IntelliSys 2016
September 21-22, 2016
London, UK

A Logo-Based approach for Recognizing Multiple Products on the Shelf

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SAI Intelligent Systems Conference 2016
21-22 September 2016 London UK

What is the Problem?

Multiple instance Recognition in Retail Scenario

Figure 1 Grocery Shelf Images from Grocery Products Database

Applications

Companies to monitor brands

Smarter Inventory Management

Help Visually Impaired

Challenges

1. Ever growing dataset (many products have similar appearance, with only minor differences in the color of the package, size of the package, or some text on the box)
2. Per-exemplar training
3. Diverse backgrounds
4. Deformable products

Dataset

We used the Grocery Products Dataset[1].

- Cross-dataset settings
- Our algorithm was tested on 238 different products over 80 Shelves distributed over 3 categories[2].
- Logos were extracted manually from training images of the products.

[1] George, Marian, and Christian Floerkemeier. "Recognizing Products: A Per-exemplar-label Image Classification Approach." In Computer Vision–ECCV 2014, pp. 440-455. Springer International Publishing, 2014.

[2] Results have been reported on the subset of this dataset

Dataset

Figure 2 Product Images from Grocery Products Dataset. cereals, tea, rice (row-wise)

Dataset

Figure 3 Grocery Shelf Images from Grocery Products Dataset

Dataset

Figure 4 Manually Extracted Logos of the Products from Grocery Products Database

Our Approach

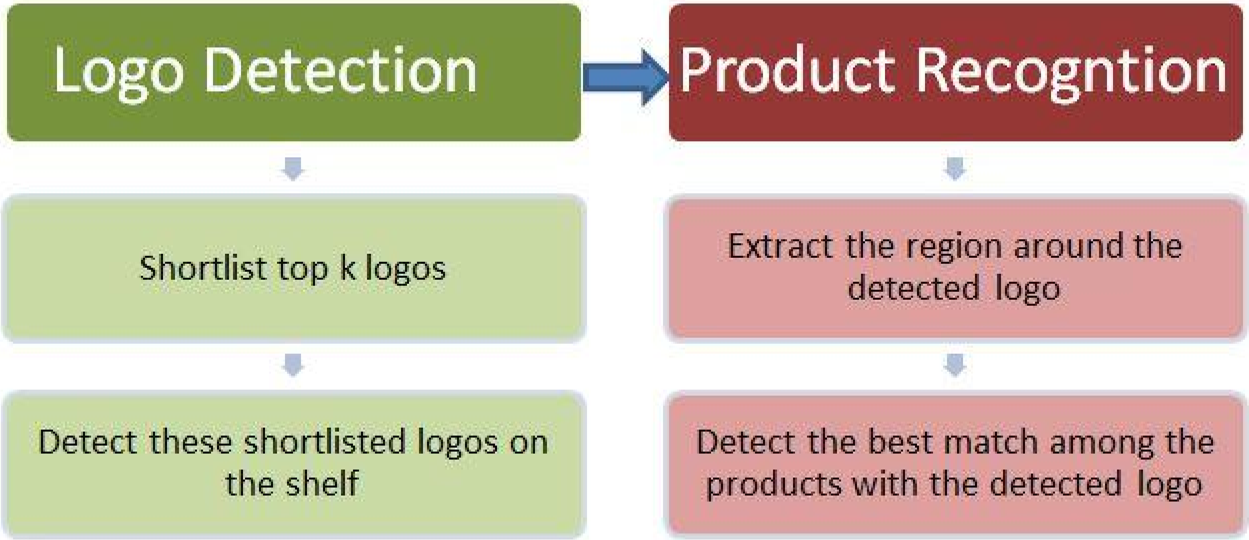

Figure 5 Flowchart representing the methodology followed.

