

# Computer-aided Diagnosis

*Engineering Improved Health Care*

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University of Calgary  
Calgary, Alberta, Canada



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**So...  
What is  
CAD?**





# CAD is...

- ❖ “an ill-bred man, especially one who behaves in a dishonorable or irresponsible way toward women” [www.dictionary.com](http://www.dictionary.com)
- ❖ Canadian Dollar
- ❖ Computer-Aided Drafting
- ❖ Computer-Aided Design
- ❖ Computer-Aided Detection
- ❖ *Computer-Aided Diagnosis!*



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# Computer-aided Analysis of Biomedical Signals and Images

Application of computational procedures including digital signal processing, digital image processing, and pattern recognition methods to enhance biomedical signals and images, segment and characterize regions of interest (ROIs), identify normal patterns and structures, and detect abnormal features and diseases for ***computer-aided diagnosis (CAD)***

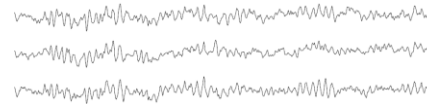
*Note: "aided" or "assisted" and not "automated"*



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# Signals and Images from the Human Body

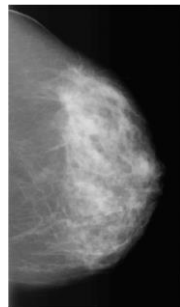
X-ray CT  
image of  
the brain



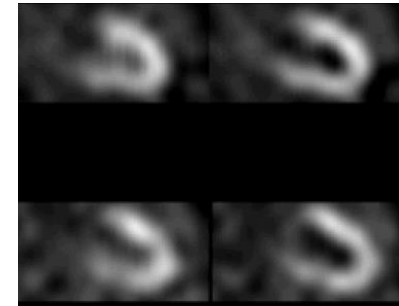
Brain waves: EEG



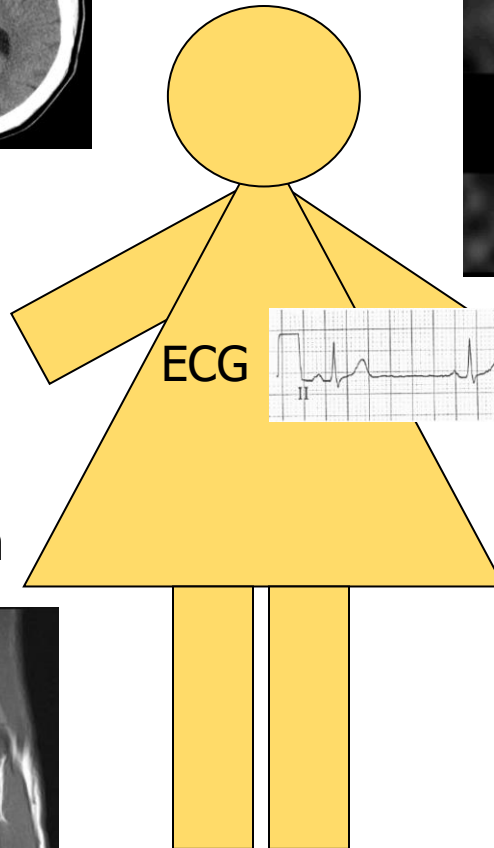
Chest X-ray image



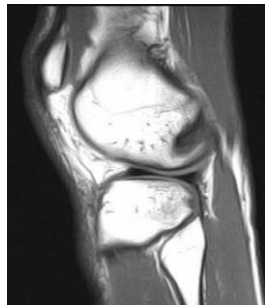
Mammogram



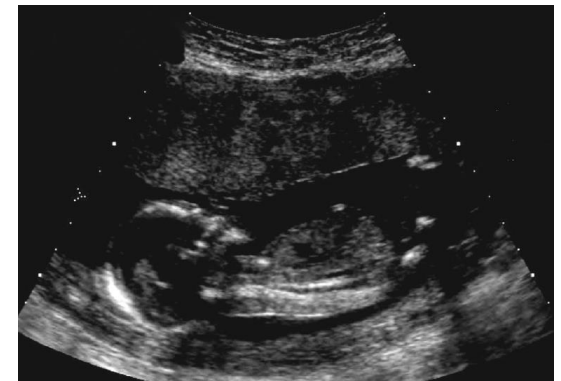
Nuclear  
medicine  
(SPECT)  
images of  
the heart



ECG



MR image  
of the knee

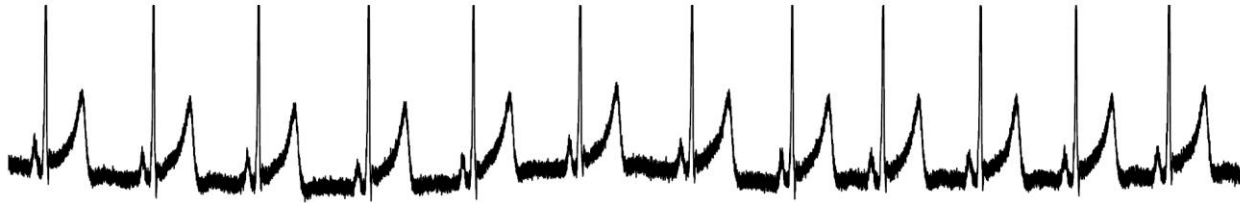


Fetal ultrasonography

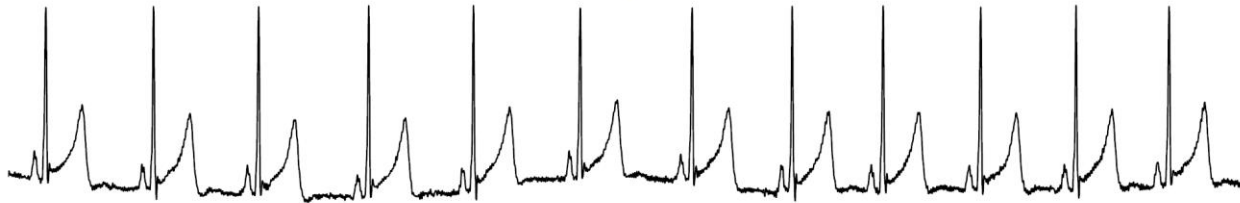


# Filtering of ECG to Remove Artifacts

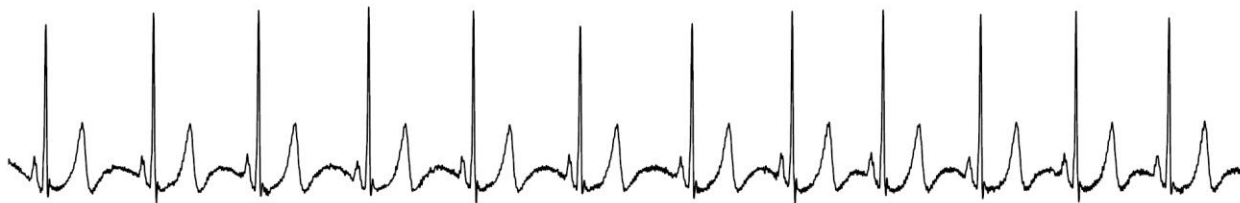
Original ECG



After lowpass filter



After highpass filter

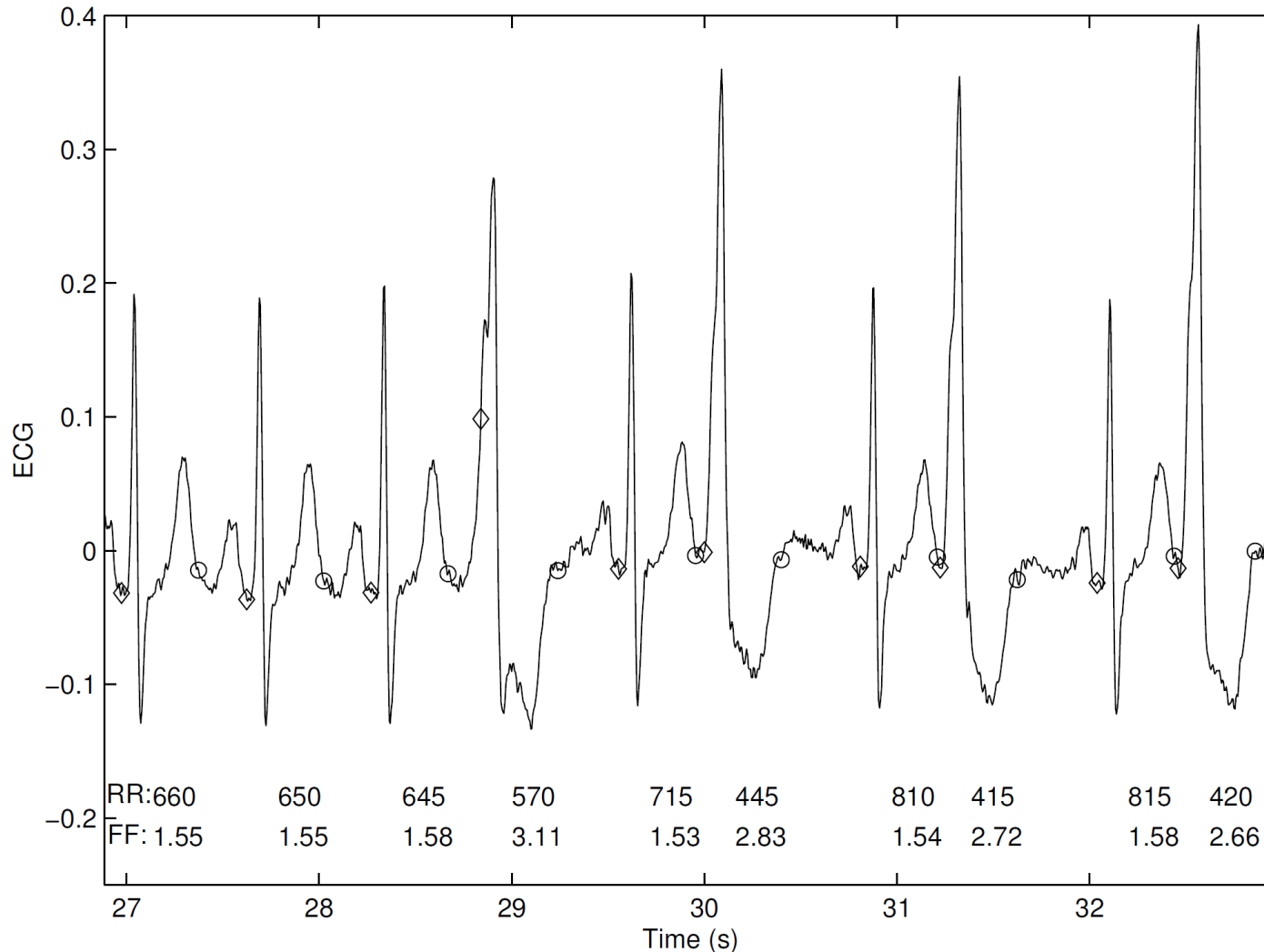


After comb filter





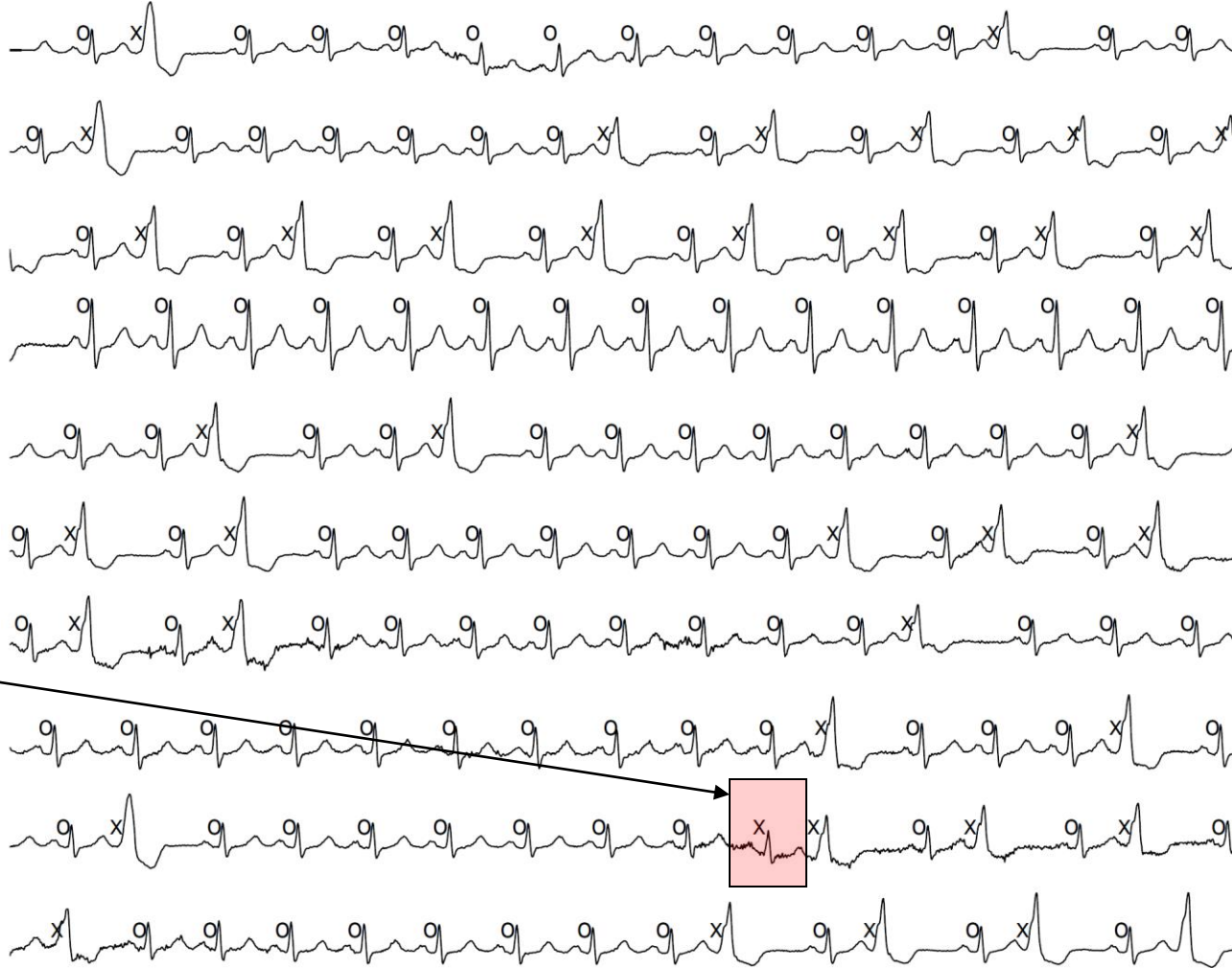
# Computer Analysis of the ECG: Feature Extraction





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# Computer Analysis of the ECG: Pattern Classification



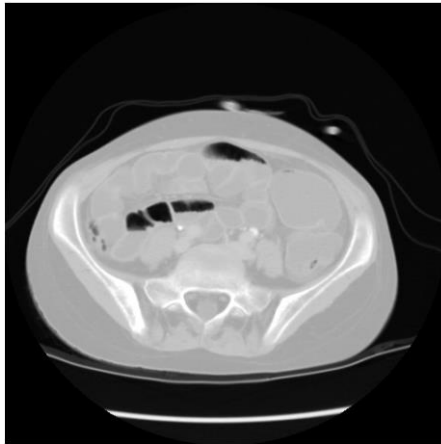
False positive:  
normal beat  
misclassified  
as PVC



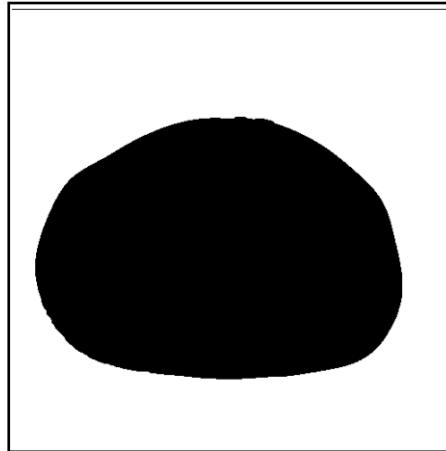


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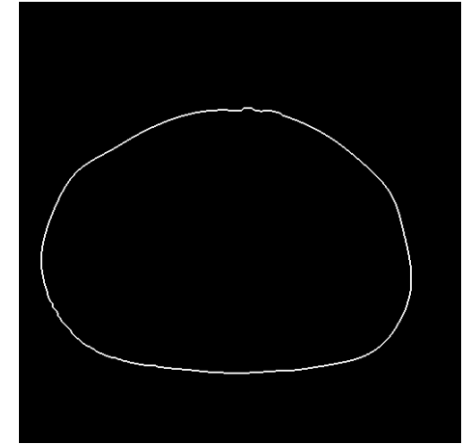
# Landmarking of 3D CT Images: Removal of peripheral artifacts and tissues in computed tomographic images



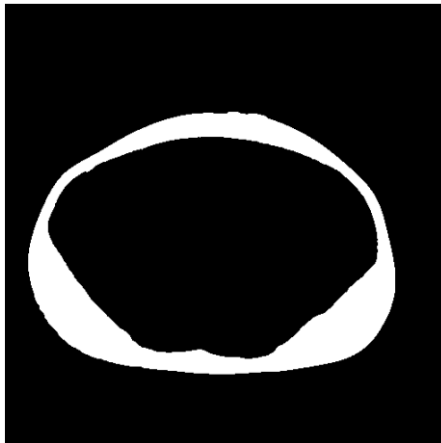
before processing



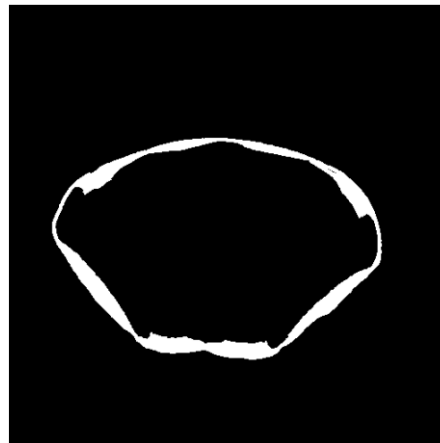
peripheral artifacts



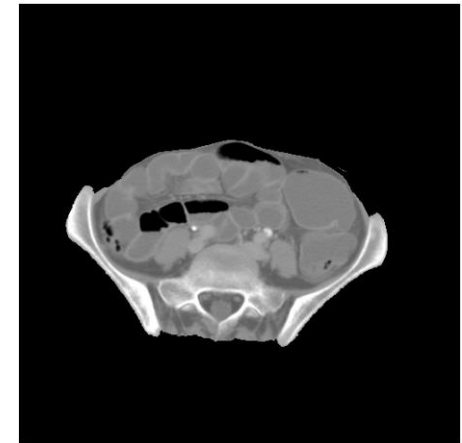
the skin layer



the peripheral fat region



the peripheral muscle



after processing



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# Preprocessing Steps

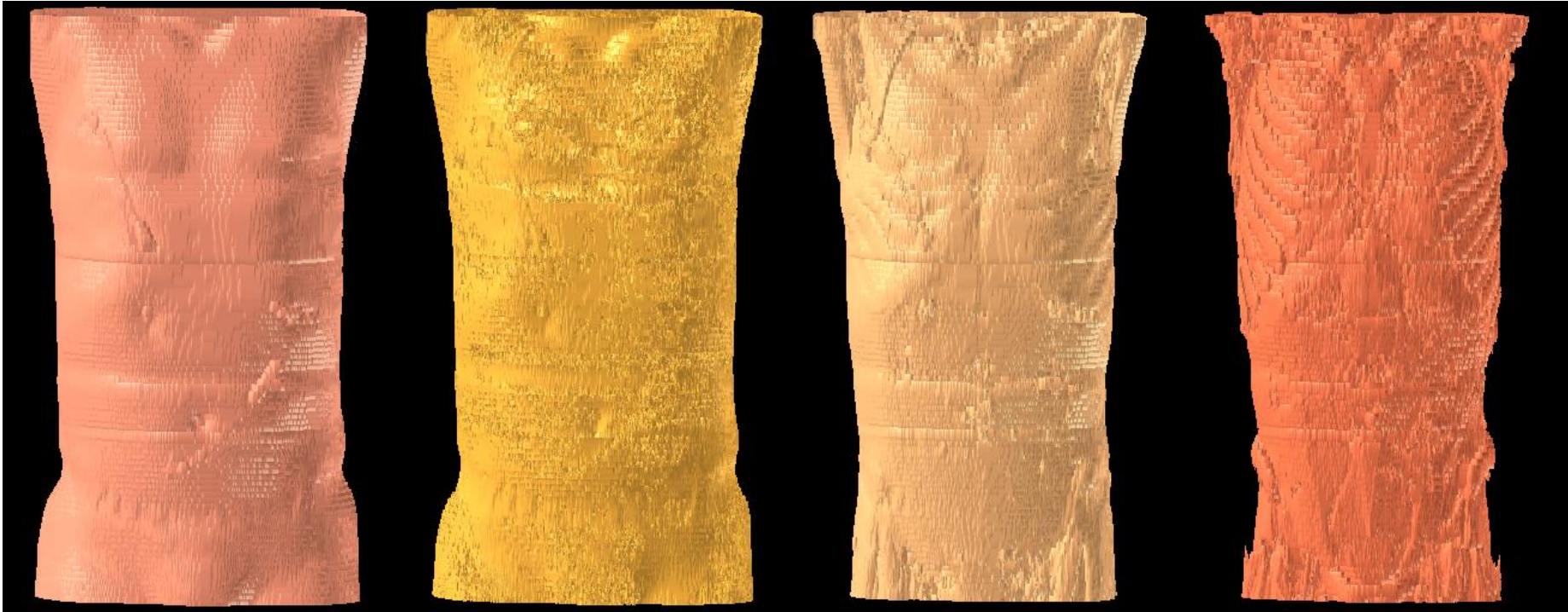
## Surface after removal of

peripheral artifacts

the skin layer

the peripheral fat

the peripheral muscle





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# Detection of the Spinal Canal



Original image

V.C.: vertebral column



Cropped V.C.



