Combining local and global Bag-of-Words representations for semantic segmentation.

Centre de Visió per Computador

Universitat Autònoma de Barcelona

MIPRCV CONSOLIDER INGENIO 2010

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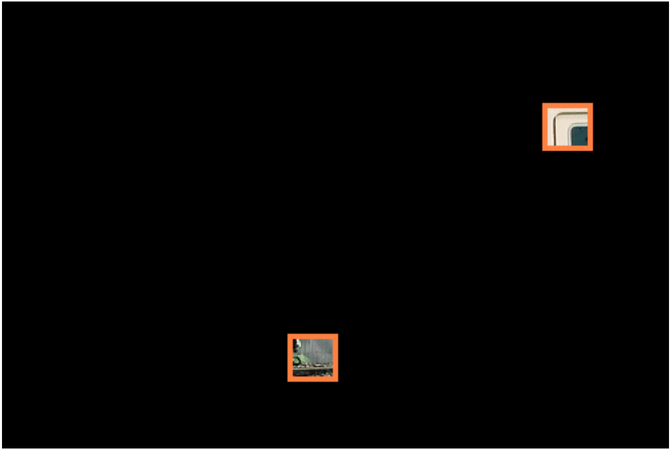
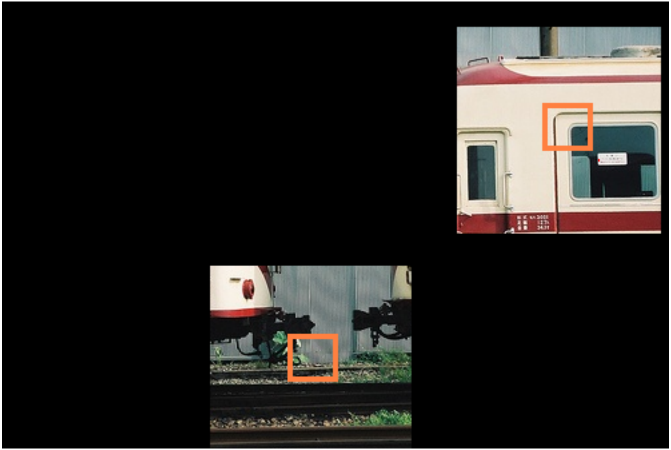
A. Bagdanov, M. Pedersoli, J. González, J. Serrat

Motivation



What's inside a local segment?

Motivation

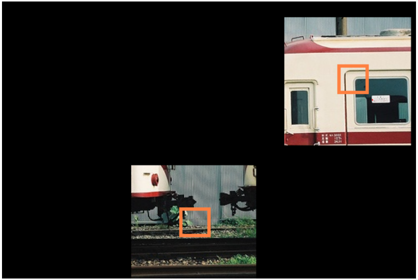


...and with context? [FulkersonICCV09]

Motivation

Global classifier

What's inside a local segment?



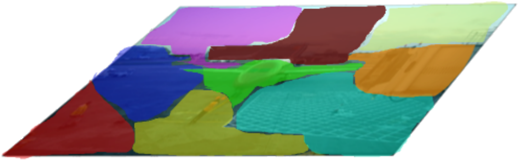
Contributions

- Novel segmentation method that jointly uses global and local information.
- Concatenating the description of a superpixel and its context.
- Learn a per class normalization of the classification scores.

Model

- **Original Image**
- Unsupervised Segmentation
- Superpixel Nodes
- Global Node
- Local Classification
- Global Classification
- Inference with Graph-Cuts

Model



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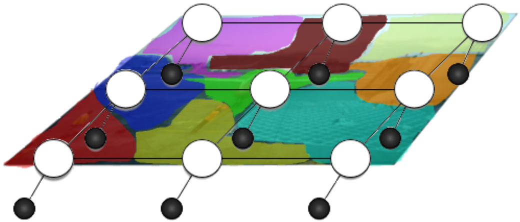

