

Marginal Space Learning

An Introduction

Felix Meister

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Friedrich-Alexander University Erlangen-Nuremberg



FRIEDRICH-ALEXANDER
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Marginal Space Learning

- Introduction
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Introduction

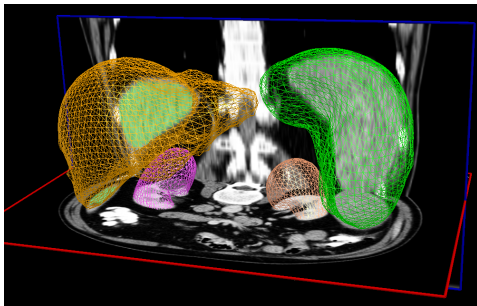
Segmentation in medical field

... is an important component for:

- help with diagnosis
- training for students
- dosimetry-analysis

Many different approaches:

- level-sets
- active shape models
- atlas-based methods
- ...



www.fraunhofer.sg/wpcontent/uploads/2012/12/AutomaticModelBasedSegmentation.png

Most algorithms lack a proper automatic initialization!

Previous work on initialization

Ad hoc solutions

- Works only on one system

Atlas-based method

- Not robust for large deformations

Learning-Based Approaches

- state-of-the-art in 2D object detection



One of our training datasets

Previous work on initialization

Ad hoc solutions

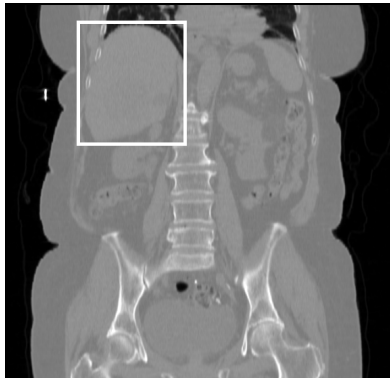
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Learning-Based Approaches

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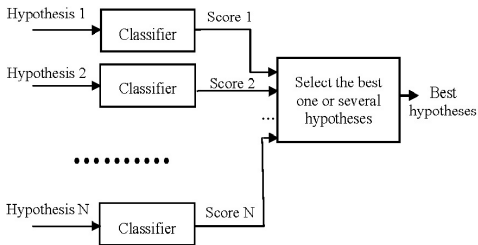


One of our training datasets

Full-Space Learning

A bounding box in 2D has 5 degree of freedom:

- two parameter for position: x, y
- one parameter for orientation: θ
- two parameter for scale: s_x, s_y



Example of a learning-based method: Zeng14-MSL

Full-Space Learning - Difficulties in 3D

A bounding box in 3D has 9 degree of freedom:

- three parameter for position: x, y, z
- three parameter for orientation: three Euler angles (θ, Φ, Ψ)
- three parameter for scale: s_x, s_y, s_z

Number of hypotheses increases exponentially w.r.t. the parameter space.

Full-Space Learning - Difficulties in 3D

An Example:

- Consider a volume of $64 * 64 * 64$ voxels
- Take 1000 possibilities for orientation and
- 1000 possibilities for scale

We get a total number of $64 * 64 * 64 * 1000 * 1000 = 262.144.000.000$ hypotheses.

This is very inefficient!

Bachelor Thesis

Title: Bounding Box Segmentation of the liver in a CT volume using Marginal Space Learning

Marginal Space Learning is:

- state of the art
- an automatic initialization or segmentation algorithm
- an extension of full space learning

Marginal Space Learning

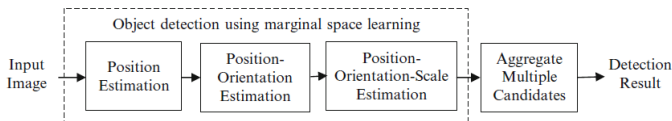
Theory

A bounding box in 3D has 9 degree of freedom:

- three parameter for position: x, y, z
- three parameter for orientation: three Euler angles (θ, Φ, Ψ)
- three parameter for scale: s_x, s_y, s_z

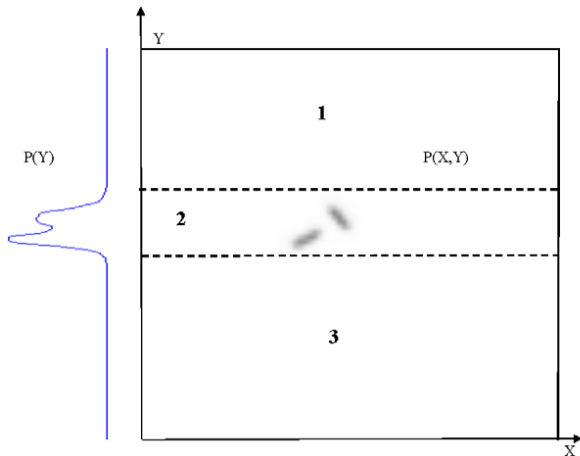
Instead of full space search the search is divided into those three subspaces

For each subspace we train a random forest classifier for classification



Typical process of marginal space learning: Zeng14-MSL

An Example



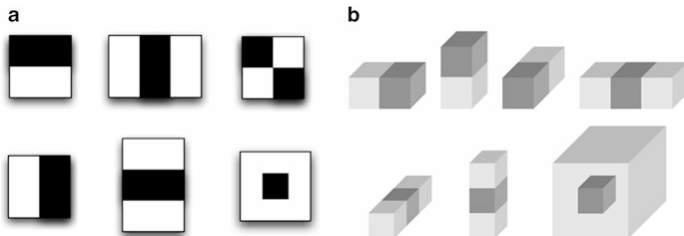
A 2D example from Zeng14-MSL

3D haarlike features

Extension of Viola and Jones' 2D features

Consists of cuboids, which are subtracted from each other

Fast computation using integral images



(a) 2D haarlike features and (b) 3D haarlike features from Zeng14-MSL

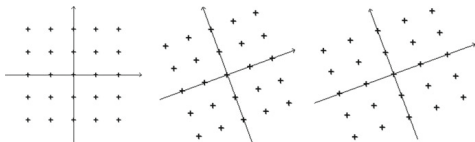
Steerable features

Combination of global information and local features

Consists of a sampling pattern that is steered over the volume

For each sampling point we extract 24 local features:

- intensity
- gradient
- transformation of values
- ...



Steerable features from Zeng14-MSL

Summary

Take home messages

Full-Space Learning

- State-of-the-art in 2D object detection
- Not suitable for 3D case

Marginal Space Learning

- State-of-the-art in 3D object detection
- There are three classifiers instead of one

Thank you very much for your attention!

Further Readings

Zeng14-MSL : Y. Zheng and D. Comaniciu. *Marginal Space Learning for Medical Image Analysis*. Springer, 2014.

The End