

# Analysis of echocardiographic movies by variational methods

Massimiliano Pedone

e-mail: [pedone@dmmm.uniroma1.it](mailto:pedone@dmmm.uniroma1.it)

Dipartimento di Metodi e Modelli Matematici per le Scienze Applicate



SAPIENZA  
UNIVERSITÀ DI ROMA

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- Biomedical Movie Processing
  - A posteriori non-invasive medical parameter determination
  - Graphic application developed for Patient's signal synchronization
- Images segmentation and enhancing
  - Level-set method
    - Curve evolution by eikonal equation
    - Speed term choice
  - Image Pre-Processing
    - Energy-based-Functional minimization
    - Dynamic approach for time series image
- Applicability of methods
  - Discrete and continuous consideration
- Numerical algorithm
  - Parallel and sequential computation
- Simulation results

# Ventricular AREA recognition of Echographic frame

We focus our attention to a ventricular cavity:

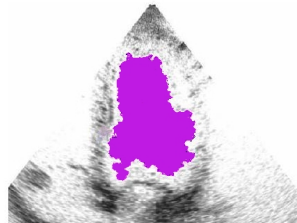
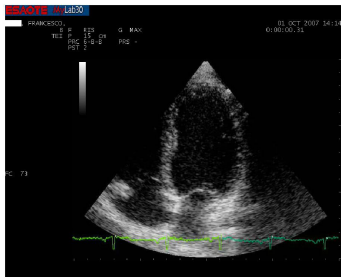
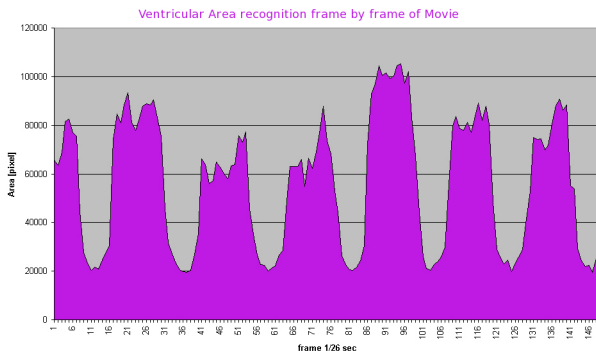


Figure: Echocardiographic frame and its recognized Area

# Ventricular AREA trends in the movie

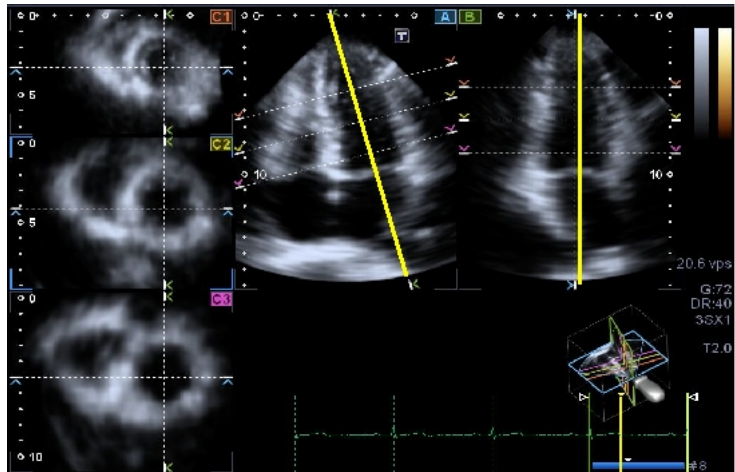
Results of the final elaboration on entire clinical movies