Edge map



Detected best-fitting  
circle and its center

# Delineation of the Diaphragm

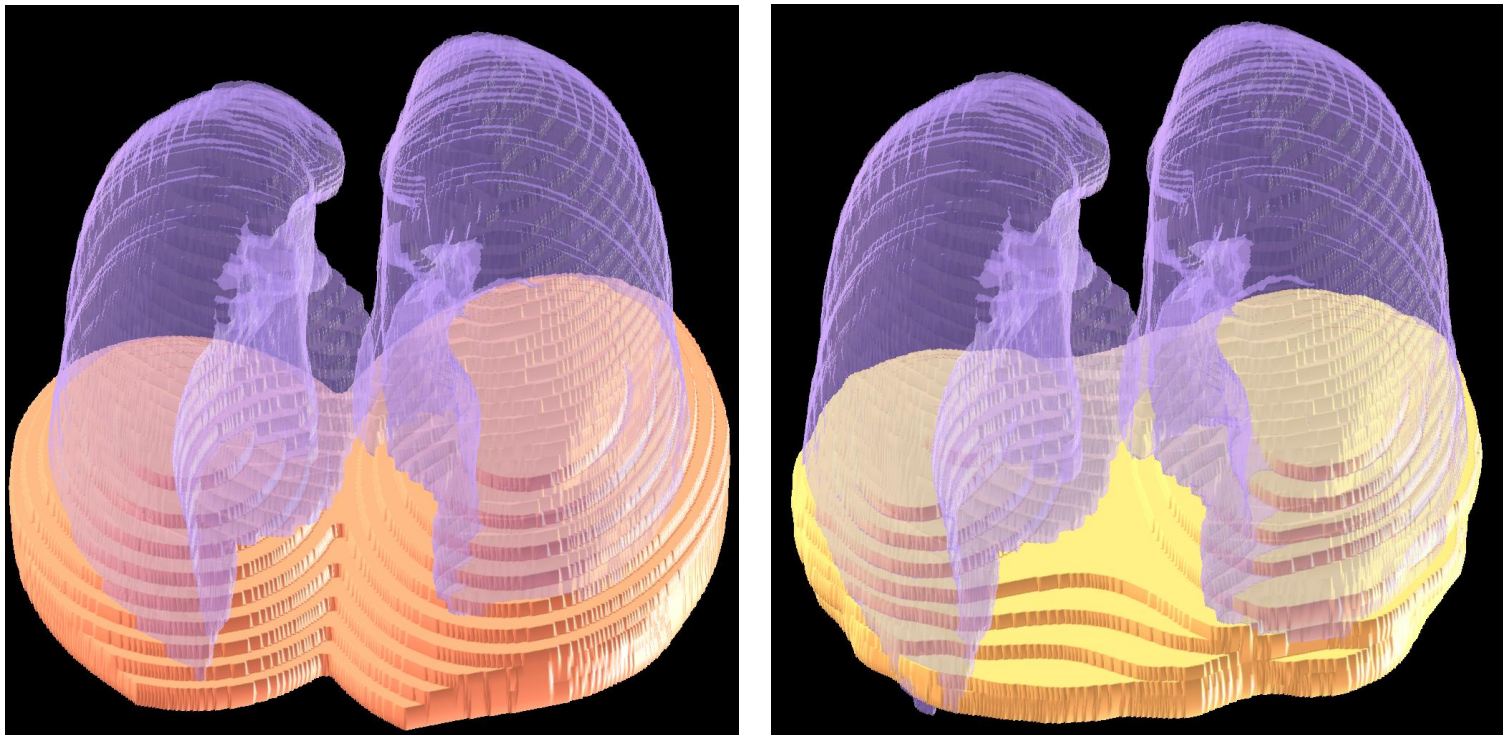


*--- contours drawn by a radiologist*

*--- contours obtained by our methods*

# Delineation of the Diaphragm

Representation of the diaphragm using  
linear least squares and active contours

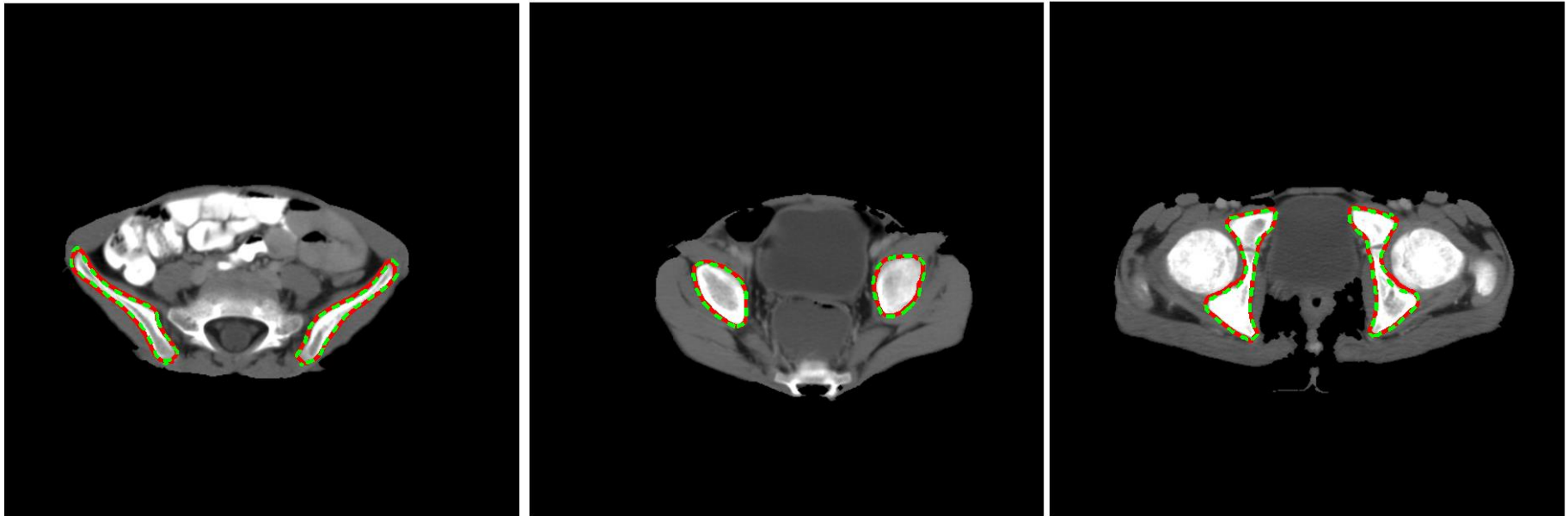


Segmented lungs and the diaphragm



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# Detection of the Pelvic Girdle



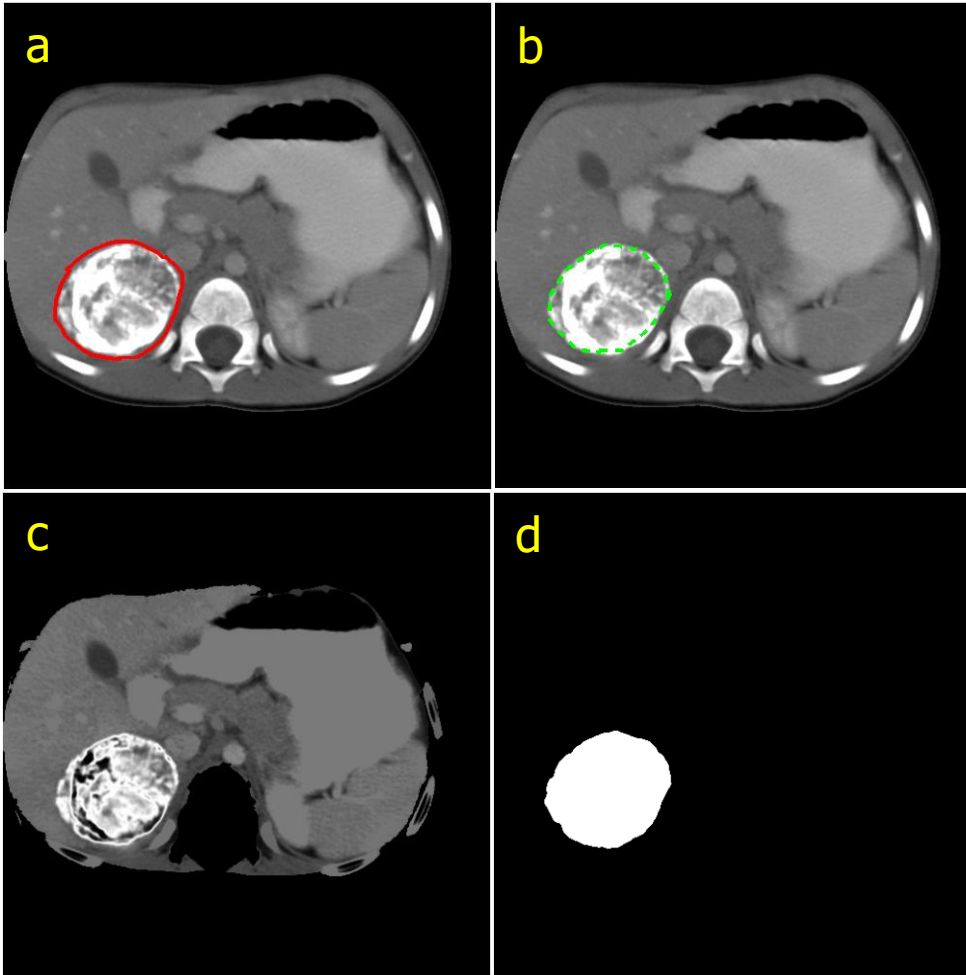
--- contours drawn by a radiologist

--- contours obtained by our methods



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# Segmentation of Neuroblastoma



a. tumor segmented by  
a radiologist

b. user-selected region  
marker

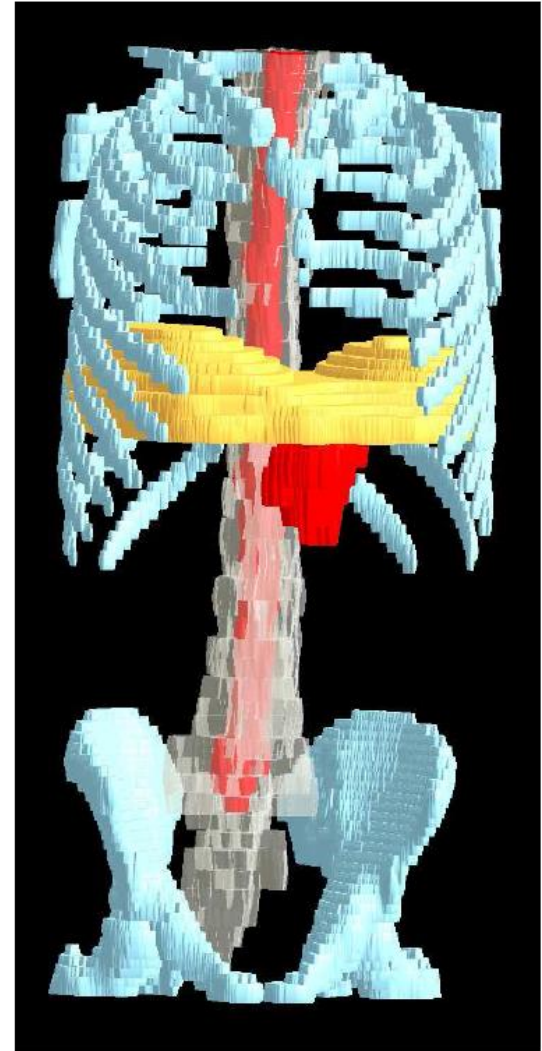
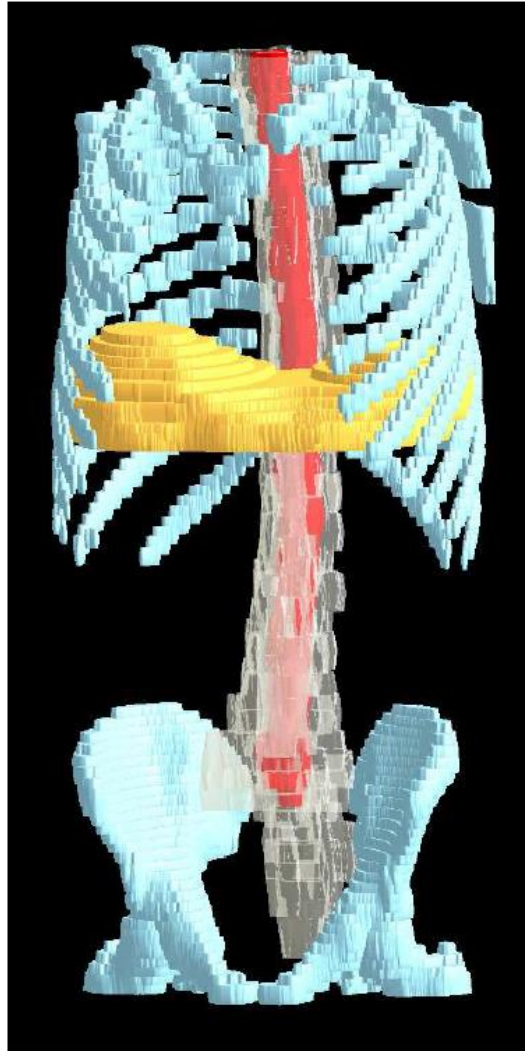
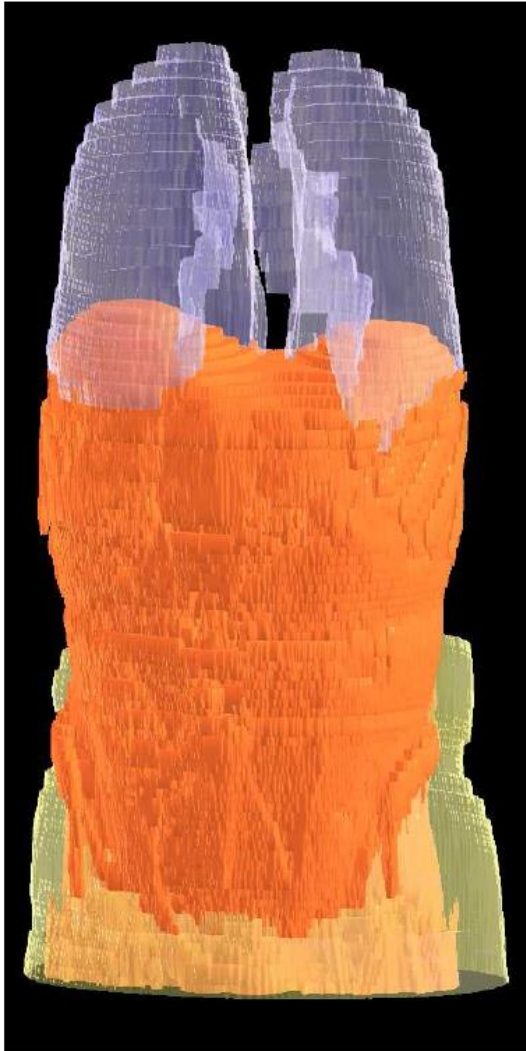
c. result of opening-  
by-reconstruction

d. final result of  
segmentation



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# Anatomical Landmarks and the Tumor in 3D

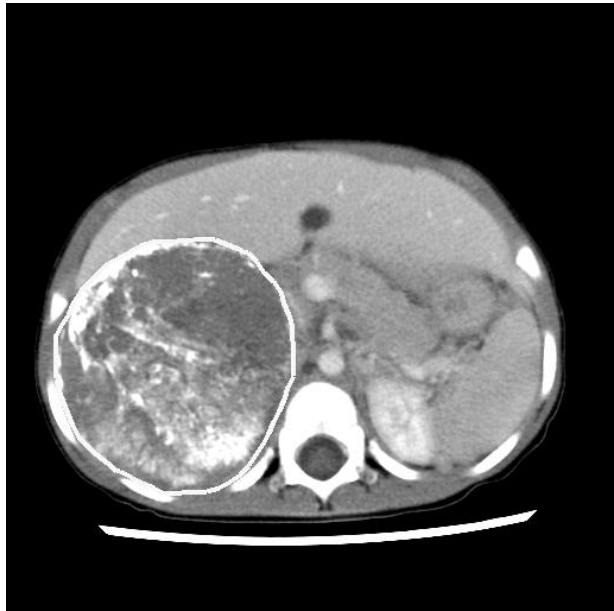




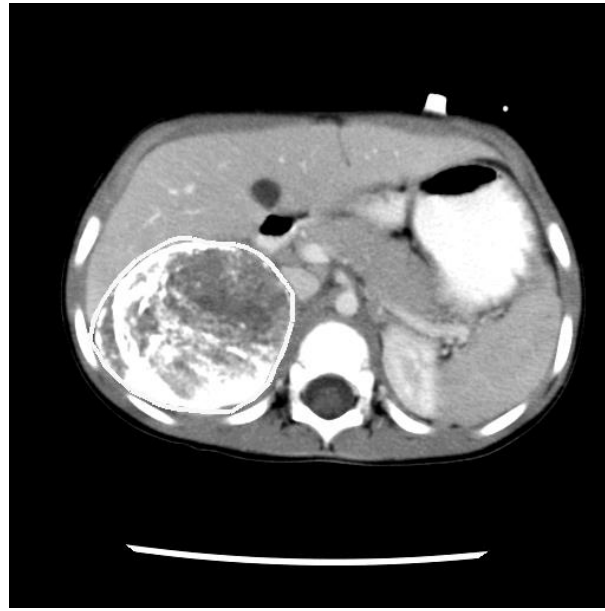


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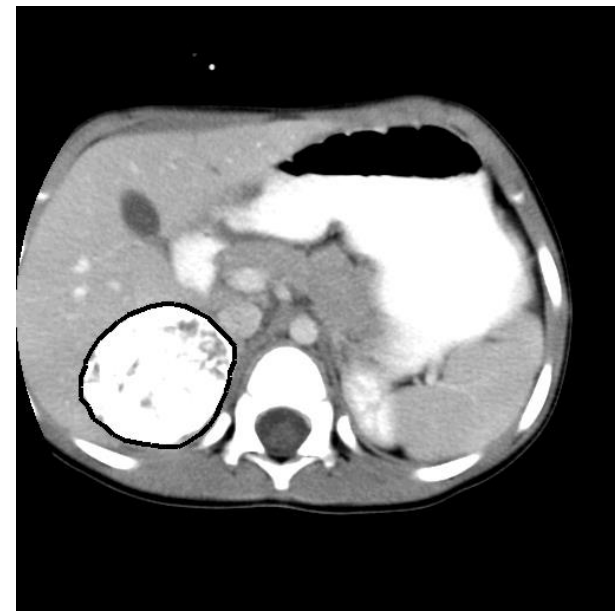
# Follow up of Treatment of Neuroblastoma



