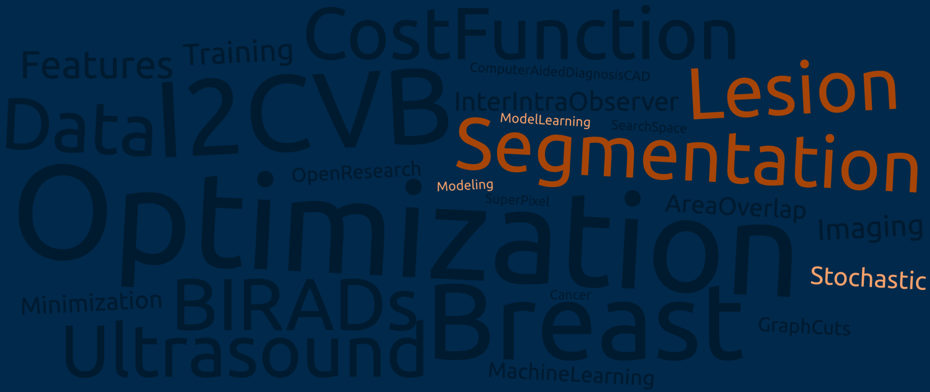
Breast Ultrasound Image Segmentation: an optimization approach based on super-pixels and high-level descriptors

Joan Massich
joan.massich@u-bourgogne.fr

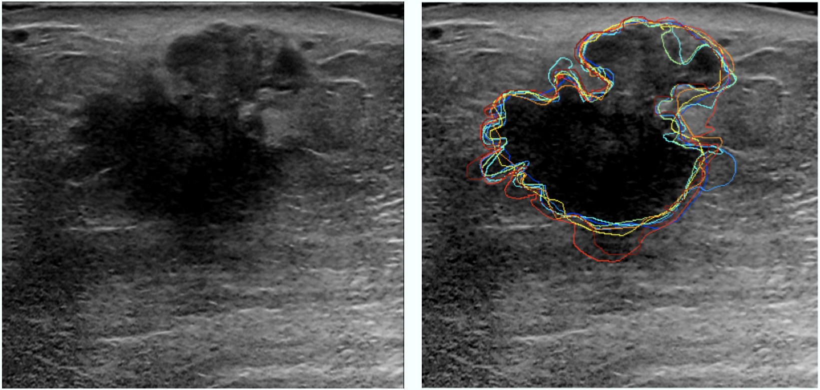
Université de Bourgogne

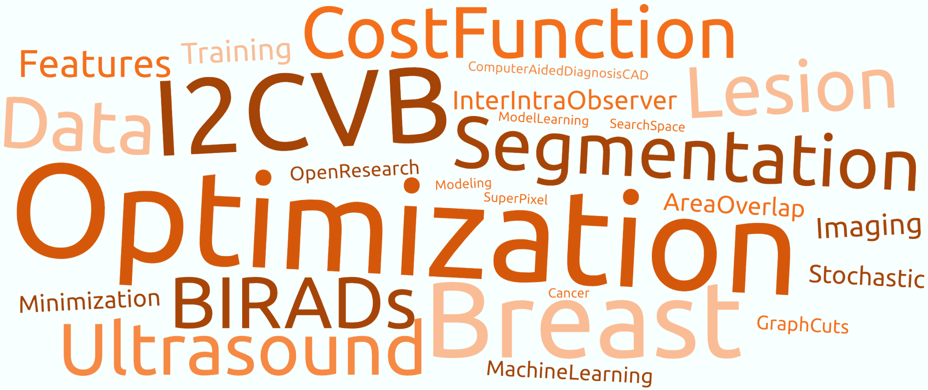
Quality Control by Artificial Vision
4th June 2015

CostFunction
Training
Features
ComputerAidedDiagnosisCAD
Lesion
I2CVB
InterIntraObserver
Data
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
AreaOverlap
Optimization
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
GraphCuts
Ultrasound
MachineLearning

