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# MOTION ESTIMATION AND SEGMENTATION OF CARDIAC MAGNETIC RESONANCE IMAGES USING VARIATIONAL AND LEVEL SET TECHNIQUES

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## ABSTRACT

*A new method for motion estimation and segmentation of cardiac magnetic resonance images, based on variational and level set techniques is presented. The variational method for motion estimation is based on a total variation approach following a matrix implementation. It has been integrated with a level set method for segmenting the endocardial wall, providing a valuable tool for motion estimation and segmentation together. The results obtained have been compared with a reference method. The robustness and accuracy of these results have been proved.*

## 1. INTRODUCTION

Motion estimation certainly belongs to one of the most crucial and well investigated tasks in computer vision, in particular, the computation of the optical flow. The first works on this field were proposed by Horn and Schunk [1] and Lucas and Kanade [2]. Numerous improvements in the quality of the optical flow estimation techniques have been achieved since then. One of them is carried out by the variational approach, which is motivated by the need to preserve the discontinuities on the optical flow [3]. Several experiments give evidence for the superior performance of this method, in terms of accuracy, robustness and computational time [4].

An important application for the motion estimation is found in the heart-wall motion quantification in medical imaging. Myocardial ischemia is a frequently encountered pathological dysfunction. Therefore, non-invasive estimation of myocardial contractility is of interest in order to detect regions with abnormal contraction and suspected obstructed arteries [5].

Among all the available imaging methods, Cardiac Magnetic Resonance (CMR) is one of the reference methods to perform the dynamic exploration of the cardiac function [6]. Nevertheless, the mayor source of the limitations of conventional cardiac function measurements is their inability to follow the motion of individual portions of the heart wall [7]. CMR has improved the results obtained in cardiac function measurements, but the paucity of reliable identifiable landmarks in the heart wall largely limits the assessment of the intramural motion. To achieve a better value of a quantitative assessment of intra-myocardial contractile function, the most reliable method is the Tagged MRI method [7]. Tagged-MRI uses specific sequences to create two orthogonal sets of parallel planes of magnetic saturation, which appear as a grid pattern of dark lines or tags [8].

Nevertheless, the assessment of myocardial function not only requires the motion estimation but also the segmentation of the myocardium over a cardiac cycle [9]. One of the most common used techniques based on geometric active contours is the level set method. This technique was introduced by Osher and Sethian [10], and later it has been investigated to cope with the image segmentation problem in several publications [11].

The work described in this paper combines the advantages of the variational technique for motion estimation to support the process of segmentation of the endocardial borders by means of the well-known level set technique. Real Tagged Cardiac Magnetic Resonance images have been used in this work for a better motion tracking. Comparison with the established method of reference HARP [12, 13] for motion estimation has been performed.

This paper is organized as follows. In section 2 we introduce the variational technique and its total variation extension. The Level Set method and the integration of the two previous sub-systems are presented. In section 3 results are shown. Section 4 ends with the conclusions and discussion.

## 2. METHODS

The method proposed for the motion estimation of tagged cardiac magnetic resonance images is one belonging to the well-known differential techniques. Several experiments give evidence for the superior performance of these techniques [14] against other alternative techniques. The basis of these methods is the constancy of the intensity structures of local time-varying image regions under motion, at least for a short period of time [1]. The use of this method actually assumes an intensity conservation between

consecutive frames that can be admitted in the case of tagged MR image frames separated by short time intervals as compared with T1 recovery [15]. However, if required, the T1 signal modulation could also be included in the criterion [15].
Formally, if $u(x_1,x_2,t)$ is the intensity of the pixel $(x_1, x_2)$ at time $t$,

$$u(x_1(t),x_2(t),t)=u(x_{10},x_{20},t_0) \qquad \forall t \qquad (1)$$

where $x_{10} = x_1(t_0)$. Taking the derivative with respect to time yields,

$$\boldsymbol{\sigma}(x_1,x_2)\cdot\nabla u(x_1,x_2,t_0)+u_t(x_1,x_2,t_0)=0 \qquad (2)$$

where $\sigma_1=\frac{\partial x_1}{\partial t}$ and $\sigma_2=\frac{\partial x_2}{\partial t}$ are the velocity fields. Equation (2) is known as the optical flow constraint equation. Nevertheless, this equation is scalar, which is not enough to find both components of the velocity. This phenomenon is known as the aperture problem. Because this problem is ill-posed, additional constraints are required. The most common is based on second-order derivatives, choosing a parametric model of velocity or regularizing the velocity fields [16].