Case 1a  
April 2001



Case 1b  
June 2001

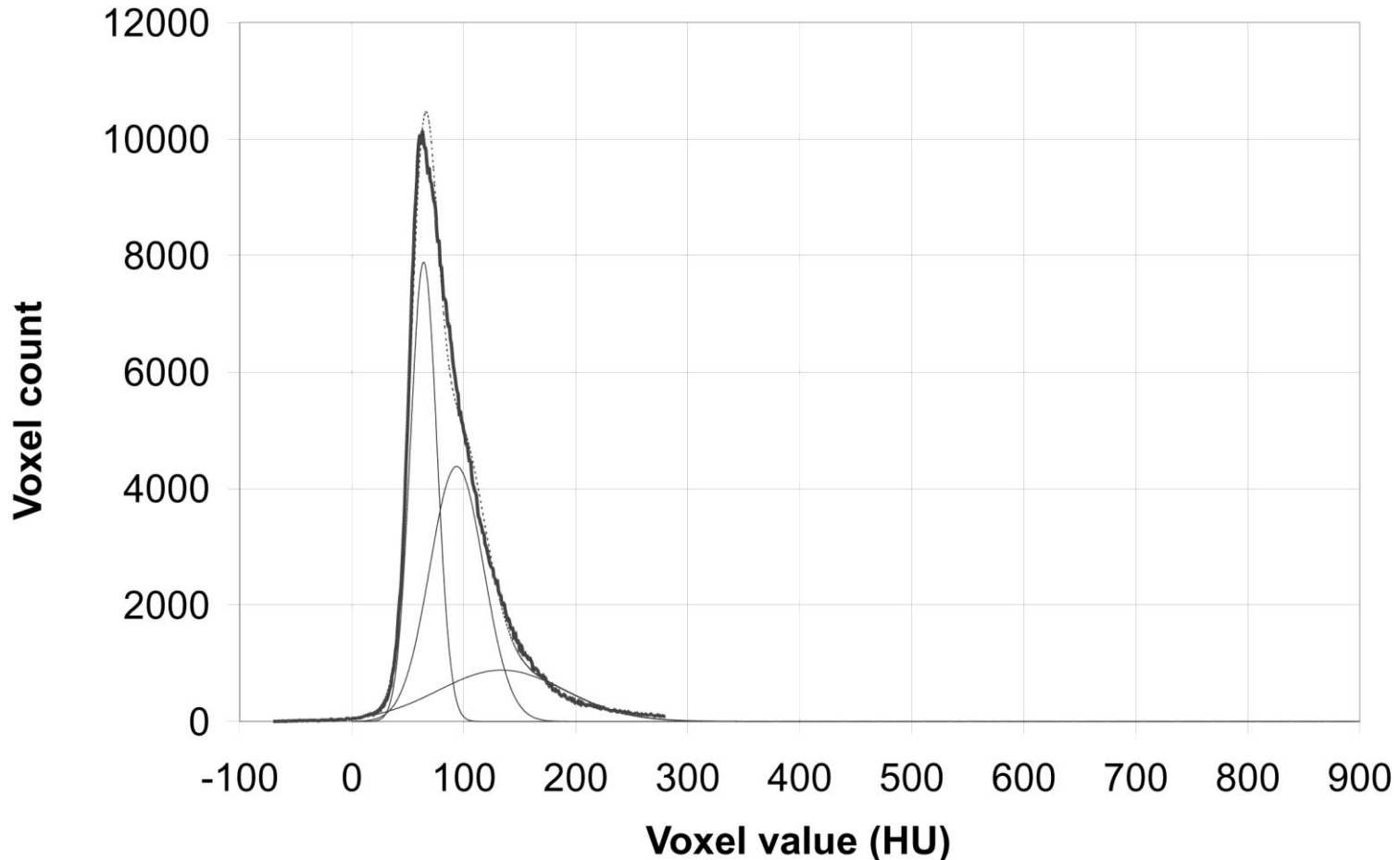


Case 1c  
Sept 2001



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# Estimation of the Tissue Composition of the Tumor

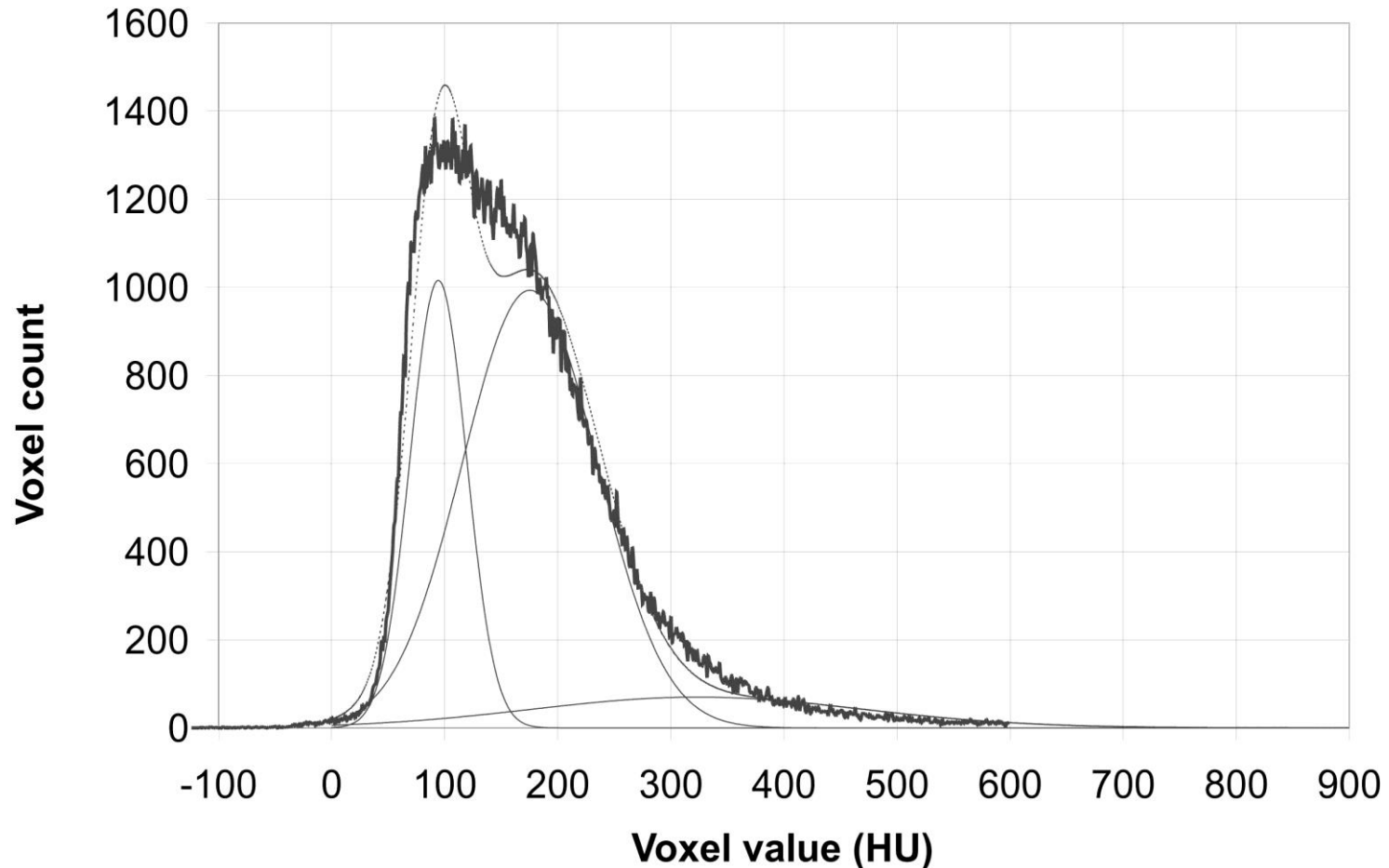


GMM for Case 1a,  $M = 3$



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# Estimation of the Tissue Composition of the Tumor

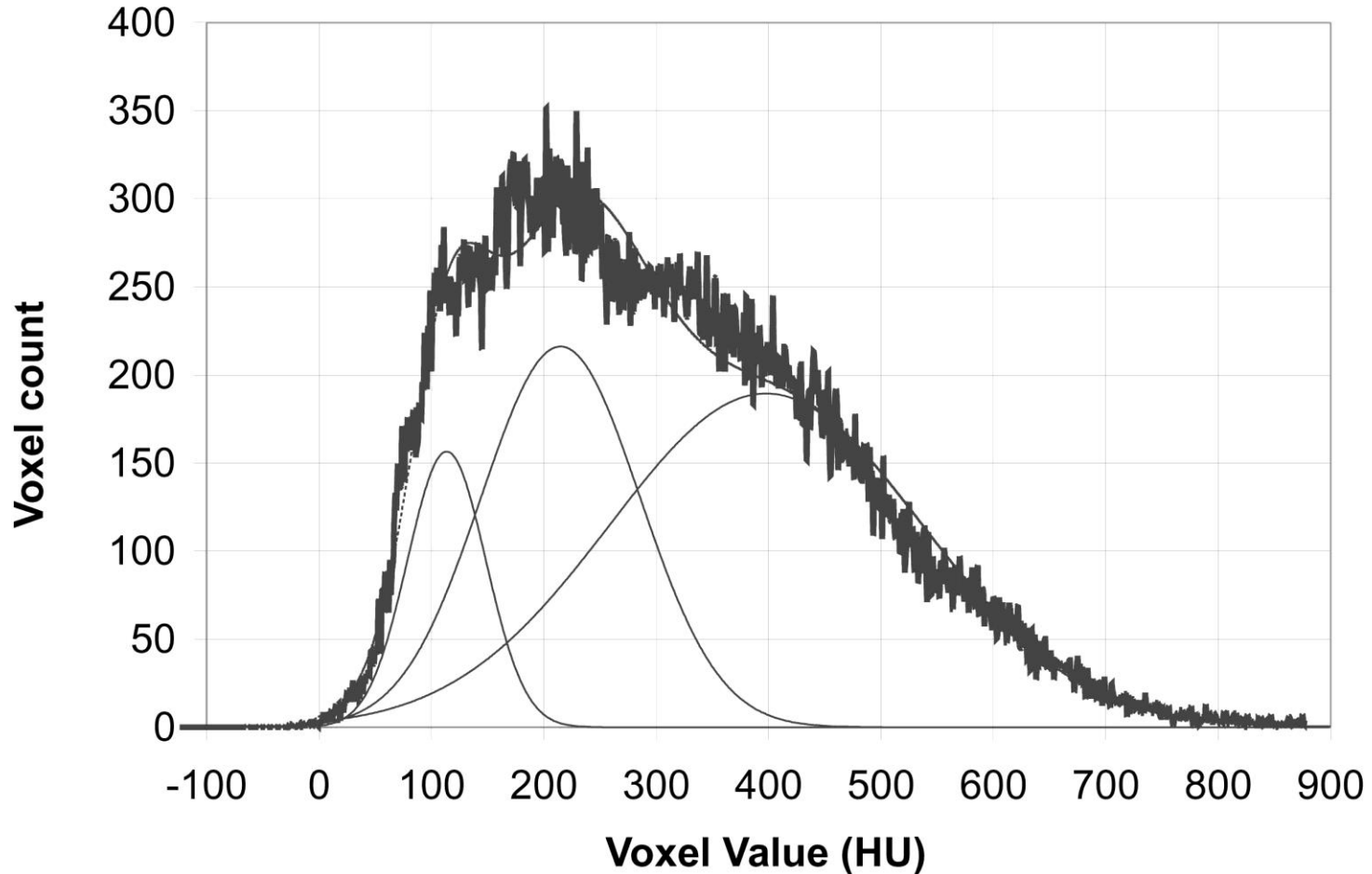


GMM for Case 1b,  $M = 3$



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# Estimation of the Tissue Composition of the Tumor

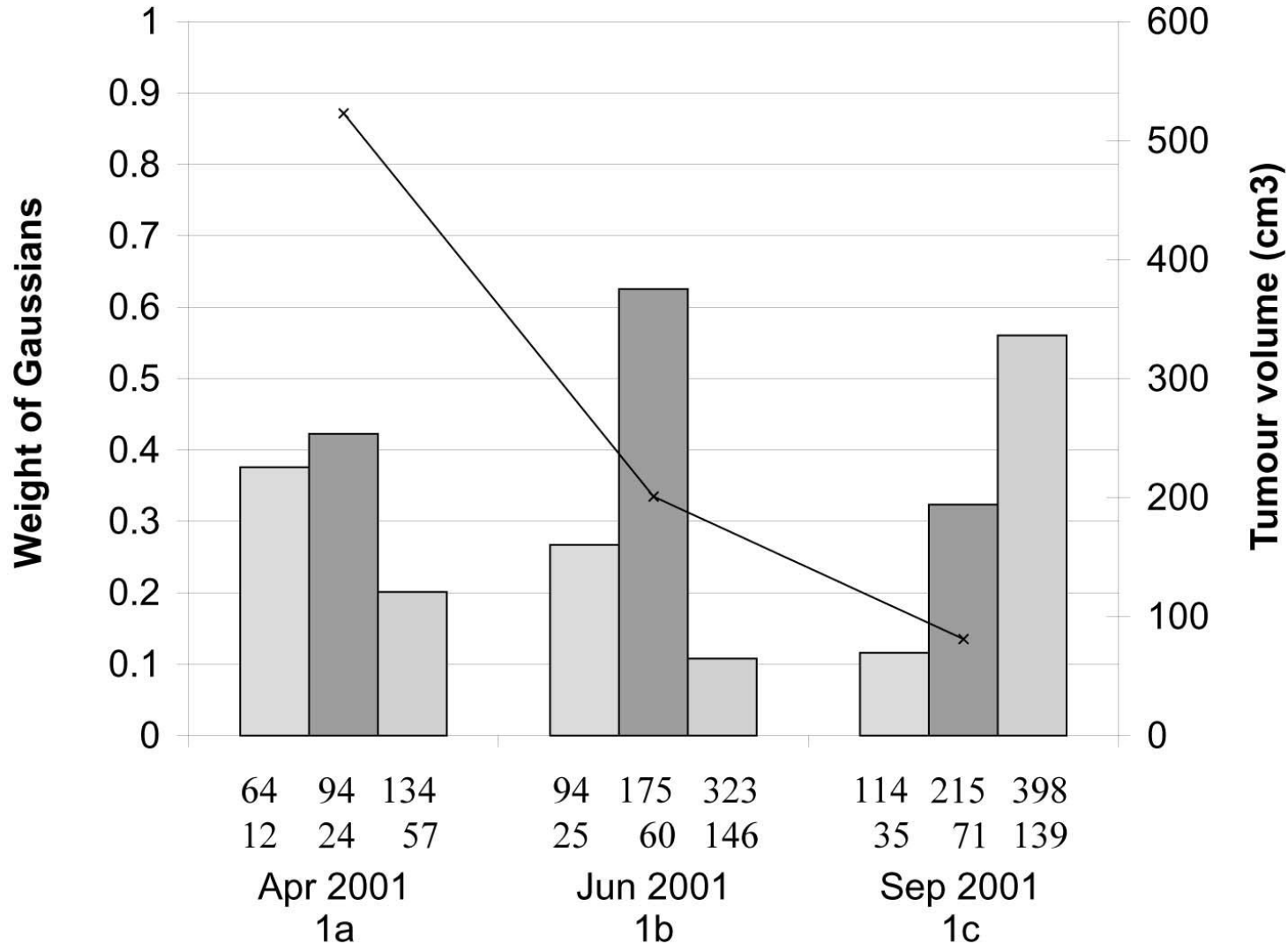


GMM for Case 1c,  $M = 3$



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# Analysis of the Response to Treatment of the Tumor

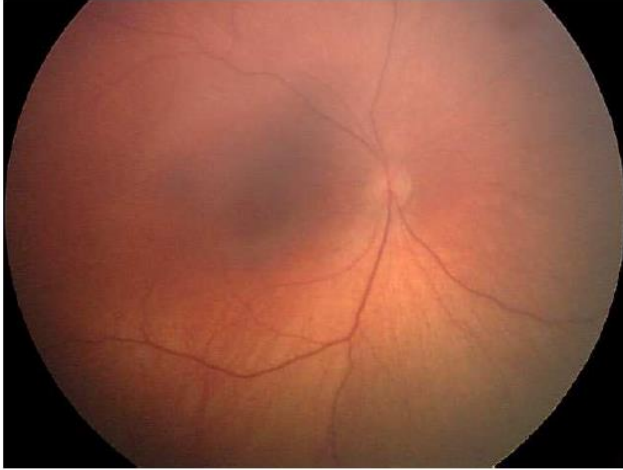




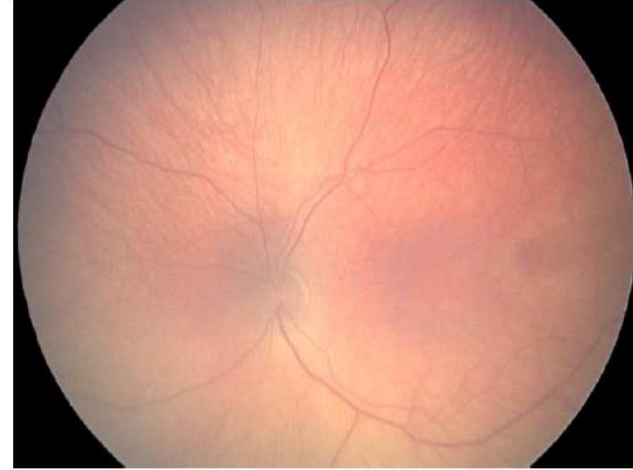
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# Retinopathy of Prematurity: RoP and Plus Disease

RoP 0



RoP 1



RoP 2



RoP 3





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# Objectives of CAD of RoP

- ❖ Detection of vessels and measurement of the thickness of the major temporal arcade (MTA)
- ❖ Quantification of the openeness of the MTA via parabolic modeling and measurement of the temporal arcade angle (TAA)
- ❖ Quantification of vascular tortuosity

