Siamese网络在视觉跟踪中的应用

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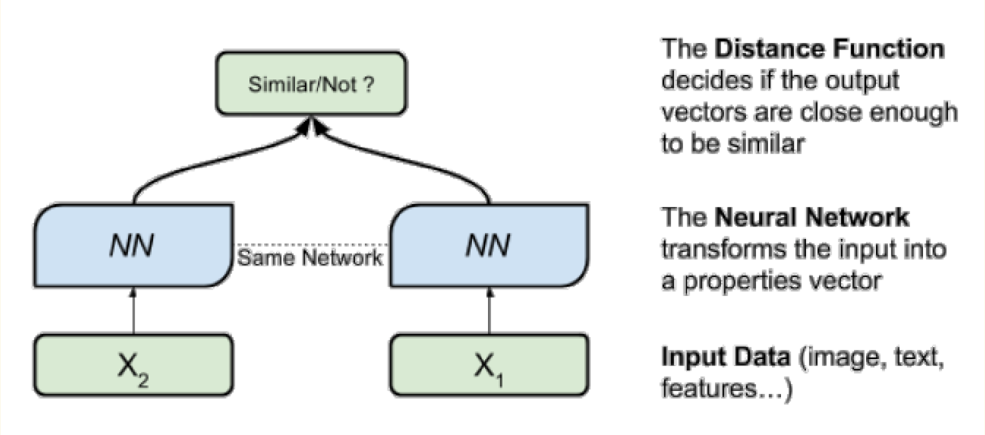
2019.07.14

