The Challenge of Appearance-Free Object Tracking with Feedforward Neural Networks

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Abstract

Nearly all models for object tracking with artificial neural networks depend on appearance features extracted from a “backbone” architecture, designed for object recognition. Indeed, significant progress on object tracking has been spurred by introducing backbones that are better able to discriminate objects by their appearance. However, extensive neurophysiology and psychophysics evidence suggests that biological visual systems track objects using both appearance and motion features [1]. Here, we introduce Pathtracker: a visual challenge inspired by cognitive psychology, which tests the ability of observers to learn to track objects solely by their motion. We find that standard 3D-convolutional deep network models struggle to solve this task when clutter is introduced into the generated scenes, or when objects travel long distances. This challenge reveals that tracing the path of object motion is a blind spot of feedforward neural networks. We expect that strategies for appearance-free object tracking from biological vision can inspire solutions these failures of deep neural networks.

1. The Pathtracker Challenge

We introduce a novel synthetic visual tracking challenge, called Pathtracker. The challenge, inspired by the multi-object tracking paradigm of cognitive psychology [13, 3], is designed to test the ability of observers to learn to track an object in the presence of clutter over long distances (Fig. 1). Pathtracker joins a growing body of work which uses visually simple challenges, inspired by cognitive science, to identify limitations of feedforward models and inspire solutions that push the state of the art in computer vision [8, 9].

The goal of Pathtracker is to determine whether or not a “target” dot starting on a red marker travels to a blue “finish” marker. These two markers are stationary and placed at random positions in each video. The target and distractor dots are white squares that follow procedurally-generated trajectories (Fig. 2; see §2 for details). In positive examples, the target dot finishes its trajectory in the blue marker at the end of the video. In negative examples, a distractor dot, finishes its trajectory on the blue marker, while the target dot ends up somewhere else.

In the most basic version of Pathtracker, observers have to track the target over a 32-frame video, while ignoring a single distractor. The task is made harder by increasing (i) the number of distractors, (ii) the length of the video, or (iii) the speed of the target and distractors. Increasing the number of distractors makes it more likely that target and distractors cross – requiring an observer to distinguish between identical objects and bind identity with motion trajectories. Gestalt principles such as the principle of continuity may provide robust cues to solve such challenge but it is unknown whether modern feedforward neural networks are capable of learning such spatiotemporal features.

2. Stimulus design

Challenge videos consist of 32, 64 or 128 frames of $32 \times 32$ pixels. Target and distractor trajectories are curved and variably shaped. On two successive frames, the dis-
placement between the coordinate positions of the dot is constrained to be not more than 2 pixels and to not bend more than 20°. This means that all dots look like they are meandering through the scene, never turning at acute angles. Start (red) and finish (blue) markers are placed at the starting and ending positions of the target in positive examples. In negative examples, these markers are placed at the start of the target and the end of a randomly selected distractor. Targets and distractors move at the same speed in all videos. In our challenge we produce videos with one target and one distractor, forcing observers to handle occlusion in individual frames and making it difficult for neural architectures to learn shortcut solutions to the challenge.

3. Benchmark Models: 3D-CNNs

Fiaz et al. [6] noted that deep learning-based tracking algorithms rely on appearance: they use the correlation between appearance-based feature maps of successive frames to track target objects. More recent methods have shown incremental improvements by using this same approach on object-proposals from instance segmentation models applied to individual frames [2]. The number of deep network architectures that can be used for appearance-free video processing are fairly limited. Although tracking is a well studied subfield in computer vision, to our knowledge there are no deep learning-based methods for “feature agnostic” tracking based on motion.

We focus our experiments on Inception 3D (I3D) networks [4], which are a standard approach to action recognition in natural videos. We split Pathtracker dataset into separate train/test folds, and perform a large-scale search over I3D hyperparameters to optimize its performance. In total, we explore the following hyperparameters: (i) random weight initializations vs. pretrained Kinetics initializations, (ii) learning rates of \{1 \times 10^{-4}, 3 \times 10^{-4}, 1 \times 10^{-5}, 1 \times 10^{-6}\}, and (iii) \(L_2\) weight decay scaled at \{4 \times 10^{-5}, 1 \times 10^{-6}\}. All models were trained for 1000 epochs on batches of 64 videos. Here, we report best performance across our hyperparameter search. (See section S1 in supplementary materials for details of our experiments with hyperparameter search.)

