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Blending of Learning-based Tracking and Object Detection for Monocular Camera-based Target Following

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Abstract: Deep learning has recently started being applied to visual tracking of generic objects in video streams. For the purposes of robotics applications, it is very important for a target tracker to recover its track if it is lost due to heavy or prolonged occlusions or motion blur of the target. We present a real-time approach which fuses a generic target tracker and object detection module with a target re-identification module. Our work focuses on improving the performance of Convolutional Recurrent Neural Network-based object trackers in cases where the object of interest belongs to the category of *familiar* objects. Our proposed approach is sufficiently lightweight to track objects at 85-90 FPS while attaining competitive results on challenging benchmarks.

Keywords: Tracking, Image recognition, Neural-network models, Data fusion, Robot vision.
AMS subject classifications: 68T45; 68W27; 62M45

1. INTRODUCTION

Object tracking is an essential activity for robots interacting with dynamic elements in their environment, for instance inspection of pieces moving along a conveyor belt or pursuit of other robots. Object tracking has also been employed in other fields, for instance tracking moving bacteria seen through a microscope (Wood et al., 2012).

Over the years, the robotics community has produced various object trackers with properties catering to different circumstances. For example, pedestrian tracking (Choi et al., 2011), (Wu et al., 2005) using RGB or RGB-D data for surveillance purposes. Or, for vehicle tracking via RGB data or 2D/3D range data for counting number of vehicles on the road and for traffic congestion control. These kinds of object-specific trackers are generally trained offline given that the shape and/or motion model of the object of interest is known in advance. Our work falls in between object-specific trackers and generic object trackers. That is, our object tracker assumes that the appearance model of the object of interest is known in advance, but the motion model is not known. It should also be noted that even in the absence of an appearance model of the object, our proposed method still tracks the object but not accurately. The remainder of the paper is described assuming that the appearance model of the object of interest is known in advance.

Our work addresses the problem of tracking fast moving targets in mobile robotics. These targets can be anything from Unmanned Aerial Vehicles to ground rovers. As these targets have complex motion, it is not feasible to assume a fixed motion model in advance. Moreover, due to various effects such as occlusion or motion blur, track of the object might be lost and hence generic object trackers (Gordon et al., 2017), (Bertinetto et al., 2016), (Held et al., 2016), (Valmadre et al., 2017) cannot be used as they cannot re-identify objects once track is lost. Therefore, we propose an object tracking system which can track fast moving objects and also has the ability to regain track of the object if required.

To tackle the problem of visual object tracking we take inspiration from evolution, which has enabled humans and other animals to survive in their ecosystem and effectively interact with their environment. The Human visual system outperforms artificial visual systems primarily because of the brain's ability to perform global data association. Moreover, performing robust target tracking is a complex task which requires multiple subsystems working together. Thus, our target tracking system is composed of individual subsystems for solving different problems that arise in tracking of fast moving targets.

In this paper, we present a tracker that uses a fusion of motion tracking and object detection. Our algorithm is governed by a heuristic but its major sub-components are adaptive learning models. The main contributions of the work are:

(1) Formulation for target tracking based on a heuristic fusion of a generic object tracker (Gordon et al., 2017) with a detector (Redmon and Farhadi, 2017).
(2) Reducing the impact of motion blur while tracking fast moving objects.

(3) Demonstrating that our approach to object tracking significantly improves the quality of tracking with respect to the performance obtained solely by the motion tracker and object detector modules used in our algorithm.

We provide the full implementation of our algorithm, whose source code is written in Python. We provide two versions of this code: one as a standalone Python program, and another as a ROS package ready for use in robotic applications. The code is available at `https://bitbucket.org/Pranoy97/fusion`.

2. METHOD

Our object tracking pipeline consists of three modules: an Object and Blur Detection module, a Motion Tracking module and a Re-identification module. The proposed method takes an initial bounding box as input from the user and then starts the tracking procedure. The object enclosed in the bounding box is classified as either a *familiar* (seen before by the object detection module) or *unfamiliar* object. Our work deals only with the *familiar* object case, but for the sake of completeness we handle the *unfamiliar* case by deploying only the motion tracking algorithm.

