Computer-aided Diagnosis for Breast 2D/3D/Automated Ultrasound and MRI

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International Forum on Medical Imaging in Asia (IFMIA) 2009

- 2-D Breast US CAD
- Elastography CAD
- 3-D US CAD
- ABUS CADe and CADx
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- MRI CADx

Prof. Giger, U. Chicago, 2007.12

NTU CAD Lab

1997 2-D US → 2000 3-D US → 2002 Whole Breast → 2004 PC-based US

- 1997 Aloka SSD 1200
- 2003 Acuson, GE, Medison, ATL, Philips

- 1999, Free-hand 3D US
- 2000, Voluson 530
- 2002, GE 730
- 2010, GE E8 and E6

- 2002, Free-hand
- 2003, Aloka ABUS
- 2005, U-systems

- 2004 Telemed, Lithuania Echo Blaster 128
- 2005 Terason t3000

2006 Elastography → 2008 MRI → 2011 Automated US → 2011 Shearwave

- 2006 Hitachi Elastography
- 2010 Siemens Elastography

- 2008 Morphology, Kinetic
- 2009, Tofts Model
- 2010, DWI

- 2011 Siemens ABVS

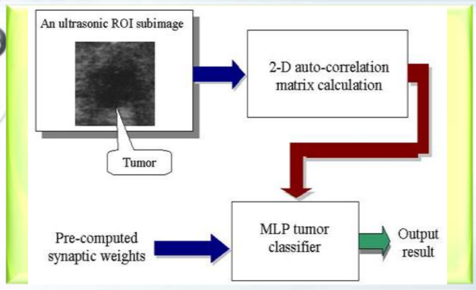
- 2010 Siemens ARFI
- 2011 Supersonic Shearwave

K computer, Riken, Japan, 2011.11

2-D Breast US CAD

- "Computer-aided Diagnosis Applied to US of Solid Breast Nodules by Using Neural Networks", Radiology, vol. 213, no. 2, pp.407-412, 1999.
- "Computer aided classification system for breast ultrasound based on breast imaging reporting and data system (BI-RADS)," Ultrasound in Medicine and Biology, vol. 33, no. 11, pp. 1688-1698, 2007.
- "Breast ultrasound computer-aided diagnosis using BI-RADS features," Academic Radiology, vol. 14, no. 8, pp. 928-939, 2007.

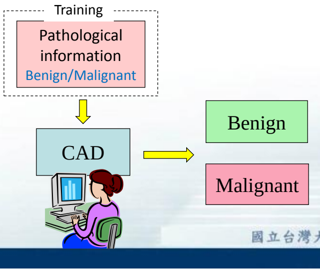
2D US CAD



"Computer-aided Diagnosis Applied to US of Solid Breast Nodules by Using Neural Networks", Radiology, vol. 213, no. 2, pp.407-412, 1999.
Editorial: Georgia D. Tourassi, "Journey toward Computer-aided Diagnosis: Role of Image Texture Analysis," Radiology, vol. 213, no.2, pp.317-320, Nov. 1999.

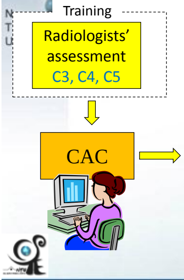
Conventional Breast CAD

- A conventional CAD system will classify the tumor into benign and malignant.
- The CAD system is trained by the pathological information.



Proposed Breast CAC

- BI-RADS Computer-aided classification (CAC)
  - Classify the tumors into BI-RADS 3, 4, 5
- Unlike CAD, CAC is trained by the Radiologists' assessment.

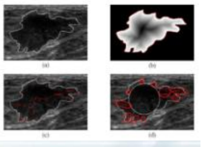


C0	Need additional imaging evaluation
C1	Negative
C2	Benign finding
C3	**Probably benign finding**
C4	**Suspicious abnormality**
C5	**Highly suggestive of malignancy**
C6	Known biopsy-proven malignancy

BI-RADS Features

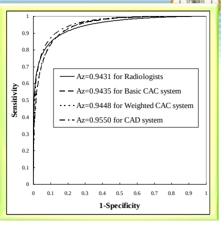
- Shape
  - Oval, Round, Irregular
- Orientation
  - Parallel, Not parallel
- Margin
  - Circumscribed
  - Not circumscribed
    - Indistinct, Angular, Microlobulated, Spiculated
- Lesion boundary
  - Abrupt interface, Echogenic halo
- Echo pattern
  - Anechoic, Hyperechoic, Complex, Hypoechoic, Isoechoic
- Posterior shadowing
  - No posterior acoustic features, Enhancement, Shadowing, Combined patter

BI-RADS Atlas



CAC Results

Radiologists	Machine Type						Total
	HDI 5000		Voluson 730		Philips iU-22		
	B	M	B	M	B	M	
Category 3	115	4	63	1	28	0	211
Category 4	68	39	103	38	27	17	292
Category 5	0	46	3	60	0	14	123
Total	272		268		86		626