**Figure:** Biomedical parameters of cardiological efficiency are determined on this area trends.

# Future Project with 3D echographic sampling

Sapienza Math dep. Policlinico Umberto I and Toshiba collaboration

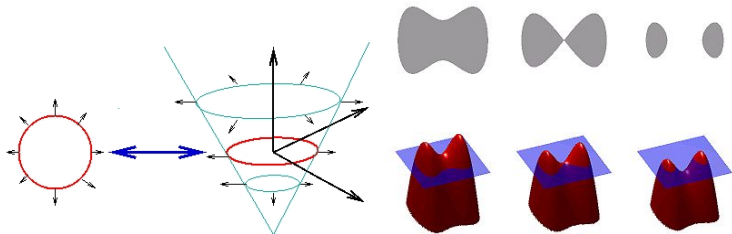


# Presentation OUTLINE

- 1 Model Problem and Numerical Approximation
- 2 Protocol building and Simulation results
- 3 Developed Software for Clinical Application

# Curve as the level-set of a surface in $\mathbb{R}^3$ .

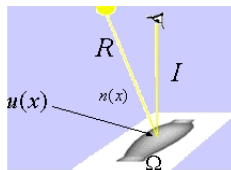
Area recognition as the level-set of a surface evolving by outward normal direction:



Adoption of a model where the speed of the front is related to the presence of an object in the image.

# Edge-detector as function of the Brightness Intensity

A detector of contours is a positive real coefficient, which is dependent of  $I(x)$ 's gradient



represented by a filter function decreasing with  $z$

$$g : \mathbb{R}^+ \longrightarrow \mathbb{R}^+, \quad g(z) = \frac{1}{1+z}, \quad \lim_{z \rightarrow \infty} g(z) = 0$$

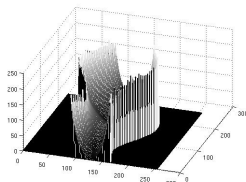
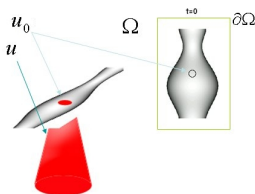
such that  $0 \leq g$  and  $g(0) = 1$ . We use this kind of filter to represent the speed along the normal outward direction of the parametrized curve in each of its points.  $g_I(x) \quad \forall x \in \Omega$ .



# The *level – set* standard model (Sethian, [8], [6]et al.).

The segmentation problems:

$$\begin{cases} u_t(x, t) - g_I(|\nabla I(x)|)|\nabla u(x, t)| = 0 \\ u(x, 0) = u_0(x) \end{cases} \quad \begin{array}{l} x \in \Omega \subset \mathbb{R}^2 \times [0, T] \\ x \in \Omega \subset \mathbb{R}^2 \end{array} \quad (1)$$



where  $\nabla I = \nabla_x I = (I_{x1}, I_{x2})^T$  is the spatial gradient.

A threshold parameter assure the border detection  $g_I(x) \leq th \Rightarrow g_I(x) = 0$ .

The filter function involving the dependence of  $I(x)$ . For a continuous problem, we have to control that is possible to calculate the Gradient and it remains bounded.

# Eikonal equation solution

M. Falcone '97[4], HJPACK M.Rorro (CASPUR)

We refer to an open library package developed for the solution of the Hamilton-Jacoby equation.

$$\begin{cases} u_t(x, t) + H(\nabla u(x, t)) = 0 & x \in \Omega, t \in [0, T] \\ u(x, 0) = u_0(x) & x \in \Omega. \end{cases}$$

Description of the library use:

- $u_T = \text{HJ1D}(H, L(\Delta x, \Delta y, \Delta t), I(x), u_0, th, T)$
- Retrieve the OpenMP calculation time and  $u_T$  at level 0
- Matlab Area calculation of the closed curve is performed with a pixel measure unit.

It require  $u_0(x)$  such that it is a Lipschitz continuous function. where

$$\text{lip}(f) := \sup_{x, y \in \Omega; x \neq y} \frac{|f(x) - f(y)|}{|x - y|} < \infty$$

# Consideration about continuous approach

In the continuous model problem the image has treated as a surface, the speed term  $V(x, t, \nabla(I(x))) = g_I$  in the equation depends of its gradient. If exists a fracture the gradient jumps to infinity value. Then a regularization is needed!