### 2.1 Variational approach for motion estimation

Horn & Schunk in [1] where the first authors to propose the following regularization term (part B in Eq. 3),

$$\min_{\sigma}\underbrace{\int_\Omega(\boldsymbol{\sigma}\cdot\nabla u+u_t)^2dx}_{A}+\alpha^r\underbrace{\int_\Omega\left(\|\nabla\sigma_1\|^2+\|\nabla\sigma_2\|^2\right)dx}_{B} \qquad (3)$$

Nevertheless, this term (B) smoothes isotropically, and does not consider the optical flow discontinuities [17]. More robust norms have to be considered to cope with discontinuities, for instance

$$\alpha^r\cdot\left(\int_\Omega\phi(\|\nabla\sigma_1\|)dx+\int_\Omega\phi(\|\nabla\sigma_2\|)dx\right) \qquad (4)$$

where functions $\phi$ allow noise removal and border conservation. Among the different $\phi$ functions [3], in this paper the norm $L^1$ has been implemented. It is also known as the Total Variation (TV), $\phi(t)=t$, which has very good anisotropic denoising properties [3]. Since solving the minimization problem in (4) by solving directly its Euler Lagrange equation is highly nonlinear and not continuous, a special attention must be paid to its discretization. Several relaxed linearization schemes were proposed. We follow the half-quadratic regularization scheme in [18] that introduces an auxiliary variable.

When there is a homogeneous region characterized by low image gradients magnitude, no visible motion can be locally detected. To minimize this undesirable motion, an extra term of this form is added to the previous equation

$$\int_\Omega c(x)\left|\boldsymbol{\sigma}\right|_2^2dx \qquad (5)$$

where $|\ |_2$ is the Euclidean norm, and

$$c(x)=\frac{1}{\sqrt{(u_{x_1})^2+(u_{x_2})^2}} \qquad (6)$$

Equation 5 represents a penalizing term, which is low for high image gradients and high for low image gradients. Finally, the energy minimization equation yields as

$$\min_{\sigma}\left(\int_\Omega(\boldsymbol{\sigma}\cdot\nabla u+u_t)^2dx+\alpha^r\int_\Omega\phi(\|\nabla\boldsymbol{\sigma}\|)dx+\alpha^c\int_\Omega c(x)\left|\boldsymbol{\sigma}\right|_2^2dx\right) \qquad (7)$$

*2.1.1 Implementation*

To solve the energy minimization in (3), a matrix implementation has been chosen. The problem has been reduced to one equation constructed by matrices ($U$ denotes the diagonal matrix implementation of $u$), whose unknowns are the velocity fields $\sigma_1$ and $\sigma_2$.

$$\begin{pmatrix}[U_{X1}U_{X1}+\alpha^r L_1+\alpha^c c] & [U_{X1}U_{X2}]\\ [U_{X1}U_{X2}] & [U_{X2}U_{X2}+\alpha^r L_2+\alpha^c c]\end{pmatrix}\begin{pmatrix}\sigma_1\\ \sigma_2\end{pmatrix}=-\begin{pmatrix}U_tU_{X1}\\ U_tU_{X2}\end{pmatrix} \qquad (8)$$

where $U_{X1}=\partial U/\partial x_1$ and $U_{X2}=\partial U/\partial x_2$.

The regularization term has been inserted as a discretization value in the form $\sigma_1^T L_1(z)\sigma_1$ and $\sigma_2^T L_2(z)\sigma_2$ [19], where $z$ is the auxiliary variable introduced by the half-quadratic scheme which is updated in each iteration according to

$$z(x,y)=\frac{\phi'(|\nabla u(x,y)|)}{|\nabla u(x,y)|} \qquad (9)$$

Matrices $L_1(z)$ and $L_2(z)$ are Toeplitz matrices, positive semidefinite constructed by $z$, which performs shift-variant convolution with $z$. To avoid division by zero, $z$ is defined for the TV case as,

