Image Analysis (FMAN20) Lecture F15, 2019

MAGNUS OSKARSSON

Image Analysis - Motivation

LUND UNIVERSITY

Overview – image processing

1. **Noise reduction**
2. Anisotropic filtering
3. Application: low light video enhancement
4. Block matching and collaborative filtering
5. Deep learning architectures for image processing
6. Application: low light image processing using learning

Noisy image

Gaussian smoothing

Gaussian smoothing - blurs edges!

Overview – image processing

1. Noise reduction
2. **Anisotropic filtering**
3. Application: low light video enhancement
4. Block matching and collaborative filtering
5. Deep learning architectures for image processing
6. Application: low light image processing using learning

Structure/Orientation Tensor

Construct the matrix

$$M = \begin{bmatrix} W_{xx} & W_{xy} \\ W_{xy} & W_{yy} \end{bmatrix} = \begin{bmatrix} (\frac{\partial f}{\partial x})^2 * G_b & (\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}) * G_b \\ (\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}) * G_b & (\frac{\partial f}{\partial y})^2 * G_b \end{bmatrix},$$

where G_b denotes the Gaussian function with parameter b.
M - orientation tensor.
Note: We construct a matrix for every pixel.

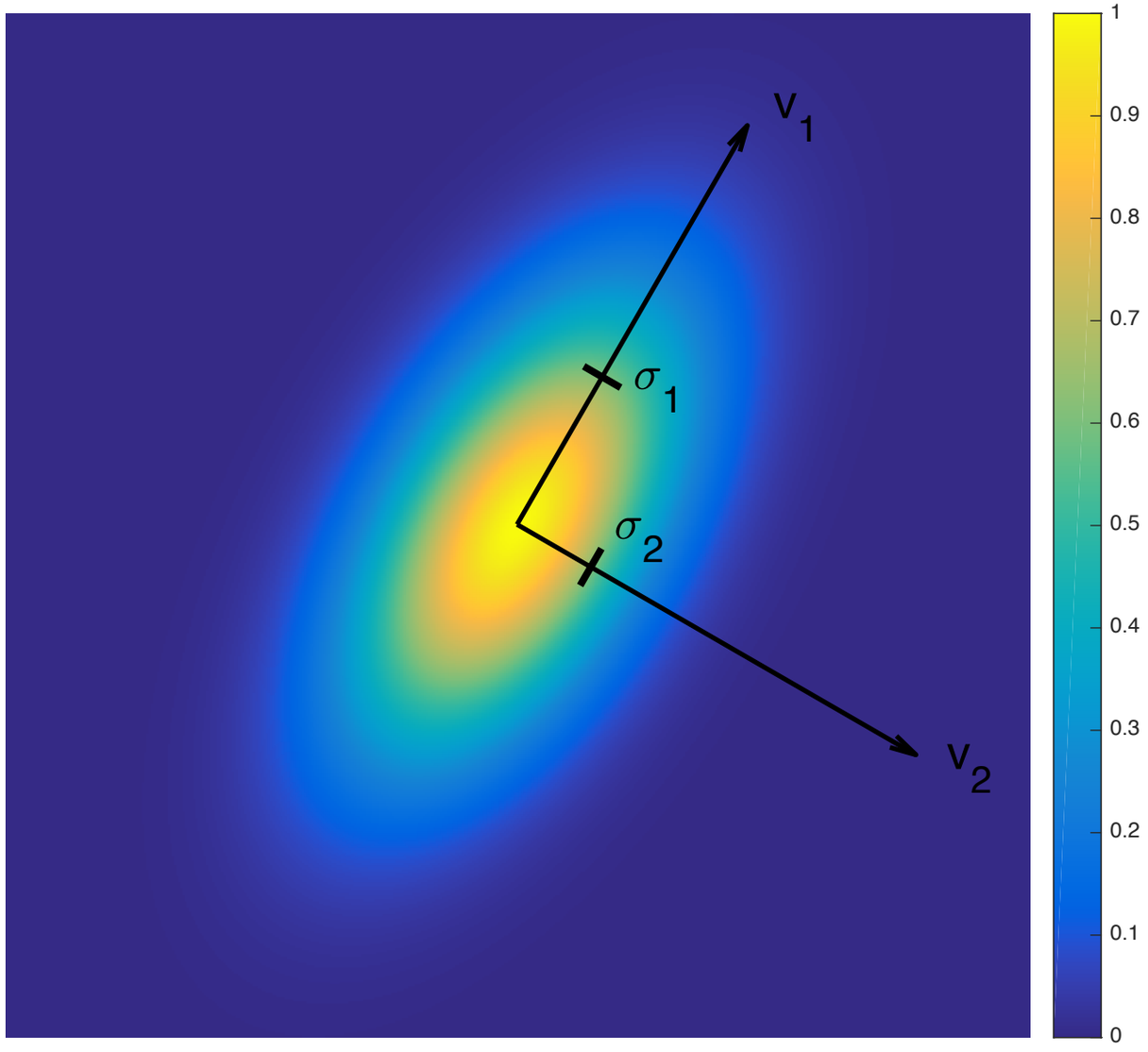
Structure Tensor

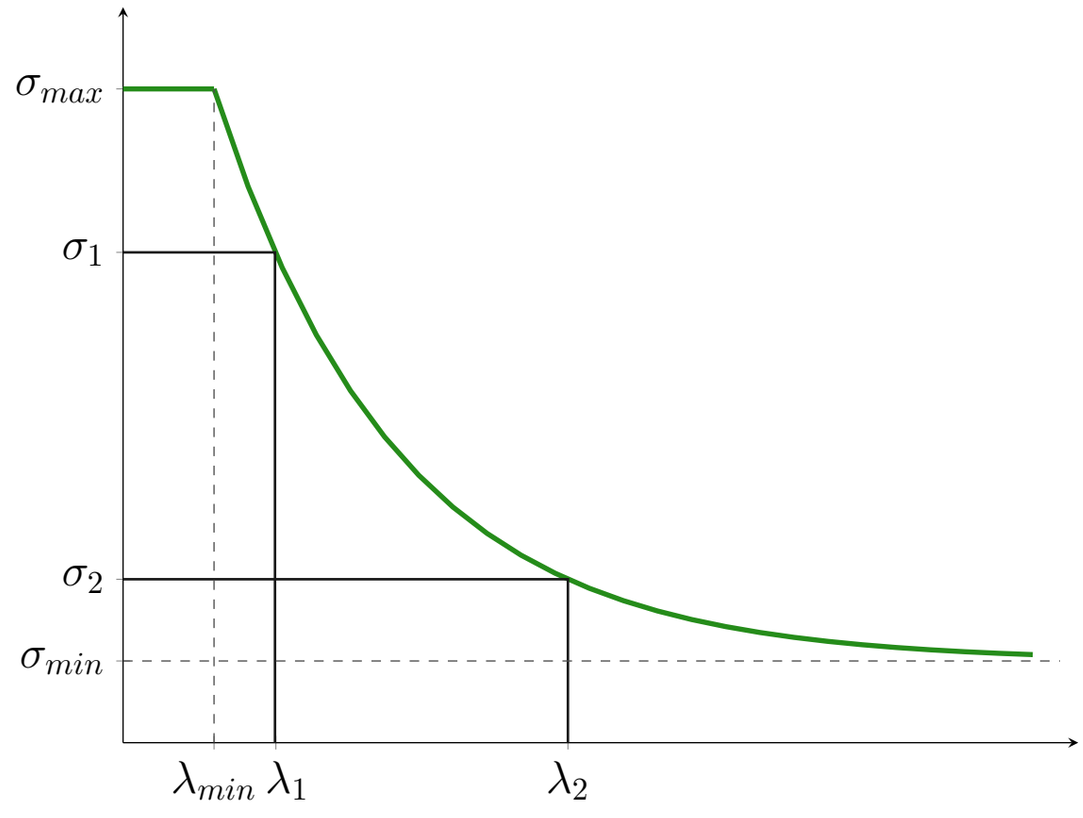
The matrix M has the following properties:

- (Flat) Two small eigenvalues in a region - flat intensity.
- (Flow) One large and one small eigenvalue - edges and flow regions.
- (Texture) Two large eigenvalues - corners, interest points, texture regions.

This can be used in algorithms for segmenting the image into (flat, flow, texture).

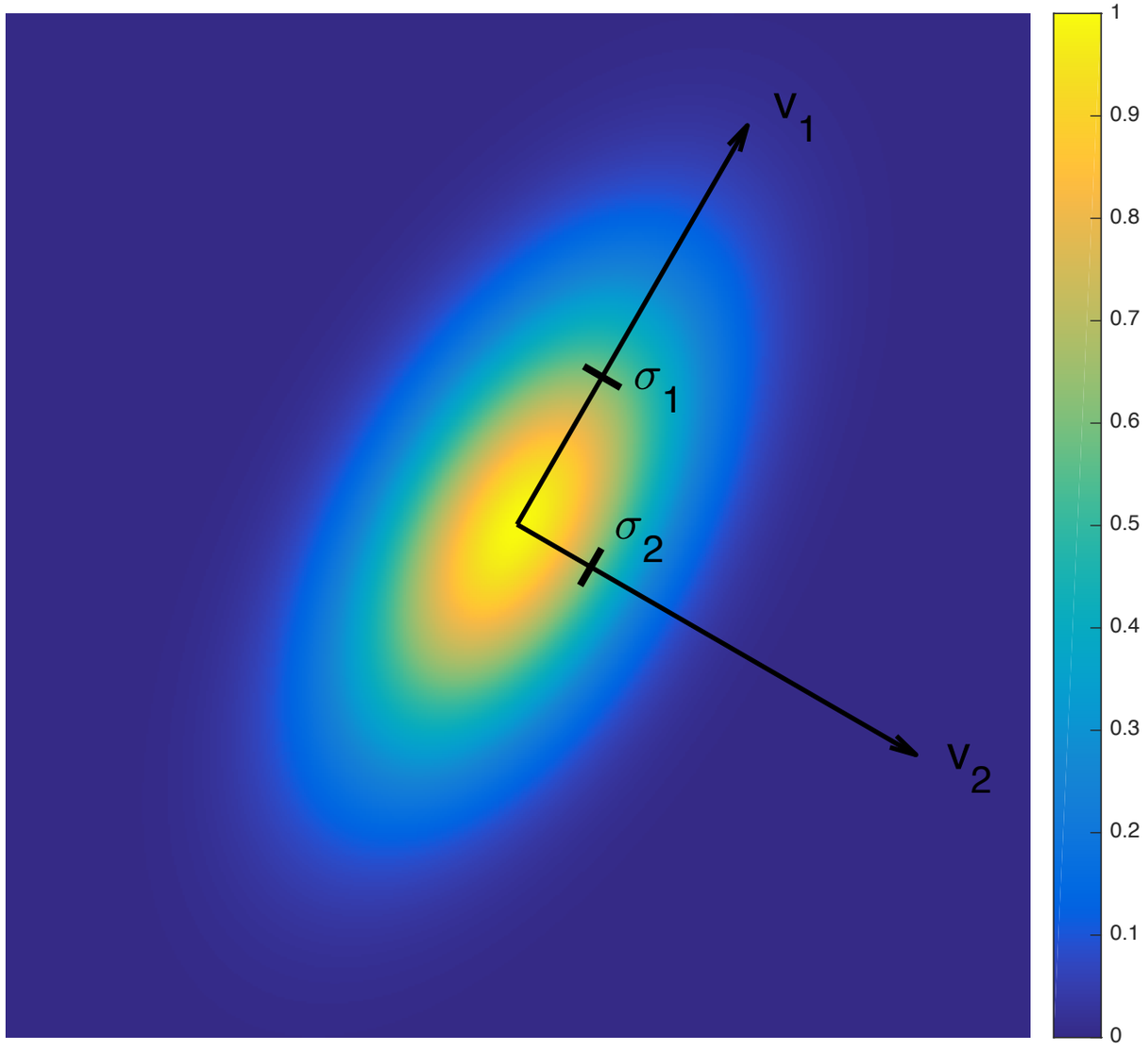
Rotate Gaussian kernels using eigenvectors of the structure tensor

