Bounding Box Segmentation of the Liver in a CT Volume Using Marginal Space Learning

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Introduction

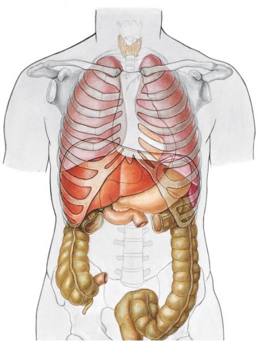
Liver Anatomy – Some Information

Largest gland in the human body

Average weight: 1,200 – 1,800 gramms

Located intraperitoneal

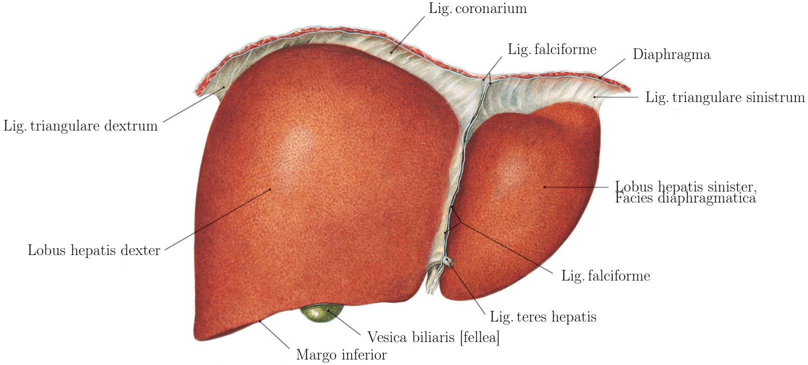
Central metabolistic organ



Topological anatomy from Paulsen10-SAD

25% of cardiac output within a patient in resting state arrives here

Liver Anatomy



Front view onto liver anatomy from Paulsen10-SAD

Liver Segmentation

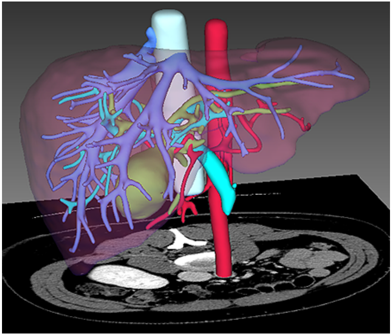
Increased liver size is an incident for:

- Cirrhosis
- Hepatocellular cancer

Segmentation is auxiliary for diagnostics

A variety of algorithms were proposed:

- Level-sets
- Active shape models
- Atlas-based methods
- ...



Liver segmentation from http://radiology.ucsf.edu

Most algorithms lack an appropriate initialization

Previous work on initialization

Ad hoc solutions

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

Atlas-based method

- Not robust for large deformations

Learning-Based Approaches

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

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

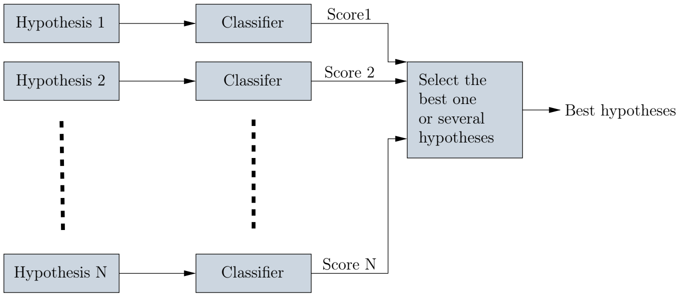


Illustration of basic scheme of full space learning from Zheng14-MSL

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!

Basics

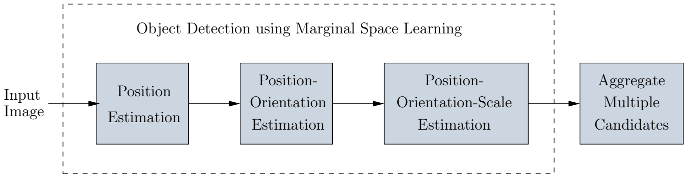
Theory of marginal space learning

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

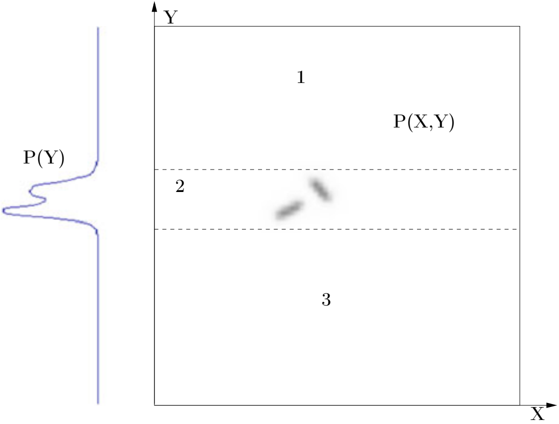
Instead of full space search the search is divided into those three subspaces

