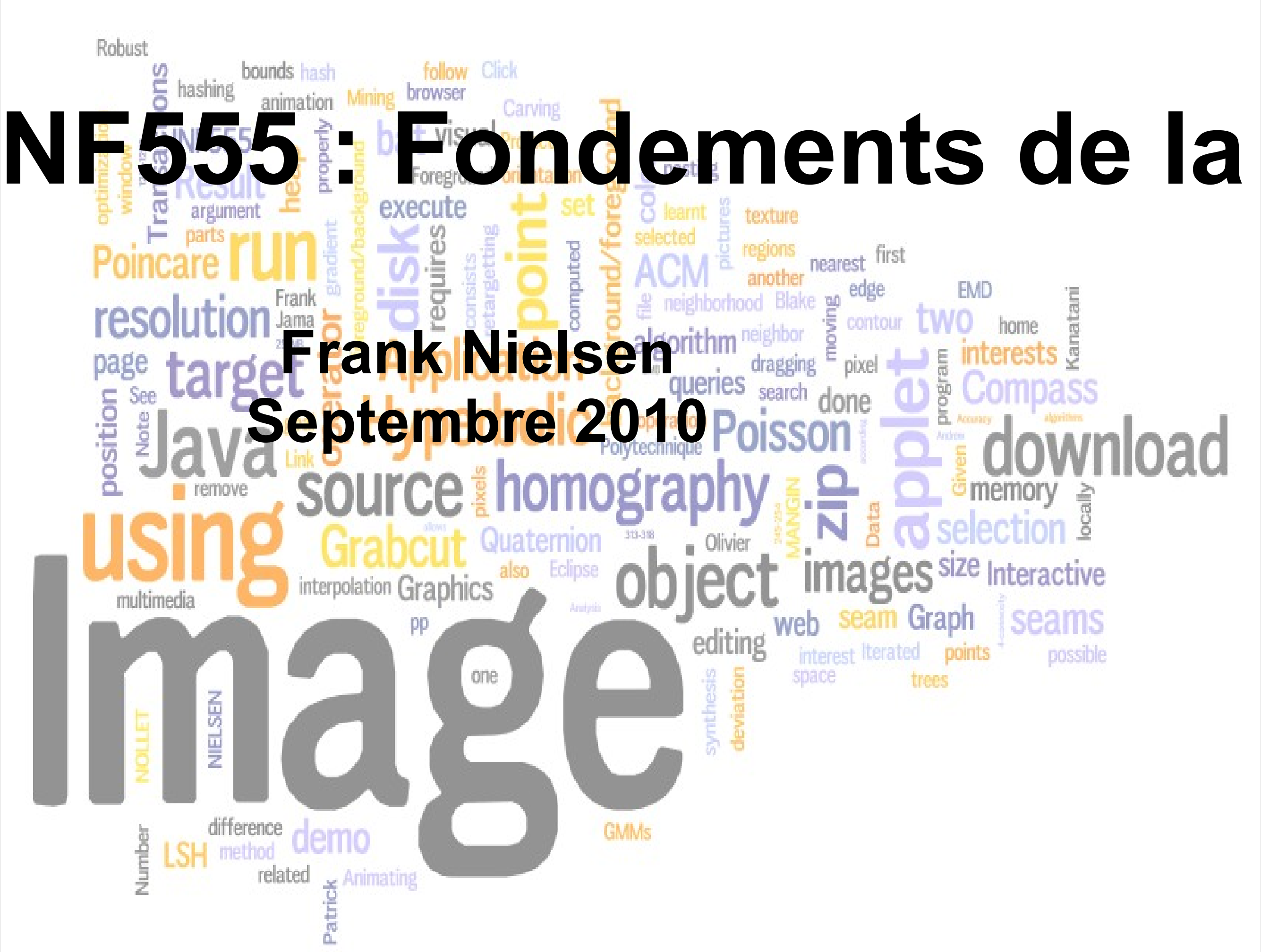
Projets INF555 : Fondements de la 3D

Frank Nielsen
Septembre 2010

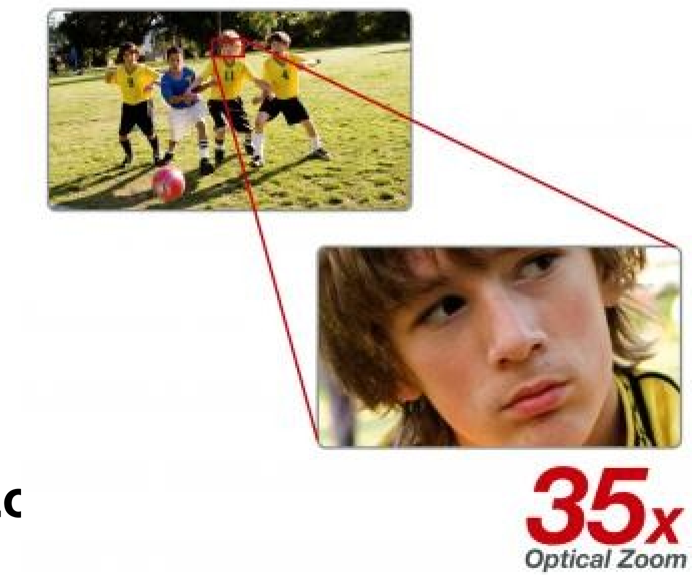


- 1 projet par personne
- Codez en Java (ou en C++)

- Esprit <u>critique</u>, travaillez des <u>nouvelles</u> extensions...
  ... plutôt qu'une finition
- Bien choisir ses jeux de données (mieux <u>les créer</u>)

P1. Hyperlinks image with large zoom factors

Consider optical zoom x10-x100 image sets...
...where images are included in others: Stitch and hyperlinks them
(powers of 2 kind of smooth viewer)



Extend to videos: stitch a video in a still with large zc

Paper: Randomized Adaptive Algorithms for Mosaicing Syste

Zoom x30 http://olympus-imaging.jp/product/compact/sp800uz/index.html
http://www.sony.jp/cyber-shot/products/DSC-HX5V/
http://www.sony.jp/cyber-shot/products/DSC-HX1/
http://www.digitalphotographywriter.com/2010/08/fujifilm-finepix-hs10-30x-optical-zoom.html