## Regularization choice.

- **Convolution with Mollifier:** *level – set* standard model

$$g_I(x) = g(|\nabla(G_\sigma * I(x))|) = \frac{1}{1 + |\nabla(G_\sigma * I(x))|},$$

(Osher, Sethian et al.[8, 6], '95-2000, P. Master thesis, 2003).

- **Regularization and Edge Enhancing** by functional minimization

$$g_I(x) = \frac{1}{1 + |\nabla u_{k_\epsilon}(x)|}, u_{k_\epsilon} \text{ minimum of an energy functional}$$



## Mollifying by heat eq. solution

With null source function and Dirichlet boundary conditions:

$$\begin{cases} u_t - \Delta u(x, t) = 0 & (x, t) \in \Omega \times [0, T] \\ u(x, 0) = u_0(x) & x \in \Omega \end{cases} \quad (2)$$

Solving (2) is equivalent to carrying out a Gaussian linear filtering.

The explicit solution is:

$$u(x, t) = \int_{\Omega} G_{\sqrt{2t}}(x - y) u_0(y) dy = (G_{\sqrt{2t}} * u_0)(x), \quad G_{\sigma}(x) = \frac{e^{-\frac{|x|^2}{2\sigma^2}}}{2\pi\sigma^2}$$

$G_{\sigma}(x)$  denotes the two-dimensional Gaussian Kernel. It corresponds to low-pass filtering.

On standard mesh:  $\Delta x = (b - a)/M$ ,  $\Delta y = (d - c)/N$

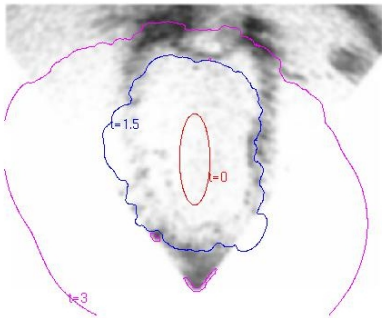
five-point approximation scheme become:

$$u^{n+1} = u^n + \Delta t \frac{u_{i+1}^n - 2u_i^n + u_{i-1}^n}{\Delta x^2} + \Delta t \frac{u_{j+1}^n - 2u_j^n + u_{j-1}^n}{\Delta y^2} \quad (3)$$

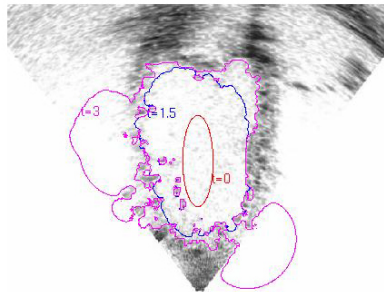
where T is the time horizon with a time step  $\Delta t$ .

# Convolution with Mollifier: Curve evolution on smoothed frame

threshold  $th=0.125$ , time horizon=3.



Smooth-Iterations=10,  $\sigma = 10\sqrt{2}$



Smooth-Iteration=1,  $\sigma = \sqrt{2}$

# Ambrosio-Tortorelli(A-T) (I. Birindelli, S. Finzi Vita, '98) [3].

Approximated discrete minimization by iterative solve two systems:

$$F_\epsilon(u, S) = \mu \int_\Omega (u - g)^2 dx + \int_\Omega S^2 |\nabla u|^2 dx + \alpha \int_\Omega \left( \epsilon |\nabla S|^2 + \frac{1}{4\epsilon} (1 - S)^2 \right) dx$$

we implement a discrete minimization algorithm:

- $S^{(0)} = 1$ ;  $u^{(0)} = g := I(x)$  for fixed  $Nit$  and a tolerance  $\epsilon$

