Filter Learning from Deep Descriptors of a Fully Convolutional Siamese Network for Tracking in Videos

Hugo de Lima Chaves[1], Kevyn Swhants Ribeiro[1], André de Souza Brito[1], Hemerson Tacon[1], Marcelo Bernardes Vieira[1], Augusto Santiago Cerqueira[1], Saulo Moraes Villela[1], Helena de Almeida Maia[2], Darwin Ttito Concha[2] and Helio Pedrini[2]

[1]*Department of Computer Science, Federal University of Juiz de Fora (UFJF), Juiz de Fora, MG, Brazil*

[2]*Institute of Computing, University of Campinas (UNICAMP), Campinas, SP, Brazil*

{*hugo.chaves, swhants, andre.brito, hemerson*}*@ice.ufjf.br*, {*marcelo.bernardes, augusto.santiago, saulo.moraes*}*@ufjf.edu.br*, {*helena.maia, darwin.ttito*}*@liv.ic.unicamp.br, helio@ic.unicamp.br*

Keywords: Video Tracking, Siamese Network, Deep Descriptors.

Abstract: Siamese Neural Networks (SNNs) attracted the attention of the Visual Object Tracking community due to their relatively low computational cost and high efficacy to compare similarity between a reference and a candidate object to track its trajectory in a video over time. However, a video tracker that purely relies on an SNN might suffer from drifting due to changes in the target object. We propose a framework to take into account the changes of the target object in multiple time-based descriptors. In order to show its validity, we define long-term and short-term descriptors based on the first and the recent appearance of the object, respectively. Such memories are combined into a final descriptor that is the actual tracking reference. To compute the short-term memory descriptor, we estimate a filter bank through the usage of a genetic algorithm strategy. The final method has a low computational cost since it is applied through convolution operations along the tracking. According to the experiments performed in the widely used OTB50 dataset, our proposal improves the performance of an SNN dedicated to visual object tracking, being comparable to the state of the art methods.

1 INTRODUCTION

Video Object Tracking (VOT) is one of the fundamental problems in computer vision. It consists of providing an object trajectory along a video given its initial coordinates. VOT is a key component in many applications: surveillance system, robotics, autonomous driving, intelligent traffic control, augmented reality, sports video analysis. The traditional approaches to this problem are grounded on mathematical models designed to detect and extract features of a target. These features are manually designed, or handcrafted, beforehand by human experts for very specific issues such as: occlusions, illumination changes and many others (Nanni et al., 2017).

However, since the advent of Deep Learning approaches through Convolutional Neural Networks (CNNs), the Computer Vision community has made a notorious effort to obtain feature descriptors based on data instead of those designed by experts. A specific type of Deep Neural Network (DNN) employed in the feature design task is the Siamese Neural Network (SNN). Designed for template comparison, it is used for a wide range of applications, including: signature verification, audio analysis and face recognition (Bromley et al., 1994; Taigman et al., 2014; Manocha et al., 2018). The capability to generate descriptors for similarity comparison between a reference and candidate image has inspired works for VOT applications (Valmadre et al., 2017).

In this paper, the VOT problem is addressed by enhancing a specific type of SNN for visual tracking, the SiamFC (Bertinetto et al., 2016). Our premise is that one may obtain tracking improvements by combining the descriptor outputted by this SNN along the video. More specifically, we propose a method to learn a set of linear time-invariant filters from a video subset. The supervised filter learning is performed by a Genetic Algorithm (GA). By filtering the descriptors provided by the network over time, we capture the short-term memory of the tracked object. We also use a reliable descriptor obtained from the initial frames of the video. This is the long-term object memory to be used along the whole tracking. As our results show, the combination of the long-term and short-term descriptors outperforms the SiamFC tracker and is comparable to the state-of-the-art methods.

The main contributions of this work are the filter learning approach and the framework to use multiple representations of the object to improve video tracking. The combination of long and short-term memory descriptors is also a major contribution, improving the tracking with a very low computational cost.

2 RELATED WORK

The usage of SNN for VOT problems is a very recent approach, presenting noticeable performance in the latest public evaluations (Kristan et al., 2017; Kristan et al., 2018). The SINT was the first tracker that relied on an SNN (Tao et al., 2016) with a simplistic framework to compare a reference image patch, the Region Of Interest (ROI) in the first frame, with each frame of the video. It compares several Bounding Boxes (BB) close to the region where the object was detected in the previous frame and picks the most similar as output for the current frame. This simple model reached the state-of-the-art performance in its time, outperforming well-established methods, such as TLD (Kalal et al., 2012), which has occlusion detection and object model updating. Likewise, Bertinetto et al. (Bertinetto et al., 2016) proposed a fully convolutional SNN that compares a frame to an object image. It only uses a pre-trained SNN to localize the object. No model update is included. Its innovation is the use of a Fully Convolutional Neural Network (FCNN). The SiamFC shows a score-map that indicates the confidence of the object to be found in a particular image region. Due to its simplicity, performance and the strong evidence that SNNs are a very promising approach for VOT, the SiamFC has been used as baseline to many works to demonstrate new tracking concepts, as online weight adaptiveness, correlational filters, rotation invariance and others (Guo et al., 2017; Rout et al., 2018; Valmadre et al., 2017). Another SNN for template matching is proposed by (Guo et al., 2017). They argue that the SiamFC lacks adaptiveness during tracking. They apply an online transformation on the weights of the static SNN based on the information of recent frames, adding temporal information. It also learns a background suppression transformation for the query image. In a different way, Rout et al. (Rout et al., 2018) improved the SiamFC by providing a rotation-invariant framework. They assume smooth rotations of the object along consecutive frames. Then, several images are presented with different rotation angles, giving it more robustness when compared to SiamFC.