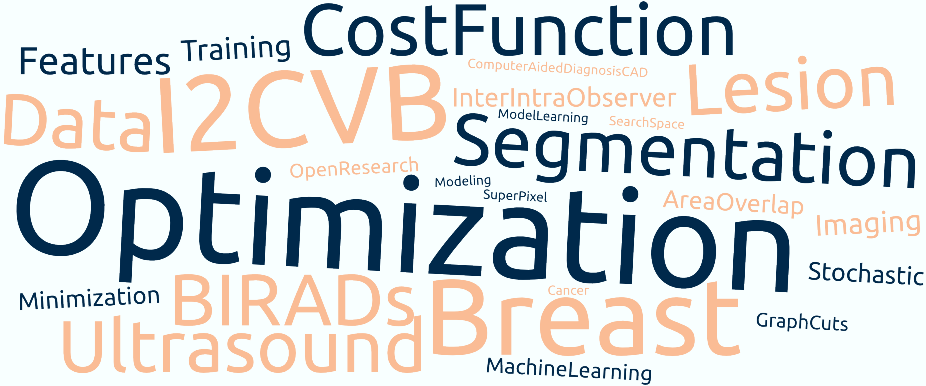

CostFunction
Training
Features
ComputerAidedDiagnosisCAD
Lesion
Data
I2CVB
InterIntraObserver
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
AreaOverlap
Optimization
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
GraphCuts
Ultrasound
MachineLearning

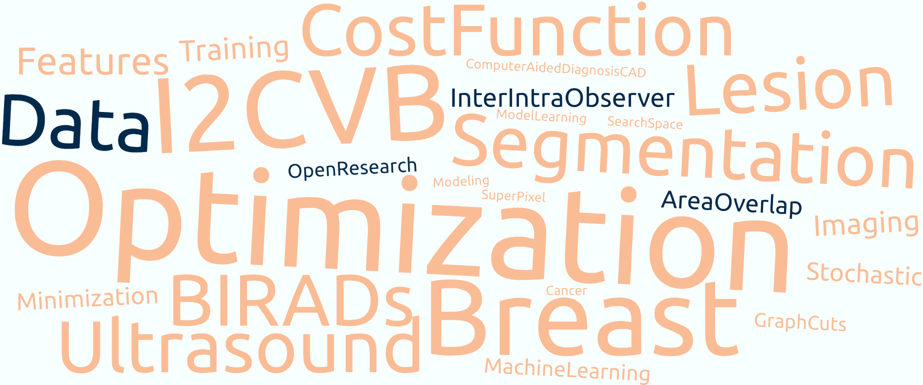
Breast Lesion Segmentation in US images




CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Lesion
Data
I2CVB
InterIntraObserver
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
Optimization
AreaOverlap
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
Ultrasound
GraphCuts
MachineLearning

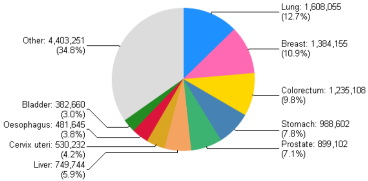

CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Lesion
Data
I2CVB
InterIntraObserver
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
AreaOverlap
Optimization
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
Ultrasound
GraphCuts
MachineLearning


CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Lesion
Data
I2CVB
InterIntraObserver
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
Optimization
AreaOverlap
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
Ultrasound
GraphCuts
MachineLearning

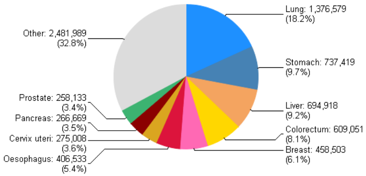

CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Data
I2CVB
InterIntraObserver
Lesion
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
AreaOverlap
Optimization
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
Ultrasound
GraphCuts
MachineLearning

Motivations

Statistics



(a) # of cancer cases



(b) # of cancer deaths

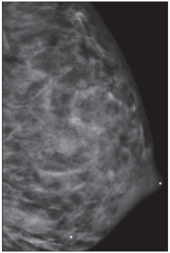
Implications

- 1.4 million cases per year
- 10.9% of diagnosed cancers
- 5th cause of cancer death (1th females)

