Multi-layer Features Template Update Object Tracking Algorithm Based on SiamFC++

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Multi-layer Features Template Update Object Tracking Algorithm Based on SiamFC++

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Abstract: SiamFC++ only extracts the object feature of the first frame as a tracking template, and only uses the highest-level feature maps in both the classification branch and the regression branch, so that the respective characteristics of the two branches are not fully utilized. In view of this, the present paper proposes an object tracking algorithm based on SiamFC++. The algorithm uses the multi-layer features of the Siamese network to update template. First, FPN is used to extract feature maps from different layers of Backbone for classification branch and regression branch. Second, 3D convolution is used to update the tracking template of the object tracking algorithm. Next, a template update judgment condition is proposed based on mutual information. Finally, AlexNet is used as the backbone and GOT-10K as training set. Compared with SiamFC++, our algorithm obtains improved results on OTB100, VOT2016, VOT2018 and GOT-10k datasets, and the tracking process is real-time.

Key words: Object Tracking; Fully Convolutional Siamese Networks; Template Update; Mutual Information; FPN

1 Introduction

Object tracking is a research hotspot in the field of computer vision. Object tracking technology is widely used in fields such as intelligent video surveillance, human-computer interaction, robot visual navigation, virtual reality, and medical diagnosis. The object tracking field is mainly divided into single object tracking [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12] and multiple object tracking [13, 14].

The algorithm in this paper is a single object tracking algorithm. Early object algorithms such as Optical Flow method [1], Kalman filter [2], and Kernel method [3] are all processed in the time domain. Their calculation involves complex matrix inversion, the heavy computational load of which leads to poor real-time performance. The MOSSE algorithm [4] creatively introduced correlation filtering into the object tracking field. By converting the calculation from the time domain to the frequency domain, it utilizes the nature of the circulant matrix that can be diagonalized in the frequency domain, thus greatly reducing the amount of calculation and increasing its speed. Moreover, KCF [5] introduced a cyclic matrix on the basis of correlation filtering to increase the number of negative samples and improve the quality of classifier training. In the meanwhile, the Gaussian kernel, which can transform nonlinear problems into a high-dimensional linear space, was added to the ridge regression, thus simplifying the calculation.

With the maturity of deep learning technology, researchers began to apply it to object tracking. However, the increase in the number of convolutional layers and the complexity of the training network have led to poor real-time performance of the algorithms, failing to realize the real-time tracking of fast-moving objects. Nevertheless, the tracker based on the Siamese network [7, 8, 9, 10, 11, 12] could obtain image features through the Siamese network, and then perform matching

operations to achieve a balance between accuracy and real-time performance. Therefore, it has become another key research direction after correlation filtering.

SINT [6] applied the Siamese network to the object tracking field firstly, thus pioneering the conversion of the object tracking problem into a patch matching problem. Through obtaining the patch block from the training data and acquiring the similarity function by training the network, it uses the trained network to track objects (match by patch block) and gets the tracking results. The SiamFC [7] algorithm proposes an end-to-end object tracking network based on the Siamese network, and thus obtains a very high tracking speed and is capable of analyzing the influence of padding in the network. However, compared with the algorithm that combines correlation filtering and depth feature, it possesses poor robustness and accuracy. On the basis of SiamFC, SiamRPN [8] applies the RPN module in object detection to the tracking task, thereby improving both the accuracy and the speed. It is also verified to be able to exert a better tracking effect on a larger data set. In addition, the main idea of SiamMask [9] is to add a mask branch on the basis of SiamRPN to improve the tracking effect. By using a network, the bounding box and mask of the tracking object are obtained at the same time. However, given that the baseline networks of these algorithms are all AlexNet networks, the tracking effects of deep networks such as ResNet and Inception tend to be worse. Noteworthy, SiamDW [10] and SiamRPN++ [11] have solved the problem of poor tracking effect using deep network from different perspectives.

