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BIT: Biologically Inspired Tracker

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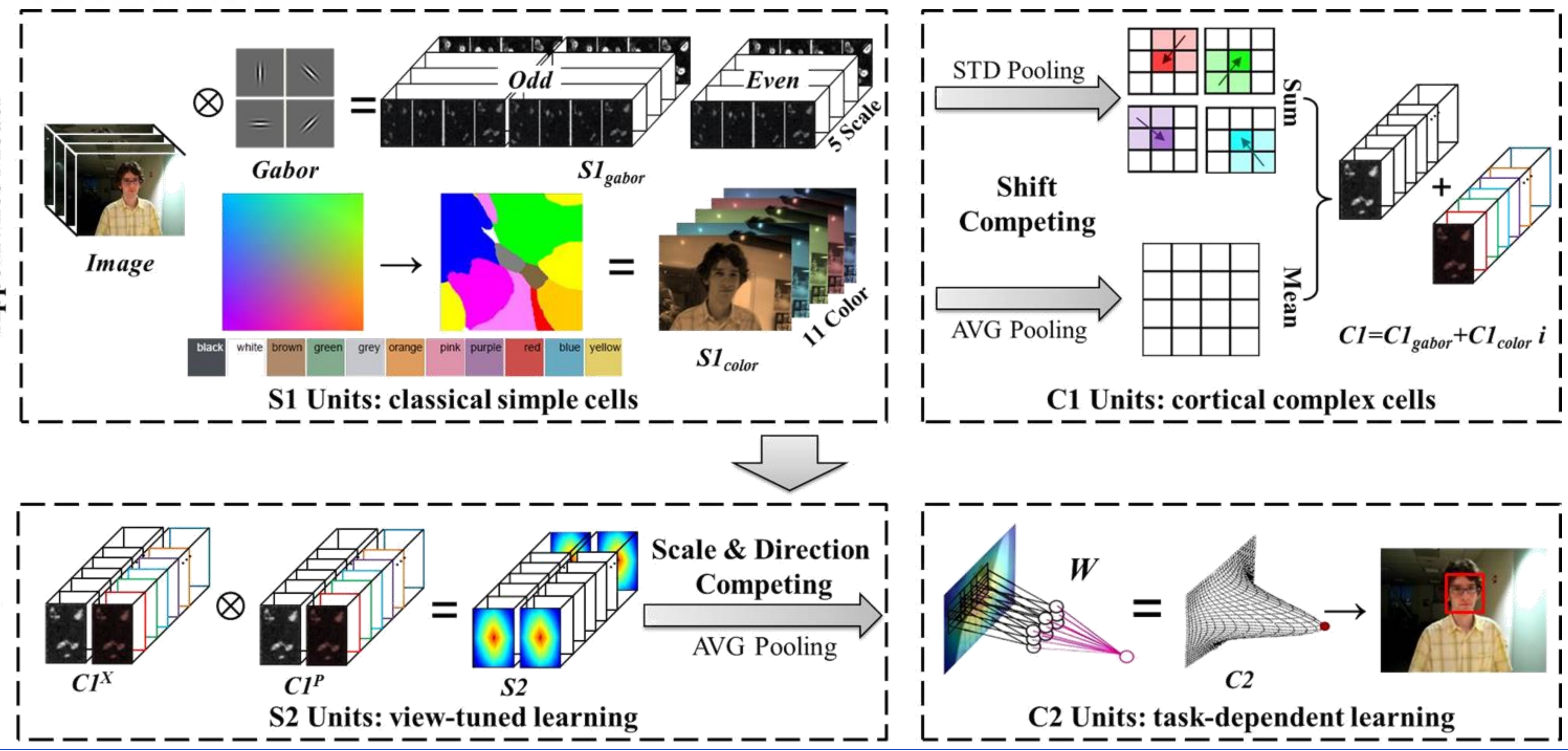
Abstract

Visual tracking is challenging due to various factors. Given the superior tracking performance of human visual system, an ideal design of ***Biologically Inspired Model*** is expected to improve visual tracking. Based on the analysis of the ventral stream in the visual cortex, the ***biologically inspired tracker (BIT)*** simulates shallow neurons (S1 units and C1 units) to extract low-level features for the target appearance and imitates an advanced learning mechanism (S2 units and C2 units) to combine generative and discriminative models for target location. In addition, ***Fast Gabor Approximation (FGA)*** and ***Fast Fourier Transform (FFT)*** are adopted for real-time learning and detection in this framework.