-for  $n = 1, 2, \dots$ ,  $Nit$  find  $u^{(n+1)}$  for  $S := S^{(n)}$  fixed, by solving:

$$\begin{cases} \hat{u}_{i,j}^{(n)} = (u_{i+1,j}^{(n)} + u_{i-1,j}^{(n)} + u_{i,j+1}^{(n)} + u_{i,j-1}^{(n)}) \\ \frac{u_{i,j}^{(n+1)}}{\mu h^2 g_{i,j}} = \frac{\hat{u}_{i,j}^{(n)} (S_{i,j}^2 + K_\epsilon) + (S_{i+1,j}^2 + K_\epsilon)(u_{i+1,j}^{(n)}) + (S_{i-1,j}^2 + K_\epsilon)(u_{i-1,j}^{(n)}) + (S_{i,j+1}^2 + K_\epsilon)(u_{i,j+1}^{(n)}) + (S_{i,j-1}^2 + K_\epsilon)(u_{i,j-1}^{(n)})}{(\mu h^2 + 4S_{i,j}^2 + S_{i+1,j}^2 + S_{i-1,j}^2 + S_{i,j+1}^2 + S_{i,j-1}^2 + 8K_\epsilon)} \\ \frac{\partial u_n}{\partial n} = 0, \text{ in } \partial\Omega. \end{cases}$$

and  $S^{n+1}$  for  $u := u^{(n+1)}$  fixed by solving:

$$\begin{cases} S_{i,j}^{(n+1)} = \frac{\alpha \epsilon (S_{i+1,j}^{(n)} + S_{i-1,j}^{(n)} + S_{i,j+1}^{(n)} + S_{i,j-1}^{(n)}) + \alpha \frac{h^2}{4\epsilon}}{4\alpha \epsilon + h^2 |\nabla u|_{i,j}^2 + \alpha \frac{h^2}{4\epsilon}} \\ \frac{\partial S_n}{\partial n} = 0, \text{ in } \partial\Omega. \end{cases}$$

-stop for  $n + 1 = Nit$ . To obtain  $F_{k_\epsilon}^{(n+1)}(u_{k_\epsilon}^{(n+1)}, S_{k_\epsilon}^{(n+1)})$ .

# Regularization: Conjecture for continuous model

Bounded gradient at given iteration, Pedone '08.

If  $u_{k_\epsilon}$  represents a solution at  $k^{\text{th}}$  iteration of the Ambrosio-Tortorelli sequence ([1]) given from alternate solution of the elliptic system for fixed number of iteration, then  $u_{k_\epsilon}$  is enough smooth to calculate  $|\nabla u_{k_\epsilon}(x)|$  i.e.  $\|\nabla u_{k_\epsilon}(x)\|_\infty < \infty \quad \forall x \in \Omega^\circ$  □

In the internal points of the domain  $\Omega$  the amplitude of the fracture is  $\epsilon$ 's proportional, then we can found, at every step of the iterative solution of  $AT_\epsilon$  algorithm, a constant  $C_{Nit}$  such that

$$|\nabla u_{k_\epsilon}(x)| \leq \frac{C_{Nit}}{\epsilon} \quad \text{then} \quad v(x) = \frac{1}{1 + |\nabla u_{k_\epsilon}(x)|} \geq \frac{1}{1 + \frac{C_{Nit}}{\epsilon}} > 0.$$

It is then possible to calculate the speed term in the eikonal equation.

# Regularization: Critical points

We can observe that the function  $u_{k_\epsilon}$  has in every direction passing to the internal point  $x \in \Omega$ , a profile regularized by a  $C^2$  arcs in the fracture. (A. Francfort et al. [5], 2009.)

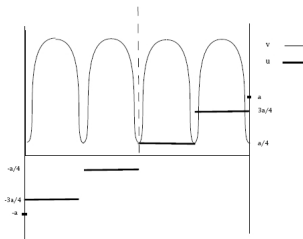


Figure: Approximation of the one dimensional fracture



# Image Enhancing: Discrete approach, time dependence

From a computational point of view the discretized image has bounded intensity profile, so we can assume as lipschitz costant the difference between the maximum and the minimum of the  $u_{k_\epsilon}$ 's points around the jump set given by the AT sequence at the  $Nit^{th}$  iteration.

