

PROGRAM

16u30 End of workshop

09u30	Welcome and coffee
10u00	Official welcoming & introduction EAVISE
10u15	Introduction object categorization + a look at the algorithm
11u00	Break with coffee
11u15	First hands-on: object annotation tool and preprocessing of the necessary data
12u30	Warm lunch & coffee (sponsered by 🔥 data vision)
13u30	Second hands-on: a deeper look at the training process, training an object model and testing the actual detector
15u00	Break with refreshments
15u15	Some downsides to the techniques / discussion on the quality of an object detector model
16u15	Questions & evaluation of workshop

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EAVISE
Embedded Artificially intelligent VISion
Engineering
Translating state-of-the-art
image processing



- Implementing advanced image processing techniques on embedded systems.
- Optimizing vision algorithms to reach real time performance.
- Applying new Artificial Intelligence techniques in computer vision applications.





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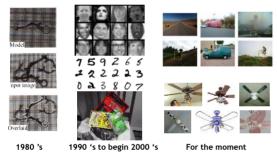
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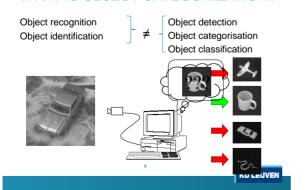
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RECENT EVOLUTION OF VISUAL



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WHAT IS OBJECT CATEGORIZATION?



WHAT IS OBJECT CATEGORIZATION?

• FOCUS → objects within a same class show in between variations in color, shape, size, ... e.g. cars









• It becomes harder when more and more variation occurs









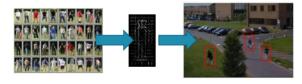




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OVERAL APPROACH WITH OBJECT CATEGORIZATION TECHNIQUES

- Training step: learning a general description from and object class and store it into a model
- **Detection step:** searching in new images for objects by comparing the existing model with the input image



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OVERAL APPROACH WITH OBJECT CATEGORIZATION TECHNIQUES



3

A LOT OF VARIATION CHALLENGES

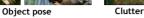


















Viewpoint

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GETTING A ROBUST DETECTOR







- State-of-the-art techniques are able to do alot:
 - Learning variation (appearance, scale, shape, ...) contained in object classes.
 - Compensating for clutter occlusion and overlapping objects.

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AIM OF TOBCAT PROJECT



- Introducing these modern state-of-the-art techniques of object classification to the target group of industrial companies.
- Making the available technology transparent and easy to use for industrial companies, making them able to use the technology themselves.
- Introducing object categorization in companies of the user group, so that they can solve their problems using these techniques







APPLICATIONS IN TOBCAT (1)



APPLICATIONS IN TOBCAT (2)



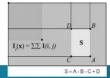
APPLICATIONS IN TOBCAT (3)



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STATE-OF-THE-ART ALGORITMES	
1. Viola&Jones : Haar/AdaBoost [CVPR2001] (workshop)	
Dalal&Triggs: HOG/SVM [CVPR2005] Felzenswalb: deformable part models [CVPR2010]	
4. Dollár : integral channel features [BMVC2009]	
1. 2.	
gradienthistogram grad. LUV	
3.	
TOP AVEC LIGED TECHNIQUE	
TODAY'S USED TECHNIQUE VIOLA & JONES	
Short wrap-up of all steps needed in the algorithm	
It all starts from a sliding window approach	
Selecting features from window	
Building a set of weak classifiers	
Combining weak classifiers to a single	
strong classifier	
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TODAY'S USED TECHNIQUE VIOLA & JONES

- 1. Selecting features from window
 - Using HAAR-like wavelets
 - Small filters on image by comparing pixel values in square regions
 - Sum pixel intensity values grey area
 - sum pixel intensity values white area
 - 24x24 pixels → +-50,000 features
 - Use of integral image
 - Fast calculation of sums



TODAY'S USED TECHNIQUE VIOLA & JONES

- 2. Building a set of weak classifiers
 - AdaBoost algorithm
 - Which feature or combination of features can be used to separate objects and non-objects in a rough way
 - Do this until a certain preferred level of separation is reached, e.g. 50% good separation.







