Renal Lesion Detection on Medical Ultrasound Images

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Outline

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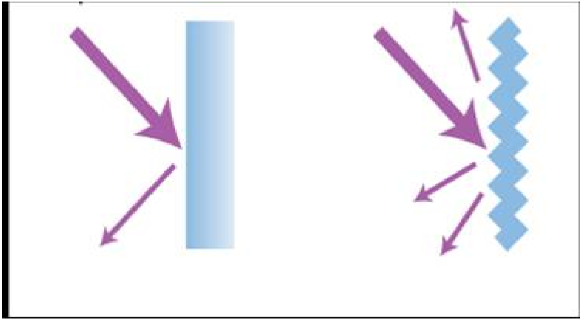
Ultrasound Imaging

- Attenuation
- Refraction
- Reflection



Specular reflector Scattering reflector(scatterer)

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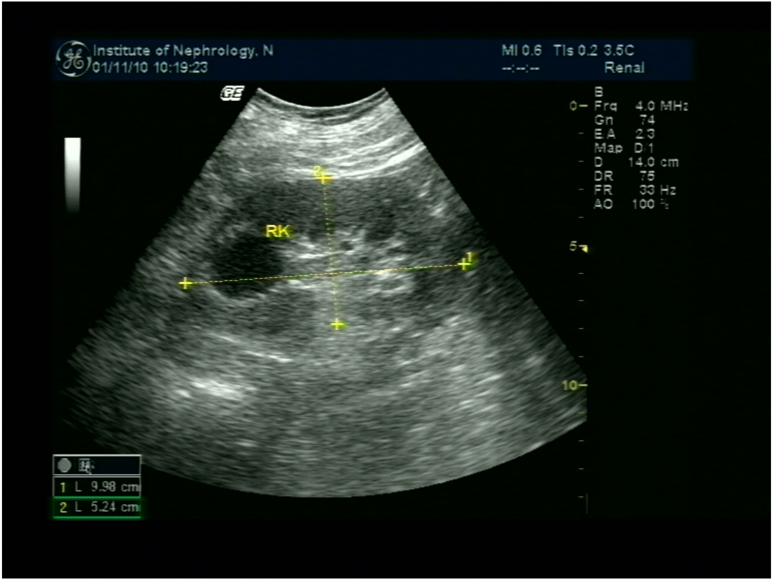
Speckles

- Generated by random distributed scatteres
- Multiplicative noise

OR

- Feature of the tissue

content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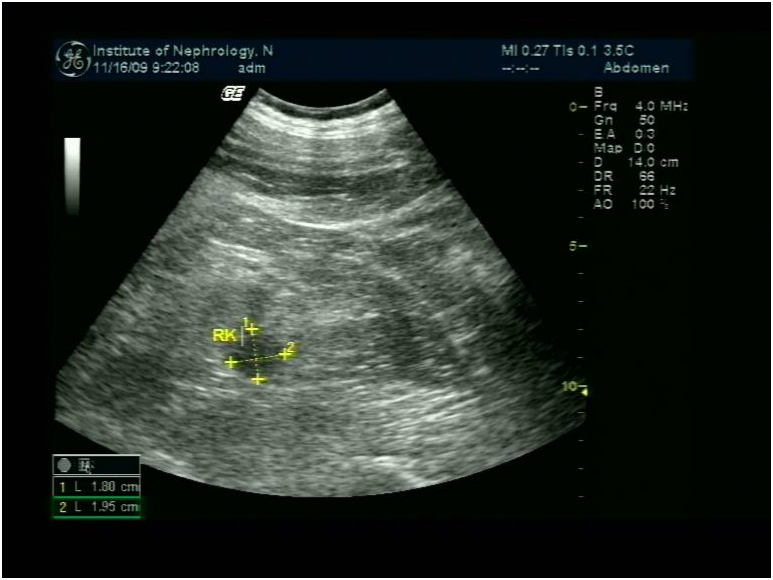
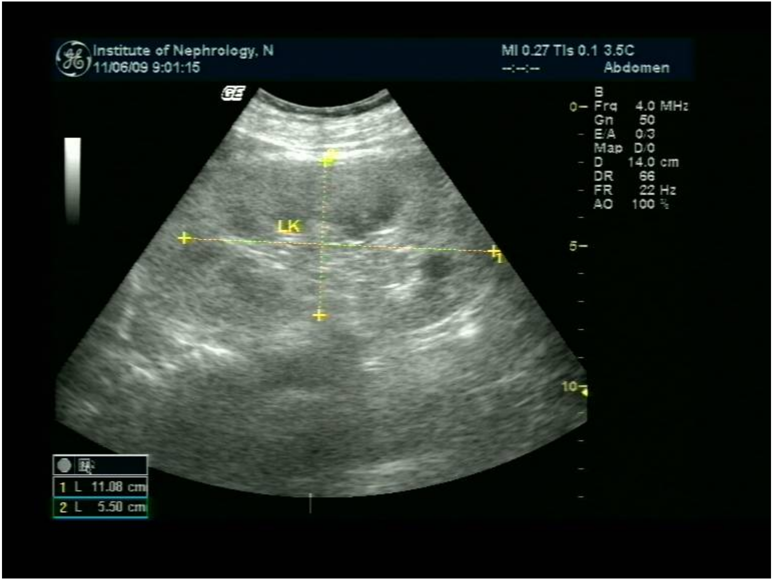
01/11/10 10:19:23
MI 0.6 TIs 0.2 3.5C
Renal
B
Frq 4.0 MHz
Gn 74
Map D/1
D 14.0 cm
DR 75
FR 33 Hz
AO 100
RK
1 L 9.98 cm
2 L 5.24 cm


