# Recognizing groceries *in situ* using *in vitro* training data

Michele Merler[†], Carolina Galleguillos[‡], Serge Belongie[‡]
Univ. of Trento[†], U. California San Diego[‡]

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# Outline

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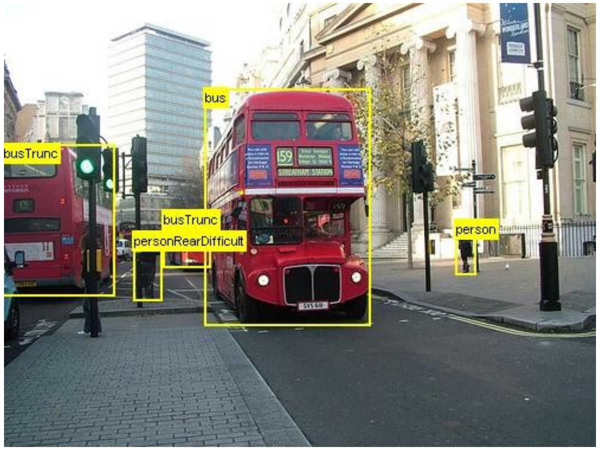
# Introduction

- Object recognition algorithms demand large amounts of training data acquired under different environmental conditions.

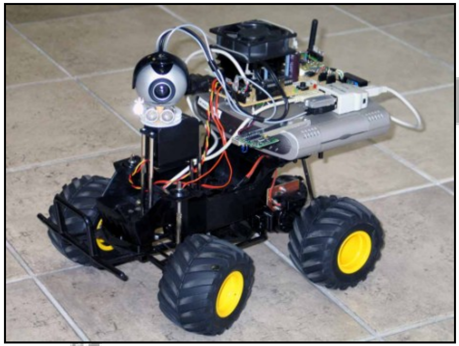



- Many real world applications need training data for which the appearance is drawn from different distribution that the test data.

# Introduction

- Assistive vision technology for the blind, e.g: Grozi[1] project @ UCSD.

- Object recognition for mobile robots, e.g: Semantic Robot Vision Challenge[2] @ CMU.

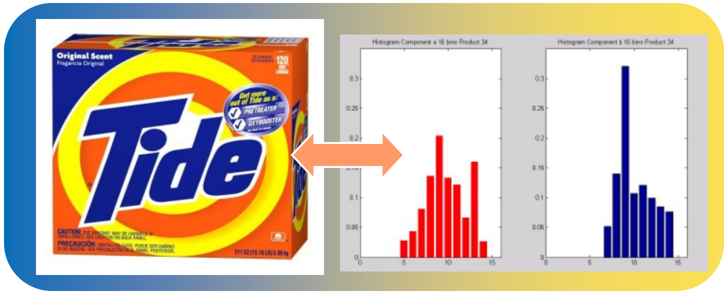


[1] http://grozi.calit2.net
[2] http://www.cs.cmu.edu/~prybski/SRVC

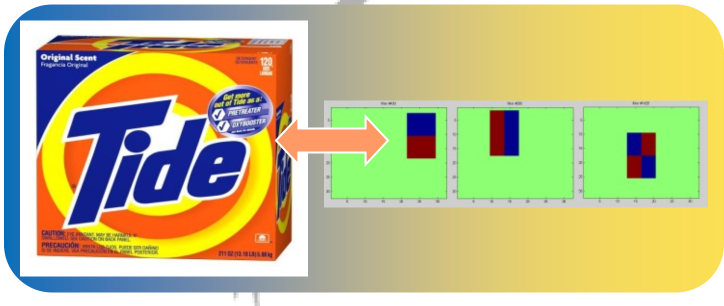
# Related Work

Object recognition algorithms:

- Color Histograms (LAB) features with integral image computation [Swain & Ballard '91].
- SIFT descriptor [Lowe '99].
- Boosted Haar-like features [Viola & Jones '01].