P2. Vectorization of Cartoon Animation

→ Rendering to multi-size displays
→ Interaction with image semantic

Vectorizing Cartoon Animations
July/August 2009 (vol. 15 no. 4)
pp. 618-629

(a) Composition of two clips (b) Object Editing

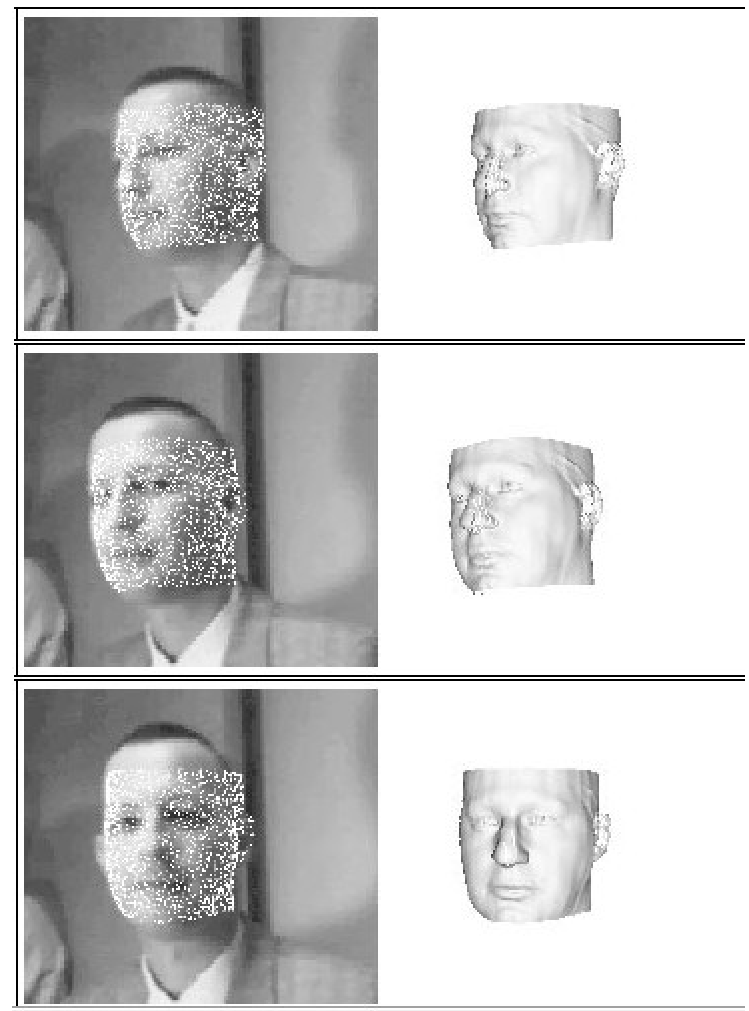
Fig. 10. Editing: (a) taking a character from one scene and putting him in another, (b) changing the shape of the character's ears

P3. Alignment by Maximization of Mutual Information

IJCV 1997

Multimodal registration

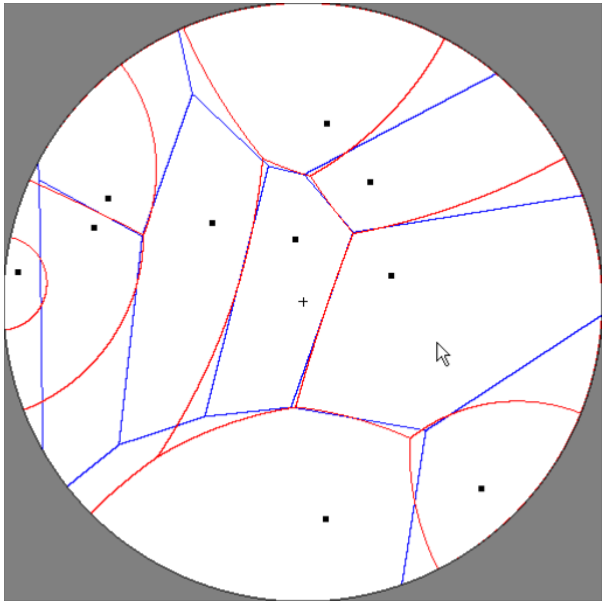
Example:
Match 3D model with 2D images

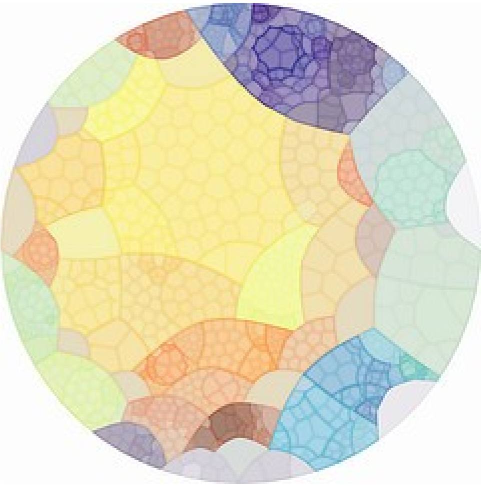


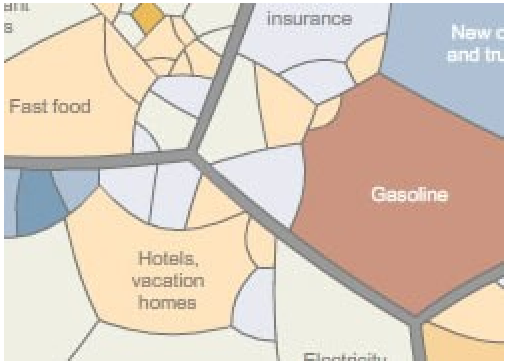
Keywords:
Mutual information
Stochastic optimization

P4. 2D/3D Hyperbolic Voronoi treemaps

→ Generalize treemaps to hyperbolic geometry







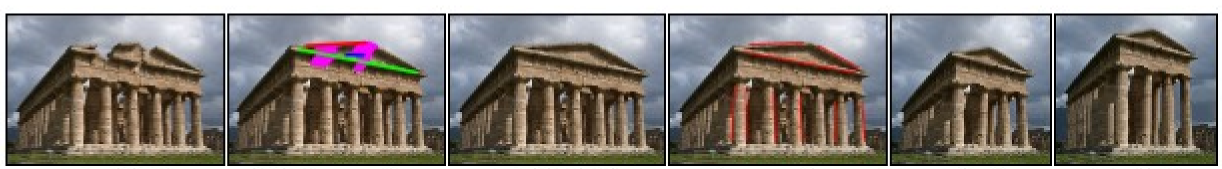
Animated, Dynamic Voronoi Treemaps, 2010

+ Dynamic viewing (using Moebius transformations)
[0903.3287] Hyperbolic Voronoi diagrams made easy

P5. The Generalized PatchMatch Correspondence Algorithm

(a) (b) (c) (d) (e)

Denoising using Generalized PatchMatch. Ground truth (a) is corrupted by Gaussian noise (b). Buades et al. [2] (c) denoise by averaging similar patches in a small local window: PSNR 28.93. Ou method (d) uses PatchMatch for nonlocal search, improving repetitive features, but uniform regions remain noisy, as we use only k = 16 nearest neighbors: PSNR 29.11. Weighting matches from both algorithms (e) gives the best overall result: PSNR 30.90.



