Recognising Animals

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E-team work summary

1. Choosing a challenging problem:
   - Animal recognition in still images
2. Preparing a dataset
   - Manual annotation of the Corel dataset of 60000 images
3. Feature extraction and segmentation
4. Classification experiments

E-team Members

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- Trinity College, Dublin, Ireland (TCD)
  - Katarina Domijan, Simon Wilson
- University of Freiburg, Germany (UFR)
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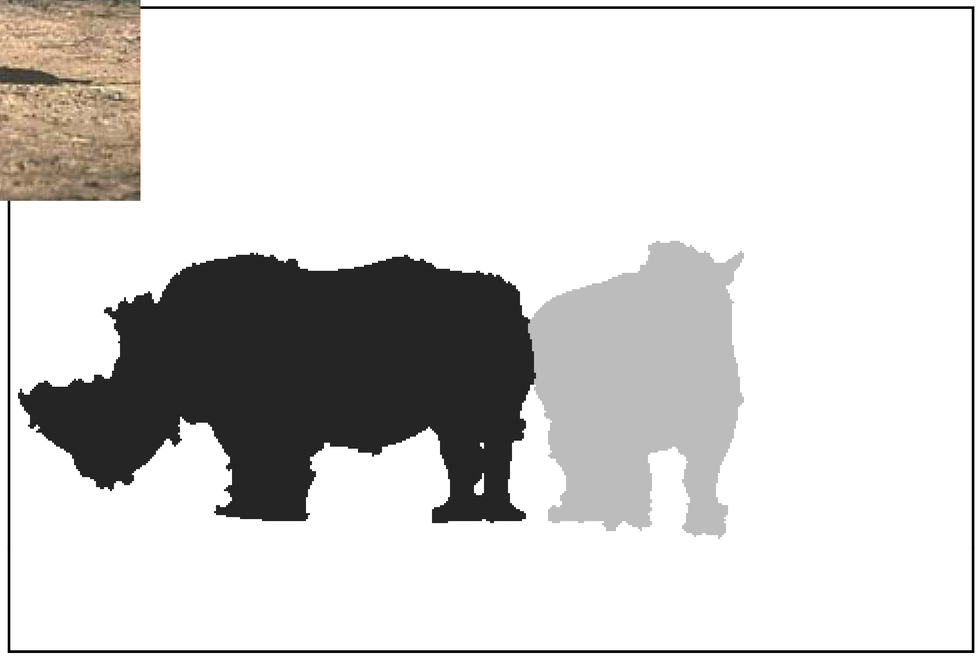
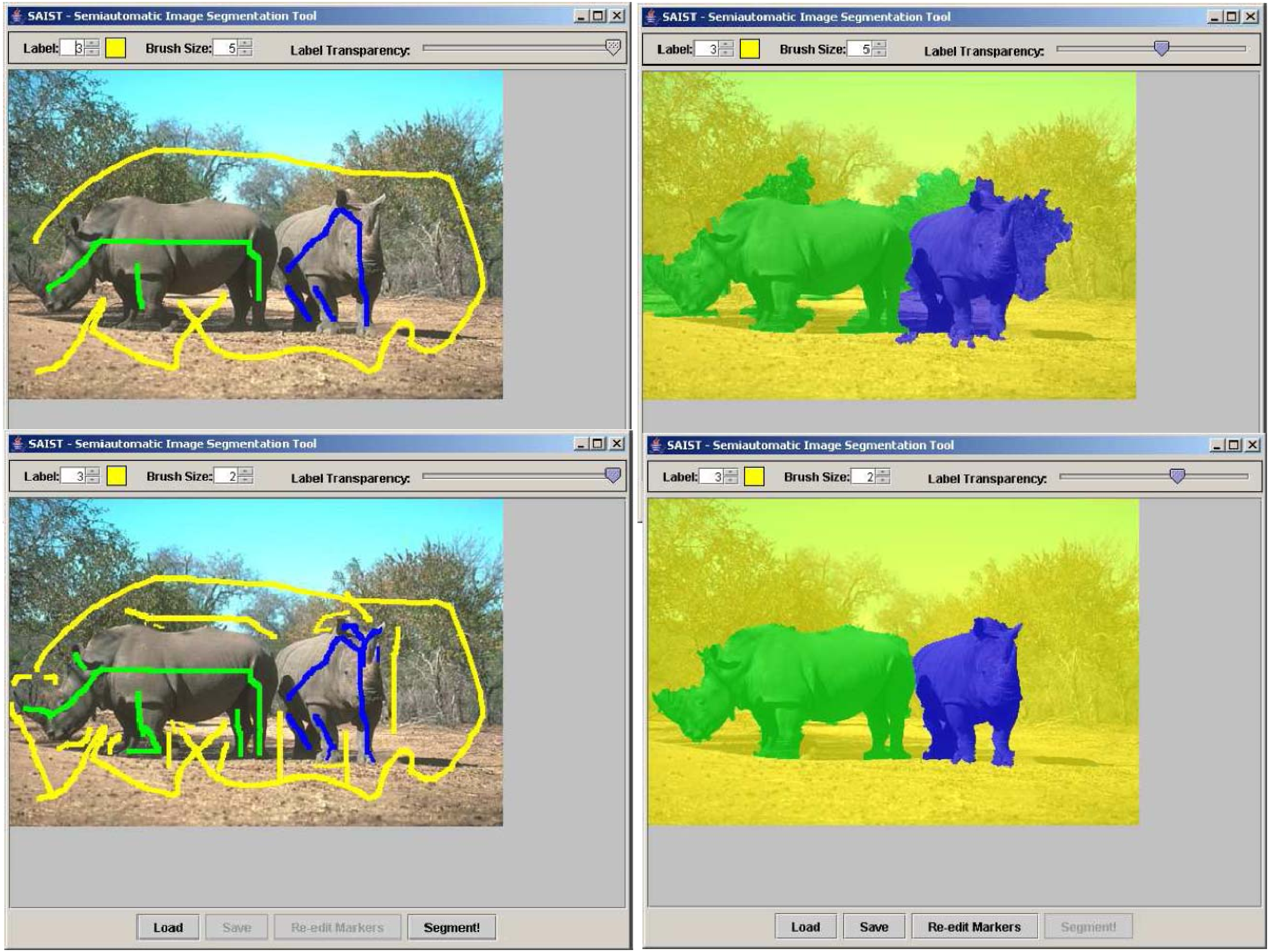
- Polytechnic University of Catalunia, Spain (UPC)
  - Montse Pardas, Xavier Giró

