Locally Adaptive Speed Functions for Level Sets in Image Segmentation

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Abstract. We propose a framework for locally adaptive level set functions. The impact of well-known speed terms for the evolution of the active contour is adjusted by parameterising them with functions based on pre-defined properties. This allows for the application of level set methods even if image features are subject to large variations or if certain properties of the model are only valid for parts of the segmentation process. We present a number of examples and applications for the proposed concept and also address advantages and drawbacks of combinations of locally adaptive speed terms.

Key words: Image Segmentation, Level Set Methods

1 Introduction

Level set methods have become very popular in recent years in many image processing domains. They allow for the segmentation of images even if the shape of the desired object is unknown or has large variances between data sets. Level sets can adapt to topological changes, usually only require a small number of parameters to be adjusted and their extension to higher dimensions is straightforward.

An implicit active contour $\phi_t + F|\nabla\phi| = 0$ is evolved either in a propagation process [11] or via energy minimisation [2]. Each point on the zero level set is moving along its surface normal with a speed F. This speed is calculated according to pre-defined properties of the desired object. In image processing these properties are usually image features like gradients [10], texture measures [12] or image intensities [2]. To compensate for image artefacts such as noise or imperfect boundaries a second class of speed terms is often needed for regularisation of the contour. Regularisation of the front ranges from smoothness terms based on mean curvature [11] to more sophisticated approaches such as incorporation of model-based knowledge based on shocks [1], geometric shapes like circles or ellipsoids [16] or the topology of the desired object [8]. Other approaches even incorporate explicit shape knowledge [3][9].

Unfortunately the use of sophisticated speed terms has a number of drawbacks in certain situations. The definition of level sets is very general, allowing for their application to data sets from many different domains. By incorporating highly specialised speed terms, the method becomes limited to specific applications. Interesting properties of the method, such as the extension to any number of dimensions, are lost. Also, for a number of segmentation problems it is not possible to incorporate any of these advanced speed terms because the shape of the desired object is not known in advance. Examples in medical image analysis are the segmentation of the cerebral grey and white matter or segmentation of the vascular or bronchial tree. We propose a new framework for the design of level set speed functions that is also suitable for this kind of application.

2 Locally Adaptive Speed Terms

Many speed terms for level set functions can be incorporated for the segmentation of different kinds of images and data sets simply by adjusting a parameter that controls the impact of that particular speed term. For example, the often used speed function $F = F_g(F_\nu + F_\kappa)$ includes the well-known gradient-based speed term $F_g(\alpha) = (1 + \alpha|\nabla G_\sigma * I(\mathbf{x})|)^{-1}$ and the curvature-based term $F_\kappa(\epsilon) = \epsilon\nabla\frac{\nabla\phi}{|\nabla\phi|}$. In the first case, the value of α affects how large gradients need to be for the front to stop. In the second example, ϵ determines how smooth the contour is going to be and how much it will be affected by image noise.

Unfortunately, these parameter values are usually constant for the whole propagation process. If certain properties of the image differ substantially over image space, adjustment of the parameters is difficult. An example are field inhomogeneities in magnetic resonance imaging. Model-based properties may change in the same way. In the segmentation of the human brain, thickness of the cortical grey matter is different in various regions of the brain. Even the established coupled surface approach [7] does not account for that. More generally, smoothness of the contour may be desired only for certain parts of the objects but not for others. With other deformable models such as the active shape model [4] or mass spring models [15] it is possible to address this kind of variability by adjusting the modes of variation or the parametrisation of springs, respectively. To allow for the incorporation of such functionality in level sets and thus increase the application spectrum these methods, we propose the concept of locally adaptive speed terms for level set methods.

A speed term $F_i = F_i(\mathbf{f})$ is dependent on one or more features $\mathbf{f}$. Instead of controlling the influence of F_i on the active contour with a constant parameter, a function $\omega_i = \omega_i(\mathbf{g})$ is used for adjusting the impact of F_i based on a second set of features $\mathbf{g}$. The definition of a level set speed term $\hat{F}_i$ is then given by

$$\hat{F}_i = \omega_i F_i = \omega_i(\mathbf{g}) F_i(\mathbf{f}). \tag{1}$$

Note that the properties $\mathbf{g}$ need not be based on image features. Below we will give examples of weighting functions ω based on distance-measures and position in image space. Using ω_i it is possible to adjust the influence of F_i, to apply it only for certain parts of the image or to set it to zero if it would otherwise impede the desired evolution of the active contour. If all ω_i and F_i are continuous functions