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TODAY'S USED TECHNIQUE VIOLA & JONES

- 3. Combining weak classifiers to a single strong classifier
 - Cascade / waterfall structure
 - Weak classifiers → faster calculation / less features
 - To reduce the error (individually very high)
 - 'Early rejection' principle





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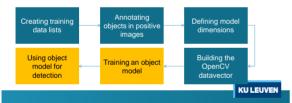
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IDEA OF FIRST HANDS-ON SESSION

- From a dataset, prepping all data to be able to built a complete object model.
- Goal: make a company able to detect an object class on different backgrounds.
- Required steps:



SOME GUIDELINES FOR HANDS-ON PARTS OF THE WORKSHOP

- Login on computers using tobcat account, pwd = tobcat
- Open a terminal window
 - Standard ~/ directory
 - We will work from

o vve will work from

/home/tobcat/workshop/

- Some of the most used commands
 - o cd <path> → changing folder
 - $_{\circ}$ Is \rightarrow summing the contents of a folder
 - $_{\circ}$./<executable_name> [green color in ls] \rightarrow code snippets
 - o If executable is not green → chmod +x <executable>

SOME GUIDELINES FOR HANDS-ON PARTS OF THE WORKSHOP	
As a C++ development environment we use Code::Blocks. • Preinstalled on the system	
 Folder software contains all configured projects Folder code_blocks contains code for second hands-on Re-occuring problem = Code::Blocks 'forgets' OpenCV 	
 Project – Build Options – Linker settings – Additional Linker Commands 	
 Add `pkg-config opencvlibs` [with correct quotes!] If there are any software problems, do not hesitate to call for an assistant or to interrupt the hands-on! 	
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OBJECT ANNOTATION TOOL & PREPROCESING STEPS	
Lets changed the directory towards/workshop/data/mini_model/	
There is an existing structure	
 Positive folder contains images with objects Negative folder contains images without objects 	
 This structure needs to be manually composed Names of folders are not important, however choosing a meaningful name can help to understand everything. 	
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OD IFOT ANNOTATION TOOL 9	
OBJECT ANNOTATION TOOL & PREPROCESING STEPS	
Which steps do we have to take in order to be able to train an object model of a specific object class?	
All code snippets work using txt files with references to the	
actual data	

SNIPPET – ./folder_listing

SNIPPET - ./annotate_images

background information

NEEDED – positives.txt / negatives.txt / testset.txt

2. Object annotation – segmenting positive objects from their

NEEDED – annotation of each object – universal format

OBJECT ANNOTATION TOOL	8
PREPROCESING STEPS	

1	NAME	#DETECT	IONS	X1	Y1	W1	H1		Xn	Xn v	n H	n.						
	D:\cooki																	
	D:\cooki																	
	D:\cooki																	
	D:\cooki																	
	D:\cooki																	
7	D:\cooki	ies\posi	tives_	3a.pn	g 3	81	34	143	15	4 25	20	6 17	4 1	46	6	347	13	7
В	D:\cooki	ies\posi	tives_	4.png	6	132	57	153	3 12	9 19	9 1	95 1	43	13	7 2	61	349	1
	D:\cooki																	
	D:\cooki																	
	D:\cooki																	
2	D:\cooki	ies\posi	tives_	6.png	6	87	89	149	154	180	21	9 15	3 1	43	22	8 1	4 1	48
3	D:\cooki	ies\posi	tives_	7.png	6	197	19	148	14	6 75	11	6 14	6 1	53	17	3 2	39	14

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OBJECT ANNOTATION TOOL & PREPROCESING STEPS

Which steps do we have to take in order to be able to train an object model of a specific object class?

- 3. The annotated data has to be translated to an OpenCV specific data storage format
 - Universal format for model training
 - Reshapes training data to average dimensions
 SNIPPET ./average_dimensions & ./create_samples
 NEEDED datavector.vec

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OBJECT ANNOTATION TOOL & PREPROCESING STEPS

Usefull tools - snippets for companies

- ./video2images lots of data is captured as video material. This snippet will make sure that videos can be cut into frames without compression loss.
- Jgenerate_negatives a lot of companies collect images from objects but not the actual backgrounds without objects
 - o Reads an annotation file
 - \circ $\;$ Cuts the annotations from the positive images
 - o Uses the cut result as negative background images
 - $_{\odot}\;$ Has influence on performance! (unnatural image constructions)

LUNCH	
The lunch is offered to us by 💠 data vision	
A system of self service (dessert / soup / lunch)	
We eat in dining room 'de fruytenborg'	
Coffee afterwards is included	
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PITCH – Data Vision	
A small company pitch by 💠 data vision	
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TRAINING PROCES + TESTING	
DETECTOR WITH OBJECT MODE	L

Until now, we prepared data for training an actual object model.

