Predictability of eye movements analyzed in a machine learning framework

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Introduction

Motivation

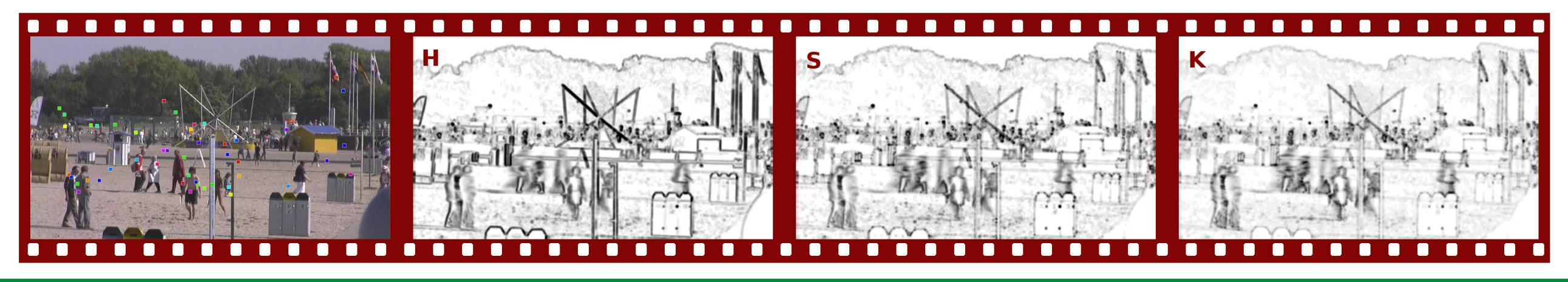
We investigate the extent to which a simple model of low-level saliency based on local spectral energy computed on different visual representations can predict saccade targets in natural dynamic scenes. Our objective is to learn transformations that alter the saliency distribution of the scene in real time, thus implementing gaze guidance [1].

Experimental setup

and their scanpaths, thus eliminating the cen- i2D, or i3D. tral fixation bias.

Representations

A large dataset of ~40,000 saccades was ob- It is well known that changes in space and in tained from 54 subjects free-viewing 18 high- time of the visual input often attract attention. resolution movie clips of outdoor scenes of ~20 The intrinsic dimension (ID) is a simple and unsec durations each (29.97 fps, subtending 48x27 biased way to encode the spatio-temporal signal deg of visual angle). The saccade landing points change of the visual input. It denotes the number were used to label image regions as fixated. For of degrees of freedom that are necessary to repthe non-fixated class, we shuffled the movies resent the signal. A movie can be locally i0D, i1D,



Eye Movement Prediction

Estimating the ID

We use the structure tensor defined in terms of the spatio-temporal gradient of the image intensity function (f_x, f_y, f_t) are partial derivatives):

$$J = \int_{\Omega} egin{bmatrix} f_x^2 & f_x f_y & f_x f_t \ f_x f_y & f_y^2 & f_y f_t \ f_x f_t & f_y f_t & f_t^2 \end{bmatrix} d\Omega$$

x =

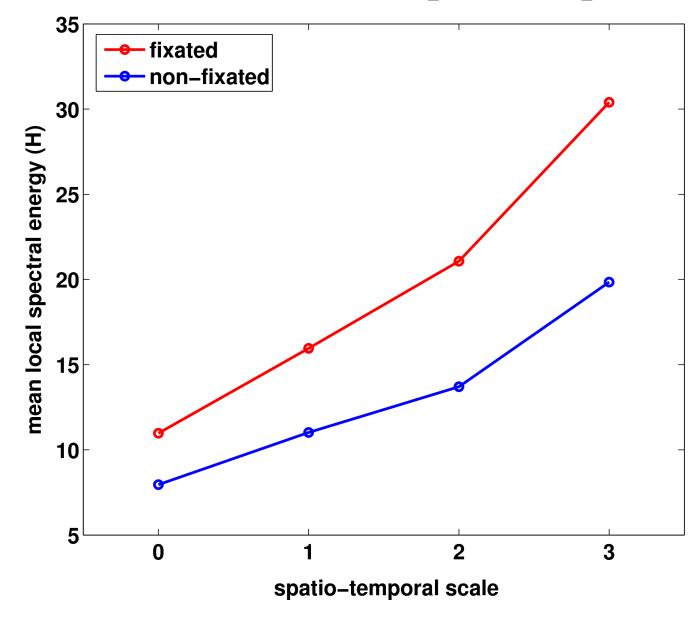
data

Our saliency measures (I) are its symmetric invariants (M_{11}, M_{22}, M_{33}) are minors of J):