The representation of objects based on deep descriptors is a common point in recent VOT works (Tao et al., 2016; Wang and Yeung, 2013; Bertinetto et al., 2016; Danelljan et al., 2016; Danelljan et al., 2017). Some of them process the deep descriptors using a correlation filter with the drawback of having high computational cost. The main concern is to extract spatial relations from feature maps of deep descriptors. In contrast, temporal component analysis and descriptor filtering is an open branch to be explored (Huang, 2017).

Recently, Valmandre et al. (Valmadre et al., 2017) adapted the SiamFC to use a correction filter and proposed an adaptive method to weight the temporal variation of feature maps. Instead of having a single representation of the object based only on the first frame, a new template is computed for each frame. The templates are combined with the previous ones in a moving average. That work showed evidence that the performance can be improved by temporal filtering. Since the moving average is a linear time-invariant filter, we argue that it is possible to find filters more suitable for tracking purposes. Our motivation is to explore methods to weight the consecutive descriptors obtained during tracking. We estimate filters based on observations of annotated tracking data. In summary, our goal is to learn a set of filters to process deep descriptors in time.

In this context, Cemes and Ait-Boudaoud (Cemes and Ait-Boudaoud, 1993) showed a comparison between GA and other methods to find FIR (Finite Impulse Response) filters. Similarly, Dey et al. (Dey et al., 2010) showed the advantages of FIR filter design using GA. Despite the GA computational cost, it has a strong potential to overcome local minima and is a suggestive choice to find filters. Details about the encoding scheme used in our work that is useful for GA convergence are presented by (Ahmad and Antoniou, 2006).

3 PROPOSED METHOD

Our proposed method is based on a frozen version of the SiamFC pre-trained on the ImageNet Video dataset. Originally, the SiamFC is composed of two twin networks, i.e. identical networks sharing weights, where the first one processes a reference image (the first frame) and the second one processes the current frame. The networks are inspired by the AlexNet architecture (Krizhevsky et al., 2012). Both networks output descriptors from the images that are used in an object localization module. This module is

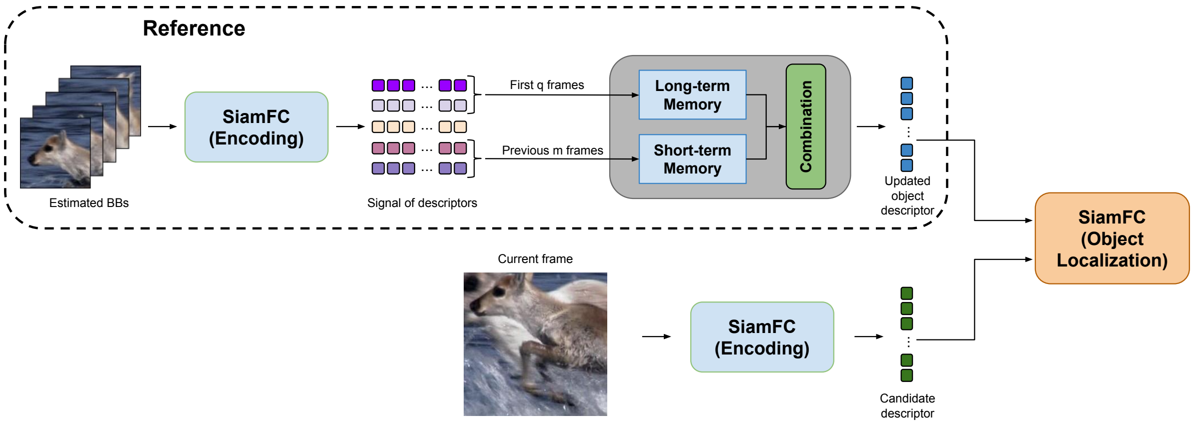


Figure 1: Method overview. The BBs identified in the video are encoded by the SiamFC, resulting in a signal of descriptors. Memories cover different parts of the video to provide suitable descriptors for different appearances of the object. Descriptors are combined to better represent the original object. Notice that the target localization is performed as defined by the original SiamFC.

composed of a cross-correlation layer that generates a score map indicating the likelihood of the object in the reference image to be found in a given region of the candidate image.

Trackers based on SNNs, as SINT and SiamFC, rely only on the descriptor generated in the first frame, computed from the ROI contents. The SNNs do not consider the multiple dynamic instances of the object along the video. They also tend to fail when objects from the ROI background eventually appear. One way to overcome the mapping limitation of these SNNs is to use more than one instance of the same object to compose the final target descriptor. To this end, in our method (Figure 1), we propose a novel module that considers the available BBs estimated by the tracker to update the reference descriptor at each time. The reference descriptor is computed through the combination of a long and a short-term memory.

A sequence of descriptors $\mathbf{z}[n]$ is generated by the encoded BBs outputted by the tracker along the video, as shown in Figure 1. The descriptor for the frame n is defined as

$$\mathbf{z}[n] = \mathbf{w}(\mathrm{BB}_n), \tag{1}$$

where BB_n is the n-th BB into which the tracked object is estimated to be, and $\mathbf{w}$ is a function encoding the object into a k-dimensional feature vector from the weights of the twin networks.

Thus, a descriptor $\mathbf{z}[n]$ is a k-dimensional feature vector representing the object in a given frame n. The consecutive set of descriptors are interpreted in this work as k independent unidimensional signals in function of time.