Institute of Nephrology. N
11/16/09 9:22:08
adm
MI 0.27 TIs 0.1 3.5C
Abdomen
B
Frq 4.0 MHz
Gn 50
D 14.0 cm
DR 66
FR 22 Hz
AO 100 %
RK
1 L 1.80 cm
2 L 1.95 cm


Institute of Nephrology, N
11/06/09 9:01:15
MI 0.27 TIs 0.1 3.5C
--:--:--
Abdomen
GE
B
Frq 4.0 MHz
Gn 50
E/A 0/3
Map D/0
D 14.0 cm
DR 66
FR 22 Hz
AO 100 %
0
5
10
LK
1 L 11.08 cm
2 L 5.50 cm

- Advantages

– Inexpensive
– Noninvasive

- Disadvantages

– Low contrast
– Inhomogeneous
– Low signal-noise-ratio

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Backgrounds and Preliminaries

- Chan-Vese Model
- Gabor Filter
- Dampster-Shafer Evidence Theory

Chan-Vese Model

$$F(\varphi) = \mu \cdot Length(\varphi) + \lambda^+ \int_{inside(\varphi)} |u_0(x,y) - c^+|^2 dxdy$$
$$+\lambda^- \int_{inside(\varphi)} |\, u_0(x,y) - c^- \,|^2 \, dxdy$$

where $\mu > 0$ and $\lambda^+, \lambda^- > 0$. φ is the contour which splits the image into two parts. c^+ and c^- are the average values of the image inside and outside the contour, respectively.

$$E(\varphi) = \mu \int_{\Omega} | \bigtriangledown H(\varphi) | \, d\Omega - \int_{\Omega} [H(\varphi) log p_1 + (1 - H(\varphi)) log p_2)] d\Omega$$

where p_1 and p_2 are probability densities of the two separated parts, and $H(s)$ is a Heaviside function

The associated Euler-Lagrange equation:

$$\frac{\partial \varphi}{\partial t} = \delta(\varphi)[\nu \; div(\frac{\nabla \varphi}{|\nabla \varphi|}) + log \frac{p_1}{p_2}]$$

where $\delta(s)$ is the derivative of $H(s)$.