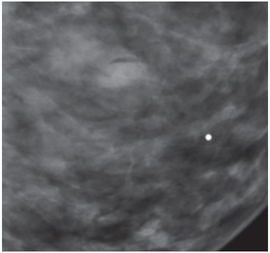
Breast Imaging

Ultra-Sound(US) imaging, the most common adjunct modality

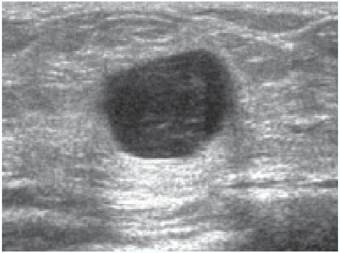
- Ability to discern solid lesions typologies
- Lesions shielded by dense breast in Digital Mammography(DM) are distinguishable in US



(c) DM



(d) DM, Region of Interest (ROI)



(e) Breast Ultra-Sound(BUS), ROI

Breast structures under US screening

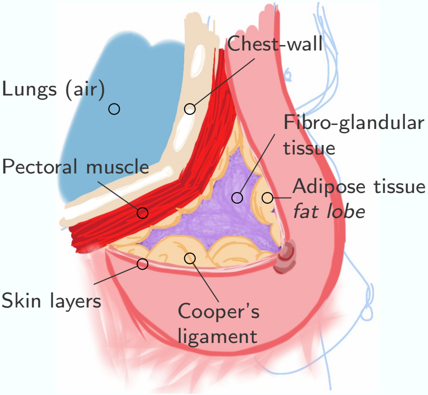


Figure: Breast structure elements.

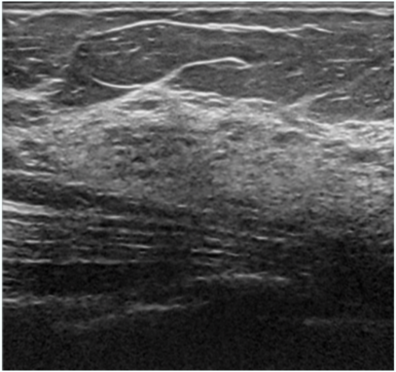


Figure: Breast US image example.

State of health from image visual Inspection

Radiologic diagnosis error rates are similar to any other human visual inspection

- Quality of the images.
- Ability to interpret the physical properties of the images.

1. Double readings.
2. Computer Aided Diagnosis(CAD).

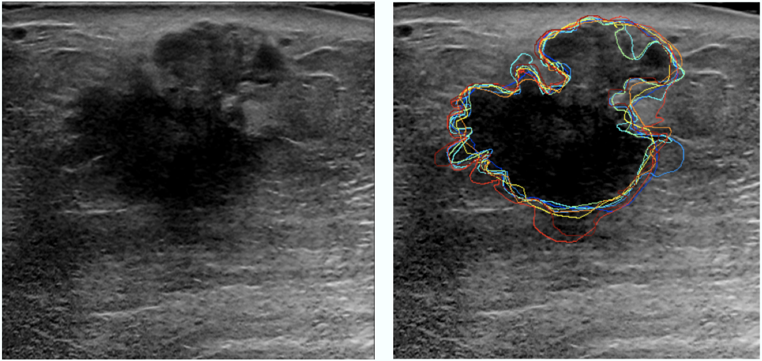
BI-RADs Lexicon
A standardized toolkit tested for diagnosis