The object template of the aforementioned object tracking algorithms is always the same during the tracking process, but object change associated with such factors as illumination, scale change, rotation, partial occlusion, or full occlusion during the tracking process is inevitable. In order to effectively improve the accuracy of the tracking algorithm, the tracking template should be updated in time according to the changes of the object to reflect its current state more accurately. At the same time, in multi-branch tracking algorithms (such as SiamRPN [8] and SiamFC++ [12]), both the classification branch and the regression branch use the last layer feature of backbone. In the past two years, the backbone network of the object tracking algorithm has become increasingly complex, such as ResNet and GoogleNet. Such a complex network requires a lot of computing power in the tracking process, and it will also reduce the tracking speed.

Thus, the present paper proposes the following optimizations to the network structure on the SiamFC++ [13] framework. First, use FPN to extract feature maps from different layers of backbone for classification branch and regression branch, and make full use of the respective functions of the two branches; second, use 3D convolution to update the tracking template of the object tracking algorithm, and propose a template update judgment condition based on mutual information. It is verified that the object tracking algorithm based on Siamese network needs template update during the update process, and that mutual information can be used as a judgment condition for template update. Finally, use AlexNet as the backbone and GOT-10k as the training set to reduce training costs. Through template update, AlexNet can reach the tracking level of GoogleNet. After experimental verification, the new tracker has improved on OTB2015 [15], VOT2016 [16], VOT2018 [17], and GOT-10k [18].

2 Related Work

2.1 Object tracking based on Siamese network

Since Ran Tao [6] proposed the first object tracking algorithm SINT based on

Siamese network, tracking algorithms based on Siamese network have gradually become a hot spot in the field of object tracking. From the perspective of the tracking network structure, the Siamese object tracking algorithms can be divided into single-branch object tracking and multi-branch object tracking.

Early tracking algorithms based on Siamese networks, such as SiamFC [7] and CFNet [19], are all single-branch algorithms. The main feature is that the template image and search image are passed through the Siamese network to obtain two feature maps and directly perform cross-correlation operations to obtain the heat map. The bounding box is determined by the maximum response value of the heat map. These algorithms possess fast tracking speed, but they are not ideal for object tracking with frequent changes in size, especially for small objects.

Later, SiamRPN introduced the RPN network into the tracking model, and proposed a dual-branch tracking model with classification branch and anchor-based regression branch. Subsequent tracking models based on this dual-branch model such as SiamMask have also been proposed. SiamFC++ designed an anchor-free multi-branch object tracking model. These algorithms all obtain tracking results through the joint action of classification branch and regression branch. The use of regression branch optimizes the detection of object edges in the object tracking process. But the classification branch and regression branch of these algorithms use the feature map at the highest level of backbone. Therefore, in view of the different characteristics of the two branches, this paper optimizes the network framework of SiamFC++ using different features of backbone for object tracking in classification branch and regression branch.

2.2 FPN

FPN (Feature Pyramid Networks) was proposed by Tsung-Yi Lin [20] in 2017. It mainly overcame the shortcomings of object detection in dealing with multi-scale changes. Many algorithms use a single high-level feature. Faster R-CNN [21] is a good case in point which uses a four-fold down-sampling convolutional layer-Conv4 for subsequent object classification and bounding box regression. However, an obvious defect in doing so lies in that the small object itself has less pixel information and is easily lost during the down-sampling process. In order to deal with the detection problem with very obvious object size differences, the current paper proposes a feature pyramid network structure which can handle the multi-scale change problem in object detection with a very small increase in the amount of calculation.

SiamFC++ uses the highest-level feature of backbone in both the classification branch and regression branch. However, the focus of the two branches in the tracking process is different. The classification branch is mainly used to distinguish the object and the background, and the determination of the center position of the object requires

higher semantic information. The regression branch mainly determines the boundary size of the object, which requires higher position information. It can be seen from FPN that the low-level features contain less semantic information, but the object location is accurate. By contrast, the high-level features contain richer semantic information, but the object location is relatively rough. Therefore, this paper uses FPN to obtain the multi-layer feature maps of the backbone, with the classification branch using the high-level feature map, and the regression branch using the low-level feature map.