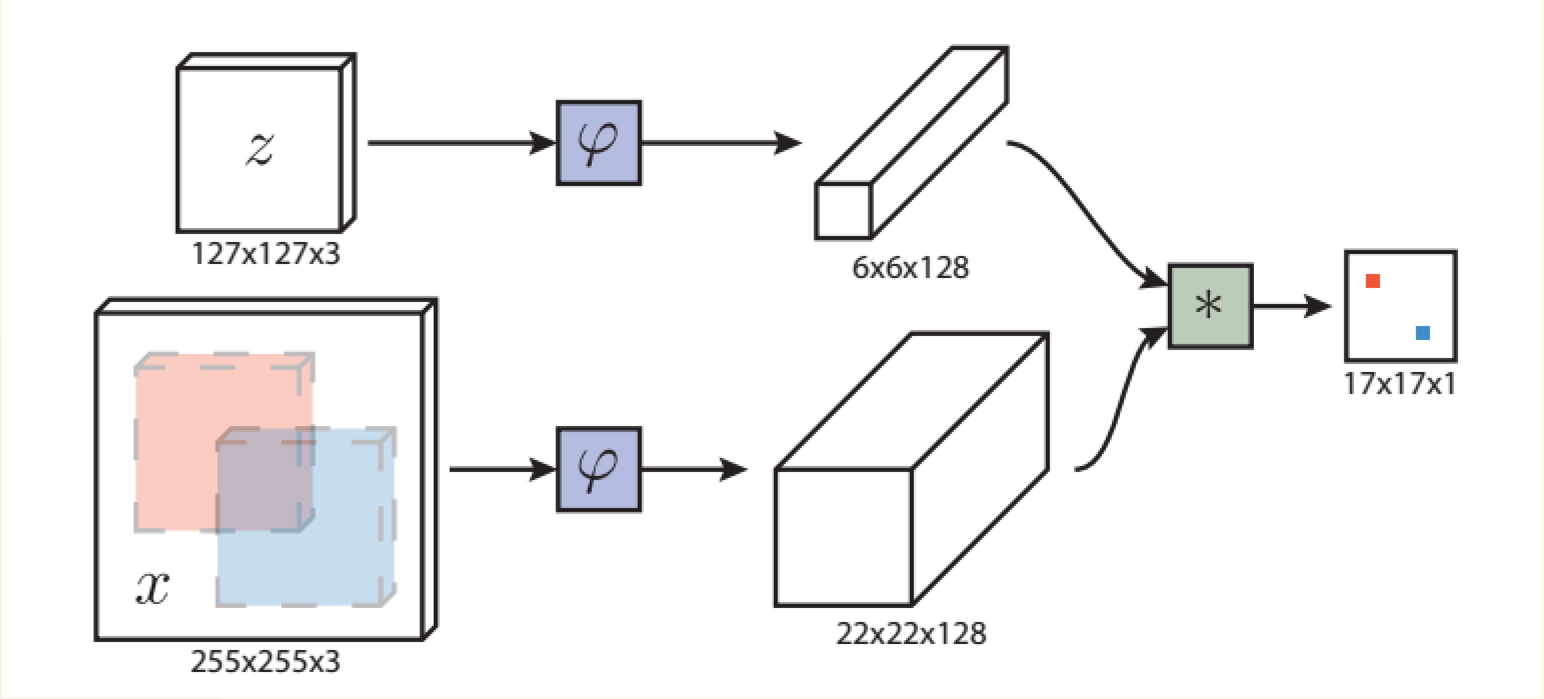
什么是Siamese网络

- 权重共享
- 度量学习(属于同一物体相似度大，不同物体相似度小)
- 应用于人脸验证，重识别(Re-ID)



Siamese FC(全卷积孪生网络)

- 模板图和搜索区域
- 卷积特征进行互相关，互相关结果包含搜索区域上每个位置与模板图的相似度



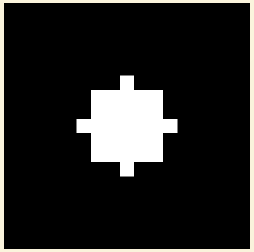
Siamese FC

- 保持全卷积特性（不能加padding）
- 使用ImageNet Video Dataset进行训练
- 训练样本为模板-搜索区域对

Fig. 2: Training pairs extracted from the same video: exemplar image and corresponding search image from same video. When a sub-window extends beyond the extent of the image, the missing portions are filled with the mean RGB value.

Siamese FC

- 训练损失函数(Logistic Loss)
  $l(y, v) = \log(1 + \exp(-yv))$
  $L(y, v) = \frac{1}{|D|} \sum_{u \in D} l(y[u], v[u])$
- 训练目标
  $$y[u] = \begin{cases} +1, & k||u - c|| \leq R \\ -1, & otherwise \end{cases}$$

