IMAGE CATEGORIZATION USING CODEBOOKS BUILT FROM SCORED AND SELECTED LOCAL FEATURES

By

Bala S. Divakaruni and Dr. Jie Zhou

Northern Illinois University

OUTLINE

- Background.
- Method.
- Results.
- Discussion.
- Conclusion.

AIM

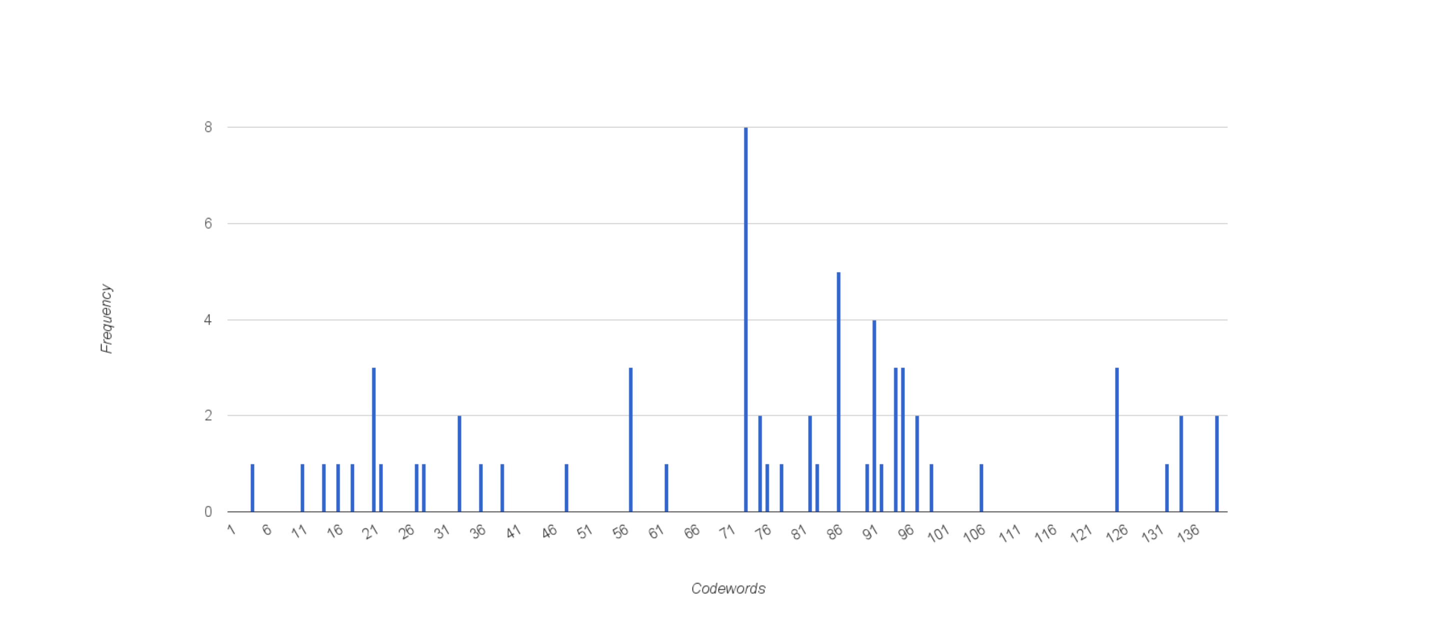
Classify an entire image to a known category using sparse local features.

RELATED WORK

- Local Features(J. Zhang IJCV 2007, G. Csurka ECCV 2004).
- Bags of keypoints(G. Csurka ECCV 2004).
- Weighted Codes(H. Cai CVPR 2010, J. C. van Gemert ECCV 2008).
- Codeword binary weighting(J. Winn ICCV 2005).

CODEBOOK

Codebook(dictionary, vocabulary) is often generated to facilitate image representation and the subsequent classification.