3.1 Object Memory: Combining SiamFC Descriptors

This work is based on the VOT-dedicated SNN SiamFC. However, the following concepts can be adapted to other VOT SNNs. Given a sequence of descriptors $(\mathbf{z}[0], \cdots, \mathbf{z}[n-1])$, one may define an operation $\mathbb{O}$ to generate a *combined descriptor* that better represents the object for use in frame n. In other words, the operation $\mathbb{O}$ takes into account the $n-1$ previous feature vectors to compute a combined vector $\mathbf{z}_{comb}[n]$. It is analogous to take into account the $n-1$ BBs returned by the tracker as

$$\mathbf{z}_{comb}[n] = \mathbb{O}(\mathbf{z}[0], \ldots, \mathbf{z}[n-1]). \tag{2}$$

The goal is to find a combination of descriptors that improves the performance of the system instead of relying on the information of a single descriptor $\mathbf{z}[0]$.

We propose to use limited sequences of descriptors to capture different mappings of the object over time. Each sequence is referred to as an *object memory*. As shown in Figure 1, multiple memories can be used to better track the object.

This work focuses on two types of memories. The first one is a long-term object representation. It has to keep the original object information from the early frames of the video. It works as an *anchor memory* for not losing the reference to the target object. The second one is a short-term object representation that combines the most recent descriptors. Its goal is to capture the latest appearances of the object. We propose the use of linear time-invariant filters to compute the short-term descriptor. A filter bank of k filters, one for each descriptor component, is learned from a training set of videos using a GA approach. The multiple memory combination and the filter based memory are the main contributions of our work.

3.2 Computing the Long-term Memory

The long-term memory comprises the set of descriptors of the earliest appearances in the video to preserve the original object information. Therefore, it provides a reliable static representation of the object, instead of using only a imprecise descriptor $\mathbf{z}[0]$. It is based on two assumptions:

1. the tracker provides fair outputs (BB) for the first frames of the video;
2. the object appearance is roughly the same in the initial frames.

Considering that two similar inputs cannot be mapped into a very different location in feature space by definition (Koch et al., 2015), the long-term memory is the expected value $E()$ of the q descriptors of the first BBs provided by the tracker

$$\mathbf{z}_{long}[n] = E([\mathbf{z}[0], ..., \mathbf{z}[q-1]]). \qquad (3)$$

Notice that, for $n \geq q$, the long-term memory is a constant signal based on the first q frames of the video. Therefore, any change in the object appearance in a frame $n \geq q$ is not considered.

3.3 Computing the Short-term Memory

We propose the short-term memory to be based on the m previous frames, computed by filtering the descriptors. The filter bank $\mathbf{h}$[n] is composed of k unidimensional FIR filters $h_i = \{c_{m-1}, \cdots, c_1, c_0\}$, where m is the filter order, $1 \leq i \leq k$, $c_j \in \mathbb{R}$, and the origin c_0 corresponds to the frame $n-1$. Let $\mathbf{S}[n] = (z[n-m], \cdots, z[n-1])$ be the sequence of the m previous descriptors, from the oldest to the newest. The filtered signal of descriptors is given by the convolution of the sequence and the filter bank

$$\mathbf{z}_{short}[n] = \mathbf{S}[n] * \mathbf{h}[n]. \qquad (4)$$

It is required to extend the videos for the first $m-1$ frames, to complete the sequence $\mathbf{S}[n]$. We extend the video by filling the missing positions with the descriptor $\mathbf{z}[0]$ of the first frame.

Different from the long-term memory $\mathbf{z}_{long}[n]$, the short memory $\mathbf{z}_{short}[n]$ changes according to the latest appearance of the tracked object.

3.4 Final Object Descriptor from Memory Combination

The memory descriptors have complementary information about the tracked object and can be combined as

$$\mathbf{z}_{comb}[n] = \alpha \cdot \mathbf{z}_{long}[n] + (1-\alpha) \cdot \mathbf{z}_{short}[n], \qquad (5)$$

where $0 \leq \alpha \leq 1$ is a *conservative factor* to balance the reliability of the long-term memory and the adaptiveness of the filtered memory. This k-dimensional descriptor is used to localize the object in the current frame, as shown in Figure 1. More precisely, the improved descriptor $\mathbf{z}_{comb}[n]$ is plugged into the SiamFC's cross-correlation module in order to localize the object, providing an adapted representation of the original object for detection in frame n.

3.5 Filter Bank Estimation

We propose to learn the filter bank $\mathbf{h}[n]$ from Ground Truth (GT) videos with known object BBs. Let $\mathbf{g}_{(v)}[n]$ be the evaluation of labeled GTs in a video v by a fully convolutional SNN. Also, consider the sequence of descriptors $\mathbf{z}_{(v)}[n]$ obtained from the BBs generated by the tracker using the same SNN. We seek a filter bank $\mathbf{h}[n]$ that, applied to $\mathbf{z}_{(v)}[n]$, generates the combined descriptor $\mathbf{z}_{comb(v)}[n]$ that is closer to the GT descriptors $\mathbf{g}_{(v)}[n]$, as expressed by the minimization problem

$$\arg\min_{\mathbf{h}[n]} \sum_{v} ||\mathbf{g}_{(v)}[n] - \mathbf{z}_{comb(v)}[n]||^2, \qquad (6)$$

where $\mathbf{z}_{comb(v)}[n]$ is given by Equation (5).

