

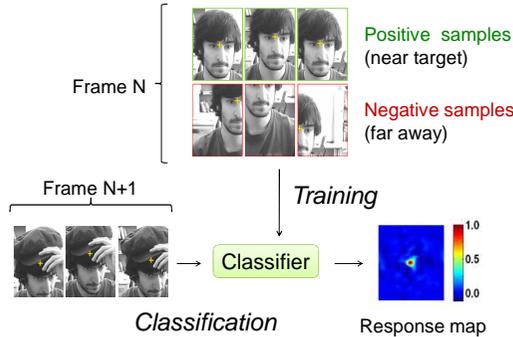
EXPLOITING THE CIRCULANT STRUCTURE OF TRACKING-BY-DETECTION WITH KERNELS

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1. Motivation

- In tracking-by-detection, a classifier is trained with **several patches** from a **single image**.

The data matrix has **extreme redundancies**.



This is a hint that **classic algorithms do unnecessary work**.

2. Idea

- Instead of random patches, use **all patches**.
- Look for a pattern that we can take advantage of.

It turns out that in this case,

The data matrix is **Circulant**.

$$C(\mathbf{u}) = \begin{bmatrix} u_0 & u_1 & u_2 & \dots & u_{n-1} \\ u_{n-1} & u_0 & u_1 & \dots & u_{n-2} \\ u_{n-2} & u_{n-1} & u_0 & \dots & u_{n-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ u_1 & u_2 & u_3 & \dots & u_0 \end{bmatrix}$$

Image
Image shifted by 1 element
Image shifted by 2 elements
⋮
Image shifted by n-1 elements



3. Circulant matrices

- Easy to manipulate algebraically.
- Allow **standard learning methods** to be transformed into efficient **Fourier domain operations**.

Circulant Matrix Standard algebra operations	Fourier Domain Cheap element-wise operations
$X = C(\mathbf{x}), Y = C(\mathbf{y}), Z = C(\mathbf{z})$	$\bar{\mathbf{x}} = F(\mathbf{x}), \bar{\mathbf{y}} = F(\mathbf{y}), \bar{\mathbf{z}} = F(\mathbf{z})$
$Z = X + Y$	$\bar{\mathbf{z}} = \bar{\mathbf{x}} + \bar{\mathbf{y}}$
$Z = XY$	$\bar{\mathbf{z}} = \bar{\mathbf{x}} \odot \bar{\mathbf{y}}$
$\mathbf{z} = X\mathbf{y}$	$\bar{\mathbf{z}} = \bar{\mathbf{x}}^* \odot \bar{\mathbf{y}}$
$Z = X^{-1}$	$\bar{\mathbf{z}} = 1/\bar{\mathbf{x}}$

4. Linear classification

Ridge Regression + Circulant data \Rightarrow MOSSE filter (Bolme et al., CVPR 2010)

$$\mathbf{w} = F^{-1} \left(\frac{F(\mathbf{x}) \odot F^*(\mathbf{y})}{F(\mathbf{x}) \odot F^*(\mathbf{x}) + \lambda} \right)$$

- Independent proof** from a risk minimization point-of-view.
- Circulant matrices **link** two fields:
 - Generic learning algorithms**, and
 - Classic signal processing** (frequency-domain filter synthesis)

5. Kernel classification

- Kernel matrix** is Circulant for unitary kernels (Thm. 1).
- Compact and exact representation $\mathbf{k} \xrightarrow{n^2 \times n^2 \quad n^2 \times 1} K = C(\mathbf{k}) \Rightarrow$ The full kernel matrix is never built explicitly!

- Solutions for:**

- Kernel Ridge Regression $\alpha = F^{-1} \left(\frac{F(\mathbf{y})}{F(\mathbf{k}) + \lambda} \right)$
- Classification $\hat{\mathbf{y}} = F^{-1} (F(\bar{\mathbf{k}}) \odot F(\alpha))$
- Computation of kernels $\mathbf{k}^{\text{rbf}} = h(\|\mathbf{x}\|^2 + \|\mathbf{x}'\|^2 - 2F^{-1}(F(\mathbf{x}) \odot F^*(\mathbf{x}')))$

For all patches **simultaneously**

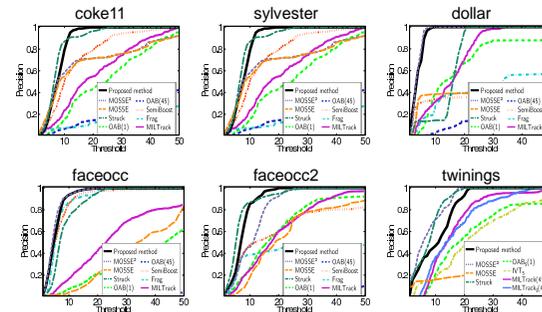
- Linear
- Polynomial
- Gaussian ...

- Kernel algorithm with same complexity as linear.**

Fast Fourier Transform \Rightarrow

Tracking with kernels at 100-400 FPS

Results



Source code

Training image \mathbf{x} (current frame) and test image \mathbf{z} (next frame) must be pre-processed with a cosine window. \mathbf{y} has a Gaussian shape centered on the target. \mathbf{x} , \mathbf{y} and \mathbf{z} are M -by- N matrices. All FFT operations are standard in MATLAB.

```
function alphaf = training(x, y, sigma, lambda) % Eq. 7
    k = dfgk(x, y, sigma);
    alphaf = fft2(y) ./ (fft2(k) + lambda);
end

function yhat = detection(alphaf, x, z, sigma) % Eq. 9
    k = dfgk(x, z, sigma);
    yhat = real(fft2(alphaf .* fft2(k)));
end

function k = dfgk(x1, x2, sigma) % Eq. 16
    c = fftshift(fft2(fft2(x1) .* conj(fft2(x2))));
    d = x1(:)' * x1(:) + x2(:)' * x2(:) - 2 * c;
    k = exp(-1 / sigma^2 * abs(d) / numel(x1));
end
```