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Deep Convolutional Particle Filter with Adaptive Correlation Maps for Visual Tracking

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# **Abstract:**

The robustness of the visual trackers based on the correlation maps generated from convolutional neural networks can be substantially improved if these maps are used to employed in conjunction with a particle filter. In this article, we present a particle filter that estimates the target size as well as the target position and that utilizes a new adaptive correlation filter to account for potential errors in the model generation. Thus, instead of generating one model which is highly dependent on the estimated target position and size, we generate a variable number of target models based on high likelihood particles, which increases in challenging situations and decreases in less complex scenarios. Experimental results on the Visual Tracker Benchmark vl.0 demonstrate that our proposed framework significantly outperforms state-of-the-art methods.

# SECTION 1. Introduction

One important aspect of visual target tracking is to accurately determine the target position as well as its size. Particle filters have been employed in visual tracking for years because of their ability to perform these tasks robustly [1]. Recently, deep convolutional neural networks have been used to produce highly discriminative target features [2]. Trackers such as HCFT and HDT [3], [4], which employ convolutional features in conjunction with correlation filters have shown better visual tracking performance than traditional trackers such as MEEM [5], KCF [6], Struck [7], SCM [8] and TLD [9]. Despite the substantial performance gains obtained in recent years by the aforementioned CNN -correlation methods, their main disadvantage is their inability to vary the size of the target bounding box [3], [4]. By combining CNN-based correlation maps with particle filters, we can overcome this limitation and improve overall tracking accuracy and robustness.

We propose two new mechanisms to improve the performance of our previous visual tracker named Deep Convolutional Particle Filter (DCPF) [10]. Briefly, DCPF uses multiple particles as inputs to VGG-Net [2]. For each particle, it then applies the correlation filter used in HCFT on the extracted hierarchical convolutional features to construct the correlation map. The target position at the current frame is calculated based on the response of the correlation maps. However, similar to HCFT, DCPF tracks a bounding box of fixed size. Another limitation of DCPF and other trackers based on conventional correlation filters is the fact that they generate only one target model. Thus, errors in calculating the final target state cause the target model to be incorrectly updated. In our new visual tracker named DCPF2, we address the first limitation by extending DCPF's particle filter to estimate the target size. In addition, we employ an adaptive correlation filter, which produces a variable number of target models based on the number of high-likelihood particles that have been generated in the previous frame. In frames where the target can be easily tracked, this number is low because the best particle has a high likelihood and fewer particles have similar likelihoods. Conversely, in challenging situations, the target is less similar to the model and hence the likelihood of most particles decreases and the particle weight distribution becomes less centralized. We used the Visual Tracker Benchmark v1. 0 [11] to evaluate the performance of the proposed tracker and showed that it performs favorably with respect to other state-of-the-art methods.

# SECTION 2. Proposed Algorithm

In this section, we first explain how our particle filter estimates the target size and its position. Then, our adaptive correction filter is discussed. Fig. 1 illustrates the proposed approach.

## 2.1. Particle Filter to Estimate the Target Bounding Box

Let the target position and size be represented by

(1)

where  and  are the locations of the target on the horizontal and vertical image axes at frame , and  and  are its width and height. The target state is given by

(2)

where  is the velocity of . The tracker employs a linear motion model to predict the current state of the target  based on the previous target state . The predicted target state is given by

(3)

where  is a standard constant velocity process matrix. Then, particles are generated by adding samples  drawn from a zero-mean normal distribution. That is.

(4)

where  and  is the number of the particles. In order to limit the number of particles needed, rather than drawing  directly from an eight-dimensional distribution, we draw its samples individually, and change its height and width simultaneously using the same sample (i.e., we change the target scale but not its aspect ratio).

