Learn++ for Robust Object Tracking

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Figure 1: Assuming that the best classifiers for the previous frames are available, which classifiers should be used in the current frame (bottom right)? f_2, f_5 or their combination? Also, when the target moves out of view then comes back, which classifiers are the best to be used? This paper tries to solve these problems in object tracking.

Motivation. Most machine learning algorithms can learn from data that are assumed to be drawn from a fixed but unknown distribution. However, this assumption cannot be valid in case of the tracking problem. Traditional machine learning methods applied to the tracking problem, such as tracking-by-detection approaches [1, 2], will fail when there is a "concept drift" in the non-stationary environment, because the function learnt on a fixed sample set previously collected may not reflect the current state of nature due to a change in the underlying environment [3]. In object tracking, the distribution of samples changes a lot due to the deformation of the object and the change of the background. Especially during the transition between different difficulties (sub-problems), such as from occlusion to varying viewpoints, the samples in the two different situations differ significantly. Thus, the separability of features and classifiers used in previous frames will decrease in the new situation as shown in Fig. 1.

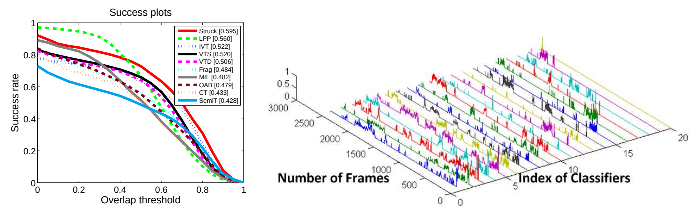
Contributions. Our idea is to build a basic classifier for each sub-problem and these basic classifiers learnt fromdifferent sample sets are independent from each other. In this paper, by enabling and designing these critical and flexible functions, we propose a new Learn++ method for robust and long-term object tracking, named as LPP tracker. LPP tracker dynamically maintains a set of basic classifiers $f_i \in \Omega_e^t$ which are trained sequentially without accessing original data but preserving the previously acquired knowledge. The "concept drift" problems can be solved by adaptively selecting the most suitable classifiers (called the active subset $\Omega_a^t \subset \Omega_e^t$) which are corresponding to the non-zero weights w_i^t. Thus, given the samples x_l^t and their labels y_l^t, the objective function is defined as:

$$\mathbf{w}^t = \arg\min_{w^t} \sum_l L\Big(\sum_{f_i \in \Omega_e^t} w_i^t f_i(x_l^t), y_l^t\Big) + \lambda \,||w^t||_0 \qquad (1)$$

where L and λ are the loss function and regularization parameter, respectively.

By using the classifiers that have yielded good performance in recent n frames or in the same situations, the optimal classifier $\mathbf{f}^t$ in the present environment can be fast approximated in a function space linearly spanned by these basic classifiers in the active subset. For each frame, the democratic mechanism can be adopted, where all classifiers should compete with each other to be added into an active subset to suit the present environment. To achieve this goal, four steps are adopted, including reviving old classifiers, training a new one, resampling and evaluating all of them. Therefore, we obtain the hypothesis:

$$\mathbf{f}^t = \sum_{f_i \in \Omega_e^t} \mathbf{w}_i^t f_i \qquad (2)$$



(a) (b)

Figure 2: (a) The success plot and AUC rankings of 10 tracking methods on challenging sequences. (b) The weights for the optimal classifier $\mathbf{f}^t$.

	LPP	Struck	VTS	IVT	VTD	MIL	CT	SemiT
IV	0.932	0.860	**0.957**	0.900	0.888	0.569	0.704	0.463
OPR	**0.858**	0.775	0.754	0.718	0.766	0.670	0.625	0.544
SV	**0.928**	0.816	0.763	0.779	0.771	0.769	0.805	0.449
OCC	**0.772**	0.659	0.723	0.749	0.733	0.583	0.608	0.519
DEF	**0.871**	0.682	0.595	0.674	0.6000	0.618	0.643	0.677
MB	**0.919**	0.776	0.726	0.513	0.710	0.847	0.614	0.293
FM	**0.875**	0.856	0.546	0.459	0.547	0.767	0.571	0.448
IPR	0.861	0.867	0.869	0.819	**0.885**	0.778	0.659	0.489
BC	0.882	**0.912**	0.725	0.769	0.709	0.714	0.594	0.609
Overall	**0.844**	0.817	0.736	0.734	0.664	0.658	0.605	0.552

Table 1: The precision rankings of 10 tracking methods on challenging sequences. Bold numbers denote the best precision scores.

Results. Our experiments follow the setting in [4] and compare with the results of 9 state-of-the-art methods from this report as well. From Fig. 2(a) and Table 1, we can see that, in total, LPP tracker gains six firsts, two seconds and one fourth by the precision ranking, and it gains three firsts, three seconds and two fourths by the AUC ranking. Further investigations are given in Fig. 3, Struck fails when the target starts to move out of view but LPP tracker tackles all the problems. From Fig. 2(b), we can see that the weights are very sparse and just a few members will be selected for each frame.

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Figure 3: Results on three more challenging sequences between LPP tracker (Red) and Struck (Green).