Segmentation in echocardiographic imaging using parametric level set model driven by the statistics of the radiofrequency signal

Olivier Bernard
Ph.D. defense
Lyon, December 04, 2006
Medical context

- Cardiovascular diseases
  - Major cause of mortality in industrialized countries
  - Important issue of public health

Olivier Bernard (CREATIS) Segmentation of echocardiographic imaging

PET MRI

PET

MRI

Echography

MRI with tag
Medical context

- Interest of echography

- Real time, high frame rate (25-350 frames per second)

- Non-invasive, no special preparation of the patient

- Low cost, reasonable size
Medical context

Clinical applications

- Needs of automatic or semi-automatic segmentation tools of cardiac sequences

→ Algorithms dedicated to the location of blood and myocardial regions

difficult and open problem

[Cootes et al. 1988] [Herlin et al. 1994] [Boukerroui et al. 2001]
[Lin et al. 2002] [Chen et al. 2002] [Sarti et al. 2005]
Objective

Segmentation of cardiac structures over time
Difficulties with echocardiographic image processing

- Unsharp boundaries
- Variation of topology
- Speckle phenomenon
- Attenuation

Choices:
- Active contours
- Region-based approach
- Level set implementation
Problematics

Difficulties with echocardiographic image processing

- Unsharp boundaries
- Speckle phenomenon
- Variation of topology
- Linear attenuation

Choice:

- Statistical approach
Problematics

- Active contours based on statistics
  - Separate regions having different statistical properties

  - Non parametric methods
    - [Aubert et al. 2003]
    - [Martin et al. 2006]

  - Parametric methods
    - a priori knowledge of the statistical distribution
    - [Zhu & Yuille 1996]
    - [Paragios & Deriche 2002]

  - Global descriptors methods
    - [Chan & Vese 2001]
    - [Jehan-Besson et al. 2003]
Problematics

- Active contours based on statistics
  - Parametric methods

  - The physical process of image formation provides strong a priori about the distributions
  - Generally yields faster algorithms
  - Based on the first-order statistics of the ultrasound signal
    - potentially less sensitive to the linear attenuation effect
1. Statistical model of cardiac ultrasound signals
   - Physical model: $K_{RF}$
   - Approximation model: Generalized Gaussian

2. Segmentation of echocardiographic images
   - Discrete level set model
   - Exploitation of the Generalized Gaussian distribution

3. Segmentation of echocardiographic sequence
   - Parametric level set model
   - Application of temporal constraints using Kalman filtering
Outline

1. Statistical model of cardiac ultrasound signals
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Part 1

Statistical model of cardiac ultrasound signals

Objective

Determination and validation of an a priori distribution well adapted to characterize both blood and myocardial regions with robust parameters estimation
Statistical model of cardiac ultrasound signals

- **Echographic signals**
  - Radio-frequency signal (RF)
    - *frequencies: 2 – 5 MHz*
  - Envelope signal

Logarithm operation
Speckle - definition

- Due to acoustic inhomogenities of the reached medium
- Regions containing scatterers whose sizes are smaller than the wavelength
- Resolution cell (impulse response of the equipment)
Statistical model of cardiac ultrasound signals

- Speckle - statistical models

- Ultrasound images $\rightarrow$ Stochastic process

- Characterization of the position and the echogeneity of the scatterers inside a resolution cell

  Random walk principle

  Ultrasound statistical models
Ultrasound statistical models for envelope signal

Based on the discrete scattering model introduced by Bamber and Dickinson [Bamber and Dickinson 1980]

- Rayleigh (1983)
- Rice (1983)
- K distribution (1993)
- Nakagami (2000)
- Compound (2003)
Statistical model of cardiac ultrasound signals

- Rayleigh distribution [Wagner et. al. 1983]

  - Assumptions: high density of scatterers
  - Well suited to characterized blood pool
  - Equivalent to a Gaussian distribution for the RF signal
  - Robust parameter estimator with a simple expression

  used for segmentation of blood pool

  [Sarti et. al. 2005]
Statistical model of cardiac ultrasound signals

- Rayleigh distribution

Does not represent properly the statistics of the myocardial regions

**MYOCARDIUM**

Envelope histogram

**BLOOD**

Envelope histogram
K distribution  [Jakeman et. al. 1978]

