Soft Level Set Coupling for LV Segmentation in Gated Perfusion SPECT

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Abstract. We present a new segmentation approach for the myocardium in gated and non-gated perfusion SPECT images. To this end, we represent the epi- and endocardium by separate signed distance functions and couple them by a soft constraint to give explicit control over the wall thickness. By an explicit modeling of the basal plane, the volume of the blood pool as well as the myocardium are determinable. Furthermore, prior shape information is incorporated by applying a kernel density estimation on a number of expert segmentations in a low-dimensional PCA subspace. Thereby, information along the time axis is fully taken into account by employing 4-dimensional embedding functions.

1 Introduction

Model-based imaging analysis of the left ventricle (LV) has gained an important role in diagnosis and treatment of heart diseases. Segmentation of the blood pool and myocardium has found to be a significant prerequisite of further quantitative analysis, such as the estimation of the ejection fraction within one cardiac cycle. The simultaneous assessment of myocardial perfusion and function with single photon emission computed tomography (SPECT) is a standard in clinical imaging practice [9].

In general, shape modeling has been done with either explicit representations by landmarks or binary images/volumes are employed, or implicit ones, describing the separating three-dimensional contour as the zero-level set of a four dimensional function [8]. In most cases, Principal Component Analysis (PCA) thereby is employed, which is, in case of explicit shape representations, either directly applied to the landmark coordinates or the components of deformations fields relative to a mean shape, or, for the implicit representations, to the components of the embedding level set functions. In addition, a prior shape probabilities are inferred from a number of representative training samples, in order to compensate for sparse image information.

On the other hand, prior information can also be incorporated in a non-statistical manner, such as the prior knowledge that the boundaries of an anatomical structure adhere to a certain geometrical relation. With the LV for example, it is known that the Euclidean distance (thickness) between the epi- and endocardium varies within a certain range. The same holds true for the cerebral

cortex as the outermost layer of the gray matter in the brain. Several work has been done exploiting this fact for either application scenario, either by highly heuristical, explicit approaches [4,2], or implicit ones [11,5,6,10,13]. With respect to the modeling of the thickness prior, all approaches being known to us thereby modify well-known edge-based or region-based data terms mostly on the basis of propagation equations, by adding more or less continuous scalar modulator functions measuring the Euclidean distance between the two surfaces. By this, the surface propagating 'forces' are adapted in order to keep the two surfaces at a certain distance in a more or less strict manner. Furthermore, with all approaches only closed surfaces are considered, which is not true for the epi- and endocardiac shape when excluding the basal plane.

As opposed to them, in Section 2, we present a new soft thickness term for the epi- and endocardium, which is separate from the existing data terms. This is realized via a formulation as an energy minimization, thereby giving a clear geometrical meaning without any heuristics involved. In addition, we address and give a solution to the problem of coupled open surfaces. In Section 3 we approximate the level sets description by a compact PCA subspace representation, which is followed by the introduction of a known prior shape probability term [12]. Subsequently, we extend the approach to spatio-temporal domain (4D) in application to gated SPECT data. After giving details on the energy minimization in Section 3.4, in Sec. 4 we present experimental results on 3D phantom data as well as expert annotated 4D data showing promising qualitative and quantitative results.

2 The Data Model

Let $I \in H^1(\Omega)$ denote a function of SPECT intensities on the closed rectangular volume $\Omega \in R^3$. We propose to model the epi- and endocardium implicitly as the zero level sets of the two signed distance functions $\phi_{ep}(\mathbf{x})$ and $\phi_{en}(\mathbf{x})$, [8], by which the bloodpool segment is described by $\{\mathbf{x} \mid \phi_{en}(\mathbf{x}) > 0\}$, the myocardium segment by $\{\mathbf{x} \mid \phi_{en}(\mathbf{x}) < 0 \wedge \phi_{ep}(\mathbf{x}) > 0\}$, and the background locations by $\{\mathbf{x} \mid \phi_{ep}(\mathbf{x}) < 0\}$.