# Image Enhancing: Gradient calculus, time series

Different approach in Gradient calculus:

- Standard spatial way:
- Following the **optical flow** model (see page 184 [2]), we introduce dependence on time in the gradient term ( $|\nabla u|^2$ ).

$$(|\nabla u|_{i,j}^{(f)})^2 = \frac{1}{4h^2} \left( (u_{i+1,j} - u_{i-1,j})^2 + (u_{i,j+1} - u_{i,j-1})^2 + (u_{i,j}^{(f-1)} - u_{i,j}^{(f+1)})^2 \right)$$

$$(|\nabla u|_{i,j}^{(f)})^2 = \frac{1}{4h^2} \left( \frac{(u_{i+1,j} - u_{i,j})^2 + (u_{i,j} - u_{i-1,j})^2}{2} + \frac{(u_{i,j+1} - u_{i,j})^2 + (u_{i,j} - u_{i,j-1})^2}{2} \right) + \quad (4)$$

$$+ \frac{1}{4h^2} \left( \frac{(u_{i,j}^{(f-1)} - u_{i,j}^{(f)})^2 + (u_{i,j}^{(f)} - u_{i,j}^{(f+1)})^2}{2} \right).$$

Represents a new formulation of the model with a dynamic "mean" between frame.

# Time dependence: Open problem

R. March, G. Riey

Complete dynamical formulation of Time series functional: where  $\varphi_{\eta,L}$  is a cut function.

$$g : \Omega \times [0, T], \Omega \in \mathbb{R}^2$$

$$u \in \mathbb{R}^2 \times [0, T],$$

$$F(u) = \int_0^T dt \int_{\Omega} \left| u - g \cdot \varphi_{\eta,L} \left( \left| \frac{\partial g}{\partial t} \right| \right) \right|^2 dx + \int_0^T dt \int_{\Omega} |\tilde{\nabla}_x u|^2 dx + \int_0^T dt \cdot \mathcal{H}^1(S_{u(t)}) + \\ + \int_0^T dt \left( \frac{\partial u}{\partial t} \right)^2 dx + \int_0^T dt \int_{\Omega} |\tilde{\nabla}_x \left( \frac{\partial u}{\partial t} \right)|^2 dx + \int_0^T dt \cdot \mathcal{H}^1(S_{\frac{\partial u}{\partial t}})$$

is the time regularization parts.

# Approximated functional

As in A-T way:

$$\begin{aligned}
 F_\epsilon(u) = & \int_0^T dt \int_\Omega \left| u - \mathbf{g} \cdot \varphi_{\eta,L} \left( \left| \frac{\partial \mathbf{g}}{\partial t} \right| \right) \right|^2 dx + \\
 & \int_0^T dt \int_\Omega S^2 |\nabla_x u|^2 dx + \int_0^T dt \int_\Omega \left\{ \epsilon |\nabla_x S|^2 + \frac{1}{4\epsilon} (1 - S)^2 \right\} dx + \int_0^T dt \left( \frac{\partial u}{\partial t} \right)^2 dx + \\
 & \int_0^T dt \int_\Omega Z^2 \left| \nabla_x \left( \frac{\partial u}{\partial t} \right) \right|^2 dx + \int_0^T dt \int_\Omega \left\{ \epsilon |\nabla_x Z|^2 + \frac{1}{4\epsilon} (1 - Z)^2 \right\} dx.
 \end{aligned}$$

Then we obtain the system:

$$\begin{cases}
 u - \mathbf{g} \varphi_{\eta,L} \left( \left| \frac{\partial \mathbf{g}}{\partial t} \right| \right) - \operatorname{div} (S^2 \nabla_x u) - \frac{\partial^2 u}{\partial t^2} + \frac{\partial}{\partial t} [\operatorname{div} (Z^2 \nabla_x \frac{\partial u}{\partial t})] = 0 \\
 S |\nabla_x u|^2 - \epsilon \Delta_x S - \frac{1}{2\epsilon} (1 - S) = 0 \\
 Z |\nabla_x (\frac{\partial u}{\partial t})|^2 - \epsilon \Delta_x Z - \frac{1}{2\epsilon} (1 - Z) = 0.
 \end{cases}$$