(a) original (b) hole+constraints (c) hole filled (d) constraints (e) constrained retarget (f) reshuffle

http://www.cs.princeton.edu/gfx/pubs/Barnes_2010_TGP/generalized_pm.pdf

P6. Image co-segmentation

Given a pair of images containing an identical object, segment the pair simultaneously.

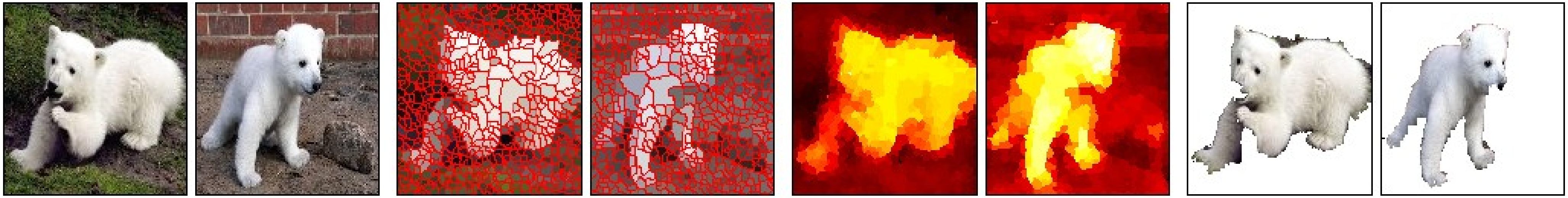


Figure 1. Illustrating the co-segmentation process on two bear images; from left to right: input images, over-segmentations, scores obtained by our algorithm and co-segmentations. $\mu = 0.1$.

Generalize to multi-way segmentation (triples, etc.)

Discriminative Clustering for Image Co-segmentation, CVPR 2010

P7. Outlier Removal Using Duality

Figure 2. *Left: A pair of images of a road warning sign with candidate matches found using SIFT descriptors. Middle: Resulting homography estimated using the dual SOCP approach. Right: Histogram of the number of measurements removed at each iteration using LP and SOCP formulations.*

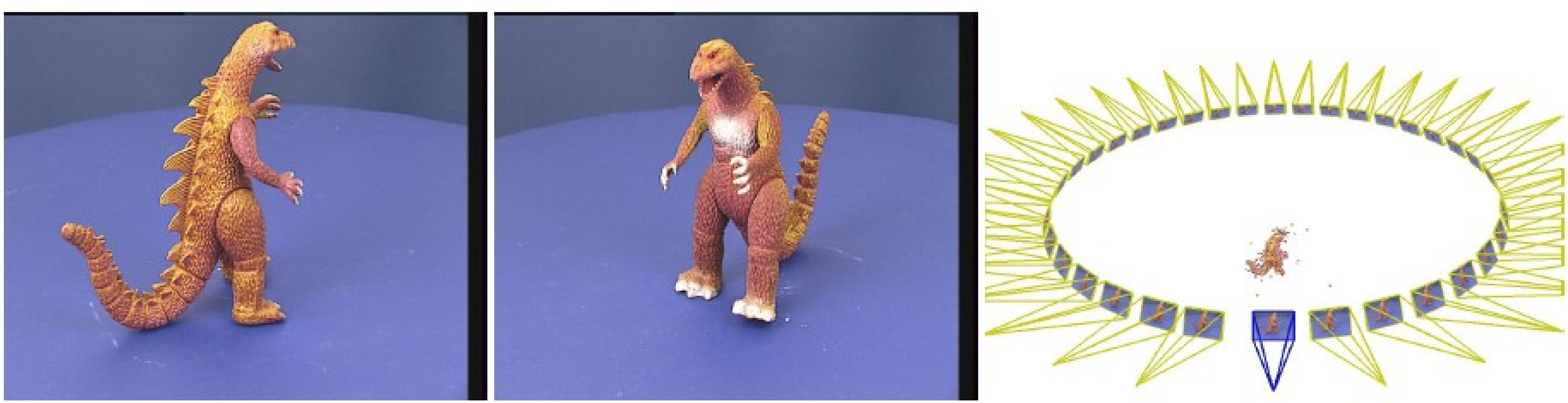


Figure 3. *Two images from the dinosaur sequence, and the resulting reconstruction.*

http://www.maths.lth.se/matematiklth/vision/publdb/reports/pdf/olsson-eriksson-etal-c2-10.pdf

P8. Single Image Depth Estimation From Predicted Semantic Labels

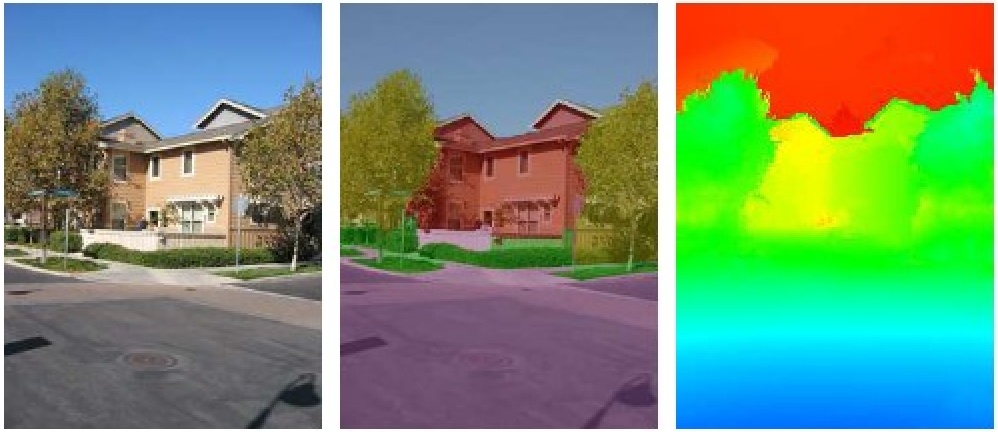


Figure 1. Example output from our model showing how semantic class prediction (center) strongly informs depth perception (right). Semantic classes are shown overlayed on image. Depth indicated by colormap (red is more distant). See Figure 6 for color legend.