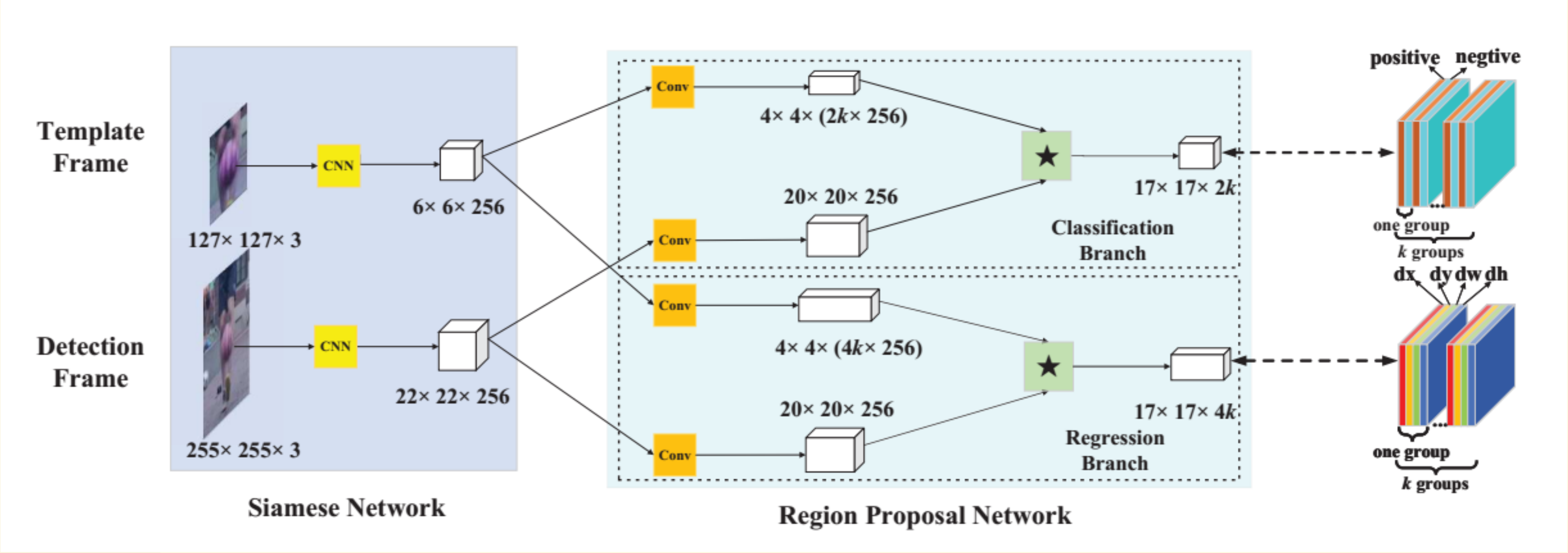


Siamese FC

- score map通过双三次插值到原尺寸.
- 尺度自适应：在多个尺度上检测$1.025^{\{-2,-1,0,1,2\}}$
- embedding function: AlexNet
- 单GPU上速度58~86 fps
- Siamese网络特点：无需模型更新