Our Approach

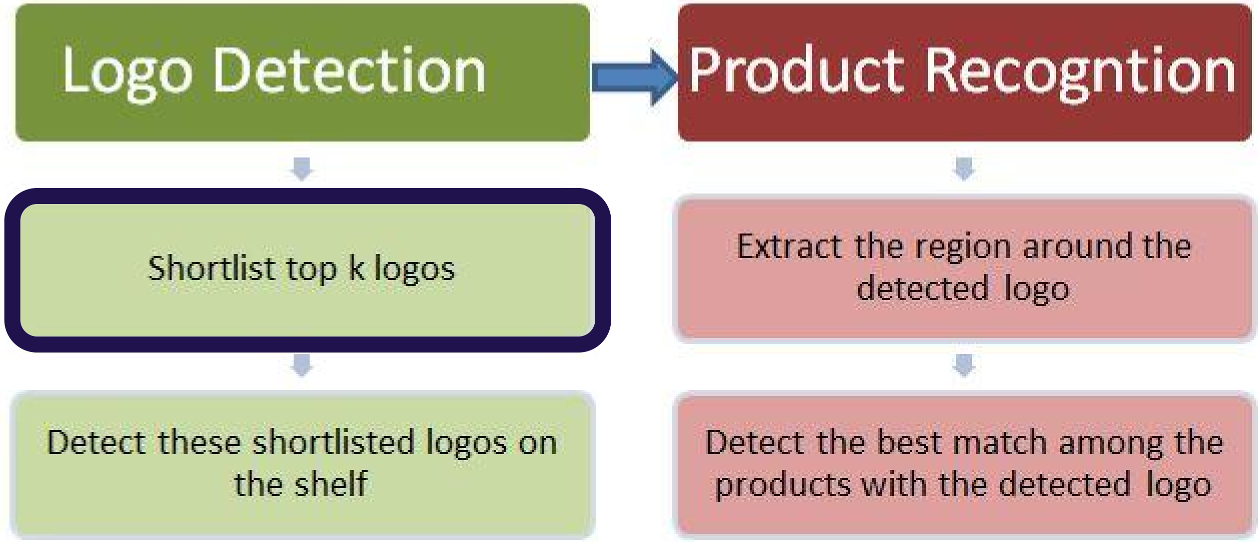

Figure 5 Flowchart representing the methodology followed.

Our Approach

- To shortlist a set of k logos from the logo space, we compute the SIFT keypoints and descriptors **(logo keypoints)** of the logos in the training data, which are then extracted and stored. This is a one time computation.
- Then we extract the SIFT keypoints and descriptors of the particular shelf image **(shelf keypoints)**. Each of the shelf keypoints are matched with the logo keypoints using a FLANN matcher.
- Once this is done, for every shelf we count the number of keypoints that got matched with it and pick top k logos based on these matched keypoints.