(a) Test image (b) F_i (c) ω_i (d) $\hat{F}_i$

Fig. 1: Example for a locally adaptive speed term based on distance. Bright intensities indicate a high velocity, dark intensities a low velocity. An image-based speed term F_i based on image intensities is parameterised by a function ω_i depending on distance and prevents the front from evolving if its distance to the light grey region on the right side is less than 15 pixels. The resulting speed term $\hat{F}_i$ is superimposed on figure (a) for better visualisation.

the method is numerically stable and the combination of locally adaptive speed terms

$$F = \omega_1 F_1 + \omega_2 F_2 + \ldots + \omega_n F_n, \quad (2)$$

will be a continuous function as well. If for some speed terms no weighting function is necessary, ω_i can be chosen such that $\hat{F}_i = id(F_i)$. Figure 1 shows a simple example for a locally adaptive speed function based on distance. Similar to model-based speed terms, the influence of more sophisticated parameterising functions ω_j might also change over time.

The proposed concept allows for the use of comparatively basic speed terms even for challenging segmentation tasks. By using parameterising functions, well-known speed terms can be incorporated even if certain properties that define the object of interest do not hold for all parts of that object. Vice versa, they can also be employed if such properties are only needed for a correct segmentation of few or small parts of the object. A number of previously published examples that fit into this framework are summarised below. Applications are given in section 3.

2.1 Speed Terms Based on Distance

We demonstrated the possibilities of locally adaptive speed terms based on distance measures to introduce additional knowledge to the segmentation process in [13]. A number of segmentation results are depicted in figure 2. Given figure 2a, a segmentation process was startet with a single seed point within object A. Figure 2b shows a segmentation where the level set stops based on image-features but keeps a minimum distance of 15 pixels to region F (the corresponding speed function has been visualised in figure 1). In figure 2c a speed function that used a