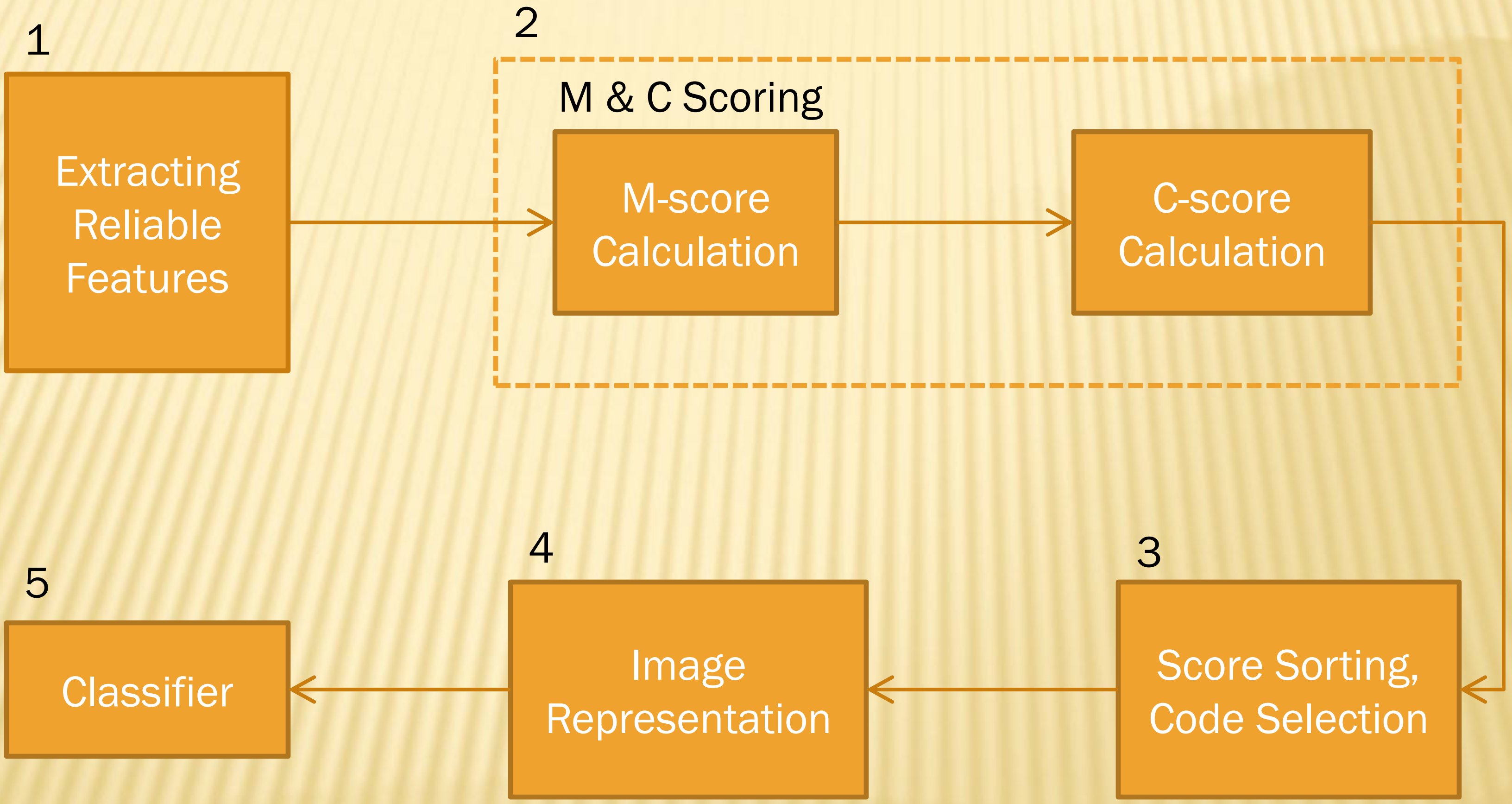
CHALLENGES

- K-Means clustering.
  - Favoring dense areas.
- Large codebooks.
- Codebook Uncertainty and plausibility.

METHOD HIGHLIGHTS

1. Scored codes – Most representative Features
2. Local features, feature selection – no aligning or segmentation required, not based on shapes.
3. Smaller codebook sizes – computational feasibility.