Challenging problem

- Recognition of Animals in Still Images
- Manual text annotation of 60000 Corel images with animal type or (no animal)

- 1289 images have manual segmentations :




SAIST - Semiautomatic Image Segmentation Tool
Label: 3
Brush Size: 5
Label Transparency:
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Label: 3
Brush Size: 5
Label Transparency:
SAIST - Semiautomatic Image Segmentation Tool
Label: 3
Brush Size: 2
Label Transparency:
Load
Save
Re-edit Markers
Segment!
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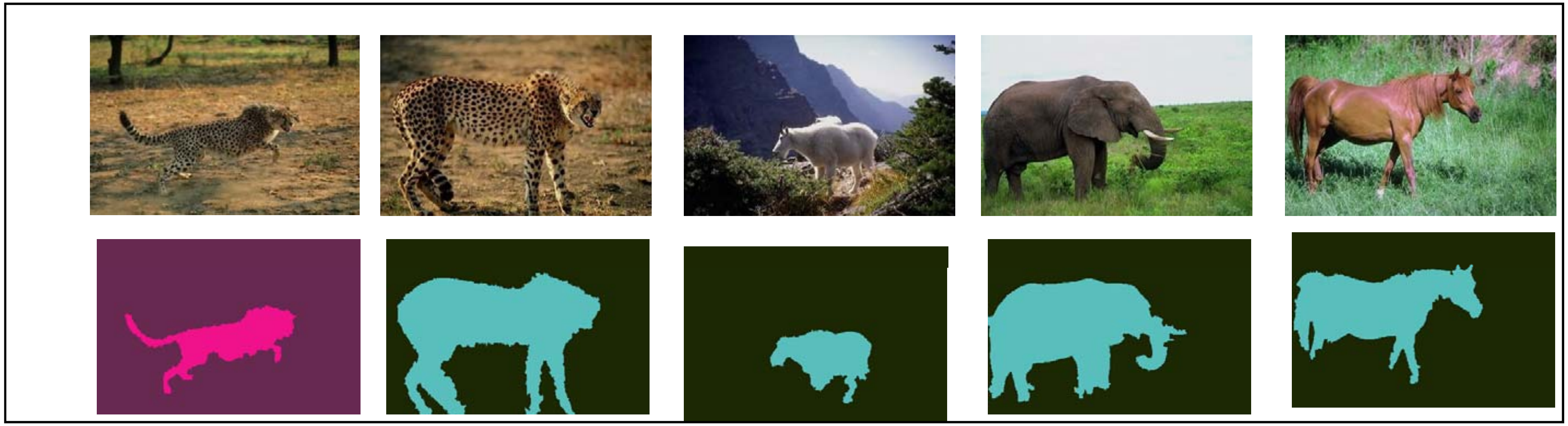
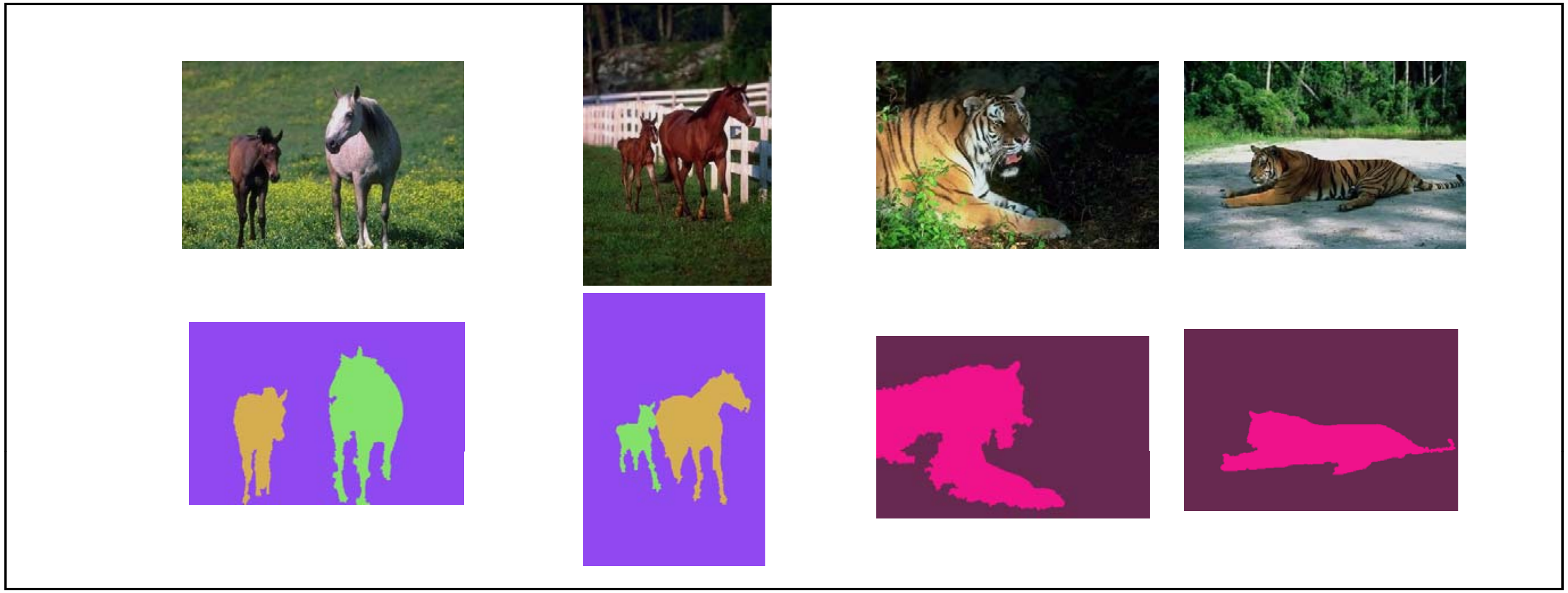
Label: 3
Brush Size: 2
Label Transparency:
Load
Save
Re-edit Markers
Segment!