BIT: Biologically Inspired Tracker

BIT

- **S1 units：classical simple cells**

In the primary visual cortex (V1), a simple cell has the characteristics of multi-orientation, multi-scale and multi-frequency selection. and can be described as Gabor filters:

$$\begin{cases} G_{even}\left(x,y,\theta,s\left(\sigma,\lambda\right)\right)=\exp\left(-\frac{X^2+Y^2}{2\sigma^2}\right)\cos\left(\frac{2\pi}{\lambda}X\right) \\ G_{odd}\left(x,y,\theta,s\left(\sigma,\lambda\right)\right)=\exp\left(-\frac{X^2+Y^2}{2\sigma^2}\right)\sin\left(\frac{2\pi}{\lambda}X\right) \end{cases}$$

$$S1_{gabor}\left(x,y,\theta,s\right)=I\left(x,y\right)\otimes G_{even/odd}\left(x,y,\theta,s\right)$$

The color units are inspired by the color double-opponent system in the cortex, and are defined by Color Names:

$$S1_{color}\left(x,y,c\right)=Map\left(R\left(x,y\right),G\left(x,y\right),B\left(x,y\right),c\right)$$

- **C1 units：cortical complex cells**

The cortical complex cells (V2) receive the response from V1 and have the function of linear feature integration.

$$C1_{gabor}\left(x,y\right)=\sum_{(x,y)\in\Sigma}\frac{S1_{gabor}\left(x,y\right)}{N_{\delta_x,\delta_y}\left(x,y\right)} \quad N_{\delta_x,\delta_y}\left(x,y\right)=\left(S1^2_{gabor}\left(x,y\right)+S1^2_{gabor}\left(x+\delta_x,y+\delta_y\right)+S1^2_{gabor}\left(x+\delta_x,y\right)+S1^2_{gabor}\left(x,y+\delta_y\right)\right)^{0.5}$$

- **S2 units：view-tuned learning**

View-tuned learning from V2 to IT as a generative model, in which S2 units is RBF distance between new input X and stored prototype P.

$$r_{S2}=\exp(-\frac{1}{2\sigma^2}\|X-P\|^2)=\exp(-\frac{1}{2}(X^TX+P^TP-2X^TP))\sim\exp(X^TP)\sim X^TP$$

- **C2 units：task-dependent learning**

An CNN corresponding to task-dependent learning from IT to PFC for the discrimination between target and background as

$$C2\left(x,y\right)=W\left(x,y\right)\otimes S2(x,y)$$

Real-time BIT

- **Fast Gabor Approximation (FGA)**

Using several pairs of 1-D orthogonal Gabor filters G_x, G_y, the approximate response of S1 units is defined as

$$\begin{cases} D_x\left(x,y,s\left(\sigma,\lambda\right)\right)=I\left(x,y\right)\otimes G_x\left(x,s\left(\sigma,\lambda\right)\right) \\ D_y\left(x,y,s\left(\sigma,\lambda\right)\right)=I\left(x,y\right)\otimes G_y\left(y,s\left(\sigma,\lambda\right)\right) \end{cases} \Rightarrow \begin{cases} \Theta\left(\cdot\right)=\tan^{-1}\left(\frac{D_y\left(x,y,s\left(\sigma,\lambda\right)\right)}{D_x\left(x,y,s\left(\sigma,\lambda\right)\right)}\right) \\ A\left(\cdot\right)=\sqrt{D_x^2\left(x,y,s\right)+D_y^2\left(x,y,s\right)} \end{cases}$$

$$S1_{odd}\left(\cdot\right)=\begin{cases} A\left(\cdot\right), if\ \Theta\left(\cdot\right)\in\left[\theta-\pi/8,\theta+\pi/8\right) \\ 0, otherwise \end{cases} \quad S1_{even}\left(\cdot\right)=\begin{cases} A\left(\cdot\right), if\ \Theta\left(\cdot\right)\in\left[\theta-\pi/8,\theta+\pi/8\right)\cup\left[\theta+7\pi/8,\theta+9\pi/8\right) \\ 0, otherwise \end{cases}$$

