DeepDCF

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1 Discriminative Correlation Filters

1.1 DSST

(PCA-HOG+Gray)+DCF+Scale Esimation
key word: circular correlation,Parserval's identity, dense feature

1.1.1 Single Feature(gray)

patch: $x_1, ..., x_t$
label: $y_1, ..., y_t$
filter: w_t
test patch: z

$$\epsilon = \sum_{j=1}^{t} \left\| w_t \star x_j - y_j \right\|^2 = \sum_{j=1}^{t} \left\| \overline{W}_t \odot X_j - Y_j \right\|^2$$

$$W_t = \frac{\sum_{j=1}^{t} \overline{Y}_j \odot X_j}{\sum_{j=1}^{t} X_j \odot \overline{X_j}}$$

$$y = \mathfrak{F}^{-1}\left(\overline{W}_t \odot Z\right) = \mathfrak{F}^{-1}\left(\frac{\sum_{j=1}^{t} \overline{X}_j \odot Y_j \odot Z}{\sum_{j=1}^{t} \overline{X_j} \odot X_j}\right)$$

This is a little different between MOSSE[1] and this Derivation. No regularization term.

1.1.2 Multidimensional Features

patch: $f^l, l \in \{1, ..., d\}$ label: g filter: h^l test patch: z^l

$$\epsilon = \sum_{l=1}^{d} \left\| h^l \star f^l - g \right\|^2 + \lambda \sum_{l=1}^{d} \left\| h^l \right\|^2$$

$$H^l = \frac{\overline{G} F^l}{\sum_{k=1}^{d} \overline{F^k} F^k + \lambda}$$

To obtain a robust approximation, here we update the numerator A_t^l and denominator B_t

$$A_t^l = (1-\eta) A_{t-1}^l + \eta \overline{G}_t F_t^l$$

$$B_t^l = (1-\eta) B_{t-1}^l + \eta \sum_{k=1}^{d} \overline{F}_t F_t^l$$

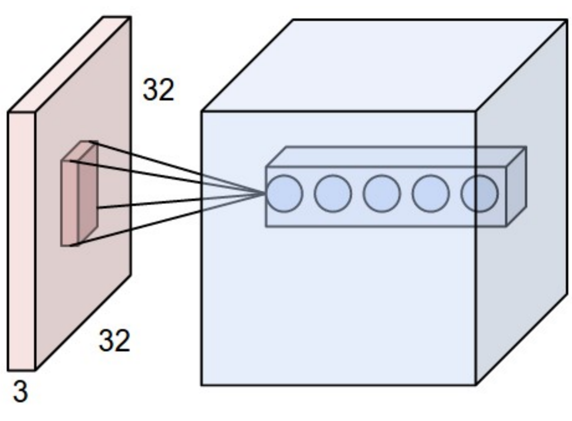
$$y = \mathfrak{F}^{-1} \left\{ \frac{\sum_{l=1}^{d} \overline{A^l} Z^l}{B + \lambda} \right\}$$

1.2 CN

1.3 SRDCF

2 CNN

CNN can be treated as a encode function $\Phi(x)$ of receptive field.



$$\Phi(x) = f^l$$

$x \in \mathbb{R}^{m\times n} \longrightarrow f \in \mathbb{R}^d$

It is sparse (only a few input units contribute to a given output unit) and reuses parameters (the same weights are applied to multiple locations in the input)

3 DeepDCF

target patch: $x^l, l \in \{1, ..., d\}$ idea label: y filter: w^l test patch: z^l test output: g

For the learing part.

$$\epsilon = \sum_{l=1}^{d} \left\| w^l \star x^l - y \right\|^2 + \lambda \sum_{l=1}^{d} \left\| w^l \right\|^2$$

$$W^l = \frac{\overline{Y} \odot X^l}{\sum_{k=1}^{d} \overline{X^k} \odot X^k + \lambda}$$

$$g = \mathfrak{F}^{-1} \left\{ \frac{\sum_{l=1}^{d} \overline{A^l} \odot Z^l}{B + \lambda} \right\}$$

$$g = \mathfrak{F}^{-1} \left\{ \frac{\sum_{l=1}^{d} \overline{A^l} \odot Z^l}{B + \lambda} \right\} = \mathfrak{F}^{-1} \left\{ \frac{\sum_{l=1}^{d} \overline{\overline{Y} \odot X^l} \odot Z^l}{\sum_{k=1}^{d} \overline{X^k} \odot X^k + \lambda} \right\} = \mathfrak{F}^{-1} \left\{ \frac{\sum_{l=1}^{d} (Z^l \odot \overline{X^l}) \odot Y}{\sum_{k=1}^{d} \overline{X^k} \odot X^k + \lambda} \right\}$$

```
g=ifft2((sum(fft2(z).*conj(fft2(x)), 3).*fft2(y))./...
        (sum(fft2(x).*conj(fft2(x)), 3)+lambda)));
```

The forward pass derivation should be familiar to us by now. There need some patience for the backward pass.