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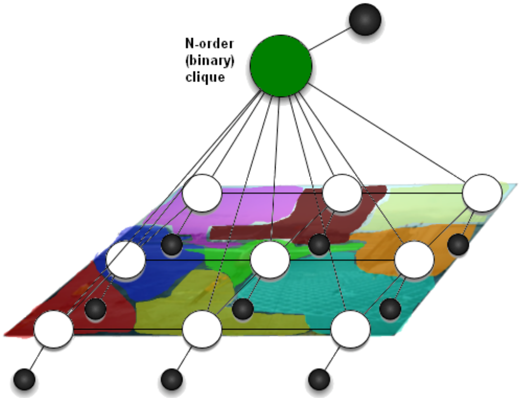

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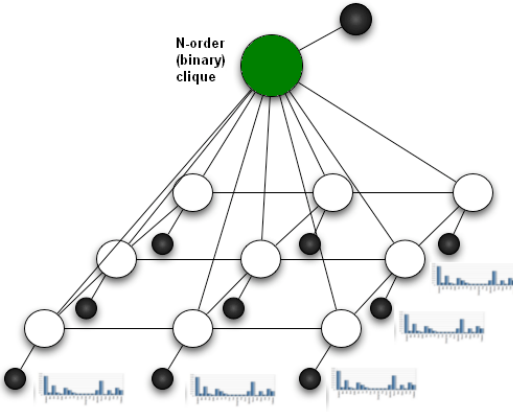

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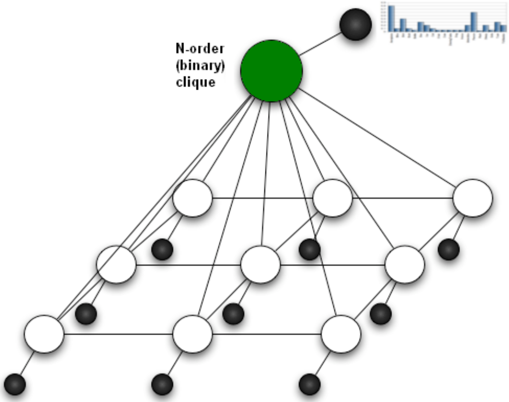

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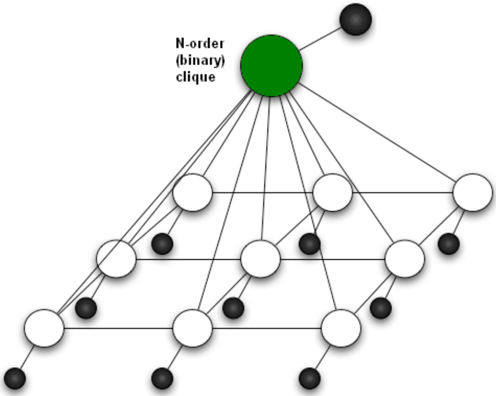

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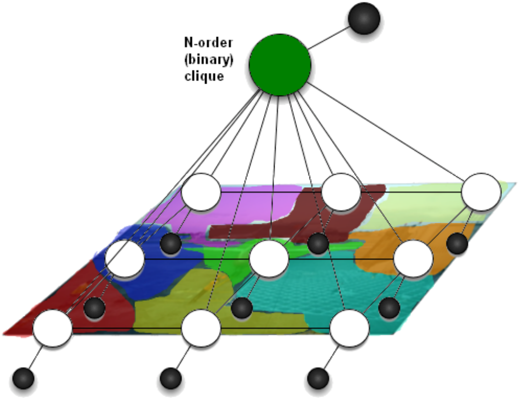
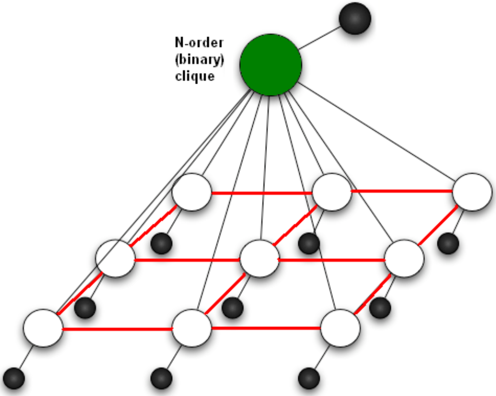


$$\sum_{s \in \mathcal{S}} \text{local} + \sum_{(p,q) \in \mathcal{N}_{\mathcal{S}}} \text{smoothness} + \sum_{g \in \mathcal{G}} \text{global} + \sum_{(p,q) \in \mathcal{N}_{\mathcal{SG}}} \text{consistency}$$