Following the approach by Mumford and Shah, we then assume the SPECT intensities inside these three regions (bloodpool, myocardium, background) have similar values. While denoting the intensity means for each of the regions by μ_{bp} , μ_{my} , and μ_{bg} , we implicitly seek for those region boundaries which minimize the sum of deviations from each of the corresponding (empirical) means. We formulate this by minimizing the energy

$$E_{rn}(\phi_{ep}, \phi_{en}) = \int_{\Omega} |I - \mu_{bp}|^2 H_{\epsilon}(\phi_{en}) + |I - \mu_{my}|^2 (1 - H_{\epsilon}(\phi_{en})) H_{\epsilon}(\phi_{ep}) \\ + |I - \mu_{bg}|^2 (1 - H_{\epsilon}(\phi_{ep})) d\mathbf{x} \quad (1)$$

with respect to ϕ_{ep} and ϕ_{en} , where H_{ϵ} refers to the approximate Heaviside step function, see [1]. However, E_{rn} obviously has many local minima with respect to ϕ_{ep} and ϕ_{en} and thus a minimization algorithm's result would highly depend on

the initialization. In order to narrow down the number of local wrong minima, we suggest to introduce a soft constraint on the wall thickness of the myocardium. In terms of mathematical modeling, note that such a distance constraint can be easily realized here due to the implicit representation of the epi- and endocardium by signed distance functions. Excluding all locations beyond an infinite plane B , which is considered an approximation of the real basal plane section, a hard thickness constraint can be stated by $\phi_{ep}(\mathbf{x}) - d_{wall} - \phi_{en}(\mathbf{x}) = 0$, where d_{wall} denotes a given wall thickness. As a soft constraint, this can be realized by weighting and adding the energy term

$$E_{th}(\phi_{ep}, \phi_{en}) = \int_{\Omega} \left(\phi_{en} - (\phi_{ep} - d_{wall}) \right)^2 d\mathbf{x} \quad (2)$$

to (1). Unfortunately, (2) results in undesired solutions for ϕ_{ep} and ϕ_{en} for locations at or above the approximate basal plane B , since at B the zero level sets of both distance functions are assumed to coincide. As a remedy, we propose to limit the support of either distance function, such that the new support $\Omega_B \subset \Omega \in \mathbb{R}^3$ is bounded by B from above (excluding B), and replace every previous occurrence of ϕ_{ep} and ϕ_{en} by

$$\tilde{\phi}_{ep,B}(\mathbf{x}) := \begin{cases} \phi_{ep}(\mathbf{x}) & : \mathbf{x} \in \Omega_B \\ -d_{wall} & : \mathbf{x} \in \Omega \setminus \Omega_B \end{cases} \quad \tilde{\phi}_{en,B}(\mathbf{x}) := \begin{cases} \phi_{en}(\mathbf{x}) & : \mathbf{x} \in \Omega_B \\ -2d_{wall} & : \mathbf{x} \in \Omega \setminus \Omega_B \end{cases} \quad (3)$$

respectively¹. By this, E_{th} has no effect at locations above and on B , whereas with E_{rn} they are considered as background, due to the substitutes $\tilde{\phi}_{ep,B}$ and $\tilde{\phi}_{en,B}$ being negative there. Furthermore, because of $\tilde{\phi}_{ep}$ and $\tilde{\phi}_{en}$ being negative at locations at or above B , with the region model in (1), they are considered as background. Finally, the data model is crafted as a minimization of the weighted energies

$$E_{data}(\phi_{ep}, \phi_{en}, B) := E_{rn}(\tilde{\phi}_{ep,B}, \tilde{\phi}_{en,B}) + \omega_{th} E_{th}(\tilde{\phi}_{ep}, \tilde{\phi}_{en}), \quad (4)$$

with respect to ϕ_{ep} and ϕ_{en} on Ω_B , as well as the location and orientation of the basal plane B . Thereby, the scalar weight ω_{th} allows to adjust the extend of deviations from the given thickness.

3 The Shape Model

3.1 Parametrization in PCA Subspaces

Despite the additional thickness constraint, own experiments suggest that E_{data} still exhibits too many local minima of wrong segmentations, thus leaving the minimization highly dependent on the initialization. For that reason, we propose to incorporate prior shape knowledge derived from a shape model in addition.

¹ Note that $\tilde{\phi}_{ep,B}$ $\tilde{\phi}_{en,B}$ are not signed distance functions and are possibly discontinuous at B .

In particular, given a set of N expert-segmented training shapes $\{\phi_i(\mathbf{x})\}_{i=1\dots N}$ of the epi- and endocardium, and the basal plane, we follow the approach by Rousson et al. [12] where a kernel density estimation is employed in a finite subspace spanned by the training shapes.