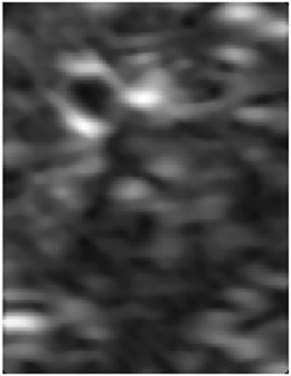
Gabor Filter

A 2D Gabor function is defined as:

$$g(x, y; \lambda, \theta, \sigma, \gamma) = exp(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}) exp(i(2\pi \frac{x'}{\lambda} + \psi))$$

where $x' = x\, cos\theta + y\, sin\theta$ and $y' = -x\, cos\theta + y\, sin\theta$.

original image



its gabor feature

Dempster-Shafer Evidence Theory

- Introduced by A.P.Dempster and formalized by G.Shafer
- Described as a generalization of the Bayesian theory
- Deal with the inaccuracy and uncertainty information

Definitions

- If Θ is a space of hypotheses:

$$\Theta = \{A_1, A_2, ..., A_N\}$$

- The basic probability assignment defined as:

$$m : 2^{\Theta} \rightarrow [0, 1]$$

and satisfy:

$$m(\phi) = 0 \qquad and \qquad \sum_{A_n \subseteq \Theta} m(A_n) = 1$$

- Belief function:

$$Bel(A) = \sum_{A_n \subseteq A} m(A_n)$$

Dempster's rule of combination

$$m(A) = (m_1 \bigoplus m_2 \bigoplus \dots \bigoplus m_n)(A)$$
$$= \frac{\sum\limits_{\lambda \in \Lambda_A^n} \prod\limits_{\substack{i=1 \\ A_{\lambda_1} \bigcap A_{\lambda_2} \bigcap \dots \bigcap A_{\lambda_n} = A}}^{n} m_i(A_{\lambda_i})}{1-K},$$

where
$\Lambda_A^n = \{\lambda = (\lambda_1, \lambda_2, ..., \lambda_n), A_{\lambda_i} \in 2^{\Theta}, s.t. \bigcap A_\lambda = A\}$.
In the same way,
$\Lambda_\phi^k = \{\lambda = (\lambda_1, \lambda_2, ..., \lambda_k), A_{\lambda_j} \in 2^{\Theta}, s.t. \bigcap A_\lambda = \phi\}$,
$K = \sum\limits_{\lambda \in \Lambda_\phi^k} \prod\limits_{\substack{j=1 \\ A_{\lambda_1} \bigcap A_{\lambda_2} \bigcap \dots \bigcap A_{\lambda_k} = \phi}}^{k} m_j(A_{\lambda_j})$ measures the degree of conflict between the evidences.

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Flow Chart

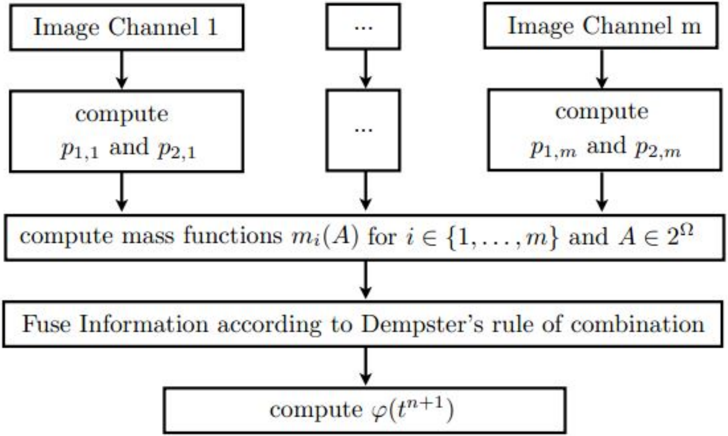
Image Channel 1
...
Image Channel m
compute
$p_{1,1}$ and $p_{2,1}$
...
compute
$p_{1,m}$ and $p_{2,m}$
compute mass functions $m_i(A)$ for $i \in \{1, \dots, m\}$ and $A \in 2^\Omega$
Fuse Information according to Dempster's rule of combination
compute $\varphi(t^{n+1})$

- Euler-Lagrange equation for CV model:

$$\frac{\partial C}{\partial t} = \delta(C)\left[\log(\frac{p_1}{p_2}) + \mu \cdot div(\frac{\nabla C}{|\nabla C|})\right]$$