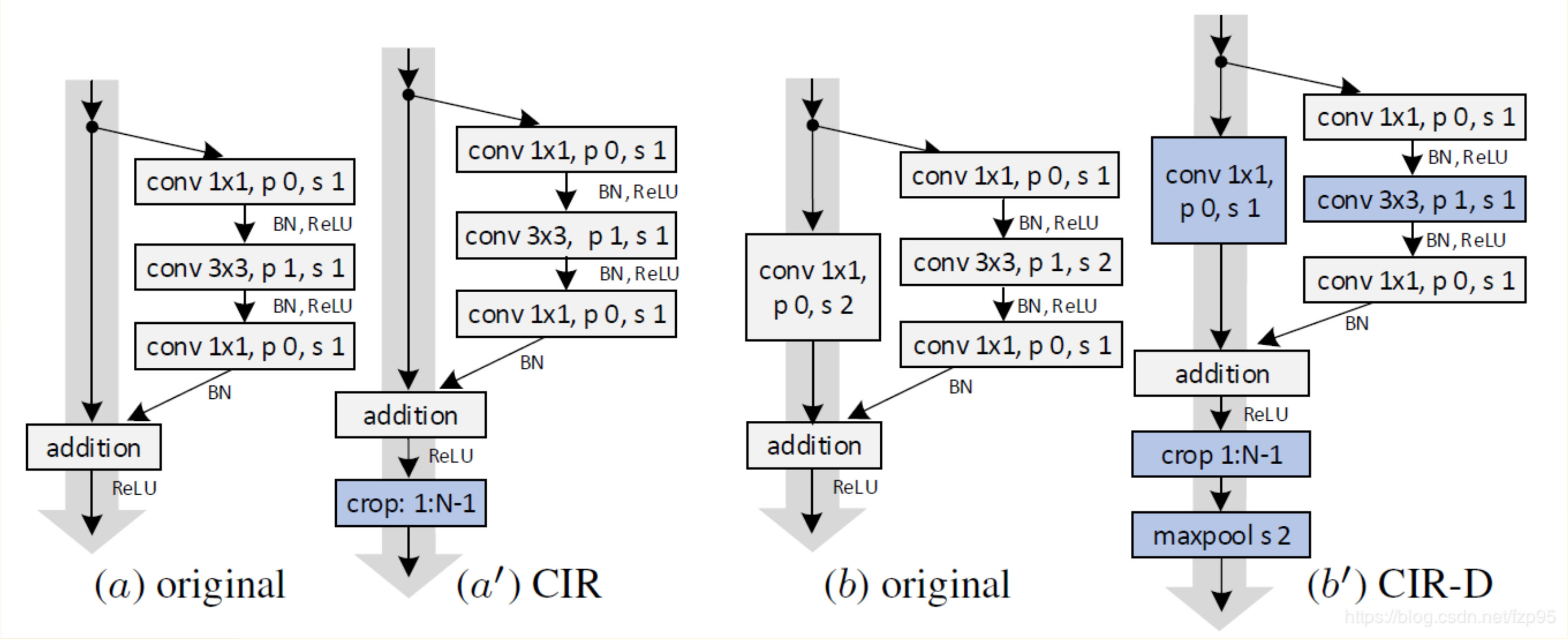
Siamese RPN

- 类似Faster-RCNN
- 一个分类分支和一个目标框回归分支
- 选出最大的K个anchor, 非极大值抑制(NMS)
- 宽高比自适应



SiameDW

- Siamese网络不能应用更深网络的原因：padding会破坏平移不变性
- 提出CIR模块，通过裁剪中心减小padding的影响



DaSiamRPN

- 在损失函数中加入相似物干扰抑制

SiamRPN++

- 训练中spatial aware采样策略
- Layer-wise Aggregation
- Depthwise Cross Correlation

NFS数据集

- Need for Speed: A Benchmark for Higher Frame Rate Object Tracking
- 现有跟踪数据集大多在较低帧率(30fps)下采集的视频
- 在较高帧率的视频下，使用手工特征的相关滤波跟踪算法超过了基于深度学习的跟踪算法
- 用iPhone和iPad采集了75个240fps的视频进行实验
- 间隔8帧采样模拟较低帧率视频
- 用AE(Adobe After Effects)模拟运动模糊