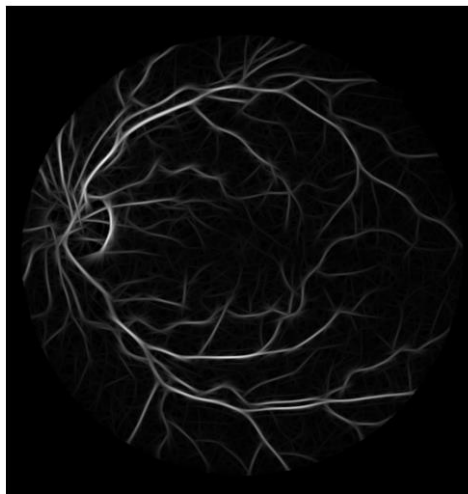


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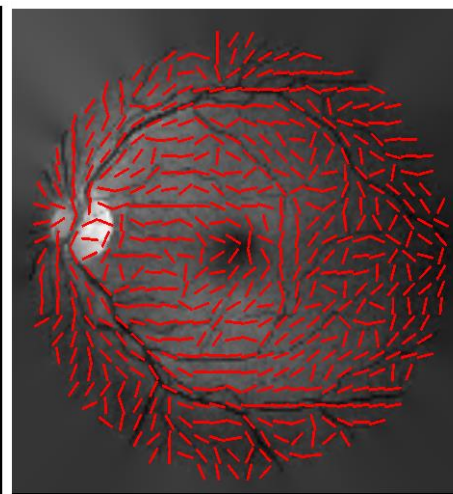
# Detection of Vessels and the Center of the Optic Disk



DRIVE  
Image 01



Magnitude  
response of  
Gabor filters



Orientation  
field



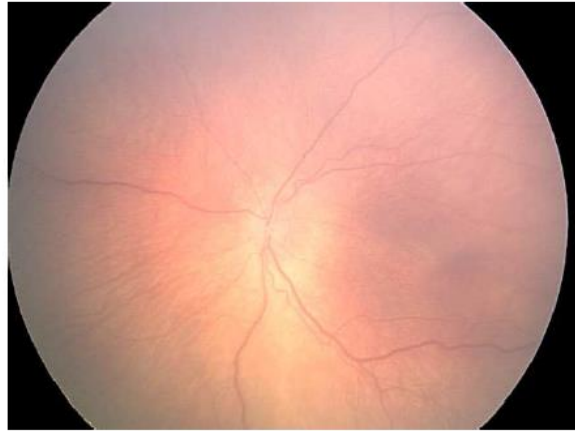
Detected center  
of the optic disk  
using phase  
portrait analysis



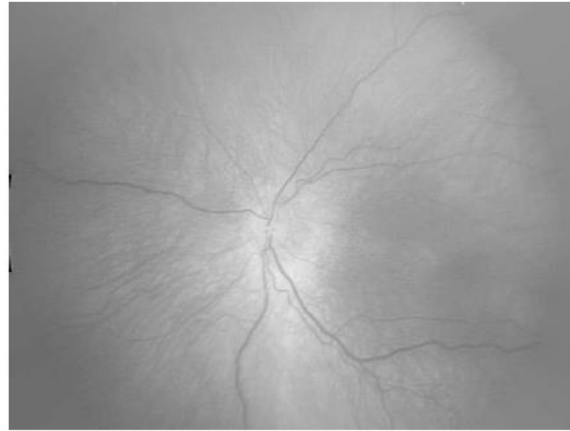


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# Vessel Width Measurement: No Plus Disease $111 \pm 18 \mu\text{m}$



(a)



(b)



(c)



(d)

(e)

(f)

(g)

(h)

(i)

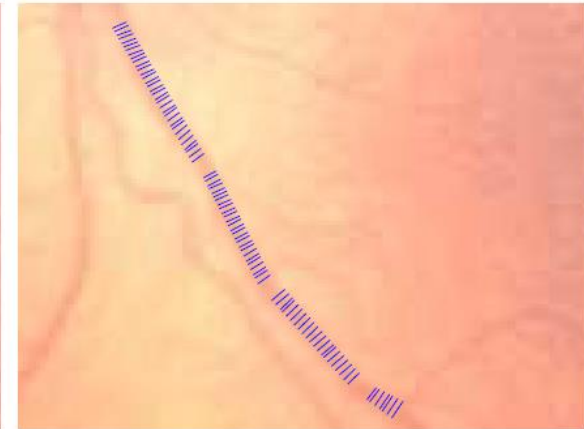
(j)



(k)



(l)



(m)

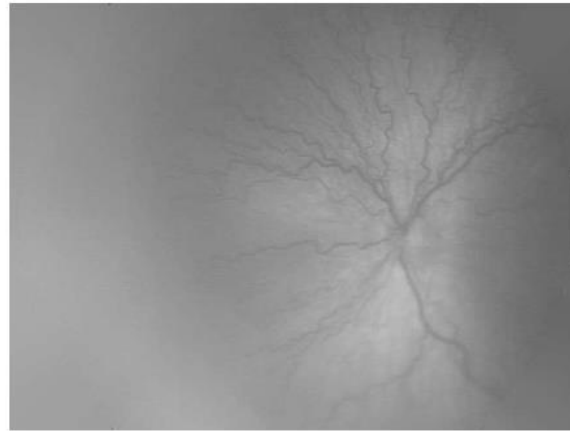


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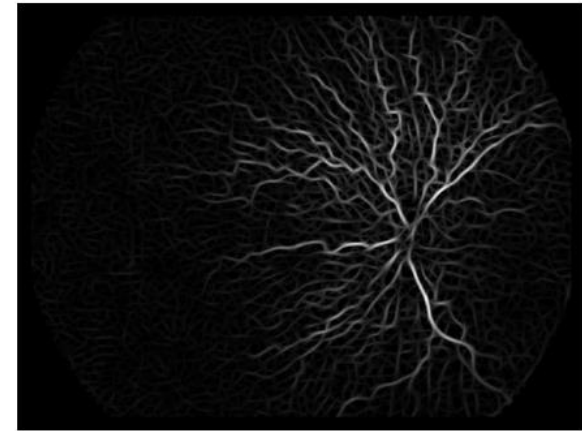
# Vessel Width Measurement: Plus Disease $125 \pm 17 \mu\text{m}$



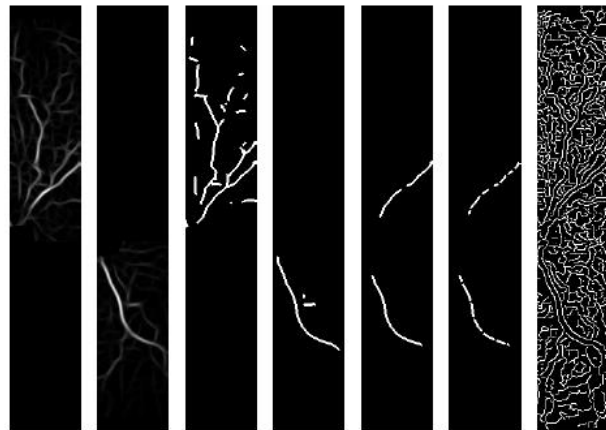
(a)



(b)



(c)



(d)

(e)

(f)

(g)

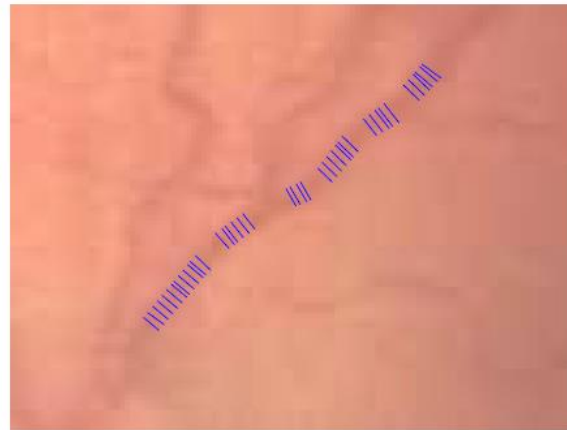
(h)

(i)

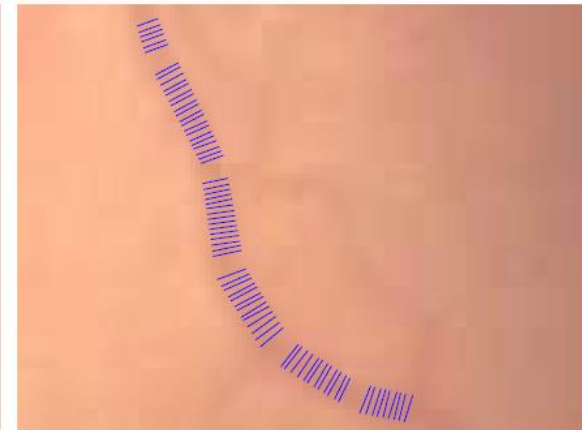
(j)



(k)



(l)

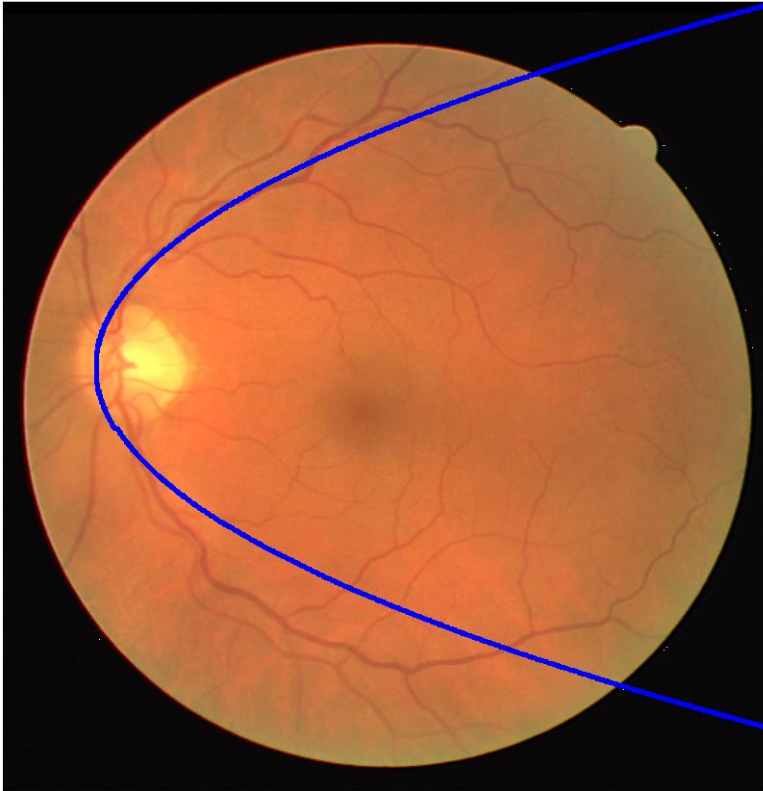


(m)

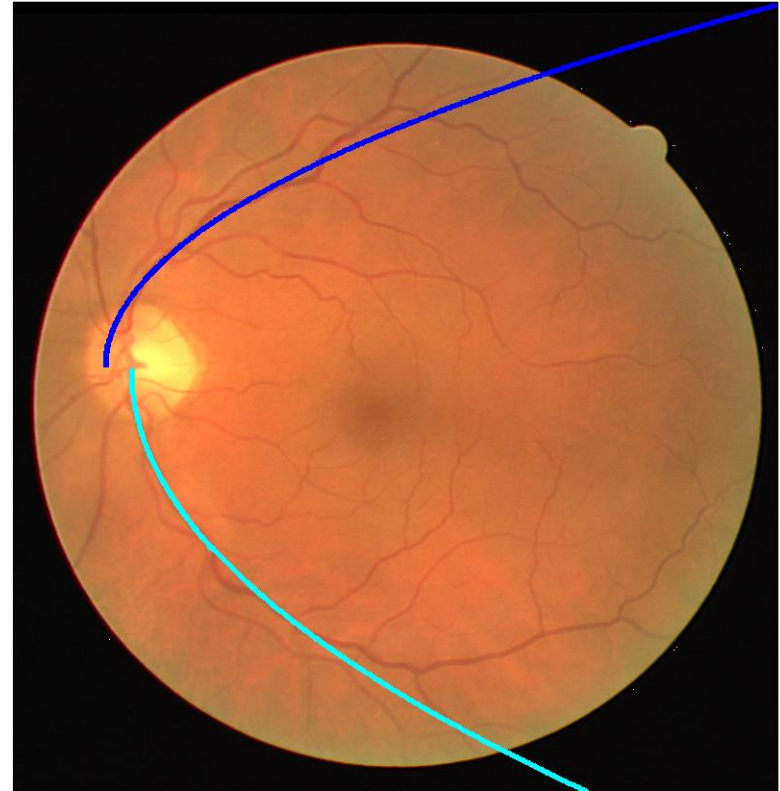


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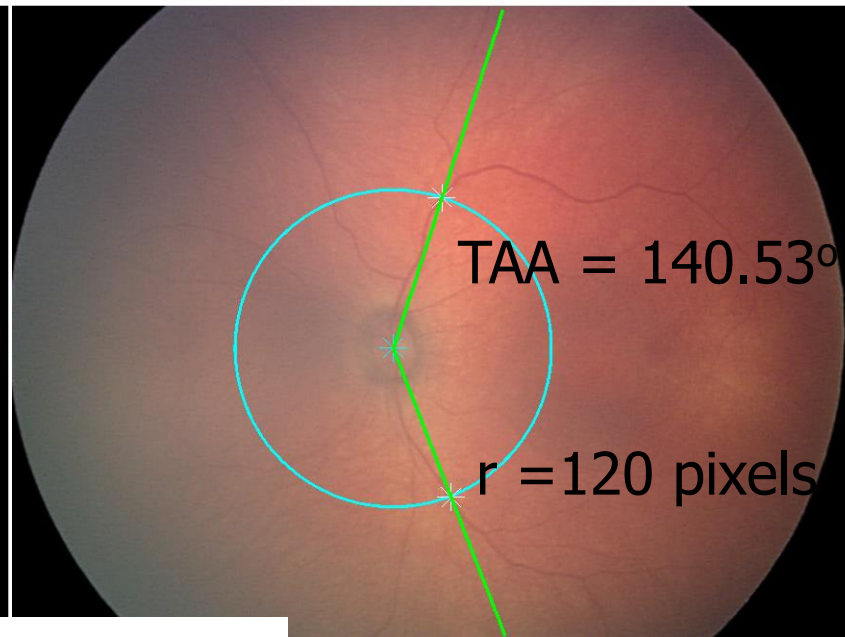
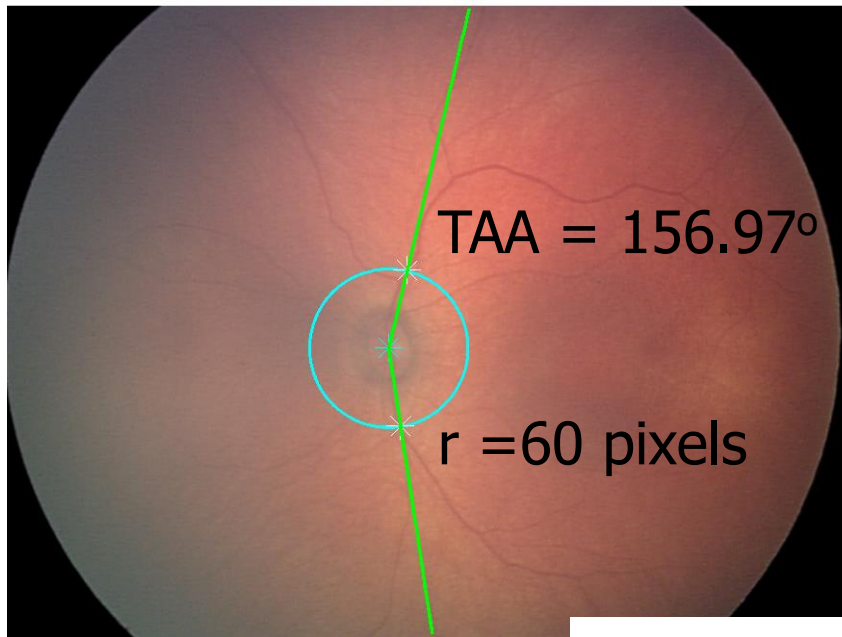
# Dual-parabolic Modeling using the Hough Transform



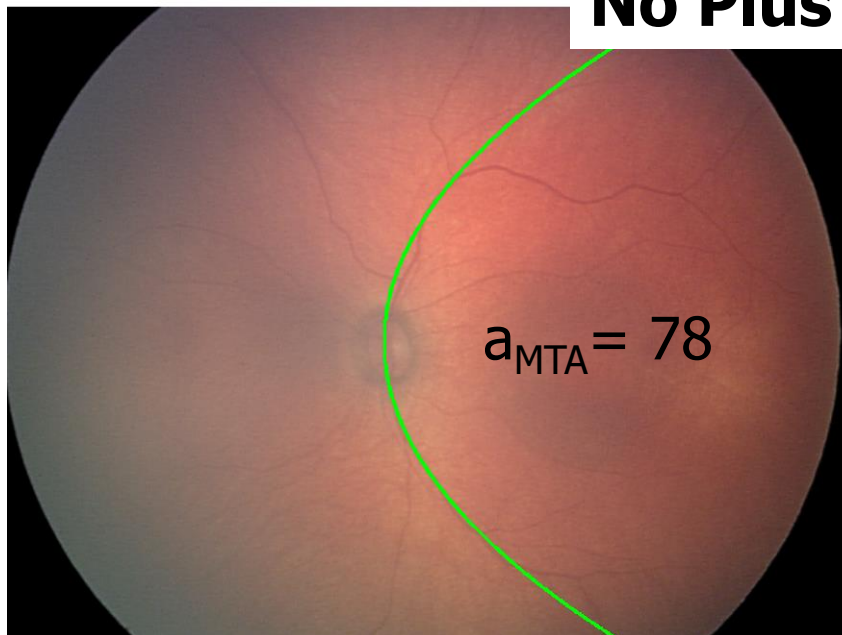
Single-parabolic fit

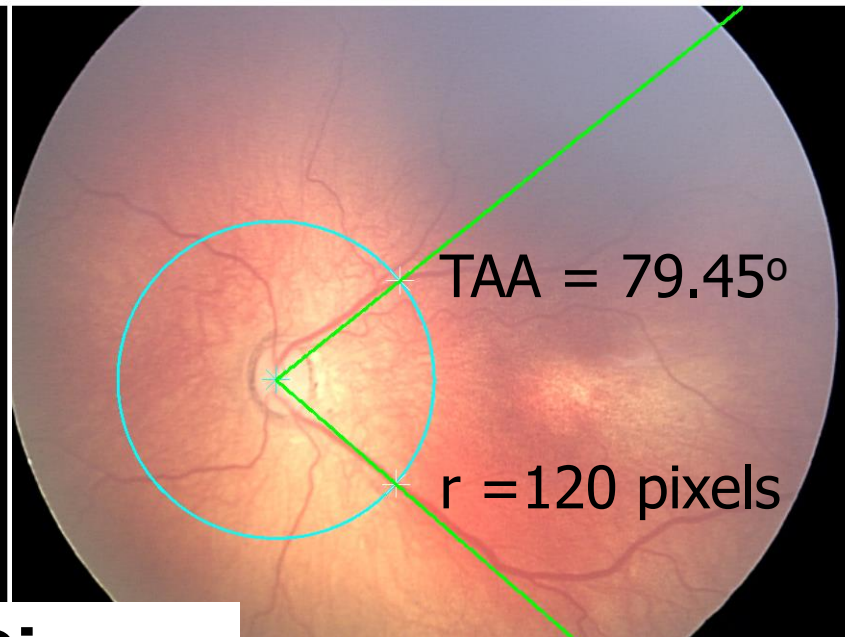
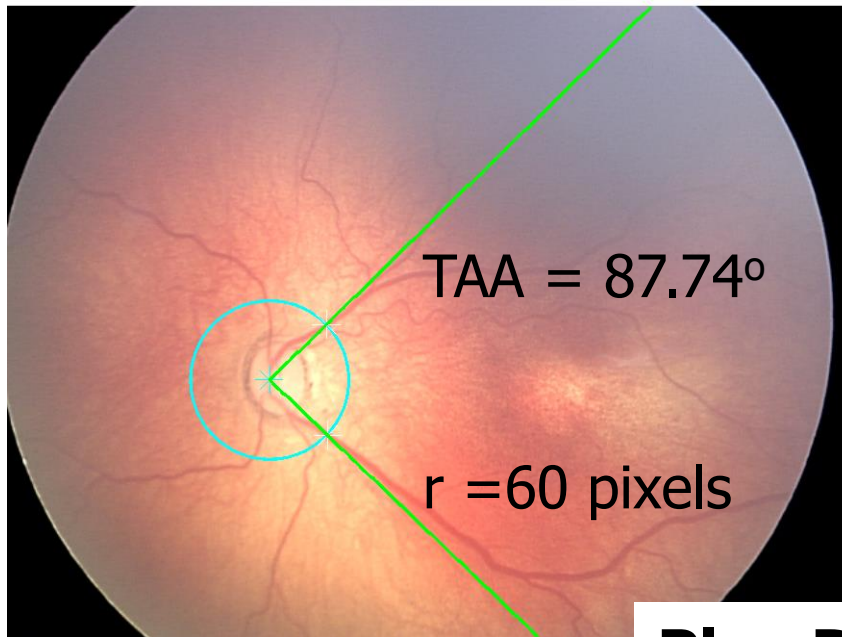