2.3 Tracking template update

During the tracking process, SiamFC++ is the same as SiamFC, the tracking template is unchanged which is always the first frame's feature map of the video, but the object will be deformed or occluded by other objects. Therefore, the algorithm should introduce a template update mechanism to improve the update effect. However, if there is no template update judgment condition, the template will be contaminated, resulting in poor tracking results for subsequent frames. And updating every frame will seriously reduce the tracking speed. Thus, the algorithm should add a template update judgment mechanism. After the template update condition is established, the image that is input to the Siamese network will be updated. The object area of the new image is generated by the Siamese network to produce a new object template for the update of subsequent video frames.

3 Methods

In order to make full use of respective characteristics of classification branch and regression branch, designed a new tracker model. The proposed tracker was optimized based on SiamFC++. This part mainly describes in detail the structure of the template update object tracker based on the multi-layer feature maps of the fully convolutional Siamese network.

The algorithm framework is shown in Figure 1. In Template Frames, $z-p$ is the object area of the first frame of the video, $z-n$ is the object area of the current frame, and $z-q$ is the object area of the picture frame used in the previous update. In the initial state, all 3 frames are the object area of the first frame. Detection Frame refers to the current detection frame of the video. Input the three pictures in Template Frames were input into Siam-FPN to get their respective high-level feature map ($z-h$) and low-level feature map ($z-l$). At the same time, input the Detection Frame was input into the same Siam-FPN to get the high-level feature map ($x-h$) and low-level feature map ($x-l$) of the detection frame, and copy the feature was copied twice. 3D-cls was used for feature fusion of high-level feature maps of Z and X , and 3D-reg was used for feature fusion of low-level feature maps. 3D-cls and 3D-reg are both convolution nuclei of $3 \times 3 \times 3$ for multi-frame feature maps fusion and branch classification. Then Z and X of the two branches are cross-correlated and down sampled to obtain the heat maps of classification branch and regression branch. Next, cls head and reg head of SiamFC++ are used to determine object positions in the search graph and generate bounding box of the current frame. Whether the template update conditions are met was then checked. If so, $z-n$ was assigned to $z-q$, and the images in the current frame bounding box are assigned to $z-n$ to update the template, and the new template was used to track the objects

of subsequent frames.

Figure 1. The structure of the template update object tracker

3.1 Siam-FPN

In this paper, Siam-FPN [8] was the backbone, mainly composed of two parts, AlexNet and FPN. The structure is shown in Figure 2. First, AlexNet was used to obtain the convolutional feature map of each layer. Next, up-sampling was used to magnify the small feature map to the same size as the feature map of the upper layer, and then the two were added together and transmitted to the next layer until the last layer was reached. The up-sampling was realized by nearest neighbor interpolation. By this method, the semantic information of the feature map could be retained to the maximum extent in the up-sampling process, and then it could be fused with the feature map with rich spatial information in the bottom-up process. In this way, the feature map with both good spatial information and semantic information could be obtained. Finally, P5 was selected as the high-level feature, and P3 as the low-level feature.

Figure 2: The C5 layer first went through 1×1 convolution to change the number of channels in the feature map ($d=256$ was set in the paper). M5 was obtained by up-sampling and 1×1 convolution of the feature map of C4 (direct addition of elements at the same position in the feature map). This was repeated twice to get M3 and M2. The M layer feature map then went through 3×3 convolution (to reduce the aliasing effect caused by the nearest neighbor interpolation, and the surrounding numbers were all the

same). Finally, P2, P3, P4, and P5 layers were obtained.