- Assumptions: wide range of density of scatterers
- Well suited to characterize both blood and myocardial regions  [Clifford et. al. 1993]
- No known expression for RF signal
- Inconsistency with parameters estimators
  haven’t been used for segmentation
Statistical model of cardiac ultrasound signals

- K distribution

**MYOCARDIUM**

- Envelope histogram

**BLOOD**

- Envelope histogram

Ray, Kdis
Statistical model of cardiac ultrasound signals

K distribution

- Assumptions: wide range of density of scatterers
- Well suited to characterized both blood and myocardial regions
- No known expression for RF signal
- Inconsistency with parameters estimators

Not used for segmentation
Statistical model of cardiac ultrasound signals

- K distribution
- Inconsistency with parameter estimators

Bias

Blood situation

Shape parameter

Blacknell

[Blacknell 2001]
Our contribution

Exploitation of the radio-frequency signal

→ Develop a physical model well adapted to characterize both blood and myocardial regions

→ Approximation of the physical model by a distribution having robust parameters estimator
Statistical model of cardiac ultrasound signals

- Design a physical model for the statistics of the RF signal [Bernard et. al. 2006] IEEE trans UFFC

- Based on the assumptions of the K distribution

\[ P_{Krf}^{rf}(x, \nu, b) = \frac{b}{\sqrt{\pi} \Gamma(\nu)} \left( \frac{b |x|}{2} \right)^{\nu-0.5} K_{\nu-0.5} (b |x|) \]

- \( K \) : Bessel function
- \( \Gamma \) : Gamma function

- Derivation of parameters estimators

\[ \frac{E[X^2 \log |X|]}{E[X^2]} - E[\log |X|] = 1 + \frac{1}{2\nu} \]
Statistical model of cardiac ultrasound signals

- Design a physical model for the statistics of the RF signal
  
  [Bernard et. al. 2006] IEEE trans UFFC

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**MYOCARDIUM**

**RF histogram**

**K\textsubscript{RF}**

**BLOOD**

**RF histogram**

**K\textsubscript{RF}**
Approximation of the $K_{RF}$ using the Generalized Gaussian distribution

\[
P^{rf}_{GG}(x, \alpha, \beta) = \frac{\beta}{2\alpha \Gamma(1/\beta)} \exp \left( - \left( \frac{|x|}{\alpha} \right)^\beta \right)
\]

- Simple expression
- Robust parameter estimation using Maximum likelihood estimate
Statistical model of cardiac ultrasound signals

Approximation of the $K_{RF}$ using the Generalized Gaussian distribution

- Comparison between parameters estimators performance

<table>
<thead>
<tr>
<th>$\nu$</th>
<th>$K_{RF}$ B $[\hat{\nu}]$</th>
<th>$K_{RF}$ V $[\hat{\nu}]$</th>
<th>$\beta$</th>
<th>Generalized Gaussian B $[\hat{\beta}]$</th>
<th>Generalized Gaussian V $[\hat{\beta}]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>0.006</td>
<td>0.001</td>
<td>0.6</td>
<td>0.005</td>
<td>0.001</td>
</tr>
<tr>
<td>1.0</td>
<td>0.014</td>
<td>0.010</td>
<td>1.0</td>
<td>0.003</td>
<td>0.003</td>
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<tr>
<td>3.2</td>
<td>0.117</td>
<td>0.417</td>
<td>1.5</td>
<td>0.011</td>
<td>0.007</td>
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<tr>
<td>4.4</td>
<td>0.330</td>
<td>1.631</td>
<td>1.6</td>
<td>0.012</td>
<td>0.011</td>
</tr>
</tbody>
</table>

**Blood situation**
Evaluation of the ability of the $K_{RF}$ and the Generalized Gaussian distribution to characterize normal myocardium tissue and blood pools

[Bernard et. al. 2006] UFFC conf.