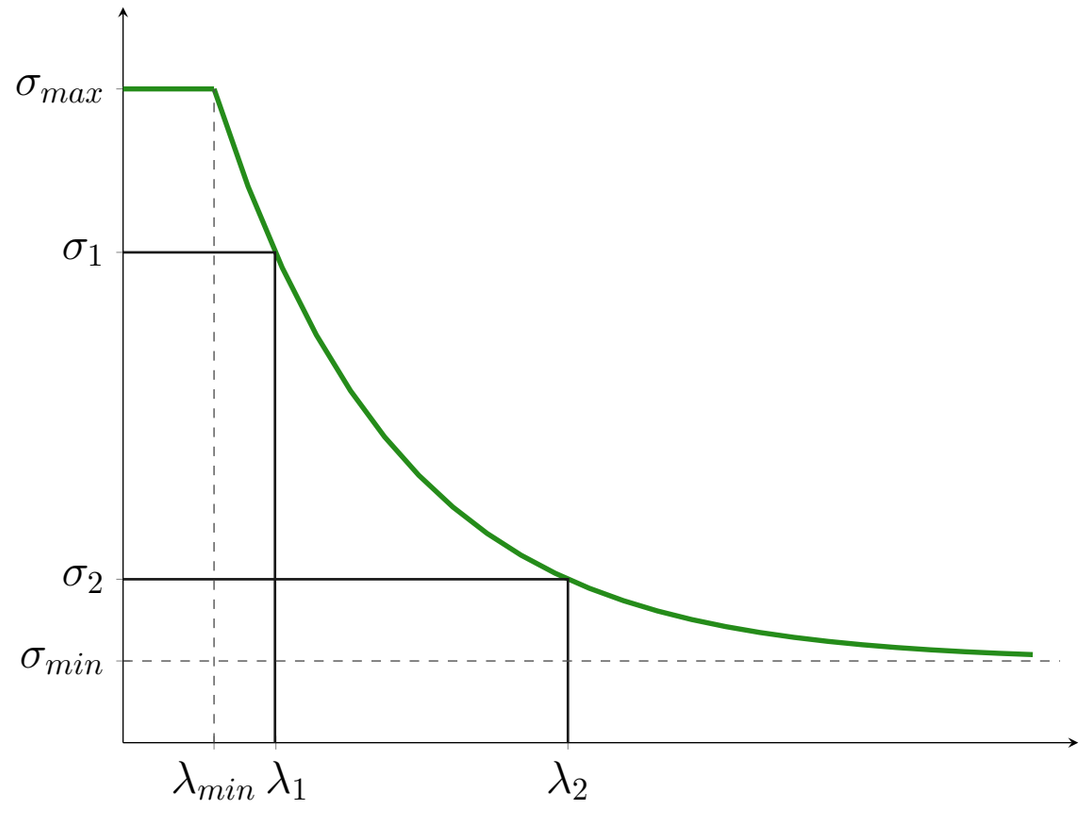




LUND UNIVERSITY

Scale Gaussian kernels using a function of the eigenvalues of the structure tensor



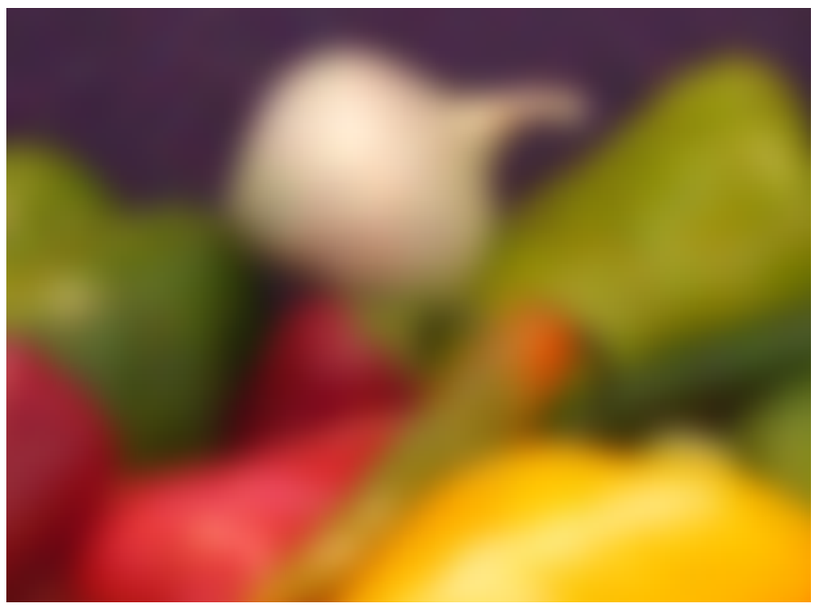


LUND UNIVERSITY

Structure adaptive smoothing

Close-up comparison

Noisy input



Gaussian

Structure adaptive

Overview – image processing

1. Noise reduction
2. Anisotropic filtering
3. **Application: low light video enhancement**
4. Block matching and collaborative filtering
5. Deep learning architectures for image processing
6. Application: low light image processing using learning