# Related work

Object recognition databases:

- PASCAL VOC
- Caltech 101(256)
- SOIL-47
- ALOI
- ETH-80

# Grozi -120

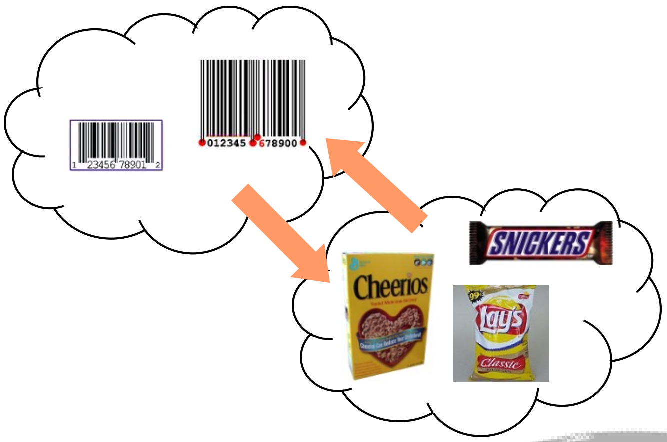
- Multimedia database of 120 grocery products.
- Objects vary in color, size, opacity, shape and rigidity. They are found in different lighting conditions and in presence of clutter and occlusion.
- ***In vitro*** and ***in situ*** image representations (for training and testing data respectively).

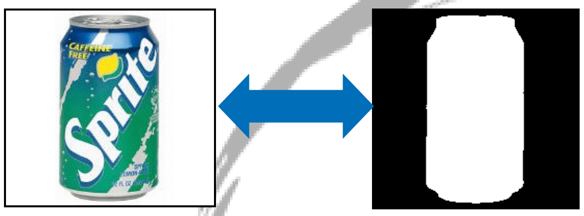
# *In vitro* data

- Isolated images captured under ideal imaging conditions (e.g stock photography studio or lab).
- They can be found in the web (e.g Froogle, Amazon, etc).

# *In vitro* data

- 676 training images (average 6 images per object).
- Obtained from the web (Froogle, Shopwiki, Amazon Groceries, Yahoo images) using a list of 4000 UPC codes.
- Clear foreground–background distinction (binary mask)



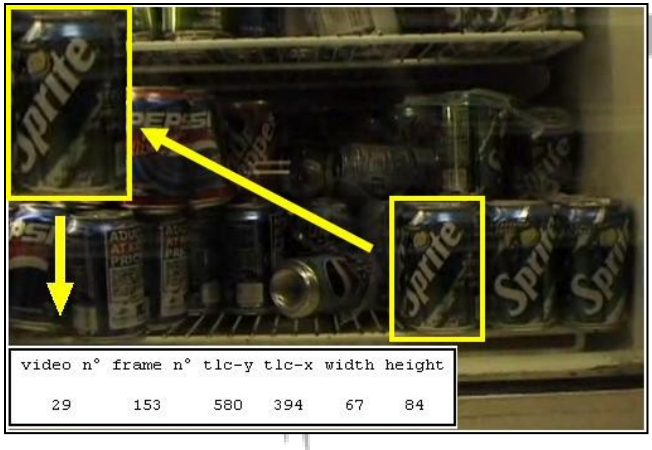



# *In situ* data

- Images from objects captured in natural environments (real world).
- They were shot inside a grocery store, using a MiniDV camcorder and includes every ***in vitro*** object.

# *In situ* data

- 29 videos containing all products.
- Product location in coordinates saved every 5 frames.
- A total of 11194 *in situ* images (average 93 per product).