For each subspace we train classifier



Marginal space learning workflow from Zheng14-MSL

An Example



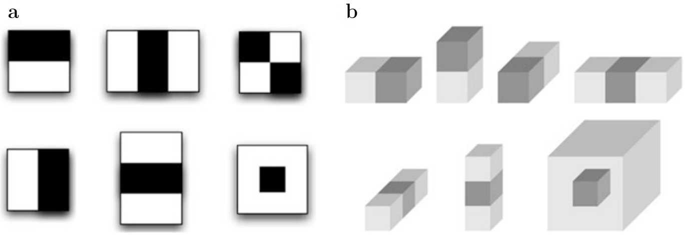
2D example from Zheng14-MSL

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

Feature Selection

Haar features are translated and scaled within a detector window

Viola and Jones claim over 160,000 features within a window of 24×24

Here: Initialization with mean size of object

Infeasible computation of over 2 billion features

Feature Selection

Find a subset of features, which describes the present situation best

Different evaluation measurements:

- Error of the utilized classifer
- Bayes distance
- Gini index
- ...

We used the mutual information:

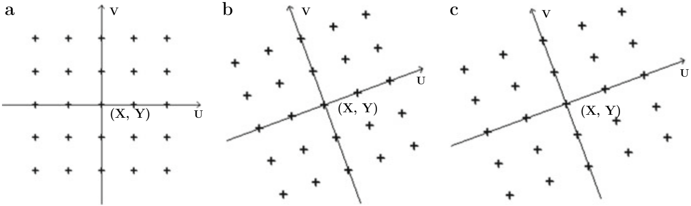
$$
\begin{aligned}
G^T &= -\sum_{\kappa} \int_{\mathbb{R}_m} p(\boldsymbol{c},\ \Omega_\kappa) \ln \frac{p(\boldsymbol{c},\ \Omega_\kappa)}{p(\boldsymbol{c}) p_\kappa} d\boldsymbol{c} \qquad (1) \\
&= H(\boldsymbol{c}) + H(\Omega) - H(\boldsymbol{c},\ \Omega) \qquad (2)
\end{aligned}
$$

Steerable features

Combination of global information and local features

Sampling pattern that is steered over the volume

For each sampling point we extract 24 features (Intensities, gradients, . . .)



Steerable features from Zeng14-MSL

Object Detection

Training of estimators

Two class classification task

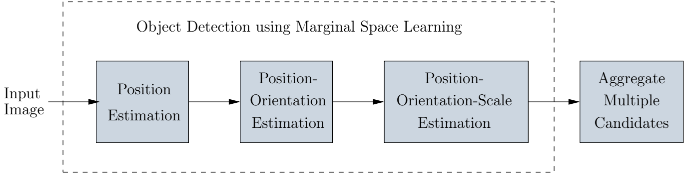
Split hypotheses by step-normalized distance:

$$E = \max_{i=1,\ \dots,\ D} |\boldsymbol{P}_i^e - \boldsymbol{P}_i^t| / \text{SearchStep}_i \tag{3}$$

Positive samples satisfy $E \leq 1.0$

Negative samples satisfy $E > 2.0$

Training of estimators



Marginal space learning workflow from Zheng14-MSL

Workflow :

- Train position estimator
- Test hypotheses and preserve best n candidates
- Train position-orientation estimator
- Test hypotheses and preserve best n candidates
- Train position-orientation-scale estimator

Constrained Marginal Space Learning

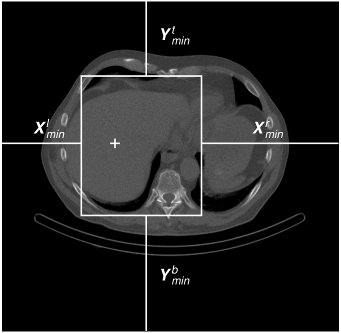
Position Space Constraint

Main assumption: Center of object is not located close to the volume border

Candidates close to volume border can be safely skipped

Find minimum distances to the border:

- X^l_{min} and X^r_{min}
- Y^t_{min} and Y^b_{min}
- Z^u_{min} and Z^d_{min}

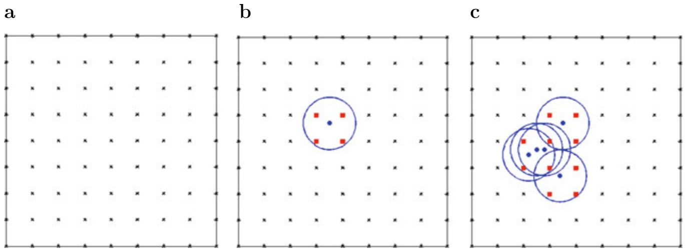


Example of position constraint

Orientation and Scale Space Constraint

Main assumption: Correlation between parameters in the same space

Solution: Example-based sampling to generate hypotheses



Example-based constraint from Zheng14-MSL

Evaluation

Data Description

13 low-dose CT datasets from a SPECT/CT survey on co-registration and attenuation correction

Imaging modality information

Property	Siemens Symbia T2	Siemens Symbia T6
Collimation	2×2.5 mm	6×2.0 mm
Tube voltage	130 kV	
Tube current	30 mAs	
Pitch	1.8	
Rotational velocity	0.6 s	0.8 s
Intraslice resolution	0.97 mm $\times$ 0.97 mm	
Slice matrix	512×512 pixel	
Slice thickness	3 mm	2.5 mm
Slice increment	1.5 mm	1 mm

Test Procedure

Split database into two sets:

- A set for feature selection consisting of 5 datasets
- A set for training and test consisting of 8 datasets

Perform feature selection and save best 500 features

For each step train a balanced random forest classifier

Crossvalidation via “leave-one-out” tests

Results – position estimation

Average error of different settings

Setting (# features | # trees)	Minimum error	Average error	Maximum error
50 | 100	38.4 mm	96.9 mm	261.7 mm
50 | 200	39.6mm	82.1mm	142.0 mm
50 | 400	39.5 mm	70.9 mm	143.0 mm
100 | 100	43.9 mm	77.6 mm	137.5 mm
100 | 200	42.7 mm	74.3 mm	140.1 mm
100 | 400	30.0 mm	68.2 mm	139.2 mm
200 | 100	38.5 mm	69.0 mm	138.0 mm
200 | 200	37.7 mm	72.3 mm	142.0 mm
200 | 400	34.2 mm	56.7 mm	135.0 mm
400 | 100	32.0 mm	67.0 mm	124.1 mm
400 | 200	43.8 mm	66.7 mm	121.5 mm
400 | 400	39.9 mm	64.3 mm	121.0 mm

Results – orientation estimation

Average error of different settings

Setting (# features | # trees)	Minimum error	Average error	Maximum error
50 | 100	9.8°	26.2°	115.6°
50 | 200	9.8°	25.4°	119.0°
50 | 400	9.6°	25.7°	119.2°
100 | 100	0.0°	24.5°	119.2°
100 | 200	0.0°	25.2°	119.2°
100 | 400	4.1°	23.7°	119.0°
200 | 100	9.8°	26.0°	119.0°
200 | 200	9.8°	24.4°	119.0°
200 | 400	0.0°	23.5°	119.0°
400 | 100	0.0°	25.5°	124.0°
400 | 200	9.8°	27.0°	128.1°
400 | 400	0.0°	25.9°	121.0°

Results – scale estimation

Average error of different settings

Setting (# features | # trees)	Average error (s_x)	Average error (s_y)	Average error (s_z)
50 | 100	29.1 %	10.3 %	25.7 %
50 | 200	16.7 %	17.8 %	24.8 %
50 | 400	17.7 %	14.6 %	15.2 %
100 | 100	18.9 %	20.2 %	29.1 %
100 | 200	12.4 %	13.5 %	26.6 %
100 | 400	14.3 %	15.6 %	32.9%
200 | 100	17.5 %	17.1 %	36.4 %
200 | 200	15.5 %	13.6 %	31.7 %
200 | 400	20.9 %	16.3 %	20.4 %
400 | 100	14.1 %	17.7 %	27.9 %
400 | 200	19.9 %	19.2 %	27.8 %
400 | 400	20.0 %	24.3 %	33.2 %

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
- Search in subspaces instead of full space

Constrained Marginal Space Learning

- Uniform sampling is not necessary
- Restriction enables major performance boost

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.

Paulsen10-SAD : F. Paulsen and J. Waschke. Sobotta–Atlas der Anatomie des Menschen – Innere Organe, Elsevier – Urban & Fischer, München, 2010.

The End