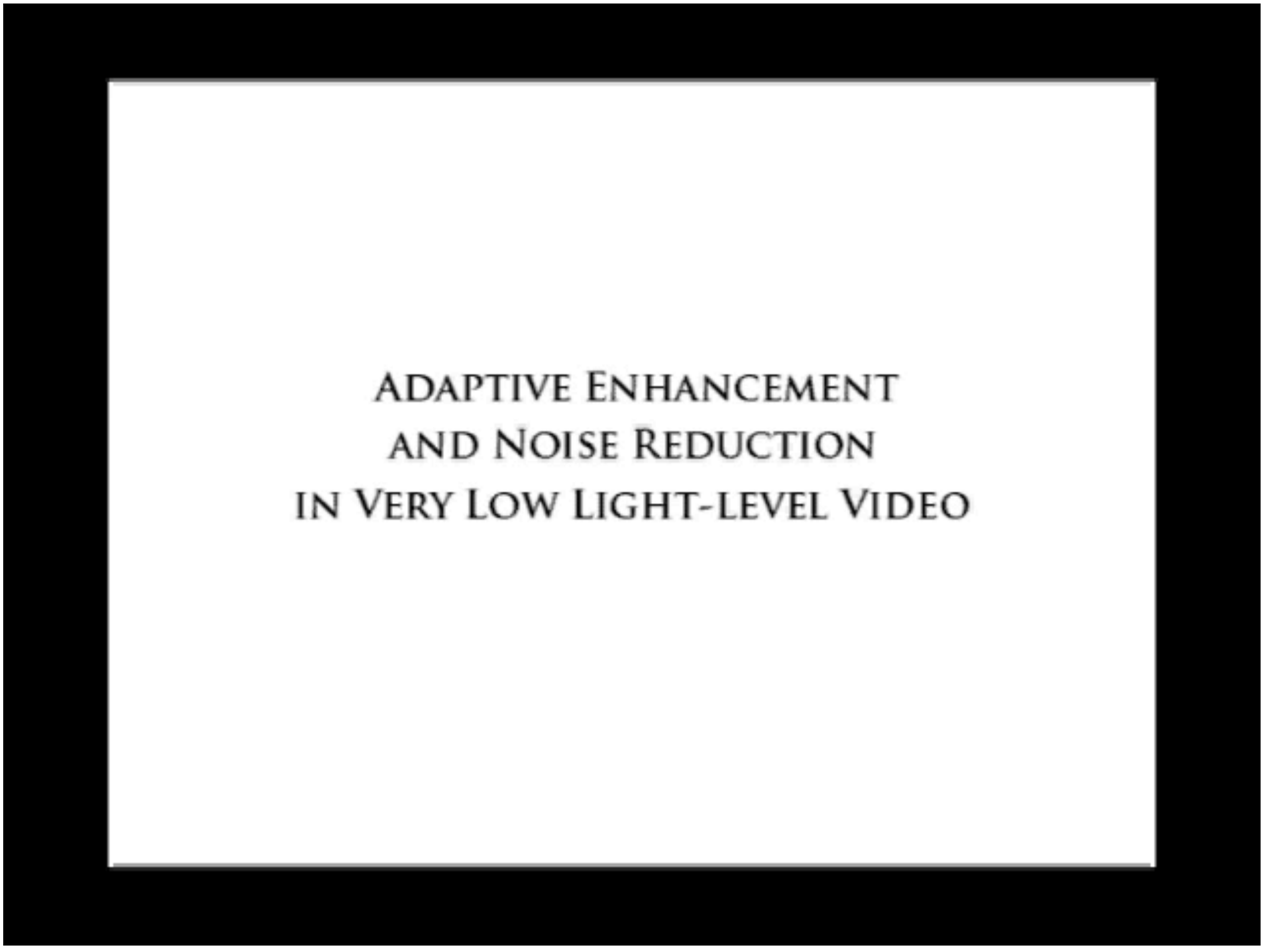
Low light enhancement

1. Amplify signal
   using eg scaling or histogram equalization
   Introduces noise

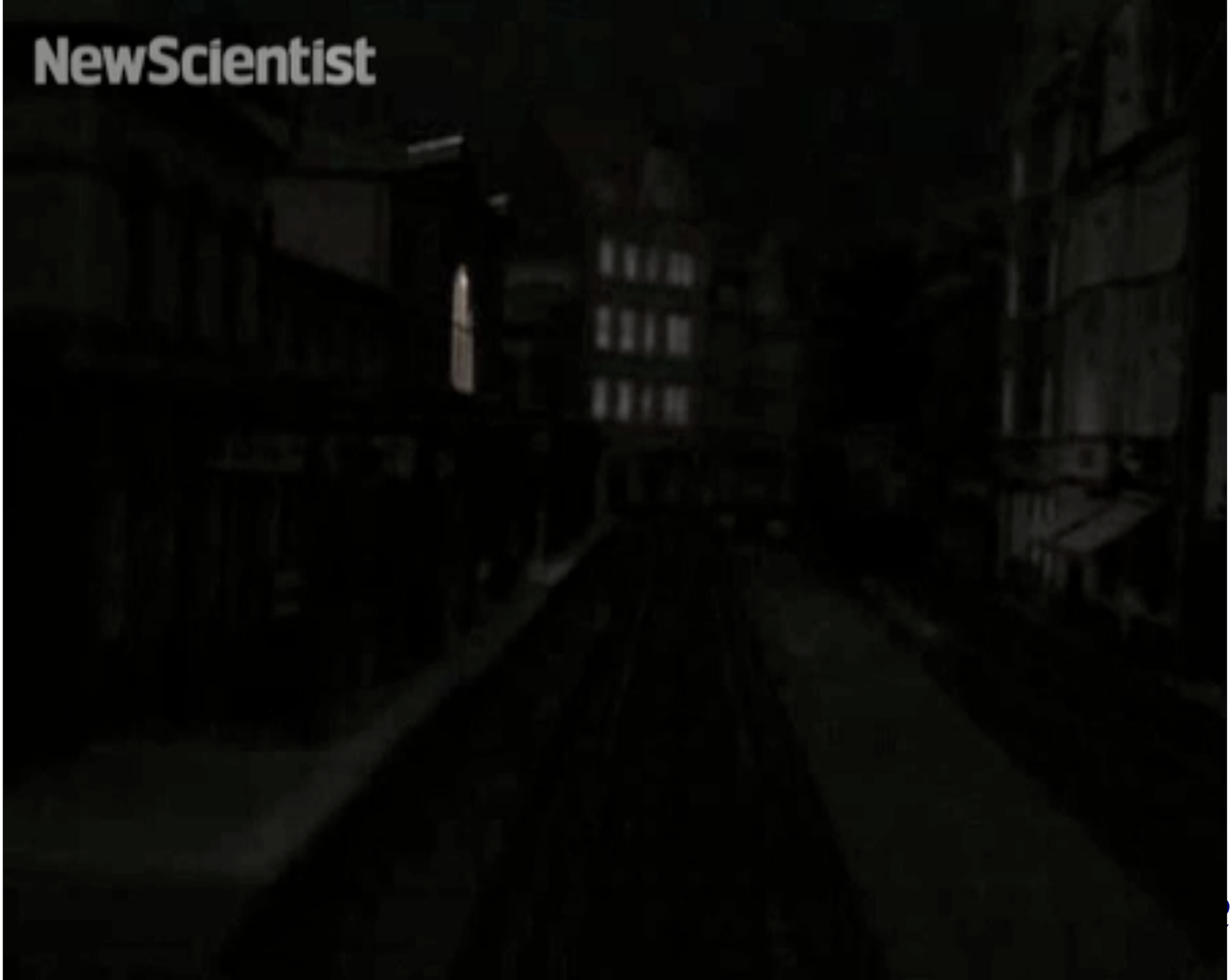
2. Anisotropic filtering of noise


BRIO
Dragon
Mint

Low light video enhancement



LUND UNIVERSITY