$$z(i\pm1/2,j\pm1/2)=\begin{cases}\dfrac{1}{|\boldsymbol{\sigma}(i\pm1,j\pm1)-\boldsymbol{\sigma}(i,j)|} & \text{if} \quad |\boldsymbol{\sigma}(i\pm1,j\pm1)-\boldsymbol{\sigma}(i,j)|>\varepsilon\\ \dfrac{1}{\varepsilon} & \text{otherwise}\end{cases} \qquad (10)$$

where $\varepsilon$ is the relaxation parameter [20]. Note that in the relatively flat regions, $|D\boldsymbol{\sigma}(x)|\le\varepsilon$ ($D\boldsymbol{\sigma}$ denotes the gradient distribution of $\boldsymbol{\sigma}$), $L(z)$ becomes the Laplacian op-

erator. In regions with high image gradient, $|D\boldsymbol{\sigma}(x)| \geq \varepsilon$, $\boldsymbol{\sigma}^T L(z)\boldsymbol{\sigma}$ approximates the TV semi-norm of the velocity $\boldsymbol{\sigma}$.

## 2.2 Segmentation through Level Sets and a Variational approach

*2.2.1 Level Set Method with a Variational formulation*

The method proposed for the segmentation of the video sequence of tagged cardiac magnetic resonance images is a modified version of the variational formulation for geometric active contours principle proposed in [21]. The main idea is to evolve the boundary C from some initialization in direction of the negative energy gradient. This is done by implementing the gradient descent equation [22]:

$$\frac{\partial C}{\partial t} = -\frac{\partial E(C)}{\partial C} = F \cdot \mathbf{n} \qquad (11)$$

and modelling the evolution along the normal **n** with a speed function F[3]. In the implicit contour representation theory, the contour C is represented as the zero level line of some embedding function $\varphi$, as

$$C(t) = \{(x,y) | \varphi(t,x,y) = 0\} \quad (12)$$

In the method proposed by Osman and Sethian in [10], a contour is propagated by evolving a time-dependent embedding function $\varphi$ according to an appropriate partial differential equation. The evolution equation of the level set function $\varphi$ can be written in the following general form

$$\frac{\partial \varphi}{\partial t} = -|\nabla \varphi| F \qquad (13)$$

which is called the level set equation [10]. Nevertheless, the level set function $\varphi$ can suffer of transients, very sharp and/or flat shape during the evolution. For this reason, it is necessary to initialize the function $\varphi$ as a signed distance function before the evolution starts, and then "reshape" (or "re-initialize") the function $\varphi$ to be a signed distance function periodically during the evolution. Re-initialization has been extensively used as a numerical remedy in traditional level set methods [23, 24], but in our implementation we have used the Variational approach explained in [21]. Provided that a signed distance function must satisfy a desirable property of $|\nabla \varphi| = 1$, the minimization of the following integral is proposed

$$P(\phi) = \int_{\Omega} \frac{1}{2}\left(|\nabla \varphi| - 1\right)^2 dxdy \qquad (14)$$

With the above defined functional $P(\varphi)$, it is proposed the following variational formulation

$$E(\varphi) = \mu P(\varphi) + E_m(\varphi) \qquad (15)$$

where $\mu > 0$ is a parameter controlling the effect of penalizing the deviation of $\varphi$ from a signed distance function, and $E_m(\varphi)$ is a certain energy that would drive the motion of the zero level curve of $\varphi$.

*2.2.2 Integration of the motion estimation and segmentation approach*

The main idea of the integration of the two sub-systems is to minimize computational cost of the segmentation process together with a better accuracy of the segmentation. In order to segment myocardial edges in tagged images, a pre-processing stage is proposed. This allows to get rid of the tags of the image. This can be done very easily, by filtering in the Fourier domain the periodical frequency concentration and by taking the inverse Fourier transform.

The block diagram of the system is shown in Figure 2

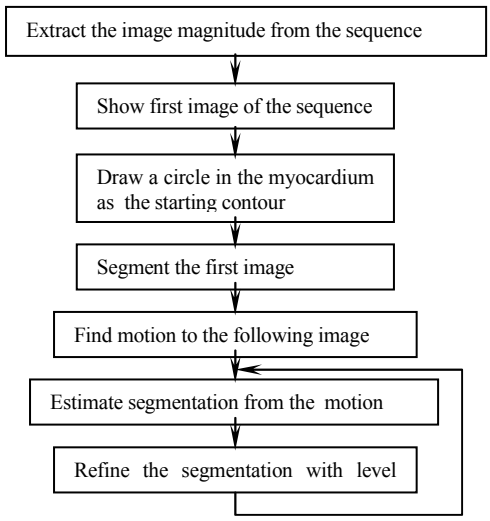


Figure 2 - Block diagram of the system of the motion estimation and segmentation

By means of this algorithm, the computational time of the segmentation is considerably reduced, because we only need to compute the segmentation for the first image of the sequence. For the rest, the iteration process of the segmentation is stopped when the evolution of the level-set implementation is below a given threshold.