Figure 7. Example 3d reconstructions from our model.

http://www.stanford.edu/~sgould/papers/cvpr10-depth.pdf

P9. Clustering Dynamic Textures with the Hierarchical EM Algorithm

Antoni Chan, Emanuele Coviello, Gert Lanckriet

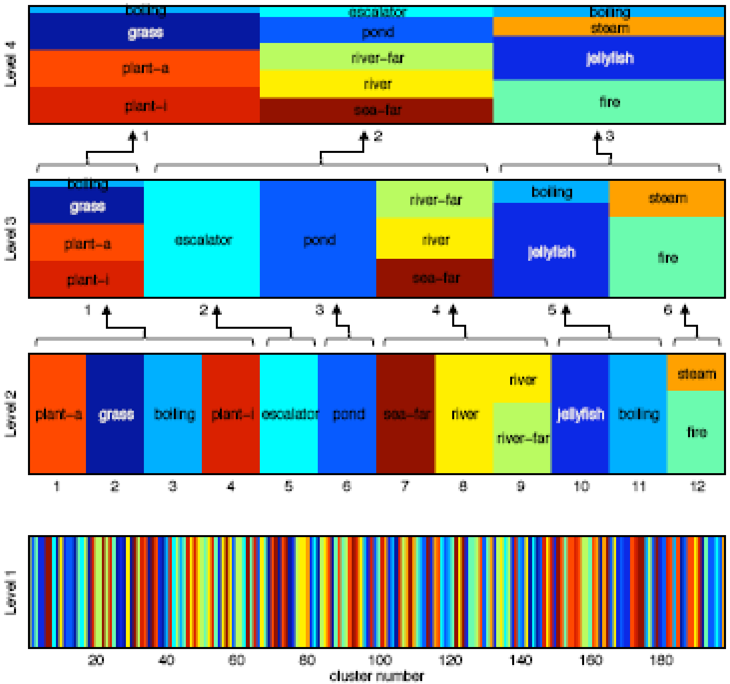
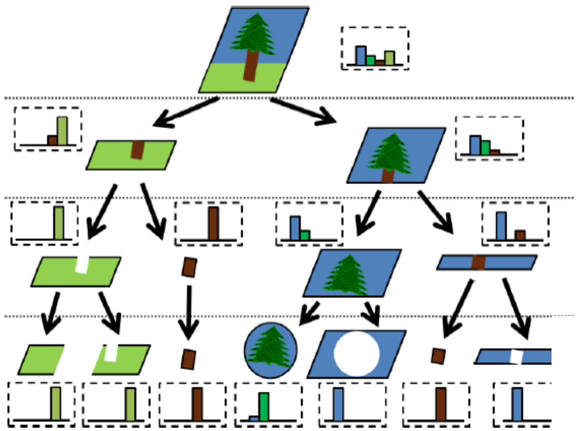


Figure 1. Hierarchical clustering of video textures: each level in the hierarchy is obtained by clustering the DT models from the preceding level. The arrows and brackets show the cluster membership from the preceding level (the groupings between Levels 1 and 2 are omitted for clarity).

→ Extend to arbitary exponential families (jMEF)

http://cosmal.ucsd.edu/~gert/papers/hemdtm_cvpr.pdf

P10. Stacked Hierarchical Labeling



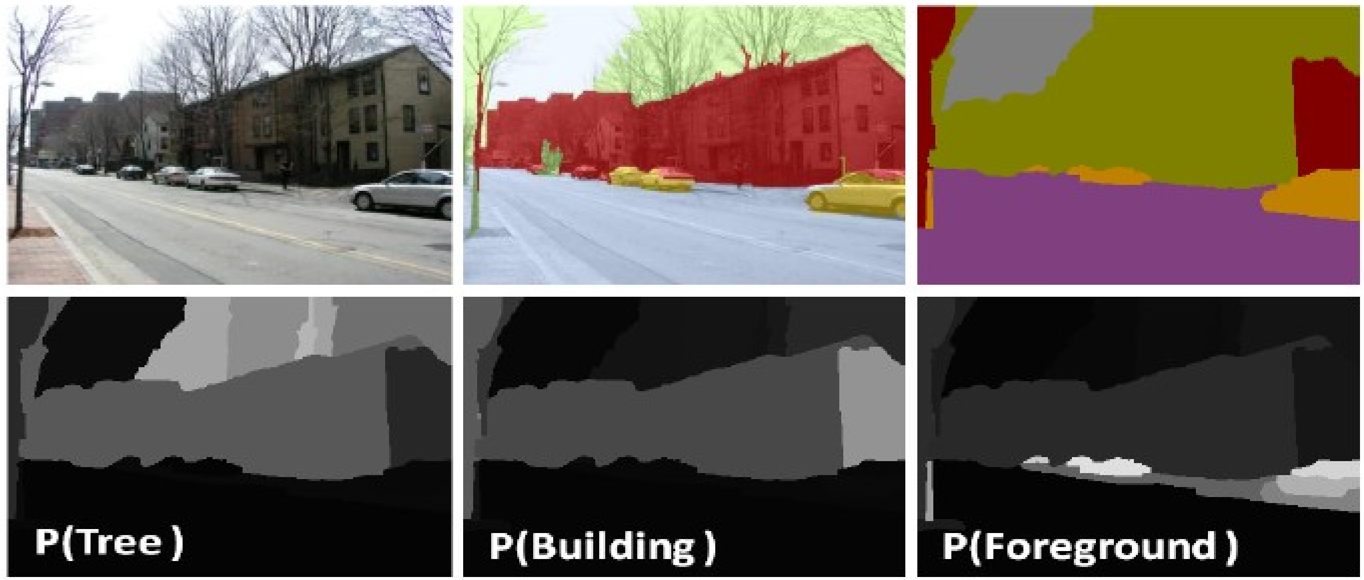


Fig. 9. The ambiguity in ground truth label (top, middle) is correctly modeled in our predictions (bottom row), resulting in a labeling for the building that is *uncertain*.

http://www.cs.cmu.edu/~dmunoz/pubs/munoz_eccv_10.pdf

P11 Spherical Embeddings for non-Euclidean Dissimilarities
Richard Wilson et al., CVPR 2010