Each of the training shapes are first aligned with respect to translation and scale in R^3 , which is implemented by minimizing the squared L^2 -distance between ϕ_i and a chosen reference shape ϕ_{ref} :

$$\min_{\theta, \mathbf{t}} \int_{\Omega} \left(\phi_i(\mathbf{R}(\theta)\mathbf{x} - \mathbf{t}, t) - \phi_{ref}(\mathbf{x}, t) \right)^2 d\mathbf{x} , \quad (5)$$

where $\mathbf{t} \in R^3$ denotes a translation vector and $\mathbf{R}(\theta) \in \mathbb{R}^{3 \times 3}$ a rotation matrix depending on orientation descriptors θ , e.g. a quaternion. Based on the aligned training shapes, the mean $\bar{\phi} = \frac{1}{N} \sum_{i=1}^N \phi_i$ is determined and a principal component analysis (PCA) employed in order to obtain the eigenmodes $\{\phi_i(\mathbf{x})\}_{i=1\dots N}$ which reflect the shape variations within the aligned training set, relative to $\bar{\phi}$. Subsequently, new distance functions, which lie in the linear subspace given by the training set, can be approximated as linear combinations of the first $n < N$ eigenmodes:

$$\phi_{\alpha}(\mathbf{x}) = \bar{\phi}(\mathbf{x}) + \sum_{i=1}^n \alpha_i \psi_i(\mathbf{x}) , \quad (6)$$

cf. [8]. By this, a low-dimensional approximate representation of the distance functions is reached.

In our case, however, each of the training shape ϕ_i can have a different support, depending on the position and orientation of the basal plane. Extending the support as done in (3) obviously would not lead to a feasible training set to the PCA, because of possible strong discontinuities of $\tilde{\phi}_{ep}$ and $\tilde{\phi}_{en}$ at B . Alternatively we propose to align them in a way that all basal planes B_i to coincide. The common support then is given by the intersection of all aligned supports Ω_{B_i} based on which the PCA can be applied in a straightforward manner.

In terms of the implementation of this special alignment, a simple method is given by first choosing a reference shape ϕ_{ref} whose basal plane B_{ref} is colinear with one of the Euclidean coordinates planes, say the x/y-plane. Secondly, each training shape ϕ_i is first aligned to ϕ_{ref} with respect to a rigid transform. Thirdly, assuming the basal plane B_i of the rigidly aligned ϕ_i to be approximately colinear with B_{ref} , a subsequent translation along the normal vector of B_{ref} by the distance between B_{ref} and B_i is made.

Finally, such parametrized realizations of epi- and endocardium shapes, $\phi_{ep, \alpha}$ and $\phi_{en, \alpha}$, are bound to the position and orientation of the reference shapes $\phi_{ep, ref}$ and $\phi_{en, ref}$ they were aligned to. In aiming to represent shapes at any location and orientation, we make use of the common approach to replace $\phi_{\kappa, \alpha}(\mathbf{x})$ ($\kappa \in \{ep, en\}$) by $\phi_{ep, \alpha}(\mathcal{T}_{\theta, \mathbf{t}}(\mathbf{x}))$, with $\mathcal{T}_{\theta, \mathbf{t}}$ being the rigid transform: $\mathcal{T}_{\theta, \mathbf{t}} : \mathbf{x} \mapsto \mathbf{R}(\theta)\mathbf{x} - \mathbf{t}$.

3.2 Prior Shape Probabilities by Kernel Density Estimation

In aiming at introducing prior shape information, Rousson et al. [12] suggest inferring a prior probability by utilizing a Parzen-Rosenblatt kernel density estimator:

$$P(\boldsymbol{\alpha}) = \frac{1}{N\sigma^n} \sum_{i=1}^N \exp\left(-\frac{(\boldsymbol{\alpha} - \boldsymbol{\alpha}_i)^2}{2\sigma^2}\right). \quad (7)$$

Thereby it is assumed single Gaussian distributions of uniform width σ at each training function ϕ_i being projected to the linear subspace by $\boldsymbol{\alpha}_i = \int_{[1,T]} \int_{\Omega} \psi_i(\mathbf{x}, t) (\phi(\mathbf{x}, t) - \bar{\phi}(\mathbf{x}, t)) d\mathbf{x} dt$. As proposed in [12], reasonable choices for σ are given by the average nearest neighbor distance $\sigma^2 = \frac{1}{N} \sum_{i=1}^N \min_{j \neq i} |\boldsymbol{\alpha}_i - \boldsymbol{\alpha}_j|$. As opposed to implying one multivariate Gaussian as deployed in [8] (while utilizing the covariance σ^{-1} matrix of the PCA), the Parzen estimator results both in a more flexible and more accurate shape model based on the training shapes.