Dual-parabolic fit

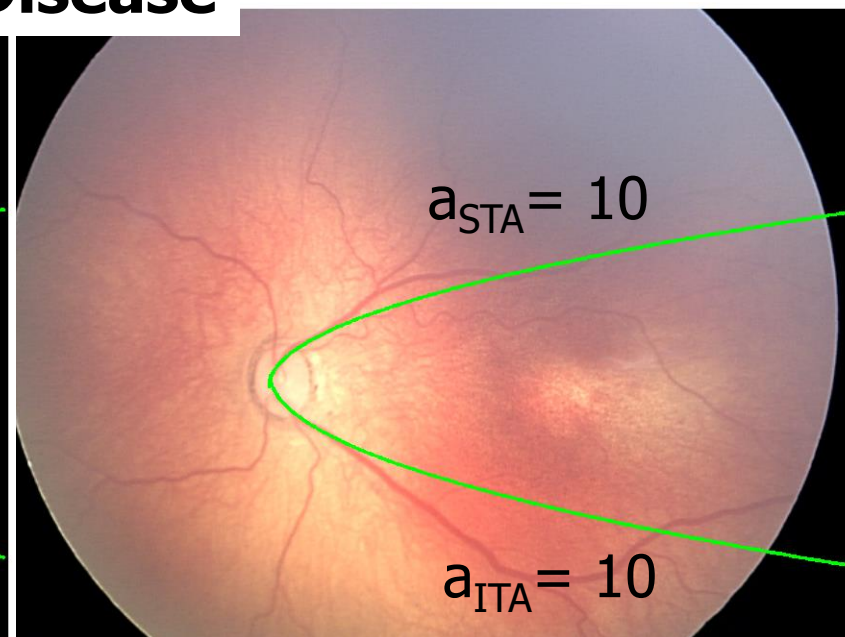
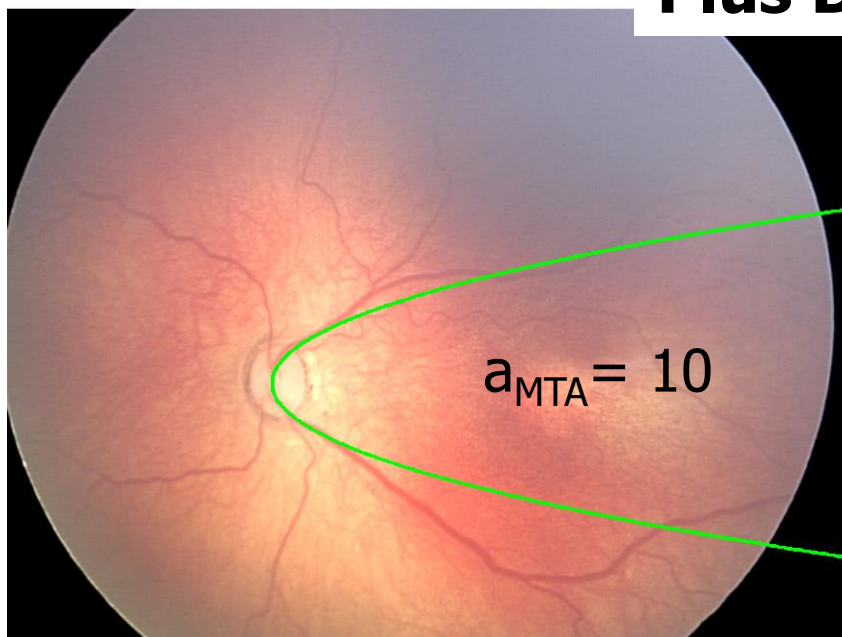


**No Plus Disease**





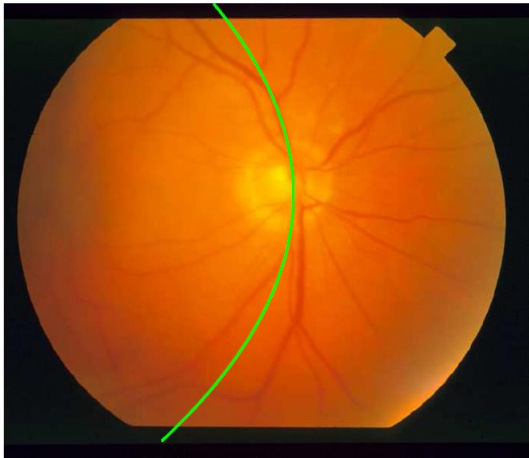
**Plus Disease**



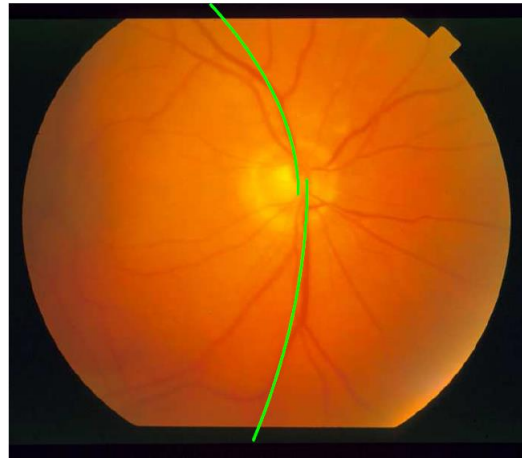


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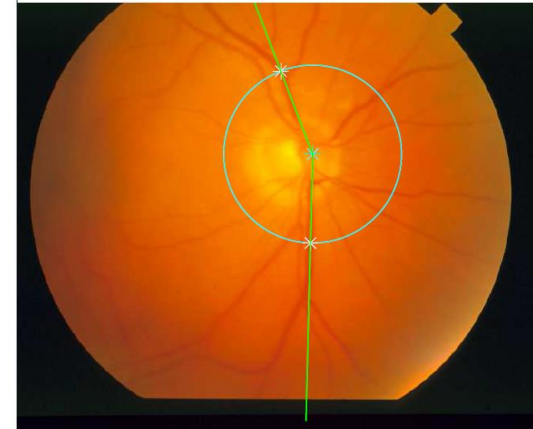
# PDR: Proliferative Diabetic Retinopathy



Normal: aMTA = 153



aSTA = 138, aITA = 420



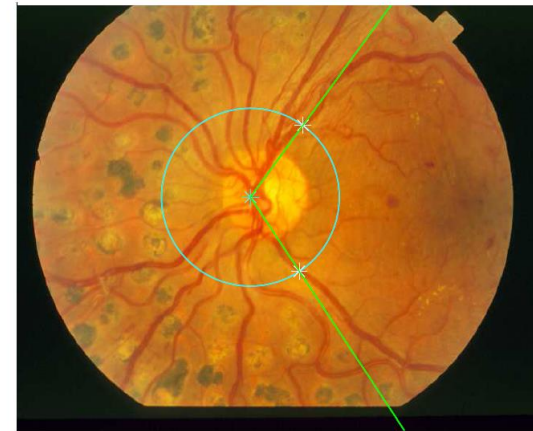
TAA = 157.8°



PDR: aMTA = 55



aSTA = 36, aITA = 48



TAA = 110.4°



# Measure of Tortuosity based on Vessel Angle

- ❖ Angle-variation index:

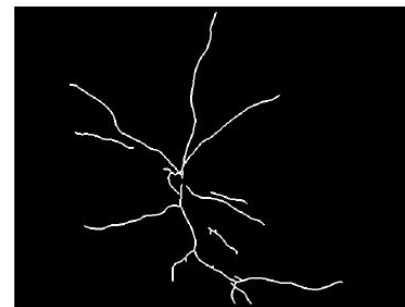
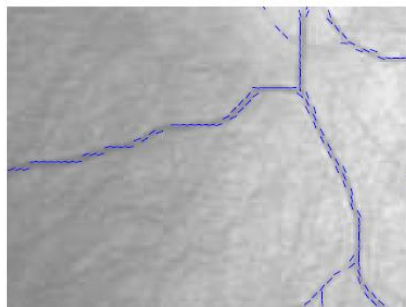
$$AVI(p) =$$

$$\frac{1}{2} \left\{ \left| \sin [\phi(p) - \phi(p - 1)] \right| + \left| \sin [\phi(p) - \phi(p + 1)] \right| \right\}$$

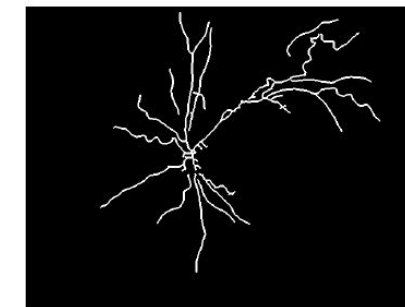
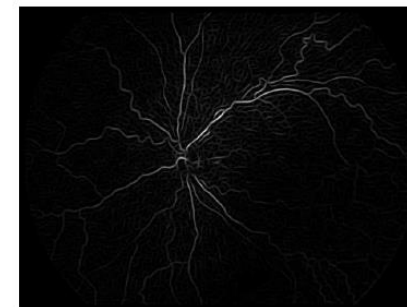
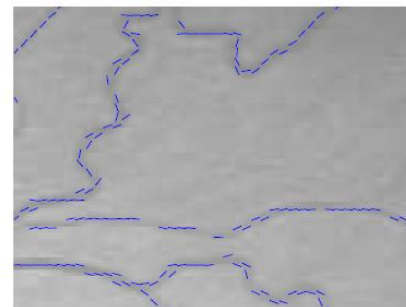
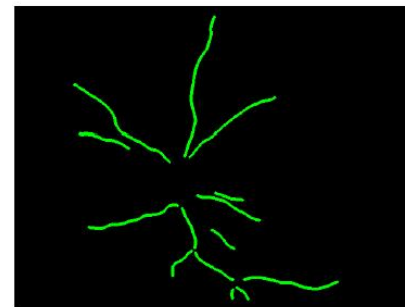
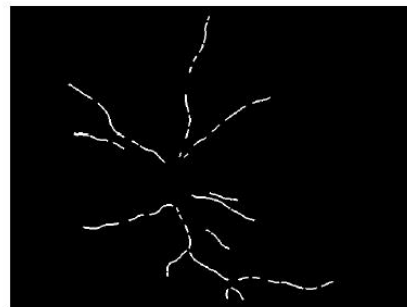
- ❖ Average AVI for a vessel segment:

$$AVT = \frac{1}{N} \sum_{n=1}^N AVI(n)$$

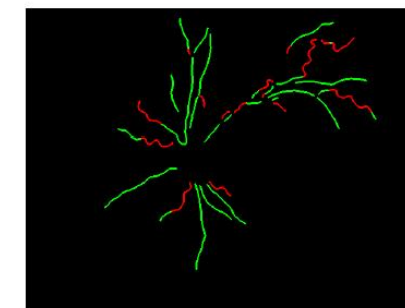
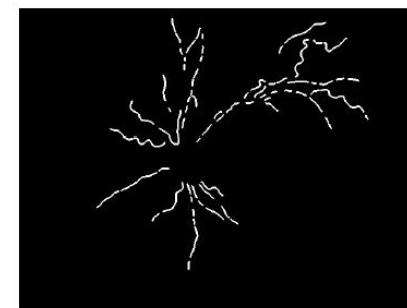
- ❖ AVT normalized to  $[0, 1]$  for each segment



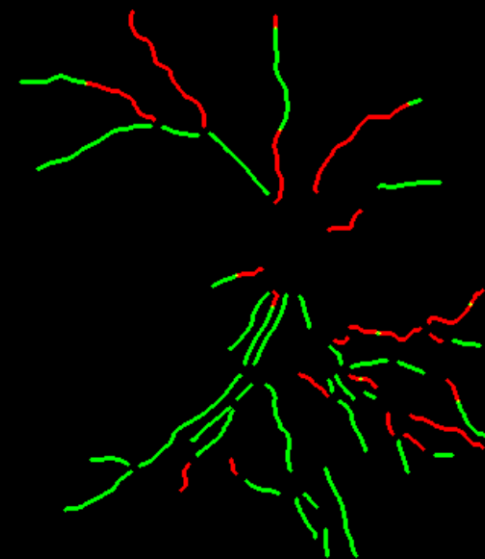
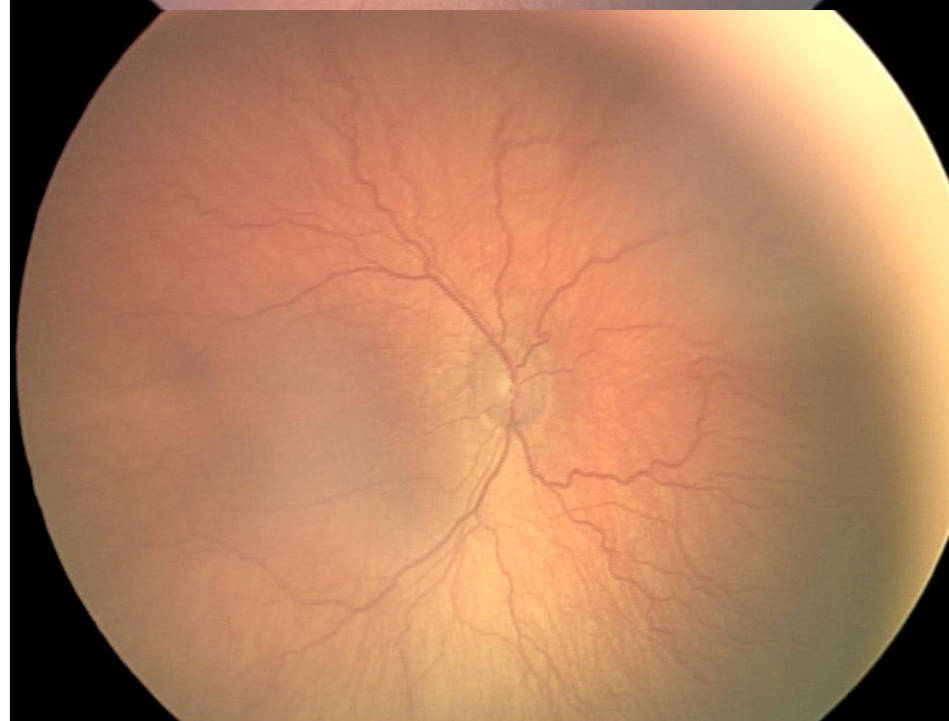
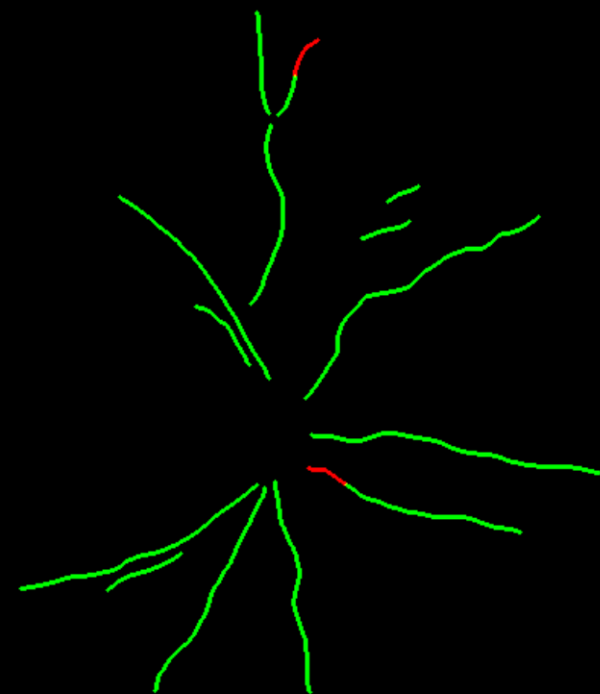
Case with no plus disease: 0 mm of tortuous vessels



Case with plus disease: 11.75, 4.20, 1.99, and 1.42 mm in the four quadrants







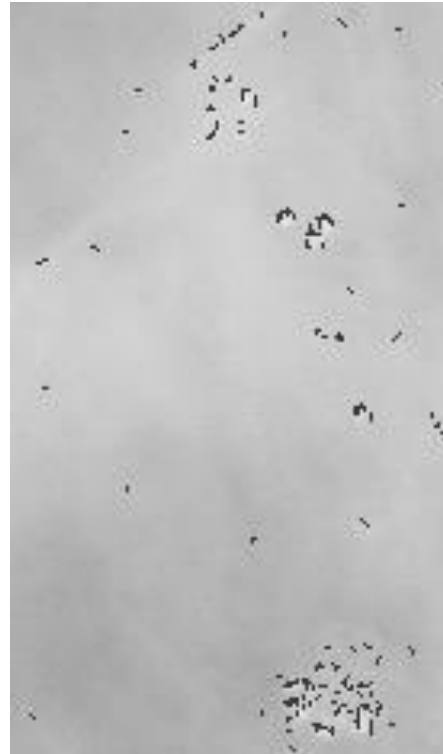


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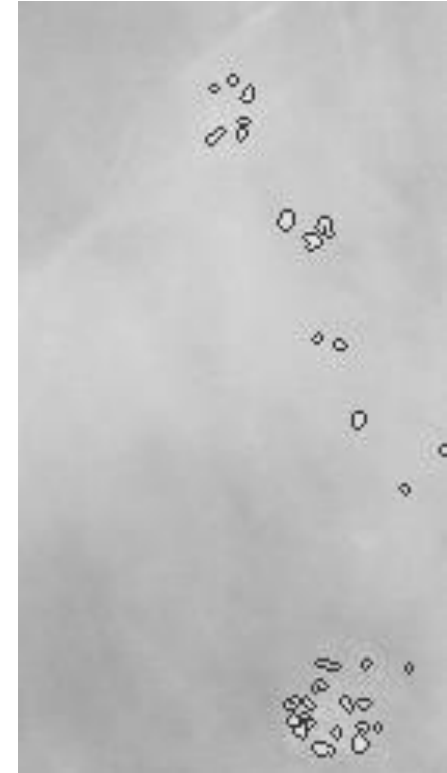
# Detection of Calcifications in Mammograms