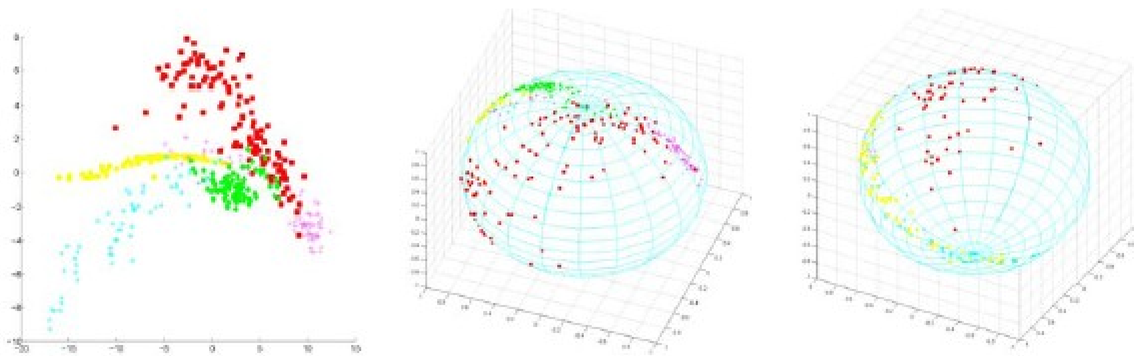
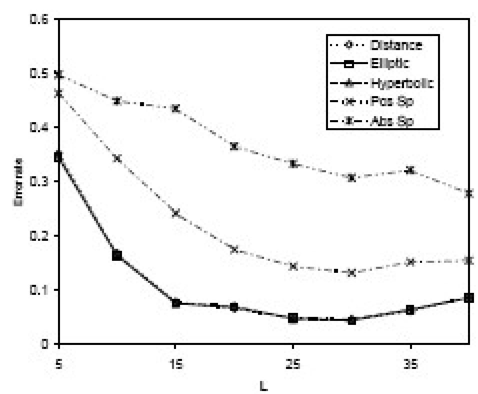


Figure 3. The 2D kernel embedding and two views of the 2D elliptic embedding of the Chickenpieces data with L=25



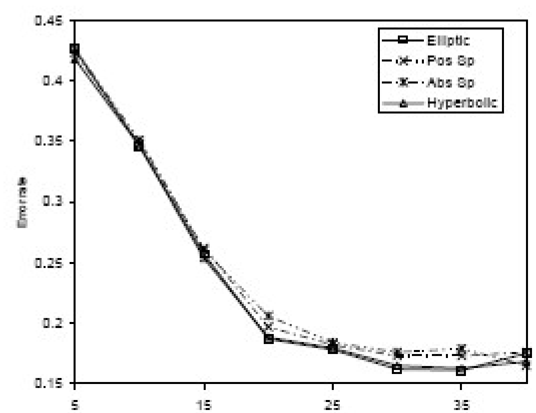
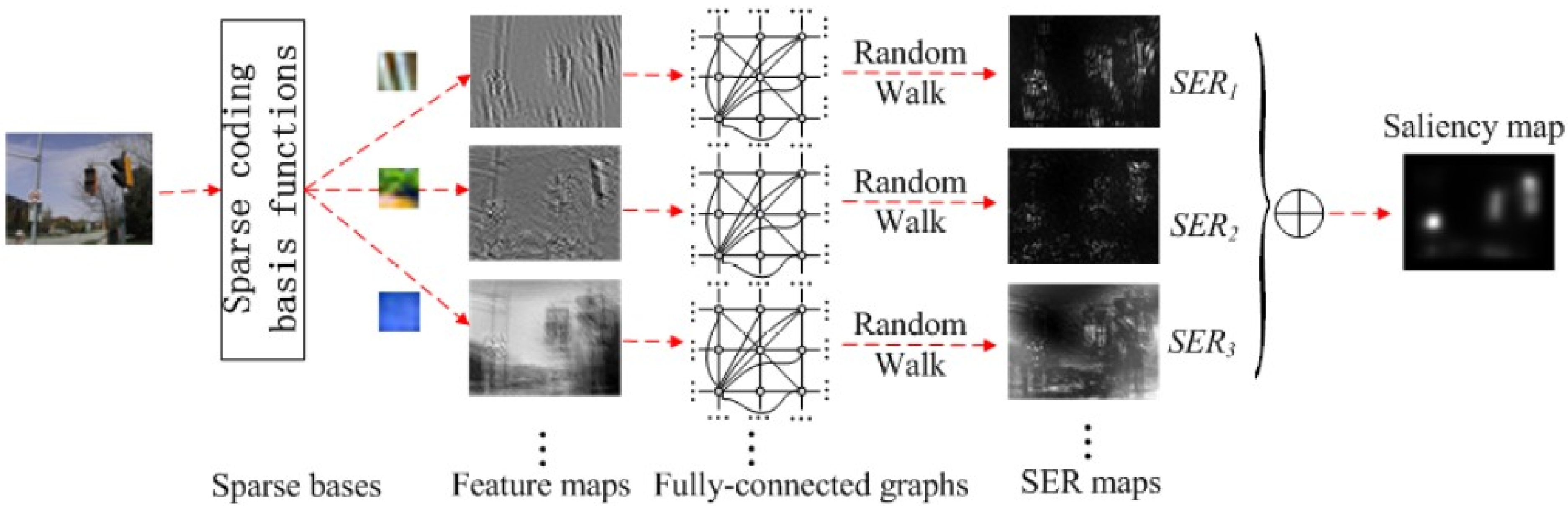


Figure 4. Estimated error rates for the Chickenpieces data with 1-

http://yoshi.cs.ucla.edu/upload/CVPR10/data/papers/1101.pdf

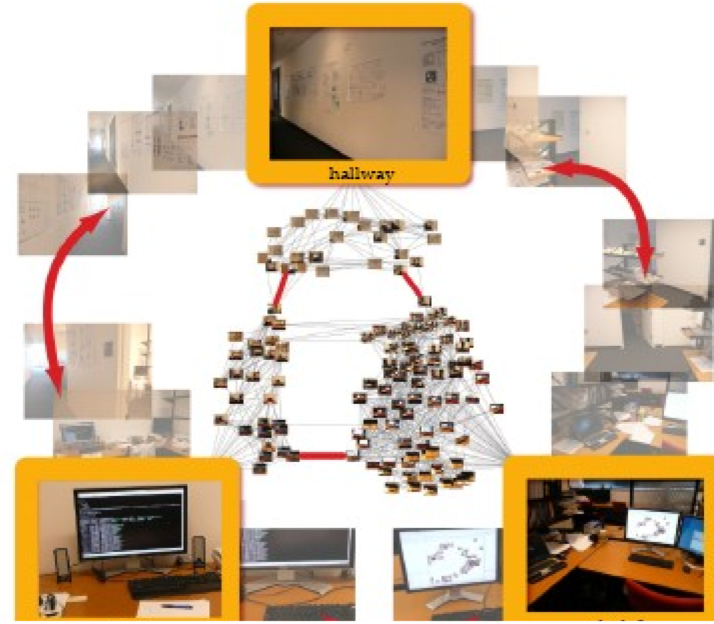
P12. Measuring Visual Saliency by Site Entropy Rate