Therefore, it is assumed that the signal of descriptors from a set of videos have components that are universally present in the tracking performed by an SNN. So the goal is to estimate a filter bank that keeps frequency components of accurate trackings and attenuate the incorrect ones.

3.6 Filter Learning

Considering the literature, we have chosen a GA to find the desired filter bank. The GA is individually applied to find each of the k filters of $\mathbf{h}[n]$ that minimize Equation (6). However, since the BBs that generate $\mathbf{z}_{comb(v)}[n]$ can be very close to those which generate $\mathbf{g}_{(v)}[n]$, it may lead to impulsive filters as trivial solutions. We propose to add white noise to the descriptors $\mathbf{z}_{(v)}[n]$ returned by the SNN before minimization in order to avoid the trivial solution.

Each individual genotype is composed of a string of integers, where the genes that form a chromosome represent the filter coefficients. Thus, a filter of order m is represented by a chromosome of m integers. We generate a population of P_s individuals where the genetic operators are performed.

The selection attempts to discard individuals with lower fitness values and keep the ones with the highest fitness as:

$$\Theta(h_i) = \sum_{v,n} \left(||g_{(v)_i}[n] - z_{comb(v)_i}[n]||^2 + \delta \right)^{-1}, \quad (7)$$

where δ is a small number to guarantee a finite fitness and $1 \leq i \leq k$. This step is probabilistic and not all of the best individuals pass to the next generation. This randomness eliminates local minima in the optimization process (Dey et al., 2010). After selection, the crossover and mutation are computed to generate new individuals for a new population. This is repeated until a number of iterations is reached. The whole process is performed k times to find the complete filter bank $\mathbf{h}[n]$.

4 EXPERIMENTAL RESULTS

In this Section, we present and evaluate the experimental results obtained with our method.

4.1 Experimental Setup

The SiamFC and the proposed method were written in Python3.5. We use the public implementation of the SiamFC provided by (Zhang, 2017). We also used: TensorFlow 1.10.0 for the implementation of the SiamFC, Numpy 1.14.5 for numerical computation, OpenCV 3.4.3, and the evolutionary computation framework DEAP 1.2.2. Experiments were run in two Intel E5-4607 @ 2.20GHz processors with 24 cores and 32 GB Memory. In this setup, the SiamFC gives the tracking rate of 0.1 frames per second in average.

Two datasets are used in this work. The VOT2015 provides videos for training the filter learning step, while the performance is evaluated in the OTB50 dataset. The training videos from VOT2015 are: "bag", "racing", "ball1", "octopus", "bolt2", "pedestrian", "road". The SiamFC presented outputs close to the GT for these videos, i.e., the tracking had a good average performance.

The performance is compared by the location precision and overlap success rates given their respective thresholds (Tao et al., 2016).

Regarding the GA parameters, the probability of gene mutation is $p_g = \frac{1}{m}$ to introduce about one mutation in the filter each time it is selected. The probability of selecting an individual for mutation is $p_m = 90\%$. The crossover probability is $p_c = 95\%$. The convergence criterion is the maximum number of iterations $m_i = 600$. The population size is $P_s = 5M$.

4.2 Parameter Setting and Method Evaluation

The number of descriptors q, for the long-term memory, the filter order m, for the short-term memory, and the conservative factor α can be better evaluated in conjunction. But in this work, they are explored empirically due to the high computational cost of the learning step. For the filter order $m = 31$, each learning run took 16 hours to complete. The number of training videos also strongly impacts the runtime since each population is computed with complete track evaluations over them. But it is worthy to mention that, once the filter is learned, our method requires unidimensional convolutions along the tracking with very low overhead.

Table 1: Varying the filter order m for short-term memory.

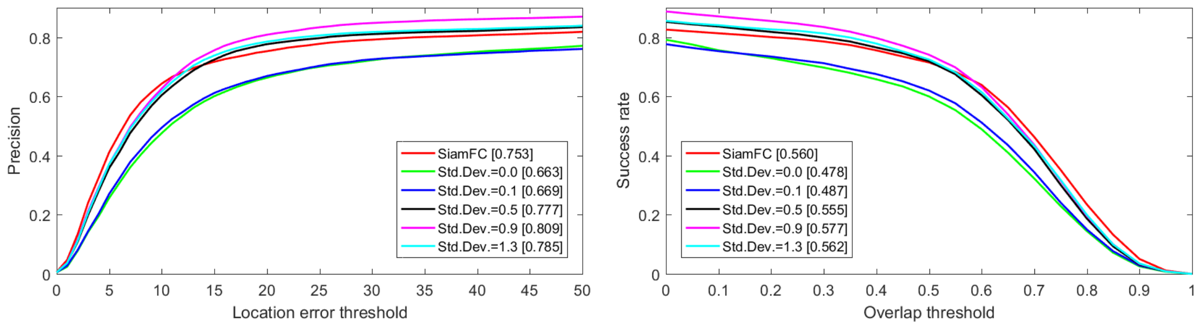
Filter Order m	Precision Plots (AUC)	Success Plots (AUC)
21	0.792	0.563
31	**0.809**	**0.577**
41	0.788	0.559
51	0.768	0.556

Table 2: Varying the number of descriptors for the long-term memory.