ALGORITHM FLOW

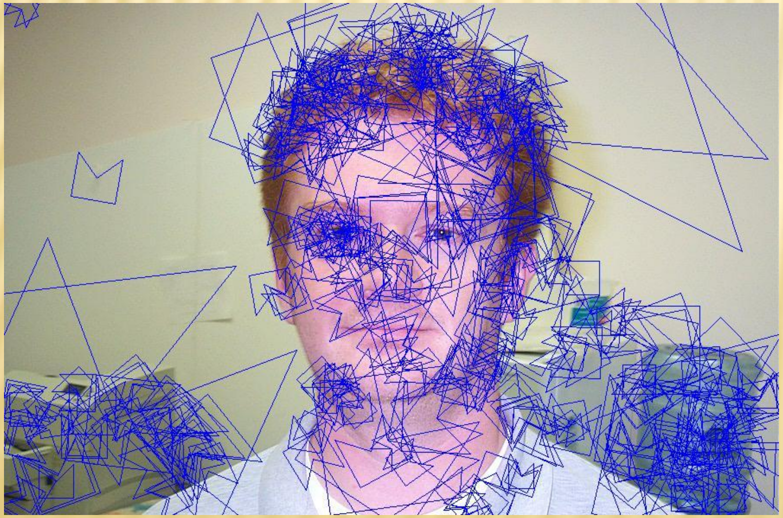


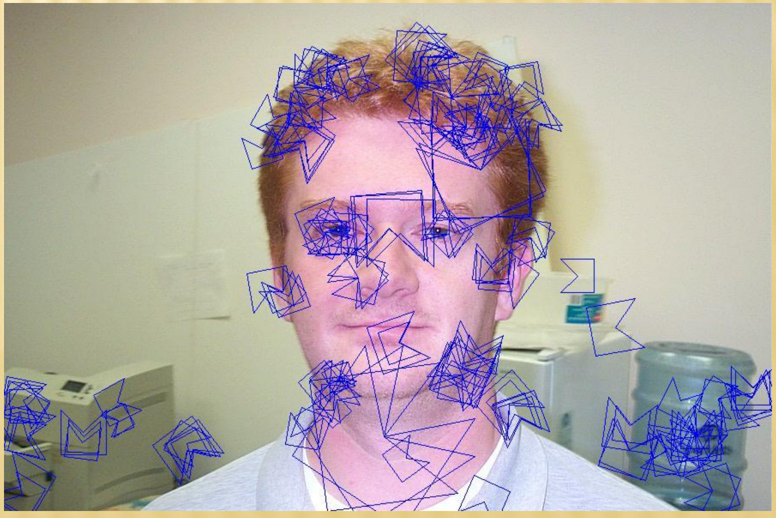
SIFT FEATURE EXTRACTION

- SIFT features are distinctive scale-invariant keypoints defined as maxima and minima of Difference of Gaussian (DoG) at various scales.
- A raw SIFT feature extractor consists of 2D location, scale and orientation, and the keypoint descriptor.

SIFT FEATURE EXTRACTION

To reduce the computational complexity of feature scoring as well as the inference of some background clutters and outliers, we apply Hough transform to the raw SIFT features.





MATCHING AND THE M-SCORE

The setting is similar as in image retrieval, with features to be matched in the query image, and the remaining images viewed as reference images.

MATCHING AND THE M-SCORE

$$M(f_{ij}^{x}) = 1 - fd(f_{ij}^{x}) * rod(f_{ij}^{x})$$

The M-score reflects the level of matching of the feature with different features in other images of the same category.