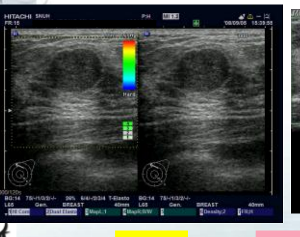
Index	Radiologists	CAD	Weighted CAC system	
			Original (C3,C4,C5)	Adjustment (C3,C5)
			Score	Score
Accuracy	67.09%	89.46%	73.00%	97.22%
Sensitivity	97.72%	87.67%	98.17%	96.43%
Specificity	50.61%	90.42%	59.46%	97.58%
PPV	51.57%	83.12%	56.58%	94.74%
NPV	97.63%	93.16%	98.37%	98.37%

Elastography CAD

- "Analysis of elastographic and B-mode features at sonoelastography for breast tumor classification", Ultrasound in Medicine and Biology, Vol. 35, No. 11, pp. 1794–1802, 2009.
- "Automatic selection of representative slice from cine-loops of real-time sonoelastography for classifying solid breast masses", Ultrasound in Medicine and Biology, accepted.
- "Breast Tumor Classification Using Fuzzy Clustering for Breast Elastography", Ultrasound in Medicine and Biology, accepted .

Strain Elastography

- A The difference in hardness between normal and diseased tissue of the breast can be estimated by measuring the tissue strain induced by probe compression.
- Siemens eSie Touch: gentle compression



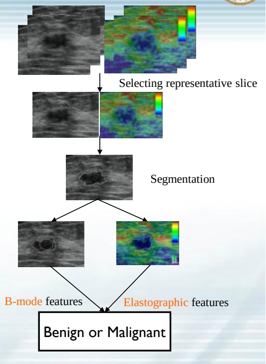
Hitachi Benign Siemens

Malignant Example

Hitachi Malignant Siemens

Elastography CAD

- A representative slice of the dynamic elastographic image needs to be selected.
- The B-mode image could be used to segment the tumor and the tumor contour could be applied to the corresponding elastographic image.
- Both the elastographic features and B-mode features could be used to diagnose the tumor.



"*Analysis of elastographic and B-mode features at sonoelastography for breast tumor classification*", *Ultrasound in Med. & Biol., Vol. 35, No. 11, pp. 1794–1802, 2009.*

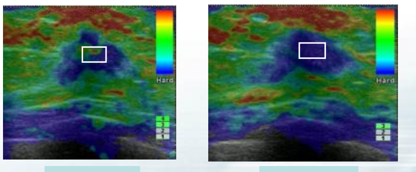
Representative Slice

- For elastography using manual compression, the operators need to lightly compress a tumor to obtain a dynamic elastographic image.
  - A representative slice of the dynamic elastographic image sequence needs to be selected by the physician.
  - The quality of this selected slice will affect the diagnosis result.
- We propose a representative slice selection method
  - To quantify the elastographic image quality
  - To select a representative slice from an elastography movie file.

Image Quality Quantification

- Signal to Noise Ratio (SNR) and Contrast to Noise Ratio (CNR) are used to quantify the elastographic image quality.
  - The middle block in the tumor is uses to calculate the SNR.

$$SNR = \frac{mean}{standard\_deviation}$$



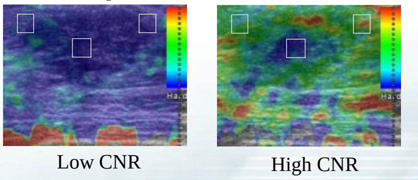
Low SNR High SNR

Image Quality Quantification

- In the CNR method, not only the middle block but also two outside blocks are used.

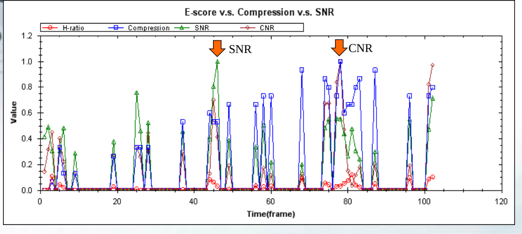
$$CNR = \frac{(middle\_mean - outside\_mean)^2}{middle\_SD^2 + outside\_SD^2}$$

Over-compressed



Low CNR High CNR

The Strain Curve



Stiffness Ratio

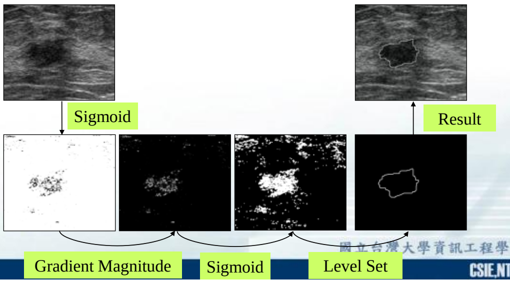
- In this study, the stiffness ratio of a tumor is proposed to diagnosis a tumor.

$$stiffness\ ratio = \frac{number\ of\ stiffness\ pixels}{total\ number\ of\ tumor\ pixels}$$

- A threshold value (200) is defined the stiffness pixels.

Tumor Segmentation

- The contrast-enhanced gradient image is used to segment the tumor using the level set method.



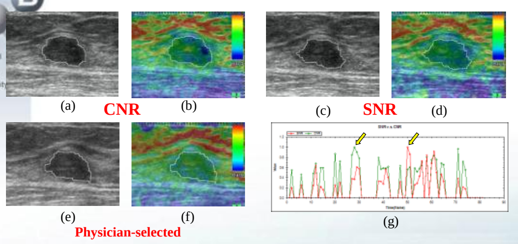
Experimental Results

- The data consisted of 151 biopsy-proved lesions (89 benign and 62 malignant lesions).