We hypothesize that for tracking objects that follow complex trajectories, better tracking can be achieved by interim tracker initialization i.e. the tracker is initialized after every n frames. The intuition behind this hypothesis is that, if n is sufficiently small, then the tracker has to essentially learn a piece-wise linear model of the motion. Thus, this initialization procedure greatly reduces the location estimation error and drift error of the motion tracker.

In the case of a *familiar* object, in accordance with our hypothesis, our object detection module is run on every n^{th} frame while the tracking algorithm is employed in the $n-1$ frames in between. Validation of the track of the object of interest is done by the object detection module. If the track is lost, the object detection module scans the entire frame and reports all the objects in the scene that belong to the class of the object of interest. For example, if the object of interest is a human, then all the humans in the scenes are reported. Then, we invoke the re-identification module to find the best possible match. If the re-identification score for the best match is above an empirically determined threshold, we declare that the object of interest is re-identified. Else, we keep on scanning the frame until we find the object. When the object of interest is re-identified, we resume the normal tracking procedure described previously.

The remainder of this section describes the exact formulation of each of the modules and the pseudo-code for our algorithm.

2.1 Object and Blur Detection module

Existing object tracking algorithms inherently track the motion of an individual target. This means they will lose track of the object in the event of overly long occlusion or if the object moves faster than the tracking algorithm can handle. It is also common for existing tracking algorithms to accumulate errors such that the bounding box tracking the object slowly drifts away from the object it is tracking. To fix these problems we propose to do two things. First, to add an Object Detector. Here, we run a fast and accurate object detector (we use YOLO v2 (Redmon and Farhadi, 2017) in our work) on every n^{th} frame while the motion tracking module is employed in the $n-1$ frames in between. This means that the tracking procedure is initialized in every n^{th} frame. The value of n is chosen such that it is small enough to prevent the accumulation of error and at the same time large enough to enable the tracker to adapt to the object's motion.

Secondly, we introduce a Blur detector. Since motion blur significantly hinders the tracking of fast moving objects, we quantitatively evaluate a metric which gives the measure of the amount of motion blur in the neighbourhood of the object of interest. Specifically, let X_c, Y_c be the center of the bounding box of the object of interest at time t, and W, H be respectively the width and height of the bounding box. Then, the region of interest (ROI) is defined as the crop of the input image at time $t+1$ centered at X_c, Y_c and having width and height as $2W, 2H$ respectively.

A blurry image has fewer sharp edges than a less blurry version. This implies that in the frequency domain, high frequency components (which contribute to sharp edges) have a lower magnitude for blurry images. To evaluate the high spatial frequencies associated with sharp edges in an image, we use the variance of Laplacian method (Pech-Pacheco et al., 2000). It quantitatively evaluates the amount of blur in a given frame, and if the blur is found to be greater than a threshold value then we deem that frame to be blurry. The exact formulation of the method is given next.

The Laplacian mask l is defined as

$$l = \frac{1}{6}\begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

Now, let L be the convolution of the input image I with the mask l, and (M, N) be the resolution of image I. The variance of Laplacian is defined as follows

$$LAP\_VAR(I) = \sum_{m=1}^{M}\sum_{n=1}^{N}\left[|L(m,n)| - \bar{L}\right]^2$$

where $\bar{L}$ is the mean of absolute values given by

$$\bar{L} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}|L(m,n)|$$

The entire algorithm to check whether a frame is blurry or not is as follows:

IsImageBlurry function

```
1: $(X_c, Y_c) \leftarrow$ Center of bounding box
2: $(W, H) \leftarrow$ Width and Height of bounding box
3: $ROI \leftarrow I\Big[(X_c - W) : (X_c + W), (Y_c - H) : (Y_c + H)\Big]$
4: if $LAP\_VAR(ROI) > blurThresh$ then
5:     return True
6: else
7:     return False
8: end if
```

In summary, we propose that when a blurry image is detected(via the **IsImageBlurry** procedure), the object detection algorithm (which is a priori trained on both blurry and non-blurry images) is employed on that particular frame and the tracker module is re-initialized. Because of its training, the object detection algorithm can detect blurry objects up to a certain extent and therefore help improve the tracking performance of fast-moving objects.