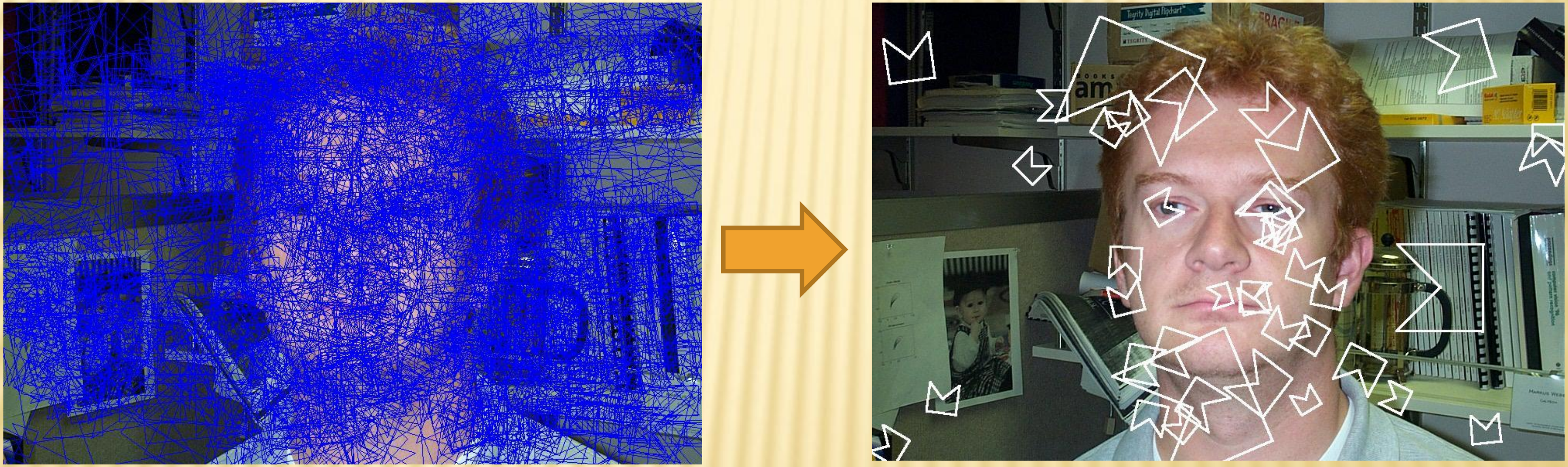
CONSENSUS PROCESS AND THE C-SCORE

$$C(f_i^x) = \frac{1}{L-1} \sum_{j=1,,,i-1,i+1,,,L} \delta(M(f_{ij}^x) - t) M(f_{ij}^x)$$

Consensus is the process of determining how representative the matched features are for a particular class.

C-score is consensus weighted by level of matching.