Number of Descriptors q	Precision Plots (AUC)	Success Plots (AUC)
1	0.785	0.569
10	0.765	0.552
15	0.778	0.563
17	0.805	0.578
20	0.794	0.574
30	**0.809**	**0.577**

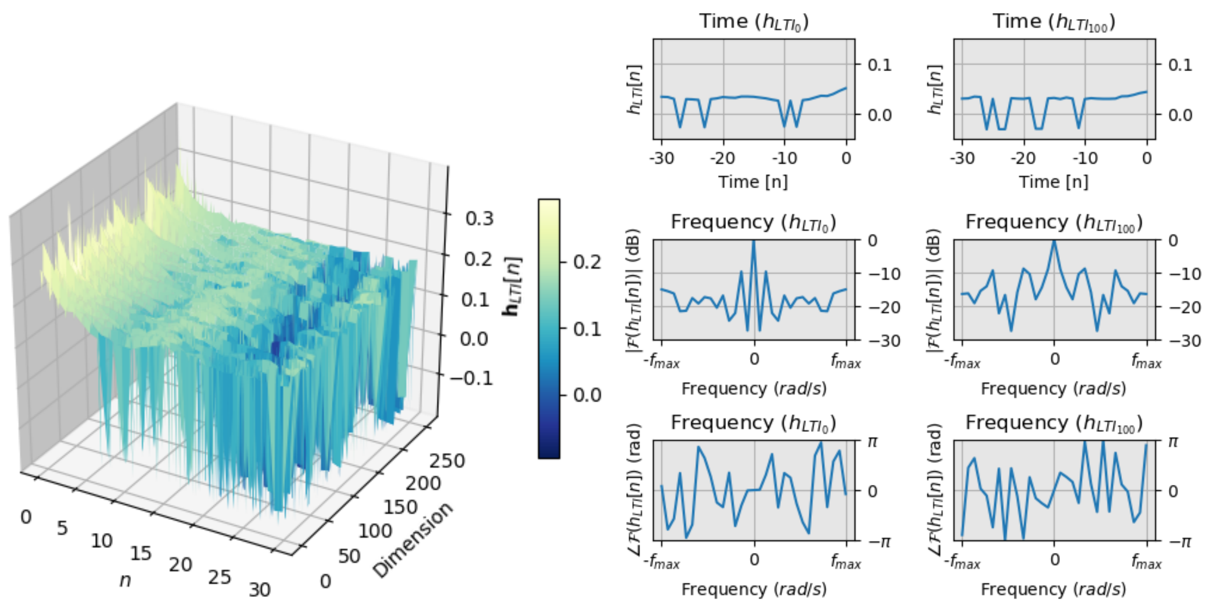
After preliminary tests, we fixed $q = 17$ and $\alpha = 0.65$ and varied the filter order m to test the short-term memory. As shown in Table 1, $m = 31$ presented the best Area Under Curve (AUC). Considering the average frame rate of 25 FPS of the dataset videos, it means that 1.24s of past descriptors are used to represent the object as short-term memory.

In Table 2, $m = 31$ and $\alpha = 0.65$ were fixed and q varied to show other results. Considering several combinations of m and α, better results were achieved around $q = 30$ which averages the first 1.2s of the videos as long-term memory.



(a) (b)

Figure 2: Results for the white noise standard deviation.



(a) (b)

Figure 3: Representation of the learned filter bank. a) the 256 filters in the time domain. b) filters from tracks 0 and 100. From top to bottom: time domain, magnitude response in the frequency domain, phase response in the frequency domain.

Figure 2(a) and Figure 2(b) present the performance curves with multiple levels of white noise added in the filter learning step. The poor performance with $\sigma = 0$ in all thresholds shows the importance of the noise addition to avoid the trivial impulsive filters. The performance is improved as the standard deviation grows up to $\sigma = 0.9$. Beyond this value, the noise starts corrupting the signal and the performance decreases. Since only videos having high F-measure with the SiamFC are used, the detected BB has a high overlap with the GT. The addition of noise forces the GA to find filters capable of rejecting the white noise plus the SiamFC imprecise descriptors.

Based on previous experiments, the best filter bank obtained has order $m = 31$, conservative factor $\alpha = 0.65$ and white noise standard-deviation $\sigma = 0.9$. The resulting 256 filters in the time domain are illustrated in Figure 3(a). Notice that the filters have a similar distribution in time. Figure 3(b) shows two filters from the bank to a more in-depth analysis. Notice the strong DC component in the two filters that can be verified by their Fourier transform at the bottom. Although we have discussed the limits of performance of an SNN, one of its fundamental characteristics is keeping the descriptor insensitive for different instances of the objects. Also, notice that the strongest coefficients of the filters are usually the first ones. This means that the last descriptors in the video are the most relevant ones on average. It is an intuitive consideration, as the change in the appearance of ROI in the latest frames looks to be more important

Table 3: Location Error precision and IoU success for different thresholds. From the fourth row, each line corresponds to the performance of one category of the OTB50 dataset. The best performance for each category and for each of the thresholds is highlighted in bold.