3.2 Classification head and regression head based on SiamFC++

After the response map was obtained, the relevant head operation was performed. This paper used the classification head and regression head proposed by SiamFC++ [12]. As shown in Figure 3, the classification head took the heat map of cls branch as input, and the classification of each point in the feature map was the classification of corresponding patches on the original map. In order to balance the relationship between the background and object position, the quality score was introduced, and the score of the final selection box was obtained by multiplying the quality score and the predicted score. The regression head took the heat map of the reg branch as input and output an offset ($17 \times 17 \times 4$) to optimize border position.

Figure 3. Classification head and regression head based on SiamFC++

For cls-score, pixel points on the heat map were mainly categorized into positive sample points and negative sample points through the ground truth input of the image. If the corresponding position $(\lfloor \frac{s}{2} \rfloor + xs, \lfloor \frac{s}{2} \rfloor + ys)$ of (x, y) on CLS was within the ground truth of the original image, (x, y) would be regarded as positive sample, and the rest as negative samples (s is AlexNet's stride, which is 8).

For quality-assessment, if the classification branch was directly used to select the final prediction bounding box, the positioning accuracy might be reduced. Given the lack of good correlation between classification confidence and positioning accuracy, it was assumed that feature

pixels around the object center had better estimated quality than other pixels. A 1×1 convolutional layer was added in parallel to the classification head for quality assessment. This output was used to estimate Prior Spatial Score (PSS), as defined below:

$$PSS^* = \sqrt{\frac{\min(l^*, r^*)}{\max(l^*, r^*)} \times \frac{\min(t^*, b^*)}{\max(t^*, b^*)}} \quad (1)$$

where l^*, t^*, r^*, b^* are respectively the distance between the corresponding positions of the final output prediction (x, y) on the original map and the left, top, right, and bottom frames of the ground truth. The predicted PSS^* was multiplied by the corresponding classification score to calculate the final score. The classification branch was then obtained.

For reg-out, if the corresponding point (x, y) on the classification branch feature map of the original image was $(\lfloor \frac{s}{2} \rfloor + xs, \lfloor \frac{s}{2} \rfloor + ys)$, the regression branch would output the predicted value of ground truth at this point, expressed as a four-dimensional vector $t = (l^*, t^*, r^*, b^*)$. The calculation process of each ground truth component is described as:

$$\begin{aligned} l^* &= \left(\left\lfloor \frac{s}{2} \right\rfloor + xs \right) - x_0, \quad t^* = \left(\left\lfloor \frac{s}{2} \right\rfloor + ys \right) - y_0 \\ r^* &= x_1 - \left(\left\lfloor \frac{s}{2} \right\rfloor + xs \right), \quad b^* = y_1 - \left(\left\lfloor \frac{s}{2} \right\rfloor + ys \right) \end{aligned} \quad (2)$$

where (x_0, y_0) and (x_1, y_1) represent the corner points at the upper left and lower right corners of ground truth respectively.

Finally, the result of classification branch was combined with that of regression branch to get the tracking result of the current frame.

3.3 Template update judgment condition based on mutual information

This paper used 3D convolution fusion time series feature of frames to update the classification branch and regression branch template. However, the object may be blocked by other objects or intersect with other object images during the object tracking process. If no update judgment condition is added, the model updating will not stop. The template will also be polluted, thus greatly affecting the tracking of subsequent frames. And if there is no template update judging mechanism, updating every frame will seriously affect the tracking speed. Therefore, an update judgment mechanism must be added. This paper proposed a template update judgment method based on mutual information [22]. Mutual information represents the amount of information contained in one random variable about another random variable. The larger the mutual information value, the greater the amount of the same information contained in the two variables. Assuming that the heat map obtained by performing correlation operations on the classification branch of the first frame of the image is the most ideal and the heat map of the classification branch of the subsequent detection frame is calculated for mutual information with it, the larger the mutual information value is, the more suitable the current frame will be for updating the template. In order to facilitate the calculation, this paper converted the obtained mutual information value into a normalized mutual information

value.