Protocol

- Probe: central frequency = 3.5 MHz
- Five different patients
- Four clinical views for each patients
- Each region delimited by a trained cardiologist
- Goodness of fits measure: Kolmogorov-Smirnov measure
### Blood

<table>
<thead>
<tr>
<th>View</th>
<th>Kolmogorov measure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$K_{RF}$</td>
</tr>
<tr>
<td>PALA – Blood</td>
<td>0.004</td>
</tr>
<tr>
<td>PASA – Blood</td>
<td>0.004</td>
</tr>
<tr>
<td>A4CH – Blood</td>
<td>0.003</td>
</tr>
<tr>
<td>A2CH – Blood</td>
<td>0.003</td>
</tr>
</tbody>
</table>

#### KS

- $K_{RF} = 0.005$
- $KS_{GG} = 0.007$
- $KS_{Gauss} = 0.014$
### Tissue

<table>
<thead>
<tr>
<th>View</th>
<th>Kolmogorov measure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$K_{RF}$</td>
</tr>
<tr>
<td>PALA – Tissue</td>
<td>0.04</td>
</tr>
<tr>
<td>PASA – Tissue</td>
<td>0.03</td>
</tr>
<tr>
<td>A4CH – Tissue</td>
<td>0.03</td>
</tr>
<tr>
<td>A2CH – Tissue</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Radio frequency histogram:

- $K_{RF} = 0.03$
- $KS_{GG} = 0.02$
- $KS_{Gauss} = 0.08$
Conclusion

- Study of the statistics of the radio-frequency signal
- Design a physical model well adapted to characterize both blood and myocardial regions from the RF signal
- Approximation of the physical model by a distribution which has a simple expression with consistent parameter estimation
Outline

1. Statistical model of cardiac ultrasound signals
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2. Segmentation of echocardiographic images
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3. Segmentation of echocardiographic sequence
   - Parametric level set model
   - Application of temporal constraints using Kalman filtering
Segmentation of echocardiographic images

Objective

Exploitation of the Generalized Gaussian as an a priori distribution in a statistical parametric method for the segmentation of echocardiographic images
Variational active contours approach

- Class of segmentation method
- Minimization of an energy criterion
- Derivation of an evolution equation of the active contour

\[
\frac{\partial \Gamma(\tau)}{\partial \tau} = V \cdot \vec{N} \quad \text{where} \quad \begin{cases} \Gamma : \text{evolving contour} \\ \vec{N} : \text{normal vector} \\ V : \text{velocity function} \end{cases}
\]

\[\Gamma(\tau = 0) = \Gamma_0\]
Variational active contours approach

Contour representation

- Explicit representation - Lagrangian framework
- Implicit representation - Eulerian framework

Variational active contours approach

$\Gamma(p, \tau)$

- Explicit representation
- Lagrangian framework

$z = f(p, \tau)$: implicit function

$f_0 = \Gamma(p, \tau)$

Zero level set of the implicit function

$\frac{\partial \Gamma}{\partial \tau} = \nabla \cdot \vec{N}$

$\frac{\partial f}{\partial \tau} = \nabla \cdot \| \nabla f \|$
Segmentation of echocardiographic images

Example of segmentation using level sets method

- implicit function $f$
- zero level set $f_0$
- segmented image
Segmentation of echocardiographic images

- Parametric approach
  - Exploitation of an a priori distribution

Energy criterion: Maximum Likelihood functional

[Zhu & Yuille 1996]

Separate two regions modelled by an a priori distribution $P_{\text{img}}$ having different parameter $w$ values
Segmentation of echocardiographic images

- Maximum Log-Likelihood (ML) functional with a regularization term

\[ J_{\text{ML}} (\Gamma(p)) = \mu \int_{\Gamma} ds + \left\{ \iint_{\Omega_{\text{in}}} - \log (P_{\text{img}} (p/\omega_{\text{in}})) \, dp + \iint_{\Omega_{\text{out}}} - \log (P_{\text{img}} (p/\omega_{\text{out}})) \, dp \right\} \]

- with \( P_{\text{img}} \): a priori distribution
- \( \omega \): parameters of the a priori distribution
Segmentation of echocardiographic images

- Evolution of the active contour using level set representation

\[
\frac{\partial f(p)}{\partial \tau} = \left( \mu \kappa - \log \left( \frac{P_{\text{img}}(p/\omega_{\text{in}})}{P_{\text{img}}(p/\omega_{\text{out}})} \right) \right) \| \nabla f \|
\]

\[
\begin{align*}
\mathbf{f} : & \text{ implicit function} \\
\kappa : & \text{ local curvature}
\end{align*}
\]
Segmentation of echocardiographic images

