Visual Object Recognition using Template Matching

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Quick Overview of Template Matching

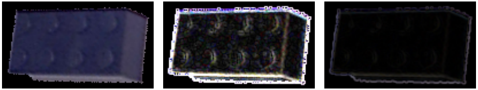
- This is an old well established technique.
- A simple task of performing a correlation between a template image (object in training set) and a new image to classify.
  - Sum of All Differences (SAD)
  - Sum of Square Differences (SSD)
  - Normalised Cross Correlation (NCC)
- Below: Raw Template (left), Edge Based Template (right). For each image set: test image (left), template (right).



The Research

- Template Matching is a rich object detector. Captures entire essence of an object (not the case for many "higher-order" techniques).
- Some object have no or poor internal features so they are not well suited to "higher order" techniques. E.g. aspect graphs use edge features. It's not always possible/easy to detect edges.
- So what is the problem with Template Matching? It's expensive!
- This research addresses this scaling problem with results based on 91 classes and 140 000 extracted blobs each of size 680x480.
- Biologically inspired for real time long-term visual robotic systems.

Not always easy to detect edges



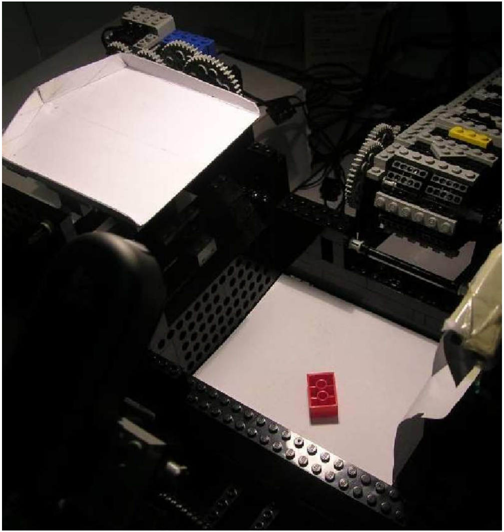
Approach Introduction

- Training database acquisition and extraction.
- Training database reduction to create template images.
- Random classification via NCC's as it is the best form of correlation and the most expensive.

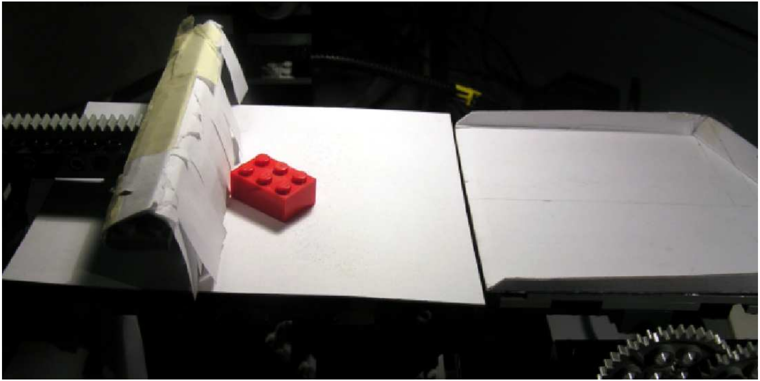
The Object Database

- **Lego Bricks**
- 140 000 image with 91 bricks, approximately 1000 different views for each class.
- Why is it a good database?