The judgment process based on mutual information is shown in Figure 3. In the tracking process, the first frame of the video was used as the Template Frame. Moreover, the first frame was used as the Detection Frame to obtain the heat map of the classification branch as the 1-heat map, and the classification branch of the subsequent frames was in its classification branch. The t-heat map and 1-heat map were used as two variables to get their mutual information value. The mutual information calculation formula is shown as follows:

$$I(X, Y) = \sum_{x \in X} \sum_{y \in Y} p(x, y) \log \frac{p(x, y)}{p(x)p(y)} \quad (3)$$

where X and Y are the heat maps of the first frame and the heat map of the current detection frame respectively, $p(x)$ and $p(y)$ are the marginal distributions of X and Y respectively, and $p(x, y)$ is the joint distribution of X and Y . The obtained mutual information value was converted into normalized mutual information [23] value, as shown in Formula 4:

$$U(X, Y) = 2 \frac{I(X, Y)}{H(X) + H(Y)} \quad (4)$$

where $H(X)$ and $H(Y)$ are the entropy of X and Y respectively.

Figure 4: 1-heat map and t-heat map were cropped to the same size with the maximum value as the center, and the part beyond the map boundary was filled with the average value. Two new heat maps were obtained, and the normalized mutual information value of the two heat maps was calculated. If the normalized mutual information value was greater than the predetermined threshold, the update condition would be established.

When the obtained normalized mutual information was greater than the $V_{threshold}$ selected in this paper, the object area of the current frame could be used for template update. Otherwise, the template update was not performed, and the tracking process of the next frame was directly started after the tracking result of the current frame was obtained.

In order to make the mutual information judgment more accurate, the paper used dynamic thresholds. The larger the mutual information value, the more the same information. Therefore, the dynamic threshold was set as a local maximum in this paper. The threshold dynamic update formula is as follows:

$$\begin{cases} I(t) > V_{threshold} \\ I'(t) = 0 \\ I''(t) > 0 \end{cases} \quad (5)$$

where t represents the current detection frame, it represents the normalized mutual information value of the current detection frame classification branch heat map and 1-heat map and $I'(t) = 0$ and $I''(t) > 0$ indicate the local maximum point of mutual information. Because the mutual information value of the heat map and 1-heat map of each search frame was discrete, Formula 5 can be expressed as:

$$\begin{cases} I(t) > V_{threshold} \\ I(t) - I(t-2) \approx 0 \\ I(t) + I(t-2) - 2I(t-1) > 0 \end{cases} \quad (6)$$

where $I(t-1)$ represents the standard mutual information of the previous frame of t , and $I(t-2)$ represents the standard mutual information of the previous frame of $t-1$. Because the algorithm required the value of the mutual information of the three-frame search image, but the first frame and the second frame did not meet the conditions required by the formula when searching, the thresholds of the first frame and the second frame were set separately. In addition, the object area obtained from the first search image was generally not much different from that of the first frame template image of the video, so it could be used for direct update. At the same time, because there were very few videos that would be occluded in the second frame, the $V_{threshold}$ of the first and second detection images was set to a fixed value.

4 Experiment Analysis

4.1 Training process

This paper used the same one-shot learning [24] as SiamFC++ [7] for training, and randomly selected a PAIR in each video. Each PAIR contained four video frames. Specifically, the first video frame was the first frame of the video, and the next three frames were randomly selected from the video. The interval between the second and the third video frames did not exceed 15 frames in the original video, and the interval between the third and the fourth video frames did not exceed 100 frames. The first three video frames were used as Template Frames, and the last video frame was used as Detection Frame. In Detection Frame, the three pictures imported into the 3D convolutional network were the same, all being the last pictures of PAIR. The loss function was the same as that of the three branches of SiamFC++. Furthermore, cls-score used focal loss, quality-assessment used IoU loss, and reg-out used BCE loss. The total loss function is shown in Formula 7:

$$\begin{aligned} L(\{p_{x,y}\}, q_{x,y}, \{t_{x,y}\}) &= \frac{1}{N_{pos}} \sum_{x,y} L_{cls}(p_{x,y}, c_{x,y}^*) \\ &+ \frac{\lambda}{N_{pos}} \sum_{x,y} 1_{c_{x,y}^* > 0} L_{quality}(q_{x,y}, q_{x,y}^*) + \frac{\lambda}{N_{pos}} \sum_{x,y} 1_{\{c_{x,y}^* > 0\}} L_{reg}(t_{x,y}, t_{x,y}^*) \end{aligned} \quad (7)$$

where $1\{\cdot\}$ is 1 if the point is a positive sample, and 0 if otherwise. $c_{x,y}^*$ represents the label of cls-score and is 1, and if (x, y) is a positive sample, and 0 if is a negative sample. $q_{x,y}^*$ represents the label of quality-assessment, and some pixels similar to Gaussian distribution was sprinkled in the feature map within the range is $[0, 1]$; $t_{x,y}^*$ represents the label of reg-out, and the feature map areas of the four channels were assigned to (x_0, y_0, x_1, y_1) of the detection frame.

4.2 Experimental environment and parameters

The experimental platform of the paper was Python 3.8.3, the CPU of the server was Intel(R) Core(TM) i7-4790 3.6GHz 8G, and the GPU was NVIDIA GeForce RTX 2080Ti. During the experiment, the parameters of SiamFC++ remained unchanged. The GOT-10k [18] was employed as the training set, and the GOT-10k toolkit in Python was used as the test tool

4.3 Regression branch uses different layer feature maps

When using FPN to extract feature maps from different layers, four feature maps (P2, P3, P4, P5) were obtained, but which feature map could achieve the best performance in the regression branch? This part mainly verifies the influence of the regression branch using feature maps of different layers on the tracking results. To ensure the validity of the experimental results, all parameters, training times, and image preprocessing during the experiment were the same, and only the regression branch used the feature maps of different layers of FPN. The experimental results are shown in Figure 5. The regression branch used P3 as the low-level feature map to examine the tracking effect.

Figure 5. The experimental results of the regression branch using feature maps of different layers

4.4 Template update judgment

When to update the template during the tracking process is a very important question. This part verifies the superiority of the judgment mechanism based on NMI through comparative experiment. In order to ensure the validity of the experimental results, all parameters, training times, and image preprocessing during the experiment were the same. The tracking results are shown in Figure 6. It is clear that the use of mutual information algorithm as a judgment condition could more effectively update the tracking template and improve the tracking effect.

Figure 6. The results of the template update judgment comparison experiment

4.5 Threshold of mutual information

After calculating the NMI between the current detection frame and the first frame of the video, how to set the threshold becomes a key issue. This paper used the local maximum of the mutual information value of the video frame as the template update point, and the fixed threshold was 0.75. The experimental results are shown in Figure 7. Clearly, using the local maximum value as the judgment condition for template update could improve the tracking effect.

Figure 7. Results of different thresholds of NMI

5 Results and Discussion

5.1 Evaluation on OTB

There are one test set, namely OTB-15 [15], in the OTB dataset. Its evaluation follows the evaluation criteria proposed in [15]. The paper mainly evaluated the precision and Area under Curve (AUC) on OTB-15. As shown in Table 1, the AUC of our algorithm on OTB-15 was 0.673,

and the precision was 0.888. Compared with SiamFC++ using Alex Net, our algorithm increased the AUC by 3% and precision by 2%.

Table1 Evaluate on OTB

	Accuracy	Precision	FPS
SiamFC	0.581	0.771	86
SiamRPN	0.637	0.851	160
ECO	0.691	0.910	8
ROAM	0.680	0.908	13
SiamFC++(AlexNet)	0.655	0.872	170
SiamFC++(GoogLeNet)	0.683	-	90
OURS	0.673	0.888	169

5.2 Evaluation on VOT

VOT (Visual Object Tracking) [16, 17] is a testing platform for single object tracking. It has different evaluation indicators from OTB, and has been continuously improved since its inception. The evaluation algorithm in this paper mainly used the three most important indicators of VOT: accuracy (A), robustness (R), and EAO. Because the contents of the VOT2017 and VOT2018 datasets were the same, the evaluation was carried out on VOT2016 [16] and VOT2018 [17]. The evaluation results are shown in Table 2. In terms of VOT2016, the accuracy of our algorithm was improved by 0.031 compared to that of SiamFC++ (AlexNet), the EAO was improved by 0.034, and the robustness was improved by 0.062.

