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Detection of Data Matrix Encoded Landmarks in Unstructured Environments using Deep Learning

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Presentation Outline

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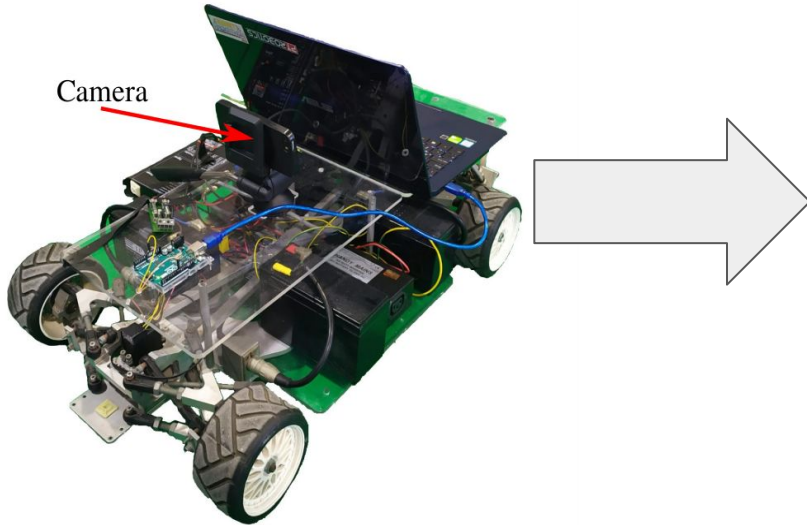
1. Introduction

Produtech Project

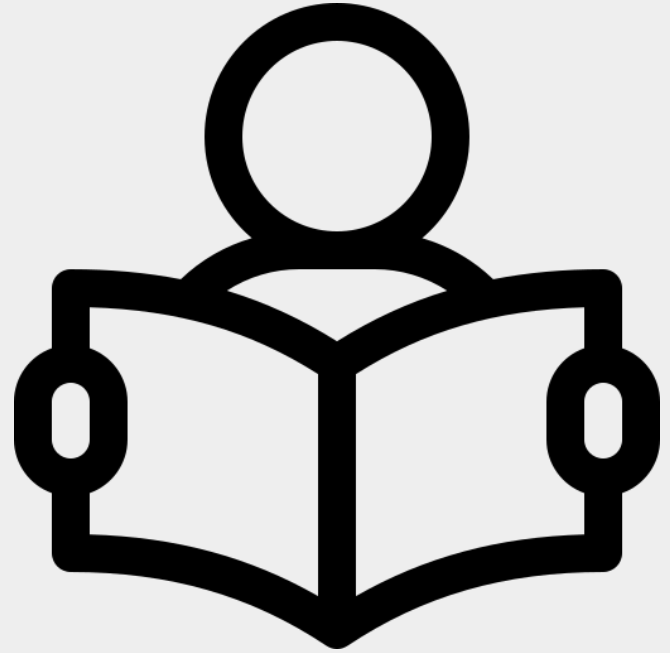
- Development of a flexible and low-cost localization and navigation system
- Mobile robot capable of computing its own location in real-time
- Robust system to perform in complex and unstructured environments such as production facilities
- Detect encoded landmarks (with its own location) and then apply triangulation/trilateration techniques

1. Introduction

How do we do that?



2. Related Work

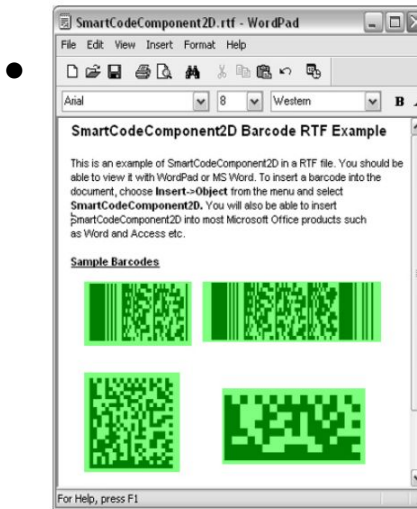


2. Related Work

Object Detection DL Approaches

- Faster RCNN
- YOLO (all versions)
- SSD (Single Shot Detection)