$$H = 1/3 \operatorname{trace}(J)$$
 $S = |M_{11}| + |M_{22}| + |M_{33}|$
 $K = |J|$

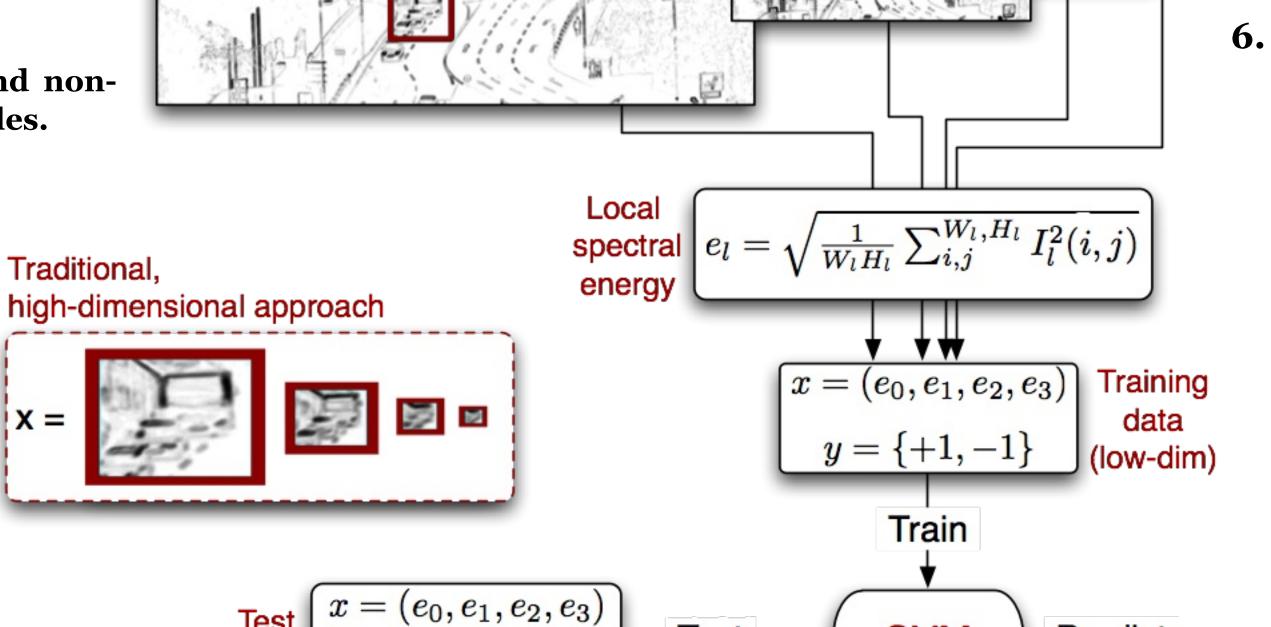
If $K \neq 0$, the ID is 3, if $S \neq 0$ it is at least 2, and if $H \neq 0$ it is at least 1.

Average local spectral energy at attended and nonattended locations over 4 spatio-temporal scales.