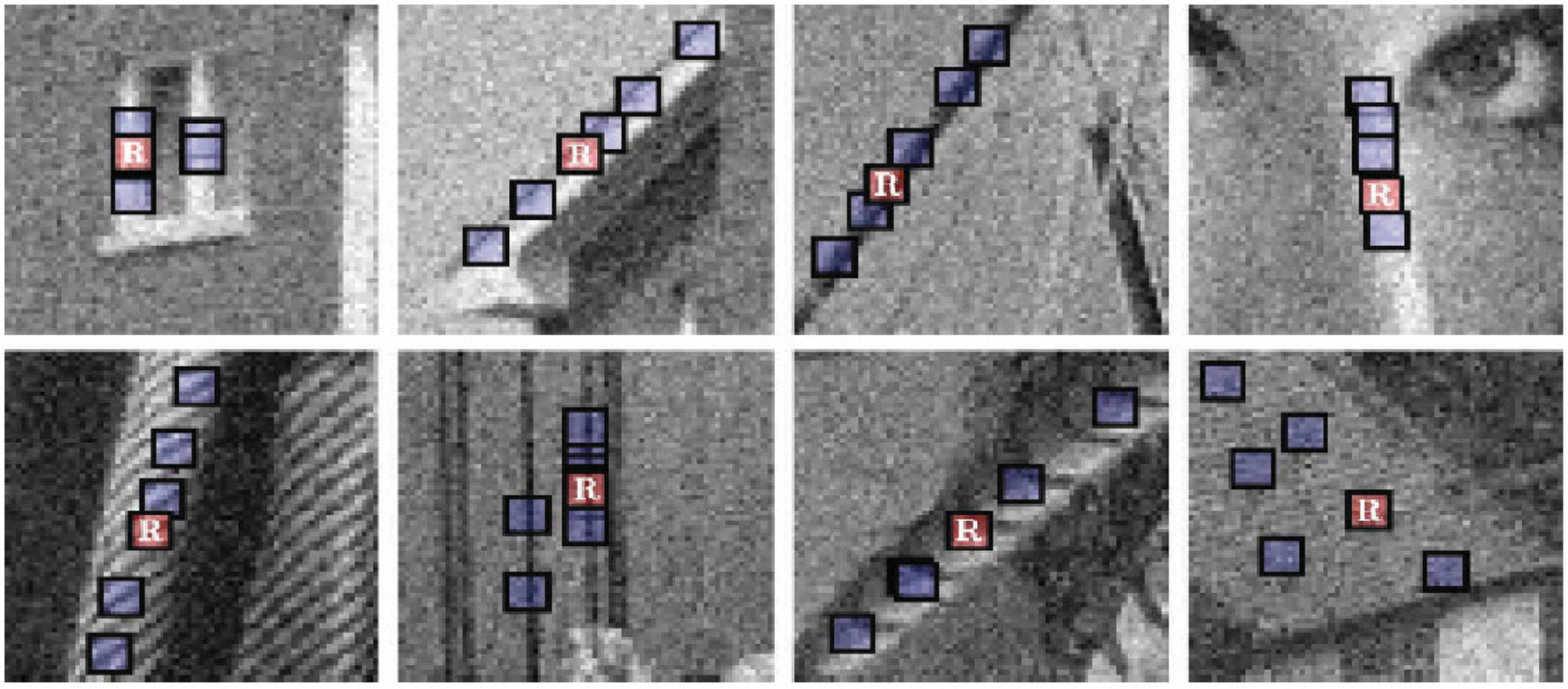

NewScientist

Overview – image processing

1. Noise reduction
2. Anisotropic filtering
3. Application: low light video enhancement
4. **Block matching and collaborative filtering**
5. Deep learning architectures for image processing
6. Application: low light image processing using learning