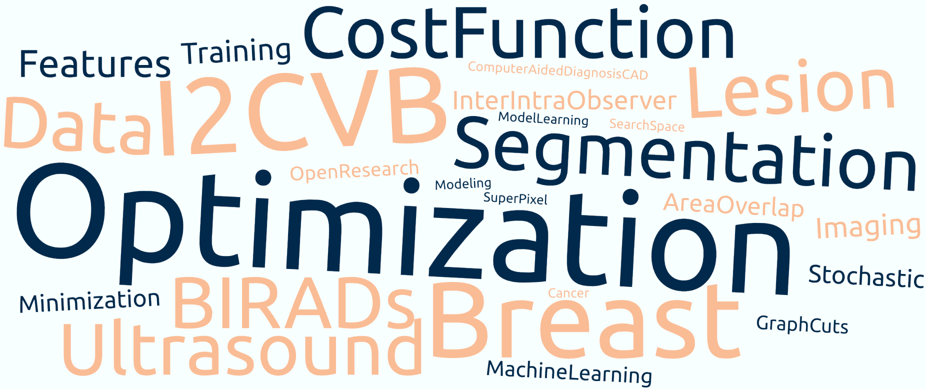
- BKGD Echotexture : adipose, fibro-glandular, heterogeneous
- Mass shape : Oval, Round, Irregular, Lobular
- Mass orientation : Parallel, Non-parallel
- Mass margin : Circumscribed, Indistinct, Angular, Microlobulated, Spiculated
- Lesion boundary : Abrupt Interface, Echogenic halo
- Echo pattern : Anechoic, Hyperechoic, Complex, Isoechoic, Hypoechoic
- Posterior acoustic pattern : Shadowing, Combined, Enhancement, No pattern

---

[0] benign, malignant and undetermined

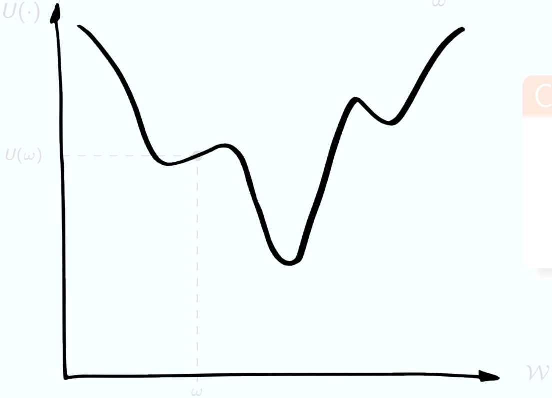
Take away
Accurate delineations to develop CAD systems for BUS




CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Lesion
Data
I2CVB
InterIntraObserver
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
Optimization
AreaOverlap
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
Ultrasound
GraphCuts
MachineLearning