Every variant of Pathtracker had 20K training and 20K test samples. Models were trained on TPUs and evaluated on versions of the challenge with different numbers of distractors, frames, and speeds. We also include experiments where I3D was trained on optic flow encodings of the datasets (see supplementary material).

Table 1: I3D evaluation accuracy on variable length Pathtracker datasets of “normal” speed.

| Video Dimension (D,H,W) | Distractors |
|-------------------------|-------------|
|                         | 32,32,32    | 64,32,32 | 128,32,32 |
| 1                       | 93.88       | 81.29    | 58.20     |
| 6                       | 86.90       | 67.39    | 56.40     |
| 15                      | 83.59       | 65.13    | 56.55     |
| 26                      | 81.03       | 64.29    | 56.06     |

Table 2: I3D evaluation accuracy on Pathtracker datasets with variable dot speed. Dots travel longer distances when speed is increased above “normal”. We generated “fast” and “very fast” versions of Pathtracker videos, in which dots traveled 2× or 4× their normal distance, respectively. We set the maximum path length to be consistent with dot path length in the 128-frame videos; hence, we do not generate “very fast” versions of the 64×32×32 datasets. See §2 for details on speed variations.

| Video Dimension (D,H,W) | Dist. |
|-------------------------|-------|
|                         |       |
|                         | 32,32,32 | 32,32,32 | 64,32,32 | 128,32,32 |
| 1                       | Fast   | Very Fast | Fast   | Normal     |
|                         | 81.50  | 59.82     | 59.79  | 56.66      |
| 6                       | 68.13  | 55.56     | 57.30  | 56.40      |
| 15                      | 63.04  | 55.40     | 56.12  | 56.54      |
| 26                      | 62.89  | 51.10     | 51.62  | 50.81      |
4. Results

I3D performed well on a 1-distractor, 32-frame version of mixed-channel version of Pathtracker dataset (Fig. 1), reaching 93% accuracy. However, I3D’s performance monotonically decreased as clutter and tracking length increased (Table 1). Indeed, we found a sharp drop in I3D’s performance for 64-frame videos when more than one distractor was included (see the drop from 1→6 in Table 1). I3D also struggled to learn the task, even when only a single distractor was present, in longer 128-frame videos.

We further found that I3D struggled to learn Pathtracker when we increased the speed of dots in the videos. I3D was unable to break 60% accuracy when dots moved “very fast” in a 32-frame video or “fast” in a 64-frame video (see Table 2).

One possible explanation why I3D struggled in so many conditions of the Pathtracker challenge is that it was either over- or under-parameterized, which caused unstable learning. To address this, we repeated our experiments with wider and narrower I3D networks, containing 4× and 1/4th the number of features as the original model.

Narrower Network: We reduced the feature maps on all but readout layers to 1/4th of their original size. We observed a monotonic decrease in accuracy, as in case of original feature maps. We observe a 4-5% increase in accuracy on the datasets with path lengths corresponding to a 128-frame task and 26 distractors. Accuracy on other datasets remain constant. See tables 3 and 4 for constant and variable speed experiments respectively.

Wider Network: We increased the feature maps on all but readout layers to 4× of their original size. We again observed a similar monotonic decrease in accuracy, as in case of experiments with the original feature maps. Contrary to the belief of large feature maps being able to learn better representation of objects, we observe a 14% drop in accuracy for 64-frame 26 distractor version of the dataset. For other longer path length datasets, we also observed small drops in accuracy. Only the shorter path length videos show an insignificant increase in accuracy. See tables 5 and 6 for constant and variable speed experiments respectively.

Table 3: Evaluation accuracy of I3D with narrower network with variation in the number of frames.

| Distractors | Video dimension (D,H,W) |
|-------------|-------------------------|
| 1 dist      | 32,32,32 64,32,32 128,32,32 |
| 6 dist      | 92.53 80.44 56.71 |
| 15 dist     | 84.58 64.45 56.80 |
| 26 dist     | 80.11 64.19 56.18 |
|             | 79.10 63.28 55.70 |

Table 4: Evaluation accuracy of I3D with narrower network with variable speed datasets, compared to the longer constant speed version.

| Dist.       | Video dimension (D,H,W) |
|-------------|-------------------------|
| Speed       | 32,32,32 64,32,32 128,32,32 |
| 1 dist      | 93.42 79.56 53.59 |
| 6 dist      | 87.28 64.40 52.68 |
| 15 dist     | 85.23 64.49 50.77 |
| 26 dist     | 82.86 50.95 50.75 |