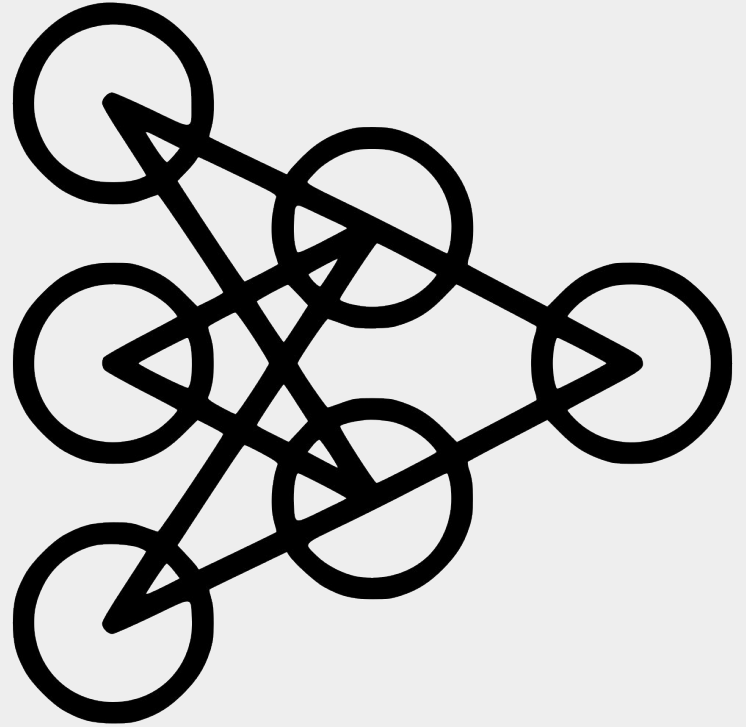
Data Matrix Detection



from: A.Zharkov and I. Zagaynov,
“Universal barcode detector via
semantic segmentation”,
Available:
<http://arxiv.org/abs/1906.06281>

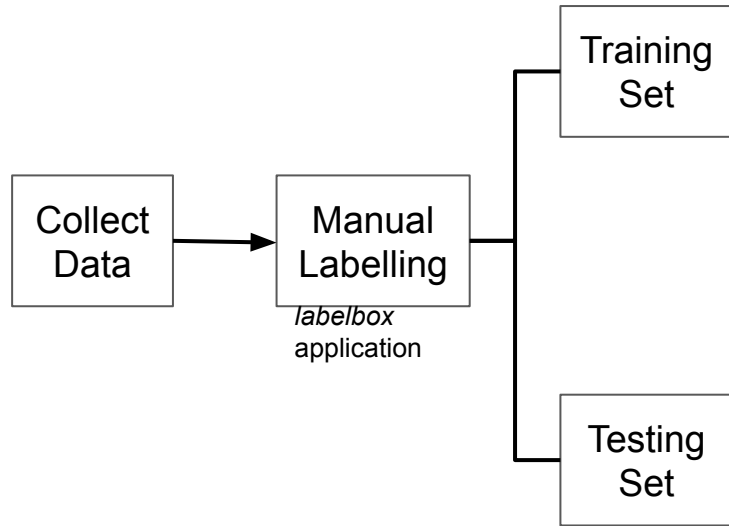
- Classic algorithm from libdmtx (Python library)

3. Proposed Approach



3. Proposed Approach

a. A dataset of Data Matrix Images



Lab (78 frames)



Workshop I (78 frames)



Hallway (158 frames)



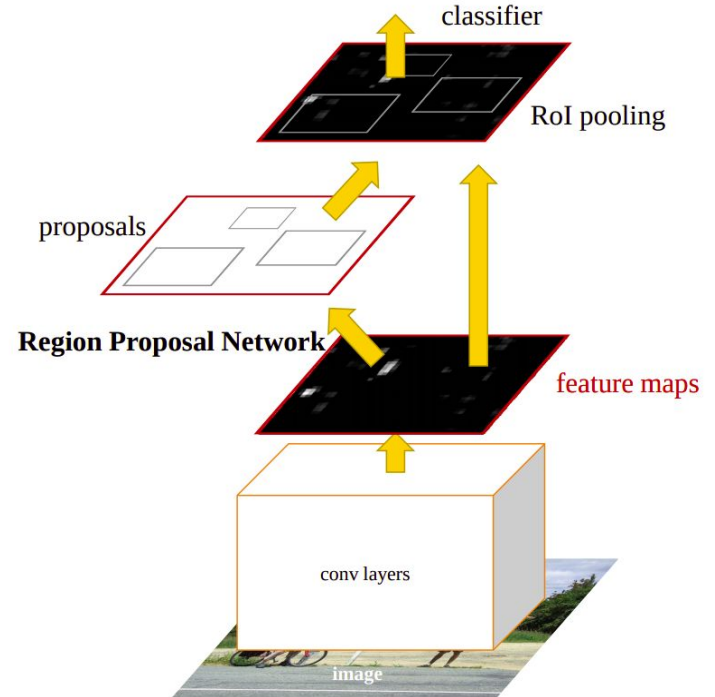
Workshop II (66 frames)



3. Proposed Approach

b. Faster RCNN Architecture

- 2 modules(deep fully convolutional network and classifier)
- Region Proposal Network (RPN)
- Faster R-CNN detector
- Non-Maximum Suppression (NMS)





3. Proposed Approach

c. DNN Training Details

- Detectron2 research platform (Pytorch)
- Training images size: 8000×6000
- Data Augmentation: image resizing and random flip
- Learning rate: 0.00025 during 4000 iterations
- NVidia RTX2080ti GPU
- NMS threshold: 0.7

4. Experiments and Results





4. Experiments and Results

Evaluate the trained model on the test set

- COCO dataset metrics:

- Average Precision (AP):

$$P = \frac{T_P}{T_P + F_P} \quad T_P \text{ (True Positive)}$$

F_N (False Positive)