# 3. RESULTS

## 3.1. Motion estimation results with real images

The algorithms presented in section 2 have been tested with six sequences of tagged cardiac magnetic resonance images. According to the standardized myocardial division of segments [25], the myocardium has been divided into six regions. In each region, one point has been selected and tracked manually along each sequence. In figure 3, a comparison among the manually tracked points (stars in red colour), the HARP method (triangles in magenta colour) and the Variational method (points in green colour) is shown for one of the sequences. Four frames of the sequence are represented.

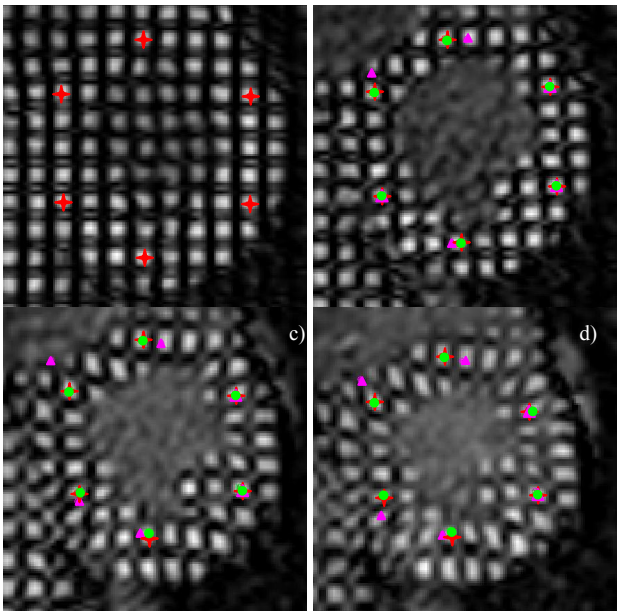


Figure 3 – a) First image of the sequence. b) 2nd image of the sequence. c) 4th image of the sequence. d) 6th image of the sequence. For all the images, red stars are the results on manually tracked points, magenta triangles are those of HARP method, and green points are the Variational method.

As it is shown, the results obtained with the Variational method are very accurate and close to those tracked manually. Compared with the HARP method, our results are more stable and accurate, due to the tag jumping suffered for some of the points when this method is used. This can be seen in Figure 4.

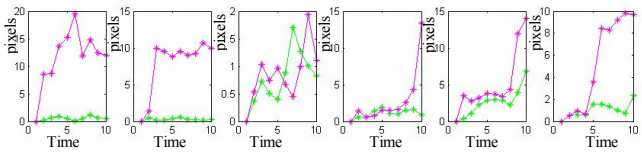


Figure 4 –Tracking error in each point in time respectively of the HARP method (magenta colour) and Variational Method (green colour) compared to the points tracked manually.

Figure 4 displays the error of the HARP method (magenta colour) and the Variational method (green colour) compared to the manually tracked points for the images in Figure 3. According to it, it can be seen that the Variational method fits better with the expected results and it can be observed that the error of the variational method is smaller in general.

For the six points selected initially and ten images of the sequence, the error of both methods has been computed. In this case, the average error of the Variational method is 1.0325 pixels, undoubtedly smaller than the result obtained for the HARP method, 5.5452 pixels.

### 3.2. Segmentation results with real images

Figure 5 shows the results obtained for the segmentation of the previous sequence. As it can be seen, results are accurate. Unfortunately, it was not possible to provide a quantitative estimation of the segmentation error made because annotated sequences were not available. The computational time has been tested for the program with the integration of both segmentation and motion estimation modules. A comparison of the proposed procedure computational cost and that of the independent segmentation of each image has been made. Results are shown in figure 6.