Wei Wang, Yizhou Wang



P13. Image Webs: Computing and Exploiting Connectivity in Image Collections

Kyle Heath



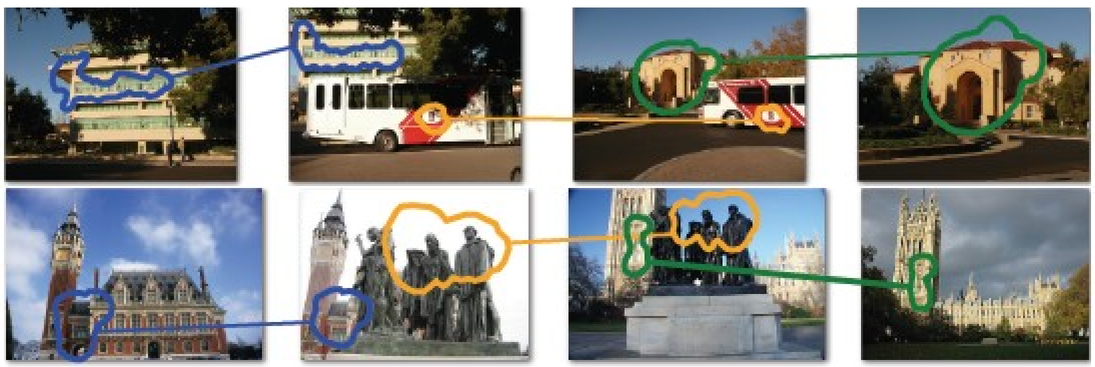
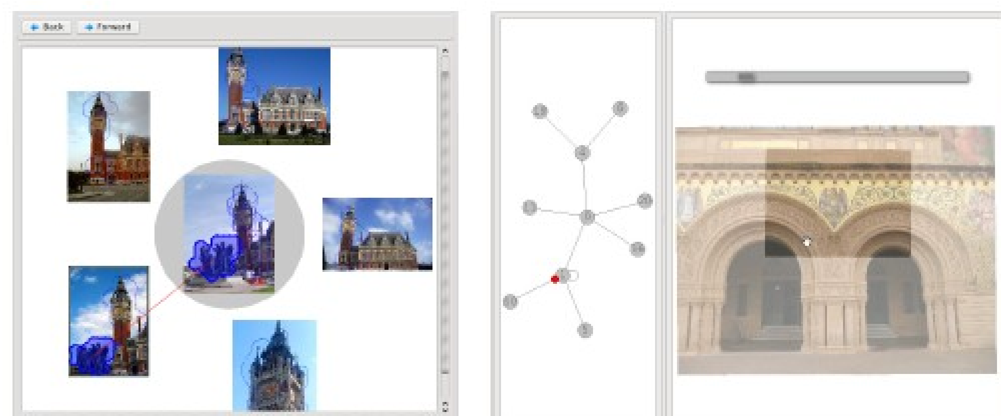


Figure 1. Image Webs can connect images of bu
bus route via the moving bus (top row) or image
London through casts of the Rodin sculpture "T
Calais", which commemorates a historical connect
two cities in the Hundred Years' War (bottom row



(a) Visual hyperlink browser (b) Summary graph browser

Figure 6. In (a), a visual hyperlink browser lets users navigate to related images by clicking on visual hyperlinks and provides a detailed view of a local neighborhood of the web. In (b), a summary graph browser provides a global view of the web allowing simple navigation around the entire web.

P14. Food Recognition Using Statistics of Pairwise Local Features

Shulin Yang, et. al.

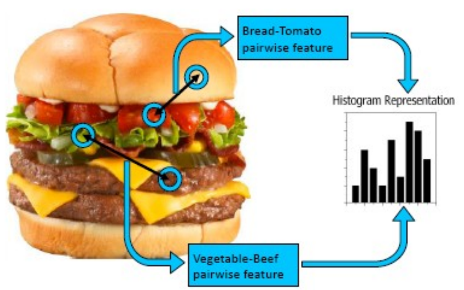
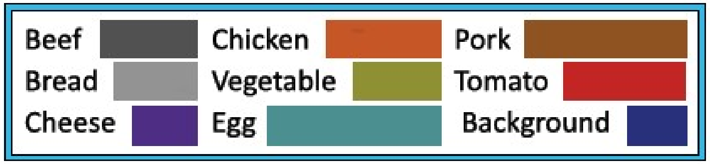
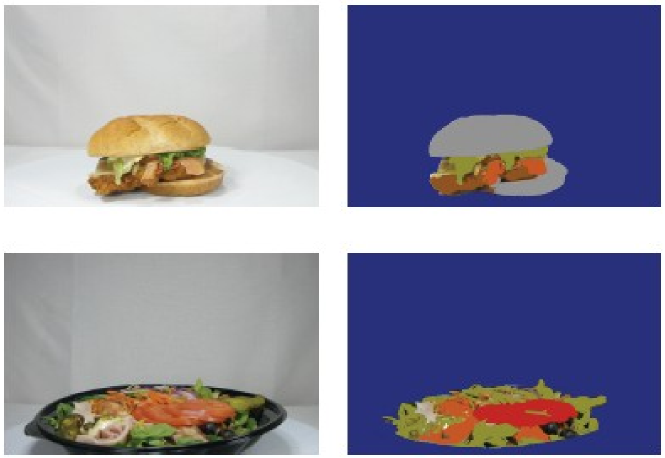


Figure 1. Exploiting spatial relationships between ingredients us-



(a)



(b)

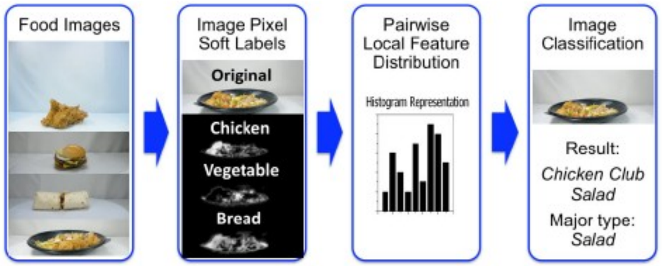


Figure 2. Framework of proposed approach: (1) Each pixel in the food image is assigned a vector representing the probability with which the pixel belongs to each of nine food ingredient categories, using STF [16]. (2) The image pixels and their soft labels are used to extract statistics of pairwise local features, to form a multi-dimensional histogram. (3) This histogram is passed into a multi-class SVM to classify the given image.