2.2 Motion tracker module

For learning the motion model of the object of interest we rely on Re^3 (Gordon et al., 2017) which was generously open-sourced by Gordon *et. al.* The Re^3 algorithm was trained for generic object tracking. Its recurrent model gives it the ability to train from motion examples offline and quickly update its recurrent parameters online when tracking specific objects. It is also very fast hence well suited for implementation on single-board computers commonly used in mobile robotics applications.

Re^3 employs a Recurrent Neural Network composed of Long Short-term memory (LSTM) units. RNN's are well suited for sequential data modeling and feature extraction (Graves, 2012). The recurrent structure and the internal memory of RNN facilitate its modeling of the long-term temporal dynamics of sequential data. LSTM is an advanced RNN architecture which mitigates the vanishing gradient effect of RNN. The basic formulation of an LSTM unit is given in Equations (1) where t represents the frame index, x_t is the current input vector, h_{t-1} is the previous output(or recurrent) vector W, U are weight matrices for the input and recurrent vector respectively, b is the bias vector, σ is the sigmoid function, and $\circ$ is point-wise multiplication. A forward pass produces both an output vector h_t, which is used to regress the current output, and the cell state c_t, which holds important memory information. Both h_t and c_t are fed into the following forward pass, allowing for information to propagate forward in time.

$$\begin{aligned} f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\ i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\ o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\ c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\ h_t &= o_t \circ \sigma_h(c_t) \end{aligned} \tag{1}$$

For the purpose of motion tracking, the recurrent parameters in the LSTM network represent the tracker state which can be updated with a single forward pass. In this way, the tracker learns to use new observations to update the motion model, but without any additional computation spent on online training. RNN's accept features as inputs and extract useful temporal information from those. But, they are not good at extracting useful information from raw images or video sequences. Hence, Re^3 uses a Convolutional Recurrent Neural Network (CRNN) for the task of motion tracking.

2.3 Re-identification module

The Object tracker can lose track of the target due to various reasons such as long term occlusions, fast motions, or other factors. To achieve robust tracking, it is necessary to have a system which can re-identify the object of interest. This system needs to be able to recognize objects in real-time. But, as the object is not known in advance, image recognition algorithms cannot be used to complete the task. Moreover, the entire pipeline for tracking has to be very fast, which means computationally intensive algorithms cannot be employed for object re-identification. Therefore, we propose a fast and fairly accurate procedure, which uses color cues and structural similarity to re-identify the object of interest. Here, we assume that the track of the object is not lost in the very first second. So, if the frame rate of the camera recording the video is k, then we have k bounding boxes of the object of interest. We store these k bounding boxes and henceforth refer to them as templates. Now, to perform the re-identification task we evaluate two scores; one from normalized cross-correlation (Lewis, 1995) of the frame with the stored templates, and the other from color histogram matching between the templates and the current frame. Then we take a sum of these two scores to evaluate the re-identification score. The exact formulation is explained below:

Normalized Cross Correlation: Let f be the current frame, and define a sum over x, y within the window containing the template t positioned at point (u, v). $\bar{t}$ is the mean of t and $\bar{f}(u, v)$ is the mean of $f(x, y)$ in the region under the template t. We calculate $\gamma(u, v)$, the correlation coefficient which gives the measure of the normalized correlation between the current frame and the template:

$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}][t(x-u, y-v), \bar{t}]}{\sqrt{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}]^2 \sum_{x,y}[t(x-u, y-v), \bar{t}]^2}}$$

The correlation coefficient is a measure of similarity between the frame and the template. It is invariant to the template size and changes in amplitude such as those caused by changing lighting conditions across the image sequence. Due to the above characteristics, this metric of evaluation of structural similarity is robust to noise and brightness change in the scene and hence suited for re-identifying objects in noisy environments.