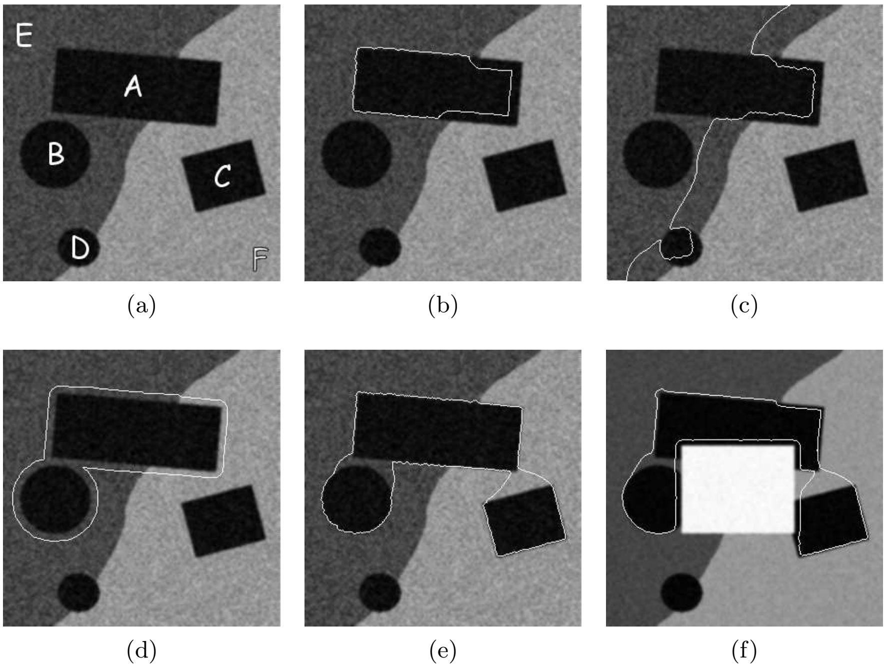


Fig. 2: Effects of distance-based speed terms for image segmentation

minimum *and* maximum distance criterion has been employed. The front keeps a minimum distance of $d_{min} = 15$ pixels to region F within objects A and D, where the properties of the desired object as defined in the speed function hold. The front does not stop at the boundary of A where the distance to F is too large. Instead it propagates into object E, but a maximum distance of $d_{max} = 30$ pixels is kept to region F. Again, the weighing functions are quite simple: the maximum distance is realised by a sigmoid function while the evolution of the front for $d_{min} < d < d_{max}$ is controlled by a regularised boxcar function (Such a function is used in section 3 for the segmentation of white matter in MR images of the brain). In figure 2d the front stops $d = 15$ pixels outside object A. Object B is segmented as well because its distance to A is smaller than d. Figure 2e visualises the segmentation result using an acceleration term that connects objects that have similar properties if their distance is smaller than a pre-defined distance d. That way, objects B and C have been connected to A. Note that the front propagated directly from A to the other objects and does not leak into the image background. Finally, figure 2f combines both approaches. Objects B and C are again connected to A but the front keeps a distance of 10 pixels to the white rectangle. For the definitions of the speed functions and further discussion the reader is referred to [13].

2.2 Speed Terms Based on Location

Speed terms can also be parameterised based on the absolute or relative position of the front in image space. In the first case the weighting function ω has the same size as the data set D that is being segmented. That is, for each pixel $\mathbf{x} \in D$ exists a parameter $\omega(\mathbf{x})$. This allows for the incorporation of information from an external source. We have applied this concept in [14] to ensure for the anatomical correct segmentation of cortical grey matter (see figure 4c). Also, Cremers et al. [5] incorporated a similar approach for allowing user interaction during the segmentation process.

If speed terms are dependent on local position, parameter values are adjusted based on pixels in the vicinity of front pixels. In [14] the image space has been subdivided into a grid of cubes of equal size to account for the effect of magnetic field inhomogeneities on the data. Within each subdivision D_i parametrisation was assumed to be constant. The transition between neighbouring subdivisions D_i and D_j have been smoothed based on the distance to the centers of D_i and D_j and the reliability of estimates for the intensity distributions. Again, the interested reader is referred to [14] for details. Obviously, it is not necessary to choose a static subdivision of image space for the calculation of parameters based on local position. A dynamically chosen set of pixel (for instance within a hyperball around $\mathbf{x}$) is also possible but computationally much more expensive.

2.3 Combinations of speed terms

Obviously weighting functions are not limited to the presented examples but can be based on any property that can calculated for each pixel on the front. The above examples have been chosen because they are available at nearly no additional computational cost. Other properties of the image or level set function that might also be incorporated in this way are image features or the speed of the active contour itself. If computational cost is not an issue, choices for weighting functions are only limited by properties of the desired object that can be formulated in mathematical terms.

Furthermore, locally adaptive speed terms can also be combined. In figure 2f a simple example has already been illustrated. In our experience a small set of weighting functions is useable for a surprisingly large number of applications. Regularised Heaviside- and Boxcar functions are easily incorporated examples. These functions also have the advantage that the set of parameters is limited to the slope of the function, which usually only needs to be slightly adjusted or not changed at all for different applications. Based on the above considerations this concept also allows for the creation of a construction kit for level set speed functions. By employing a set of weighting functions as well as a bank of well-known speed terms, the framework can thus be employed for a large number of segmentation problems.

Finally, a number of potential drawbacks of this framework should be addressed as well. Even though the number of parameters for each combination $\omega_i F_i$ is small, parameter space can get large when a number of locally adaptive