Our Approach

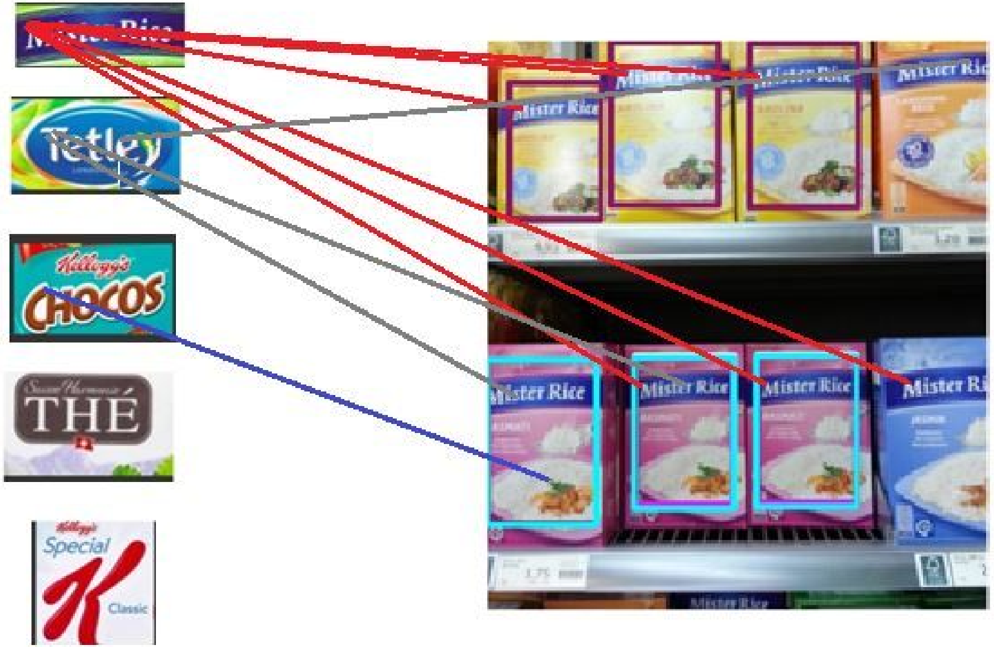

Figure 6 Selection of top k logos

Our Approach

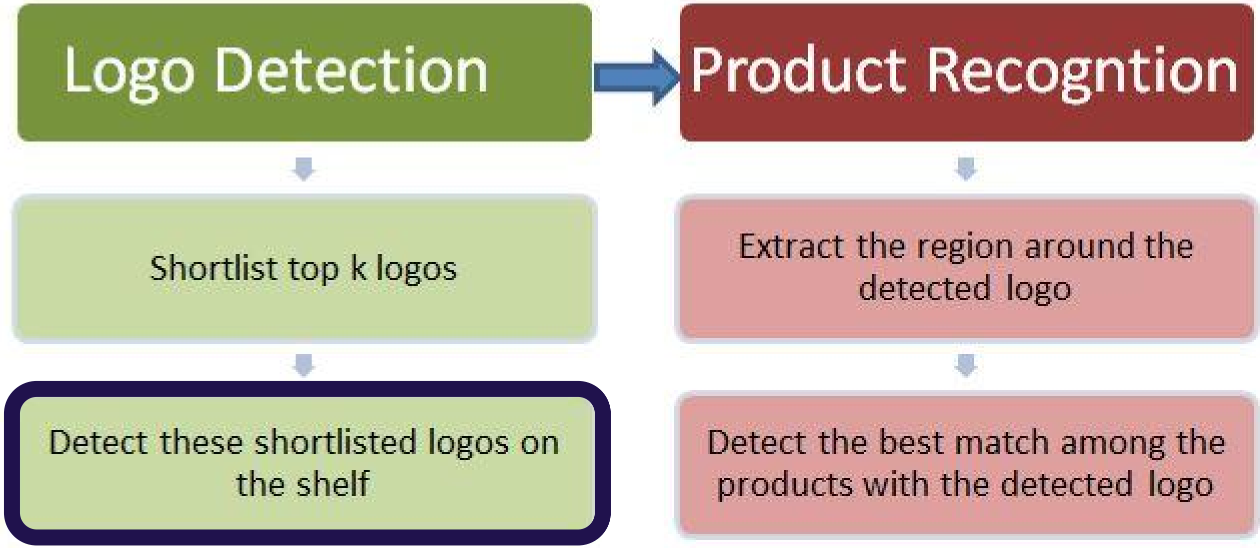

Figure 5 Flowchart representing the methodology followed.

Our Approach

- The next step is to use scale invariant template match to localize the logos. This helps in selecting a few regions rather than doing an exhaustive search.

- To get rid of the false positives, we compute SIFT keypoints and descriptors within each of the selected regions. Then, match these keypoints to the corresponding logo with a FLANN matcher. If the matches are low, we eliminate the selected region.