SELECTED CODES



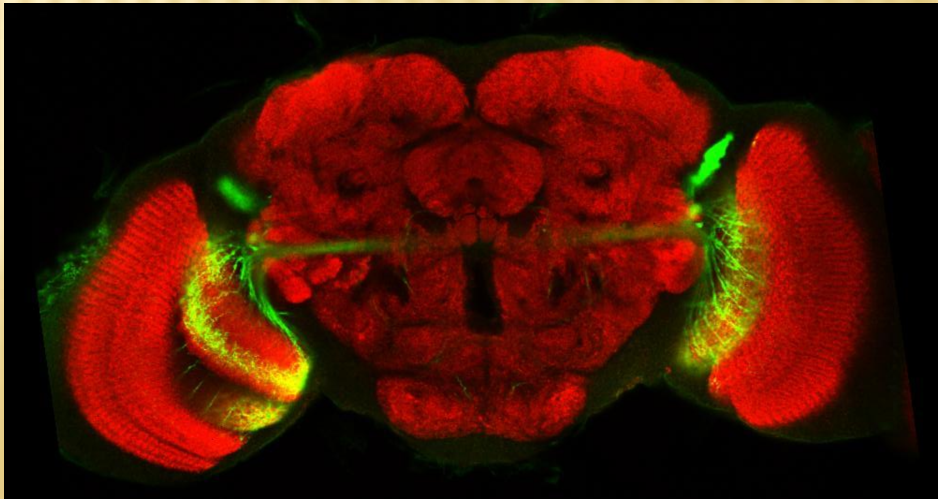
K150 DATASET

Sample image, Class 1

Sample image, Class 2

Sample image, Class 3

Sample image, Class 4



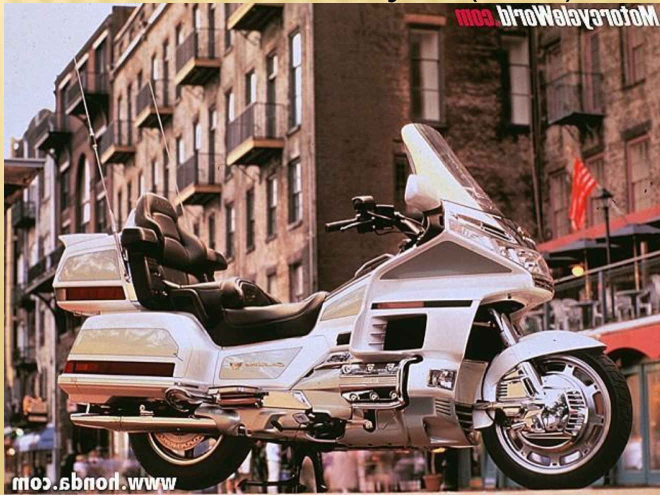
BINARY DATASETS

Graz 01- Bike

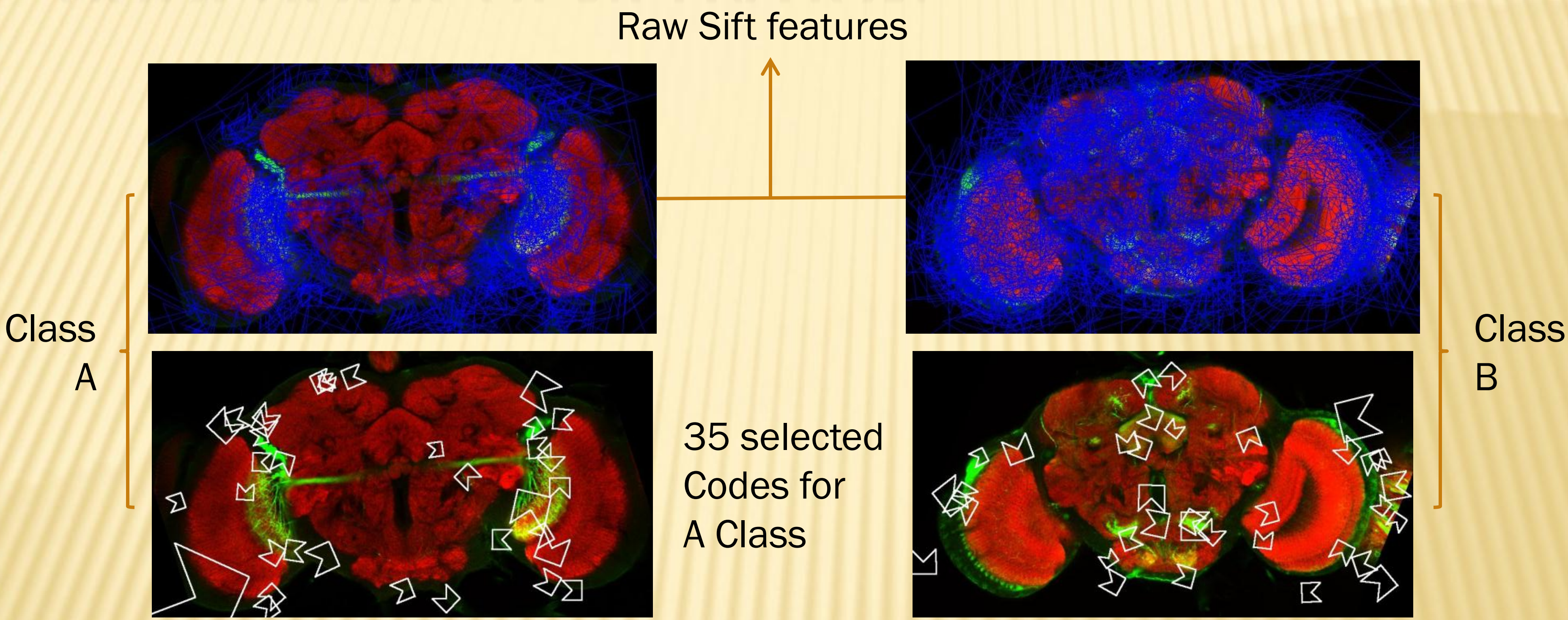
Graz 01 - Person

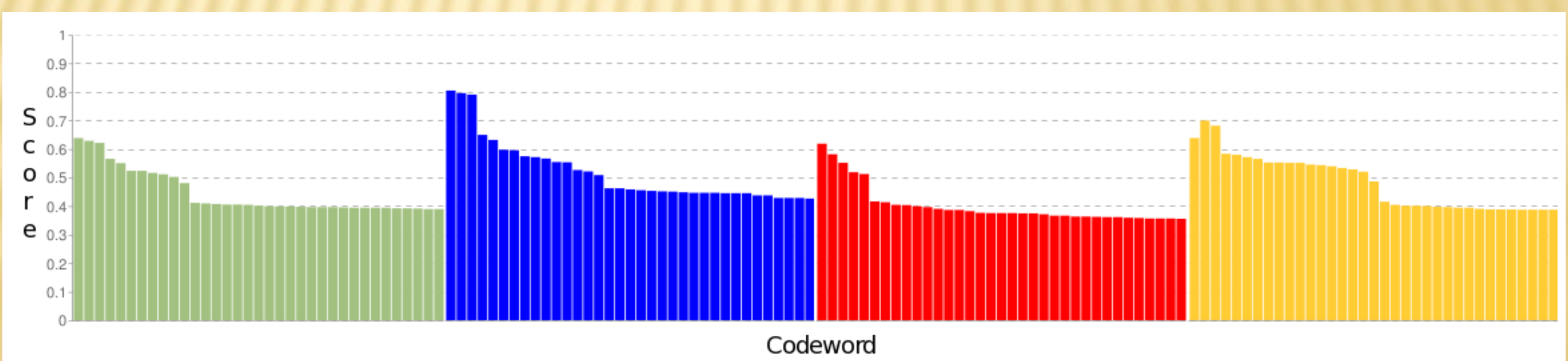
Caltech6 – Faces(front)