Features		Accuracy	Sensitivity	Specificity	PPV	NPV
CNR	B-mode	80.79%	70.97%	87.64%	80.00%	81.25%
	Elastographic	82.12%	74.19%	87.64%	80.70%	82.98%
	All Features	86.09%	82.26%	88.76%	83.61%	87.78%
SNR	B-mode	87.42%	83.87%	89.89%	85.25%	88.89%
	Elastographic	82.12%	79.03%	84.27%	77.78%	85.23%
	All Features	90.07%	90.32%	89.89%	86.15%	93.02%
Physician selected	B-mode	84.11%	77.42%	88.76%	82.76%	84.95%
	Elastographic	82.78%	74.19%	88.76%	82.14%	83.16%
	All Features	89.40%	85.48%	92.13%	88.33%	90.11%

True Negative Case

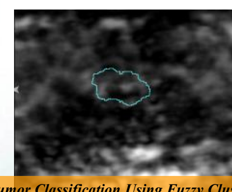
- A benign fibroadenomas case

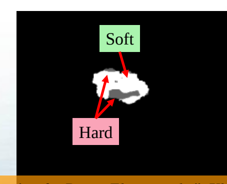


(a)(b) The slice by the maximum CNRe.(c)(d) The slice by the maximum SNRe. (e)(f) The slice by the physician-selected image.(g) The curves of different quantification methods.

Elasticity Ratio- FCM

- Fuzzy c-mean clustering could divide the tumor pixels into two groups, soft and hard.
- FCM is more robust than the conventional fixed thresholding.

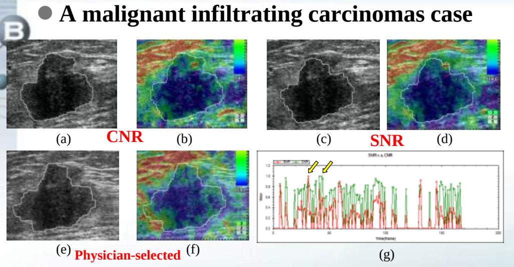




"Breast Tumor Classification Using Fuzzy Clustering for Breast Elastography", Ultrasound in Med. & Biol., accepted .

True Positive Case

- A malignant infiltrating carcinomas case

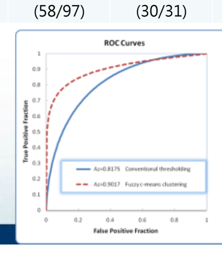


(a)(b) The slice by the maximum CNRe.(c)(d) The slice by the maximum SNRe. (e)(f) The slice by the physician-selected image.(g) The curves of different quantification methods.

Experimental Result

- The test sonoelastography database included 66 benign and 31 malignant biopsy-proven tumors.

	accuracy	sensitivity	specificity
FCM	83.5 % (81/97)	83.9% (26/31)	83.3% (55/66)
Fixed TH	59.8% (58/97)	96.8% (30/31)	42.4% (28/66)



3-D Breast US CAD

Visiting invited by GE Kretz, Austria, 2006.08

- "Characterization of Spiculation on Ultrasound Lesions", IEEE Transactions on Medical Imaging, vol. 23, no. 1, pp. 111-121, 2004.
- "Solid Breast Masses: Neural Network Analysis of 3-D Power Doppler Ultrasound Image Features for Classification as Benign or Malignant", Radiology, vol. 243, no. 1, pp. 56-62, 2007.
- "Analysis of Tumor Vascularity Using Three-Dimensional Power Doppler Ultrasound Images," IEEE Transactions on Medical Imaging, vol. 27, no. 3, pp. 320-330, 2008.

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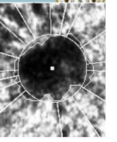
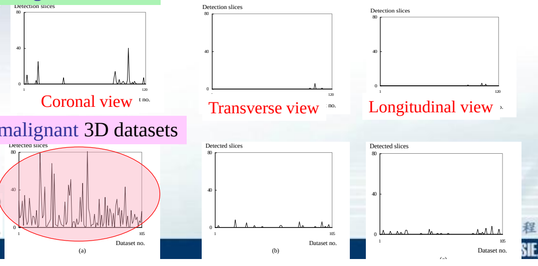
Experimental Result

- Spiculations are more easily seen in malignant tumors.
- Spiculations are more likely to appear in the coronal view.



120 benign 3D datasets

105 malignant 3D datasets



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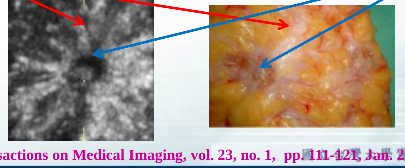
3D US Spiculation

- A kind of stellate distortion caused by the intrusion of the breast cancer.
- The spiculation displayed only on the C-view of 3D US.
  - The conventional 2D US cannot see the spiculation.

Spiculation

Tumor



*IEEE Transactions on Medical Imaging, vol. 23, no. 1, pp. 111-121, Jan. 2004.