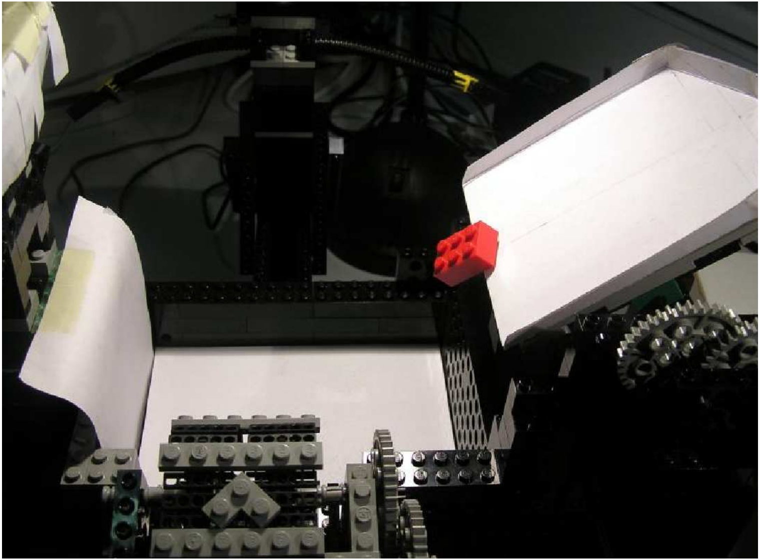
Training Database Acquisition



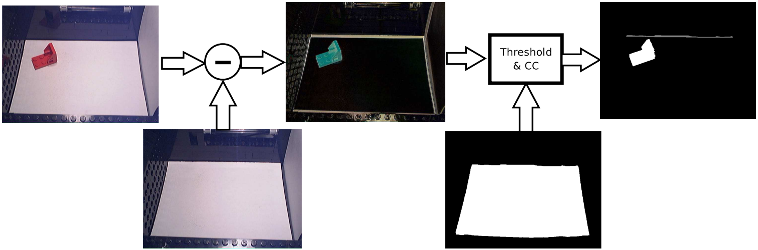
Training Database Acquisition

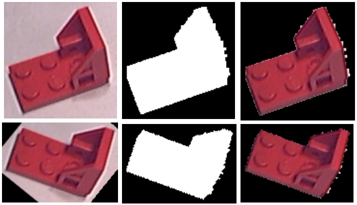


Training Database Acquisition



Training Database Extraction

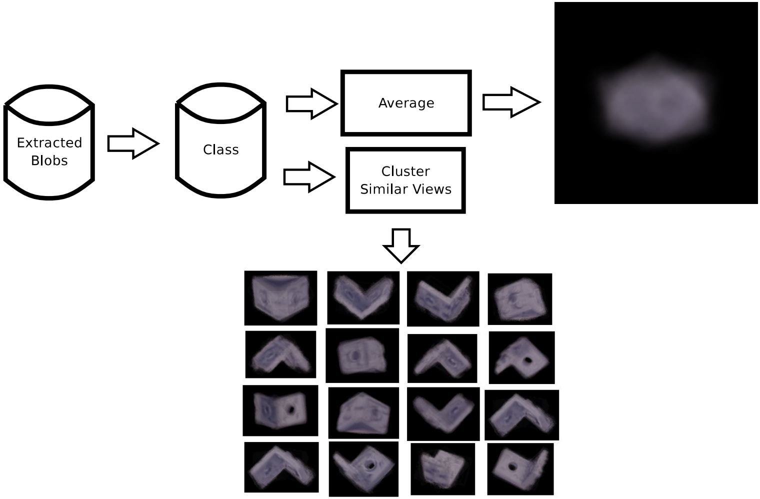




Training Database Reduction

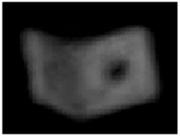
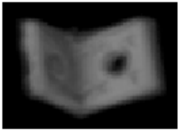
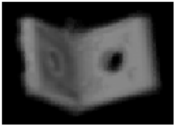
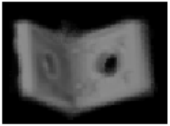
- Classifying a new test image across all the extracted blobs would be computationally infeasible.
- So we reduce the set (since we expect similar and incorrect images).
- If two images are similar, we do not simply keep one image and remove the rest. Instead, a clustering approach was taken.
- Each class is represented by a two-tier hierarchical structure.

Training Database Reduction

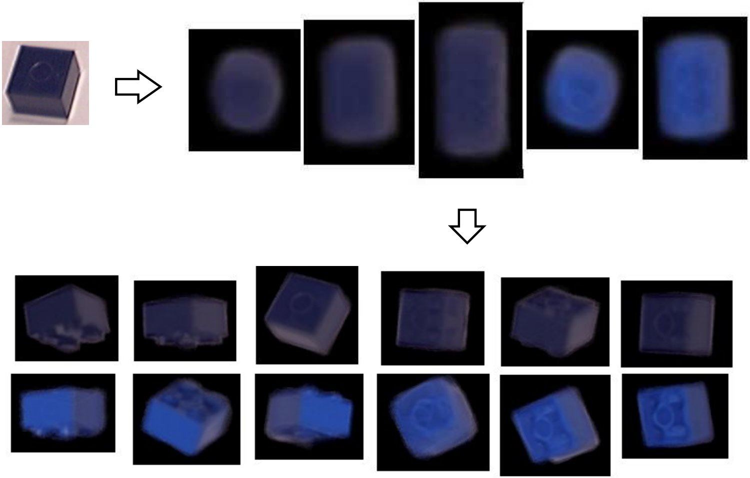


Training Database Reduction

- Obviously determining the correct NCC threshold would be a task in itself. So our results are based on four reduced sets with the NCC threshold equal to 0.75, 0.8, 0.85, 0.9.

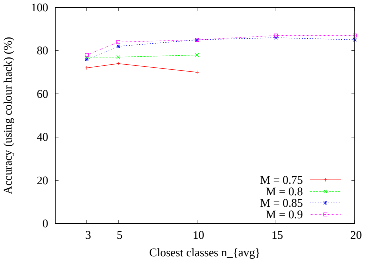
Recognition Procedure

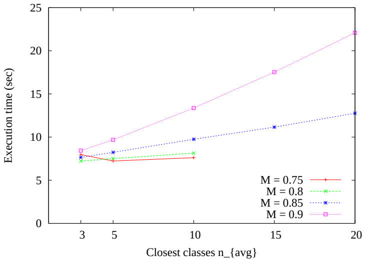


Results

- C/C++ Implementation.
- Images obtained from a standard webcam (640x480).
- Results obtained on a AMD Athon(tm) XP 2700+ with 1GB of memory, running Debian Linux.
- Different reduced sets (M) and closest classes (n_{avg}).

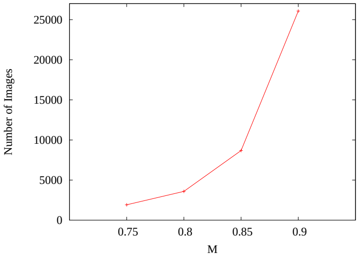
Accuracy and Execution Time

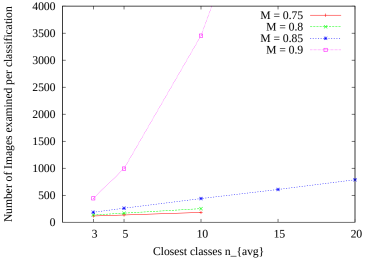




- Lastest result: 90% in 6.75 seconds for $n_{avg} = 15$, $M = 0.9$

Reduced and Examined Images





Conclusions

- Uses all of the information about each object
- Not exactly real-time, however still favorably over more complex methods that take many minutes (NCC optimizations).
- Clustering and averaging seems an interesting way to catalogue and classify an object.
- Large computation required for unsegmented recognition

Future Work

- More rigorous method to extracting and clustering.
- The green factor!
- Hardware implemention to template matching (FPGA).
- More camera views.
- Physical interaction.

Acknowledgements

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