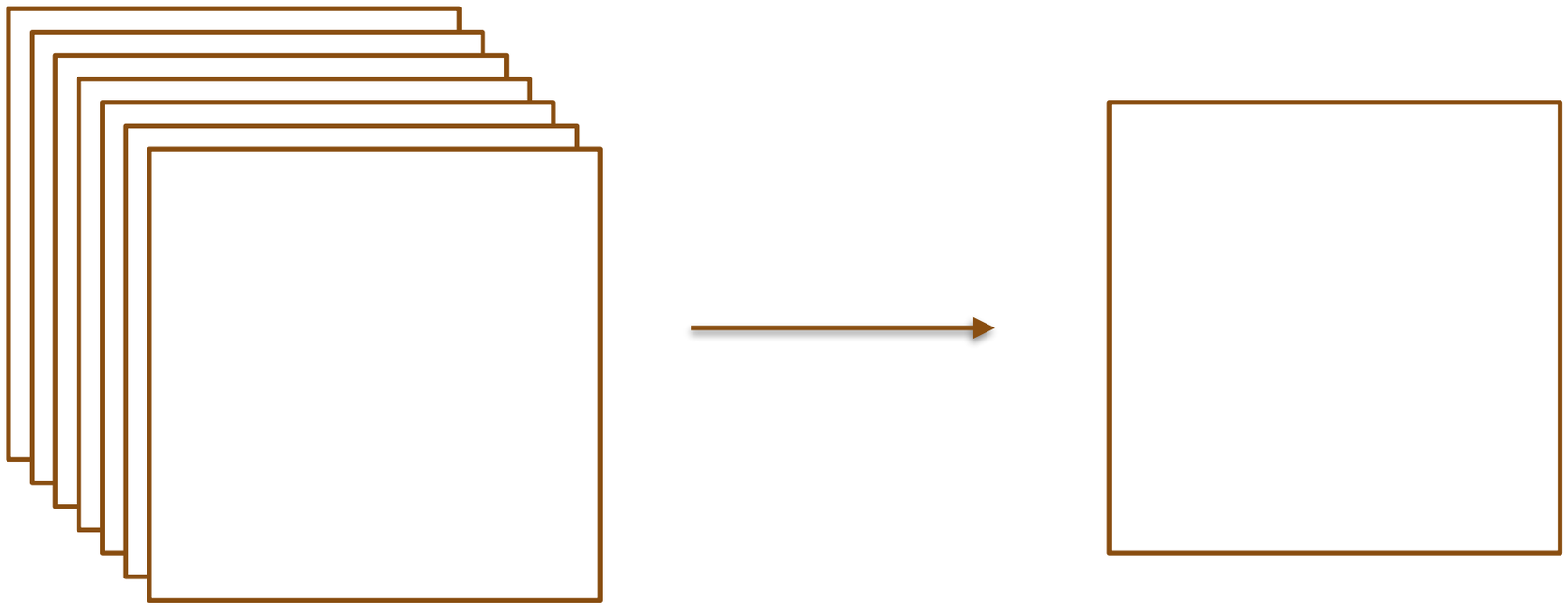
Block matching

many structures are repeated at multiple locations in an image



Collaborative filtering

Do hard filtering on each set of similar matched blocks



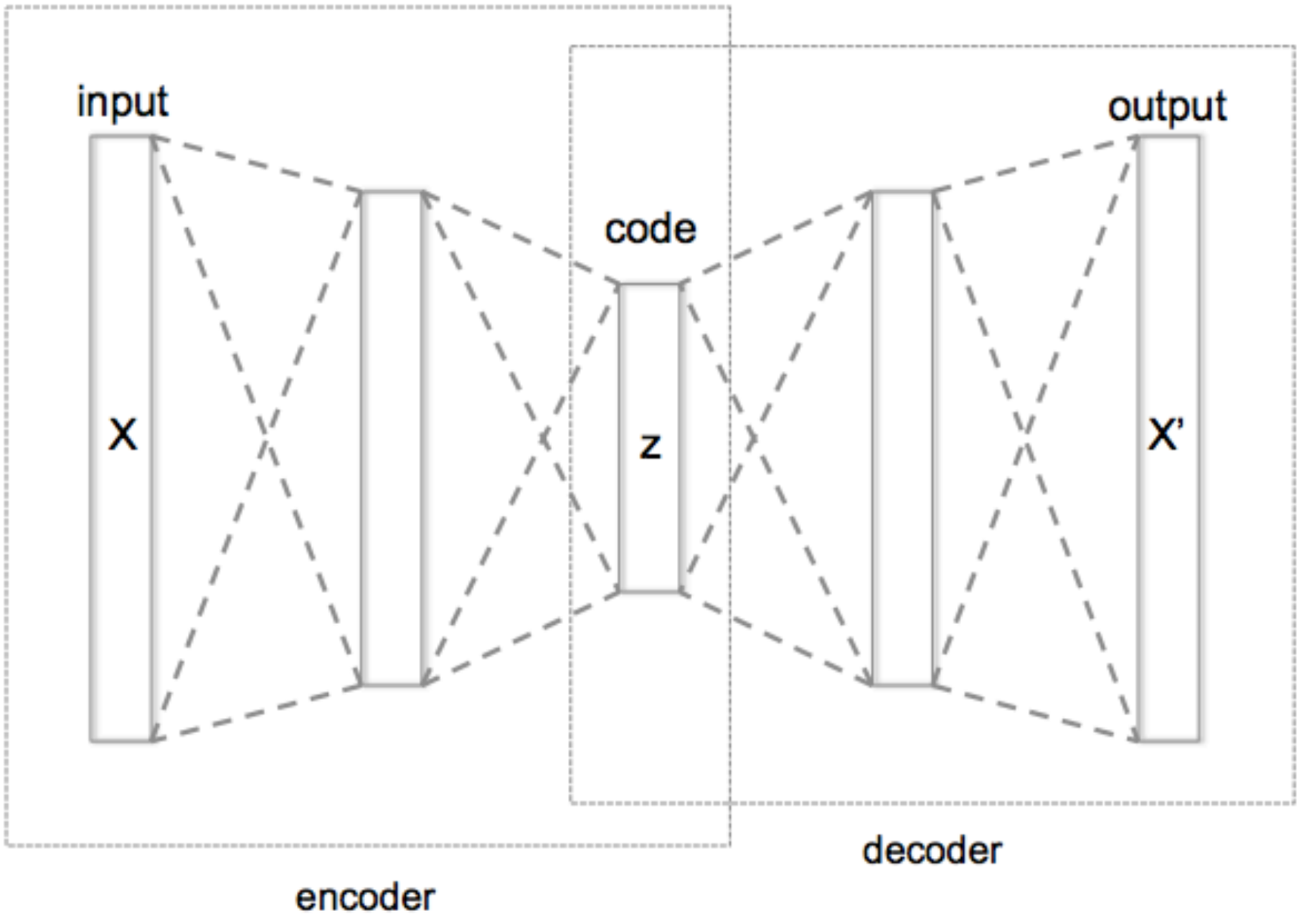
BM3D

Uses two pass version of block-matching and filtering

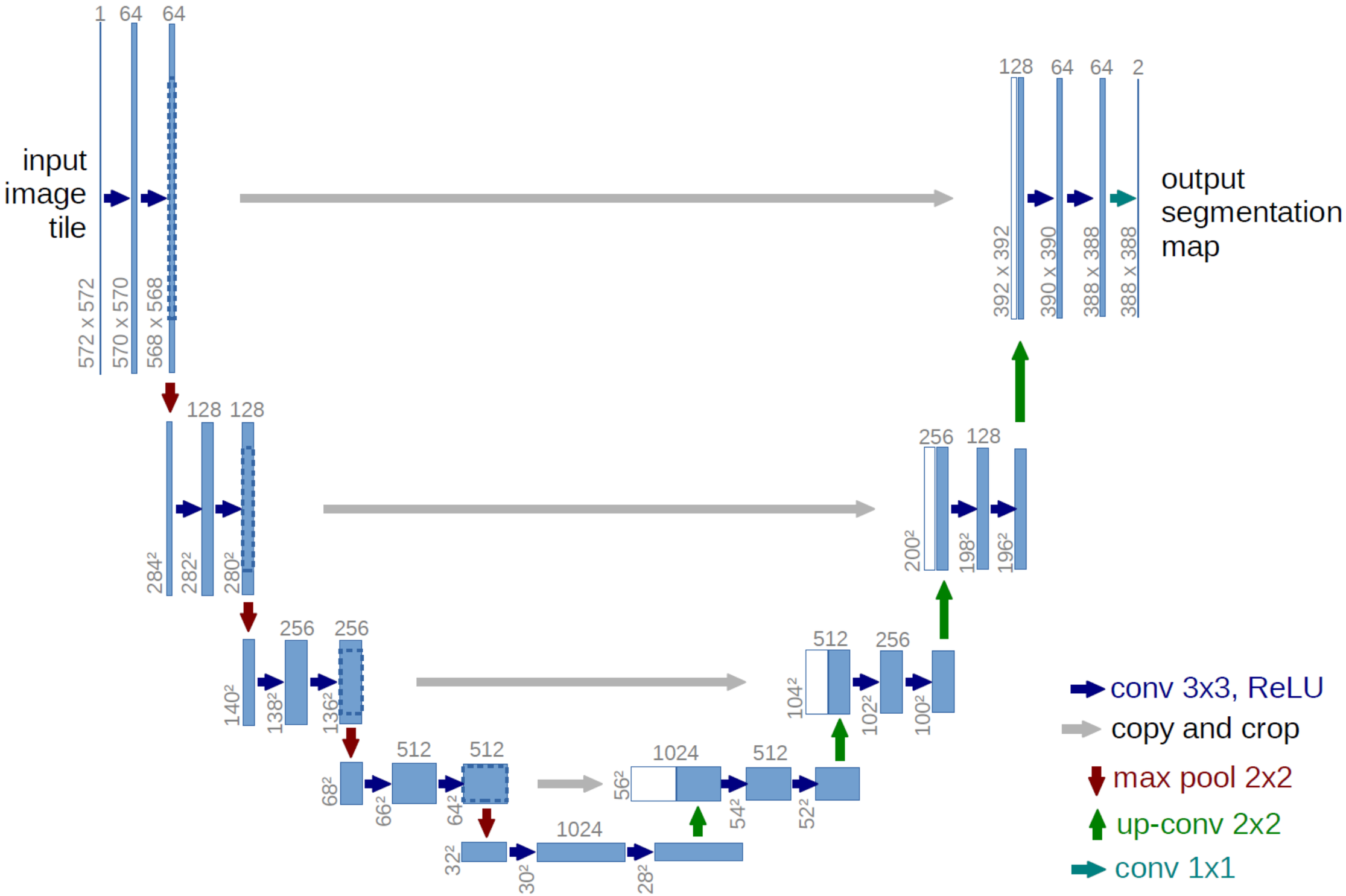
Overview – image processing

1. Noise reduction
2. Anisotropic filtering
3. Application: low light video enhancement
4. Block matching and collaborative filtering
5. **Deep learning architectures for image processing**
6. Application: low light image processing using learning

