ATLANTIS PRESS
Advances in Computer Science Research, volume 87
3rd International Conference on Mechatronics Engineering and Information Technology (ICMEIT 2019)

Improved Multi-sampling Kernelized Correlation Filter Target Tracking Algorithm

Ying Hou [a], Yemei He[b]

School of Communication and Information Engineering, Xi'an University of Science and Technology, Xi'an 710054, China.

[a]ying_hou@qq.com, [b]engine_he@163.com

Abstract. In order to solve the tracking failure of kernelized correlation filter (KCF) tracking algorithm in the case of target fast motion and motion blur, proposing a multi-sampling tracking algorithm based on KCF. Firstly, a PSNR-based judgment mechanism is introduced to determine whether the current frame target is tracking errors. If the tracking error occurs, the search range is extended to a muti-sampling search area. Finally re-detect the target of the current frame. The improved algorithm of this paper is compared with several classical correlation filter target tracking algorithms in the OTB video dataset. The experimental results show that the precision of this algorithm is 0.732 and the success rate is 0.575, ranking first, which is 5.3% and 4.3% higher than the KCF algorithm. Especially when the target has fast motion and motion blur, it has stronger tracking accuracy.

Keywords: Target tracking; Kernelized Correlation Filter (KCF); PSNR; Multi-Sampling.

1. Introduction

Visual Target tracking technology has a wide range of applications in both military and civilian areas, for instance: intelligent monitoring system, intelligent transportation, the medical field and driverless vehicle, etc. The target tracking algorithm based on kernel correlation filtering is one of the mainstream researches of tracking algorithms because of its excellent performance in tracking speed and accuracy. The first target tracking algorithm based on kernel correlation filtering is CSK [1], which used cyclic sampling and combined with kernel function to train the classifier in Fourier domain. Then in 2015, Henriques et al. proposed the improved tracker KCF [2] (Kernelized Correlation Filter), which replaced the gray feature with the HOG feature. In 2017, Matthias Mueller et al. improved on the KCF algorithm and proposed the CACF [3] (Context-Aware Correlation Filter) tracking method. By integrating the global context, the original optimization problem was redefined. And in 2018, Li Feng et al. proposed the STRCF [4] (Spatial-Temporal Regularized Correlation Filters) tracking method. By incorporating spatial and temporal regularization into the DCF framework, the STRCF model was proposed.

The KCF tracking algorithm introduces Gaussian kernel function and HOG feature, which improves the target tracking speed. However, when the target has fast motion and motion blur, it is easy to make the target tracking inaccurate or even the error tracking. Therefore, this paper proposes an improved multi-sampling KCF target tracking algorithm to improve the tracking accuracy of the algorithm, especially in complex scenes.

2. Description of Improved Algorithm

The KCF algorithm includes four stages, they are sampling, training, detection, and updating. In the target detection stage, the KCF expands the target position area of the previous frame by two times for sampling, and then uses the trained classifier to detect the target. However, this will make the background information that the classifier can learn very little. When the target has rapid motion or motion blur, it is easy to make the tracking inaccurate or even error tracking. The improved algorithm proposed in this paper first judges the KCF tracking situation through an error tracking judgment mechanism. If the error tracking occurs, multiple sampling blocks are formed by shifting the target position area of the previous frame, and then the target is re-detected.

2.1 PSNR-based Error Tracking Judgment Mechanism

In order to avoid the KCF algorithm to continue multi-sampling target detection in the success tracking video frame and increase the meaningless repetitive work, this paper introduces the error tracking judgment mechanism with PSNR as the discriminant index to judge the tracking situation. The mechanism intercepts the current frame target image tracked by the KCF algorithm and the previous frame target image. Then calculating the similarity between the two target images, and selects an appropriate similarity threshold T to determine whether the two targets are similar. If they are similar, the current frame target is successfully tracked; if not, the multi-sampled sample block is used for re-detection in the current frame.

As shown in FIG. 1, the PSNR curves of all video sequences in the OTB dataset are drawn on the MATLAB platform, and then combined with the error tracking frames to analyze. After comprehensive analysis, the threshold T is finally determined to be 17dB~20dB.