The templates contain different view-points of the object of interest. So, in order to check if the object under consideration is actually the object of interest, we take the max of correlation coefficients evaluated between the current frame and the templates. We refer to this score as *NCC_score*.

Colour Histogram Intersection Algorithm (Swain and Ballard, 1992): Colour helps the human visual system to analyze complex images more efficiently, improving object recognition. Psychological experiments have shown that color gives a strong contribution to memorization and recognition (Wichmann et al., 2002) in humans. Hence, to leverage from the above observations made by researchers in the field of cognitive science, we use the color histogram intersection algorithm as a metric to re-identify the object of interest in the scene. The histogram intersection algorithm was proposed in (Swain and Ballard, 1991). This algorithm does not require the accurate separation of the object from its background and it is robust to occluding objects in the foreground. Also, histograms are invariant to translation and they change slowly under different view angles, scales and in presence of occlusions, hence they are well suited for our purpose of object re-identification.

The mathematical formulation of the algorithm is as follows: given the histogram i of the input image I and the histogram m of a template t, each one containing n bins, the intersection Z is defined as:

$$Z = \sum_{j=1}^{n} \min(i_j, m_j)$$

The result of the intersection is the number of pixels from the template that have corresponding pixels of the same colors in the input image. To normalize the result between 0 and 1 we have to divide it by the number of pixels in the template histogram:

$$\hat{Z} = \frac{\sum_{j=1}^{n} \min(i_j, m_j)}{\sum_{j=1}^{n} m_j}$$

When an unknown object image is given as input the intersection algorithm computes the histogram intersection for all the stored templates.

The complete re-identification module can be summarized as follows:

Re-identification function

```
1: $reIdentification\_score \leftarrow \hat{Z} + NCC\_score$
2: if $reIdentification\_score > \epsilon$ then
3:     $trackFound \leftarrow True$
4: end if
```

where ϵ is a constant associated with the number of templates used. $\epsilon = 1.2$ is found experimentally.

2.4 Fusion Algorithm pseudo-code

Our overall Fusion algorithm can be summarized as follows:

Fusion algorithm

```
1: Start
2: Initialize the motion tracker with $bbox$.
3: $N \leftarrow 0$    ▷ Counter for number of frames
4: Run the object detector on the $ROI$, set the $known$ flag
5: $LostTrack \leftarrow False$    ▷ Variable for keeping Track of object
6: while $True$ do
7:     $N += 1$
8:     if $known$ then
9:         if $LostTrack$ then
10:            $bboxes \leftarrow$ ObjectDetector(Image)    ▷ Scan for object of interest
11:            if len($bboxes$) $\geq 0$ then
12:                $bbox \leftarrow$ Re-identification(bboxes)    ▷ re-identification
13:                if $bbox$ is not $None$ then
14:                    $LostTrack \leftarrow False$    ▷ Object re-identified
15:                end if
16:            else
17:                $bbox \leftarrow$ MotionTracker.track(Image) ▷ Motion Tracker
18:            end if
19:        else
20:            if (mod(N,Threshold) = 0) | IsImageBlurry then ▷ Blur Detector
21:                $bbox \leftarrow$ ObjectDetector(Image)    ▷ Object Detector
22:                if $bbox$ is $None$ then
23:                    $LostTrack \leftarrow True$    ▷ Object track lost
24:                end if
25:            else
26:                $bbox \leftarrow$ MotionTracker.track(Image) ▷ Motion Tracker
27:            end if
28:        end if
29:    else
30:        $bbox \leftarrow$ MotionTracker.track(Image)    ▷ Motion Tracker
31:    end if
32: end while
```

3. EXPERIMENTAL RESULTS

We compare our fusion algorithm to other tracking methods on two popular tracking datasets in terms of overall performance.