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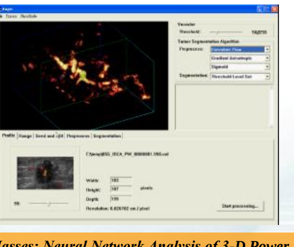
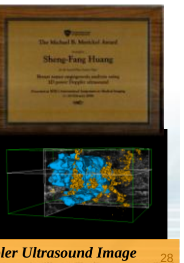
3D Power Doppler US

- A useful tool to detect the vessels.
  - 2D Doppler US can not obtain the entire 3-D vessels.
- The blood supply and vessel distribution are the important features to diagnose an tumor.





"Solid Breast Masses: Neural Network Analysis of 3-D Power Doppler Ultrasound Image Features for Classification as Benign or Malignant", Radiology, vol. 243, no. 1, pp. 56-62, 2007.

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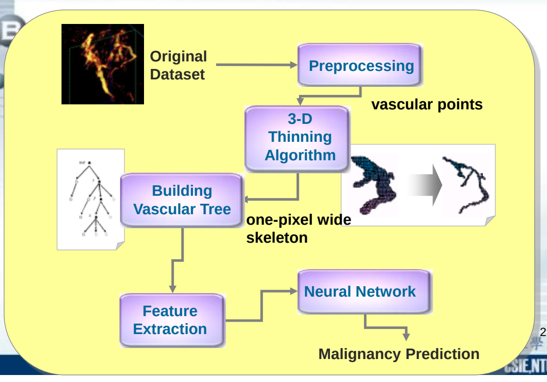
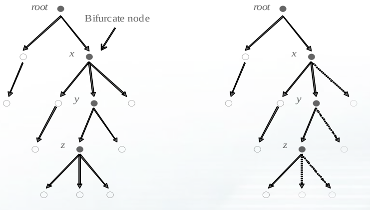
System Overview

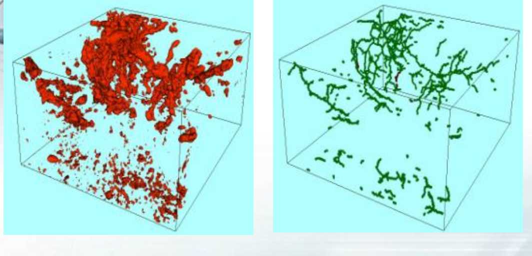


Vascular Tree Construction

- To generate a skeleton representation, the thinning result was converted into tree structure using breadth first search (BFS) algorithm.

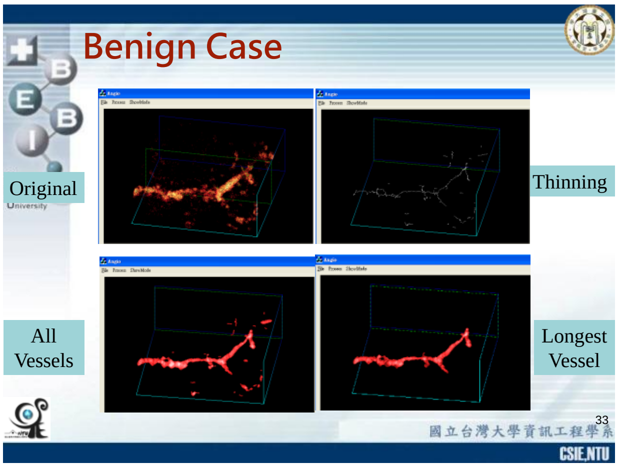


Thinning Result



Feature Extraction

- Ten features are used for the vessel tree.
  - Vessel-to-Volume Ratio (R_v)
  - Number of Vascular Trees (N_v)
  - Measurement of Length
    - **Total length (L_1)**
    - **Length of the longest path (L_2)**
  - Bifurcation (*Bn*)
  - Diameter (D_v)
  - Number of cycles (NC)
  - Tortuosity measures (DM, ICM, SOAM)