(a) Part of original  
mammogram



(b) Seeds detected  
using prediction  
error

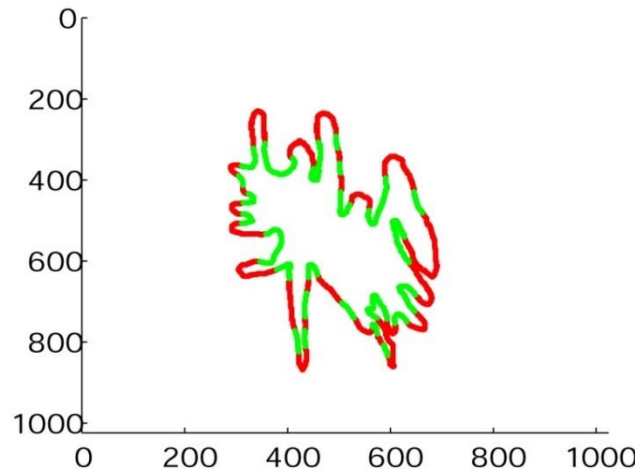
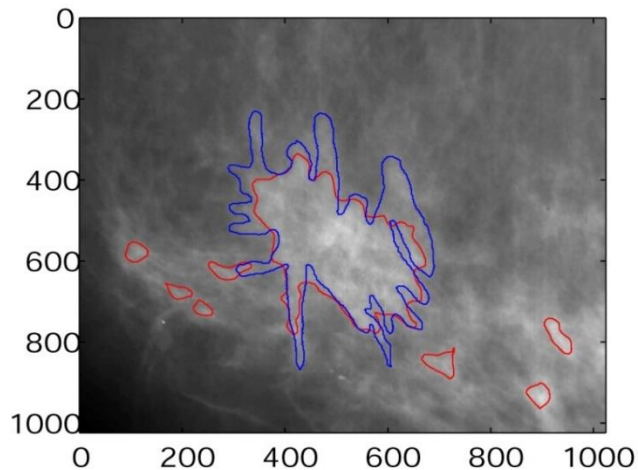
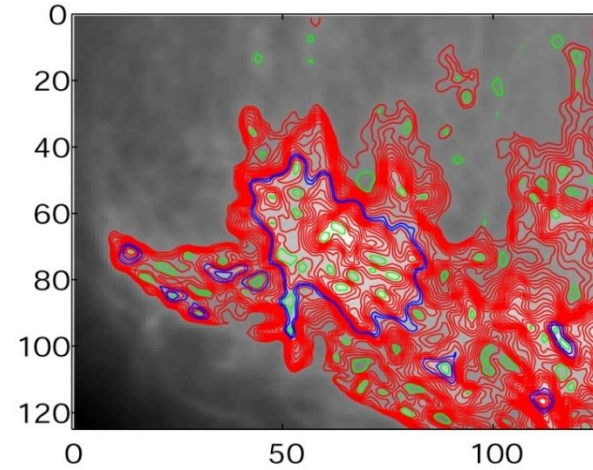
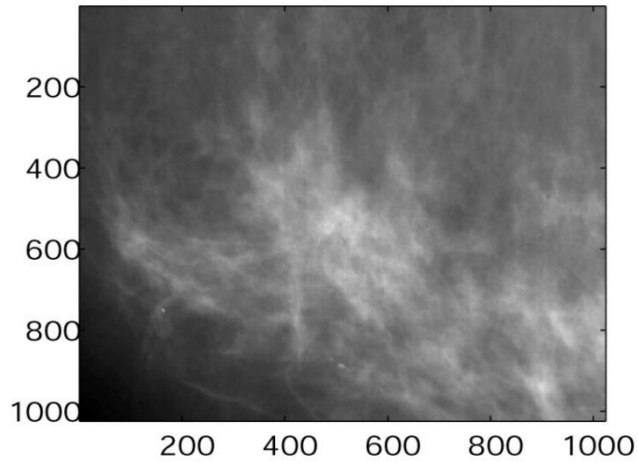


(c) Calcifications  
detected by region  
growing



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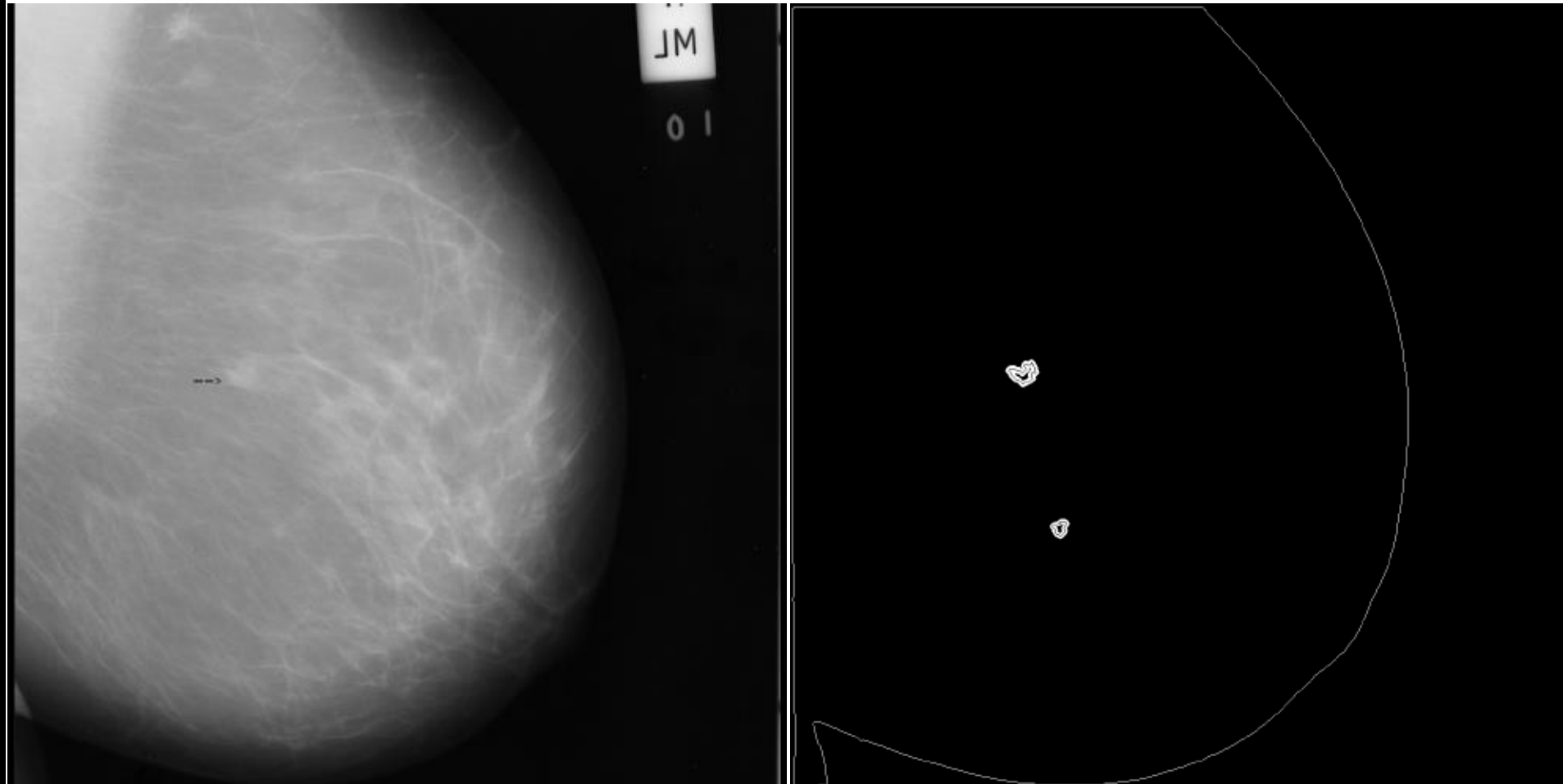
# Detection of Breast Tumors in Mammograms





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# Detection of Breast Tumors: The Problem of False Positives

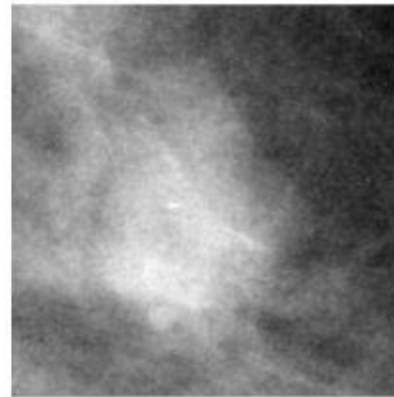




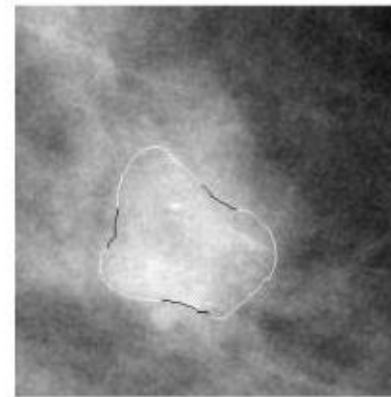
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# Analysis of Breast Masses: Feature Extraction

Mass region



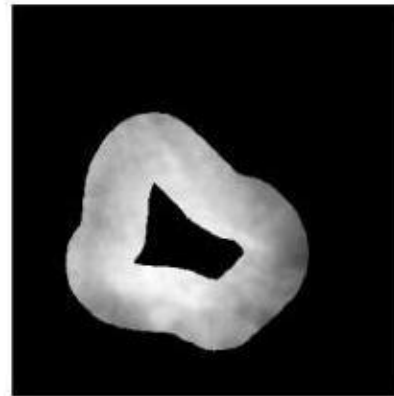
(a)



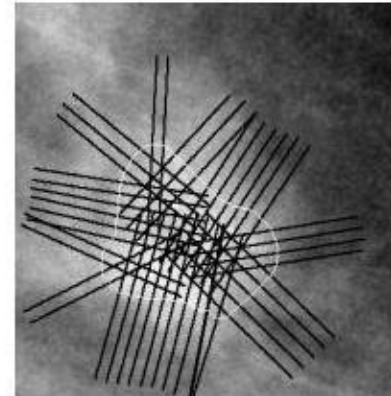
(b)

Shape  
analysis:  
Fractional  
concavity

Ribbon for  
computation  
of texture  
features



(c)



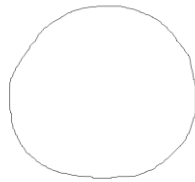
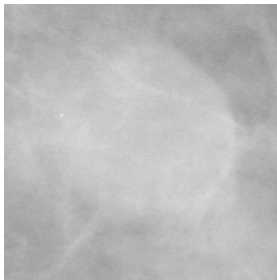
(d)

Normals to  
contour for  
computation of  
edge sharpness  
(acutance)



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# Objective Representation of Breast Masses



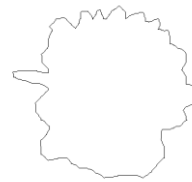
(a) b145lc95  
 $F_{cc} = 0.00$   
 $A = 0.07$   
 $F_8 = 8.11$

**benign  
circumscribed**



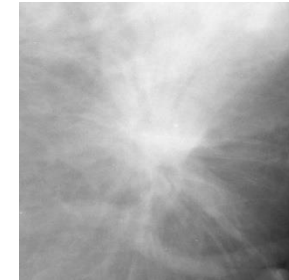
(b) b164ro94  
 $F_{cc} = 0.42$   
 $A = 0.08$   
 $F_8 = 8.05$

**benign  
macrolobulated**



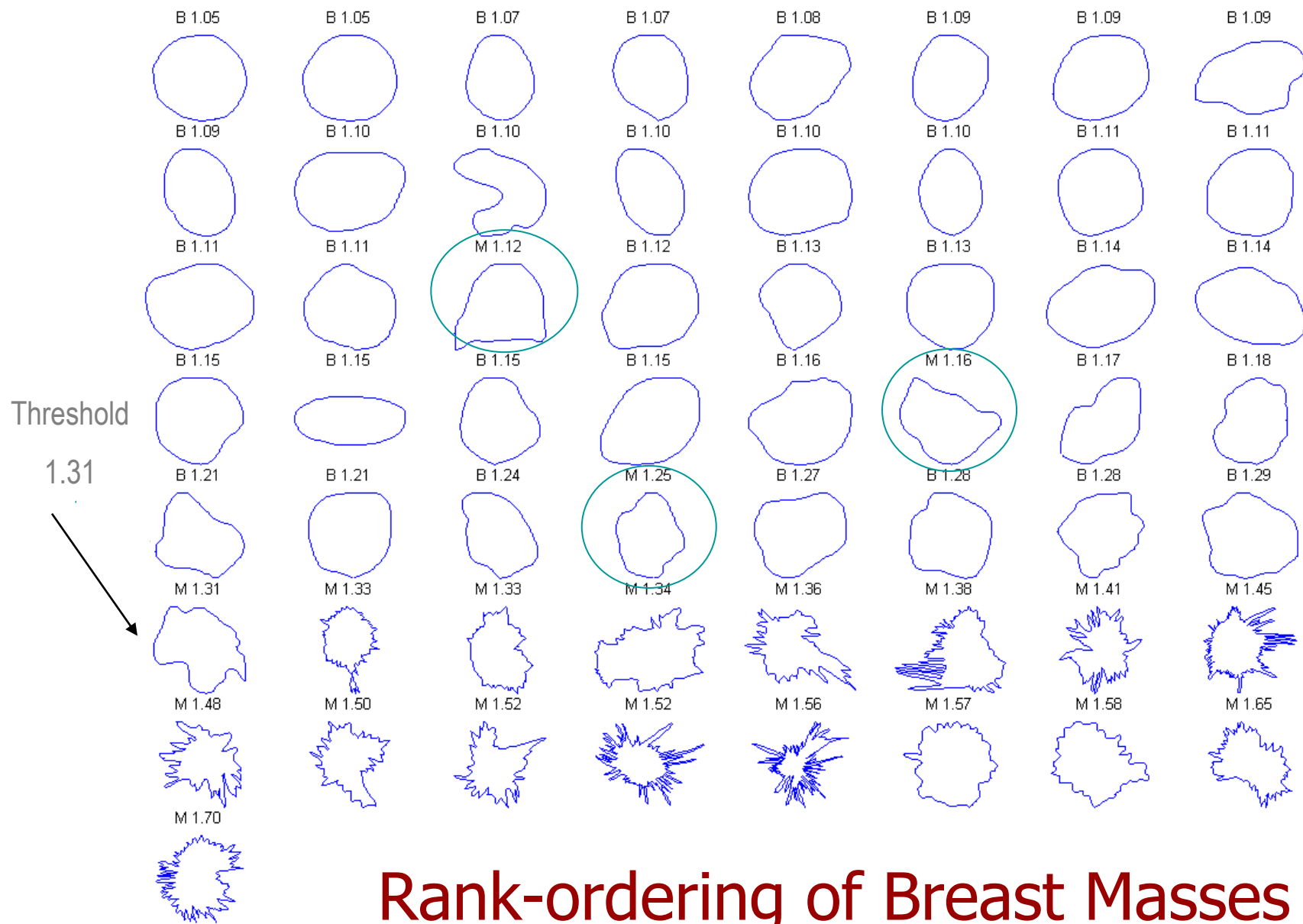
(c) m51rc97  
 $F_{cc} = 0.64$   
 $A = 0.09$   
 $F_8 = 8.15$

**malignant  
microlobulated**



(d) m55lo97  
 $F_{cc} = 0.83$   
 $A = 0.01$   
 $F_8 = 8.29$

**malignant  
spiculated**



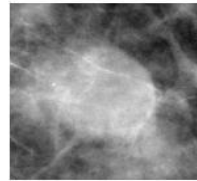
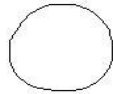
# Rank-ordering of Breast Masses using Shape Factors



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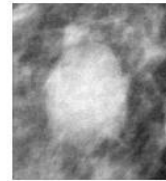
# Content-based Image Retrieval: Benign Mass

Query



b145lc95

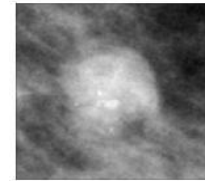
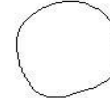
Rank 1



b62lx97

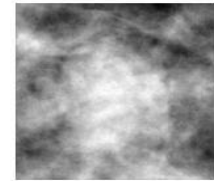
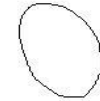
Retrieved samples

Rank 2



b164rx94

Rank 3



b148ro97

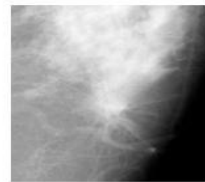
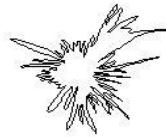




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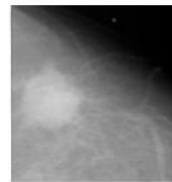
# Content-based Image Retrieval: Malignant Tumor

Query



m55lo97

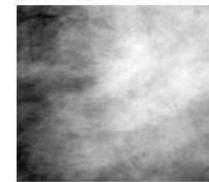
Rank 1



m58rc97

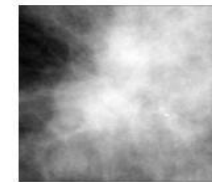
Retrieved samples

Rank 2



m61lo97

Rank 3

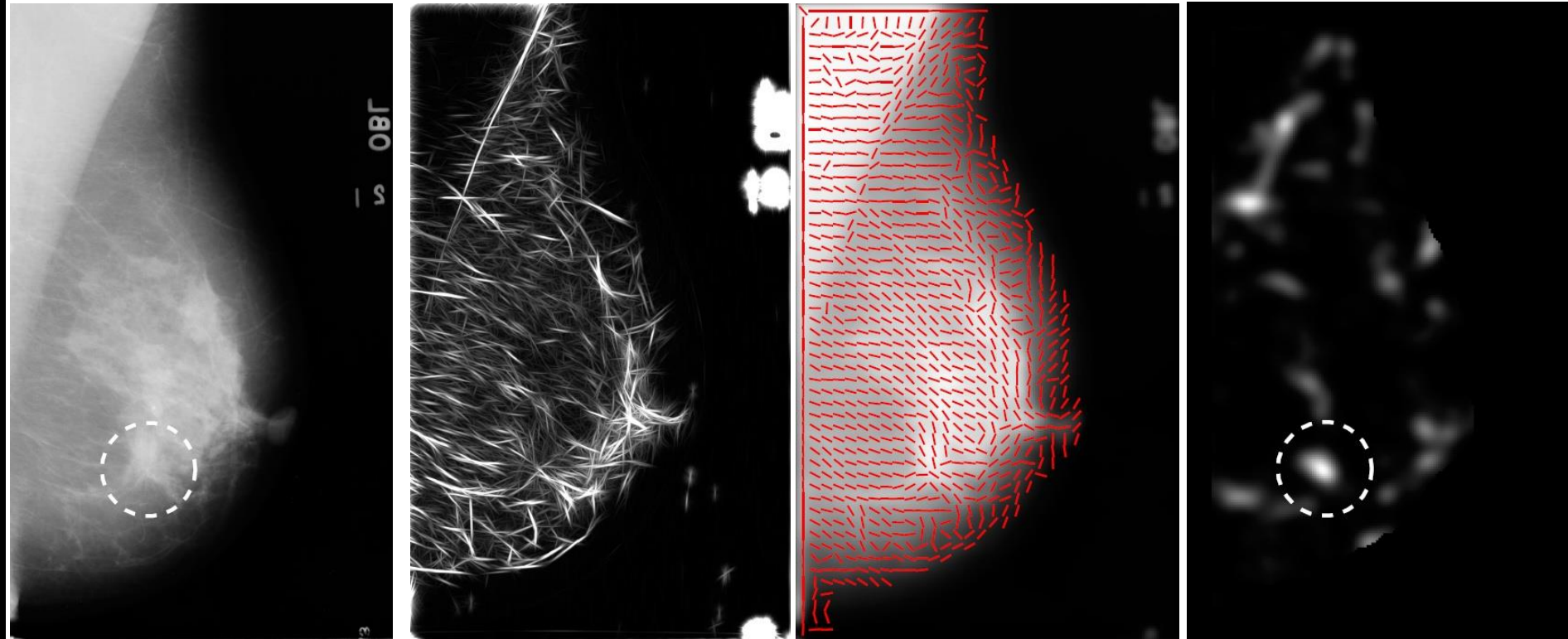


m55lc97



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# Subtle Sign of Breast Cancer: Architectural Distortion