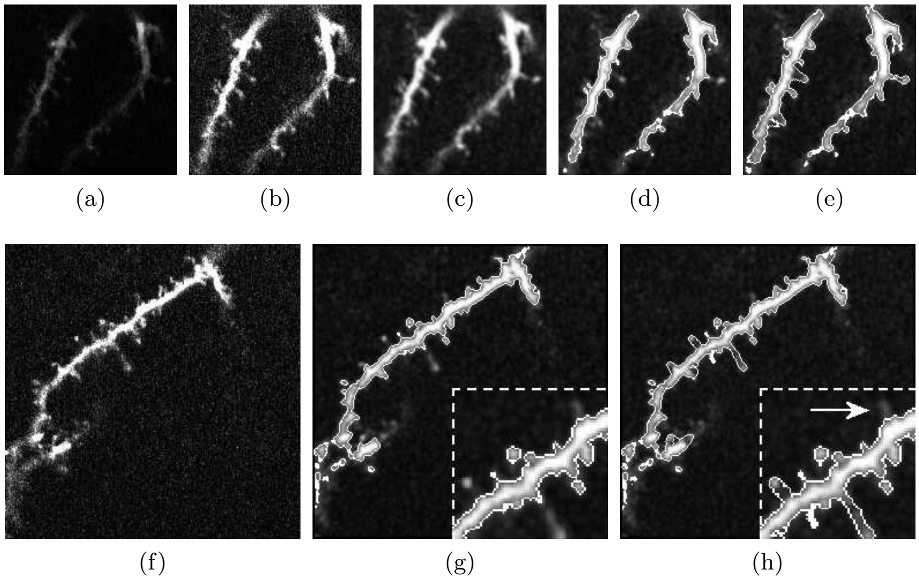
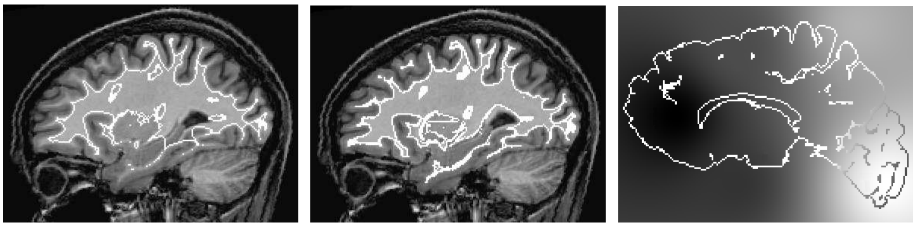


Fig. 3: Segmentation of dendritic spines using a distance based acceleration term. Figures 3a–3c shows pre-processing of data sets of the original data sets by contrast enhancement and low pass filtering. Figures 3d and 3e show segmentation results using a conventional level set speed function and the locally adaptive function, respectively. Figures 3g and 3h present results for a second example. Again most spines were found by the algorithm, although some have been missed since their image features are too similar to background noise (see enlarged region).

speed terms are combined. In this case even slight adjustments to parameters might not be straightforward anymore. In the same way, the small computational offset introduced by each parameterising function ω_i might add up when a number of adaptive speed speed are combined. And finally, since it is possible to 'switch off' speed terms it might happen that for certain pixels in image space no speed is defined. Again, this is a problem that will usually only occur with the combination of more speed terms when parameter space becomes difficult to manage.

3 Applications

We will give a few examples of application of locally adaptive speed functions to 3D medical data sets to demonstrate their benefit to various segmentation



(a) (b) (c)

Fig. 4: Segmentation of the cortical white matter in the human brain brain. (a) Result using commercial software. (b) Result using our locally adaptive algorithm. (c) Cortical thickness map according to [6].

tasks. Details on the algorithms and an evaluation of the results can be found in the respective publications.

In [13] we incorporated a distance-based acceleration term for the segmentation of dendrites in microscopic images. Due to partial volume effects, small spines attached to the dendrites do often appear unconnected in the data sets. Using a locally adaptive speed function, the propagating front is accelerated if spines are detected within a certain distance to the active contour. Segmentation results could thus be significantly improved in comparison to a conventional level set segmentation. Examples are given in figure 3.

We also employed an algorithm including locally adaptive speed functions based on local and global position in image space to guarantee for an anatomically correct segmentation of the cortical grey and white matter in MR data. Figure 4 shows a comparision between segmentation results for white matter using the commercial software BrainVoyager as well as our adaptive level set algorithm. A visual inspection by neurobiologists suggested that the boundary between grey and white matter found by our algorithm is usually more exact than the boundary found by the commercial software, which could often not provide a correct segmentation result in the presence of strong magnetic field inhomogeneities. Our algorithm uses a modified coupled surface approach [7]. The distance between inner and outer cortical surface varies between $1.5 - 2.5\,mm$ in the occipital lobe to about $4 - 5\,mm$ in the frontal lobe of the brain [6]. We employed a weighting function based on the absolute position within the brain to guarantee for a correct estimation of cortex thickness (see figure 4c). Furthermore, image-based speed terms are parameterised based on an analysis of local intensity distributions as briefly described in section 2.2.

4 Conclusions

We presented a novel framework for the design of level set speed functions using locally adaptive speed terms. By parameterising a level set speed term with a function ω_i its influence on the active contour can be adjusted depending on predefined properties. It is also possible to define speed terms for segmentation of parts of the desired object only and to switch them off when they are not needed. Examples for locally adaptive speed terms as well as possible applications have been presented. Future work includes the expansion of the concept to create a construction kit for level set speed functions.

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