Further examples



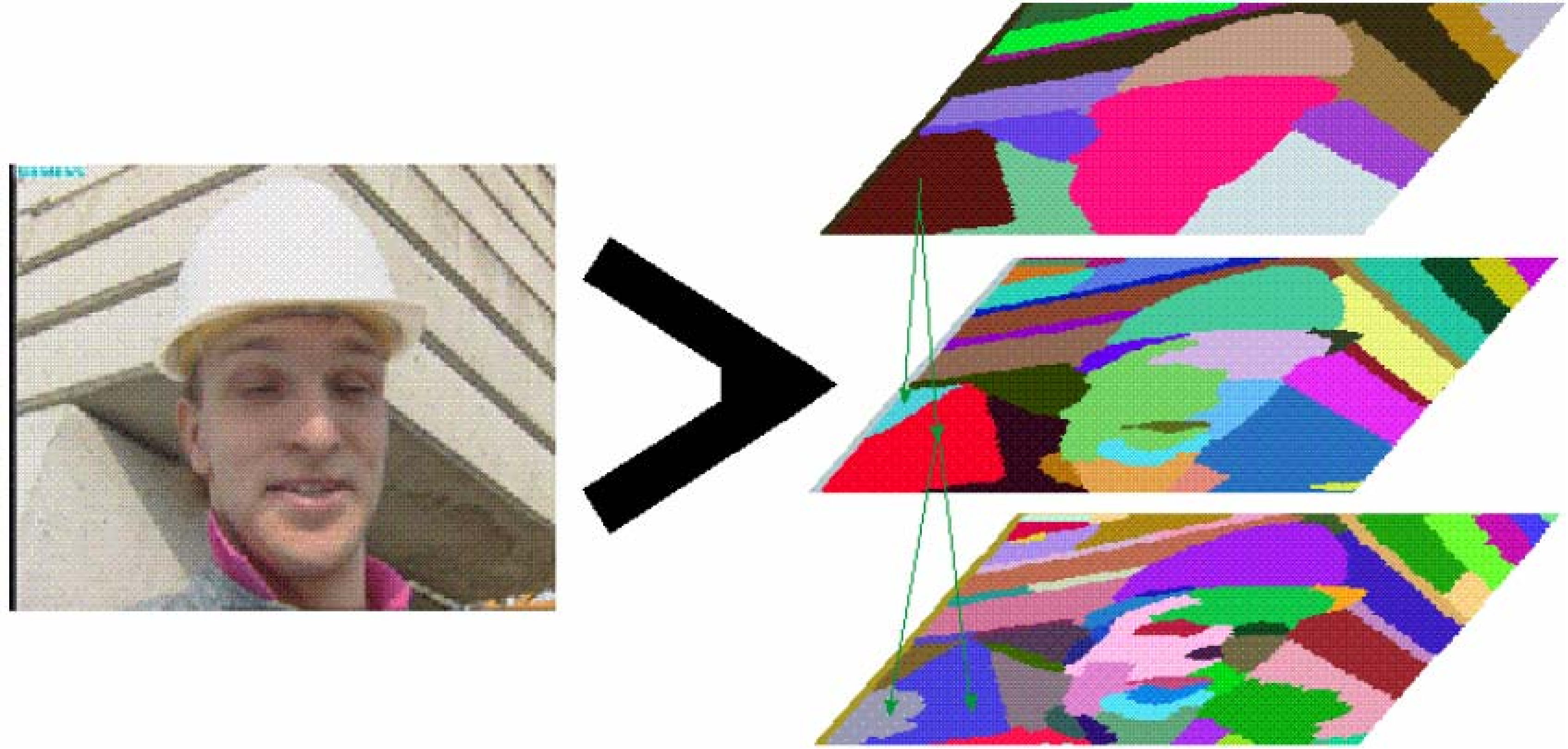


Region-based annotation tool (UPC)

- Java tool for the annotation of objects and parts.
- Region selection through Partition Tree navigation