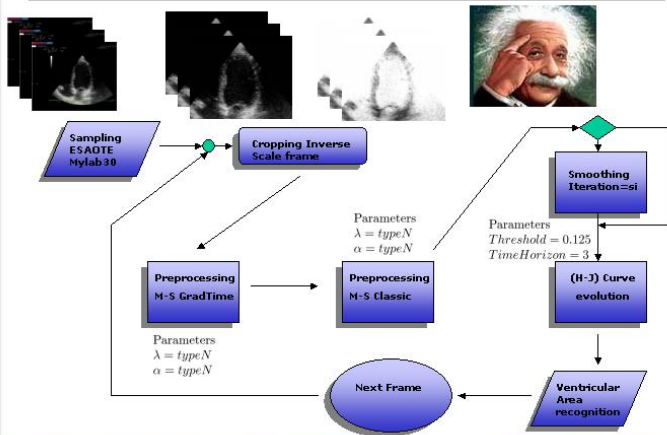
The existence of minimum and the approximation are in course of development.

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## Movie Proc. Protocol buildings: typeN

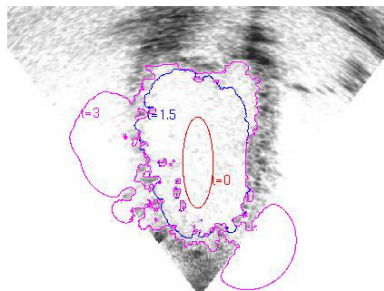
preprocessing steps and reiteration of M-S Movie processing



# Type 1: Original image

Protocol of elaboration:

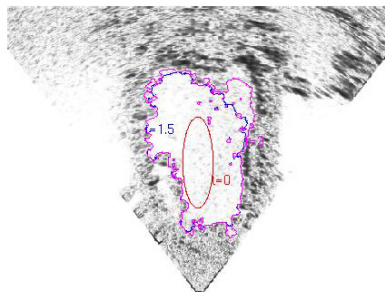
- Cropping: Frame[800,652]  $\rightsquigarrow$  Frame[501,411] [pixel]
- Preprocessing: n/a
- Processing:
  - Smoothing: eq. Heat 1 iteration
  - H-J: Threshold (th=0.125)  
Time-Horizon (3, step 0.03)  
Spatial mesh (0 ..5.0,0 ..4.1) Step (0.01,0.01)



## Type 2: Time gradient

Protocol of elaboration:

- Cropping: Frame[800,652]  $\rightsquigarrow$   
Frame[501,411] [pixel]
- Preprocessing:
  - M-S Grad Temp  
( $\lambda = 0.02, \alpha = 0.0001$ )  
( $U_{\text{Orig}}(f - 1, f, f + 1)$ )  $\rightsquigarrow$   
( $U_{\text{reg}_1}(f), S_1(f)$ )
- Processing:
  - H-J: Threshold (th=0.125)  
Time-Horizon (3, step 0.03)  
Spatial mesh (0 ..5.0,0 ..4.1) Step  
(0.01,0.01)

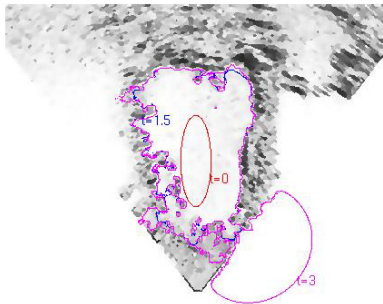




# Type 3: M-S algorithm iterated on image U

Protocol of elaboration:

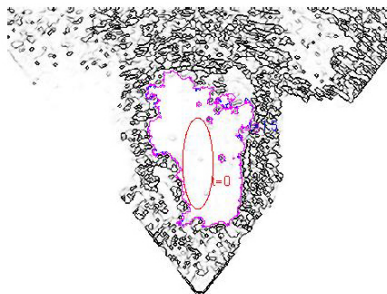
- Cropping: Frame[800,652]  $\rightsquigarrow$   
Frame[501,411] [pixel]
- Preprocessing:
  - Step1, M-S Time Grad  
( $\lambda = 0.02, \alpha = 0.0001$ )  
( $U_{Orig}(f-1, f, f+1)$ )  $\rightsquigarrow$   
( $U_{reg_1}(f), S_1(f)$ )
  - Step2, Classic M-S  
( $\lambda = 50, \alpha = 0.02$ )  
( $U_{reg_1}(f), S_1(f)$ )  $\rightsquigarrow$   
( $U_{reg_2}(f), S_2(f)$ )
- Processing:
  - H-J( $U_{reg_2}(f)$ ):  
Threshold (th=0.125)  
Time-Horizon (3, step 0.03)  
Spatial mesh(0..5.0,0..4.1)  
Step(0.01,0.01)



# Type 4: M-S algorithm iterated on the jump set $S$

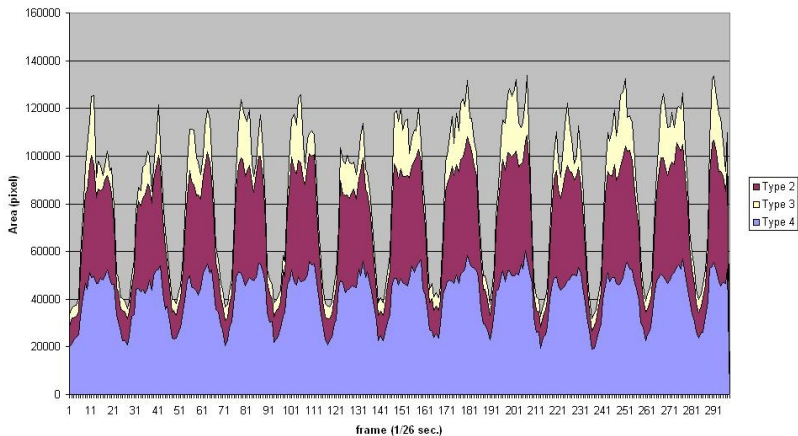
Protocol of elaboration:

- Cropping: Frame[800,652]  $\rightsquigarrow$  Frame[501,411] [pixel]
- Preprocessing: Step1, M-S Time Grad ( $\lambda = 0.02, \alpha = 0.0001$ )  
( $U_{Orig}(f-1, f, f+1)$ )  $\rightsquigarrow$  ( $U_{reg_1}(f), S_1(f)$ )
- Step2, Classic M-S ( $\lambda = 50, \alpha = 0.02$ )  
( $U_{reg_1}(f), S_1(f)$ )  $\rightsquigarrow$  ( $U_{reg_2}(f), S_2(f)$ )
- Processing:
- H-J( $S_2(f)$ ): Threshold(th=0.125)  
Time-Horizon(3, step 0.03) Spatial mesh(0 ..5.0,0 ..4.1) Step(0.01,0.01)



# Ventricular area trend in the frames

Area results: real test case



# CPU time and OpenMP parallel computing

- H-J curve evolution F90 code:
  - Parallel OpenMP: CASPUR Cluster Power5,8 CPU, 1.9 GHz, 4x32 GB Ram, AIX Fortran90.
  - Serial PC: PIV Linux RedHat Fedora core 2.
- M-S Pre-Processing Frame enhancing
  - Matlab R14 PIII 800 Mhz, 768 Mb Ram, Windows 2000 Server.
  - Matlab R14b PIV 2000 Mhz, 1GByte Ram, Linux RedHat Fedora core 2.