- Average Recall (AR):

$$R = \frac{T_P}{T_P + F_N}$$

4. Experiments and Results

Experiments and Results

AR>AP

| | IoU Thresholds | Scales | maxDets | AP/AR values |
|----|----------------------|--------|---------|--------------|
| AP | [0.50 : 0.05 : 0.95] | all | 100 | 0.619 |
| | 0.50 | all | 100 | 0.876 |
| | 0.75 | all | 100 | 0.730 |
| | 0.95 | small | 100 | 0.364 |
| | [0.50 : 0.05 : 0.95] | medium | 100 | 0.565 |
| | [0.50 : 0.05 : 0.95] | large | 100 | 0.737 |
| AR | [0.50 : 0.05 : 0.95] | all | 1 | 0.288 |
| | [0.50 : 0.05 : 0.95] | all | 10 | 0.669 |
| | [0.50 : 0.05 : 0.95] | all | 100 | 0.670 |
| | [0.50 : 0.05 : 0.95] | small | 100 | 0.438 |
| | [0.50 : 0.05 : 0.95] | medium | 100 | 0.611 |
| | [0.50 : 0.05 : 0.95] | large | 100 | 0.786 |

- Both metrics averaged over multiple IoU thresholds (threshold $\in [0.50; 0.95]$ in steps of 0.05 $\rightarrow [0.50 : 0.05 : 0.95]$)
- For AP, a constant IoU thresholds of 0.5 (), 0.75 and 0.95 are also computed
- Small objects: $area < 32^2$, medium objects: $32^2 < area < 92^2$ and large objects: $area > 92^2$
- For AR, maximum number of detections ()
 $maxDets \in \{1, 10, 100\}$



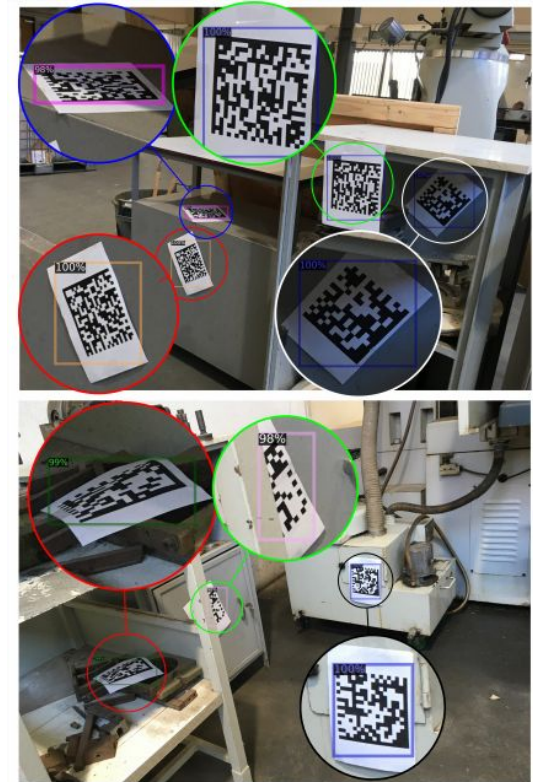
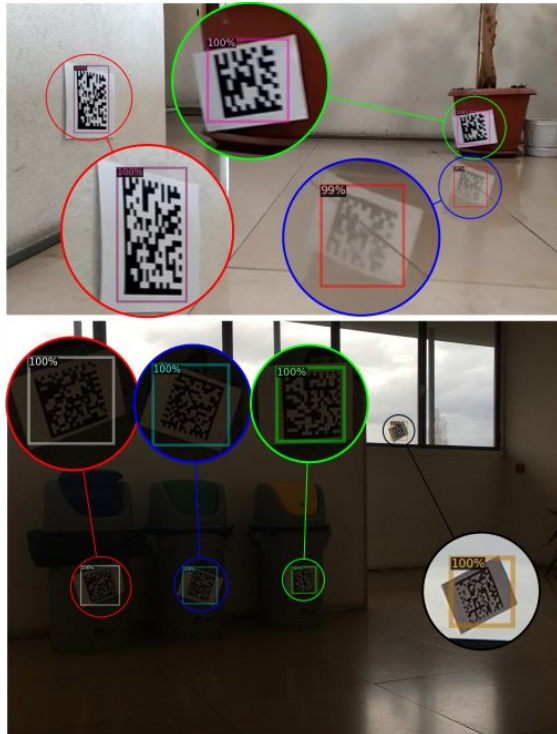
4. Experiments and Results

Running Time Results and Comparisons

- 144 ms per image (7 fps)
- Only 45% of the test set frames were accurately processed by the classic algorithm
- The running time for the classic algorithm was 4.97 s per image (40 times slower than the model that we use in this paper)

4. Experiments and Results

Qualitative Results



5. Conclusions and Future Work





5. Conclusion and Future Work

- The model performs accurately and it is consistent by detecting almost all the landmarks in the test set;
- Overcomes by far, in performance and frame rate, the traditional algorithms;
- This implies a self-localization system more robust and performant;
- Future work; the development of a DNN whose outputs are parallelograms instead of simple rectangular bounding boxes; this would provide a novel technique for finding the transformation robot-marker with only one necessary landmark.



<https://github.com/tmralmeida/faster-rcnn-data-matrix>

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