Smoothness term



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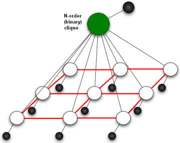
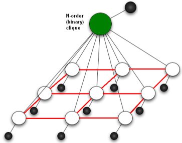


$$smoothness(s_i, s_j, c_{ij}) = \lambda\theta(c_{ij})N_{ij}\delta(s_i, s_j)$$

- ~~Pixel level~~
- Oversegmentation
- Modulated Potts
- Color conditioned

Smoothness term



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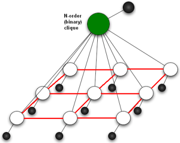

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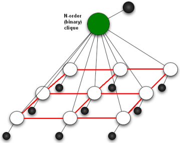

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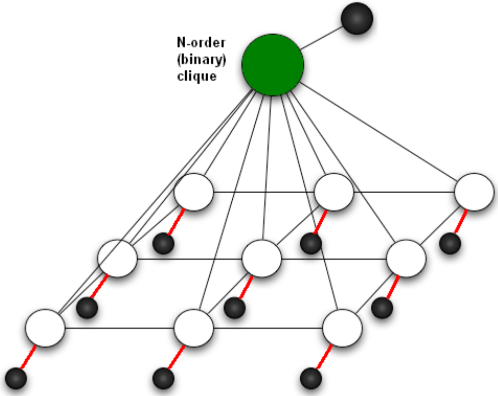
Local term



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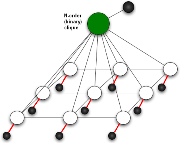
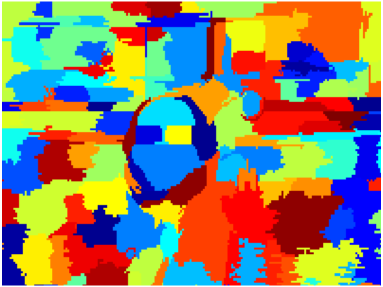
Local term

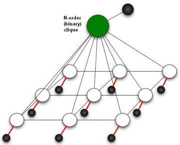


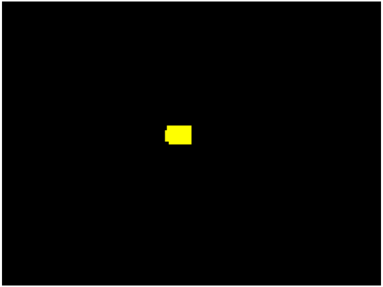


Bag-of-Words:

- Inside Region (20%)
- Contextual Regions (27%)
- Concatenate Both Regions (29%)

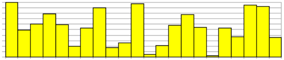
Local term



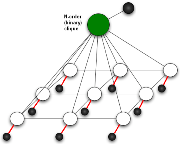


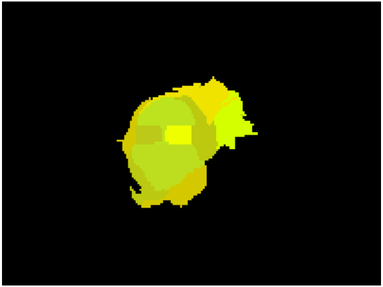
Bag-of-Words:

- **Inside Region (20.02%)**
- Contextual Regions (27%)
- Concatenate Both Regions (29%)



Local term





Bag-of-Words:

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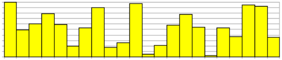
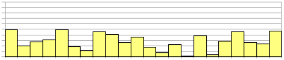
- **Contextual Regions (27.14%)**
- Concatenate Both Regions (29%)



+



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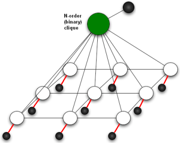

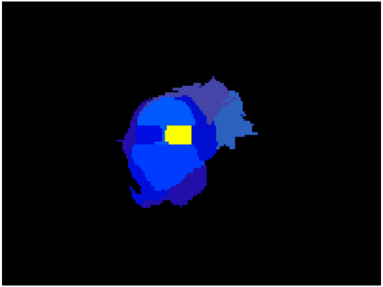

Bag-of-Words:

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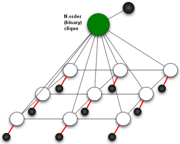
Local term



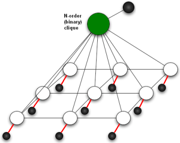
Detector:

- Dense Grid with 50% of overlapping between patches.
- 4 different scales.

Description:

- Shape feature: SIFT. (28.34%)
- Color feature: RGB Histogram. (22.5%)
- Concatenate SIFT + Color histogram. (29.53%)

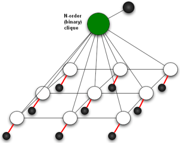
Local term



- 20 SVM with Intersection Kernel.
- 20.000 training samples for each class.

One class against all classes.

Local term



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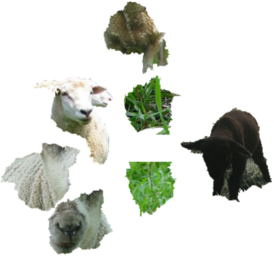
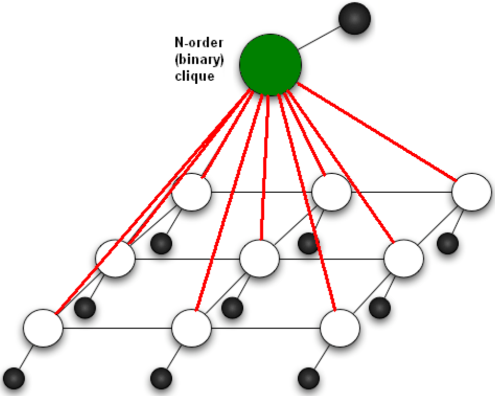


One class against its background. Similar to [CsurkaBMCV08].

Consistency term



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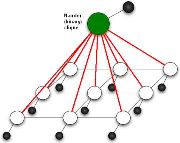
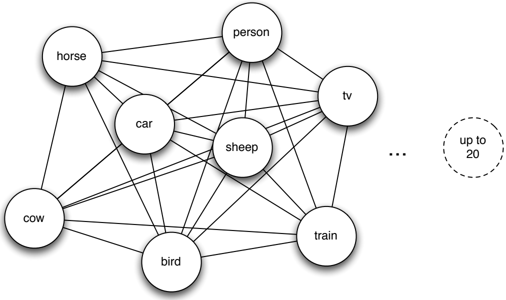
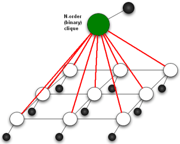




- $g_i \in \{0, 1\}$
- All global nodes are connected to each superpixel node.

$$\text{consistency}(s_i, \mathcal{G}) = \beta M_i \prod_{g_j = 1 \in \mathcal{G}} (1 - \delta(s_i, j))$$

Consistency term

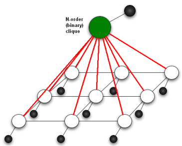


Equivalent problem:

- Substitute g_i with ONE node $g \in \{\mathcal{L}_{comb}\}$.
- Each label in $\{\mathcal{L}_{comb}\}$ represents a **combination** of classes in the image.
- Thus, g has a total amount of 2^N possible labels.

