Questions and Answers

Chapter 2

Questions

(Q1) *Define the principle idea of the level set framework for segmentation of an image given an initial contour C and a speed function* $V > 0$. *What are the advantages of using an implicit formulation of the problem?*

(Q2) *What are the limitations associated with gradient-based speed terms? Why is it especially problematic with medical images?*

(Q3) *What is a regularization term? What is its main functionality? Give some examples.*

(Q4) *What is the entropy principle for implementation of a level set deformable model with finite difference? In what case does it apply?*

(Q5) *Explain the concept of speed extension for image-based speed terms? Why is it necessary? Propose a simple algorithm to implement it.*

(Q6) *Is the standard level set framework preserving the distance function? Why is this an important concept for segmentation applications?*

(Q7) *Why is there a need for reinitialization of the distance function?*

(Q8) *Outline in a flowchart the structure of an iterative level set segmentation algorithm using a gradient-based speed term. Use a convergence criteria (without detailing it) to stop the iterations.*

(Q9) *Design a level set segmentation algorithm for extraction of the endocardial and epicardial surfaces of the left ventricle from an MRI volume? What are the properties of the data that can be used to define the speed function? Is there a way to perform simultaneous segmentation of the two surfaces?*

Answers

(A1) The level set framework defines geometric deformable models that provide an implicit formulation of the deformable contour in a level set framework. Given a close contour C deforming with a speed V along its normal direction $|VC|V = 1$, $V > 0$, the fundamental idea is to embed the curve into a higher dimension function $\phi(x, y, t)$ such that:

(1) at time zero the initial contour C_0 corresponds to the level zero of the function ϕ: $C_0 = \{(x, y)/\phi(x, y, 0) = 0\}$, (2) the function ϕ evolves with the dynamic equation: $\frac{\partial \phi}{\partial t} = |\nabla_\phi|V$. In this framework, at any time t, the front implicitly defined by $\Gamma(t) = \{(x, y)/\phi(x, y, t) = 0\}$ corresponds to the solution of the initial boundary value problem.

(A2) Level set methods based on image gradient intensity are prone to "leaking" boundaries in areas with low contrast. A second problem related to the use of the image gradient as the only image-derived speed term is that it makes the segmentation process very sensitive to the initial position of the level set function as the model is prone to converge to false edges that correspond to local minima of the functional. Medical images typically suffer from insufficient and spurious edges inherent to physics of acquisition and machine noise from different modalities.

(A3) A regularizing term is a term derived from regional statistics information of the image. Regularization of the level set speed term is desirable to add prior information on the object to segment and prevent segmentation errors when using only gradient-based information in the definition of the speed. Examples of regularizer terms are: Clustering-based regularizers, Bayesian-based regularizers, Shape-based regularizers, Coupling-surfaces regularizers.

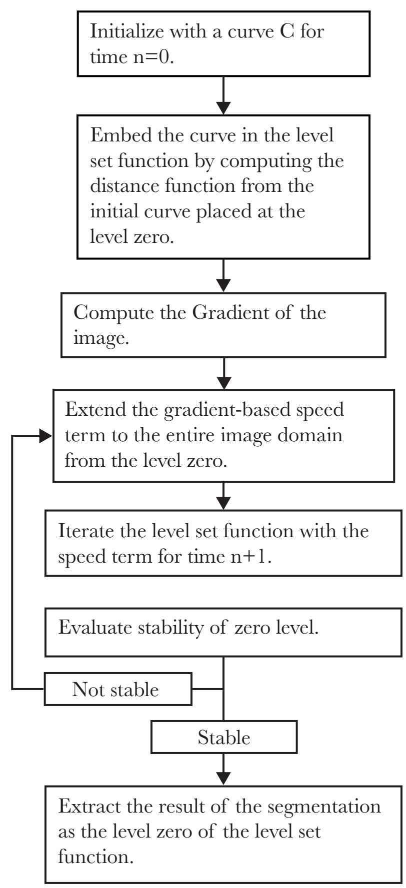
(A4) Numerical schemes for approximation of spatial derivatives with unidirectional speed terms must respect the entropy condition for propagating fronts. This entropy condition ensures that the propagating front corresponds to the boundary of an expanding region. An analogy is to consider the moving front as a source for a burning flame and expand the flame so ensuring that once a point in the domain is ignited, it stays burnt. The entropy principle puts some constraints in the choice of particular numerical schemes for temporal and spatial derivatives of the level set function.

(A5) Image-based speed terms are only defined on the zero-level of the moving front, as they are designed to stop the evolution of the front at high-gradient locations. On the other hand the energy functional is defined over the entire domain and the speed term must have a consistent definition over all values of the level set function. This is done by extending the speed term from its values defined only on the level zero. There are several methods available to perform the extension. One of the most popular methods assigns the values of the closest point on the level zero to a given point of the domain.

(A6) The solution to Hamilton-Jacobi equations underlying standard level set segmentation methods do not preserve distance functions. There are both theoretical and practical issues arising from this fact in segmentation applications. Theoretically, the signed distance function gives a unique equivalence to the implicit description of the moving front. From a practical point of view, the use of a signed distance function enables to directly extract from the level set function geometrical properties of the front and guarantees bounded values of the level set function gradient, ensuring numerical stability of the segmentation iterative process.

(A7) The need to reinitialize the distance function comes from the fact that the solution to Hamilton-Jacobi equations underlying standard level set segmentation methods do not preserve the original distance structure. Reinitialization recomputes the level set function as the distance function from the level zero.

(A8)



(A9) MRI images provide high resolution anatomical representation of the anatomy. We can therefore propose a gradient-based speed function. Two level set functions can be coupled together as detailed in the chapter and evolved simultaneously. One can for example initialize one level set inside the ventricle for the endocardial surface and one level set function inside the myocardium for the epicardial surface. The speed function should only inflate the curve towards high-gradient location while constraining the two surfaces to remain at a distance within a range of pre-defined values.