First, let's begining with some fundamental theorems of DFT and Complex-Valued Derivatives.

Because the DFT is a linear opreator, it's gradient is simply the transformation matrix it self. During the back-progation, then, the gradient is conjugated.[3]

$$Y = \mathfrak{F}\{y\}, \frac{\partial l}{\partial Y} = \mathfrak{F}\left\{ \frac{\partial l}{\partial y} \right\}$$

The second theorem we will use is Complex-Valued Derivatives. [2] Because we need pass δ throught the frequency domain. We will be more familar with the derivatives operator about complex .

$$\frac{\partial f(x, x^*)}{\partial x} = \overline{\frac{\partial f(x, x^*)}{\partial x^*}}$$

Now, Let's derive the formulas about the backward. For simplify, We start with $\frac{\partial l}{\partial g}$ and what we need is to results of $\frac{\partial l}{\partial x}$ and $\frac{\partial l}{\partial z}$.

$$G_{uv} = \frac{\sum_{l=1}^{d} (Z_{uv}^{l} \overline{X_{uv}^{l}}) Y_{uv}}{\sum_{k=1}^{d} X_{uv}^{k} \overline{X_{uv}^{k}} + \lambda}$$

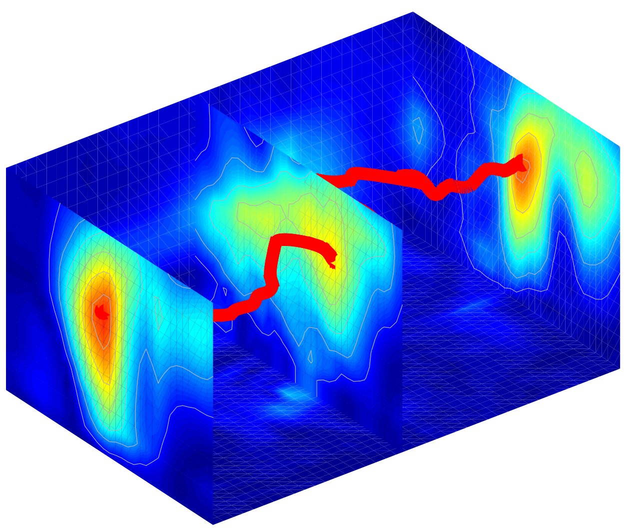
$$\frac{\partial l}{\partial Z_{uv}^{l}} = \frac{\partial l}{\partial G_{u,v}} \frac{\partial G_{u,v}}{\partial Z_{uv}} = \mathfrak{F}\left\{\frac{\partial l}{\partial g}\right\}_{uv} \frac{\overline{X_{uv}^{l}} Y_{uv}}{\sum_{k=1}^{d} X_{uv}^{k} \overline{X_{uv}^{k}} + \lambda}$$

$$\frac{\partial l}{\partial X_{uv}^{l}} = \frac{\partial l}{\partial G_{u,v}} \frac{\partial G_{u,v}}{\partial X_{uv}} = \mathfrak{F}\left\{\frac{\partial l}{\partial g}\right\}_{uv} \frac{\overline{Z_{uv}^{l} Y_{uv}} (\sum_{k=1}^{d} \overline{X_{uv}^{k}} X_{uv}^{k} + \lambda) - \overline{X_{uv}^{k}} (\sum_{l=1}^{d} (Z_{uv}^{l} \overline{X_{uv}^{l}}) Y_{uv})}{(\sum_{k=1}^{d} \overline{X_{uv}^{k}} X_{uv}^{k} + \lambda)^2}$$

$$\frac{\partial l}{\partial x_{uv}^{l}} = \mathfrak{F}^{-1}\left\{\frac{\partial l}{\partial X}\right\}_{uv}^{l}$$

3.1 Training

I think that is a very perfect visualization of the training process.



References

[1] David S Bolme, J Ross Beveridge, Bruce A Draper, and Yui Man Lui. Visual object tracking using adaptive correlation filters. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 2544–2550. IEEE, 2010.

[2] Are Hjørungnes. *Complex-valued matrix derivatives: with applications in signal processing and communications*. Cambridge University Press, 2011.

[3] Oren Rippel, Jasper Snoek, and Ryan P Adams. Spectral representations for convolutional neural networks. In *Advances in Neural Information Processing Systems*, pages 2449–2457, 2015.