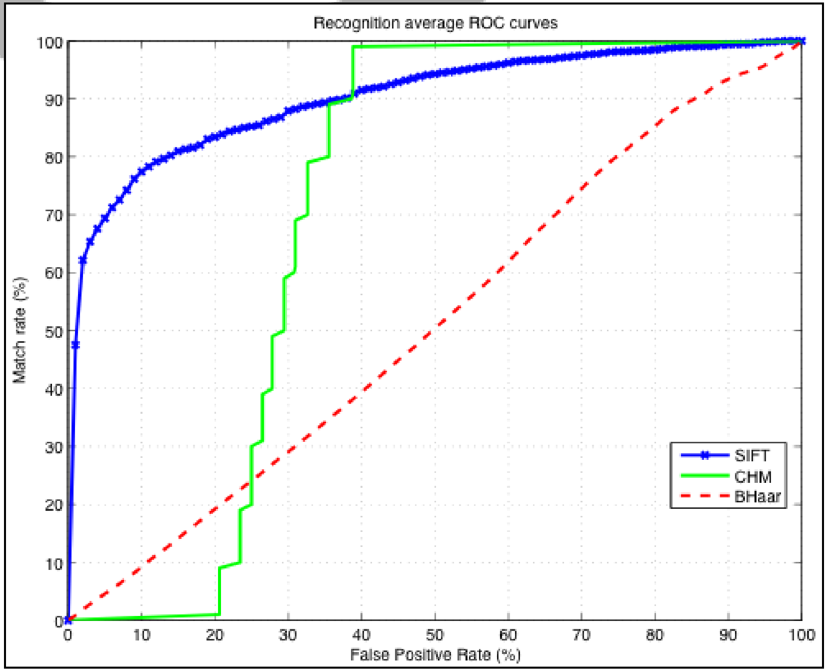
# Experiments

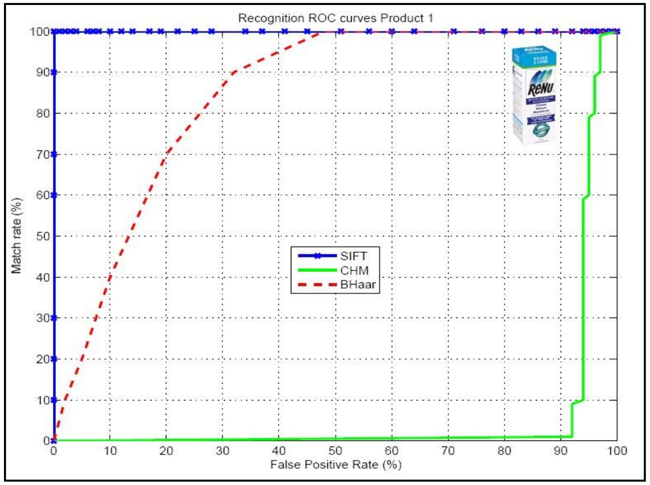
- **Color histogram matching** (CHM): Histogram template + integral image + L1 distance.
- **SIFT with bag of features approach** (SIFT): One bag per object + L2 distance.
- **Adaboost** (ADA): Data + synthetic data + Haar -like features + cascades (14 stages).

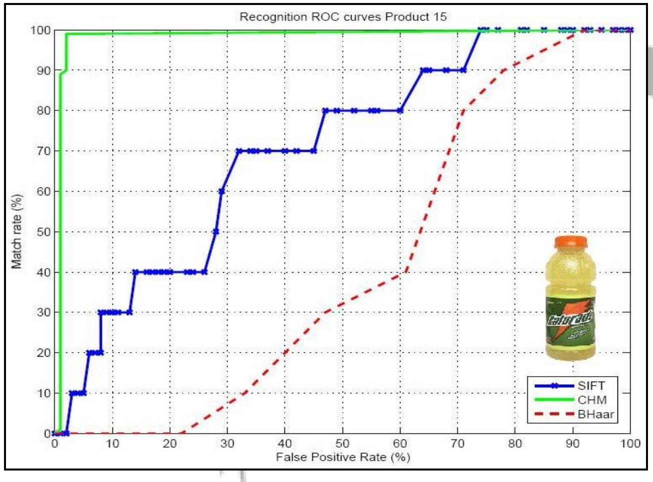
# Experiments

Recognition:

***In vitro*** training data and ***in situ*** testing images.



# Experiments

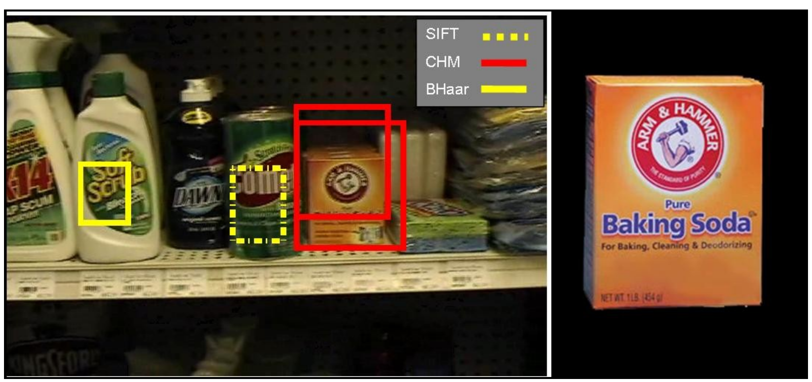
Localization:

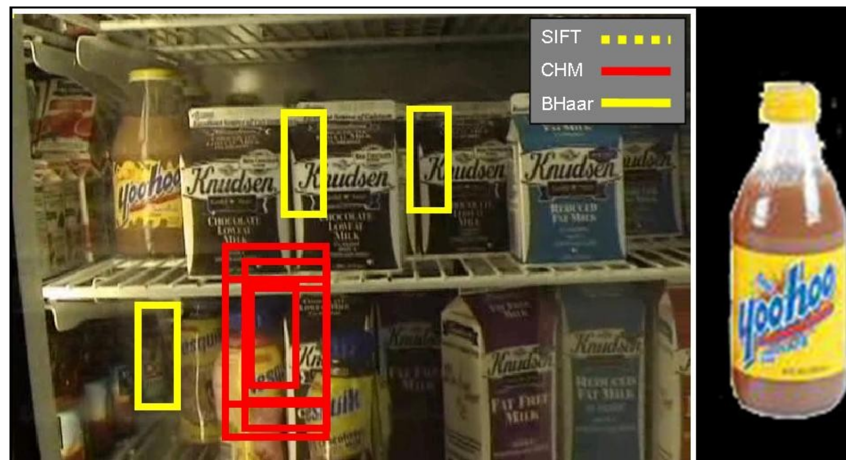
***In vitro*** training data and ***in situ*** testing videos frames (images).


| CHM | %Rec | %Pre | %TP | %FP |
|---|---|---|---|---|
| Mean | 15 | 17 | 18 | 65 |
| Std Dev | 28 | 16 | 35 | 32 |
| Best (20) | 71 | 82 | 100 | 4 |
| Worst (32) | 0.7 | 0.2 | 0 | 100 |
| **SIFT** | **%Rec** | **%Pre** | **%TP** | **%FP** |
| Mean | 72 | 18 | 22 | 62 |
| Std Dev | 20 | 17 | 26 | 28 |
| Best (34) | 14 | 83 | 93 | 25 |
| Worst (9) | 26 | 0.9 | 0 | 64 |
| **BHaar** | **%Rec** | **%Pre** | **%TP** | **%FP** |
| Mean | 15 | 17 | 18 | 65 |
| Std Dev | 13 | 13 | 19 | 24 |
| Best (92) | 35 | 74 | 50 | 38 |
| Worst (5) | 0.5 | 0.2 | 0 | 92 |

Rec = Overall Recall, Pre = Overall Precision

# Experiments

# Discussion

We presented:

- A new multimedia database for studying object recognition in presence of ***in vitro***/***in situ*** dichotomy.
- Baseline performance figures for three widely used algorithms.

The results suggest the need of more precise and elaborate recognition algorithms.

# Future Work

- We intend to include more objects and grow the number of samples per product.
- We plan to elaborate new algorithms that fuse these different approaches in order to improve results.
- We plan to make use of context information based on physical object proximity to improve localization of objects in natural scenes.