Caltech6- Motorcycle(side)



CODEBOOK GENERATION





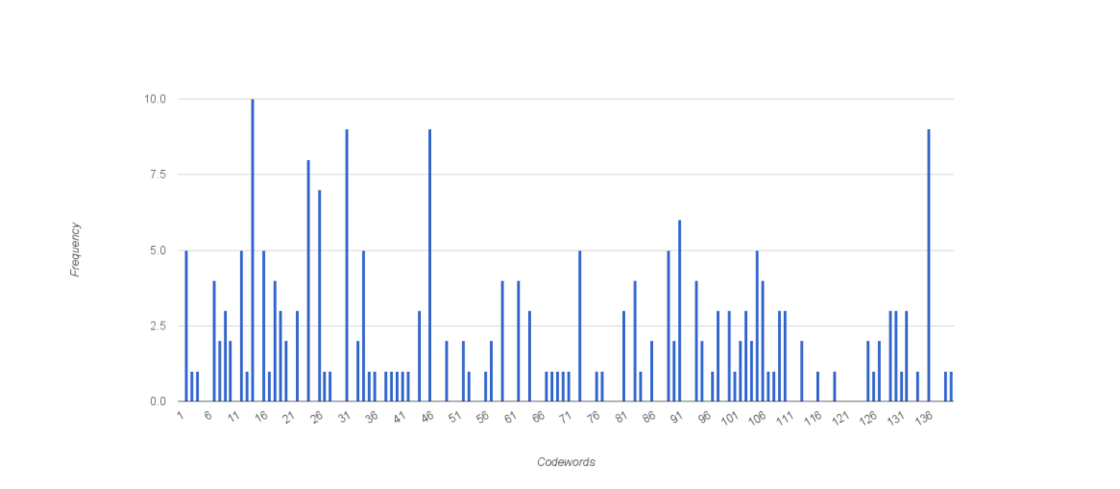
Scores of Codewords in the Codebook

CODEBOOK REPRESENTATION OF AN IMAGE

Histogram representation of images

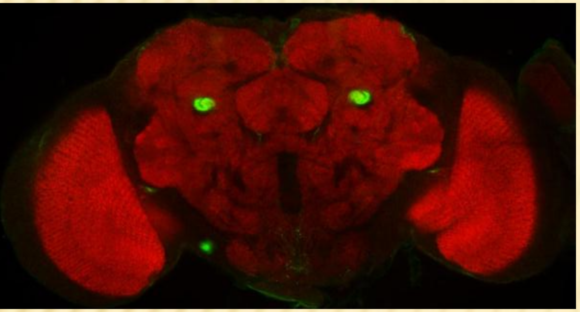
K150, class1 (a278)

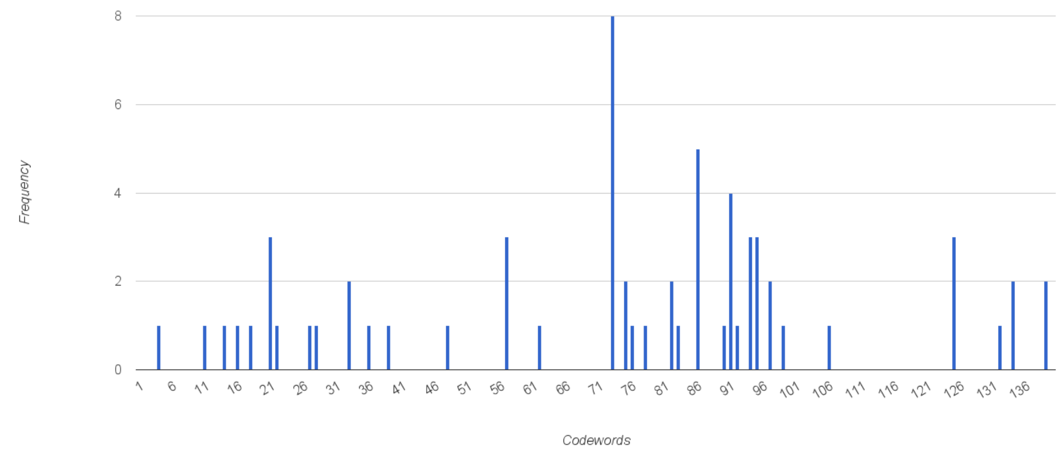
Histogram Representation



CODEBOOK REPRESENTATION OF AN IMAGE

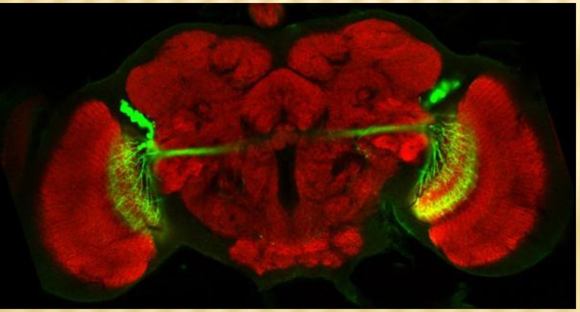
K150 class2 (a150)