In terms of computational costs, evaluating (7) obviously requires more operations than a single Gaussian distribution, since a Gaussian has to be calculated for each training shape. However, because of the much lower dimensionality of the linear subspace employed in (6), in comparison to discretizations of the $\{\phi_i\}$, this has emerged to have only a minor practical impact.

Different experiments employing the shape prior (7) to $\phi_{\boldsymbol{\alpha}_{ep}}(\mathbf{x})$ or $\phi_{\boldsymbol{\alpha}_{en}}(\mathbf{x})$, or both, suggest that a prior model with respect to the epicardium is empirically sufficient. Thereby, $\phi_{\boldsymbol{\alpha}_{en}}(\mathbf{x})$ is affected by the shape model only indirectly via the thickness constraint, which leaves it more sensitive to the image data, and thus presumably yielding blood volumes which are more independent from prior information. Hence, (4) is extended by prior energy term $\omega_{pr} E_{prior}(\cdot) = -\omega_{pr} \log P(\cdot)$, whose influence is adjusted by the scalar weight ω_{pr} .

3.3 Including the Temporal Dimension

In gated perfusion SPECT, several intensity volumes of a moving heart are available at different time points t within the heart cycle $[0, T]$. As detailed in [7], it is reasonable to take also the information along the temporal dimension into account. Therefore, we propose to extend the current approach which relies on a three-dimensional spatial support Ω to the four-dimensional spatio-temporal support $\Omega \times [0, T]$. Consequently, $I(\mathbf{x})$ in (1) is to be replaced by a sequence of intensity volumes $I(\mathbf{x}, t)$, $(\mathbf{x}, t) \in \Omega \times [0, T]$, and any distance function $\phi(\mathbf{x})$ by $\phi(\mathbf{x}, t)$, which describes separate shapes for every time point t .

By this, temporal dependencies now come into play by carrying out a PCA on a set of rigidly aligned *sequences of training shapes* $\{\phi_i(\mathbf{x}, t)\}_{i=1 \dots N}$, which, by a straightforward extension of the three-dimensional parametrization approach, yields a linear parametrization of shape sequences:

$$\phi\boldsymbol{\alpha}(\mathbf{x}, t) = \bar{\phi}(\mathbf{x}, t) + \sum_{i=1}^n \alpha_i \psi_i(\mathbf{x}, t). \quad (8)$$

Note that a linear weight α_i associated with the subspace dimension i effects the shapes at all time points $t \in [0, T]$. Consequently, $P(\phi(\mathbf{x}, t))$ in (7) now infers the probability the of a shape sequence implicitly represented by $\phi(\mathbf{x}, t)$ to occur given N training shape sequences implicitly encoded by $\{\phi(\mathbf{x}, t)\}_{1, \dots, N}$.

3.4 Minimization

In aiming at solving the energy

$$E_{rn}(\tilde{\phi}_{\alpha_{ep}, \mathbf{t}, \theta, B}, \tilde{\phi}_{\alpha_{en}, \mathbf{t}, \theta, B}) + \omega_{th} E_{th}(\tilde{\phi}_{\alpha_{ep}, \mathbf{t}, \theta, B}, \tilde{\phi}_{\alpha_{en}, \mathbf{t}, \theta, B}) + \omega_{pr} E_{prior}(\alpha_{ep})$$

with respect to the epi- and endocardial shape parameters α_{ep} and α_{en} , the rigid transform parameters $\mathbf{t}$ and θ , as well as the plane B , it is required the first variation of (3.4) w.r.t. to the first four entities to vanish. To this end, the gradients for each of the involved energy terms read:

$$\begin{aligned} \frac{\partial E_{rn}}{\partial \phi_{ep}} &= 2 \left(|I - \mu_{my}|^2 (1 - H_\epsilon(\phi_{en})) \delta_\epsilon(\phi_{ep}) - |I - \mu_{bg}|^2 \delta_\epsilon(\phi_{ep}) \right), \text{ and} \\ \frac{\partial E_{rn}}{\partial \phi_{en}} &= 2 \left(|I - \mu_{bp}|^2 \delta_\epsilon(\phi_{en}) - |I - \mu_{my}|^2 \delta_\epsilon(\phi_{en}) H_\epsilon(\phi_{ep}) \right), \\ \frac{\partial E_{th}}{\partial \phi_{en}} &= 2 \left(\phi_{en} - (\phi_{ep} - d_{wall}) \right), \quad \frac{\partial E_{th}}{\partial \phi_{ep}} = -2 \left(\phi_{en} - (\phi_{ep} - d_{wall}) \right), \text{ where} \\ \frac{\partial E_\xi}{\partial \alpha_\kappa} &= 2 \int_{[1, T]} \int_\Omega \frac{\partial E_\xi}{\partial \phi_\kappa}(\mathbf{x}) \psi_i(\mathbf{x}, t) d\mathbf{x} dt, \quad \xi \in \{\text{rn}, \text{th}\}, \kappa \in \{\text{ep}, \text{en}\}, \text{ as well as} \\ \frac{\partial E_{prior}}{\partial \alpha_i} &= \frac{1}{\sigma^2} \frac{\sum_{i=1}^N (\alpha - \alpha_i) K_i}{\sum_{i=1}^N K_i}, \quad \text{with} \quad K_i = \frac{1}{(2\pi)^{\frac{3}{2}}} \exp \left(-\frac{(\alpha - \alpha_i)^2}{2\sigma^2} \right), \end{aligned}$$

where $\delta_\epsilon(\cdot)$ refers to the regularized Dirac measure. Gradients with respect to the rigid transform parameters are of the form:

$$\frac{\partial E_\kappa}{\partial \mathbf{t}} = \frac{\partial E_\kappa}{\partial \phi_{ep}} \nabla \phi_{ep} \frac{d\mathcal{T}}{d\mathbf{t}} + \frac{\partial E_\kappa}{\partial \phi_{ep}} \nabla \phi_{en} \frac{d\mathcal{T}}{d\mathbf{t}}, \quad \frac{\partial E_\kappa}{\partial \theta} = \frac{\partial E_\kappa}{\partial \phi_{ep}} \nabla \phi_{ep} \frac{d\mathcal{T}}{d\theta} + \frac{\partial E_\kappa}{\partial \phi_{ep}} \nabla \phi_{en} \frac{d\mathcal{T}}{d\theta}$$

with $\frac{d\mathcal{T}}{d\mathbf{t}} = -(1 \ 1 \ 1)^\top$ and $\frac{d\mathcal{T}}{d\theta} = \frac{\partial \mathbf{R}}{\partial \theta} \mathbf{x}$. Minimization with respect to B can be implemented by a fitting to the upper rim of the myocardium intensities in I .

4 Experimental Results and Discussion

The proposed approach has been implemented and tested at several gated studies (8 time phases each), followed by qualitative and quantitative comparison to expert annotations. Parameters were selected manually and the same for all experiments ($\omega_{th} = 0.04, \omega_{pr} = 500, \sigma = 200$). In particular, the soft thickness constraint parameter d_{wall} was set to 13 mm. PCA was conducted and subsequent Parzen estimation carried out on 30 expert-annotated SPECT sequences (also 8 phases). $\bar{\phi}$ served as initialization of the level set propagation.

Two representative results are depicted in Fig. 1 including their corresponding blood volume diagrams, both in comparison to the expert references. The MPR views show a high overlap between the automated results and reference segmentation. Furthermore, the influence of the new thickness constraint becomes apparent, which lets the distance between the epi- and endocardium vary in a certain range. With respect to the input data, the left study shows that the algorithm

Fig. 1. Segmentation results (red) in comparison to an expert segmentations (green) for two different datasets. (a) and (b): Short axis and two long axis MPR views (left to right) for each of the eight heart phases (top to bottom, starting with ED). (c) and (d): Corresponding blood pool volume of the automated (red) and the expert segmentation(s) (green, and blue (if applicable)). Correlation factors: (c) automatic to green expert segmentation: 0.95, automatic to blue expert segm.: 0.97, green to blue expert segm.: 0.94 (inter-expert correlation), (d) automatic to expert segm.: 0.9. Ejection fractions: (c) automatic segm.: 60%, green expert segm. 52% expert, blue expert segm.: 53%, (d) automatic segm.: 52%, green expert segm. 54%.

is also able to detect the myocardial walls despite diminished image information (darker regions at the outer wall), which is compensated for by the prior shape model. In terms of the corresponding blood pool volumes, these and other experiments exhibit high correlation factors (0.95 and 0.9 here) which lie within the range of inter-expert variability, as well as close ejection fraction estimates.