Benign Case
Original
Thinning
All Vessels
Longest Vessel
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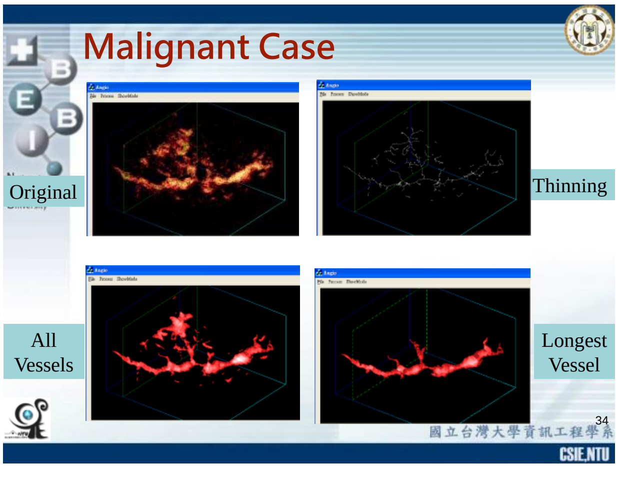
Malignant Case
Original
Thinning
All Vessels
Longest Vessel
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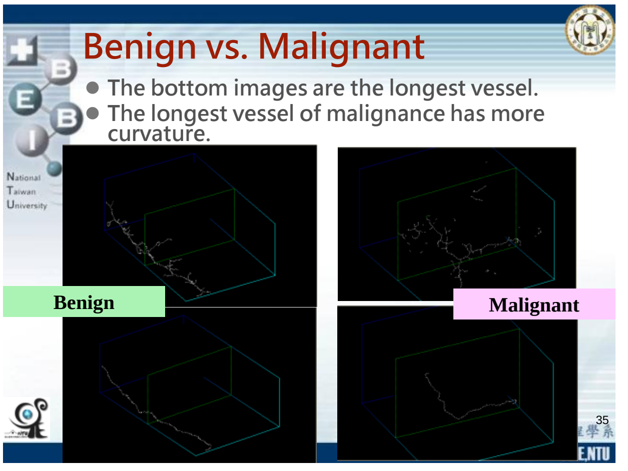
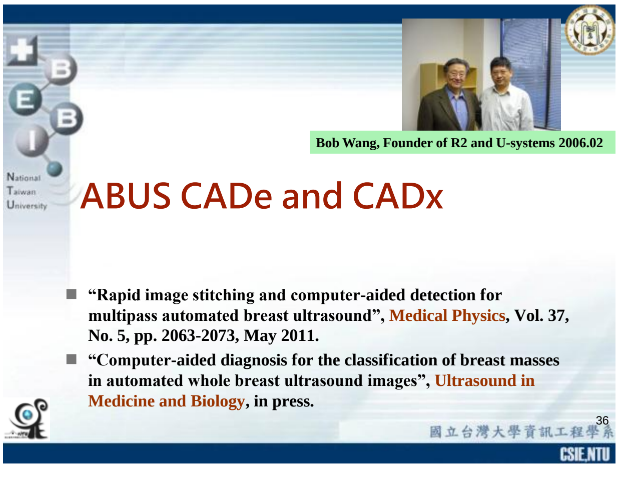

Benign vs. Malignant
The bottom images are the longest vessel.
The longest vessel of malignance has more curvature.
Benign
Malignant
35


Bob Wang, Founder of R2 and U-systems 2006.02
ABUS CADe and CADx
"Rapid image stitching and computer-aided detection for multipass automated breast ultrasound", Medical Physics, Vol. 37, No. 5, pp. 2063-2073, May 2011.
"Computer-aided diagnosis for the classification of breast masses in automated whole breast ultrasound images", Ultrasound in Medicine and Biology, in press.
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Automated Whole Breast US

- Aloka, U-systems, and Siemens have developed the automated whole breast ultrasound (ABUS) systems.

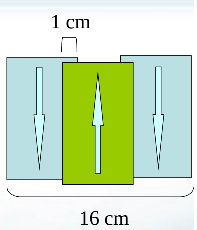
U-systems
Siemens
Aloka
Aloka, 2006.07
U-systems, 2006.09

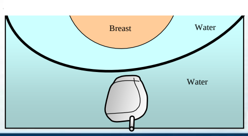
U-Systems

- 14.5-cm probe with 768 elements
  - Like 3 conventional 2-D probes (256 elements)
- Imaging plate is 15x24 cm.
  - 3-5 passes are required to scan a whole breast

Aloka 5500

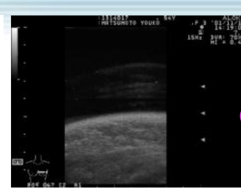
- 6 cm probe
  - three passes to cover a breast
  - 1 cm overlap and 16 cm width
- Breast is sunk in water bag and probe is scanning under water bag
  probe is also in the water



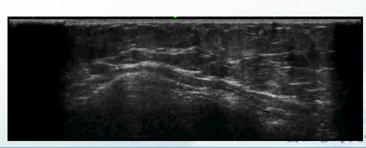


Demo

Free hand



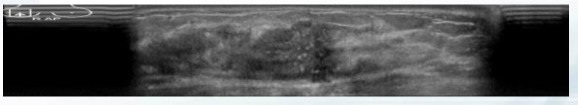
Aloka



U-Systems

Siemens ABVS

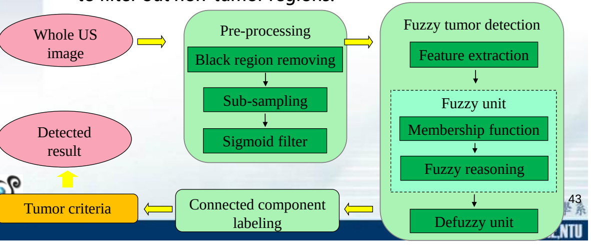
- ACUSON S2000 Automated Breast Volume Scanner (ABVS)



- **Siemens: 736x481x318 = 0.208mmx0.052mmx0.526mm**
- **U-systems: 560x348x283 = 0.285mmx0.114mmx0.599mm**

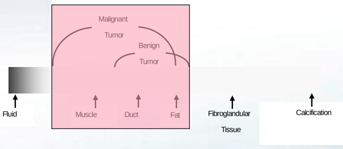
U-systems 3-D Fuzzy Tumor Detection

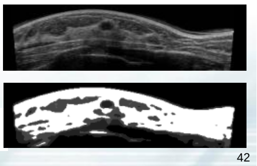
- The image is pre-processed by removing black regions, sub-sampling to reduce the detecting time, and the sigmoid filtering to enhance the boundary between tumor and normal tissue.
- A 3-D fuzzy technique is adopted to detect tumor regions in the breast.
- The connected component labeling groups each voxel of tumor regions and then some tumor criteria are proposed to filter out non-tumor regions.