Mammogram

Gabor Magnitude

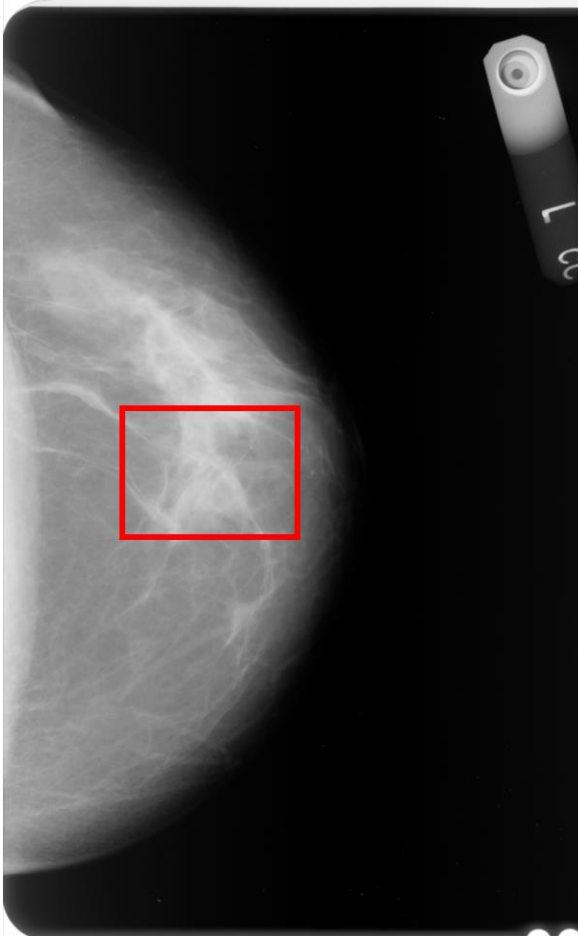
Angle Response

Node Map

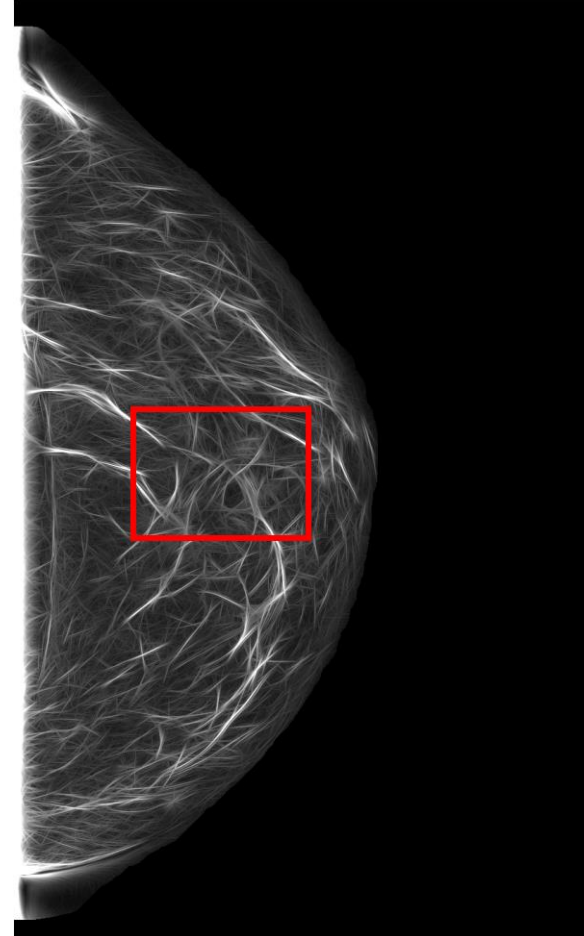


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# Prior Mammogram of Interval Cancer



Mammogram

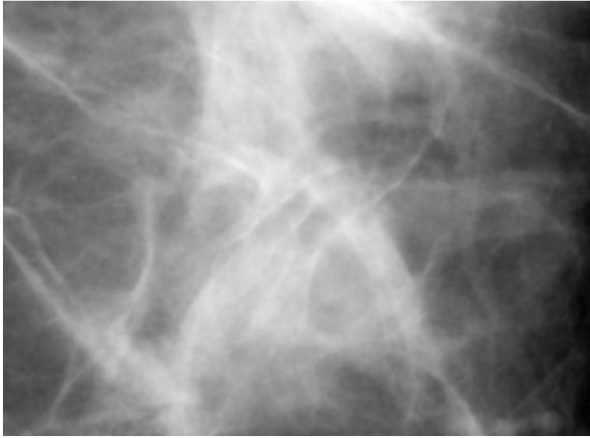


Gabor Magnitude

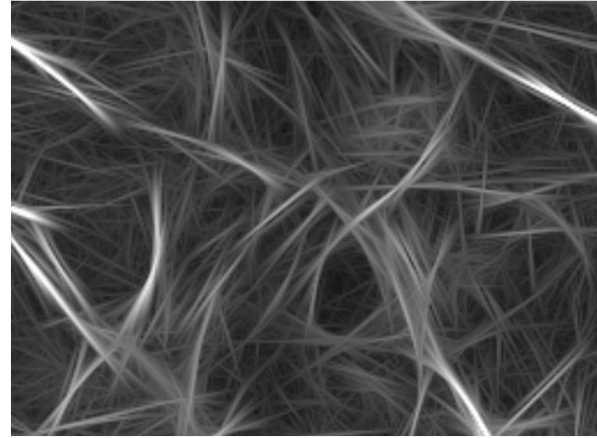


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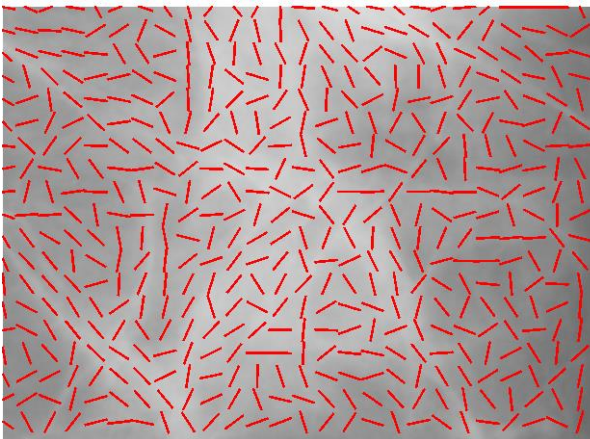
# Site of Architectural Distortion



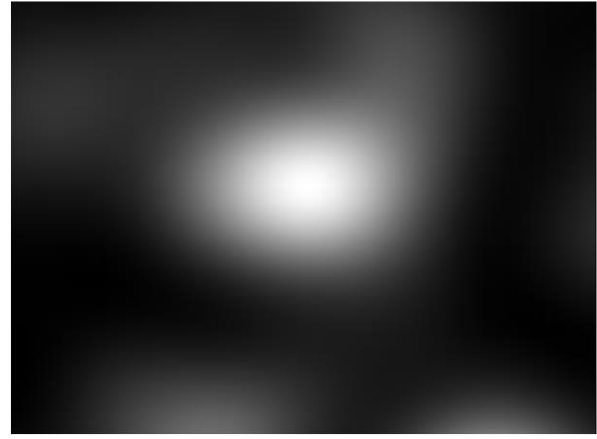
Mammogram



Gabor magnitude



Orientation field

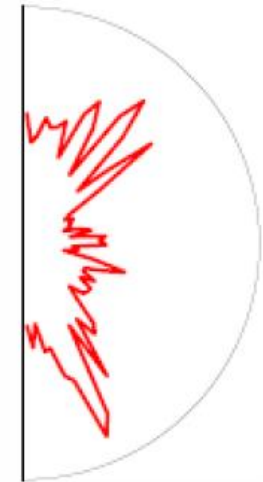
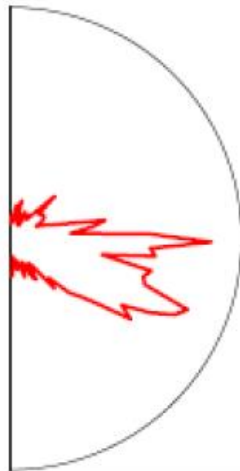
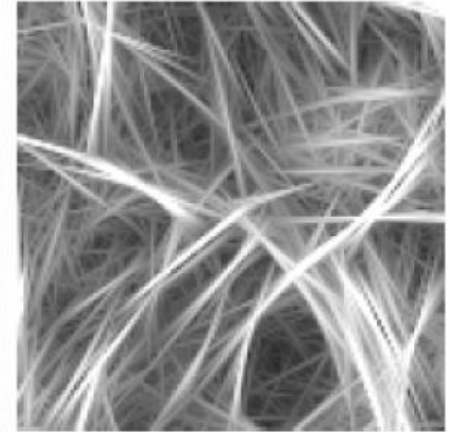
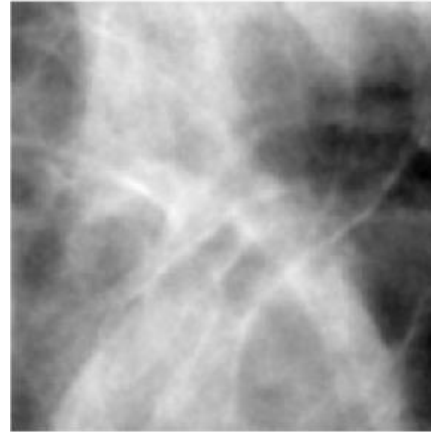
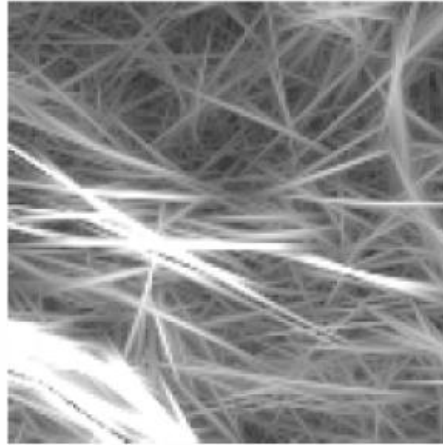
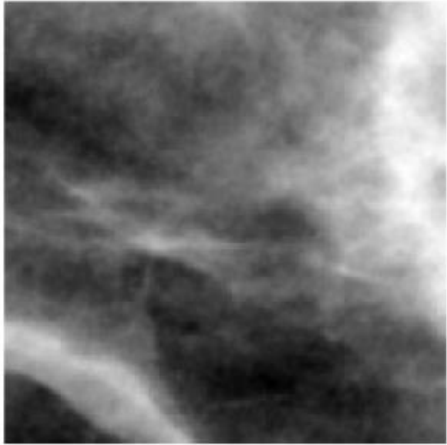


Node map



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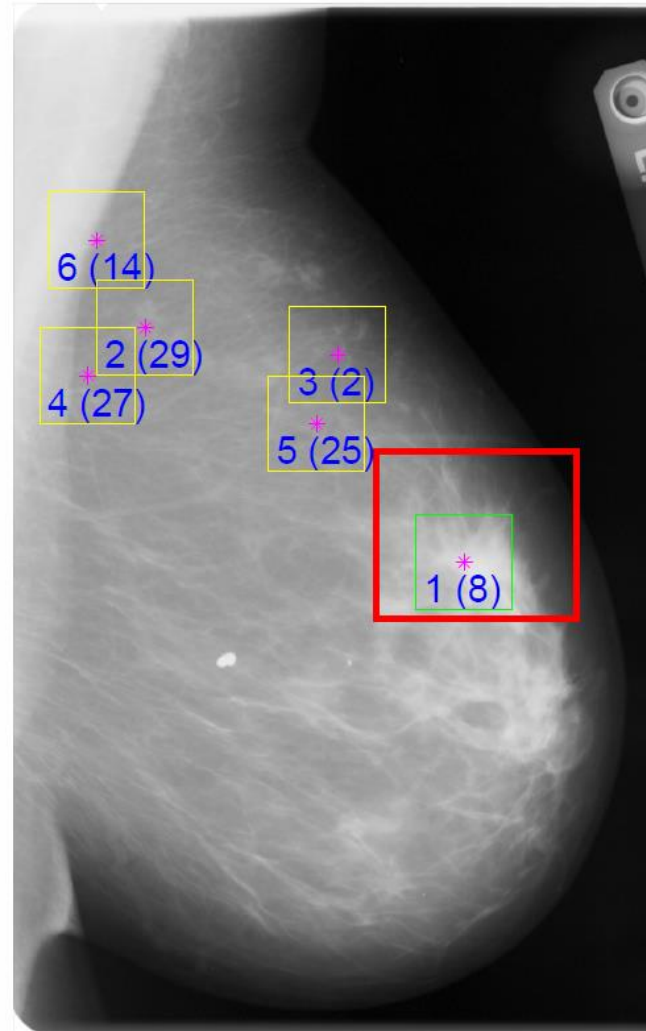
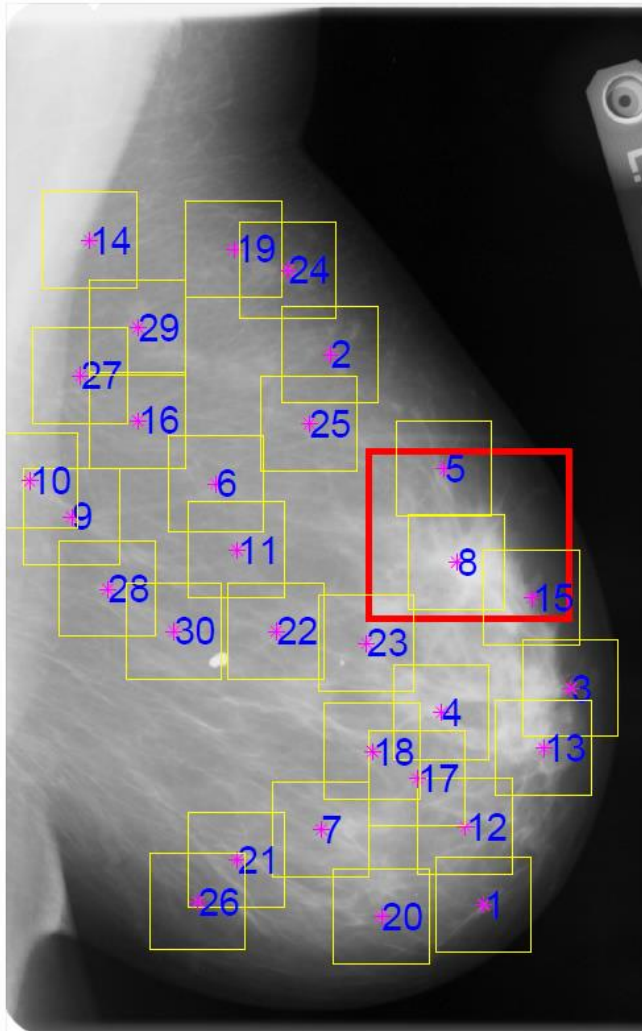
# Analysis of Angular Spread: Normal vs Architectural Distortion





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# Reduction of False Alarms via Design of Attributes and Pattern Classification Algorithms





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# CAD of Breast Cancer

“Our methods can detect early signs of breast cancer 15 months ahead of the time of clinical diagnosis with a sensitivity of 80% with fewer than 4 false positives per patient”

**Let's  
CAD!?**







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# Objectives of Computer-aided Analysis of Medical Images

- ❖ Enhancement of image quality
- ❖ Detection of subtle signs of disease
- ❖ Quantitative analysis of diagnostic features
- ❖ Objective aids to diagnostic decision
- ❖ Accurate, consistent, reproducible analysis
- ❖ *Earlier detection of breast cancer!*
- ❖ *Reduced morbidity and mortality!*



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# Why CAD?

Manual analysis of medical images, even by experts, is susceptible to

- Intraobserver errors or inconsistencies
- Interobserver errors or inconsistencies
- Limitations of manual analysis



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# Intraobserver errors

- Inconsistent application of knowledge
- Subjective and qualitative nature of analysis
- Environmental effects and distraction
- Fatigue due to workload and repetitive tasks



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# Interobserver errors

- Inconsistencies in knowledge and training
- Subjective and qualitative nature of analysis
- Differences in opinion and preferences



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# Limitations of Manual Analysis

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- Inconsistencies in identifying landmarks in images
- Errors in landmark locations due to limited dexterity
- Extensive time and effort required for manual marking and measurement of intricate details
- Limitations in the precision and reproducibility of manual measurement and calculations
- Subjective and qualitative nature of analysis



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# Benefits of CAD

- Consistent application of established rules and methods
- Objective and quantitative analysis
- Numerical precision, accuracy, and speed of computation
- Ease of repeatability and reproducibility
- Immunity to effects of work environment, fatigue, and boredom



# The CAD Way to Improve Medical Diagnosis

<b>Move from</b>	<b>Via</b>	<b>To</b>
Qualitative analysis	Computation of measures, features, and attributes using digital image processing techniques	Quantitative analysis
Subjective analysis	Development of rules for diagnostic decision making using pattern classification techniques	Objective analysis
Inconsistent analysis	Implementation of established rules and robust procedures as computational algorithms	Consistent analysis
Interobserver and intraobserver errors	Medical image analysis, medical image informatics, and CAD	Improved diagnostic accuracy



# Main Steps of CAD

1. Preprocessing of a given image for further analysis
2. Detection and segmentation of regions of interest
3. Extraction of features for quantitative analysis
4. Selection of the best set of features or related measures
5. Training of classifiers and development of decision rules
6. Pattern classification and diagnostic decision making





# Measures of Performance: Comparison with Truth

	Disease is present	Disease is absent	Measures of performance
Test is positive	TP: True positive	FP: False positive	Positive predictive value $PPV = TP / (TP + FP)$
Test is negative	FN: False negative	TN: True negative	Negative predictive value $NPV = TN / (TN + FN)$
Measures of performance	Sensitivity $TP / (TP + FN)$	Specificity $TN / (TN + FP)$	Prevalence of disease $(TP + FN) / All$
Numbers of subjects	TP + FN With disease	TN + FP Without disease	All = TP + FN + TN + FP All subjects



# Measures of Performance: Comparison with Truth

## Truth Table

<b>Test Result</b>	<b>Positive</b>	<b>Negative</b>
<b>Truth</b>		
<b>Positive</b>	<b>True positive</b>	<b>False Negative</b>
<b>Negative</b>	<b>False Positive</b>	<b>True Negative</b>



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# Measures of Performance: Comparison with Truth

Truth Table for Classification of Vibroarthrographic Signals as Normal or Chondromalacia Using Time-frequency Distributions

Actual Group	No. of Signals	Predicted Group	
		N	Ch
N	51	40 78.4%	11 21.6%
Ch	20	5 25%	15 75%
Total	71	Overall Accuracy 77.5%	



# Measures of Performance: Comparison with Truth

## Confusion Matrix in Classification of Vertebral Compression Fractures

Predicted classification			True classification
Malignant VCFs	Benign VCFs	Normal vertebral bodies	
39	5	5	Malignant VCFs
13	35	5	Benign VCFs
4	1	84	Normal vertebral bodies