2.2 Multi-sampling

As shown in FIG. 2, after the KCF tracking error is determined, the previous frame target position region R is offset by the offset step S in the x direction and the y direction to obtain four multiple sampled sample blocks: A1, A2, A3 and A4. Then the current frame target is re-detected among these sample blocks. The offset step S ranges from 10~25 pixels.

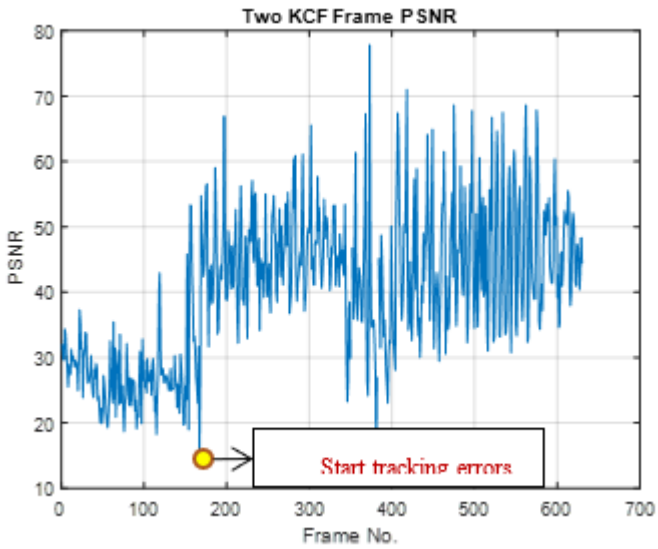

Fig.1 PSNR curve

Fig.2 Multi-sampling schematic

3. Experimental Results and Analysis

The improved algorithm includes two parameters: discriminant index threshold T and multi-sample offset step S. In order to determine the optimal performance parameter combination and compare it with other tracking algorithms, according to the literature [5], it is necessary to run the performance comparison plots in OTB dataset with the MATLAB R2015a platform.

3.1 Different Threshold T and Offset Step Size S

The different thresholds T and the offset step S are combined to obtain a plurality of improved algorithms, and the performance comparison plots of the algorithms are run in the OTB data set. As shown in FIG. 3, when the threshold T=20 and the offset step size S=18, the performance of the improved algorithm is optimal.

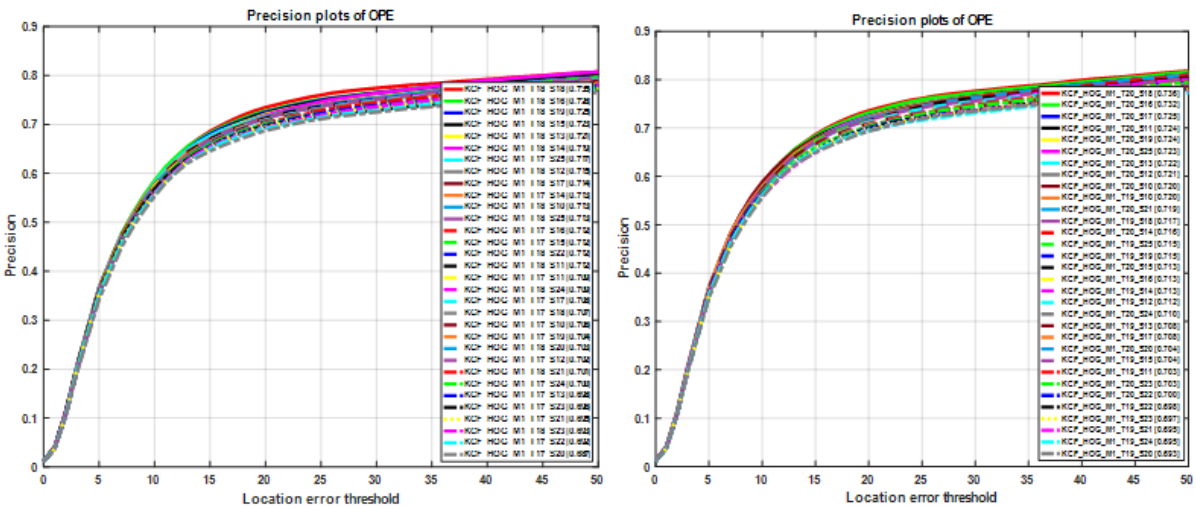

Fig.3 The precision plot of improved algorithm with different parameters

3.2 Performance Comparison and Analysis of Multiple Tracking Algorithms

The performance-optimized multi-sampling KCF target tracking algorithm is compared with various mainstream related filtering target tracking algorithms in the OTB data set. The experimental results are shown in Figure 4. The performance of the proposed algorithm is optimal, which is 5.3% and 4.3% higher than KCF algorithm.