Table 5: Evaluation accuracy of I3D with wider network with variation in the number of frames.

| Distractors | Video dimension (D,H,W) |
|-------------|-------------------------|
| 1 dist      | 93.42 79.56 53.59 |
| 6 dist      | 87.28 64.40 52.68 |
| 15 dist     | 85.23 64.49 50.77 |
| 26 dist     | 82.86 50.95 50.75 |

Table 6: Evaluation accuracy of I3D with wider network with variable speed datasets, compared to the longer constant speed version.

| Dist.       | Video dimension (D,H,W) |
|-------------|-------------------------|
| Speed       | 32,32,32 64,32,32 128,32,32 |
| 1 dist      | 80.28 56.20 57.38 53.59 |
| 6 dist      | 68.86 52.01 56.49 52.68 |
| 15 dist     | 64.15 50.79 50.76 50.77 |
| 26 dist     | 62.74 55.81 50.78 50.75 |

Another explanation for poor performance on the task is that Pathtracker videos consist of a single channel, containing dots and markers. It is possible that model performance could be improved by engineering the dataset to disentangle dots and markers at the input, ensuring that these resources do not interfere with each other when they are encoded by models [7, 14]. To test this hypothesis, we generated new versions of Pathtracker with three-channel videos, in which the first channel contained the start marker, the second channel contained the dots, and the third channel contained the finish marker (Fig. S1). However, I3D performed similarly on these datasets as it did on the original ones.

We also tested whether training on optic flow encodings of Pathtracker videos would improve I3D performance. However, this led to similar performance as when I3D was trained on the original dataset (see section S2 in supplementary materials for details and results).

5. Discussion and Conclusion

We found that I3D struggles to learn most of the Pathtracker challenge. In particular, I3D performance was...
strongly affected by dot clutter, speed, and path length. Importantly, 3D is capable of solving a baseline version of the challenge with a single distractor in relatively short (32-frame) videos. Thus, Pathtracker stands as a novel challenge for spatiotemporal neural networks.

What mechanisms do biological visual systems rely on for appearance-free tracking? Evidence from cognitive science suggests that human observers explicitly “trace” the trajectories of individual dots [12, 5]. Similar types of tracing routines have been associated with the computations of neural circuits, and specifically the ability to transitively group features according to gestalt rules like “good continuity” [10, 16, 15]. We suspect that similar circuits might help on Pathtracker, although they may need additional mechanisms for learning to detect spatiotemporal features.

Even though appearance-free tracking hasn’t received much attention in computer vision to date, solving this problem holds immense promise in resolving the brittle generalization of neural networks. Indeed, a network that can solve Pathtracker might also be expected to be able to generalize between standard object tracking benchmarks, and synthetic or real-world tracking applications, with little or no additional retraining. Furthermore, combining a good appearance-free tracker with typical appearance-based trackers might improve better performance when asked to track over long periods of time or in the presence of clutter or occlusion.

We have proposed a novel synthetic and feature agnostic tracking task inspired by cognitive psychology that challenges the long-range spatiotemporal tracking abilities of deep neural networks. Our task highlights a key limitation of the current state-of-the-art models in tracking objects without appearance cues.

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– Supplementary Information –

S1. Hyperparameter Search

We performed an extensive hyperparameter search with variable learning rates and weight decays on all constant speed RGB datasets with mixed channels (Fig. 1) to check if any combination of learning rate and weight decay yields better accuracy with our engineered dataset than our earlier experiments (see tables S1, S2, S3). The default learning rate and weight decay for our earlier experiments were set at $3 \times 10^{-4}$ and $4 \times 10^{-5}$ respectively (first cell in all tables). We found that barring 128-frame 26 distractor dataset, there was no significant improvement in accuracy compared to our default experiments.

Table S1: Evaluation accuracies from hyperparameter search on I3D with RGB datasets of dimensions 32 $\times$ 32 using given learning rates and weight decays

| 1 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 1       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 6 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 15 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 26 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

Table S2: Evaluation accuracies from hyperparameter search on I3D with RGB datasets of dimensions 64 $\times$ 32 $\times$ 32 using given learning rates and weight decays

| 1 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 1       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 1       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 6 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 15 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

| 26 dist. | Learning Rate | Weight | Weight |
|---------|---------------|--------|--------|
|         |               | Decay  | dist.  |
| 4       | $3 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-4}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-5}$ | 1.0000 | 1.0000 |
| 4       | $1 \times 10^{-6}$ | 1.0000 | 1.0000 |