Our Approach

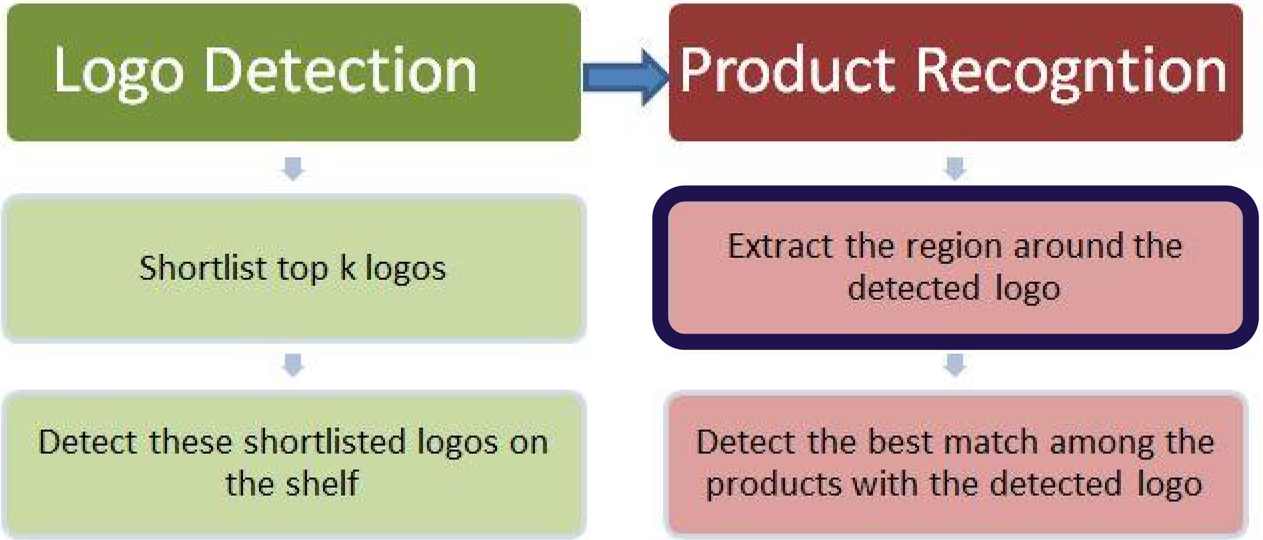

Figure 5 Flowchart representing the methodology followed.

Our Approach

Figure 7 Extraction of region around the logo.

Our Approach

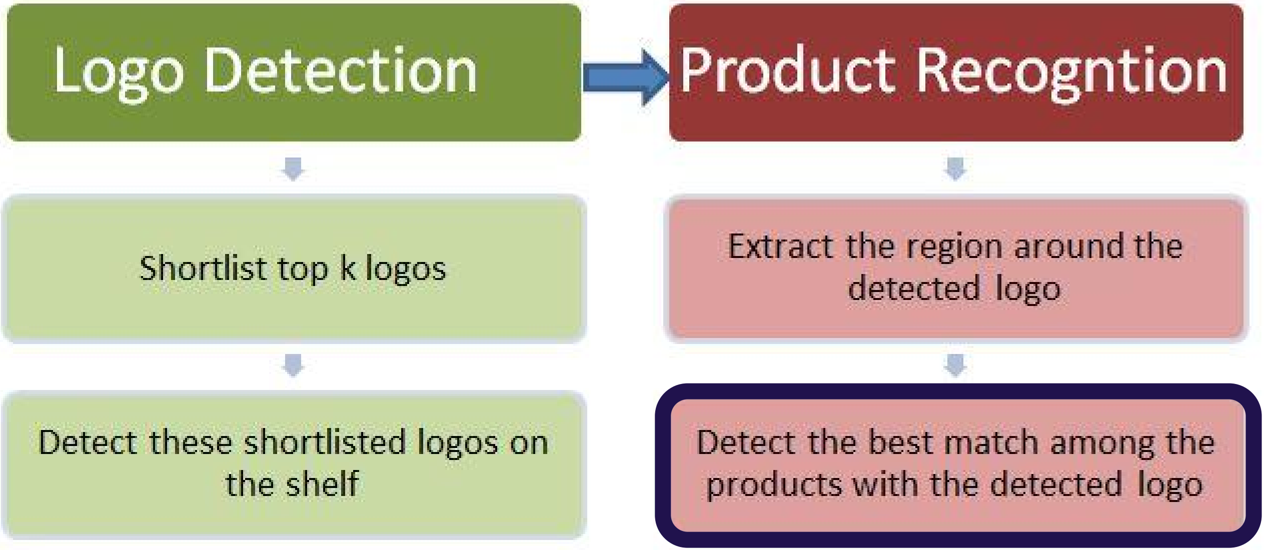

Figure 5 Flowchart representing the methodology followed.

Our Approach

- To do this, we extract a region around the logo and do a scale-invariant template match in RGB space separately. (To recognize products color plays an important role.)
- The best value of the summation of all the three indices is used to determine the product.

Figure 8 The final output of the Grocery Products Recognition System.

Results

The performance of our approach was evaluated using the mean Average Precision (mAP) measure.

$$mAP = \frac{TP}{TP + FP}$$

Where TP stands for True Positives and FP for False Positives.

Results

Category	Accuracy (mAP)
Cereal	80.58
Rice	90.22
Tea	71.86

Table 1 Accuracy for logo detection step.

Results

Category	Baseline Accuracy (mAP)	Accuracy (mAP)
Cereal	49.43	60.21
Rice	25.083	61.15
Tea	21.34	30.70

Table 2 Accuracy for the entire Grocery Product Recognition System.

Conclusion (USPs)

Scalability

Per-exemplar training

Cross-dataset setting

Thank you:)