Optimization
For image segmentation

$$\hat{\omega} = \arg\min_{\omega} U(\omega)$$

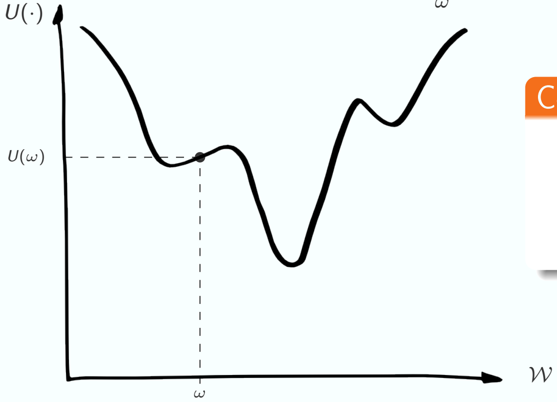


Considerations

- Search Space $\mathcal{W}$
- Cost Function $U(\cdot)$
- Minimization Strategy

Optimization
For image segmentation

$$\hat{\omega} = \arg\min_{\omega} U(\omega)$$

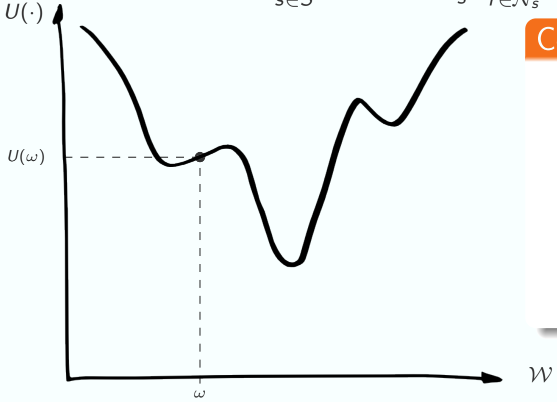


Considerations

- Search Space $\mathcal{W}$
- Cost Function $U(\cdot)$
- Minimization Strategy

Image Segmentation by Optimization
The Metric Labeling Problem

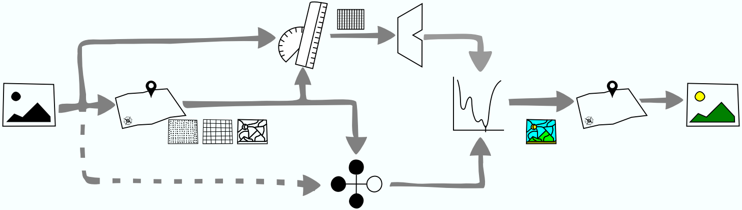
$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_{s} \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$$



Considerations

- Image as a discrete set $\mathcal{S}$
- Search Space $\mathcal{W}$ $(\omega_s = l)$, $l \in \mathcal{L}$, $\forall s \in \mathcal{S}$
- Cost Function
- Minimization Strategy

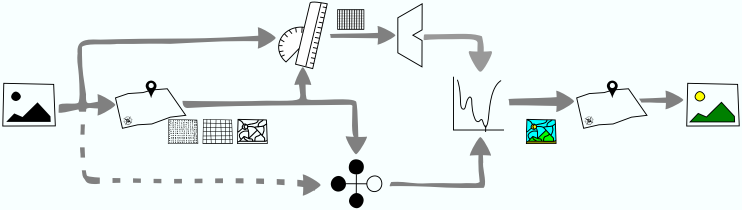
The Metric Labeling Problem
Conceptual schema



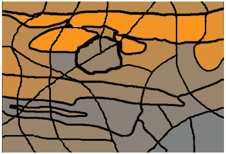
$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_s \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$

- $D_s(\omega_s = l_{\checkmark}) << D_s(\omega_s = l_{\text{✗}})$
- $$V_{s,r}(\omega_s, \omega_r) = \begin{cases} \beta, & \text{if } \omega_s \neq \omega_r \\ 0, & \text{otherwise} \end{cases}$$
- $|\mathcal{W}| = |\mathcal{L}|^{|\mathcal{S}|}$