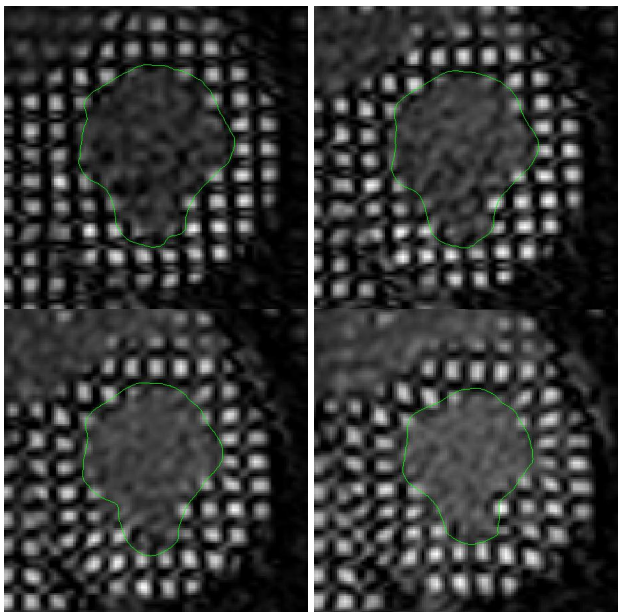

Figure 5 – Segmentation of the first four images of the sequence.

As Figure 6 shows, the computational time obtained with our implementation is more than 2.5 times faster. This segmentation technique has been tested with other two sequences, with results similar to the previously described.

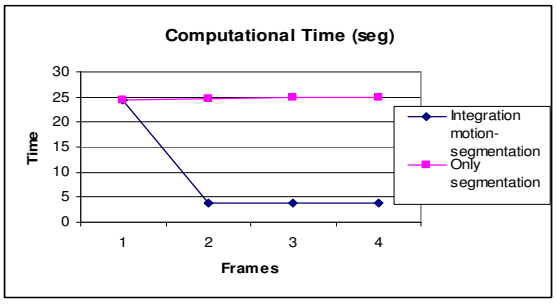


Figure 6 –Computational time for the proposed integrated solution compared with the time obtained segmenting each image.

## 4. CONCLUSIONS AND DISCUSSION

A method for segmentation and motion estimation of the myocardium based on variational and level set techniques has been presented. The variational method for motion estimation uses the total variation norm. For the segmentation, a level set method with a variational formulation has been integrated with the motion estimation algorithm. Results on Tagged Cardiac Magnetic Resonance have been presented. According to the motion estimation, six points have been selected to perform the motion tracking. Comparisons among the variational method, the HARP method and the manually tracked points have been performed. Results confirm the better performance of the variational method for the

analyzed sequence. The segmentation has been proved to be feasible in real images, having a low computational cost. Further research will explore the segmentation accuracy of the described method.

