Deep Siamese Networks with Bayesian non-Parametrics for Video Object Tracking

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Abstract

We present a novel algorithm utilizing a deep Siamese neural network as a general object similarity function in combination with a Bayesian optimization (BO) framework to encode spatio-temporal information for efficient object tracking in video. In particular, we treat the video tracking problem as a dynamic (i.e. temporally-evolving) optimization problem. Using Gaussian Process priors, we model a dynamic objective function representing the location of a tracked object in each frame. By exploiting temporal correlations, the proposed method queries the search space in a statistically principled and efficient way, offering several benefits over current state of the art video tracking methods.

1. Introduction

The problem of tracking an arbitrary object in video, where an object is identified by a single bounding-box in the first frame, requires both a robust similarity function and an efficient method for querying plausible locations of the object in subsequent frames. Early video tracking approaches have included feature-based approaches and template matching algorithms [1] that attempt to track specific features of an object or even the object as a whole. Feature-based approaches use local features, including points and edges, keypoints [2], SIFT features [3], HOG features [4] and deformable parts [5]. Conversely, template-based methods take the object as a whole offering the potential advantage that they treat complex templates or patterns that cannot be modeled by local features alone.

Through the course of a video, an object can potentially undergo a variety of different visual transformations, including rotation, occlusion, changes in scale, illumination changes, etc., that pose significant challenges for tracking. In order to obtain a robust template matching for video tracking, researchers have developed a host of methods, including mean-shift [6] and cross-correlation filtering which entails convolving a template over a search region; significant advances to cross-correlation filtering for video tracking include MOSSE [7] adaptive correlation filter and the MUSTer algorithm [8] which draws influence from cognitive psychology in the design of a flexible object representation using long and short-term memory stored by means of an integrated correlation filter.

More recently, deep learning models have been applied to video tracking to leverage the benefits of learning complex functions from large data sets. While deep models offer the potential of improved robustness for tracking, they have nevertheless presented two significant challenges to tracking research to date. First, many deep tracking models are too slow for practical use due to the fact that they require online training, and, second, many deep trackers, when trained offline, are based on classification approaches, so that they are limited to class-specific searches and frequently require the aggregation of many image patches (and thus many passes through the network) in order to locate the object [9]. In light of these difficulties, several contemporary state of the art deep learning-based tracking models have been developed as generic object trackers in an effort to obviate the need for online training and to also improve the generalizability of the tracker. [10] applies a regression-based approach to train a generic tracker, GOTURN, offline to learn a generic relationship between appearance and motion; several deep techniques additionally incorporate motion and occlusion models, including particle filtering methods [11] and optical flow [12].

[13] demonstrated the power of deep Siamese networks (see section 2.1) based on [14], achieving a new state of the art for generic object matching for video tracking. Remarkably, the SINT algorithm delivered state of the art performance despite the fact that it was not equipped with any model updating, no occlusion detection, and no explicit ge-
ometric or feature matching components. [15,19] extended this work to achieve state of the art Siamese-based tracking while operating at frame rates beyond real-time by exploiting a fully-convolutional network structure. Even with these recent successes in video object tracking, there nevertheless exists a void in state of the art video tracking workflows that fully integrate deep learning models with classical statistics and machine learning approaches. Most state of the art video trackers lack for instance a capacity to generate systematic belief states (e.g. through explicit error and uncertainty measures), or ways to seamlessly incorporate contextual and scene structure, or to adaptively encode temporal information (e.g. by imposing intelligent search stopping conditions and bounds) and the ability to otherwise directly and inferentially control region proposal generation or sampling methods in a precise and principled way. To this end, we believe that the fusion of deep models with classical approaches can provide a necessary incubation for intelligent computer vision systems capable of high-level vision tasks in the future (e.g. scene and behavior understanding).

In the current work we present the first integrated dynamic Bayesian optimization framework in conjunction with deep learning for object tracking in video.

2. Siamese Networks

We adopt the Siamese network-based approach for one-shot image recognition from [15] to learn a generic, deep similarity function for object tracking. The network learns a function \( f(z, x) \) that compares an exemplar crop \( z \) to a candidate crop \( x \) and returns a high score if the two images depict the same object and a low score otherwise. For computer vision tasks, a natural candidate for the similarity function \( f \) is a deep conv-net [16,17]. Following [14,15], a Siamese network applies an identical transformation \( \phi \) to both input image crops and then combines their representations using another function \( g \) that is trained to learn a general similarity function on the deep conv-net features, so that \( f(z, x) = g(\phi(z), \phi(x)) \).