Table2. Evaluate on VOT

	VOT2016			Vot2018		
	A	R	EAO	A	R	EAO

SiamFC	0.532	0.461	0.235	0.503	0.585	0.188
SiamRPN	0.560	0.260	0.344	0.490	0.460	0.244
ECO	0.550	0.200	0.375	0.480	0.270	0.280
ROAM++	0.599	0.174	0.441	0.543	0.195	0.380
SiamFC++(AlexNet)	0.584	0.342	0.308	0.556	0.183	0.400
SiamFC++(GoogLeNet)	-	-	-	0.587	0.183	0.426
OURS	0.615	0.270	0.346	0.578	0.383	0.271

5.3 Evaluation on GOT-10K

GOT-10k [18] is an object tracking dataset released by the Chinese Academy of Sciences. Its evaluation indices include average overlap (AO), the accuracy of successful tracking at AO of 0.5 (SR0.5), and the accuracy of successful tracking at AO of 0.75 (SR0.75). The test results are shown in Table 3. Compared with SiamFC++ (AlexNet), our algorithm increased the AO by 0.034, SR0.50 by 0.05, and SR0.75 by 0.02.

Table 3. Evaluation on GOT-10k

	AO	SR _{0.50}	SR _{0.75}
SiamFC	0.348	0.353	0.098
ECO	0.316	0.309	0.111
SiamRPN++	0.518	0.618	0.325
ROAM++	0.465	0.532	0.236
SiamFC++(AlexNet)	0.493	0.577	0.323
SiamFC++(GoogLeNet)	0.595	0.695	0.479
OURS	0.527	0.627	0.343

5.4 Evaluation Summary

It can be seen from the above experiments that the algorithm proposed in this paper was enhanced on all three datasets. As shown in Figure 8, the bounding box of our algorithm was closer

to Ground Truth than SiamFC++ (AlexNet), and it obtained better tracking results for similar objects. Furthermore, the results of our algorithm were also similar to those of other algorithms based on ResNet50, indicating that it was capable of making full use of the performance of AlexNet.

Figure 8. Comparison of tracking results

6 Conclusion

The algorithm proposed in this paper uses a small training dataset and a small backbone network. Under the condition of ensuring real-time performance, its tracking results are close to those of SiamFC++ using GoogleNet. The experiments in this paper have shown that it is necessary to first determine whether the object is occluded before using the template update module in the tracking algorithm. This is because using occluded images to update the template would cause template pollution and affect the tracking results. The update condition judgment method based on mutual information proposed in this paper can judge the timing of template update more accurately and improve the update efficiency. The experiments have also verified that the use of high-level convolutional feature map in the classification branch and the use of low-level convolutional feature map in the regression branch can effectively improve the tracking results. Using 3D convolution to fuse the timing characteristics of multiple frames as a new tracking template in the object tracking process is an effective template update method. Therefore, 3D convolution has great application prospects in the object tracking field.

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Abbreviations

Not application

Availability of data and materials

The data that support the findings of this study are openly available in “GOT-10k” at <http://got-10k.aitestunion.com/>.

The data that support the findings of this study are openly available in “OTB” at <http://cvlab.hanyang.ac.kr/trackerbenchmark/datasets.html>.

The data that support the findings of this study are openly available in “VOT2016” at <https://www.votchallenge.net/-/vot2016/>.

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Ethics approval and consent to participate

Not application

Competing interests

We have no competing interests.

Consent for publication

Consent for publication

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