Gray-level Slicing for Detection

- In general, the tumors, either benign or malignant, are the darker regions in US images.
  - we introduce the simple thresholding method, gray-level slicing, to detect tumors.

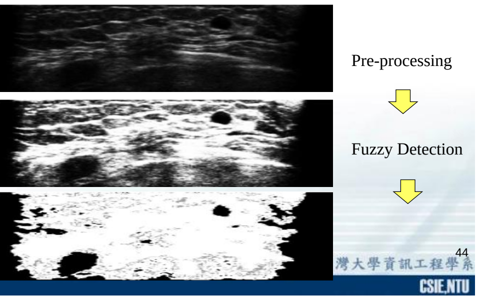




"Rapid image stitching and computer-aided detection for multipass automated breast ultrasound", Medical Physics, Vol. 37, No. 5, pp. 2063-2073, May 2011.

Fuzzy Tumor Detection

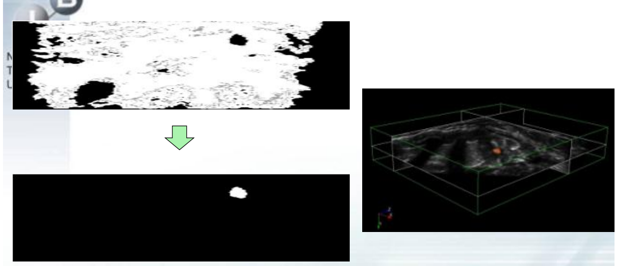
- Black regions are tumor, gray regions are boundary, and white regions are normal tissue.



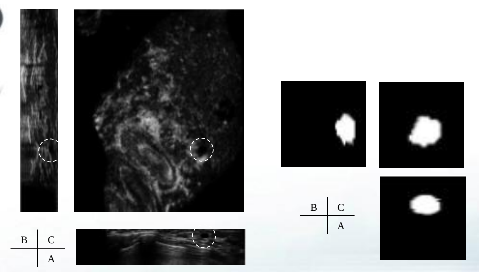
Tumor Criteria

- The tumor criteria are proposed to reduce the non-tumor regions from suspicious tumor regions obtained by fuzzy tumor detection.
- Five tumor criteria
  - Tumor size criterion
  - Mean value criterion
  - Long-short ratio criterion
  - Volume ratio criterion
  - Standard deviation criterion

Result of Tumor Criteria

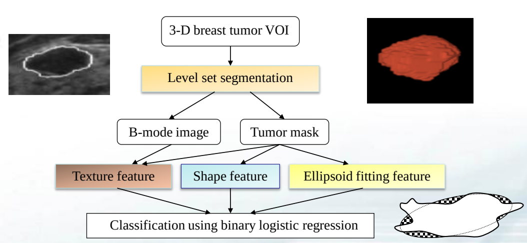


True Positive Case 1



ABUS CADx

- 2D/3D CADx could be applied for ABUS.



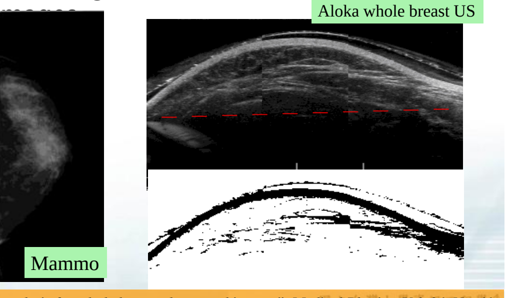
"Computer-aided diagnosis for the classification of breast masses in automated whole breast ultrasound images", Ultrasound in Medicine and Biology, in press.

- 147 cases (76 benign and 71 malignant breast masses) were obtained by U-systems ABUS.

	GLCM	Shape	Ellipsoid fitting	GLCM and shape	GLCM and ellipsoid fitting	Shape and ellipsoid fitting	ALL
Accuracy (%)	75.51 (111/147)	82.31 (121/147)	79.59 (117/147)	80.27 (118/147)	81.63 (120/147)	85.03 (125/147)	82.31 (121/147)
Sensitivity (%)	81.69 (58/71)	84.51 (60/71)	76.06 (54/71)	83.10 (59/71)	84.51 (60/71)	84.51 (60/71)	83.10 (59/71)
Specificity (%)	69.74 (53/76)	80.26 (61/76)	82.89 (63/76)	77.63 (59/76)	78.95 (60/76)	85.53 (65/76)	81.58 (62/76)
PPV (%)	71.60 (58/81)	80.00 (60/75)	80.60 (54/67)	77.63 (59/76)	78.95 (60/76)	84.51 (60/71)	80.82 (59/73)
NPV (%)	80.30 (53/66)	84.72 (61/72)	78.75 (63/80)	83.10 (59/71)	84.51 (60/71)	85.53 (65/76)	83.78 (62/74)
Az	0.8603	0.9138	0.8496	0.9153	0.8195	0.9466	0.9388

Aloka Whole Breast Density Analysis

- Breast density measured from mammograms and whole breast US images

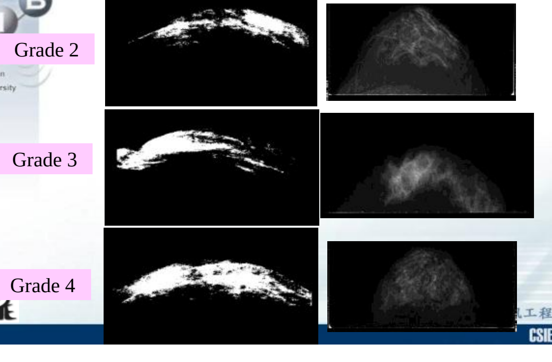


"Breast density analysis for whole breast ultrasound images", Medical Physics, Vol. 36, No. 11, pp. 4933-4943, Nov. 2009.