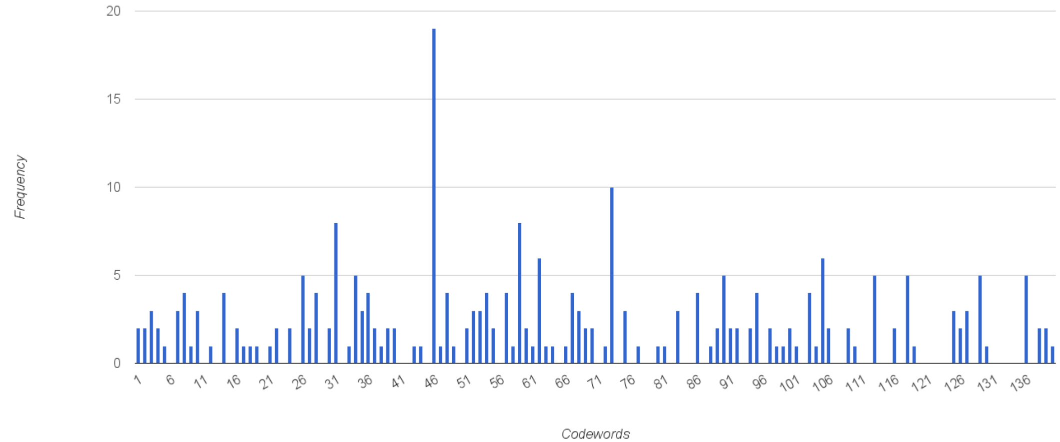




The Histogram of the image

K150 class3 (ato)





The Histogram of the image

RESULTS

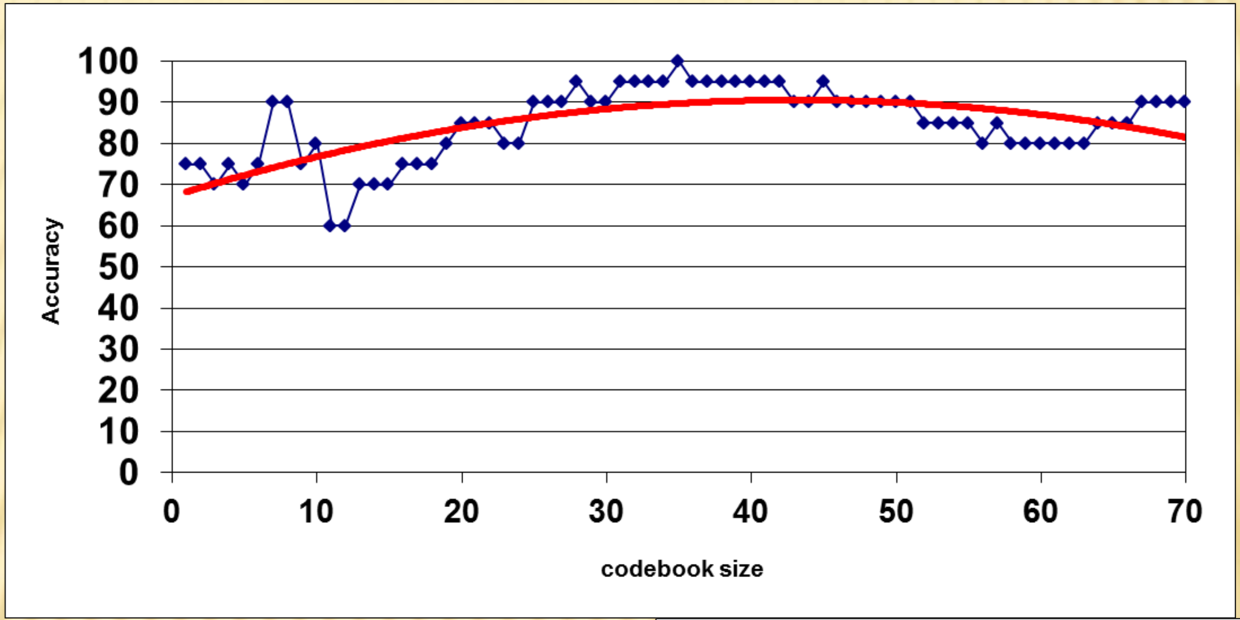
Dataset	Graz Bike	Graz People	Caltech Motorcycle	Caltech Faces
Our result	88.0	81.0	96.2	100
A. Opelt[PAMI 2006]	86.5	80.8	94.3	100
R. Fergus[CVPR 2003]	-	-	92.5	96.3
S. Lazebnik [CVPR 2006]	86.3	82.3	-	-
D. Crandall [ECCV 2004]	79.0 - 84.0	-	-	-
J. Zhang[IJCV 2007]	92.0	88.0	98.5	100
H. Cai[CVPR 2010]	83.3 - 86.7	80.7 - 84.0	-	-