CPU Table	Power5	PIV	PIII 800 Mhz
H-J F90 OpenMP	239.8 sec.	288.0 sec.	312.0 sec.
M-S Matlab		1.06 sec.	
M-S gradt(2 point) 3 frame		1.34 sec.	
M-S gradt(3 point) 3 frame		1.61 sec.	

# Cardiovascular physiology parameter

Ejection Fraction ( $E_f$ ) is the fraction of blood pumped out of a ventricle at each heart beat.

We identify the volume of blood within a ventricle:

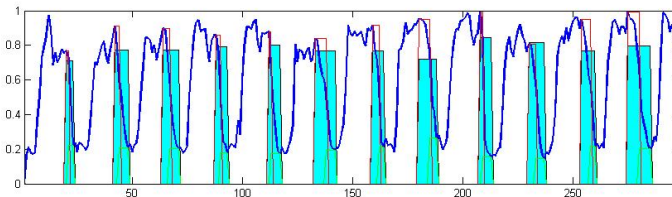
- immediately before a contraction: end-diastolic volume(EDV).
- at the end of contraction: end-systolic volume (ESV).

$$E_f = \frac{EDV - ESV}{EDV}$$

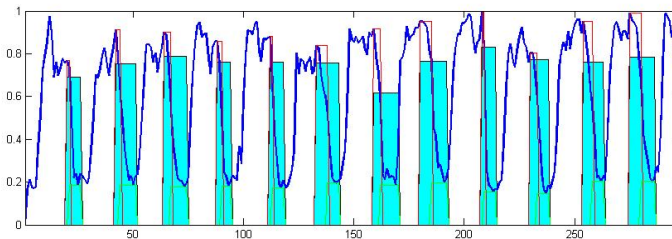
By calculating the mean value of the desired profile of ventricular area, we can perform a zero value detection, with a standard method. Than for every decreasing front determine the two interesting point: (ESV), (EDV)

# Ejection Fraction

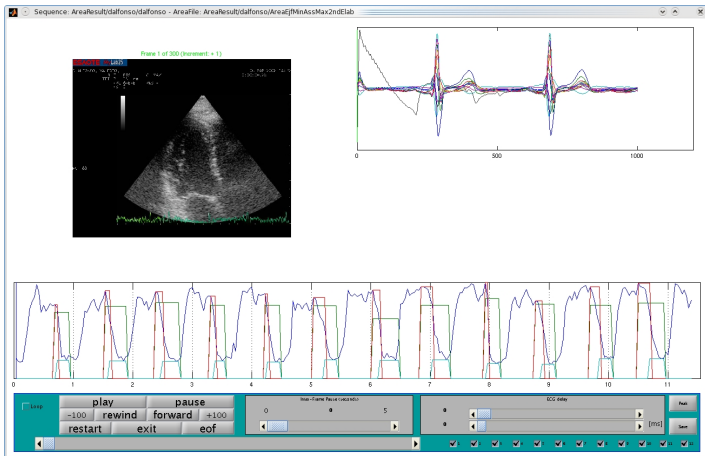
First minimal point of decreasing front for end-systolic phase (ESV):



Absolute minimal point of end-systolic phase (ESV):



# Application for signal synchronization



# Conclusions

Possible technical refinement in analysis of Echocardiographic image sequences for non-invasive and a-posteriori medical diagnostics of heart left-ventricle diseases:

- Determination of ventricular local pressure.
- Volume recognition by 3D Echo Images.

Mathematical framework upgrading

- Fast marching methods.
- Newer approach to time series problem.
  - Time dependent functional(Open Problem).
- Finite-element analysis to optimize echographic “cone”



# Essential references



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# Thanks

Thanks for your Attention!

Refer to the last section of the paper document for a list of persons that I wish to thank for the collaboration.

<http://pedoneweb.phys.uniroma1.it/max/phd/tesi>