As our work focuses on improving the performance in object tracking for the specific case of the object of interest being *familiar*, many of the video sequences on which we compare our algorithm with other existing algorithms contains *familiar* objects. We demonstrate our algorithm's effectiveness by testing on standard tracking benchmarks, the Visual Object Tracking 2017 challenge (Kristan et al., 2017) and Online Tracking Benchmark (OTB) (Wu et al., 2013) datasets.

3.1 Methodology for quantitative evaluation

We use the One Pass Evaluation (OPE) criterion for evaluating performance on both of the benchmark datasets. This is the conventional way to evaluate trackers which are run throughout a test sequence with initialization from the ground truth position in the first frame, then reporting the average precision or success rate. This is referred as one-pass evaluation (OPE)(Wu et al., 2013). It consists of two separate plots:

(1) **Precision plot**: This shows the percentage of frames whose estimated location is within the given threshold distance of the ground truth. As the representative precision score for each tracker we use the score for the threshold = 20 pixels.
(2) **Success Plot**: The second metric is the bounding box overlap. Given the tracked bounding box and the

ground-truth bounding box, we evaluate the Intersection over Union (IoU). To measure the performance on a sequence of frames, we count the number of successful frames whose overlap S is larger than the given threshold (here, the threshold was kept 0.5 or 50 percent overlap). The success plot shows the ratios of successful frames at the thresholds varied from 0 to 1.

3.2 VOT 2017(Kristan et al., 2017) and OTB-50(Wu et al., 2013)

The VOT 2017 object tracking dataset consists of 60 videos, made explicitly for the purpose of testing object trackers. We use 24 of those video sequences, which have most of their objects belonging to the *familiar* class, with some from the *unfamiliar* class. Many of the videos from this dataset contain difficulties such as large appearance change, heavy occlusion and camera motion. For fairness of comparison, all testing and benchmarking was performed on the same computer.

Figure 1 compares our proposed method with other trackers including CFNet (Valmadre et al., 2017), the winner of the VOT17 real time challenge (Valmadre et al., 2017). We also tested our method on a set of 9 videos (all containing objects from the *familiar* class) from the OTB dataset. Figures 1–4 compare our proposed method with other trackers. Note the performance improvement in both the Success Rate and Precision of our method over the Re^3 method by itself is significant. The corresponding numerical results are given in Table 1.

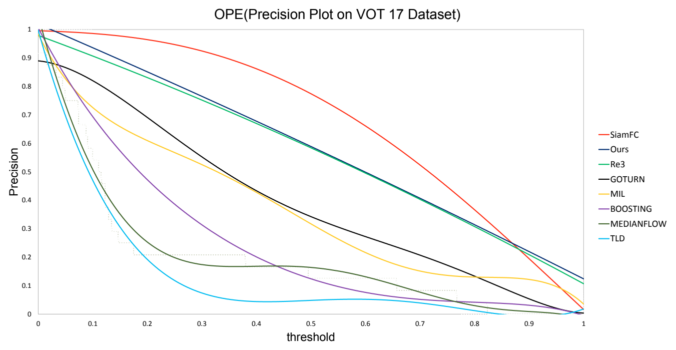


Fig. 1. Precision Plot for VOT17

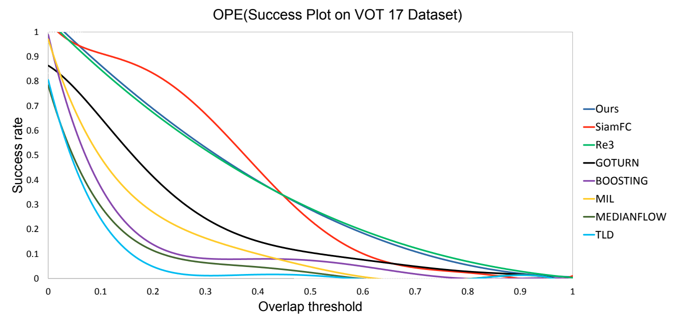


Fig. 2. Success Plot for VOT17

3.3 Qualitative Results

We also tested our algorithm on a variety of challenging videos in order to ascertain its usefulness in the real world.