		Location Error Precision						Intersection over Union (IoU) Success					
	Threshold	50		30		10		0.25		0.50		0.75	
	Method	Ours	SiamFC	Ours	SiamFC	Ours	SiamFC	Ours	SiamFC	Ours	SiamFC	Ours	SiamFC
Category	Abrupt Motion	**0.877**	0.830	**0.837**	0.795	0.469	**0.580**	**0.857**	0.817	**0.692**	0.686	0.260	**0.307**
	Background Clutter	**0.835**	0.763	**0.817**	0.727	**0.645**	0.575	**0.809**	0.727	**0.736**	0.636	**0.388**	0.321
	Blur	**0.846**	0.816	**0.806**	0.787	0.420	**0.551**	**0.812**	0.794	0.623	**0.666**	0.207	**0.291**
	Deformation	**0.847**	0.784	**0.831**	0.763	0.556	**0.568**	**0.834**	0.764	**0.684**	0.648	0.239	**0.258**
	Illumination Variation	**0.855**	0.769	**0.829**	0.741	0.534	**0.571**	**0.814**	0.739	**0.668**	0.649	0.291	**0.341**
	In-Plane Rotation	**0.836**	0.772	**0.804**	0.739	0.570	**0.592**	**0.804**	0.751	**0.697**	0.675	0.302	**0.336**
	Low Resolution	**0.819**	0.782	**0.776**	0.744	0.531	**0.548**	**0.795**	0.762	0.666	**0.674**	0.257	**0.317**
	Occlusion	**0.842**	0.795	**0.819**	0.775	0.530	**0.592**	**0.816**	0.774	**0.687**	0.678	0.238	**0.297**
	Out-of-Plane Rotation	**0.848**	0.792	**0.824**	0.763	0.590	**0.608**	**0.819**	0.765	**0.699**	0.672	0.290	**0.318**
	Out-of-View	**0.735**	0.713	0.689	**0.693**	0.358	**0.481**	**0.730**	0.708	0.638	**0.645**	0.312	**0.387**
	Scale Variation	**0.883**	0.834	**0.863**	0.804	0.670	**0.682**	**0.856**	0.813	0.716	**0.721**	0.308	**0.368**

than the earlier ones. For most filters, we observed in the frequency domain that low-frequency components tend to be higher than the high-frequency ones. It can be understood as a fast change in ROI appearance is less important than a consistent and smoother one.

4.3 Comparison with the SiamFC

The long and short memories are complementary to the SiamFC. In this section, we use SiamFC as baseline to show how it is improved. Using the mean threshold of 25 for the Location Error (LE) (Figure 2(a)), our method improves the baseline from 0.778 to 0.827, a gain of 6.4%. Likewise, with the threshold of 0.5 for the overlap error (Figure 2(b)), our method improves the baseline from 0.683 to 0.7, a gain of 2.5%.

For a deeper understanding, we applied the *post-hoc* Nemenyi test to the whole curves of SiamFC (red) and our method with $\sigma = 0.9$ (magenta) in Figure 2. The location precision rate has p-value $= 4.95 \cdot 10^{-4}$, meaning that both curves are statistically different. However, the p-value for the success rate of overlap is 0.406 meaning that the curves are statistically similar. Interestingly, a visual comparison of both results shows that our method tends to better track the object but with less precise BBs. This is due to the averaging nature of the long and short memories. The SiamFC loses the object more often but when it finds it, the resulting BB is more precise.

Besides, our method obtained the AUC location precision rate of 0.809 and overlap success rate of 0.577. Considering the performance of SiamFC, which is 0.753 and 0.560 respectively, our method improves the overall location precision rate in about 7.6% and the overlap success rate about in 3.0% without increasing the computational cost.

Finally, we present the Location Error precision and Intersection over Union success for the 11 categories of the OTB50 dataset (Table 3). The LE precision was computed for the thresholds 50, 30 and 10 and the IoU success for the thresholds 0.25, 0.50 and 0.75. For the LE precision, our method has somewhat the same performance in all categories, except the Out-of-View since it does not deal with object absences. The numbers reinforce that our method obtains BBs containing the object's center more often than the SiamFC. Observing the IoU success, our method outperforms the SiamFC in all categories for low thresholds. However, the SiamFC has superior performance for thresholds above 0.50. Thus, the SiamFC is indicated when more precision and tighter BBs are required, provided that occasional wrong object detection along the whole tracking is not critical.

4.4 Comparison with the State of the Art

Our method enhances the SiamFC performance, as observed in Figure 5. One of the advantages is its adherence to the Ground Truth BB, i.e. our method sticks to the object along the tracking (Figures 4(a) and 4(b)). Thus, it has higher precision and success rates for high threshold tolerance. The original SiamFC, is more precise in defining the BB that contains the object (Figure 4(c)). In Figure 4(d) shows