- **Fast Fourier Transform (FFT)**

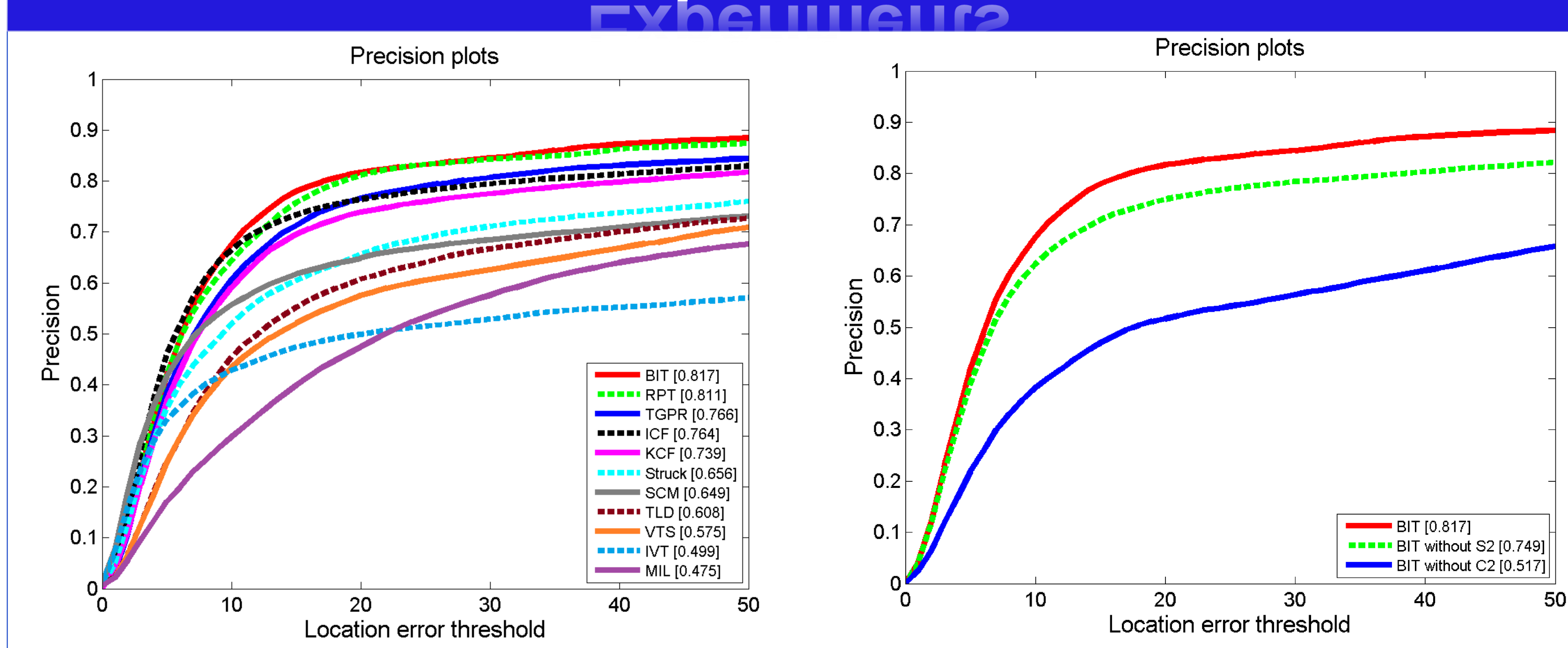
The FFT speeds up the dense sampling of S2 and C2 response calculation in the real-time BIT.

$$\mathcal{F}\left[S2_{t+1}\left(\cdot\right)\right]=\frac{1}{K}\sum_{k=1}^{K}\mathcal{F}\left[C1^X_{t+1}\left(\cdot,k\right)\right]\odot\mathcal{F}\left[C1^P_t\left(\cdot,k\right)\right]$$

$$\widetilde{C2}\left(x,y\right)=\exp\left(-\frac{1}{2\sigma_s^2}\left(\left(x-x_o\right)^2+\left(y-y_o\right)^2\right)\right)$$

Solution：$\mathcal{F}\left[W\left(x,y\right)\right]=\frac{\mathcal{F}\left[\widetilde{C2}\left(x,y\right)\right]}{\mathcal{F}\left[S2\left(x,y\right)\right]}$ Location：$\left(\hat{x},\hat{y}\right)=\arg\max_{(x,y)}C2_{t+1}\left(x,y\right)$

