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Constrained multiplicative graph cuts based active contour model for magnetic resonance brain image series segmentation ☆

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ABSTRACT

Graph cuts-based active contour model (GCACM) is often used in image segmentation, which can be categorized into additive GCACM and multiplicative GCACM. However, both the additive GCACM and multiplicative GCACM are insufficient for magnetic resonance (MR) brain image series segmentation. Considering the effectiveness of the multiplicative GCACM over the additive GCACM in local segmentation, we propose a new constrained multiplicative GCACM (CM-GCACM) for MR brain image series segmentation, in which, the constraint term is built based on the signed distance function, and can make the segmentation results obtained around the initialized contour. Generally, the deformations between adjacent slices in MR brain series are small, so we only need to give the initialized contour in one selected slice for constrained segmentation, and then the selected slice segmentation result can spread to the adjacent slices, in which case, the segmentation result of the current slicer can be served as the initialized contour for adjacent slices, and the constrained segmentation can be obtained again. By that analogy, we can realize the series segmentation. Experiments on putamen and caudate nucleus segmentation in MR brain image series demonstrate the effectiveness of proposed CM-GCACM over additive GCACM and multiplicative GCACM.

1. Introduction

Image segmentation [1–3] is an important problem in image processing, in which, graph cuts (GC) [4–7] and active contour model (ACM) [8–11] have been widely used. Recently, researchers have devoted themselves to combining GC and ACM into one framework, i.e. GC-based ACM (GCACM). Generally, GCACMs can be classified into additive GCACM [11–14] and multiplicative GCACM [15,16].

The additive GCACM is generally based on the standard GC model proposed in [4], and the standard energy form can be represented as follows:

$$E(f) = \sum_{\{p,q\} \in N} V_{p,q}(f_p, f_q) + \sum_{p \in P} D_p(f_p) \tag{1}$$

In (1), N is a neighborhood system, f is a mapping function from the set of pixels P to the set of labels L, and $p \in P$, $f_p \in L$, $f_q \in L$. Moreover, $D_p(f_p)$ measures the cost of assigning

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the label f_p to pixel p, $V_{p,q}(f_p, f_q)$ measures the cost of assigning the labels f_p and f_q to the adjacent pixels p and q.

The multiplicative GCACM is based on the modification of the standard GC energy function, and Le et al. [5] have given the modified formulation as follows:

$$E(f) = \sum_{\{p,q\} \in N} V_{p,q}(f_p, f_q) B_{p,q}(f_p, f_q) \tag{2}$$

The term $B_{p,q}(f_p, f_q)$ in (2) is the modification of the term $D_p(f_p)$ in (1), and measures the cost of assigning different labels f_p and f_q to the adjacent pixels p and q, respectively.

However, for magnetic resonance (MR) brain image series segmentation, no matter the additive GCACM or the multiplicative GCACM is insufficient. Firstly, initializing every slice in the series for segmentation is unpractical. Secondly, the image features in any one slice are different, and so we cannot achieve MR brain image series segmentation using the uniform parameters.

In [15], we have demonstrated that the multiplicative GCACMs have more advantages over the additive GCACMs in local segmentation with surrounding nearby clutter. More specifically, the t-links in additive GCACMs will create isolated segments around the desired object, and the elimination of the t-links in multiplicative GCACMs can avoid the problem.

Considering the insufficient of the GCACM in MR brain image series segmentation and the advantages of the multiplicative GCACM over the additive GCACM in local segmentation, we propose a novel constrained multiplicative GCACM (CM-GCACM) for MR brain image series segmentation.

The rest is organized as follows: In Section 2, we present proposed CM-GCACM. Section 3 takes experiments to demonstrate the effectiveness of proposed CM-GCACM, and the whole paper is summarized in Section 4.