ABUS/MRI Density Analysis

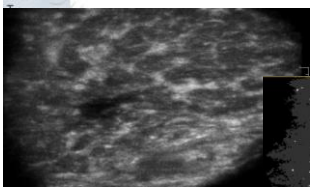
- *"Breast density analysis for whole breast ultrasound images", Medical Physics, Vol. 36, No. 11, pp. 4933-4943, Nov. 2009.*
- *"Comparative study of density analysis using automated whole breast ultrasound and MRI", Medical Physics, Vol. 38, No. 1, pp. 382-389, Jan. 2011.*

Whole Breast US vs. Mammogram

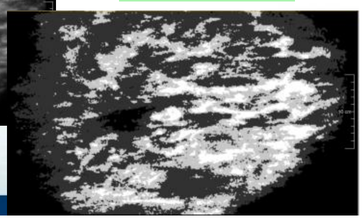


U-systems Whole Breast Density Analysis

- The similar Aloka whole breast density analysis could be applied for the U-systems.



Original C View



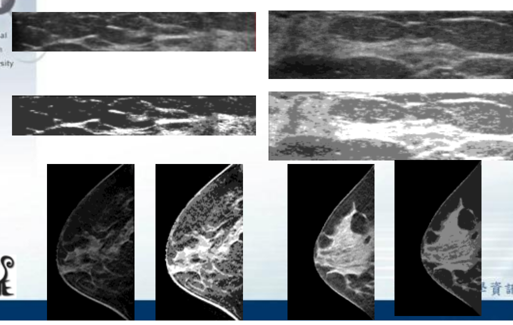
Gland/Fat Analysis

FCM Density Analysis

- The fuzzy c-mean (FCM) classifier was used to differentiate the fibroglandular and fatty tissues in ABUS and MRI images

Original

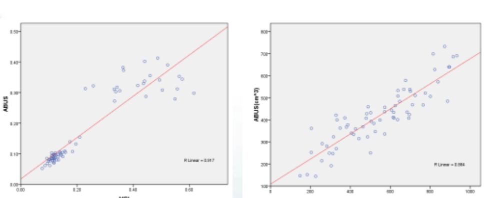
FCM



U-Systems Density Analysis

- The U-systems ABUS density and volume is highly correlated with those of MRI.

ABUS



Density

MRI

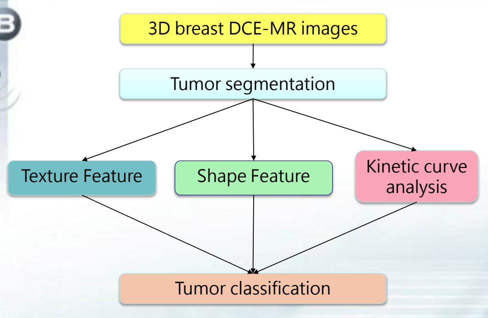
Volume

"Comparative study of density analysis using automated whole breast ultrasound and MRI", Medical Physics, Vol. 38, No. 1, pp. 382-389, Jan. 2011.

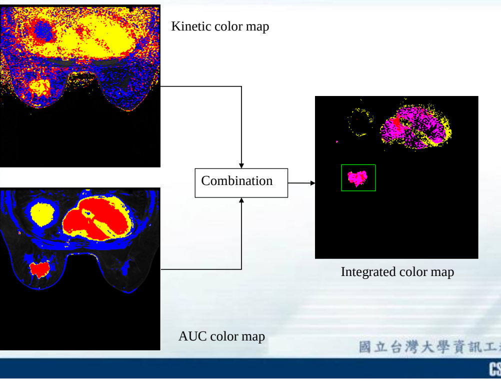
MRI CADx

Dr. Hong, CTO, Aurora MRI
2011.02

Breast MRI CADx System



Color Maps



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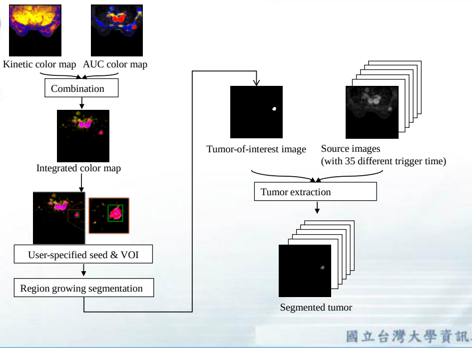
Tumor Segmentation