Application to echocardiography segmentation

- Envelope image
- $P_{\text{img}}$ : Rayleigh distribution
  
  Usually fails to segment myocardial regions

Rayleigh / envelope

Parasternal long axis view

Rayleigh / envelope

[Sarti et al. 2005]
Our contribution

Segmentation of echocardiographic images using the statistics of the radio-frequency image
Segmentation of echocardiographic images

Active contour based on the statistics of the RF signal

\[ \frac{\partial f(p)}{\partial \tau} = \left( \mu \kappa - \log \left( \frac{P_{\text{img}}(p/\omega_{\text{in}})}{P_{\text{img}}(p/\omega_{\text{out}})} \right) \right) \| \nabla f \| \]

- A priori distribution: \( P_{\text{img}} = \) Generalized Gaussian distribution
- Computation of the statistics from the radio-frequency image
- Experiments: \( \mu = 0.2 \)
Simulation

- Random image generated according to 2 Generalized Gaussian distributions

Myocardium values
- $\beta = 0.58$
- $\alpha = 180$

Blood values
- $\beta = 2.0$
- $\alpha = 85$

Initialization in blood

Initialization in tissue
Segmentation of echocardiographic images

- In vivo data - parasternal long axis view

Rayleigh / envelope

Gene. Gauss. / RF
Segmentation of echocardiographic images

- In vivo data - apical four chambers view

Rayleigh / envelope

Gene. Gauss. / RF
Conclusion

- Use a level set method based on a statistical parametric model
- Exploit the Generalized Gaussian distribution in order to improve the segmentation of echocardiographic images
- Test the ability of our model to segment myocardial regions on static images

Segmentation of echocardiographic sequences: introduction of a priori constraints to enhance temporal coherence
Outline

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Segmentation of echocardiographic sequences

Objective

Introduction of spatio-temporal constraints into level set framework for the segmentation of echocardiographic images sequence
Segmentation of echocardiographic sequences

- Incorporation of prior constraints
  
  - Shape constraints
    
    - PCA model [Chen et al. 2001]
  
  - Motion constraints
    
    - Affine [Giachetti 1998]
    - Optical flow [Mikic et al. 1998]
    - Kalman filtering [Malassiotis et al. 1999]
Segmentation of echocardiographic sequences

- Spatio-temporal constraints
  - Kalman filtering

Statistical tool which estimate state of a dynamic system over time

\[
\begin{align*}
\text{Measurement} \\
\text{Dynamic model}
\end{align*}
\]

\{ Estimation of temporal events \}

Well adapted to echocardiographic sequence segmentation

- [Jacob et al. 1999]
- [Comaniciu et al. 2002]
- [Zhou et al. 2005]
Segmentation of echocardiographic sequences

- Spatio-temporal constraints
  - Kalman filtering and active contours

  - Only applied on active contours based on a lagrangian formulation
    - Difficulties with points correspondence
    - Difficulties with variation of topology

  - We propose to apply the kalman filtering to the level set model
Segmentation of echocardiographic sequences

- Problematic
  - Implementation of the \( PDE \)

\[
\frac{\partial f}{\partial \tau} = \nabla \| \nabla f \| 
\]

- Application of the \( PDE \) to a discretization grid corresponding to the image
- Resolution of the \( PDE \) using an optimized finite difference scheme
  
  \[ [Osher & Sethian 1988] \]
- Application of the Kalman model at each pixel of the image
Our contribution

Parametric formulation of the level sets
Segmentation of echocardiographic sequences

- Parametric formulation of the level sets
  
  \[ \frac{\partial f}{\partial T} = \nabla \cdot \left( \frac{\nabla f}{\| \nabla f \|} \right) \]

- New implementation of the PDE
- Resolution of the level set equation using a collocation method based on radial basis function

- Choice of radial basis function (RBF)
  - Application to N dimension
  - Irregular grid
Parametric formulation of the level sets