We presented a segmentation approach for the bloodpool and myocardium in gated SPECT studies, which is based on a new thickness constraint between the epi- and endocardial shapes. By contrast to existing methods, this is realized on the basis of a sound energy minimization and kept separate from existing data-driven concepts, thereby giving explicit gradual control on its strength. First experiments yield good results with respect to expert annotations and suggest further studies on larger number of data sets.

References

1. Chan, T.F., Vese, L.A.: Active contours without edges. *IEEE Trans. Image Processing* 10(2), 266–277 (2001)
2. Faber, T., Cooke, C., Folks, R., Vansant, J., Nichols, K., De Puey, E., Pettigrew, R., Garcia, E.: Left ventricular function and perfusion from gated spect perfusion images: An integrated method. *J. of Nuclear Medicine* 40(4), 650–659 (1999)
3. Frangi, A.F., Rueckert, D., Schnabel, J.A., Niessen, W.J.: Automatic construction of multiple-object three-dimensional statistical shape models: Applications to cardiac modeling. *IEEE Trans. Medical Imaging* 21(9), 1151–1166 (2002)
4. Germano, G., Kavangh, P.B., Waechter, P., Areeda, J., Van Krieking, S., Sharir, T., Lewin, H.C., Berman, D.S.: A new algorithm for the quantitation of myocardial perfusion SPECT. I. *J. of Nuclear Medicine* 41(4), 712–719 (2000)
5. Goldenberg, R., Kimmel, R., Rivlin, E., Rudzsky, M.: Cortex segmentation: A fast variational geometric approach. *IEEE T. Med. Im.* 21(12), 1544–1551 (2002)
6. Gomes, J., Faugeras, O.: Reconciling distance functions and level sets. *J. Visual Com. and Image Representation* 11, 209–223 (2000)
7. Kohlberger, T., Cremers, D., Rousson, M., Ramaraj, R., Funka-Lea, G.: 4D shape priors for a level set segmentation of the left myocardium in SPECT sequences. In: Larsen, R., Nielsen, M., Sporring, J. (eds.) *MICCAI 2006*. LNCS, vol. 4190, pp. 92–100. Springer, Heidelberg (2006)
8. Leventon, M.E., Grimson, W.E., Faugeras, O.: Statistical shape influence in geodesic active contours. In: *CVPR 2000*, vol. 1, pp. 1316–1323. IEEE, Los Alamitos (2000)
9. Liu, Y., Sinusas, A., Khaimov, D., Gebuza, B., Wackers, F.: New hybrid count- and geometry-based method for quantification of left ventricular volumes and ejection fraction from ECG-gated SPECT. *J. of Nuclear Cardiology* 12, 55–65 (2005)
10. MacDonald, D., Avis, D., Evans, A.C.: Proximity constraints in deformable models for cortical surface identification. In: Wells, W.M., Colchester, A.C.F., Delp, S.L. (eds.) *MICCAI 1998*. LNCS, vol. 1496, pp. 650–659. Springer, Heidelberg (1998)
11. Paragios, N.: A variational approach for the segmentation of the left ventricle in cardiac image analysis. *Int. J. Computer Vision* 50(3), 345–362 (2002)
12. Rousson, M., Cremers, D.: Efficient kernel density estimation of shape and intensity priors for level set segmentation. In: Duncan, J.S., Gerig, G. (eds.) *MICCAI 2005*. LNCS, vol. 3750, pp. 757–764. Springer, Heidelberg (2005)
13. Zeng, X., Staib, L.H., Schultz, R.T., Duncan, J.S.: Segmentation and measurement of the cortex from 3-D MR images using coupled-surfaces propagation. *IEEE Trans. Medical Imaging* 18, 927–937 (1999)