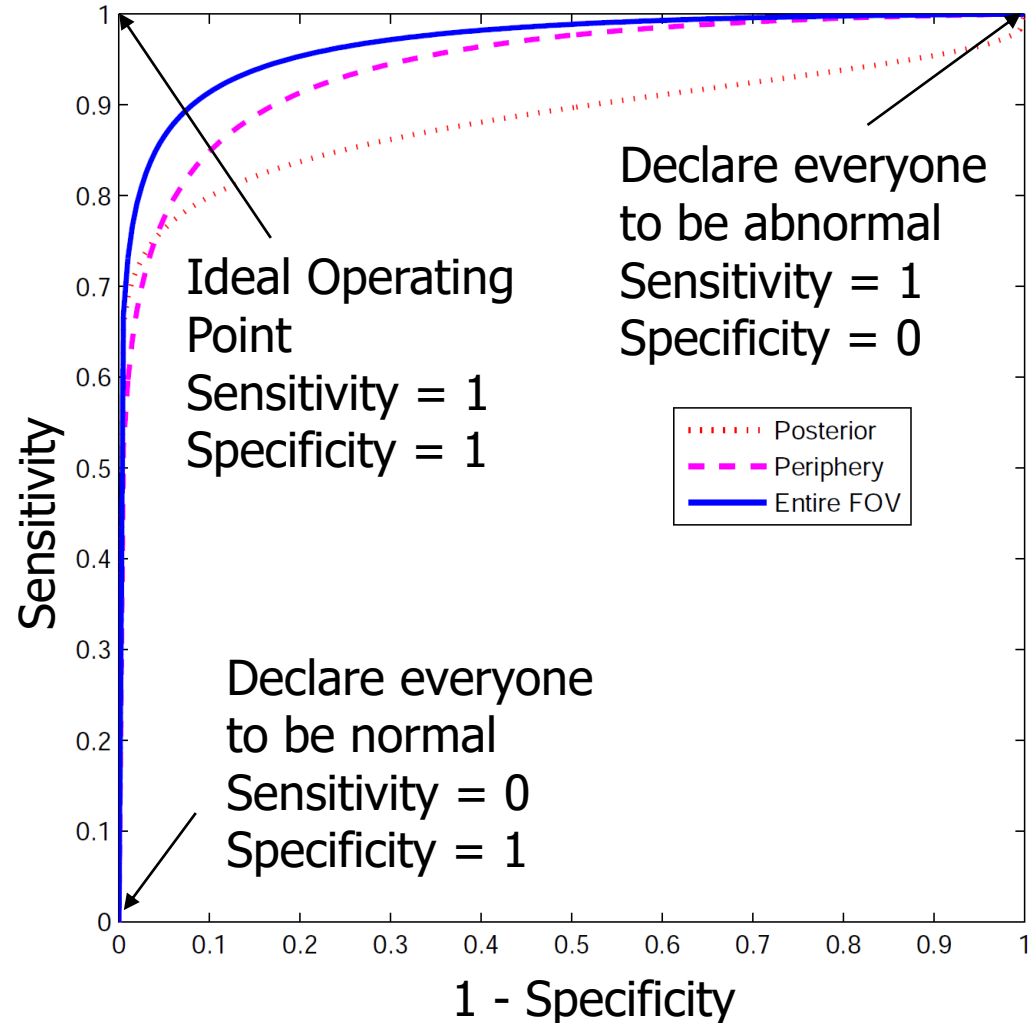
# Measures of Performance: Receiver Operating Characteristics (ROC)

Areas under the ROC curve  $A_z$  for the diagnosis of plus disease using the total length of tortuous vessels in various regions of fundus images

posterior  $A_z = 0.90$

periphery  $A_z = 0.95$

full image  $A_z = 0.98$





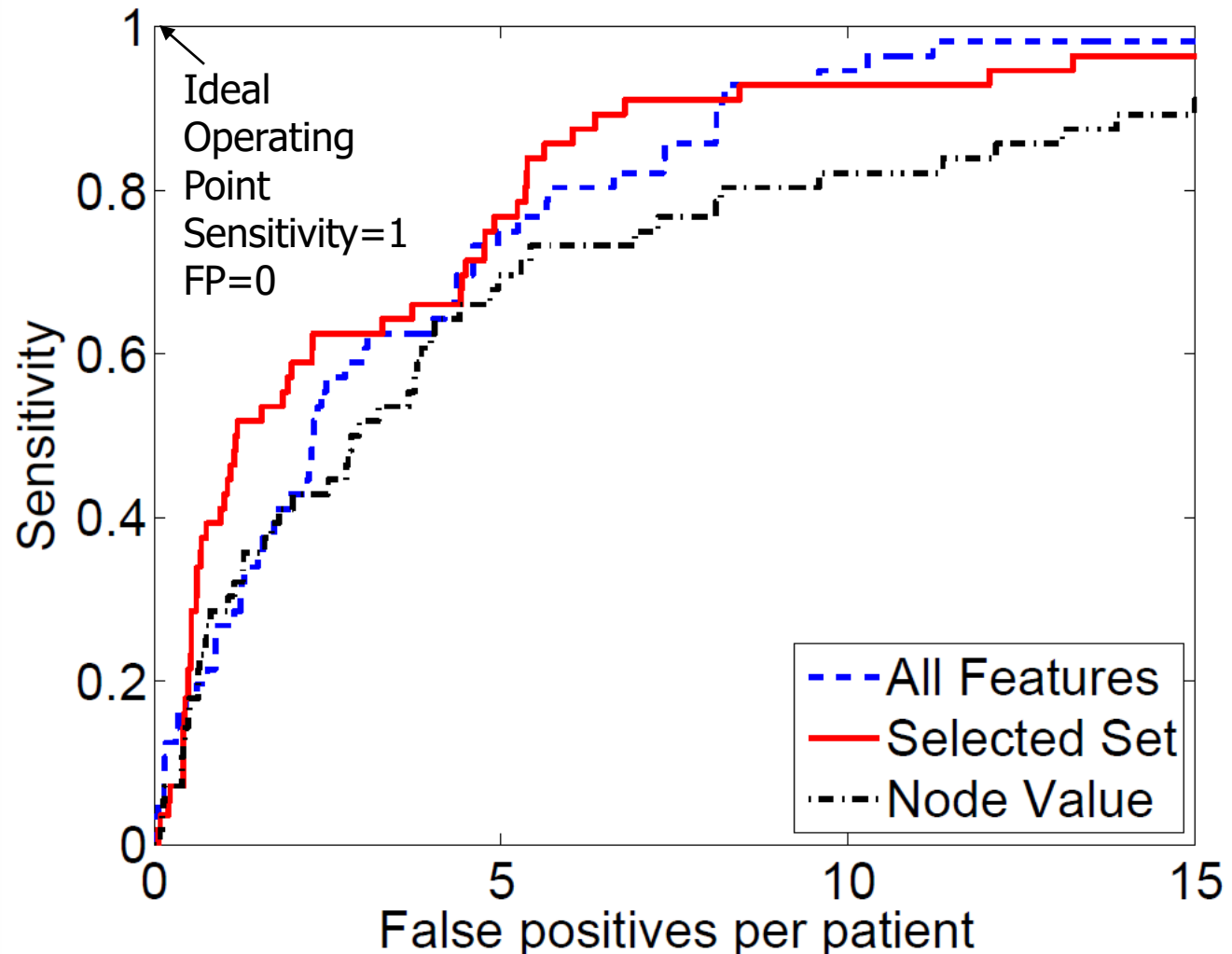
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# Measures of Performance: Free-response ROC (FROC)

Detection of  
architectural  
distortion in  
prior  
mammograms:

Sensitivity =  
80% at  
5.3 FP/patient

90% at  
6.3 FP/patient





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# Limitations of CAD

- Difficulty in translating methods of visual analysis into computational procedures
- Difficulty in translating clinical observations into numerical features
- Difficulty in dealing with large numbers of features in a classification rule: curse of dimensionality
- Substantial requirements of computational resources and annotated clinical databases
- Large numbers of false alarms or false positives: increased recall rate
- Difficulty in integrating CAD systems into established clinical workflows and protocols



# Popular Themes and Techniques

**BIG data**

Information Technology

Machine Learning

Convolutional Neural Networks

Medical Informatics

Radiomics

Deep Learning

~~Artificial~~  
Computational  
Intelligence

Information & Communication Technology

...?

Committee Machine





# Essentials of Engineering

- ❖ Scientific investigation and analysis:  
Quantitative and objective analysis
- ❖ Mathematical modeling
- ❖ Design of components, systems, and processes
- ❖ Synthesis
- ❖ Project management
- ❖ Solutions to practical problems
- ❖ Innovation and creativity



# The Multidisciplinary Field of Biomedical Engineering

- ❖ From building bridges to implanting artificial ligaments
- ❖ From electrical power plants to cardiac pacemakers
- ❖ From railway engines to prosthetic limbs
- ❖ From chemical and petroleum plants to artificial tissues and organs
- ❖ From computers to lab on a chip and control systems to manage diabetes and other diseases
- ❖ From communication and control systems to CAD



# Broad Background Required for Biomedical Engineering

- ❖ Physics and Chemistry
- ❖ Mathematics and Statistics
- ❖ Biology, Anatomy, Physiology, and Pathology
- ❖ Biochemistry
- ❖ Material Science
- ❖ Sensors and Instrumentation
- ❖ Principles of Engineering
- ❖ Knowledge of Medical Diagnosis and Therapy
- ❖ Information Processing and Analysis



# Subject Areas Contributing to Computer-aided Diagnosis

- ❖ Biomedical Engineering and Medical Physics
- ❖ Diagnostic Medical Imaging and Radiology
- ❖ Digital Signal and Image Processing
- ❖ Biomedical Signal and Image Analysis
- ❖ Statistical Analysis and Pattern Recognition
- ❖ Computer Vision
- ❖ Computer and Software Engineering
- ❖ Information and Communication Technology
- ❖ Control Systems and Diagnostic Decision Making



# ... but is CAD Artificial Intelligence?

CAD incorporates, encodes, and encapsulates the knowledge, intelligence, and expertise of several professionals from multiple disciplines:

- ❖ Radiology and Diagnostic Medical Imaging
- ❖ Engineering and Computer Science
- ❖ Physics and Mathematics ...

This is a *natural human collaborative endeavor* and the label “artificial” is demeaning!

We should recognize, admire, and respect the contributing professionals and their subject areas!



# Beyond CAD ...

- ❖ Computer-aided therapy and surgery
- ❖ Computer analysis of response to therapy
- ❖ Computer-aided prognosis
- ❖ Computer-aided risk assessment
- ❖ Computer-aided patient management
- ❖ Computer-aided clinical management
- ❖ Computer-aided treatment protocol
- ❖ Computer-aided personalized medicine



# Integrating the Healthcare Enterprise: IHE and Clinical Workflow

- ❖ CAD: Computer-Aided Diagnosis
- ❖ CAS: Computer-Aided Surgery
- ❖ CBIR: Content-Based Image Retrieval
- ❖ HIS: Hospital Information System
- ❖ RIS: Radiology Information System
- ❖ PACS: Picture Archival and Communication System
- ❖ DICOM: Digital Imaging and Communications in Medicine
- ❖ DBMS: Data Base Management System
- ❖ EHR: Electronic Health Record
- ❖ HL7: Health Level-7
- ❖ ISO: International Standards Organization
- ❖ OSI: Open Systems Interconnection



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# Opportunities

- ❖ Learn new areas of application of engineering
- ❖ Collaborate with professionals in other fields of research and investigation
- ❖ Contribute to another field with significant applications and benefit to the public
- ❖ Develop multidisciplinary perspectives and problem-solving skills
- ❖ *Contribute to the well-being of people!*

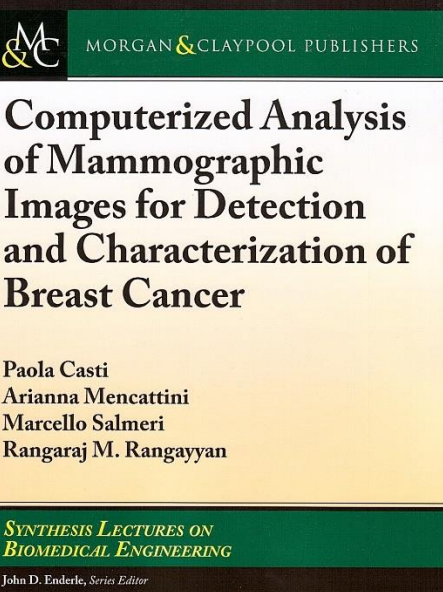
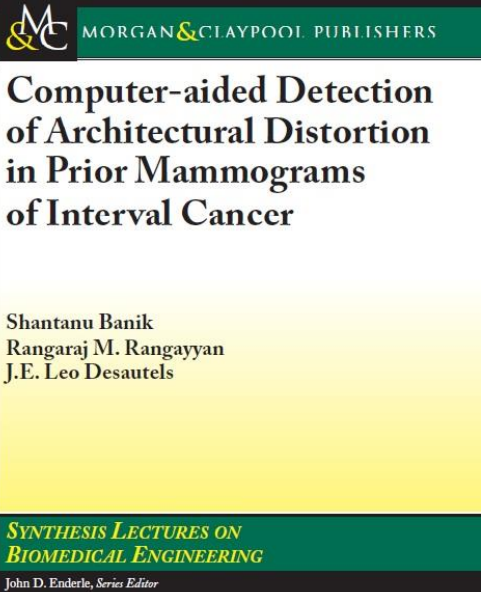
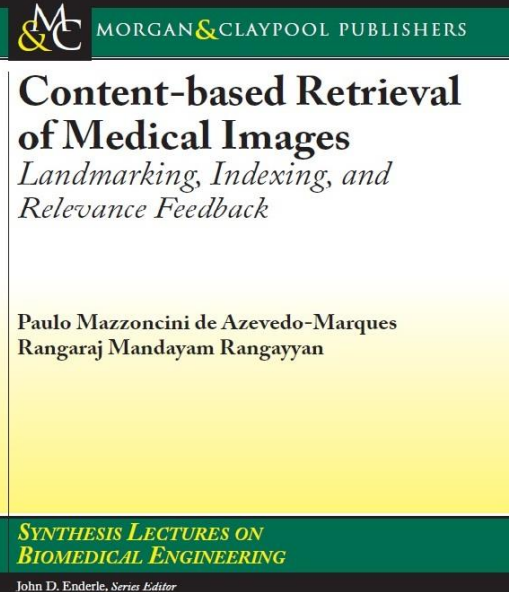
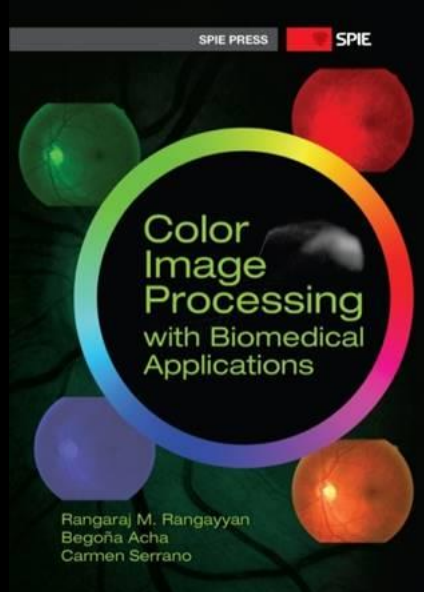
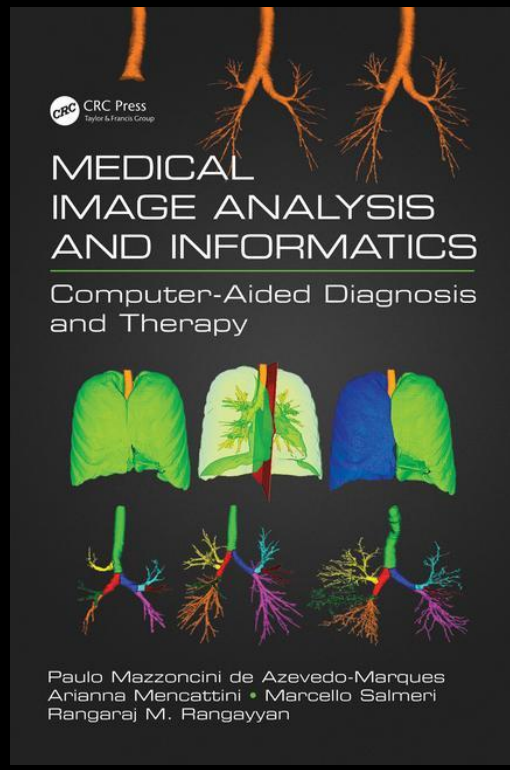
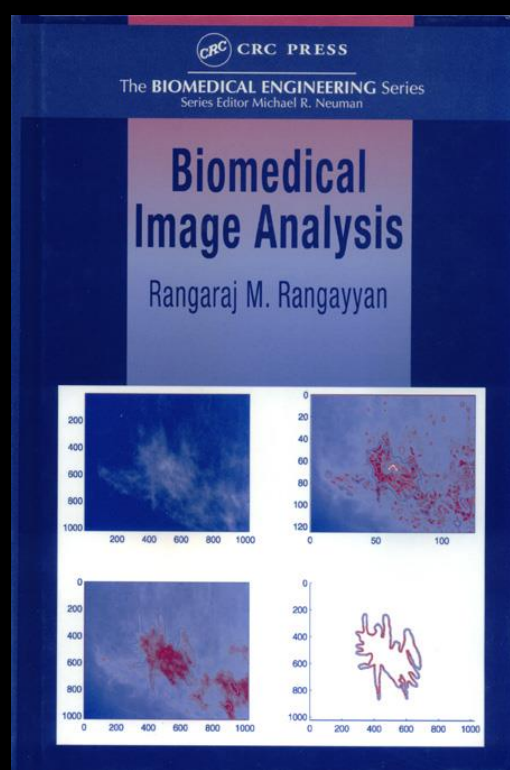
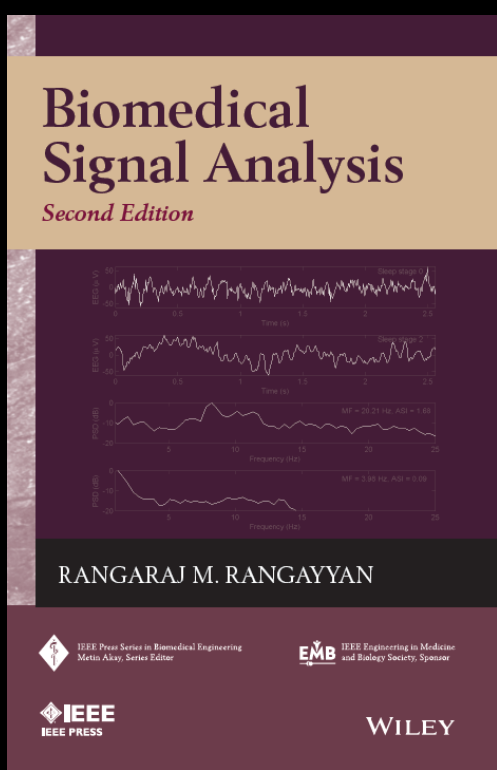


# Do you believe in CAD?

Paola Casti



If in doubt try ...





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# Thank You!

- ❖ Natural Sciences and Engineering Research Council of Canada
- ❖ Alberta Heritage Foundation for Medical Research
- ❖ Canadian Breast Cancer Foundation
- ❖ Screen Test: Alberta Program for the Early Detection of Breast Cancer
- ❖ Kids Cancer Care Foundation, Calgary
- ❖ My students and collaborators

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<http://people.ucalgary.ca/~ranga/>