- ./train cascade →SNIPPET
- Test with 'simple' model
 - Get the hang of it!
 - Variation in candies itself → segmentation here would already be a difficult task
 - On a test set background from our lab
- We will take a closer look at the output of the training

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TRAINING PROCES + TESTING DETECTOR WITH OBJECT MODEL

For the second hands-on session, we will focus on an already trained object model:

- Go to .../data/candy_model/
- 160 positive images 1000 negative images
- 18 stage classifier = # combined weak detectors

First we will test the interface of OpenCV for object detection, play with important parameters, then we will do it ourselves.

- 1. Preprocessing image grayscale / histogram equalization
- 2. Detection and parameter influence in code
- 3. Visualization and parameter influence in code

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ROTATION INVARIANCE

1 model = 1 orientation

- How can we deal with 1 single model
- Should we place all rotations in a single model?
- Should we rotate the image or the patch?

Live simulation of the rotation invariant candy detector

- Influence of parameters
- Real time performance possible using specific knowledge?
- Taking a look at parameters in source code

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SOME DOWNSIDES OF TECHNIQUES	
(ROTATION, CLUTTER, OCCLUSION)	
Rotation was already discussed before	
Technique is partially resistant to clutter Depends strongly on training data	
 Only perfect objects → imperfect objects will never be 	
detected	
Technique is not resistant to occlusion.	
Detectors fail pretty soon when occlusion happens	
 However the DPM approach is a valid alternative and a bit 	
more robust than V&J framework	
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SOME DOWNSIDES OF TECHNIQUES	
(ROTATION, CLUTTER, OCCLUSION)	
In beginning of session we discussed 4 techniques, so what	
can you expect from OpenCV and C++ possibilities?	
■ Viola & Jones in OpenCV	
Well supported – tutorials / documentation / bug free	
 Large community gives great support 	
■ SVM + HOG	
 Partial components in OpenCV, a detection framework 	
Not combined to an effective training/detection framework Mechine learning SV/M N had support/gode.	
 Machine learning SVM → bad support/code KULEUVEN 	
NO ENOTES	

SOME DOW	NSIDES OF	TECHNIQUES
(ROTATION,	CLUTTER,	OCCLUSION)

In beginning of session we discussed 4 techniques, so what can you expect from OpenCV and C++ possibilities?

- DPM model of Felzenszwalb
 - OpenCV only has detection Latent SVM module
 - Based on Pascal VOC Challenge models & software
 - Not latest implementation, no new models since challenge was stopped
 - · Training original project:
- ICF Dollar
 - OpenCV 'development' branch ...

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SOME DOWNSIDES OF TECHNIQUES (ROTATION, CLUTTER, OCCLUSION)

In beginning of session we discussed 4 techniques, so what can you expect from OpenCV and C++ possibilities?

- All software will be made available on TOBCAT website, also code developed in future.
- Also through a github account (source code repository)
 https://github.com/StevenPuttemans/tobcat

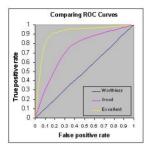
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EVALUATING OBJECT DETECTORS:	
RECEIVER OPERATING CHARACTERIST	IC



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INTRODUCTION TO ROC CURVES

- ROC = Receiver Operating Characteristic
- Started in electronic signal detection theory (1940s 1950s)
- Has become very popular in biomedical applications, particularly radiology and imaging
- Also used in machine learning applications to assess classifiers
- Can be used to compare tests/procedures

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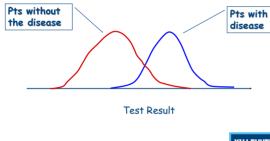
ROC CURVES: EXAMPLE CASE

- · Consider diagnostic test for a disease
- Test has 2 possible outcomes:
 - o 'positive' = suggesting presence of disease
 - o 'negative'
- An individual can test either positive or negative for the disease

True disease state vs. Test result

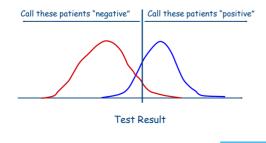
Disease Test	positive	negative
Disease	\odot	X
	True Positive TP	False Negative FN (Type II error)
No disease	X	\odot
	False Positive	True Negative
	FP (Type I error)	TN

SPECIFIC EXAMPLE

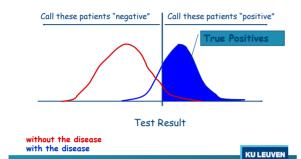


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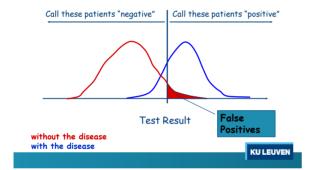
THRESHOLD



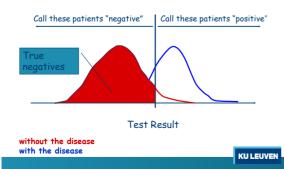
SOME DEFINITIONS ...