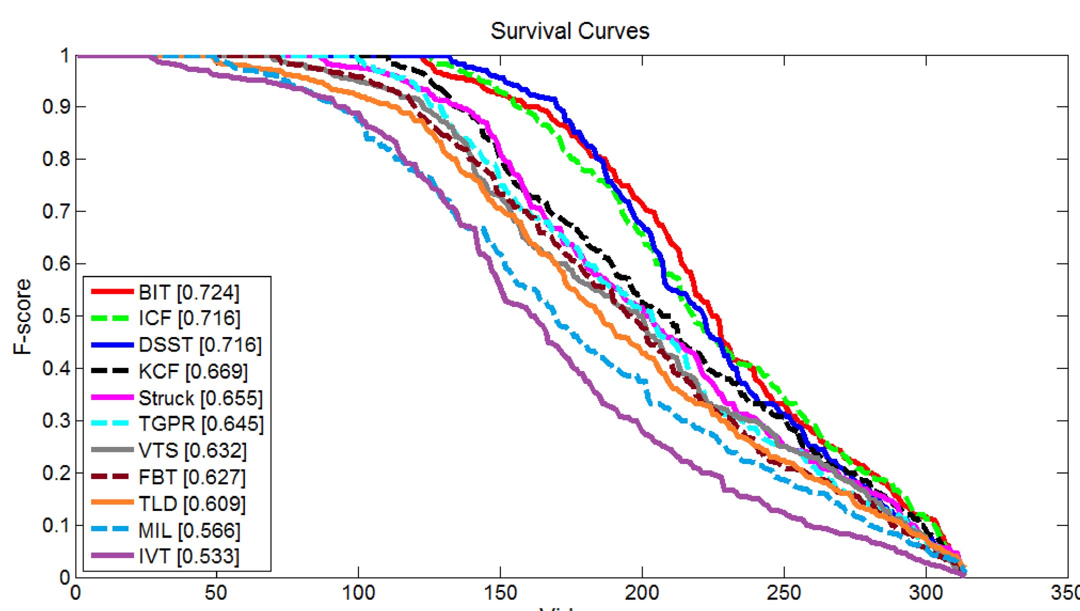
Experiments



	BIT	RPT[58]	TGPR[59]	ICF[60]	KCF[3]	Struck[23]	SCM[12]	TLD[55]	VTS[61]	MIL[25]
IV	0.764	**0.827**	0.687	0.696	0.717	0.558	0.594	0.537	0.573	0.349
SV	0.786	**0.802**	0.703	0.707	0.667	0.639	0.672	0.606	0.582	0.471
OCC	**0.854**	0.765	0.708	0.817	0.744	0.564	0.640	0.563	0.534	0.427
DEF	**0.817**	0.748	0.768	0.754	0.751	0.521	0.586	0.512	0.487	0.455
MB	0.663	**0.783**	0.578	0.654	0.621	0.551	0.339	0.518	0.375	0.357
FM	0.643	**0.745**	0.575	0.612	0.581	0.604	0.333	0.551	0.353	0.396
IPR	0.783	**0.795**	0.706	0.739	0.731	0.617	0.597	0.584	0.579	0.453
OPR	**0.831**	0.807	0.741	0.741	0.724	0.597	0.618	0.596	0.604	0.466
OV	**0.654**	0.641	0.495	0.584	0.555	0.539	0.429	0.576	0.455	0.393
BC	0.789	**0.840**	0.761	0.698	0.725	0.585	0.578	0.428	0.578	0.456
LR	0.369	0.478	0.539	0.516	0.379	**0.545**	0.305	0.349	0.187	0.171

Multi-direction Gabor filters used in S1 units contribute to the robustness of illumination (IV) and rotation (IPR and OPR). ***Pooling operations*** in C1 and S2 units provide the shift and scale competitive to deal with deformation (DEF) and scale (SV). The ***generative model*** in S2 units and the ***discriminative model*** in C2 units rise to the challenges of OCC and OV respectively.

The hybrid-model (81.7%) achieved excellent performances in comparison to single-model (74.9% and 51.7%). In addition, the performance gap between the discriminative model and the generative model in the literature is 23.2%.



Tracker	Speed (fps)	Precision (%)
BIT	44.9	**81.7**
ICF[60]	68.8	76.4
KCF[3]	**284.4**	73.9
TLD[55]	28.1	60.8
MIL[25]	38.1	49.9
IVT[9]	33.4	47.5
RPT[58]	4.1	81.1
TGPR[59]	0.7	76.6
Struck[23]	20.2	65.6
SCM[12]	0.5	64.9
VTS[61]	5.7	57.5

The survival curves and average F-scores demonstrate that the BIT achieves the best (0.724) overall performance on ALOV300++.

BIT tracks the object at an average speed of **45fps**, which is significantly faster than the second best tracker RPT (4.1 fps).

MiniEye Simple Eye 松下新加坡研发中心 三星 光电高斯 理光软件研究所 腾讯 华富睿智