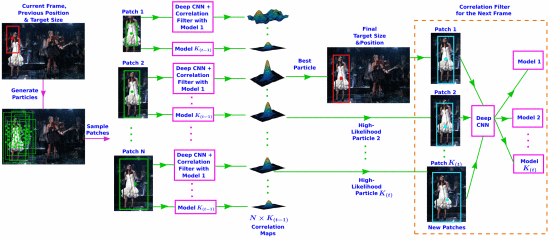
[](https://ieeexplore.ieee.org/mediastore_new/IEEE/content/media/8436606/8451009/8451069/0000798-fig-1-source-large.gif)

Fig. 1. Overview of our proposed tracker.

In the next step,  are used to sample different patches from frame . Each patch is then fed into the CNN to calculate its convolutional feature map. Let  be the convolutional feature map, where  are the width and height of the map,  is the convolutional layer and  is the number of the channels for that layer . Then, its correlation response map  is given by

(5)

where  represents the inverse Fourier transform [3],  illustrates the number of models generated in the previous frame  represents channel  of layer  of the correlation filter of the model , the bar represents complex conjugation and  is the Hadamard product. The final correlation response map  for particle  and model  is calculated based on a weighted sum of the maps for all the CNN layers as proposed in [3]. The likelihood or weight of each correlation response map is calculated by

(6)

where  refers to the element of the final correlation response map on row  and column . In total, we have  weights. The intuition behind this choice is that feature maps that correspond to the target tend to show substantially higher correlation values than background patches [12]. We then find the maximum weight  over all the particles and models

(7)

Let the indexes corresponding to  be  (the best particle) and  (the best model). Then, the final target size is given by  and . That is, the  -th patch with dimensions  and  is the most similar to the best model . Additionally, let  be the correlation response map associated with , its peak is located at

(8)

where  and . The final target position is then calculated by shifting the best particle towards the peak of its correlation map

(9)

where  and  correspond to the position of the best particle. Thus, the target state at the frame  is

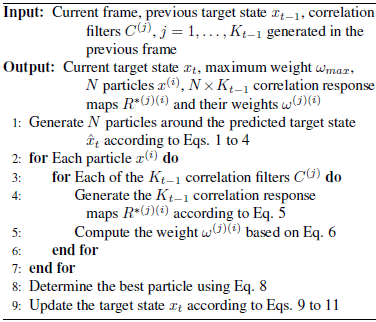
(10)

where  is the velocity of the best particle and

(11)

Algorithm 1 summarizes our method to estimate the target state.

### Algorithm 1: Calculate the Current Target State

[](https://ieeexplore.ieee.org/mediastore_new/IEEE/content/media/8436606/8451009/8451069/0000798-alg-1-source-large.gif)

## 2.2. Adaptive Correlation Filter

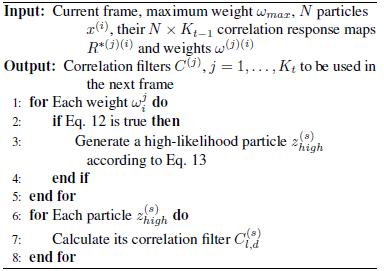
After finding ωmax, we examine the following relationship for all  weights

(12)

where  is a constant. If Eq. [12](https://ieeexplore.ieee.org/document/#deqn12) is true, the corresponding particle is considered a high likelihood particle. Let  and  be the indices of the selected weights. Then,  and  calculated by Eq. [4](https://ieeexplore.ieee.org/document/#deqn4) are considered the target size particle. Additionally, its associated correlation response map  is used to calculate the estimated target position  and similar to Eq. [8](https://ieeexplore.ieee.org/document/#deqn8) and Eq. [9](https://ieeexplore.ieee.org/document/#deqn9). Thus the corresponding high likelihood particle  is given by

(13)

### Algorithm 2: Adaptive Correlation Filter

[](https://ieeexplore.ieee.org/mediastore_new/IEEE/content/media/8436606/8451009/8451069/0000798-alg-2-source-large.gif)

Where  and  is the number of the high-likelihood particles. We then generate a patch from frame  for each of the  high-likelihood particles. In the next step, these patches are fed into the CNN to extract Kt convolutional feature maps, and a new correlation filter  is then generated for each of the  high likelihood particles. The generated models are used in frame  to be compared with the convolutional features generated by each particle.