SOME DEFINITIONS ...



SOME DEFINITIONS ...

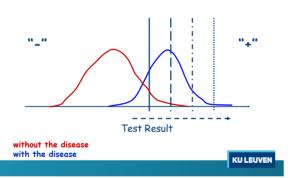


Call these patients "negative" Call these patients "positive" False negatives Test Result

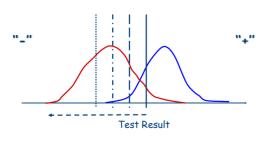
without the disease with the disease

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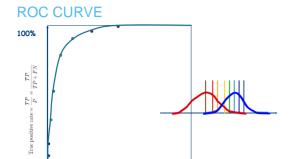
MOVING THE THRESHOLD: RIGHT



MOVING THE THRESHOLD: LEFT



without the disease



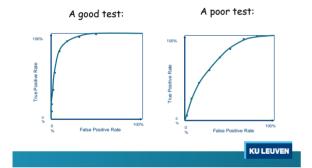
False positive rate = $\frac{FP}{N} = \frac{FP}{FP + TN}$

0%

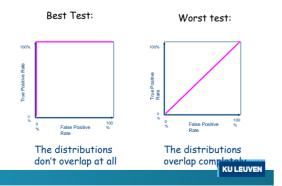
100%

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ROC CURVE COMPARISON



ROC CURVE EXTREMES



AREA UNDER ROC CURVE (AUC)

- · Overall measure of test performance
- Comparisons between two tests based on differences between (estimated) AUC
- For continuous data, AUC equivalent to Mann-Whitney U-statistic (nonparametric test of difference in location between two populations)

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AUC = 100% AUC = 100% AUC = 50% False Positive No. AUC = 90% AUC = 50% AUC = 65% Rate AUC = 65%

APPLICATION ON OBJECT DETECTORS

• Detector scans image in a sliding window fashion:



· Sliding window over image · Each sub-window is analyzed by detector



WHAT THE DETECTOR SEES



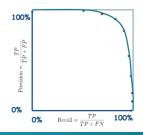
EVALUATING DETECTOR RESULTS



Detector result Ground Truth	detected	not detected
Object present	True Positive	X False Negative
Object not present	X False Positive	True Negative
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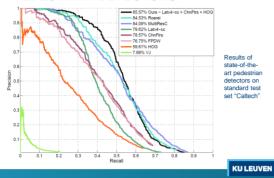
PROBLEM WITH ROC CURVES FOR DETECTORS

- Number of true negatives is not easily countable for images
- Alternative: precision-recall curve

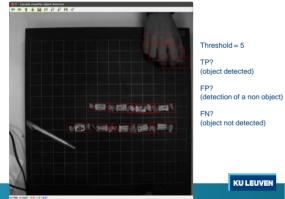




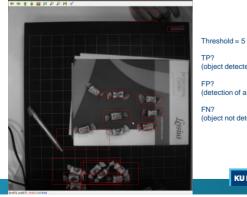
PRECISION-RECALL CURVES FOR PEDESTRIAN DETECTORS



EVALUATION OF A CANDY DETECTOR



EVALUATION OF A CANDY DETECTOR

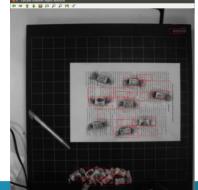


(object detected)

(detection of a non object)

(object not detected)

)F								



Threshold = 5

TP?
(object detected)

FP?
(detection of a non object)

FN? (object not detected)

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EVALUATION OF A CANDY DETECTOR



Threshold = 5

TP? (object detected)

FP? (detection of a non object)

FN? (object not detected)

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EVALUATION OF A CANDY DETECTOR

Precision = TP / (TP + FP)

Recall = TP/(TP + FN)

CONCLUSION	
 To evaluate an object detector we need to: Annotate a set of images Train the detector on a subset of those images (training set) Use the remaining images (test set) to calculate the TP, FP & FN rates 	
 Follow up by calculating precision & recall values Plot the precision-recall curves based on different threshold values for a parameter 	
Attention OpenCV: some detectors (e.g. Viola&Jones) don't give automated scores for each detection, which makes creating PR some a hard taks to do. KULEUVEN	
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of an object detector model 16u15 Questions & evaluation of workshop

First hands-on: object annotation tool and preprocessing of the necessary data

Some downsides to the techniques / discussion on the quality

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