The network is trained on positive and negative pairs, using logistic loss:

\[
I(y, v) = \log(1 + \exp(-yv))
\]

where \( v \) is the real-valued score of an exemplar-candidate pair and \( y \in \{-1, +1\} \) is its ground-truth label. The parameters of the conv-net \( \theta \) are obtained by applying Stochastic Gradient Descent (SGD) to:

\[
\arg \min_{\theta} \mathbb{E}_{(z, x, y)}[L(y, f(z, x; \theta))]
\]

where the expectation in eq. (2) is computed over the data distribution.

Pairs of image crops were obtained using annotated videos from the 2015 edition of ImageNet for Large Scale Visual Recognition Challenge [18] (ILSVRC); images were extracted from two different frames, at most a distance of \( T \) frames apart; positive image exemplars were defined as a function of their center offset distance from the ground-truth and the network stride length. Image sizes were normalized for consistency during training [15].

We use a five-layer conv-net architecture [19], with pooling layers after the first and second layers, and stride lengths of 2 and 1 throughout. The final network output is a 22x22x128 tensor, as shown in Figure 1.

3. Dynamic Bayesian Optimization

[20] define object tracking in video as a dynamic optimization problem (DOP):

\[
DOP = \{\max f(x, t) \text{ s.t. } x \in F(t) \subseteq S, t \in T\}
\]

where \( S \in \mathbb{R}^D \), with \( S \) in the search space; \( f : S \times T \rightarrow \mathbb{R} \) is the temporally-evolving objective function which yields a maximum when the input \( x \) matches the ground-truth of the target object; \( F(t) \) is the set of all feasible solutions \( x \in F(t) \subseteq S \) at time \( t \).

Bayesian optimization is a sequential framework for optimizing an unknown, noisy and/or expensive objective function \( f(x, t) \). BO works in two key stages: first, we generate a surrogate model to learn a latent objective function from collected samples; next, we determine plausible points to sample from the objective function in the search space. In the present work we use Gaussian Process Regression (GPR) to render the surrogate model. The second phase involves a secondary optimization of a surrogate-dependent acquisition function \( a(x, t) \), which strikes a balance between exploring new regions in the search space and exploiting information obtained from previous samples of the objective function. Common choices of acquisition functions include expected-improvement (EI) and probability of improvement (PI) functions [21]. We devise a novel acquisition function, which we call memory-score expected-improvement (MS-EI), that demonstrated superior performance to EI and PI on our experimental data. We define MS-EI as:

\[
MS-EI(x) = \mu(x) - f(x^*) - E[Z]\Phi(Z) + \sigma(x)\phi(Z)
\]

where \( Z = \frac{\mu(x) - f(x^*) - \xi}{\sigma(f)} \), \( x^* = \arg \max f(x) \). \( \Phi \) and \( \rho \) denote the PDF and CDF of the standard normal distribution respectively.

![Figure 1. The Siamese network \( \phi \) takes the exemplar image \( z \) and search image \( x \) as inputs. We then convolve (denoted by \( * \)) the output tensors to generate a similarity score. Similarity scores for a batch of sample search images are later rendered in a 20x20x1 search grid using a Gaussian Process (see section 3.3 for details). All images best viewed in color.](image-url)
Figure 2. Illustration of \( \hat{f}(x, t) \) for DOP: Region (1) shows previous sample instances for time instances prior to time \( t \); region (2) depicts the bounded region of the search at time \( t \); region (3) represents future time slices. Image credit: [25].

We define \( \xi = (\alpha \cdot \text{mean}[f(x)]_D \cdot n^q)^{-1}; \) where \( \alpha \) and \( q \) are tunable parameters that depend on the scale of the objective function (we use \( \alpha = 1, q = 1.1 \)); \( D \) denotes the sample data set, and \( n \) is the sample iteration number, with \( |D| = n \); \( \text{mean}[f(x)]_D \) is the sample mean of the previously observed values. Here \( \xi \) serves to balance the exploration-exploitation trade-off to the specificity of a particular search. In this way, MS-EI employs a cooling schedule so that exploration is encouraged early in the search; however, the degree of exploration is conversely dynamically attenuated for exploitation as the search generates sample points with larger output values.

### 3.1. Gaussian Processes

A Gaussian Process (GP) defines a prior distribution over functions with a joint Normality assumption. We denote \( \hat{f} \), the realization of the Gaussian process: \( f \sim \mathcal{GP}(\mu, K) \). Here the GP is fully specified by the mean \( \mu : \mathcal{X} \rightarrow \mathbb{R} \) and covariance \( K : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}, K((x, t), (x', t')) = \mathbb{E}[(f(x, t) - \mu(x, t))(f(x', t') - \mu(x', t'))] \), where \( K(\cdot, \cdot) \leq 1 \) and \( \mathcal{X} = S \times T \). See [21] for further details.

