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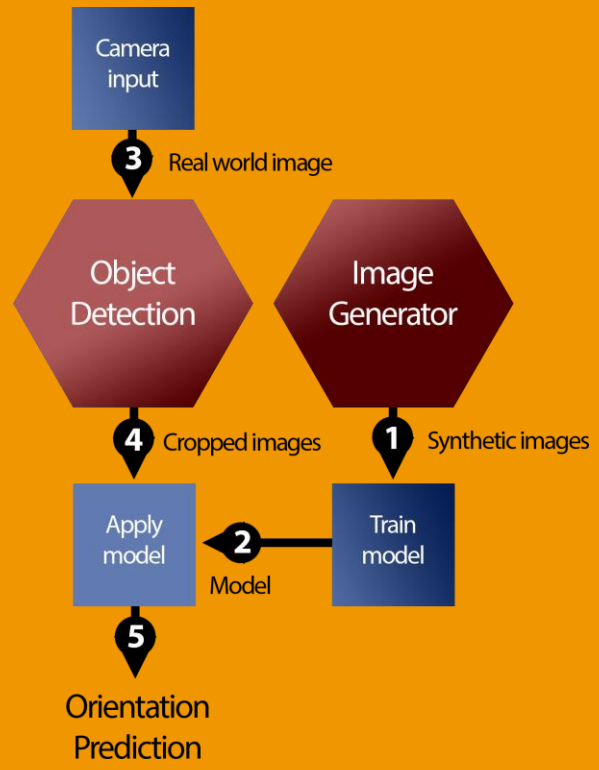
Synthetic Images for Training and Object Orientation Prediction

A concept for raising spatial awareness from 2D-images

Introduction

- our goal is to detect the position and orientation of objects in regular images
- generate synthetic images labeled with known spatial data
- train our models on the synthetic images
- apply the model to real world images

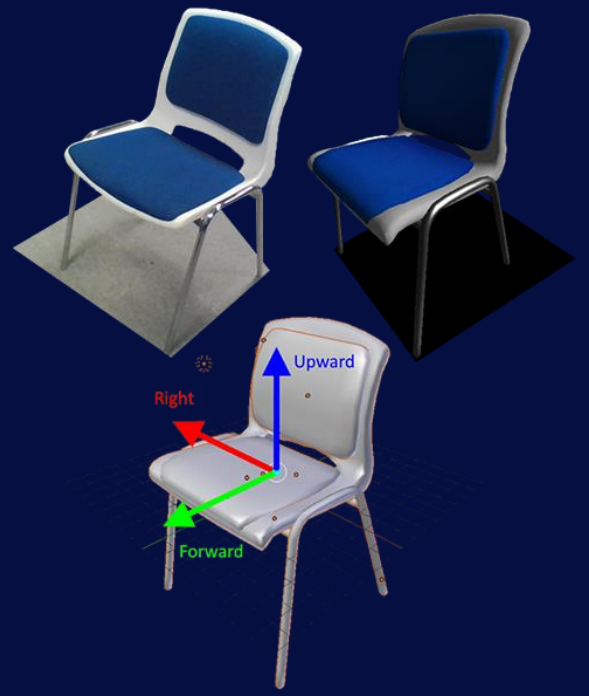


Technology

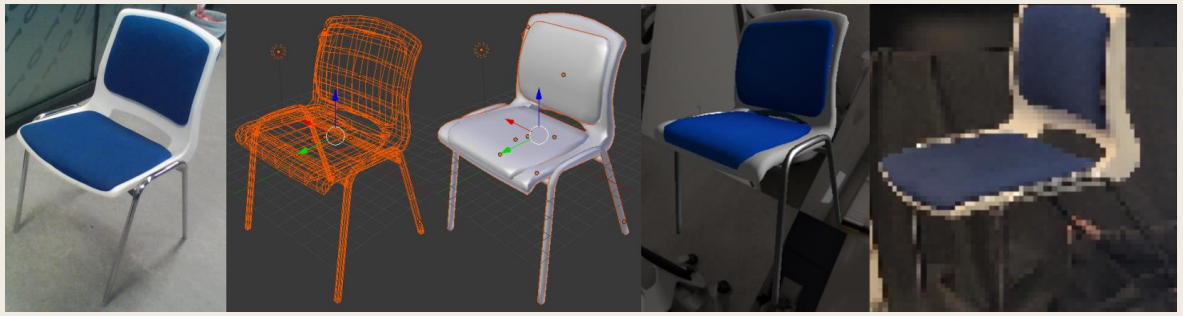
- Python
- Modeling and rendering
  - Blender
  - ModernGL
- Orientation prediction
  - Keras
- Object detection
  - OpenCV
  - YOLO v3