Parameter	Graz Bike	Graz People	Caltech Motorcycle	Caltech Faces
t	0.6	0.52	0.55	0.6
Size	112	167	424	40

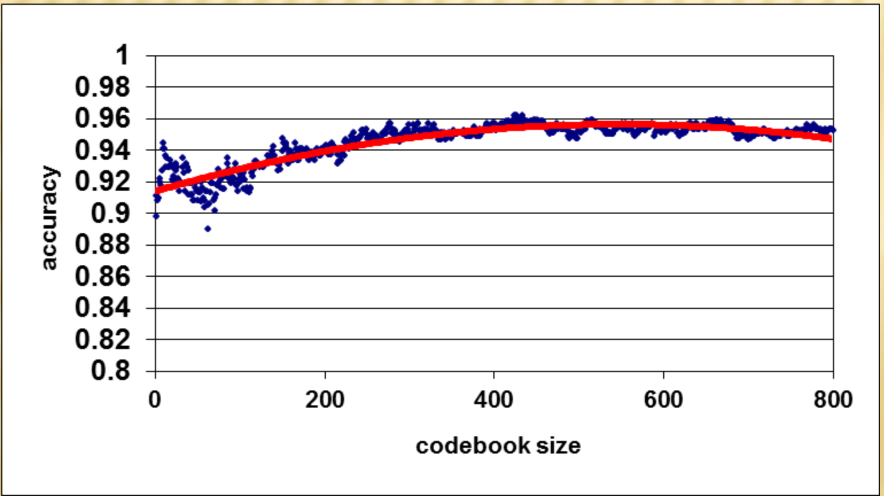
CODEBOOK SIZE VERSUS PERFORMANCE

Trends of performance versus codebook size per class.

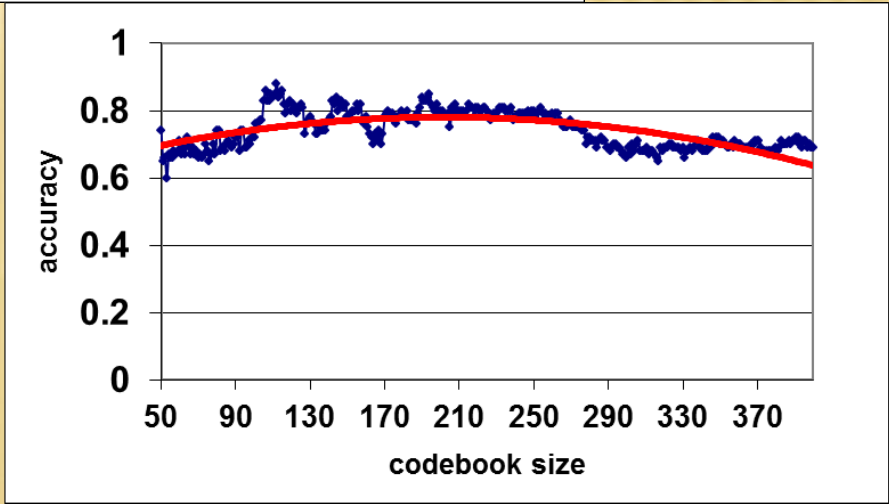
K150



Caltech Motorcycle



Graz01 Bike



CONCLUSION

- Local feature scoring and selection.
- Smaller number of codes.
- Distance metric based definitions for matching and scoring.
- Avoided possible bottleneck of computational complexity

(cont..)

CONCLUSION

(cont..)

- More representative Codebooks.
- Very satisfactory results.

THANK YOU

QUESTIONS??