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**REFERENCES**

[1] B. K. P. Horn and B. G. Schunck, "Determining Optical-Flow," *Artificial Intelligence*, vol. 17, pp. 185-203, 1981.
[2] B. D. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision," presented at Proceedings of the 7th International Joint Conference on Artificial Intelligence, Vancouver, 1981.
[3] R. Deriche, P. Kornprobst, and G. Aubert, "Optical-Flow Estimation while Preserving its Discontinuities: A Variational Approach," *Invited Session Papers from the Second Asian Conference on Computer Vision: Recent Developments in Computer Vision*, vol. 1035, pp. 71 - 80, 1995.
[4] N. Papenberg, A. Bruhn, T. Brox, S. Didas, and J. Weickert, "Highly Accurate Optic Flow Computation with Theoreti-cally Justified Warping " *International Journal of Computer Vision* vol. 67, pp. 141 - 158 April 2006.
[5] P. Clarysse, C. Basset, L. Khouas, P. Croisille, D. Friboulet, C. Odet, and I. E. Magnin, "Two-dimensional spatial and temporal displacement and deformation field fitting from cardiac magnetic resonance tagging," *Medical Image Analysis*, vol. 4, pp. 253-268, 2000.
[6] V. Sinitsyn, "Magnetic resonance imaging in coronary heart disease," *European Journal of Radiology*, vol. 38, pp. 191-199, 2001.
[7] L. Axel, A. Montillo, and D. Kim, "Tagged magnetic resonance imaging of the heart: a survey," *Medical Image Analysis*, vol. 9, pp. 376-393, 2005.
[8] A. Santos and M. J. Ledesma-Carbayo, *Cardiac Imaging*, vol. 2. New Yersey: Wiley Encyclopedia of Biomedical Engineering, John Wiley & Sons Inc, 2006.
[9] Y. Chenoune, E. Delechelle, E. Petit, T. Goissen, J. Garot, and A. Rahmouni, "Segmentation of cardiac cine-MR images and myocardial deformation assessment using level set methods," *Computerized Medical Imaging and Graphics*, vol. 29, pp. 607-616, 2005.
[10] S. Osher and J. A. Sethian, "Fronts Propagating with Curvature-Dependent Speed - Algorithms based on Hamilton-Jacobi Formulations," *Journal of Computational Physics*, vol. 79, pp. 12-49, 1988.
[11] D. Cremers and S. Soatto, "Motion Competition: A Variational Approach to Piecewise Parametric Motion Segmentation," *International Journal of Computer Vision*, vol. 62, pp. 249-265, 2005.
[12] N. F. Osman, W. S. Kerwin, E. R. McVeigh, and J. L. Prince, "Cardiac motion tracking using CINE harmonic phase (HARP) magnetic resonance imaging," *Magnetic Resonance in Medicine*, vol. 42, pp. 1048-1060, 1999.
[13] N. F. Osman, E. R. McVeigh, and J. L. Prince, "Imaging heart motion using harmonic phase MRI," *IEEE Transactions on Medical Imaging*, vol. 19, pp. 186-202, 2000.
[14] J. L. Barron, D. J. Fleet, and S. S. Beauchemin, "Performance of Optical-Flow Techniques," *International Journal of Computer Vision*, vol. 12, pp. 43-77, 1994.
[15] M. J. Ledesma-Carbayo, J. A. Derbyshire, S. Sampath, A. Santos, M. Desco, and E. R. McVeigh, "Unsupervised estimation of myocardial displacement from tagged MR sequences using nonrigid registration," *Magnetic Resonance in Medicine*, vol. 59, pp. 181-189, 2008.
[16] G. Aubert, R. Deriche, and P. Kornprobst, "Computing optical flow via variational techniques," *Siam Journal on Applied Mathematics*, vol. 60, pp. 156-182, 1999.
[17] G. a. P. K. Aubert, *Mathematical Problems in Image Processing. Partial Differential Equations and the Calculus of Variations*: Springer, 2006.
[18] P. Charbonnier, L. BlancFeraud, G. Aubert, and M. Barlaud, "Deterministic edge-preserving regularization in computed imaging," *IEEE Transactions on Image Processing*, vol. 6, pp. 298-311, 1997.
[19] F. Sroubek and J. Flusser, "Resolution enhancement via probabilistic deconvolution of multiple degraded images," *Pattern Recognition Letters*, vol. 27, pp. 287-293, 2006.
[20] F. Sroubek and J. Flusser, "Multichannel blind deconvolution of spatially misaligned images," *IEEE Transactions on Image Processing*, vol. 14, pp. 874-883, 2005.
[21] C. M. Li, C. Y. Xu, C. Gui, and M. D. Fox, "Level set evolution without re-initialization: A new variational formulation," in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol 1, Proceedings*, *Proceedings - Ieee Computer Society Conference on Computer Vision and Pattern Recognition*, C. Schmid, S. Soatto, and C. Tomasi, Eds., 2005, pp. 430-436.
[22] D. Cremers, M. Rousson, and R. Deriche, "A review of statistical approaches to level set segmentation: Integrating color, texture, motion and shape," *International Journal of Computer Vision*, vol. 72, pp. 195-215, 2007.
[23] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape Modeling with Front Propagation - A Level Set Approach," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 17, pp. 158-175, 1995.
[24] V. Caselles, F. Catte, T. Coll, and F. Dibos, "A Geometric Model For Active Contours in Image Processing," *Numerische Mathematik*, vol. 66, pp. 1-31, 1993.
[25] Cerqueira M.D., Weissman N.J., Dilsizian V., Jacobs A.K., Kaul S., Laskey W.K., Pennell D. J., Rumberger J.A., Ryan T., and V. M.S, "Standarized Myorcardial Segmentation and Nomenclature for Tomographic Imaging of the Heart: A Statement fot Healthcare Professionals from the Cardiac Imaging Committee of the Coundil on Clnical Cardiology of the American Heart Association," *Journal of the American heart Association*, vol. 105, pp. 539-542, 2002.