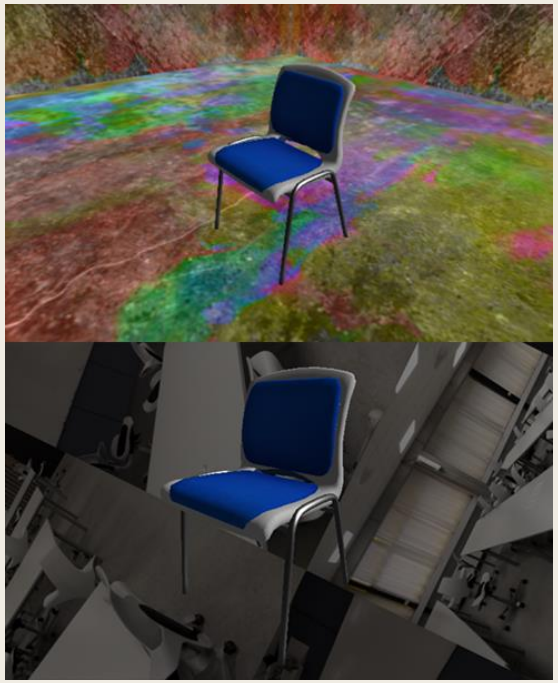
Our case

- We choose a chair as object to train on
- Recreated the chair with 3D-modeling software



Rendering

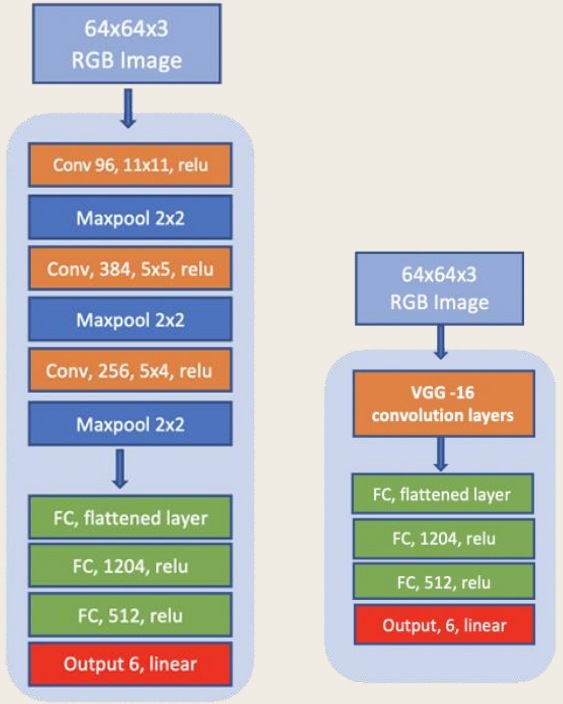




- Obtaining the training data
- ModernGL
- Blender
- Rendereing
- Describing orientation
- Background
- Visualization

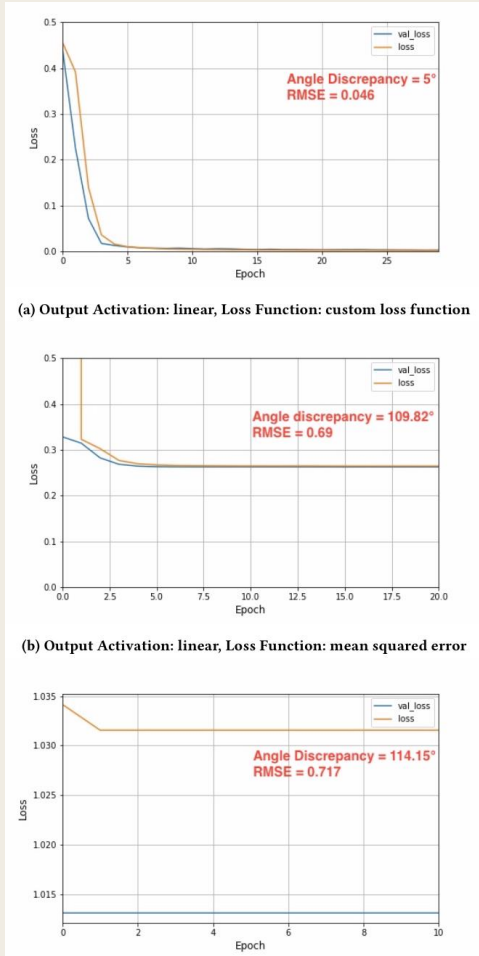
Orientation prediction

- Architechture
  - Simple CNN
  - VGG-16
  - ResNet-50



Customized Loss Function

- Modification of a standard mean squared error function implemented on Tensorflow



Experiment results

No.	VGG-16 models	RMSE	Angle Discrepancy	Runtime/epoch (during training)	no.epoch
1.	VGG-16 - Option 1	0.65	97.82°	510 s	8
2.	VGG-16 - Option 2	0.10	10.13°	502 s	25
3.	VGG-16 - Option 3	0.047	5°	191 s	30
4.	VGG-16 - Option 4	0.169	19.07°	156 s	25

Table 2: Comparison of best models

No.	Models	RMSE	Angle Discrepancy	Runtime/epoch (during training)	no.epoch
1.	VGG-16 - Option 3	0.047	5°	191 s	30
2.	Simple CNN	0.055	4.22°	460 s	34
3.	Resnet50	0.47	68.78°	60 s	30

Object detection

- Background
- YOLO
- OpenCV

Conclusion

- To predict orientation using regression is possible, with modification of loss function
- Models sensitive to small differences between the synthetic images and the real test data
- The use of pre-trained weights is useful in our case to compensate for the lack of robustness of our model.

Comparison in Predicting With Real Rest Image