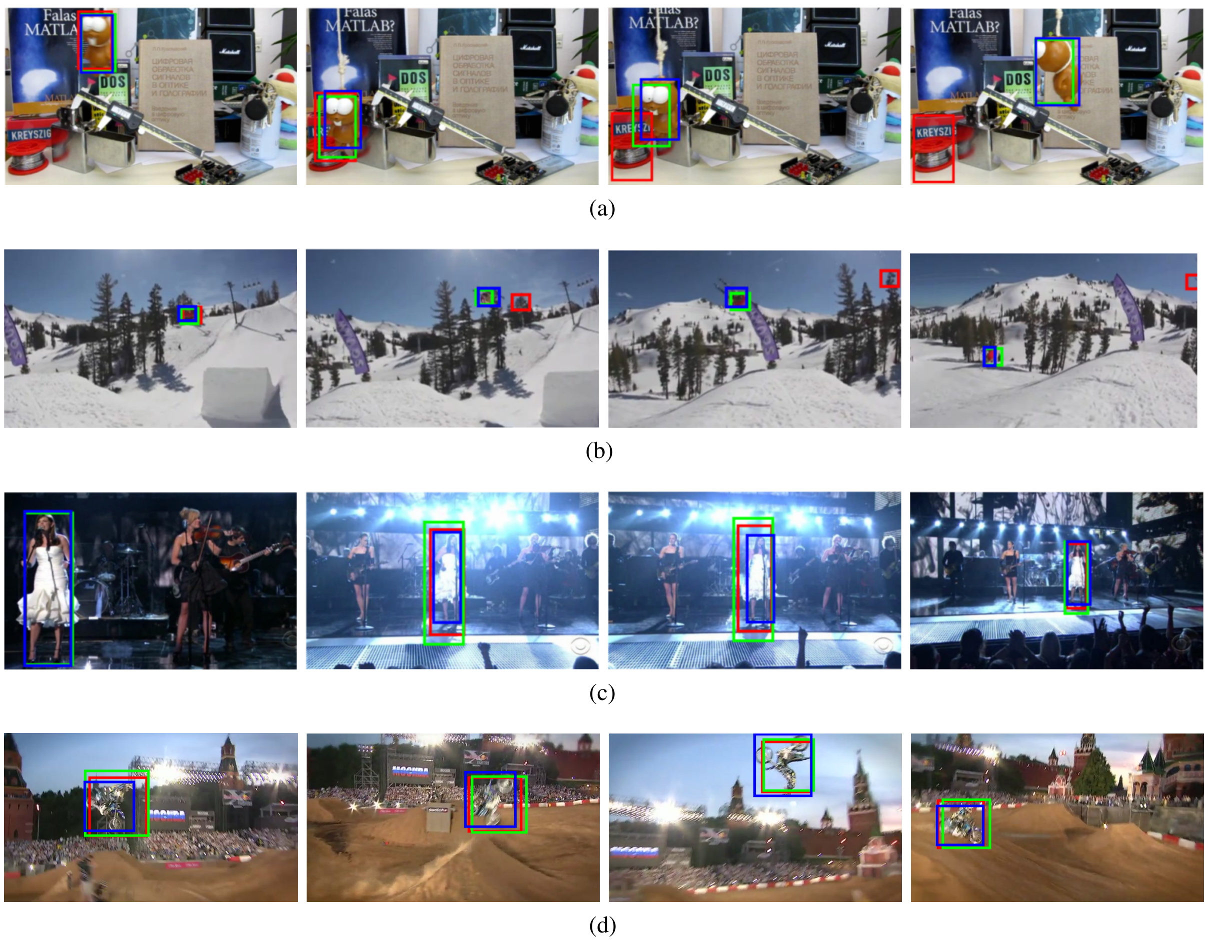


Figure 4: Proposed method (green) visually compared to the SiamFC (red). The GT is blue. OTB50 Dataset sequences: (a) lemming (b) skiing (c) singer1 (d) motorRolling.

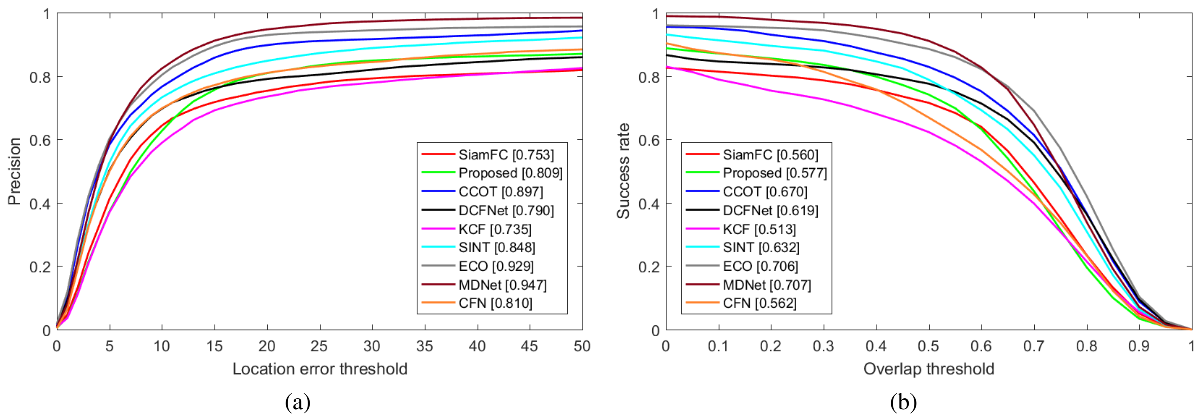


Figure 5: State-of-the-art methods: (a) Precision plots (b) IoU Success plots.

how our method tracks the object correctly but in most cases gives a BB greater or smaller than the ground truth. As a general rule, our method is more appropriate when good object localization throughout the whole video is paramount.

Figures 4(a) and 4(b) provide examples of the better adherence to the tracked object of the proposed method. Notice that it does not lose the object when

SiamFC fails. Nevertheless, the SiamFC usually outputs a more precise BB of the object, as shown in Figure 4(c). It explains higher precision and success rates by the SiamFC for small thresholds.

Figure 5 shows a comparison to several state-of-the-art trackers. Notice that MDNET, CCOT, ECO and SINT have higher AUC than our tracker. Due to its simple and effective approach, however, our method is lightweight with fairly comparable results. We remark that the lack of object occlusion detection greatly impairs our precision and success rates.

5 CONCLUSION

We proposed the use of two object descriptors for improving tracking using an SNN. A long-term memory, based on the first object appearances, is combined with a short-term memory, based on recent appearances, to form an updated object descriptor. Its dynamic nature adapts to the object and is more suitable for long tracking. We applied the method to the SiamFC descriptors but it can be adapted to other SNNs.

The proposed short-term memory is obtained by low-cost convolutions with a filter bank. The filter bank is learned by a GA strategy from videos with high F-measure. More specifically, only seven videos from the VOT2015 dataset were used for training: "bag", "racing", "ball1", "octopus", "bolt2", "pedestrian", "road". Despite the high computational cost for the GA step, the learned filter bank showed to be general enough for tracking over the 50 videos of the OTB50 dataset. Our filter learning proposal is thus capable to generalize object descriptor variations along tracking.