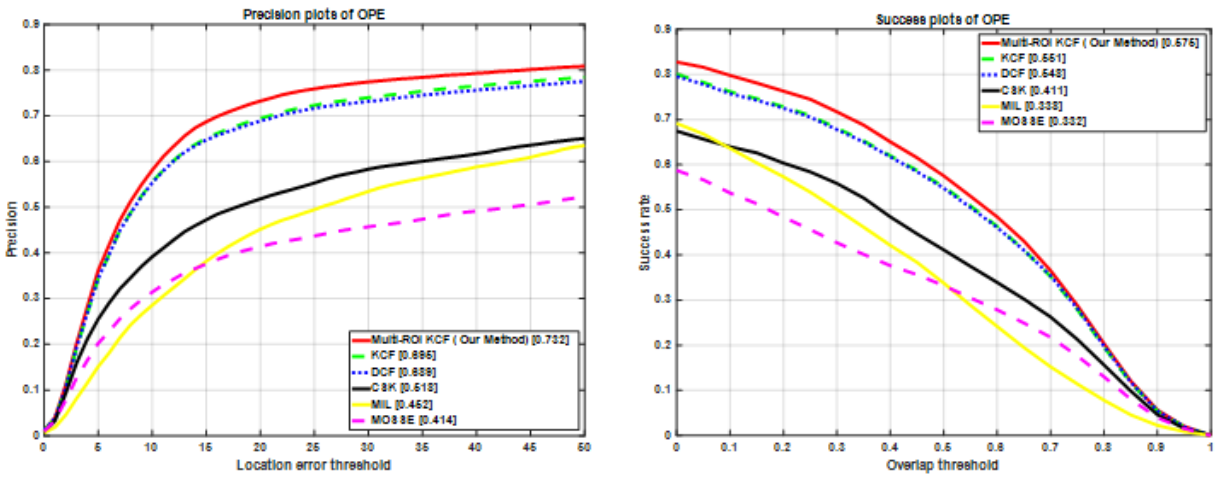

Fig.4 Comparison of various algorithm performance

The improved algorithm was tested in different video sequences of different attributes. The experimental results are shown in Table 1.

Tab.1 The performance improvement ratio of improved algorithm under different attributes videos

Video attribute	Precision	Success
Motion Blur	22.0%	16.9%
Fast Motion	17.6%	16.3%
Illumination Variation	4.9%	3.5%
Out-of-plane Rotation	1.2%	0.9%
Scale Variation	8.1%	7.0%
Occlusion	4.8%	0.8%
Deformation	5.6%	1.0%
In-plane Rotation	3.3%	5.3%
Background Clutter	5.7%	5.1%
Low Resolution	3.6%	5.2%

It is obviously that the improved multi-sample KCF target tracking algorithm tracks more accurately in the video of the Motion Blur and Fast Motion properties.

4. Conclusion

In this paper, the algorithm introduces the error tracking judgment mechanism and re-detects the multi-sample blocks, which makes the improved algorithm has stronger tracking accuracy, especially in the target "motion blur" and "fast motion" situations. It has important research and application value. In the future work, we will further study how to improve the tracking speed of the algorithm in the text.

References

[1]. Henriques J F, Rui C, Martins P, et al. Exploiting the Circulant Structure of Tracking-by-Detection with Kernels[J]. Lecture Notes in Computer Science, 2012, 7575(1):702-715.

[2]. Henriques J F, Caseiro R, Martins P, et al. High-Speed Tracking with Kernelized Correlation Filters[J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2014, 37(3):583-596.

[3]. Mueller M , Smith N , Ghanem B . Context-Aware Correlation Filter Tracking[C]// 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE Computer Society, 2017.

[4]. Li F , Tian C , Zuo W , et al. Learning Spatial-Temporal Regularized Correlation Filters for Visual Tracking[J]. 2018.

[5]. Wu Y , Lim J , Yang M H . Online Object Tracking: A Benchmark[C]// 2013 IEEE Conference on Computer Vision and Pattern Recognition. IEEE Computer Society, 2013.