $N$  steps of pixel update on the input pair  $(z_0, x_0)$  to obtain  $z'$ , the tracker performs well on  $(z', x_i)$ . To achieve this, we start by cropping the initial template image  $z_0 \in \mathbb{R}^{3 \times 128 \times 128}$  and the initial search image  $x_0 \in \mathbb{R}^{3 \times 289 \times 289}$  from the first frame using the ground truth bounding box. Then,  $z_0$  and  $x_0$  are sent to the SiamFC++ network to obtain the tracking prediction of the first frame. The tracking loss in SiamFC++ is calculated as follows:

$$L = L_{\text{cls}} + L_{\text{quality}} + L_{\text{reg}}, \quad (2.8)$$

where  $L_{\text{cls}}$  is the focal loss [1].  $L_{\text{quality}}$  is the binary cross entropy (BCE) loss for quality assessment.  $L_{\text{reg}}$  is the IoU loss [1] for bounding box regression. The gradient with respect to the template  $z_0$  is used to generate  $z_1$  according to Equ. (2.7). The updated template  $z'$  is obtained by applying a very small number of iterations of Equ. (2.7). Note that the template image is only updated with the first frame of given sequences and is kept fixed during the whole tracking process to ensure stability. The subsequent

tracking procedure remains the same as SiamFC++.

## 2.4 Experiments

In this section, we first present the implementation details. Then we compare our method with the state-of-the-art trackers on four tracking datasets: OTB2015 ?, VOT2018 ?, GOT-10k ? and TrackingNet ?. Specifically, OTB2015 ? includes 100 sequences, which are labeled with different attributes for in-depth analysis of tracking performance. VOT2018 ? uniquely applies a reset-based methodology and specially selects 60 sequences of various tracking scenarios for evaluation. GOT-10k ? and TrackingNet ? are two recent large-scale high-diversity datasets. They both cover diverse object classes and scenes in the train and test splits. For GOT-10k, there is no overlap in object classes between the train and test splits, promoting the importance of generalization to unseen object classes.

### 2.4.1 Implementation Details

We use SiamFC++ ? as our base tracker, and the backbone Siamese network adopts GoogLeNet ?. We do not perform any changes except for the model adaptation component. The parameter  $\alpha$  in Equ. (2.7) is set to 0.05. Our method is implemented in Python with PyTorch. The proposed tracker runs at over 80 FPS on an NVIDIA RTX 2080Ti GPU.

### 2.4.2 State-of-the-art Comparison

**OTB2015** We use success rate to evaluate the performance of trackers on the OTB2015 dataset. Success rate relies on the intersection over union (IOU) of the predicted bounding box and the ground truth bounding box. We compare our method with various tracking algorithms, including ECO ?, MDNet ?, SiamRPN++ ?, ATOM ? and SiamFC++\_GoogLeNet ?. The iteration number for template update is set to 16. The results are shown in Table 2.1. Our tracker outperforms the online tracker ATOM by 2.8% in terms of the success score, which demonstrates the powerful model adaptation capability of our method.

**VOT2018** We compare our method with RCO ?, UPDT ?, SiamRPN ?, MFT ?,

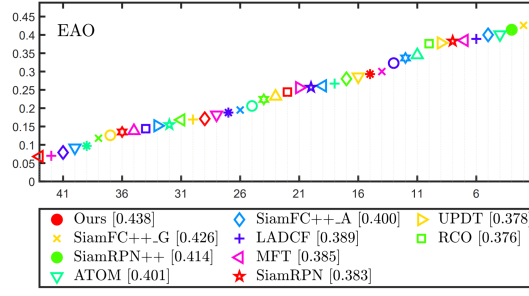


图 2.3 Expected average overlap graph with trackers ranked from right to left. The right-most tracker is the top-performing according to the VOT2018 expected average overlap values.

LADCF ?, ATOM ?, SiamRPN++ ?, SiamFC++\_AlexNet ? and SiamFC++\_GoogLeNet ? on VOT2018. The trackers are compared using the robustness and accuracy measures. Robustness indicates the number of tracking failures, while accuracy denotes the average overlap between tracker prediction and the ground-truth box. Both of the measures are combined into a single expected average overlap (EAO) score. The iteration number for template update is set to 2. As shown in Fig. 2.3, the performances of all the listed trackers are not as good as our algorithm.

**GOT-10k** We use the average overlap (AO) score as performance measure following ?. We compare our method with CF2 ?, ECO ?, CCOT ?, GOTURN ?, SiamFC ?, SiamFCv2 ?, ATOM ?, SiamFC++\_AlexNet ? and SiamFC++\_GoogLeNet ? on this dataset. The iteration number for template update is set to 2. In Fig. 2.2, we can find that the proposed algorithm achieves better tracking performance compared with the listed state-of-the-art trackers.

**TrackingNet** We compare our method with SiamFC ?, ECO ?, MDNet ?, SiamRPN++ ?, ATOM ?, SiamFC++\_AlexNet ? and SiamFC++\_GoogLeNet ?. The iteration number for template update is set to 32. Table 2.2 shows that our tracker performs best in terms of precision and the normalized precision while maintaining a very competitive success value.