- The new Euler-Lagrange equation:

$$\frac{\partial C}{\partial t} = \delta(C)\left[\log\frac{Bel(foreground)}{Bel(background)} + \mu \cdot div(\frac{\nabla C}{|\nabla C|})\right]$$

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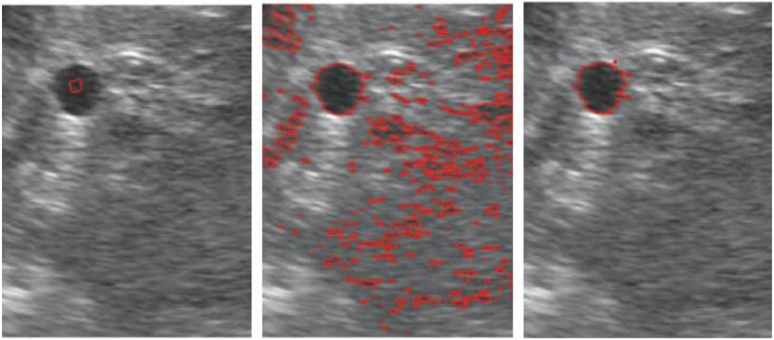
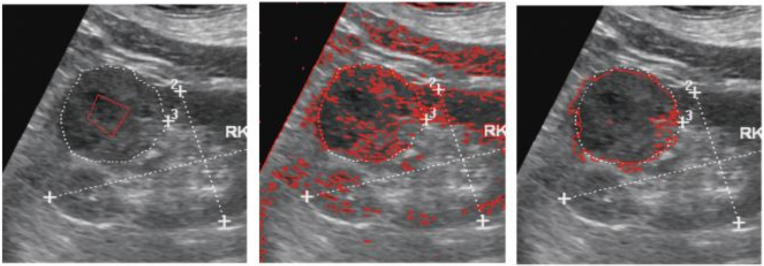
- Comparison results of CV model and our method on the ultrasound images for renal cyst

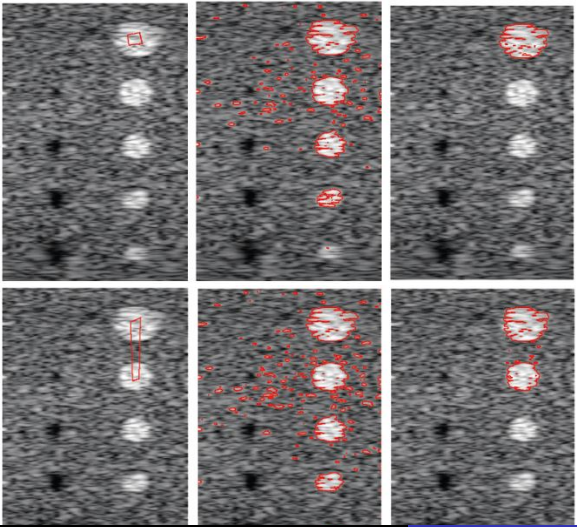



LK
LK
LK

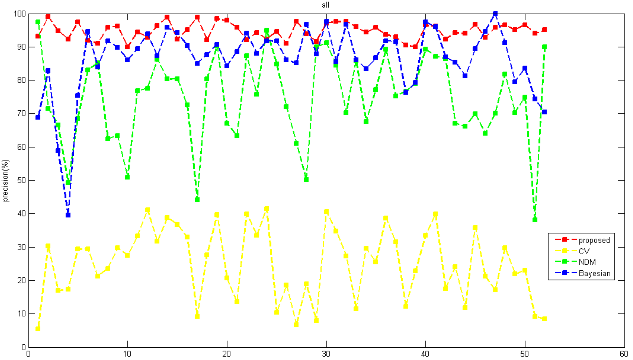
- Comparison results of CV model and our method on the ultrasound images for other renal parenchymal lesions



- Comparison results of CV model and our method with different initializations



- Precisions of our approach and other three methods



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- The isoperimetric inequality:

For any bounded Lipschitz domain $\Omega \in R^n$, $n \geq 2$

$$\frac{|\partial\Omega|}{|\Omega|^{\frac{n-1}{n}}} \geq n^{n-1} C_{n-1},$$

where $C_{n-1} = \frac{2\pi^{n/2}}{\Gamma(n/2)}$. $\partial\Omega$ is the boundary of the domain Ω, and $|\partial\Omega|$, $|\Omega|$ are the measure of the domain and the surface measure of its boundary, respectively.

