Kernel Selection by Mutual Information for Nonparametric Tracking

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Problem

Tracking a ROI without *a priori* on the pixel distribution is flexible but heavy.

Contribution

We have adapted the CMIM [3] algorithm to select independent and representative kernels from any labelled ROI.

This compresses the ROI according to the discriminative information (like foreground *vs* background) and provides a tracking at a lower cost.

1. Gaussian Kernel Generation

- M random pixels $\mathbf{x_m}(u_m, v_m)$ in the ROI.
- D uniform spaces: R, G, B, UVR, UVG, UVB, UV, RGB and $UVRGB$.

$P(\mathbf{x} \in Object) = \mathtt{K}_{\lambda,\mathtt{D}}(\mathbf{x}, \mathbf{x_m})$ with:

$$\mathtt{K}_{\lambda,\mathtt{D}}(\mathbf{x}, \mathbf{x_m}) = \begin{cases} e^{-\lambda . d_D(\mathbf{x},\mathbf{x_m})} & Y(\mathbf{x_m}) = 1 \\ 1 - e^{-\lambda . d_D(\mathbf{x},\mathbf{x_m})} & Y(\mathbf{x_m}) = 0 \end{cases}$$

0. Assumptions

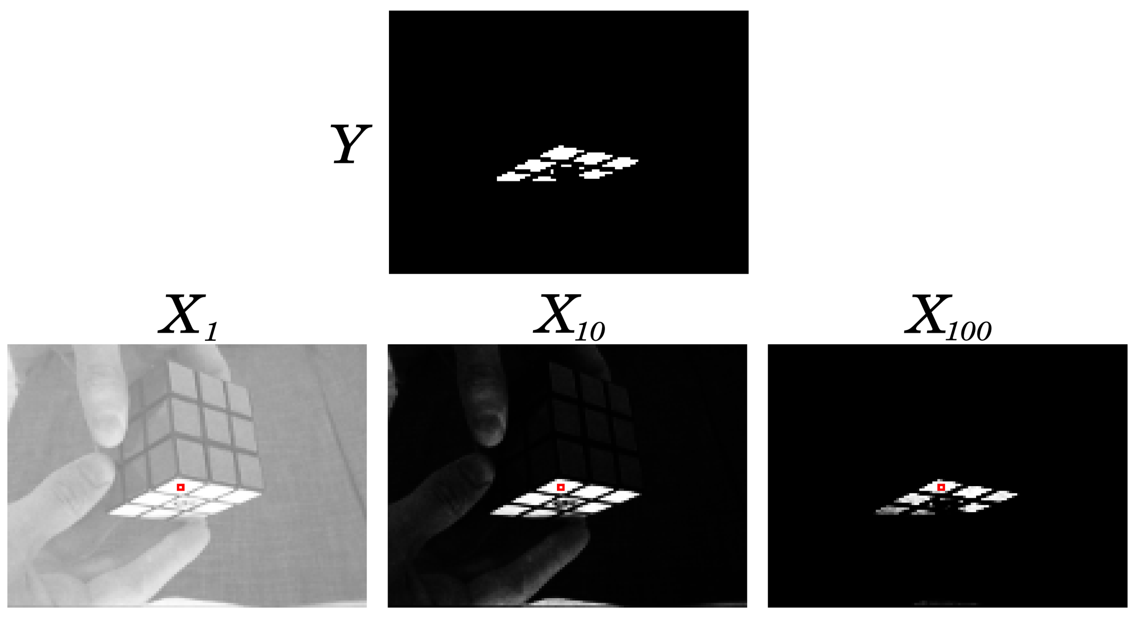
1/ ROI access in the first image of the video sequence $\} \rightarrow$