Table 1. Comparison Table (overlap threshold = 0.5, precision threshold = 0.5)

Name	Success Rate	Precision	FPS
Ours	**0.3333**	0.5833	86
SiamFC	0.2083	**0.7916**	45
Re3	**0.3333**	0.5833	120
GOTURN	0.125	0.375	60
BOOSTING	0.0833	0.1666	66
MIL	0.0833	0.333	25
MEDIANFLOW	0.0001	0.125	**250**
TLD	0.0001	0.0416	30

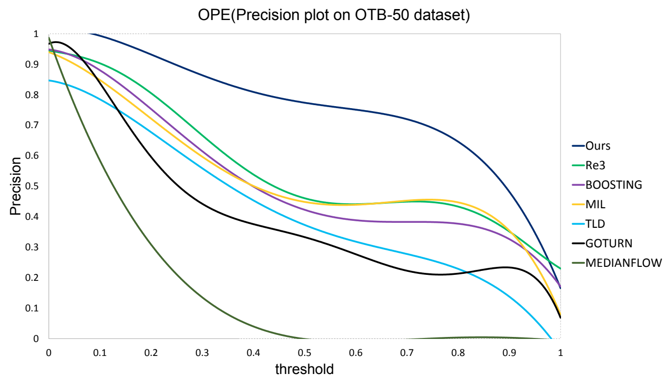


Fig. 3. Precision Plot for OTB-50

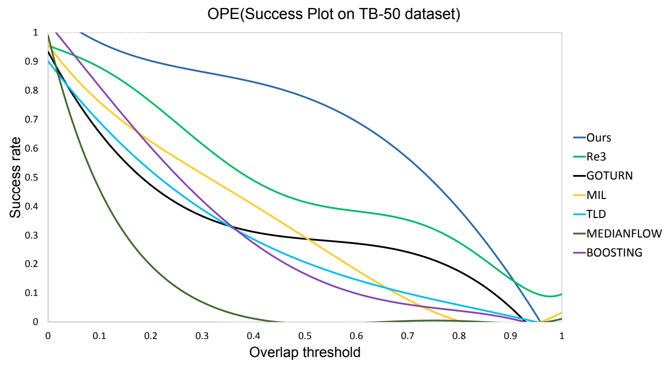
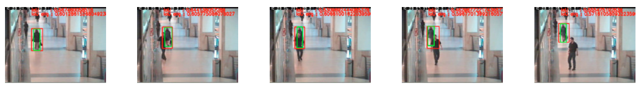


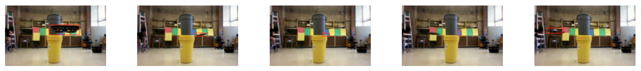
Fig. 4. Success Plot for OTB-50

Our method performs remarkably well on challenging tasks such as tracking a fast moving drone, tracking people performing acrobatics and stunts, or simultaneously tracking multiple people (≤ 4). We show excerpts from two such videos in Figures 5 and 6.



(a) t=1 (b) t=2 (c) t=3 (d) t=4 (e) t=5

Fig. 5. Tracking of occluded pedestrian



(a) t=1 (b) t=2 (c) t=3 (d) t=4 (e) t=5

Fig. 6. Tracking of flying UAV drone

4. CONCLUSION

In this paper, we presented a learning-agnostic heuristic for robust object tracking. Our work fuses the previous works of Re^3 (Gordon et al., 2017) and *YOLO v2* (Redmon and Farhadi, 2017) to build a robust vision-based target tracker usable for mobile robotic applications. Both modules are lightweight and capable of real-time performance on portable computing platforms typical in mobile robotics. Our fusion method demonstrates increased accuracy, robustness and speed compared to other trackers, especially during periods of occlusion or high speed motions of the target or the camera. We demonstrated that provided the target belongs to the *familiar* category of objects, our proposed algorithm provides accuracy similar or better than the current state of the art trackers while being able to operate at an average at 85 FPS, faster than most trackers.

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