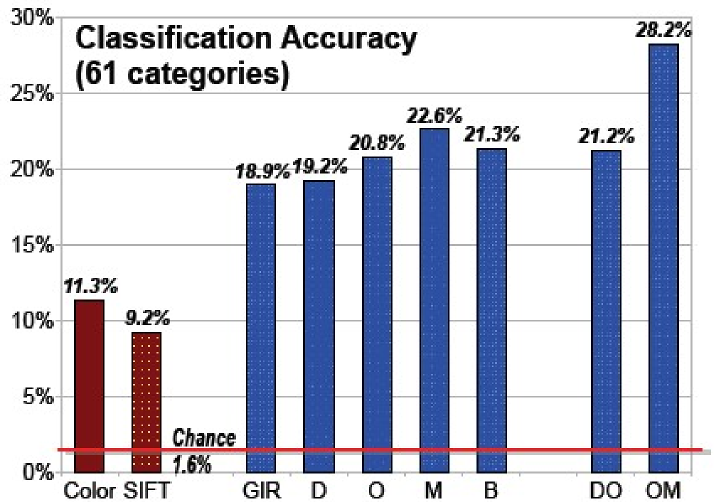


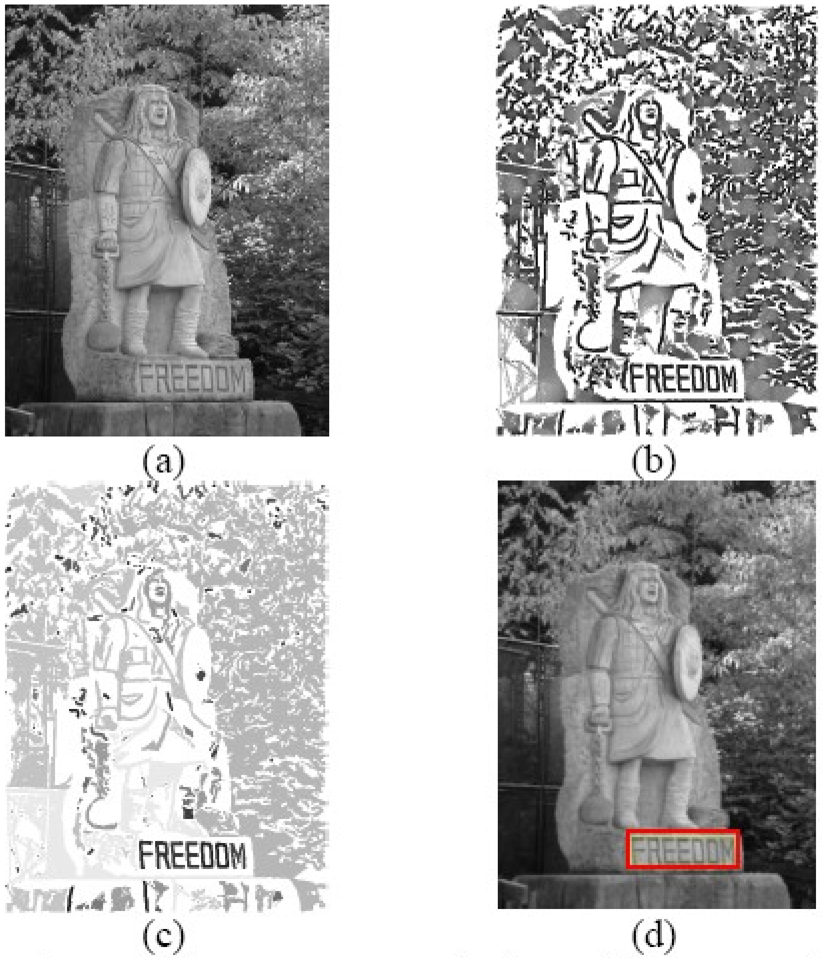
Figure 8. Classification accuracy for 61 categories

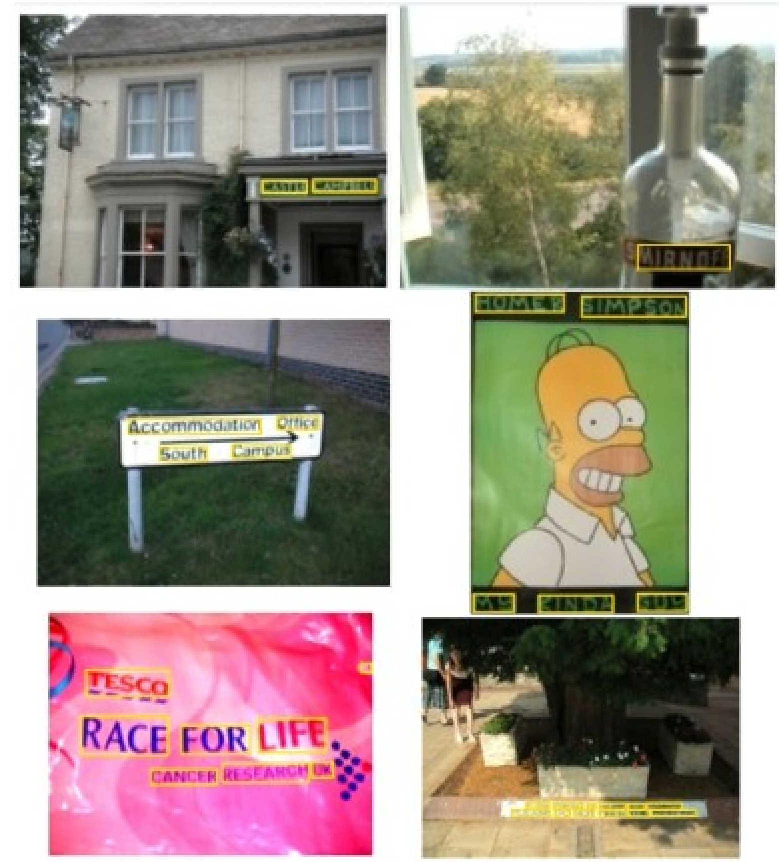
type level (7 broad categories).

Utiliser les images provenant du Magnan. Calculer les kcalories, etc.