Too many labels to be solvable in reasonable time.

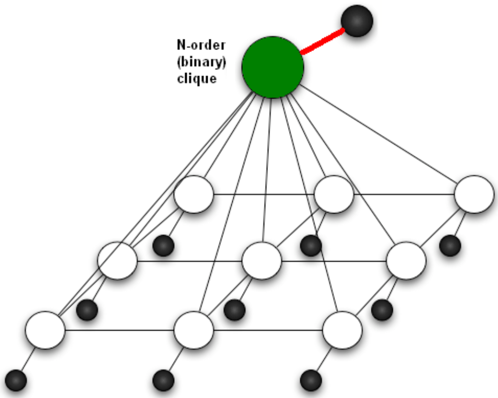
Consistency term



Approximate problem:

- Use only the most likely $\mathcal{L}_{comb}$:
  - Discard objects with very low global classification rate (≤ 0.05).
  - Possible combinations of objects in the same image.
- Solvable with standard graph-cuts (less than 2 seconds).

Global term



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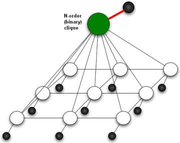
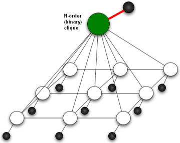
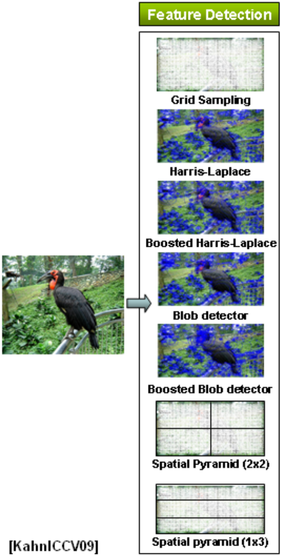


[KahnICCV09]

Global term





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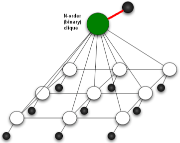

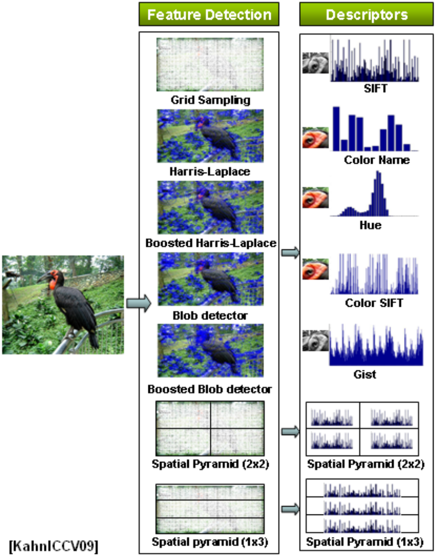

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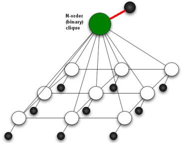

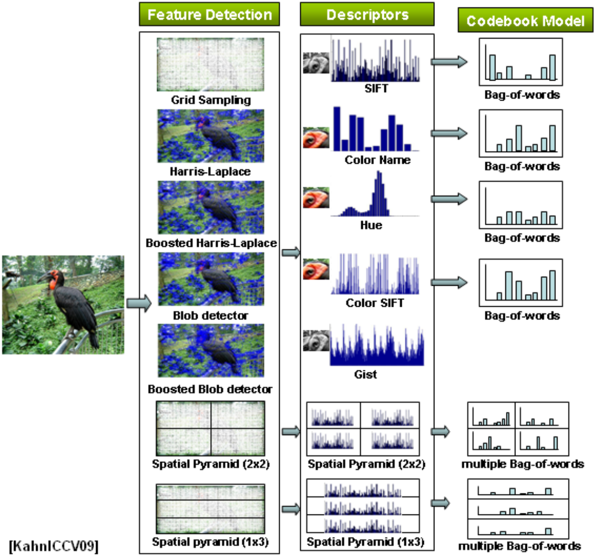

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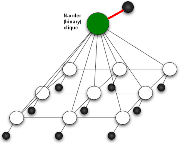

