zhaw

Deep Watershed Detector & Music Object Recognition

Deep Learning Day 2018 Friday, 14th September 2018

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Contents



- Why music scanning?
- Why build a custom detection system?
- How does it work?
- How does it really work?

Music scanning





Zürcher Hochschule für Angewandte Wissenschaften





Swiss Confederation Innosuisse - Swiss Innovation Agency



Pdfs Scans Photos

Antique / Handwriting



Page turning **Transposing Orchestra** synchronization

Music scanning









Rendering Software Audio Processing

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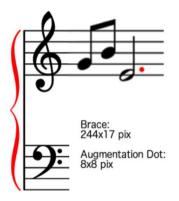
Music object recognition – challenges



Data availability

No dataset available at the time large enough for DL

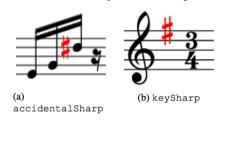
Size imbalance



Class imbalance (top 15 of 118 classes)

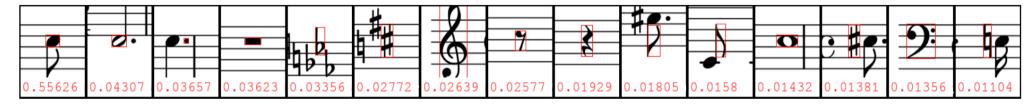
Object size & frequency, image size Next slide

Context dependency





(c) (d) augmentationDot articStaccatoAbove



Tuggener, Elezi, Schmidhuber, Pelillo & Stadelmann (2018). «DeepScores – A Dataset for Segmentation, Detection and Classification of Tiny Objects». ICPR'2018.

Mor vs Natural Images









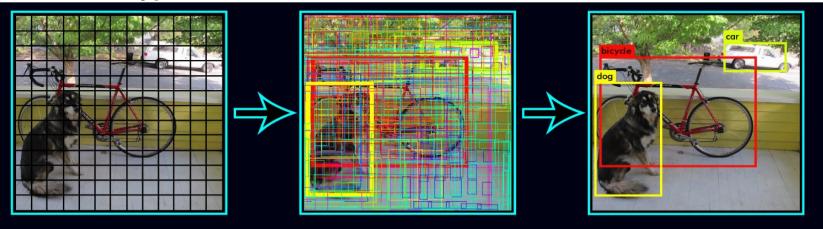






Mor vs state of the art object detectors

YOLO/SSD-type detectors



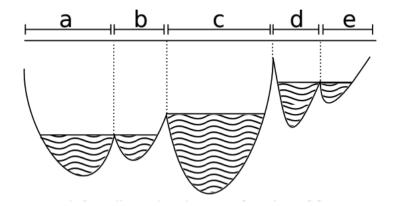
Taken from: https://pjreddie.com/darknet/yolov2/ on 11.9.2018

R-CNN

- Two-step proposal and refinement scheme
- Very large amount of proposals needed at high resolution needed

The deep watershed transform



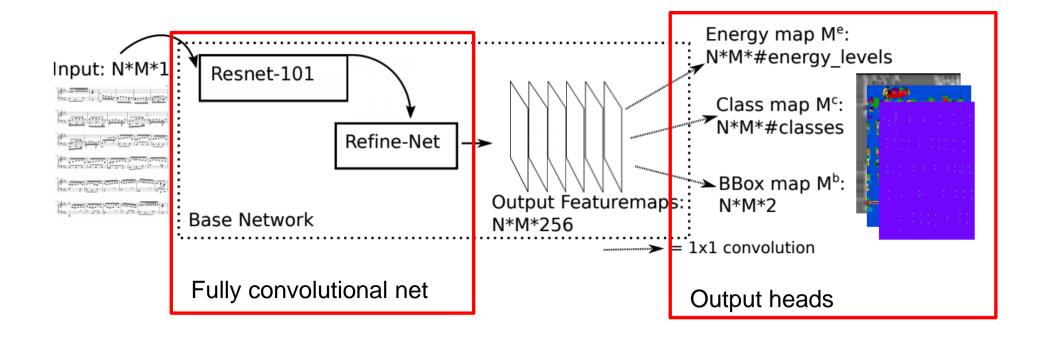


Zürcher Fachhochschule

8

The deep watershed detector





Zürcher Fachhochschule

9

The deep watershed detector



Class Bbox Energy **Ground truth** Prediction Zürcher Fa

Tweaks and improvements



1. Added sophisticated data augmentation in every page's margins



2. Put additional effort (and compute) into hyperparameter tuning and longer training

Elezi, Tuggener, Pelillo & Stadelmann (2018). «DeepScores and Deep Watershed Detection: current state and open issues». WoRMS @ ISMIR'2018

Current results



Ours:

DeepScores: 46.7%

State of the art:

	mAP (%)		
	DeepScores	MUSCIMA++	Capitan
Faster R-CNN	19.6	3.9	15.2
RetinaNet	9.8	7.7	14.5
U-Net	24.8	16.6	17.4

Ongoing and future work



Extend the model capabilities to non-synthetic data.



mAP: 47.5%

- More sophisticated balancing and stability tricks.
- Move to other tasks (natural images)

Closing Remarks



- Data is Key
 - Gathering it can be very expensive
 - Behavior outside training distribution is completely unpredictable
- The deep watershed detector can outperform state of the art
- A lot of the performance is in fine-tuning and engineering





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Download DeepScores:

• https://tuggeluk.github.io/downloads/

DWD Code:

• https://github.com/tuggeluk/DeepWatershedDetection

Happy to answer questions & requests.

Initial results



Class	AP@ 1/2	Class	AP@ 1/4
			-1
rest16th	0.8773	tuplet6	0.9252
noteheadBlack	0.8619	keySharp	0.9240
keySharp	0.8185	rest16th	0.9233
tuplet6	0.8028	noteheadBlack	0.9200
restQuarter	0.7942	accidentalSharp	0.8897
rest8th	0.7803	rest32nd	0.8658
noteheadHalf	0.7474	noteheadHalf	0.8593
flag8thUp	0.7325	rest8th	0.8544
flag8thDown	0.6634	restQuarter	0.8462
accidentalSharp	0.6626	accidentalNatural	0.8417
accidentalNatural	0.6559	flag8thUp	0.8279
tuplet3	0.6298	keyFlat	0.8134
noteheadWhole	0.6265	flag8thDown	0.7917
dynamicMF	0.5563	tuplet3	0.7601
rest32nd	0.5420	noteheadWhole	0.7523
flag16thUp	0.5320	fClef	0.7184
restWhole	0.5180	restWhole	0.7183
timeSig8	0.5180	dynamicPiano	0.7069
accidentalFlat	0.4949	accidentalFlat	0.6759
keyFlat	0.4685	flag16thUp	0.6621

Current results







APPENDIX