- In image area, we have $n = 2$:

$$L^2 \geq 4\pi A,$$

it also can be written as:

$$\frac{4\pi A}{L^2} \geq 1,$$

where L is the length of $\partial\Omega$, and A is the area of Ω. The equality is valid if and only if the domain is a disk.

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- compactness $\leftrightarrow$ roundness
- Shape energy term:

$$E_{shape} = \left(\frac{4\pi Area(inside(C))}{length(C)^2}\right)^p, (p < 0)$$

- The proposed energy functional:

$$E = \theta E_{shape} + E_{CV} \quad (\theta > 0),$$

$$E(c_1, c_2, C) = \theta\left(\frac{4\pi Area(inside(C))}{Length(C)^2}\right)^p$$
$$+\lambda_1 \int_{inside(C)} |u_0(x,y) - c_1|^2 dxdy$$
$$+\lambda_2 \int_{outside(C)} |u_0(x,y) - c_2|^2 dxdy,$$

With level set function ϕ, the energy $E(c_1, c_2, C)$ can be written as:

$$E(c_1, c_2, \phi) = \theta\left(\frac{4\pi \int_\Omega H(\phi(x,y))dxdy}{(\int_\Omega \delta(\phi(x,y))|\nabla\phi(x,y)|dxdy)^2}\right)^p$$

$$+\lambda_1 \int_\Omega |u_0(x,y) - c_1|^2 H(\phi(x,y))dxdy$$

$$+\lambda_2 \int_\Omega |u_0(x,y) - c_2|^2 (1 - H(\phi(x,y)))dxdy$$

- The Euler - Lagrange equation for ϕ is:

$$\frac{\partial \phi}{\partial t} = K \cdot \delta_\epsilon(\phi)[-L - 2A \cdot div(\frac{\nabla \phi}{|\nabla \phi|})]$$
$$+\delta_\epsilon(\phi)[-\lambda_1(u_0 - c_1)^2 + \lambda_2(u_0 - c_2)^2],$$

where

$$K = \frac{\theta(4\pi)^p \cdot p(\frac{A}{L^2})^{p-1}}{L^3},$$

and $A = Area(\phi > 0)$, $L = Length(\phi = 0)$

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- Initialization

– Imaging area extraction; speckle reduction.

- Preparatory thresholding

– Otsu's thresholding; inversion

- Conditional thresholding

– Otsu's thresholding on selected areas

- Score computation

– Intensity, compactness, location

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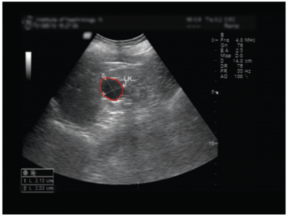
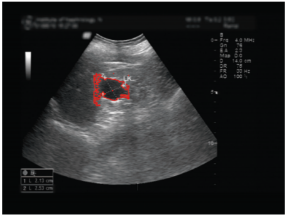
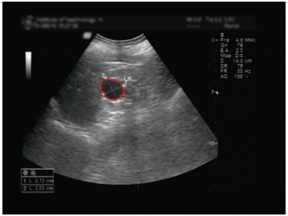
Comparative result I:



GT



CV



our method

Comparative result II:

GT

CV

our method

Quantitative Evaluation

	CV model	Proposed method
precision(%)	65.6(13.6)	96.0(3.1)
recall(%)	95.3(2.9)	84.3(6.5)
DICE(%)	77.0(9.4)	89.6(3.5)
MAD(pixel)	3.24(1.6)	0.07(0.1)
SMAD(pixel)	2.03(1.1)	0.19(0.11)

Future work

- Lesion Detection
- Classification

Thank You !