Automatic Segmentation

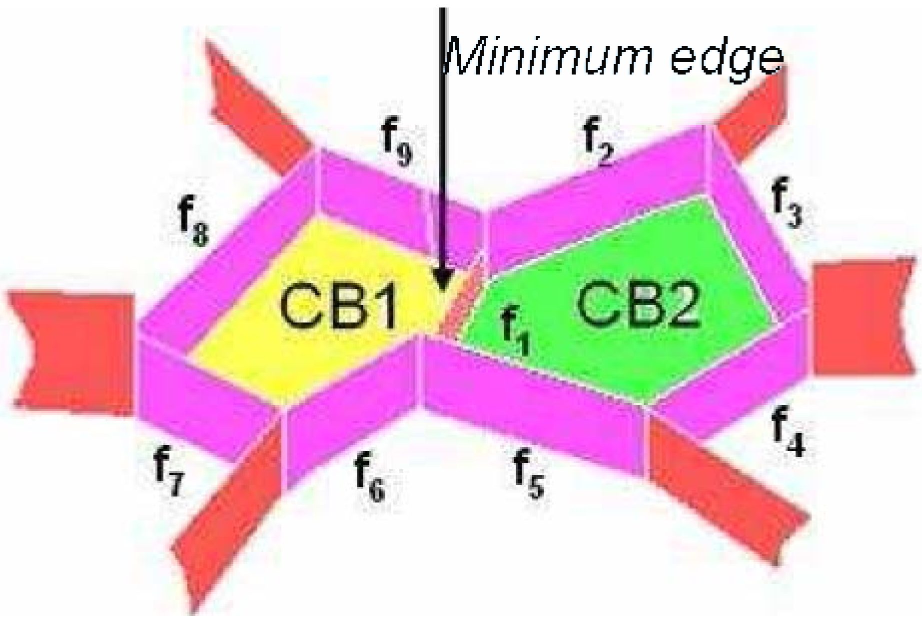
- Applied a morphological waterfall scheme



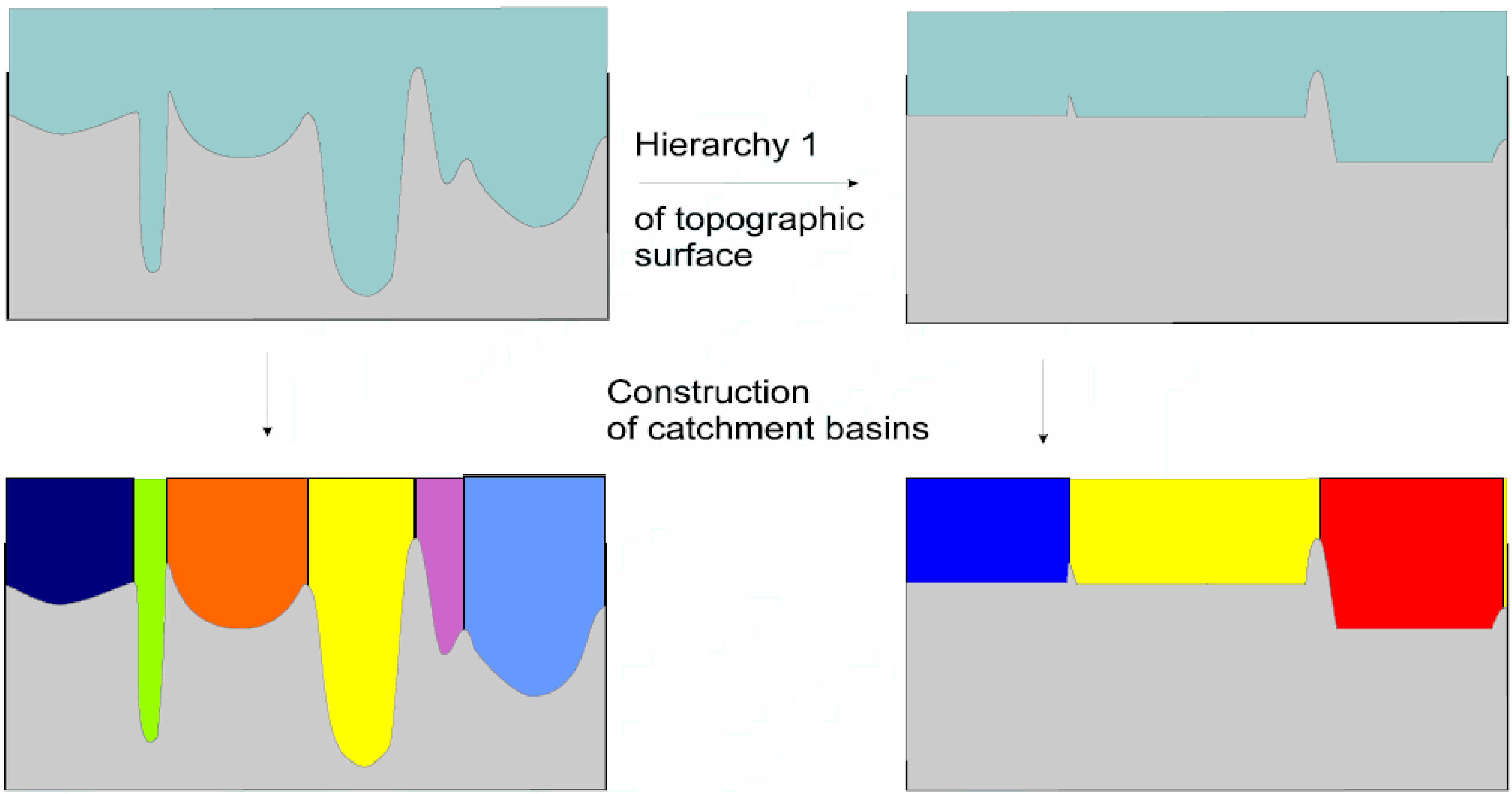
Each region of a coarse segmentation will appear identical in a finer segmentation or will be subdivided into one or more sub-regions.