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Kinetic Curve Analysis

- Two steps
  - Curve identification
    - Fuzzy c-means clustering
  - Curve analysis
    - Conventional kinetic curve characteristics
      - Maximum enhancement
      - Time to peak
      - Uptake rate
      - Washout rate
    - Tofts Model $C_t(t) = v_p C_p(t) + K^{trans}[C_p(t) \otimes e^{-k_{ep}t}]$
      - K_{ep}, v_p, K^{trans}

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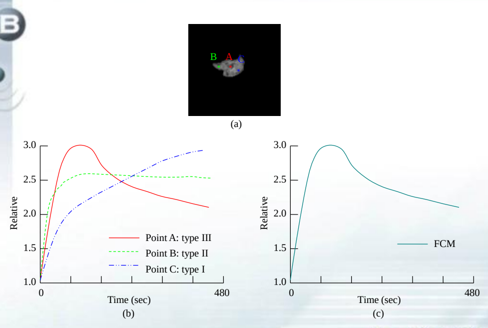
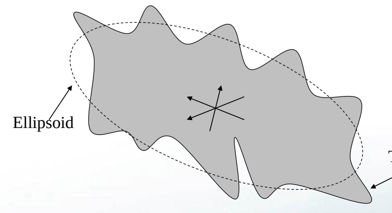
Curve Identification



Elliptic Model

- Estimate a ellipsoid from the tumor



Shape Features

- Compactness

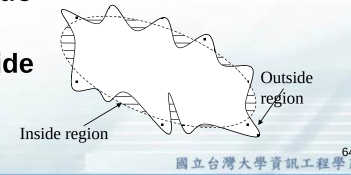
$$C_1 = \frac{36\pi \cdot V^2}{A^3} \qquad C_2 = \frac{n - \frac{A}{6a}}{n - \sqrt[3]{n^2}}$$

- Radius and spiculation

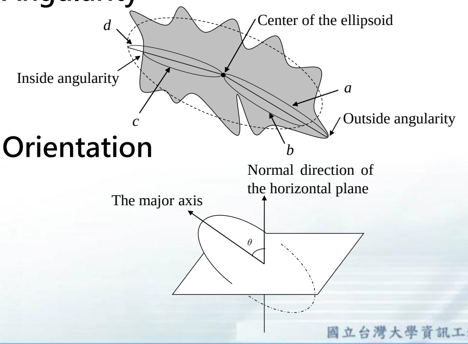
$$R = \frac{1}{n_b} \sum_{x=\begin{pmatrix} i \\ j \\ k \end{pmatrix} \in boundary} \sqrt{(i-x_c)^2 + (j-y_c)^2 + (k-z_c)^2}$$

$$R_s = \sqrt{\frac{\sum_{x \in boundary} (R_x - R)^2}{n_b - 1}}$$

- Axis ratio $ER_{axis} = \frac{\max\{L_1, L_2, L_3\}}{\min\{L_1, L_2, L_3\}}$
- Surface ratio $ER_{surface} = \frac{A}{A_e}$ $\quad A_e = 4\pi\left(\frac{(L_1L_2)^p + (L_2L_3)^p + (L_3L_1)^p}{3}\right)^{\frac{1}{p}}$
- Volume covering ratio $ER_{and} = \frac{volume(v_m \cap v_e)}{V}$
- Inside/outside regions



- Angularity



- Orientation

GLCM Texture Features

- Eight different measurement:
  - Energy: $G_1 = \sum_{i,j} g(i,j)^2$
  - Entropy: $G_2 = -\sum_{i,j} g(i,j) \log_2 g(i,j)$
  - Correlation: $G_3 = \frac{\sum_{i,j} (i-\mu)(j-\mu) g(i,j)}{\sigma^2}$
  - Difference Moment: $G_4 = \sum_{i,j} \frac{1}{1+(i-j)^2} g(i,j)$
  - Inertia: $G_5 = \sum_{i,j} (i-j)^2 g(i,j)$
  - Cluster Shade: $G_6 = \sum_{i,j} [(i-\mu)+(j-\mu)]^3 g(i,j)$
  - Cluster Prominence: $G_7 = \sum_{i,j} [(i-\mu)+(j-\mu)]^4 g(i,j)$
  - Haralick's Correlation: $G_8 = \frac{\sum_{i,j} (i,j) g(i,j) - \mu_t^2}{\sigma_t^2}$

Results

Method / Item	Conventional	Tofts model	GLCM	Shape	All
Accuracy (%)	84.85 (112/132)	86.36 (114/132)	81.82 (108/132)	80.30 (106/132)	91.67 (121/132)
Sensitivity (%)	79.71 (55/69)	85.51 (59/69)	81.16 (56/69)	78.26 (54/69)	91.30 (63/69)
Specificity (%)	90.48 (57/63)	87.30 (55/63)	82.54 (52/63)	82.54 (52/63)	92.06 (58/63)
PPV (%)	90.16 (55/61)	88.06 (59/67)	83.58 (56/67)	83.08 (54/66)	92.65 (63/68)
NPV (%)	80.28 (57/71)	84.62 (55/65)	80.00 (52/65)	77.61 (52/66)	90.63 (58/64)

Welcome to Visit NTU CAD LAB


Dr. Moon and Dr. Takada, 2008.10


Dr. Giger from U. Chicago
AAPM President, 2009.01


Dr. Hong, CTO, Aurora MRI
2011.02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