### 3.2. Dynamic Gaussian Processes

Following [22] we model a DOP \( f(x, t) \) as a spatio-temporal GP where the objective function at time \( t \) represents a slice of \( f \) constrained at \( t \). This dynamic GP model will therefore encapsulate statistical correlations in space and time; furthermore the GP can enable tracking the location of an object, expressed as the temporally-evolving maximum of the objective function \( f(x, t) \).

Let \( \hat{f}(x, t) \sim \mathcal{GP}(0, K(\{(x, t), (x', t')\})) \), where \( (x, t) \in \mathbb{R}^3 \) (\( x \) is the bounding-box spatial location), and \( K \) is the covariance function of the zero-mean spatio-temporal GP. For simplicity, we assume that \( K \) is both stationary and separable of the form [22]:

\[
K(\hat{f}(x, t), \hat{f}(x', t')) = K_S(x, x') \cdot K_T(t, t')
\]

where \( K_S \) and \( K_T \) are the spatio and temporal covariance functions, respectively. We use Mate\'rn kernel functions [21] in experiments and train the spatial and temporal covariance functions independently, following our separable assumption.

### 3.3. Siamese-Dynamic Bayesian Tracking Algorithm

We now present the details of our Siamese-Dynamic Bayesian Tracking Algorithm (SDBTA). The algorithm makes use of the previously-described deep Siamese conv-net. In the first step, we train the dynamic GP model. Then, for each current frame \( t \) in the video containing \( T \) total frames (consider \( t = 0 \) the initial frame containing the ground-truth bounding-box for the target object), we render the GPR approximation over a resized search grid of size \( d \times d \) (we use \( d = 20 \) for computational efficiency), and then subsequently apply upsampling (e.g. cubic interpolation) over the original search space dimensions. In order to allow our algorithm to handle changes in the scale of the target object, each evaluation of an image crop is rendered by the Siamese network as a triplet score, where we compute the similarity score for the current crop compared to the exemplar at three scales: \( [1.00 - p, 1.00, 1.00 + p] \), where heuristically set \( p = 0.05 \). The remaining algorithm steps are straightforward and detailed below.

#### Algorithm 1 Siamese-Dynamic Bayesian Tracking Algorithm

```python
for i in range(1, T+1):
    Render GPR with set \{y\} over \( d \times d \) grid
    Upsample grid data to dim. of search space \( S \)
    Update current location of optimum over \( S \)
```

### 4. Experimental Results

We tested our algorithm using a subset of the VOT14 [32] and VOT16 [33] data sets, the "CFNET" video tracking data set [19], against three baseline video tracking models: template matching using normalized cross correlation (TM) [29] the MOSSE tracker algorithm [7], and ADNET (2017, CVPR), a state of the art, deep reinforcement learning-based video tracking algorithm [28].

For our algorithm, we fixed the number of samples per frame at 80 (cf. region proposal systems commonly rely on thousands of image queries [9]). We report the search summary statistics for IOU (intersection over union) for each model.

Beyond these strong quantitative tracking results, we additionally observed that the comparison models suffered from either

|            | TM | MOSSE | ADNET | SDBTA (ours) |
|------------|----|-------|-------|--------------|
| mean IOU   | 0.26| 0.10  | 0.47  | 0.56         |
| std IOU    | 0.22| 0.25  | 0.23  | 0.17         |

Table 1. Experimental results summary.
significant long-term tracking deterioration or episodic instability (see Figure 3). The SDBTA algorithm in general did not exhibit this behavior based on our experimental trials.

5. Future Work

While the present algorithm has already demonstrated its effectiveness in video tracking, we nevertheless believe it can be further improved in the near future. We intend to expand the current approach to accommodate the following enhancements: (1) GP-enabled multiscaling (so the GP is generated in five dimensions, including space, size and time); (2) adaptive Bayesian optimization (ABO) which adaptively alters the bounds and sample constraints at each frame for optimizing the acquisition function based on the learned time-related length-scale parameter [25]; (3) we anticipate furthermore that incorporating a fully-convolutional [15] architecture into the Siamese conv-net with our current pipeline on the learned time-related length-scale parameter [25]; (4) we anticipate furthermore that incorporating a fully-convolutional [15] architecture into the Siamese conv-net with our current pipeline on the learned time-related length-scale parameter [25]; (4) we anticipate furthermore that incorporating a fully-convolutional [15] architecture into the Siamese conv-net with our current pipeline on the learned time-related length-scale parameter [25]; (4) we anticipate furthermore that incorporating a fully-convolutional [15] architecture into the Siamese conv-net with our current pipeline on the learned time-related length-scale parameter [25]; 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