The Metric Labeling Problem
Conceptual scheme

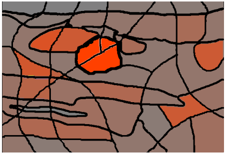


$D_s(\omega_s = l)$ Interpretation



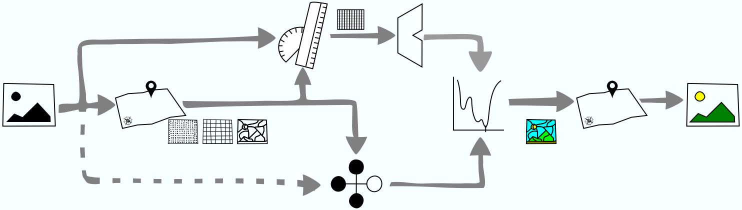
(a) l is fat

(b) l is lungs

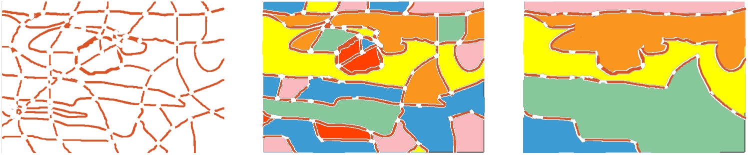


(c) l is lesion

The Metric Labeling Problem
Conceptual schema

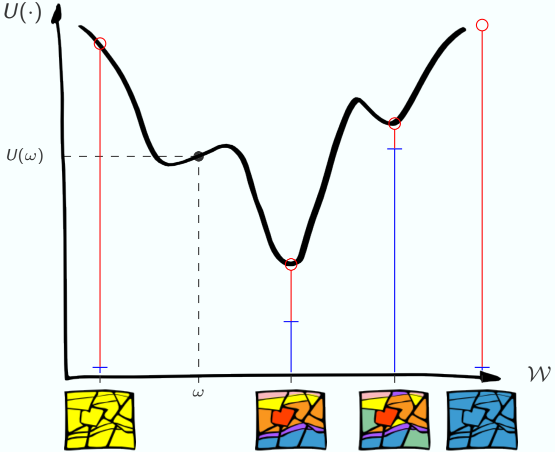


$V_{s,r}(\omega_s, \omega_r)$ Interpretation

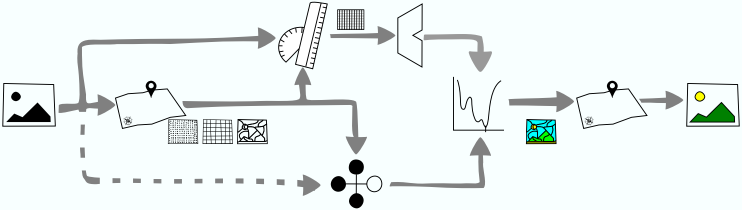


(d) (e) (f)

Interpretation of the Minimization Stage



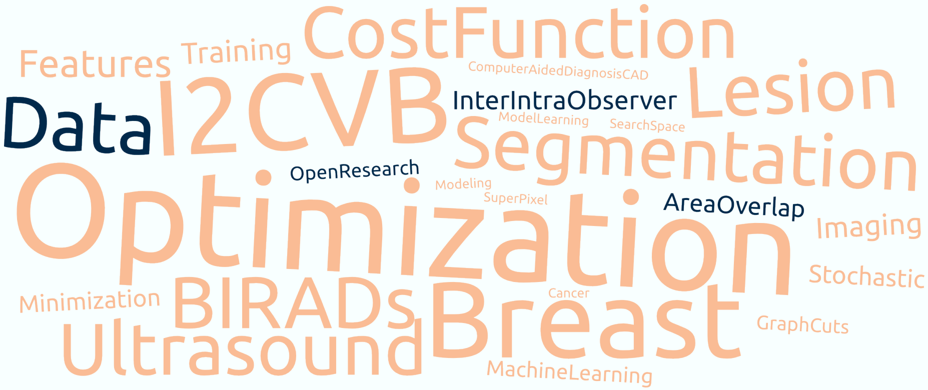
Take Away



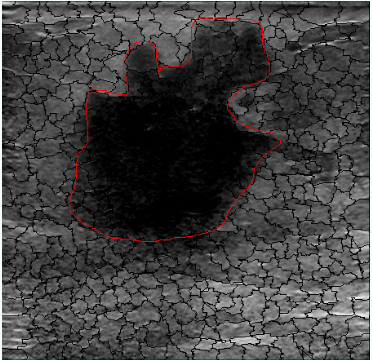
$V_{s,r}(\omega_s, \omega_r)$ Interpretation

$$\hat{\omega} = \arg\min_{\omega} \; U(\omega)$$

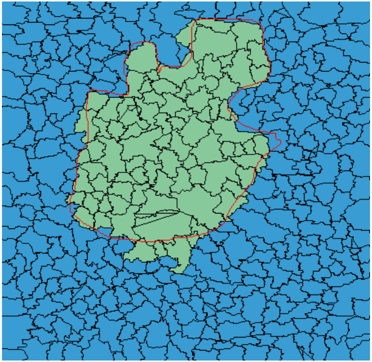
$$U(\omega) = \sum_{s \in S} D_s(\omega_s) + \sum_{s} \sum_{r \in \mathcal{N}_s} V_{s,r}(\omega_s, \omega_r)$$


CostFunction
Features
Training
ComputerAidedDiagnosisCAD
Data
I2CVB
InterIntraObserver
Lesion
ModelLearning
SearchSpace
Segmentation
OpenResearch
Modeling
SuperPixel
Optimization
AreaOverlap
Imaging
Stochastic
Minimization
BIRADs
Cancer
Breast
GraphCuts
Ultrasound
MachineLearning

