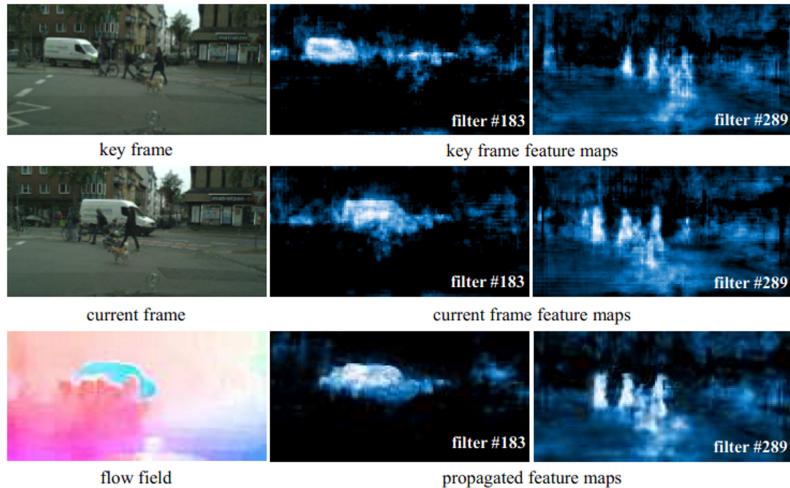


# summary

2018年11月14日 15:26

## deep feature flow

Motivation 来自于一个实验现象.



如果把目标检测任务分2步 .

$$f_c = N_{feat}(I_c) \text{ 提特征.} \quad (1)$$

$$y_c = N_{task}(f_i) \text{ 检测/分割} \quad (2)$$

过程(1) 提特征是放慢的 .

实验发现用光流场信息和关键帧融合会 .

可以用小开销在非关键帧上代替(1)

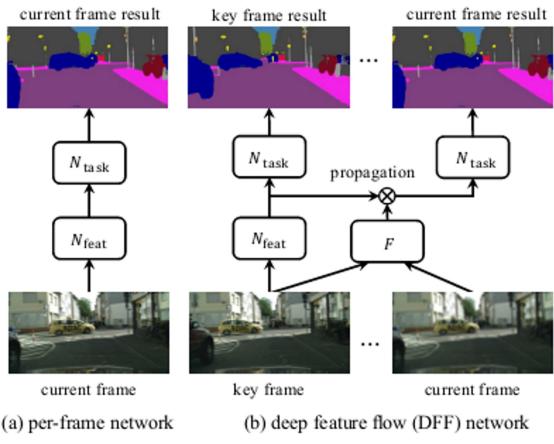


Figure 2. Illustration of video recognition using per-frame network evaluation (a) and the proposed deep feature flow (b).

**Algorithm 1** Deep feature flow inference algorithm for video recognition.

```

1: input: video frames  $\{\mathbf{I}_i\}$                                 ▷ initialize key frame
2:  $k = 0$ ;
3:  $\mathbf{f}_0 = \mathcal{N}_{feat}(\mathbf{I}_0)$ 
4:  $\mathbf{y}_0 = \mathcal{N}_{task}(\mathbf{f}_0)$ 
5: for  $i = 1$  to  $\infty$  do
6:   if  $is\_key\_frame(i)$  then                                ▷ key frame scheduler
7:      $k = i$                                               ▷ update the key frame
8:      $\mathbf{f}_k = \mathcal{N}_{feat}(\mathbf{I}_k)$ 
9:      $\mathbf{y}_k = \mathcal{N}_{task}(\mathbf{f}_k)$ 
10:    else                                                 ▷ use feature flow
11:       $\mathbf{f}_i = \mathcal{W}(\mathbf{f}_k, \mathcal{F}(\mathbf{I}_k, \mathbf{I}_i), \mathcal{S}(\mathbf{I}_k, \mathbf{I}_i))$     ▷ propagation
12:       $\mathbf{y}_i = \mathcal{N}_{task}(\mathbf{f}_i)$ 
13:    end if
14:  end for
15: output: recognition results  $\{\mathbf{y}_i\}$ 
```

The feature network  $N_{feat}$  only runs on sparse key frames.

The feature maps of a non-key frame  $\mathbf{I}_i$  are propagated from its preceding key frame  $\mathbf{I}_k$ .

The feature in the deep conv layers encode the semantic concepts and correspond to spatial locations in the image [47].

Examples are illustrated in Figure 1. Such spatial correspondence allows us to cheaply propagate the feature maps by the manner of spatial warping.

The feature maps of non-key frame  $\mathbf{I}_i$  is propagated from the key frame to current frame via flow field.

当前帧的特征图通过前一个关键帧和光流场  $\mathcal{F}(\mathbf{I}_k, \mathbf{I}_i)$  而得来.

首次估计流场  $\mathcal{M}_{i \rightarrow k} = \mathcal{F}(\mathbf{I}_k, \mathbf{I}_i)$ ,

对于点  $p$  有  $\delta p = \mathcal{M}_{i \rightarrow k}(p)$

然后通过双线性插值进行融合

$$f_i^c(p) = \sum_q G(q, p + \delta p) f_k^c(q) \quad (1a)$$

$$G(q, p + \delta p) = g(q_x, p_x + \delta p_x) \cdot g(q_y, p_y + \delta p_y) \quad (1b)$$

$$\text{where } g(a, b) = \max(0, 1 - |a - b|) \quad (1c)$$

这个操作叫作 STN.

(1a) 先是  $f_k$  和  $f_i$  根据 flow 插值 (详细讲解见 [propagation](#))

高斯过后 作者又说 .

"To better approximate the features, their amplitudes are modulated by a "scale field"  $S_{i \rightarrow k}$ , which is of the same spatial and channel dim as the feature maps

$$S_{i \rightarrow k} = S(I_k, I_i) \quad \text{这么神秘，究竟是什么？}$$

大概也能猜到 就是一个标量矩阵

看源码 就是用一个  $\underbrace{1 \times 1}_{\text{卷积}} \text{ 实现的.}$  感兴趣的看pdf文件 [conv\\_feats](#)