Modelization of the implicit function using RBFs

\[
f(p) = \sum_{i=1}^{N} \alpha_i \varphi\left(\|p - C_i\|_2\right)
\]

where

\[
\begin{align*}
\varphi &: \text{Radial Basis Function} \\
(C_i)_{1 \leq i \leq N} &: \text{RBF centers} \\
(\alpha_i)_{1 \leq i \leq N} &: \text{Scalar parameters}
\end{align*}
\]

Assumptions

→ Temporal evolution of \( f \) is only due to the variation of \( \alpha_i \)

→ RBF centers remain fixed during time

\[
f(p, \tau) = \sum_{i=1}^{N} \alpha_i(\tau) \varphi_i(p)
\]
Segmentation of echocardiographic sequences

- Parametric formulation of the level sets
  - Collocation method based on radial basis functions

- The RBF centers are placed on a fixed grid (regular or not)
- Application of the PDE only at the RBF centers

\[
\begin{align*}
\frac{\partial f(C_1)}{\partial \tau} &= \nabla (C_1) \| \nabla f(C_1) \| \\
\frac{\partial f(C_2)}{\partial \tau} &= \nabla (C_2) \| \nabla f(C_2) \| \\
\vdots & \hspace{1cm} \text{with} \\
\frac{\partial f(C_N)}{\partial \tau} &= \nabla (C_N) \| \nabla f(C_N) \|
\end{align*}
\]

\[
\begin{align*}
    f(C_1) &= \sum_{i=1}^{N} \alpha_i \varphi_i (C_1) \\
    f(C_2) &= \sum_{i=1}^{N} \alpha_i \varphi_i (C_2) \\
    \vdots & \\
    f(C_N) &= \sum_{i=1}^{N} \alpha_i \varphi_i (C_N)
\end{align*}
\]
Segmentation of echocardiographic sequences

- **Parametric formulation of the level sets**
  - Resolution of a simple ODE

\[
\frac{\partial f}{\partial \tau} = V \| \nabla f \|
\]

\[
H \frac{d\alpha}{d\tau} = B(\alpha)
\]

- **H**

\[
H = \begin{bmatrix}
\varphi_1(C_1) & \cdots & \varphi_N(C_1) \\
\vdots & \ddots & \vdots \\
\varphi_1(C_N) & \cdots & \varphi_N(C_N)
\end{bmatrix}
\]

- **\( \frac{\partial \alpha}{\partial \tau} \)**

\[
\frac{\partial \alpha}{\partial \tau} = \begin{bmatrix}
\frac{\partial \alpha_1}{\partial \tau} \\
\vdots \\
\frac{\partial \alpha_N}{\partial \tau}
\end{bmatrix}
\]

- **B(\( \alpha \))**

\[
B(\alpha) = \begin{bmatrix}
V(C_1) \| \nabla f(C_1, \alpha) \| \\
\vdots \\
V(C_N) \| \nabla f(C_N, \alpha) \|
\end{bmatrix}
\]
Parametric formulation of the level sets

- Resolution of the ODE

- Euler method

\[
H \frac{d\alpha}{d\tau} = B(\alpha) 
\]
Segmentation of echocardiographic sequences

- Parametric formulation of the level sets

  - Resolution of the ODE

- Choice of the RBF: Wendland
  
  - Compactly supported radial basis function
  
  - Each RBF has a limited influence
  
  - Reduce the complexity of the implementation

\[
\alpha^{n+1} = \alpha^n + \tau \cdot H^{-1} \cdot B^n(\alpha^n)
\]

[Wendland 1995]
Segmentation of echocardiographic sequences

- Parametric formulation of the level sets
  - Problem of steep regions

Discrete level set

- Initialization of the level set as a signed distance function
- Reshaping the level set function periodically
- Segmentation results may be affected
Segmentation of echocardiographic sequences

- Parametric formulation of the level sets
  - Problem of steep regions

**Parametric level set**

- Bounding of the gradient of the level set function
- Normalization of the RBF coefficient

- Experimentally we observe a global convergence of the level set
Segmentation of echocardiographic sequences

With normalization

Without normalization

\[ \| \alpha_t - \alpha_{t-1} \|_\infty \]

\[ \| \alpha_t - \alpha_{t-1} \|_\infty \]
Segmentation of echocardiographic sequences