Qualitative results
Super-pixel classification vs Area-Overlap



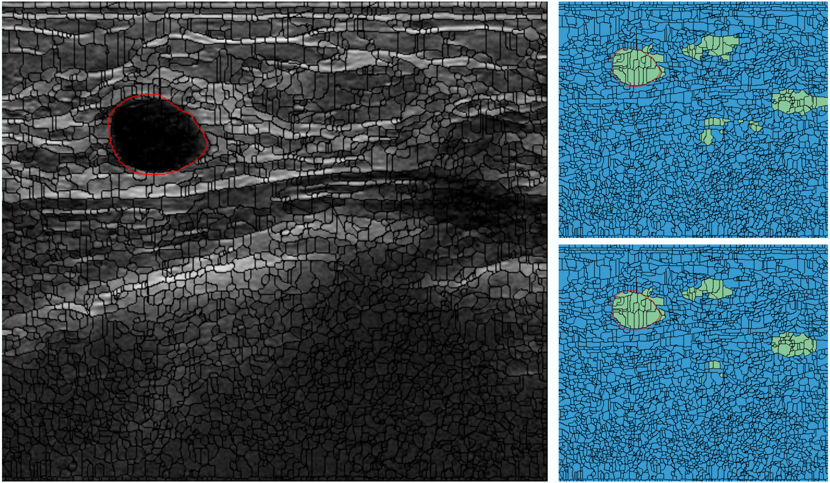
(g) Original Image, Ground Truth and Super-Pixels delineation.



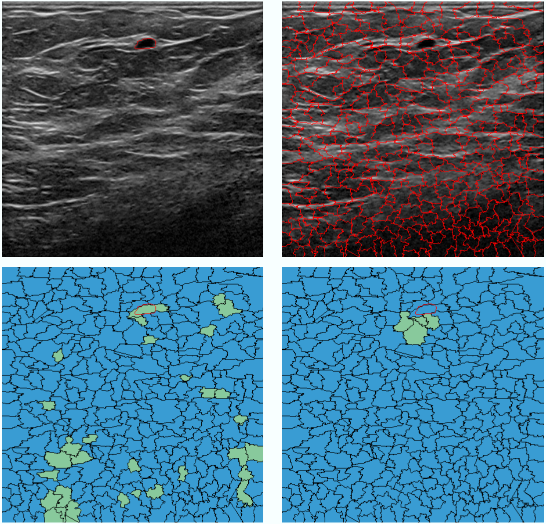
(h) $\{\text{lesion}, \overline{\text{lesion}}\}$ labeling results, GT and SP delineation.

Qualitative results

Influence of the Smoothing Term to False Positive Ratio

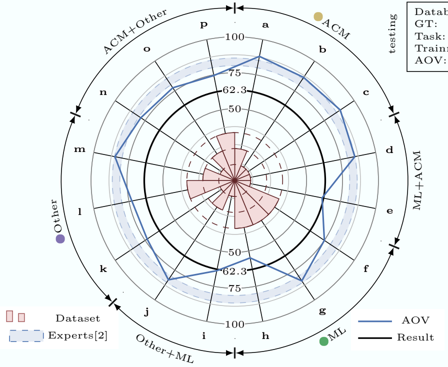


Qualitative results
When False Negative Emerge



Quantitative Results

Method Id:	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p
Dataset size:	76	20	32	20	42	480	347	352	25	120	6	400	50	20	118	488
techonlogy used for:																
detection																
segmetnation																
post-processing																
AOV (in %):	88.1	86.3	88.3	85.2	62.0	75.0	84.0	54.9	64.0	83.1	73.3	73.0	85.0	78.6	77.6	74.5



testing

Database size:	16
GT:	multi-label
Task:	$\mathcal{L} = \{\text{lesion}, \overline{\text{lesion}}\}$
Trainning:	Leave-one-Patient-Out
AOV: .623	FPR: .4 FNR: .008