$\leftarrow \{$ 2/ ROI labels Y *e.g.* foreground & background

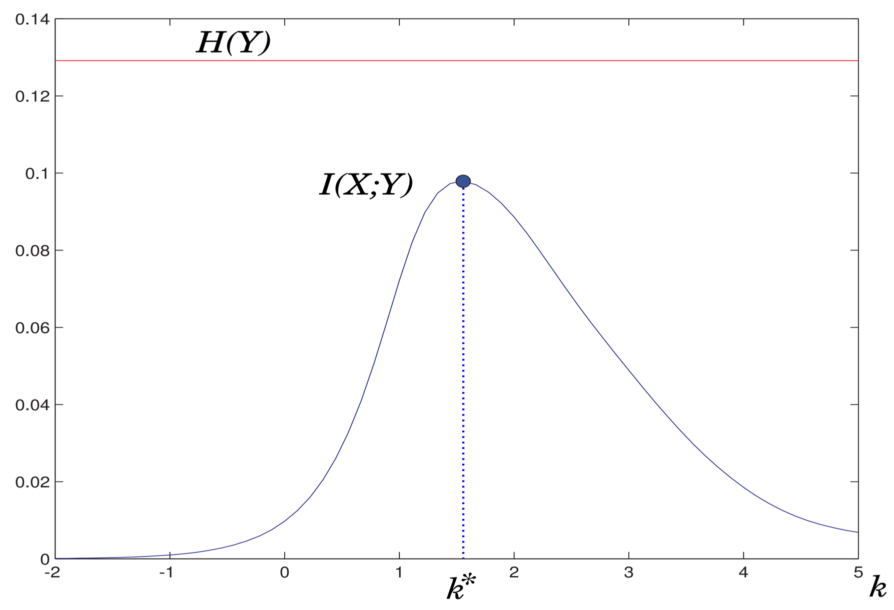
2. Kernel Bandwidth Optimization

Kernels $\mathtt{K}_{\lambda,\mathtt{D},\mathbf{x_m}}$ make their bandwidth λ move to fit the labels Y:

$\lambda^* = \arg\max_\lambda I(X_\lambda; Y)$ with $X_\lambda = \{P(\mathbf{x} \in Object)\ \forall \mathbf{x} \in \text{ROI}\}_{\lambda,D,\mathbf{x_m}}$



$X_\lambda = f(\lambda)$



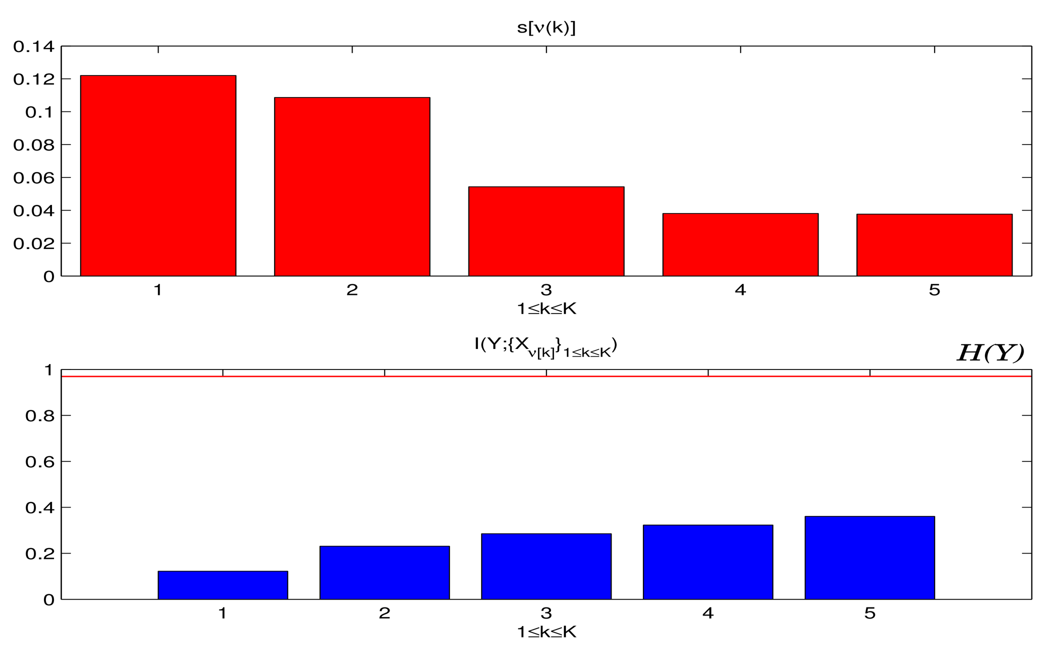
$\lambda = 10^k$

3. Kernel Selection

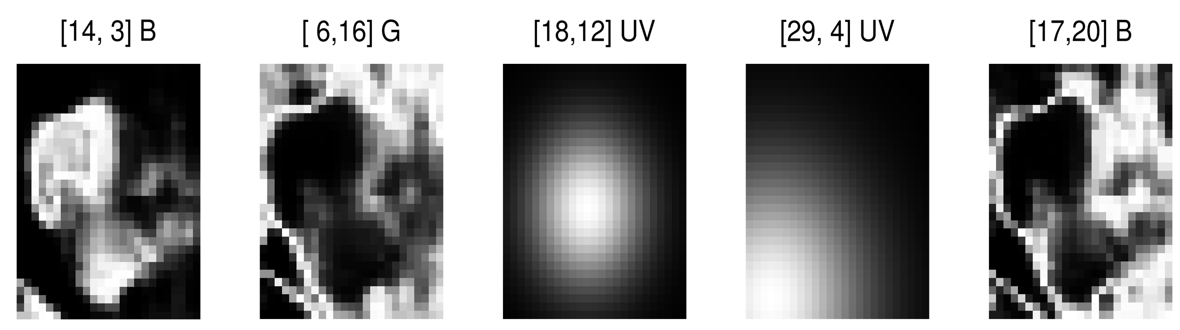
CMIM [3] selects K kernels among N:

for n=1...N **do**
  s[n] $\leftarrow I(Y; X_n)$
for k=1...K **do**
  $\nu[k]$ = arg max$_n$ s[n]
  for n=1...N **do**
    s[n] $\leftarrow$ min{s[n], $I(Y; X_n | X_{\nu[k]})$}