S2. Experiments with Optic Flow

As done in [4], we calculated optic flow for all the datasets using TV-L1 algorithm [11, 17]. We engineered our dataset (see Figure S1) to check if spreading features across different channels could help improve the performance of I3D [7, 14]. To this end, we put the starting marker in the first channel, dots in the second, and ending marker in the last channel. We further used OpenCV’s TV-L1 implementation [17] to calculate optic flow on our videos. We used two channels from the output given by the TV-L1 algorithm, and appended one channel from the raw dataset to simulate the two-stream network described in [4] in their RGB+Flow experiments. We found that engineered dataset combined with optic flow was unable to rescue the performance of I3D on our Pathtracker challenge (see table S4). In a few cases, we even observed a drop in accuracy compared to our earlier experiments without optic flow (compare with table 1).
learning rate and weight decay for our earlier experiments (see tables S5, S6, S7). The default cay yields better accuracy with our engineered dataset than check if any combination of learning rate and weight de-
speed datasets with separate channels and optic flow to
variable learning rates and weight decays on all constant
S3. Hyperparameter Search with Optic Flow

We performed an extensive hyperparameter search with variable learning rates and weight decays on all constant
speed datasets with separate channels and optic flow to
tion in the number of frames.

| Video dimension (D,H,W) | Distractors |
|-------------------------|-------------|
| 32,32,32 | 64,32,32 | 128,32,32 |
| 1 dist | 93.35 | 78.77 | 51.20 |
| 6 dist | 83.71 | 65.94 | 51.84 |
| 15 dist | 79.59 | 62.21 | 51.03 |
| 26 dist | 78.50 | 51.55 | 50.85 |

Table S3: Evaluation accuracies from hyperparameter Search on I3D with RGB datasets of dimensions 128 × 32 × 32 using given learning rates and weight decays

Table S4: Evaluation accuracy of I3D with optic flow with variation in the number of frames.

Table S5: Evaluation accuracies from hyperparameter Search on I3D with optic flow datasets of dimensions 32 × 32 × 32 using given learning rates and weight decays

Figure S1: Positive example from the engineered dataset of Pathtracker challenge. The markers and dots are spread across multiple channels. The starting marker is in the first channel, the dots are in second channel, while the ending marker is in the last channel. Everything else is same as our original dataset in Figure 1. See section 1 for description on challenge.
Table S6: Evaluation accuracies from hyperparameter Search on I3D with optic flow datasets of dimensions 64 × 32 × 32 using given learning rates and weight decays

| 1 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 78.77  | 77.81            | 70.27            | 62.20            |
|         | 1 \times 10^{-6} | 79.14  | 78.02            | 70.19            | 61.45            |

| 6 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 65.94  | 65.93            | 59.56            | 55.78            |
|         | 1 \times 10^{-6} | 66.58  | 66.06            | 60.64            | 56.91            |

| 15 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 62.21  | 61.82            | 58.05            | 54.63            |
|         | 1 \times 10^{-6} | 62.20  | 62.39            | 58.04            | 53.66            |

| 26 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 51.55  | 61.75            | 54.62            | 52.59            |
|         | 1 \times 10^{-6} | 62.07  | 60.20            | 56.26            | 52.36            |

Table S7: Evaluation accuracies from hyperparameter Search on I3D with optic flow datasets of dimensions 128 × 32 × 32 using given learning rates and weight decays

| 1 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 51.20  | 57.29            | 54.56            | 53.98            |
|         | 1 \times 10^{-6} | 54.66  | 57.22            | 55.10            | 53.60            |

| 6 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 51.84  | 54.34            | 53.45            | 52.24            |
|         | 1 \times 10^{-6} | 56.30  | 54.26            | 52.69            | 52.11            |

| 15 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 51.03  | 54.49            | 52.74            | 52.07            |
|         | 1 \times 10^{-6} | 52.96  | 55.43            | 53.03            | 51.82            |

| 26 dist. | Learning Rate | Weight | 3 \times 10^{-4} | 1 \times 10^{-4} | 1 \times 10^{-5} | 1 \times 10^{-6} |
|---------|---------------|--------|------------------|------------------|------------------|------------------|
| Decay   | 4 \times 10^{-5} | 50.85  | 50.81            | 51.80            | 50.96            |
|         | 1 \times 10^{-6} | 50.77  | 53.61            | 51.66            | 51.63            |