Autoencoders



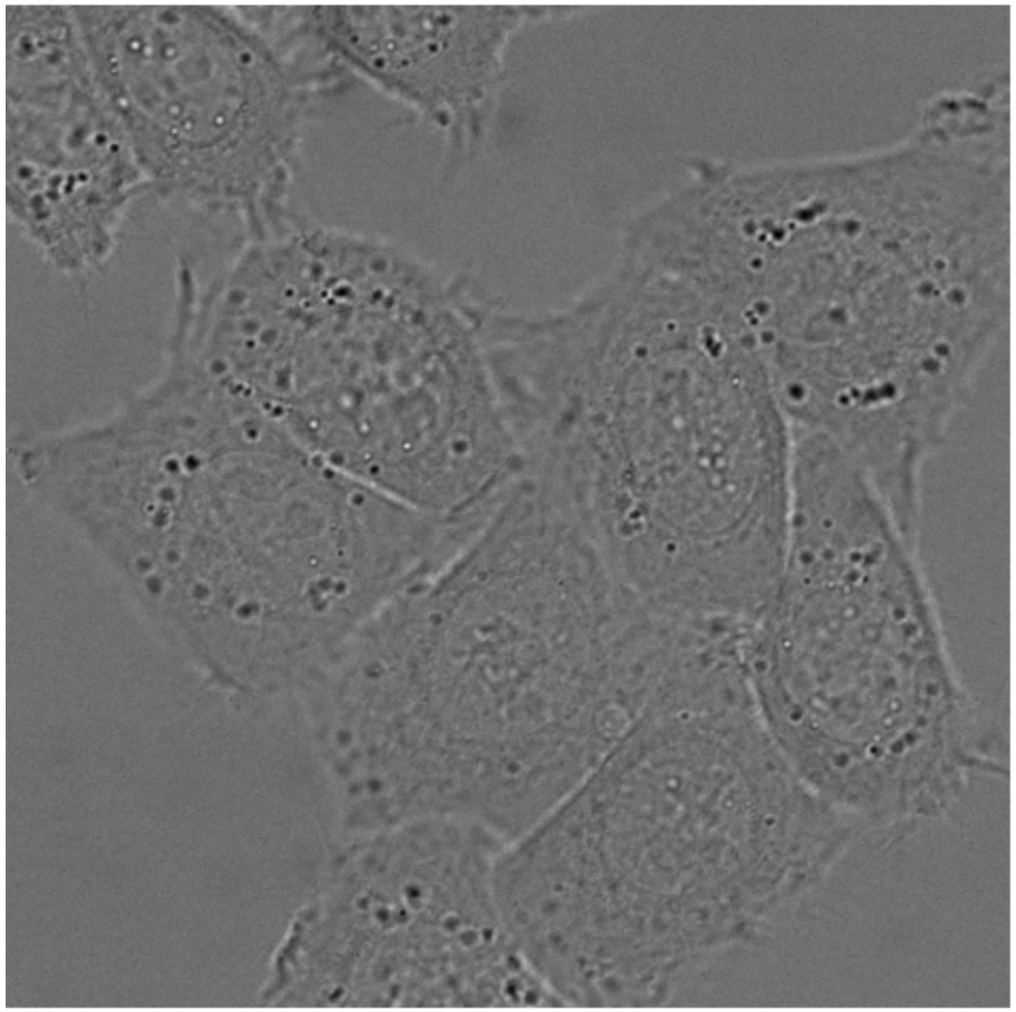
U-net


input image tile
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

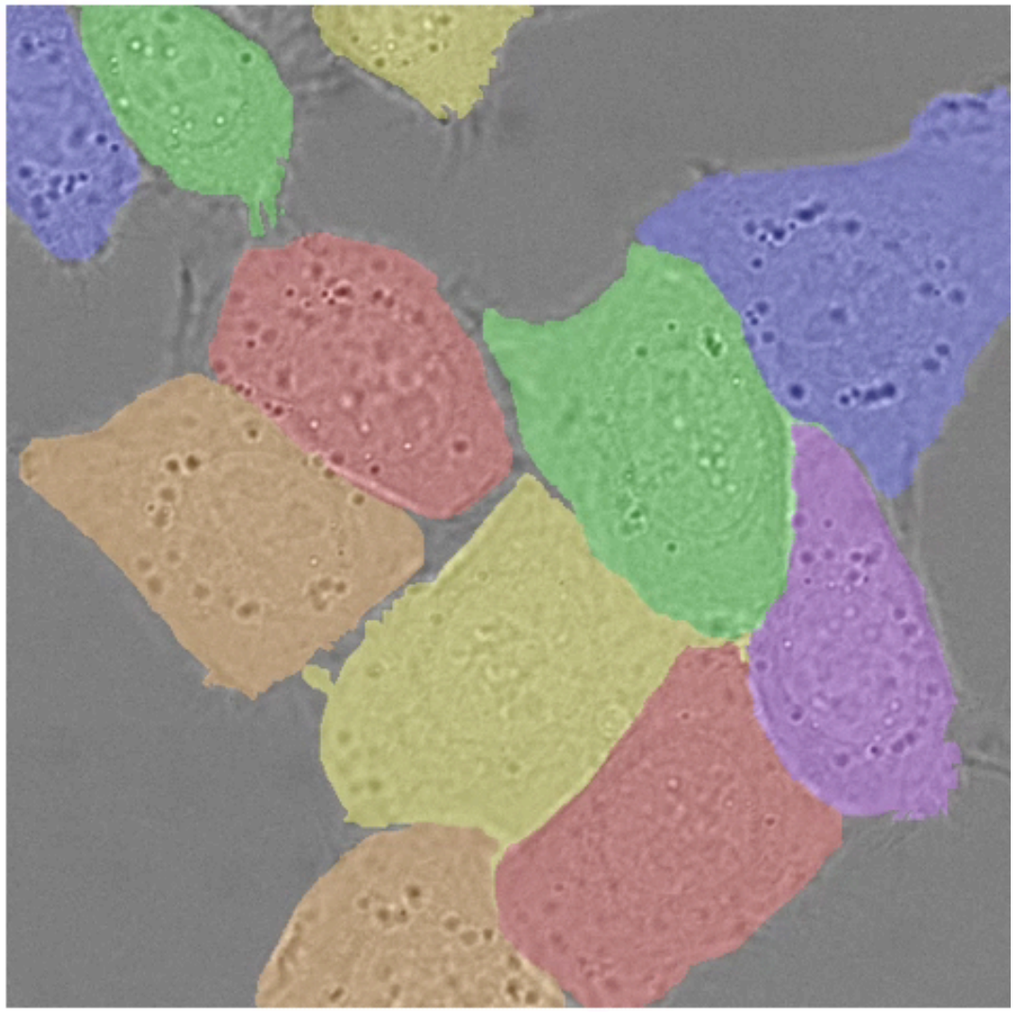
Segmentation using U-net

UNI FREIBURG

Segmentation of Touching Objects of the Same Class



HeLa cells recorded with DIC microscopy



manual segmentation
(colors: different instances)

[Data provided by Dr. Gert van Cappellen, Erasmus Medical Center. Rotterdam. The Netherlands]

Overview – image processing

1. Noise reduction
2. Anisotropic filtering
3. Application: low light video enhancement
4. Block matching and collaborative filtering
5. Deep learning architectures for image processing
6. **Application: low light image processing using learning**

Low light image enhancement using a U-net

Results

Low light video enhancement using learning

Seeing Motion in the Dark

Chen Chen
UIUC

Qifeng Chen
HKUST

Minh N. Do
UIUC

Vladlen Koltun
Intel Labs

Figure 3. The entire training phase of our method on static videos with ground truth.