Our novel approach presented promising results, showing a consistent gain for object localization. The obtained BBs on well-known datasets proved to be adherent to the tracked object over time. Compared to the state of the art trackers, our method has fair precision and success rates with a very low computational cost. Our method is appropriate when good object localization throughout the whole video is paramount, but low BB precision is not an issue. The frame rate is only dependent on the underlying SNN performance, since the proposed 1D convolutions add negligible extra cost.

Future works include investigating more powerful kernel learning approaches for temporal series, including LSTM and deep neural networks. There is the possibility of developing specific neural network models for learning the convolution filters. Furthermore, adaptive filter learning seems to be a promising approach, albeit it is a very challenging task. The use of more memories seems promising in contexts with complex interactions between objects of interest. Also, occlusion detection strategies are very important to improve the performance on the OTB50 dataset.

ACKNOWLEDGEMENTS

Authors thank CAPES, FAPEMIG (grant CEX-APQ-01744-15), FAPESP (grants #2017/09160-1 and #2017/12646-3), CNPq (grant #305169/2015-7) for the financial support, and NVIDIA Corporation for the donation of two Titan Xp (GPU Grant Program).

REFERENCES

Ahmad, S. and Antoniou, A. (2006). Cascade-form multiplierless fir filter design using orthogonal genetic algorithm. In *IEEE International Symposium on Signal Processing and Information Technology*, pages 932–937.

Bertinetto, L., Valmadre, J., Henriques, J. F., Vedaldi, A., and Torr, P. H. (2016). Fully-convolutional siamese networks for object tracking. In *European Conference on Computer Vision*, pages 850–865. Springer.

Bromley, J., Guyon, I., LeCun, Y., Säckinger, E., and Shah, R. (1994). Signature verification using a" siamese" time delay neural network. In *Advances in Neural Information Processing Systems*, pages 737–744.

Cemes, R. and Ait-Boudaoud, D. (1993). Genetic approach to design of multiplierless fir filters. *Electronics Letters*, 29(24):2090–2091.

Danelljan, M., Bhat, G., Khan, F. S., Felsberg, M., et al. (2017). Eco: Efficient convolution operators for tracking. In *Computer Vision and Pattern Recognition*, volume 1, page 3.

Danelljan, M., Robinson, A., Khan, F. S., and Felsberg, M. (2016). Beyond correlation filters: Learning continuous convolution operators for visual tracking. In *European Conference on Computer Vision*, pages 472–488.

Dey, A. K., Saha, S., Saha, A., and Ghosh, S. (2010). A method of genetic algorithm for fir filter construction: design and development with newer approaches in neural network platform. *International Journal of Advanced Computer Science and Applications*, 1(6):87–90.

Guo, Q., Feng, W., Zhou, C., Huang, R., Wan, L., and Wang, S. (2017). Learning dynamic siamese network for visual object tracking. In *IEEE International Conference on Computer Vision*.

Huang, Z. (2017). An investigation of deep tracking methods. In *Conference on Technologies and Applications of Artificial Intelligence*, pages 58–61. IEEE.

Kalal, Z., Mikolajczyk, K., et al. (2012). Tracking-learning-detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(7):1409.

Koch, G., Zemel, R., and Salakhutdinov, R. (2015). Siamese neural networks for one-shot image recognition. In *ICML Deep Learning Workshop*, volume 2.

Kristan, M., Leonardis, A., Matas, J., Felsberg, M., Pfugfelder, R., Zajc, L., Vojir, T., Bhat, G., Lukezic, A., Eldesokey, A., et al. (2018). The sixth visual object tracking vot2018 challenge results. In *European Conference on Computer Vision Workshops*, volume 3, page 8.

Kristan, M., Leonardis, A., Matas, J., Felsberg, M., Pfugfelder, R., Zajc, L., Vojir, T., et al. (2017). The visual object tracking vot 2017 challenge results. 1(1):1452 – 1459.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, pages 1097–1105.

Manocha, P., Badlani, R., Kumar, A., Shah, A., Elizalde, B., and Raj, B. (2018). Content-based representations of audio using siamese neural networks. In *IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 3136–3140. IEEE.

Nanni, L., Ghidoni, S., and Brahnam, S. (2017). Handcrafted vs. non-handcrafted features for computer vision classification. *Pattern Recognition*, 71:158–172.

Rout, L., Mishra, D., Gorthi, R. K. S. S., et al. (2018). Rotation adaptive visual object tracking with motion consistency. In *IEEE Winter Conference on Applications of Computer Vision*, pages 1047–1055. IEEE.

Taigman, Y., Yang, M., Ranzato, M., and Wolf, L. (2014). Deepface: Closing the gap to human-level performance in face verification. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1701–1708.

Tao, R., Gavves, E., and Smeulders, A. W. (2016). Siamese instance search for tracking. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1420–1429.

Valmadre, J., Bertinetto, L., Henriques, J., Vedaldi, A., and Torr, P. H. (2017). End-to-end representation learning for correlation filter based tracking. In *Computer Vision and Pattern Recognition*, pages 5000–5008. IEEE.

Wang, N. and Yeung, D.-Y. (2013). Learning a deep compact image representation for visual tracking. In *Advances in Neural Information Processing Systems*, pages 809–817.

Zhang, S. (2017). A python+tensorflow implementation of siamese-fc. `https://github.com/www0wwwjs1/tensorflow-siamese-fc`.