$$I(Y; X_n) = H(Y) + H(X_n) - H(Y, X_n)$$



Kernel scores & labelling ``explanation´´

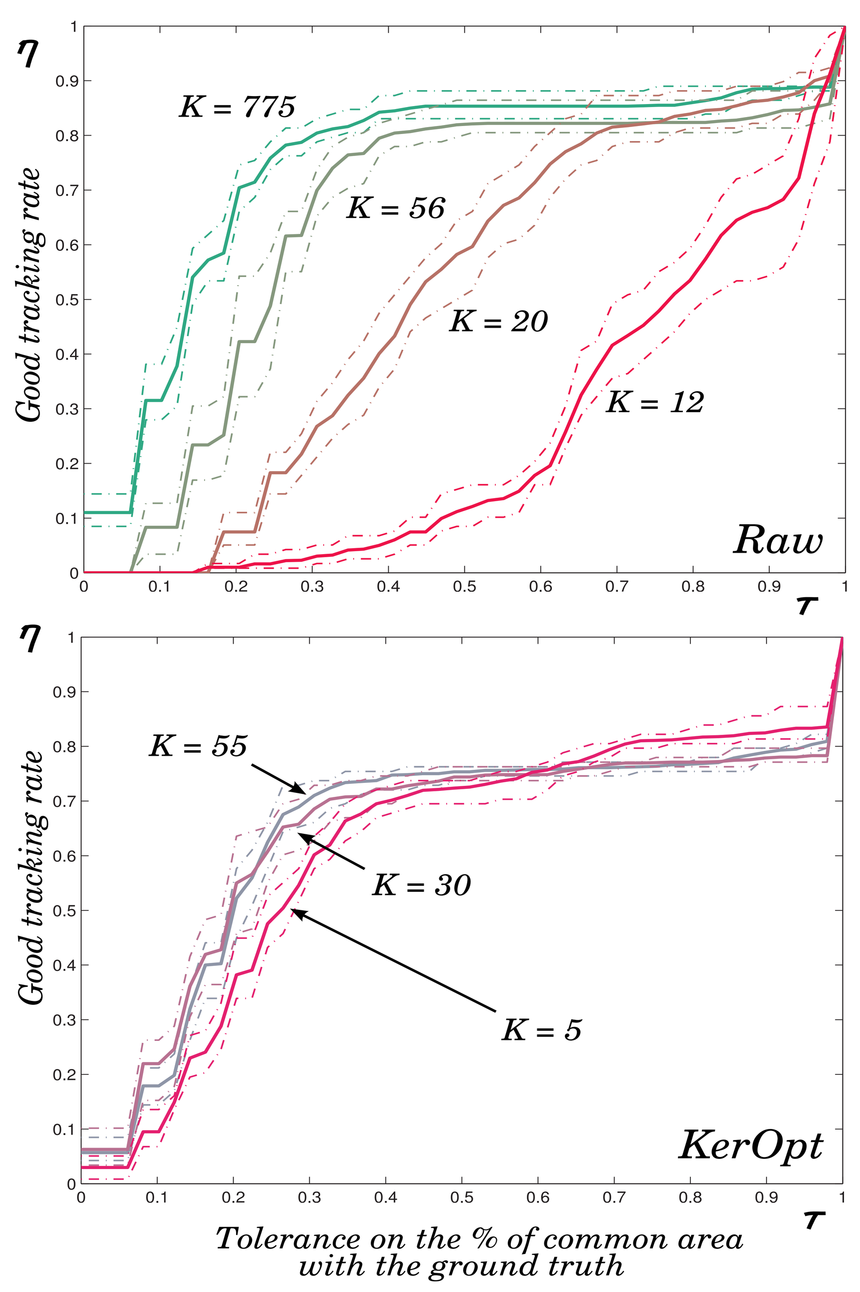


First five kernels selected by CMIM

Get the model and source code at:
`http://jean-marc.berthomme.perso.sfr.fr`

Results

CAVIAR sequence "WalkByShop1cor" - images 192–309
Ground Truth *vs* Algorithm Truth for different sampling strategies



4. Tracking

- Monte Carlo Markov Chain [4] Particle Filter [1]
- Dissimilarity metric [2] between the ROI of reference and any ROI.

References

[1] M.S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp. A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking. *Signal Processing, IEEE Transactions on*, 50(2):174–188, 2002.

[2] S. Boltz, E. Debreuve, and M. Barlaud. High-dimensional statistical measure for region-of-interest tracking. *IEEE Transactions on Image Processing*, 18(6):1266–1283, 2009.

[3] F. Fleuret. Fast binary feature selection with conditional mutual information. *The Journal of Machine Learning Research*, 5:1531–1555, 2004.

[4] Z. Khan, T. Balch, and F. Dellaert. Mcmc-based particle filtering for tracking a variable number of interacting targets. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 1805–1918, 2005.

Acknowledgements

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