LUND UNIVERSITY

Low light video enhancement using learning

Seeing Motion in the Dark

Chen Chen
UIUC

Qifeng Chen
HKUST

Minh N. Do
UIUC

Vladlen Koltun
Intel Labs

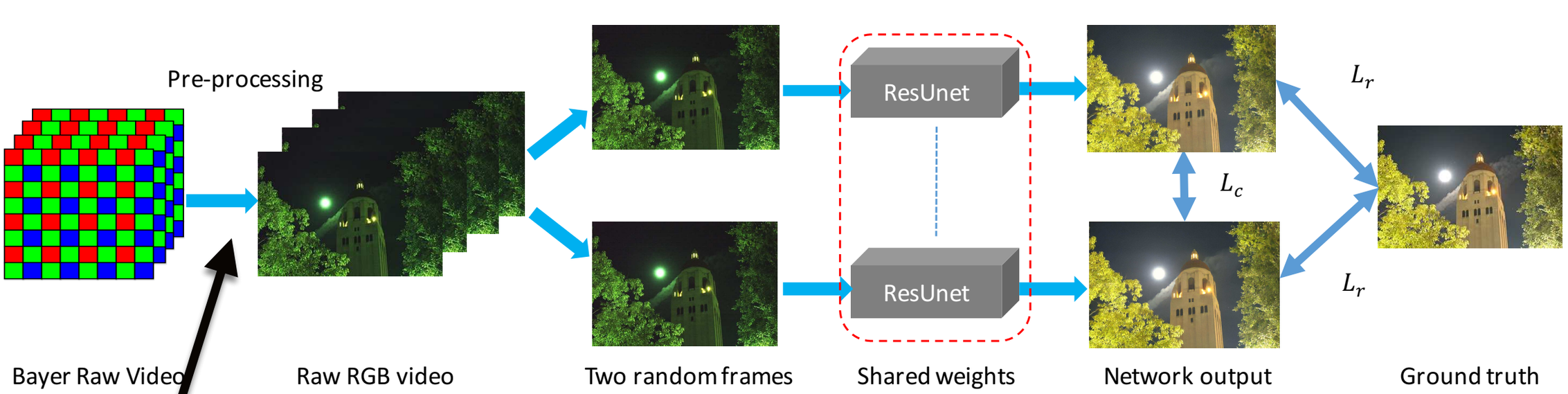


Figure 3. The entire training phase of our method on static videos with ground truth.

Note that pre-processing includes traditional spatio-temporal filtering based on VBM4D

LUND UNIVERSITY

Low light video enhancement

Seeing Motion in the Dark

Chen Chen, Qifeng Chen, Minh N. Do, and Vladlen Koltun

ICCV 2019

Evaluating results of image processing without ground truth

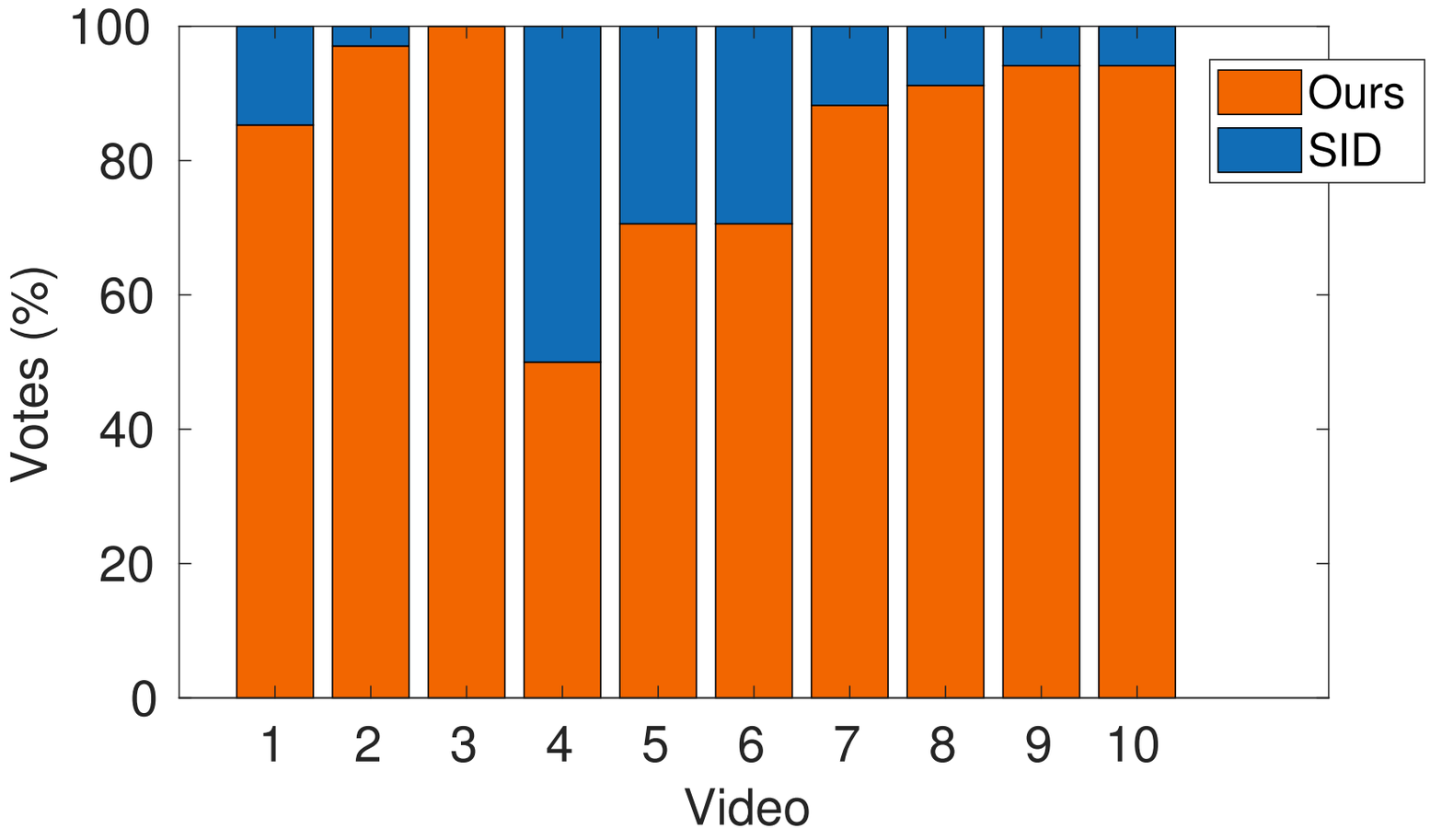


Figure 10. Perceptual experiment. Results of blind randomized A/B tests on 10 dynamic videos. The figure shows preferred percentage for each video.

LUND UNIVERSITY


LUND
UNIVERSITY