### 2.4.3 Ablation Study

**Robustness to Noisy Initial Frames** To study how robust the approach is if the first frame is noisy compared to the next frames in the sequence, we add three kinds of noise to the first frame by: changing the image brightness, applying Gaussian blur, and using non-accurate ground truth bounding box annotation. We denote  $\gamma_1 \in [0.5, 1.5]$

表 2.3 Performance on OTB2015 using noisy initial frames.

Coefficients of Noise			Success Score	
$\gamma_1$	$\gamma_2$	$\gamma_3$	SiamFC++_G	Ours
0.57	1.6	0.93	67.3	69.5
0.88	0.22	0.86	65.7	68.0
0.88	0.43	0.77	64.1	64.4
0.92	0.98	0.82	65.6	66.6
0.98	0.83	0.84	66.5	67.9
1.0	0.81	0.79	65.3	66.0
1.1	1.9	0.90	67.6	68.8
1.2	0.70	0.79	65.7	66.6
1.5	0.19	0.79	64.8	66.3

表 2.4 11 attributes comparison on OTB2015 in term of success score.

	BC	DEF	FM	IV	IPR	LR	MB	OCC	OPR	OV	SV
SiamFC++_G	62.5	63.9	68.0	69.2	69.5	<b>72.5</b>	66.7	60.9	66.9	55.8	68.4
Ours	<b>66.5</b>	<b>66.8</b>	<b>68.7</b>	<b>71.3</b>	<b>69.6</b>	69.8	<b>67.3</b>	<b>62.5</b>	<b>68.4</b>	<b>57.1</b>	<b>69.8</b>

as the coefficient of brightness variation,  $\gamma_2 \in [0, 2]$  the blur radius, and  $\gamma_3 \in [0.75, 1]$  the IoU between the non-accurate first frame bounding box annotation and the real bounding box annotation, respectively. We run both the baseline tracker and our tracker 10 times on OTB2015 with randomly sampled  $\gamma_1$ ,  $\gamma_2$  and  $\gamma_3$  (see Table 2.3). Compared with SiamFC++\_GoogLeNet ?, our tracker always performs better under different noise levels, which shows the robustness of our tracker to noisy initial frames.

**Attribute-based Analysis** For further analyses on the tracking performance, we also demonstrate the advantages of our algorithm through the attribute-based comparison on sequences of the OTB-2015 dataset (see Table 2.4). In OTB2015, each sequence is annotated with 11 different attributes, namely: background clutters (BC), deformation (DEF), fast motion (FM), illumination variation (IV), in-plane rotation (IPR), low resolution (LR), motion blur (MB), occlusion (OCC), out-of-plane rotation (OPR), out-of-view (OV) and scale variation (SV). Compared with SiamFC++\_GoogLeNet ?, our tracker achieves better performance on 10 out of 11 attributes, which demonstrates its robustness in challenging tracking scenarios such as illumination variation and motion blur.

## 2.5 Conclusion

In this letter, we propose a novel model adaptation method for Siamese trackers, achieving accurate tracking with high speed. We show that the challenging model adaptation task in visual object tracking can be handled by simply manipulating pixels of the template image using the target ground-truth in the first frame. Our model adaptation method is pluggable, in the sense that it does not alter the overall architecture of the base tracker. Numerous experimental results on four object tracking benchmarks demonstrate the effectiveness of the proposed model adaptation method.





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### A.1 论文无附录者无需附录部分

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$$\begin{cases} \frac{\partial \rho}{\partial t} + \nabla \cdot (\rho \mathbf{V}) = 0 \\ \frac{\partial(\rho \mathbf{V})}{\partial t} + \nabla \cdot (\rho \mathbf{V} \mathbf{V}) = \nabla \cdot \boldsymbol{\sigma} \\ \frac{\partial(\rho E)}{\partial t} + \nabla \cdot (\rho E \mathbf{V}) = \nabla \cdot (k \nabla T) + \nabla \cdot (\boldsymbol{\sigma} \cdot \mathbf{V}) \end{cases} \quad \dots \text{ (A.1)}$$

$$\frac{\partial}{\partial t} \int_{\Omega} u \, d\Omega + \int_S \mathbf{n} \cdot (u \mathbf{V}) \, dS = \dot{\phi} \quad \dots \text{ (A.2)}$$

$$\mathcal{L}\{f\}(s) = \int_{0^-}^{\infty} f(t) e^{-st} \, dt, \quad \mathcal{L}\{f\}(s) = \int_{0^-}^{\infty} f(t) e^{-st} \, dt$$

$$\mathcal{F}(f(x+x_0)) = \mathcal{F}(f(x)) e^{2\pi i \xi x_0}, \quad \mathcal{F}(f(x+x_0)) = \mathcal{F}(f(x)) e^{2\pi i \xi x_0}$$

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mathbf:  **$A, F, L, 2, 3, 5, \sigma$** , mathit:  $A, F, L, 2, 3, 5, \sigma$ , mathsf:  $A, F, L, 2, 3, 5, \sigma$ .

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tensor:  $\boldsymbol{\sigma}, \mathbf{T}, \mathbf{a}, \mathbf{F}, \mathbf{n}$ , untensor:  $\boldsymbol{\sigma}, \mathbf{T}, \mathbf{a}, \mathbf{F}, \mathbf{n}$

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## 致 谢

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