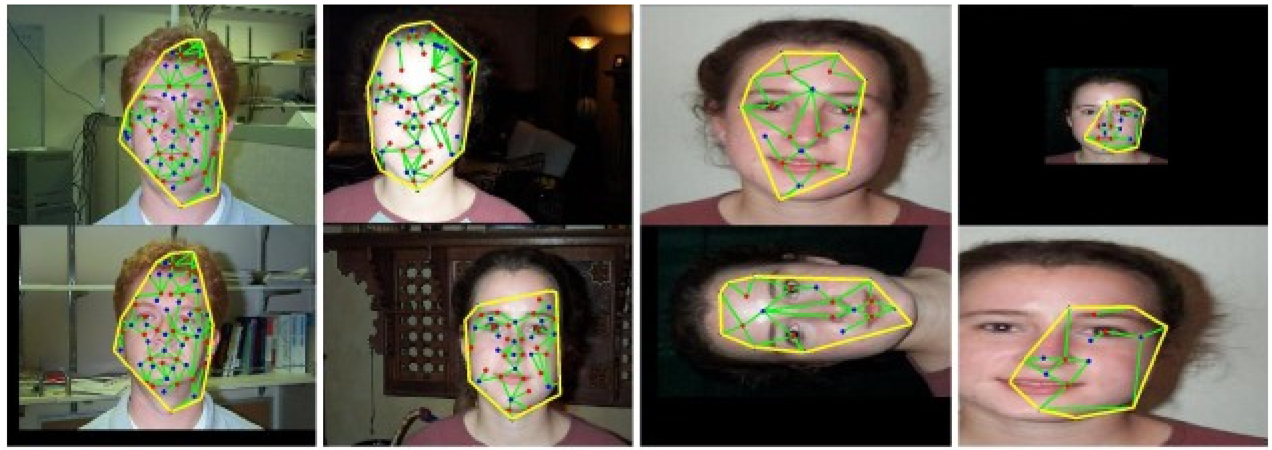
P15. Detecting Text in Natural Scenes with Stroke Width Transform

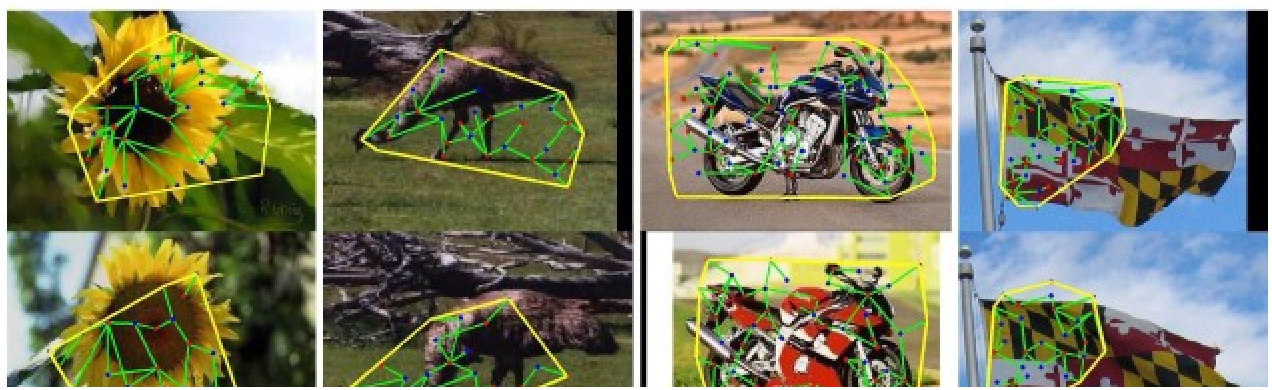
Boris Epshtein, Eyal Ofek, Yonatan Wexler



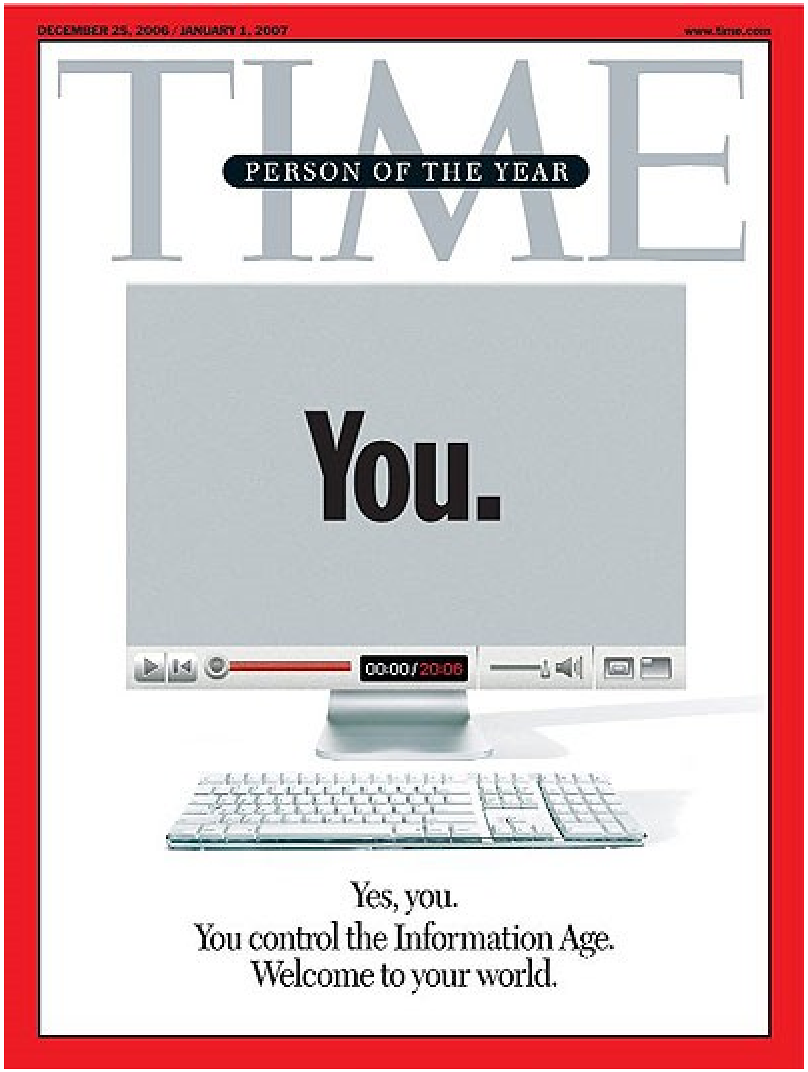


P16. Critical Nets and Beta-Stable Features for Image Matching





Pxx?. Make your own project!



Définissons ensemble votre projet