Simulation

Image dimension: 200 x 200
RBF Centers: uniform grid 50 x 50
Energy: Mumford-shah criterion
Segmentation of echocardiographic sequences

Simulation

<table>
<thead>
<tr>
<th>Noise Free</th>
<th>SNR 30 dB</th>
<th>SNR 20 dB</th>
</tr>
</thead>
</table>

Image + Initialization

Results
Segmentation of echocardiographic sequences

- In vivo data
- Resolution: angle = 0.74°
- Energy: Maximum likelihood
- RBF Centers: unif. grid 50

Initialization

- Discrete level set
- Parametric level set
Segmentation of echocardiographic sequences

- Sensitivity to initialization

Variation of Energy

Number of steps

Variation of Energy

Number of steps
Segmentation of echocardiographic sequences

Our contribution

Introduction of spatio-temporal constrains into level set framework through Kalman filtering
Segmentation of echocardiographic sequences

- Kalman filtering - principle
  - Estimation of the state of a dynamic system over time
  - State vector: $X_k$

![Diagram]

- Initialization
  - $X_0$

- Model
  - $X_{k/k}$

- Prediction
  - $X_{k+1/k}$

- Correction
  - $X_{k+1/k+1}$
Segmentation of echocardiographic sequences

- Kalman filtering - choices

- Constraint the evolution of the level set for the segmentation of each image of the sequence

State vector = RBF coefficients: $\alpha$

$X_k = \alpha_k$

Spatio-temporal constraints applied on $\alpha$
Kalman filtering - choices

- Spatial constraints

\[ \alpha_{k+1} = \alpha_k + q_k \]

Model: \[ q_k : \text{white noise} \]

Temporal smoothing constraint

\[ 0^{th} \text{ order dynamic state model} \]

Initialization

\[ \alpha_0 \]

Prediction

\[ \alpha_{k/k} \]

Correction

\[ \alpha_{k+1/k+1} \]
Segmentation of echocardiographic sequences

Kalman filtering - choices

- Measurement

\[ z_{k+1} = \alpha_k + \tau H^{-1} B(\alpha_k) \]

\[ ODE \]

Initialization

Model

Prediction

Measurement

Correction

\[ \alpha_0 \]

\[ \alpha_{k/k} \]

\[ \alpha_{k+1/k} \]

\[ \alpha_{k+1/k+1} \]
Segmentation of echocardiographic sequences

▶ Kalman filtering - choices

- Convergence criterion

\[
\left\| \alpha_{k+1} - \alpha_k \right\|_{\infty} < T
\]

\[
T \text{ : threshold value } = 10^{-4}
\]
Segmentation of echocardiographic sequences

- Kalman filtering - choices

  - Spatio-temporal constraints

  \[ \alpha_{k+1} / k \]

  Segmentation result obtained at frame \( t \) is used as an initialization at frame \( t+1 \)

\[ \alpha_{0} \]

\[ \alpha_{k/k} \]

\[ \alpha_{k+1/k} \]

\[ \alpha_{k+1/k+1} \]

Initialization

Model

Prediction

Measurement

Correction
Preliminary results
Segmentation of echocardiographic sequences

- Simulation based on Meunier’s model [Meunier et. al. 1995]

Sequence dimension: 200 x 60 x 70
RBF Centers: uniform grid 40 x 10
Energy: Maximum-Likelihood

Without Kalman

With Kalman
Segmentation of echocardiographic sequences

- In vivo: apical 4 chambers view

- Initialization
- Without Kalman
- With Kalman
Conclusions & Perspectives
Main contributions

- Statistical study of the radio-frequency signal
  - Physical model: $K_{RF}$ well adapted to characterize blood and myocardial regions
  - Approximation model: Generalized Gaussian

- Segmentation of echocardiographic images
  - Parametric method based on the Generalized Gaussian distribution and implemented using a level set model

- Segmentation of echocardiographic sequences
  - Parametric level set model
  - Application of temporal constraints using Kalman filtering
Clinical validation of our segmentation model

Methodology

- More sophisticated dynamic model

- Exploitation of the velocity information in the Kalman / level set framework
Segmentation in echocardiographic imaging using parametric level set model driven by the statistics of the radiofrequency signal

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