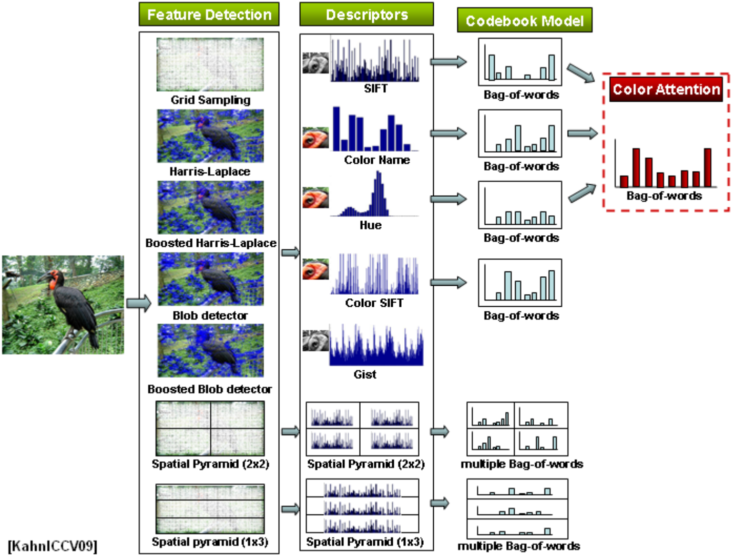

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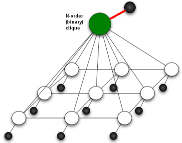

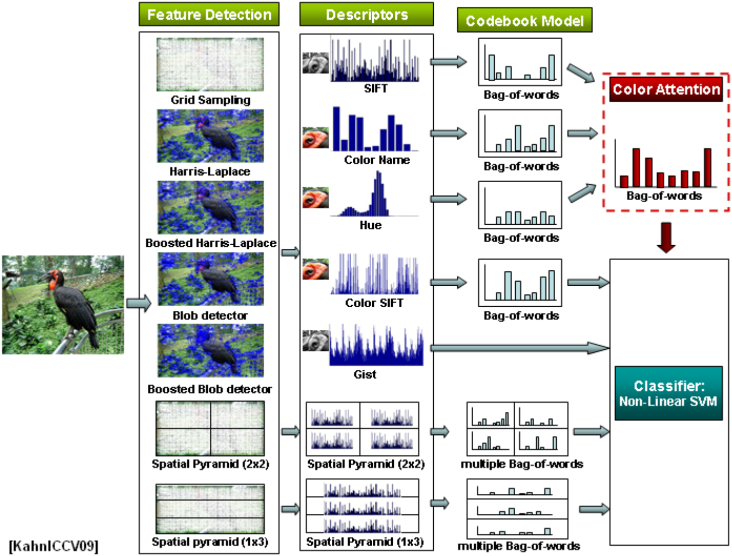

[KahnICCV09]

Learning the parameters

- The best configuration maximizes the geometric mean of the performance of all classes.
- We obtain new configurations in a **Gibbs sampler** manner:

$$x_i^{t+1} \sim \mathcal{N}(x_i^t, f(t))$$

- 2-fold cross validation.
- Learning stages:
  1. Weights of the graphical model. (29.53%)
  2. Per class normalization of the local term. (31.25%)
  3. Per class normalization of the global term. (35.1%)

Conclusions

- We propose a novel segmentation method that jointly uses global and local information.
- Using as negative examples only the segments that appear in the same image of positive samples decreases the variability of the data.
- Concatenating both the description of a superpixel and its context is helpful for classification. (+2.5%)
- We empirically prove that a per class normalization of the observed terms is able to efficiently equalize classification scores. (+5.6%)

Gràcies!

Thank you!

Arigato!

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Universitat Autònoma de Barcelona

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Multimodal Interaction in Pattern Recognition and Computer Vision