Waterfall segmentation

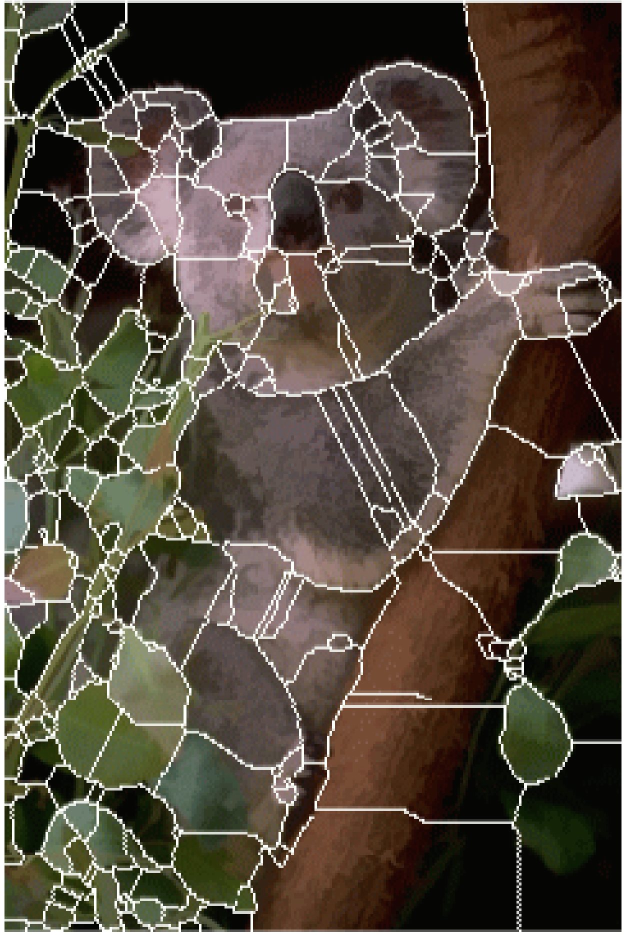
- Ranks the importance of a frontier with respect to its neighbourhood.
- If a frontier is surrounded by higher frontiers, it will disappear.



Waterfall construction



- An extremely efficient graph-based waterfall segmentation algorithm was used.
- Applied to the inverse quasi-distance function on boundaries based on learning (Malik group).



Watershed (level 0)

Waterfall (level 1)

Waterfall (level 2)