Alg. 2 summarizes our adaptive correlation filter procedure. The comparison between the best model with the most accurate target size and position generates more accurate correlation maps. As previously mentioned, by varying the number of models  with the number of high likelihood particles, we are able to maintain a larger number of tentative models in challenging scenarios such as in the presence of illumination variation, motion blur, or partial occlusion due to the wider distribution of the particle weights under these conditions.

# SECTION 3. Results and Discussion

We evaluate our tracker on the well known Visual Tracker Benchmark v1.0 [11]. This benchmark contains 50 data sequences that are annotated with 9 attributes representing challenging aspects of tracking, such as scale variation, in-plane rotation and illumination variations. We use a one-pass evaluation (OPE) in which the tracker is initialized with the ground truth location at the first frame of the image sequence [11]. Also, we heuristically set  and .

Fig. 2 qualitatively illustrates the performance of our tracker in comparison with three trackers: the CNN-based trackers HCFT and HDT as well as the correlation filter tracker SCT6 [13]. As the results in Fig. 2 indicate, the baseline trackers get easily confused in situations such as scale variation, illumination variation, in-plane and out-of-plane rotations. The proposed particle-correlation filter is able to sample several image patches and it is hence capable of overcoming these difficulties.

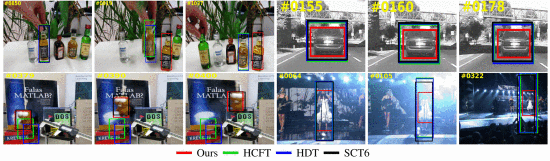
[](https://ieeexplore.ieee.org/mediastore_new/IEEE/content/media/8436606/8451009/8451069/0000798-fig-2-source-large.gif)

Fig. 2. Qualitative evaluation of our tracker, HCFT, HDT and sct6 on six challenging sequences (from left to right and top to bottom are liquor, car4, lemming and singer1, respectively).

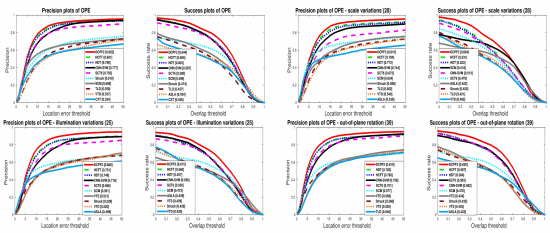
[](https://ieeexplore.ieee.org/mediastore_new/IEEE/content/media/8436606/8451009/8451069/0000798-fig-3-source-large.gif)

Fig. 3. Quantitative evaluation of our tracker and fourteen state-of-the-art trackers on ope.

Fig. 3 provides a quantitative evaluation of our proposed approach in comparison with 11 state-of-the-art trackers [3], [4], [14], [13], [7]–[8][9], [15]–[16][17][18]. In the figure, *Precision plots* correspond to the average Euclidean distance between the tracked locations and the ground truth while *Success plots* correspond to the area of overlap between the predicted bounding box and the respective ground truth [11]. In attributes such as scale variation, illumination and out-of-plane rotations where the common correlation filter loses track of the target, our adaptive correlation filter in conjunction with the particle filter are then able to recover using the weights generated by the CNN. For challenging scenarios of scale variation, illumination variation and out-of-plane rotation as well in terms of overall performance, our tracker shows improvements of approximately 14%, 10%, 9% and 7%, respectively, in comparison with the second best tracker HCFT.

# SECTION 4. Conclusion

This article proposes a novel framework named DCPF2 for visual tracking. We extend the particle filter employed in our previous tracker DCPF to estimate the target size. Additionally, because the correlation filter used in DCPF is heavily dependent upon the estimated target position, we find all of the high-likelihood particles and calculate a model for each of them. The Visual Tracker Benchmark vl.0 is used for evaluating the proposed tracker's performance. The results show that these strategies improve the performance of CNN-correlation trackers in critical situations such as scale variation, illumination and out-of-plane rotations.

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