Prediction procedure:

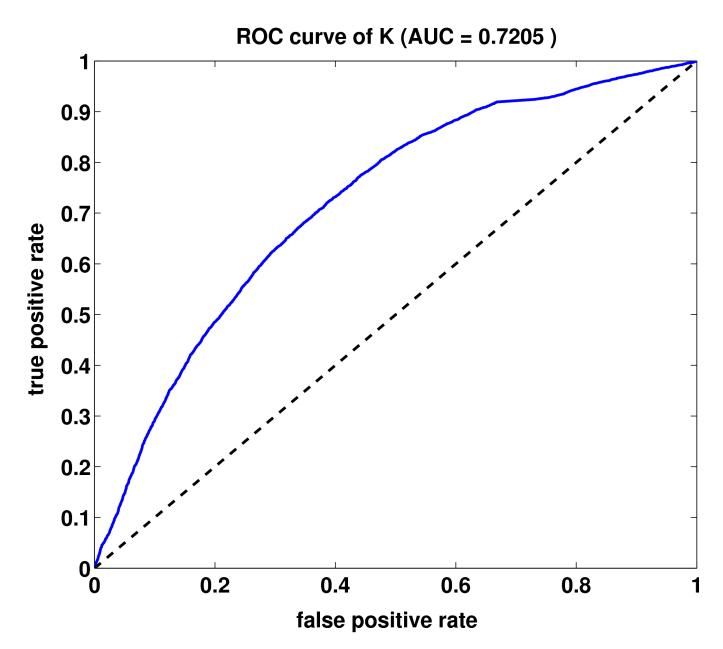




SVM

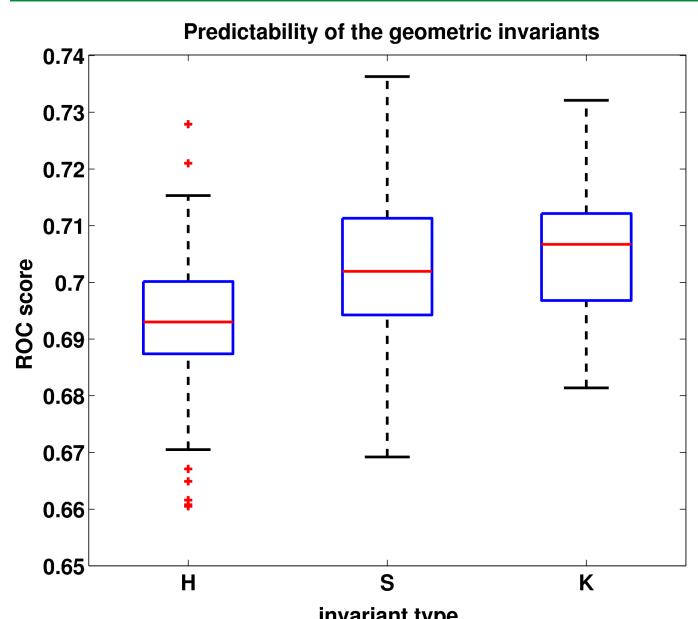
Predict →

- 1. The geometric invariants are computed on multiple scales of an isotropic spatiotemporal Gaussian pyramid.
- 2. To obtain equally sparse representations, H, S, and K are adaptively thresholded.
- 3. Local spectral energy is extracted in the neighborhood of a certain size of each location on these scales.
- 4. We obtain for each location a feature vector of the same dimensionality as the number of spatio-temporal pyramid levels.
- 5. To quantify the extent to which eye movements can be predicted, we use a support vector machine whose optimal parameters are found by cross-validation.
- 6. ROC analysis is used to test the prediction performance on unlabeled test data.



Results & Summary

Test



invariant type Quantitative differences in the distribution of prediction rates for invariants H, S, and K (window size of ~ 5 deg).

The predictability of eye movements

y = ?

- is higher (AUC of 0.71) than previously reported results on both static and dynamic scenes.
- is high although little information is used: only one feature (local spectral energy) per movie patch and per scale.
- correlates with the intrinsic dimension: the higher the intrinsic dimension (S and K) the higher the predictive power.
- increases to 0.8 AUC with a moderate increase in the number of dimensions (e.g. anisotropic Gaussian pyramid).

References

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- [2] L. Itti, C. Koch, and E. Niebur. A model of saliencybased visual attention for rapid scene analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20(11):1254-1259 (1998).
- [3] W. Kienzle, B. Schölkopf, F. A. Wichmann, and M. O. Franz. How to find interesting locations in video: a spatiotemporal interest point detector learned from human eye movements. In Proceedings of the 29 th Annual Symposium of the German Association for Pattern Recognition (DAGM 2007), 405-414. Springer Verlag (2007).