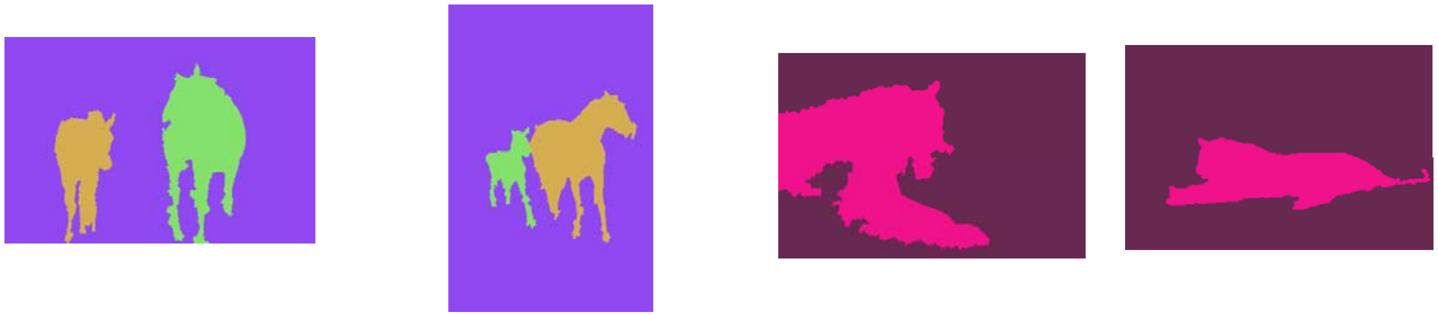
Automatic segmentation examples

Automatic segmentation examples

original

Wf 1 and 2

Manual segmentation



Feature extraction

- Local Features (UFR)
  - DoG interest points, wavelet based interest points with Laplacian scale selection.
  - For each interest point, 3 kinds of features were calculated: hsv color histograms, sift features and gloh features.
- Texture features (PRIP + CEA)
  - LEP local edge patterns: 512-bin histogram, LBPs applied to the edge image
  - Texton Histogram: 64 bins
- Color features (PRIP + CEA)
  - RGB histogram: 64-bin histogram where R, G, B are quantized in 4 values each
  - CIELAB histogram: 64 bins per channel
  - HSV histogram: 162-bins - H is quantized in 18 values, S in 3 and V in 3
- MPEG-7 features (UPC)
- …

Classification on 1289 images (CEA and UFR)

- The images having manual segmentations were used.
- 14 classes
- Compared results obtained with:
  - Local features (bags of keypoints)
    - Harris Laplace Detector
    - SIFT, HSV histograms
  - Automated Segmentation
    - Lowest level of the Waterfall segmentation hierarchy having at least 10 regions chosen.
    - Each region classified and the animal class with the highest surface area is attributed to the image.
  - Global features
    - Same features used for local features, but calculated over the whole image

Classification rate for different detection strategies	local feature histograms	automatic segmentation	global features
cheetah	50.00	**83.3**	33.33
cougar	15.00	**36.8**	20
coyote	**26.32**	25.0	25
deer	**50.00**	0	35.29
dog	**82.50**	67.5	72.5
elephant	25.00	**60.0**	40
goat	**65.00**	26.3	**65**
hippopo	50.00	12.5	50
horse	**87.50**	75.7	65
leopard	64.29	**100**	42.86
lion	**80.00**	15.8	55
moose	0	0	**33.33**
rhino	**16.67**	0	8.33
tiger	**80.00**	44.4	50
total	**58.85**	45.4	48.46

- For animal classes with distinct texture, the segmentation approach works well
- Using context information is beneficial

More difficult classification experiment

- 15000 images
- The training and testing is done using 10-fold cross-validation
- Training and testing images listed for 8 animals: tiger, elephant, goat, lion, horse, cougar, coyote, dog.
- Training set: 90 positive training images and 200 negative training images.
- Testing set: 14710 images, containing both positive and negative examples.

Some results for this experiment (UFR)

Classification rate

Fts + classifier	tiger	elephant	goat	lion
UFR-chisto-v1 + SVM	96.4 (+/- 0.01)	95.4 (+/- 0.02)	92.5 (+/- 0.02)	94.8 (+/- 0.01)
PRIP global + SVM	92.0 (+/- 0.03)	91.0 (+/- 0.0)	89.2 (+/- 0.03)	93.3 (+/- 0.01)
UFR plus PRIP + SVM	94.79 (+/- 0.01)	92.0 (+/- 0.01)	91.1 (+/- 0.02)	94.4 (+/- 0.01)

Classification rate

Fts + classifier	horse	cougar	coyote	dog
UFR-chisto-v1 + SVM	86.3 (+/- 0.02)	91.98 (+/- 0.03)	92.7 (+/- 0.03)	83.42 (+/- 0.01)
PRIP global + SVM	82.6 (+/- 0.01)	86.2 (+/- 0.01)	89.3 (+/- 0.04)	82.4 (+/- 0.0)
UFR plus PRIP + SVM	84.6 (+/- 0.01)	88.7 (+/- 0.01)	91.5 (+/- 0.03)	83.6 (+/- 0.0)

Conclusion

- Test protocol with 15000 test images difficult as only about 10-200 images are true positives – one gets a high false negative rate.

- Some features more discriminative than others
  - Advances made in classification and feature selection using Bayesian methods (TCD)
  - However still computationally intensive