NFS数据集

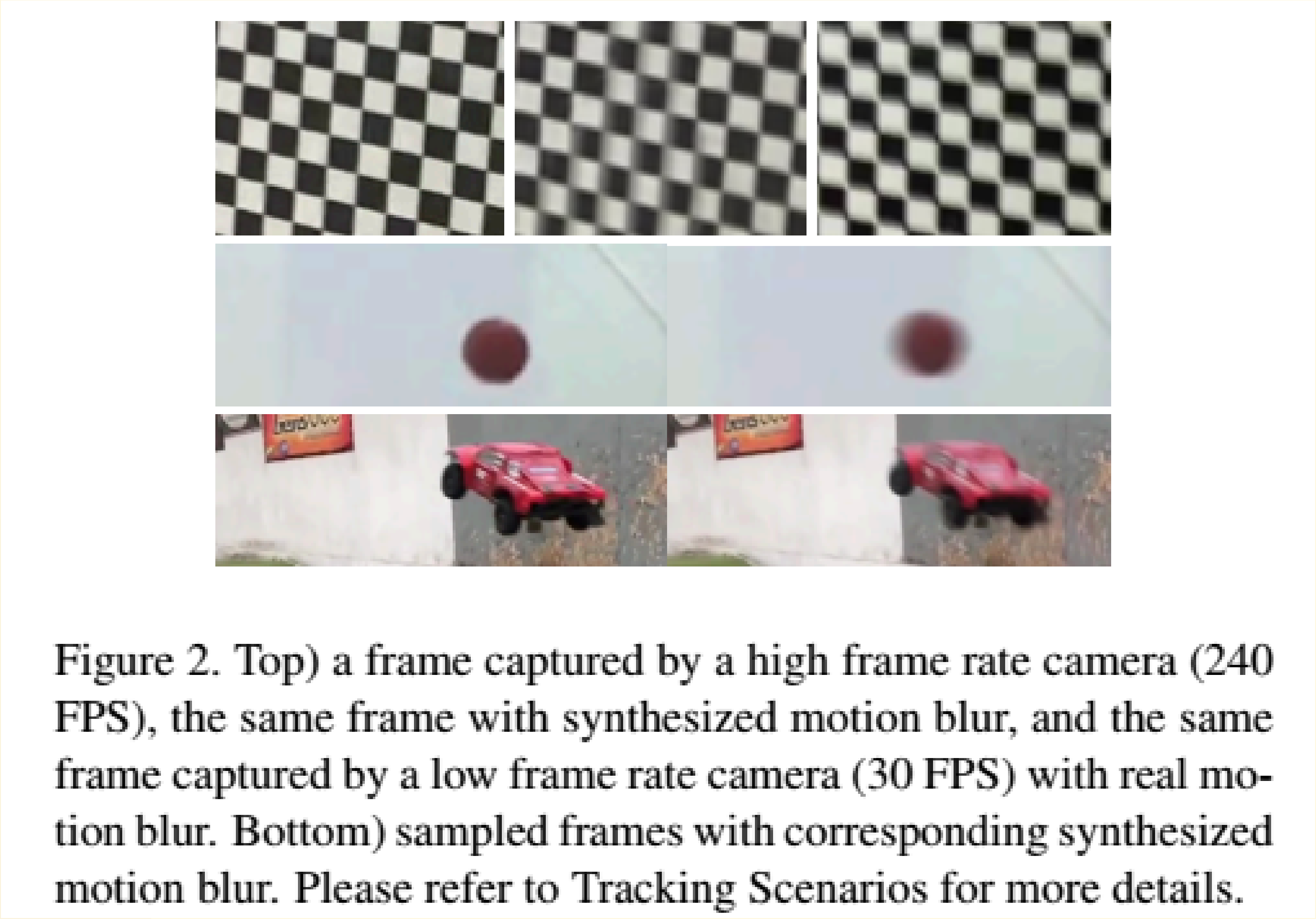


Figure 2. Top) a frame captured by a high frame rate camera (240 FPS), the same frame with synthesized motion blur, and the same frame captured by a low frame rate camera (30 FPS) with real motion blur. Bottom) sampled frames with corresponding synthesized motion blur. Please refer to Tracking Scenarios for more details.

NFS数据集

- 在较高帧率的数据集上，CF学习率调整为通常学习率的1/8会有较大提升

Table 3. Evaluating the effect of updating learning rate of each CF tracker on tracking higher frame rate videos (240 FPS). Accuracy is reported as success rate (%) at IoU > 0.50. Please refer to Section 4.1 for more details about the original and updated learning rates.

	BACF	SRDCF	Staple	LCT	DSST	SAMF	KCF	CFLB	HCF	HDT
Original LR	48.8	48.2	51.1	34.5	44.0	42.8	28.7	18.3	33.0	57.7
Updated LR	60.5	55.8	53.4	36.4	53.4	51.7	34.8	22.9	41.2	59.6

- CF类跟踪算法在较高帧率视频上性能有较大提升，而深度学习类算法提升不明显

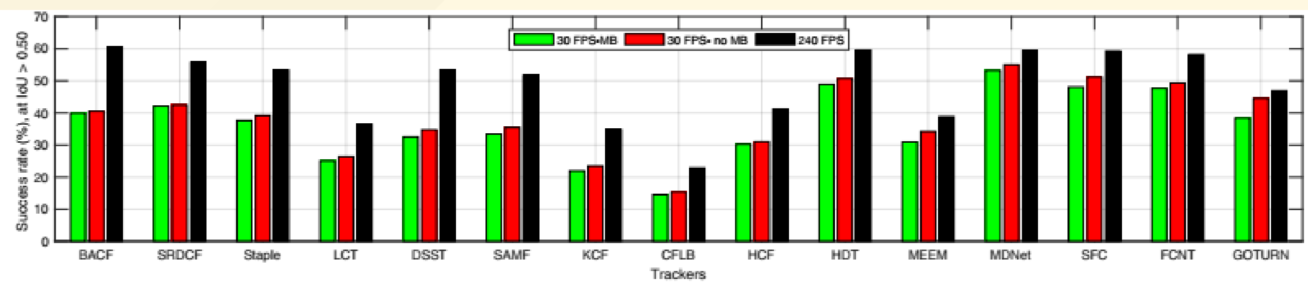


Figure 3. Comparing higher frame rate tracking (240 FPS) versus lower frame rate tracking (30 FPS) for each tracker. For higher frame rate tracking CF trackers employ updated learning rates. The results of lower frame rate tracking are plotted for videos with and without motion blur (30 FPS-MB and 30 FPS- no MB). Results are reported as success rate (%) at IoU > 0.50.

NFS数据集

- In simple terms: the accuracy of a 240 FPS tracker cannot be truly appreciated until it is run on a 240 FPS video!
- 在系统设计中，应将帧率作为一项资源进行权衡