2. The proposed method

2.1. The ACM formulation

In this paper, we consider the following ACM for MR brain image series segmentation, which contains the GAC (Geodesic Active Contours) model [8] and the LBF (Local Binary Fitting) model [10]

$$E = E_{GAC} + E_{LBF} = \int_C g_b(\nabla I(C(s)))\, ds + \left(\int_{C_{in}} (I(x) - f_{in}(x))^2\, dx + \int_{C_{out}} (I(x) - f_{out}(x))^2\, dx \right) \tag{3}$$

where $g_b(\nabla I) = 1/(1 + |\nabla G \times I(x)|)$ is the gradient operator, $f_{in}(x)$ and $f_{out}(x)$ are local versions of mean intensities inside and outside the closed curve C, respectively, $I(x)$ is the given image.

2.2. The narrow band discrete formulation

To describe the discrete formulation for the ACM in (3), we assume that each pixel p is associated with a binary variable x_p. Moreover, the binary variable x_p (0/1), source S/sink T, and the background (B)/object (O) satisfy the corresponding relations in Table 1.

Table 1
The corresponding relations of the binary variable x_p (0/1), source S/sink T, and the background (B)/object (O).

S/T	x_p (1/0)	B/O
S	0	B
T	1	O

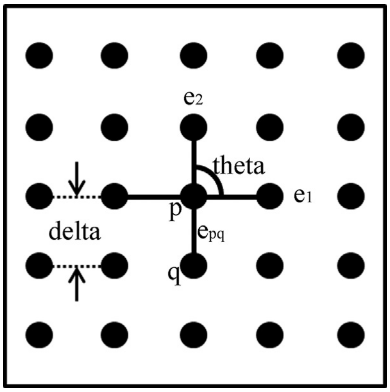

Fig. 1. The illustration of 4n-system.

In [15], we have given the discrete formulations of the ACM defined in (3) in additive and multiplicative way respectively, i.e. the additive GCACM and the multiplicative GCACM. Meanwhile, we reformulate the discrete formulations in a narrow band for local segmentation. The additive GCACM and the multiplicative GCACM in a narrow band framework can be rewritten in (4) and (5), respectively

$$E = E_{GC-GAC}(p,q) + E_{GC-LBF-1}(p), \quad p, q \in R_{NB} \tag{4}$$

$$E = E_{GC-GAC}(p,q) \cdot E_{GC-LBF-2}(p,q), \quad p, q \in R_{NB} \tag{5}$$

where R_{NB} is the narrow band, which should contain the edge of the desired object.

Term $E_{GC\text{-}GAC}(p,q)$ is the discrete GC formulation of GAC model, and has been defined in [12] as follows:

$$E_{GC-GAC}(p,q) = \sum_{p,q \in R_{NB}} \sum_{p \in N\ (q)} \frac{\omega_{pq}((1-x_p)x_q + x_p(1-x_q))}{1 + \beta |I(p) - I(q)|} \tag{6}$$

where $\beta = 1$ generally. N is the neighbor system. $\omega_{pq} = \delta^2 \theta_{pq} / |e_{pq}|$, $\delta = 1$ is the mesh size, $|e_{pq}|$ is the length of the edge e_{pq}, θ_{pq} is the angular differences between the nearest edge lines e_1 and e_2. In this paper, we use the 4n-system shown in Fig. 1, $|e_{pq}| = 1$, $\theta_{pq} = \pi/2$, and so $\omega_{pq} = \pi/2$ is a constant.

The only difference between additive GCACM and multiplicative GCACM is the discrete GC formulation of the LBF model, i.e., term $E_{GC\text{-}LBF\text{-}1}(p)$ and term $E_{GC\text{-}LBF\text{-}2}(p,q)$. In [13], El-Zehiry et al. have given the discrete GC formulation $E_{GC\text{-}LBF\text{-}1}(p)$ as

$$E_{GC-LBF-1}(p) = \sum_p (I(p) - f_t(p))^2 x_p + \sum_p (I(p) - f_s(p))^2 (1 - x_p) \tag{7}$$