Biomedical Signal Processing and Control 33 (2017) 119–131

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Modified localized multiplicative graph cuts based active contour model for object segmentation based on dynamic narrow band scheme

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ARTICLE INFO

Article history:
Received 9 April 2016
Received in revised form
14 November 2016
Accepted 22 November 2016

Keywords:
Active contour model
Graph cuts
Image segmentation

ABSTRACT

Localized multiplicative graph cuts based active contour model (LM-GCACM) has been widely utilized in object segmentation. However, the curve evolution of existing LM-GCACMs is based on static narrow band scheme generally, which is inconvenient in object segmentation because it requires the initialized curve be close to object boundary, and the narrow band is difficult to be determined. In this paper, a modified LM-GCACM based on dynamic narrow band is proposed to improve static narrow band. The dynamic narrow band allows the initialized curve to be any size or shape as long as it is inside object, and the narrow band can be built between the evolving curve and image bounding box. There are three contributions made to achieve dynamic narrow band. Firstly, the multiplicative region term is modified more suitable for segmentation. Secondly, a contrast constraint term is introduced to help evolving curve to go over false edges in the curve inflation evolution process. Thirdly, a self-constraint term is proposed to reduce the influence of surrounding clutter around object in the background, and guarantee segmentation stop on object boundary. Experiments on synthetic and medical images demonstrate the advantages of the proposed method.

1. Introduction

Active contour model (ACM) is one of the most efficient frameworks in image segmentation [1–5], which utilizes external (image) forces to pull a contour towards object boundary and internal forces to resist contour's deformation. The general energy-minimizing model for any two-phase ACM [6] can be summarized as:

$$E_{ACM} = E_b + E_r = \lambda \int_C g_b(C,s)\,ds + \left(\int_{\Omega_{in}} g_{in}(C,x)\,dx + \int_{\Omega_{out}} g_{out}(C,x)\,dx \right) \tag{1}$$

where g_b is the boundary function, g_{in} and g_{out} are region based functions for characterizing image inhomogeneity. The energy by Eq. (1) becomes to be minimal when the active contour reaches object boundary. ACMs have been widely utilized in medical image segmentation as in the case of left ventricle in Computed Tomography (CT) images [7], kidney in ultrasound images [8], brain tumor in magnetic resonance (MR) images [9], Positron Emission CT (PET) images [10] and some others [11,12]. Also, neural network has been incorporated into ACM by self-organizing maps techniques [13] to improve probability models.

Considering the characteristics of global minimization and efficient computation than level set methods, the ACMs are often optimized by graph cuts (GC). In particular, GC based methods provide an efficient and flexible formulation for image segmentation, and model image pixels as graph nodes that are connected by edges weighted by pairwise similarity measures. There are two GC frameworks for optimizing ACM defined by Eq. (2) [14–16] and Eq. (3) [17] respectively.

$$E_1(f) = \sum_{\{p,q\}\in N} V_{p,q}\left(f_p, f_q\right) + \sum_{p\in P} D_p\left(f_p\right) \tag{2}$$

$$E_2(f) = \sum_{\{p,q\}\in N} V_{p,q}\left(f_p, f_q\right) \cdot B_{p,q}\left(f_p, f_q\right) \tag{3}$$

where P is the set of pixels with $p \in P$. L is the set of labels with $f_p \in L$ and $f_q \in L$. f: $P \to L$ is the mapping function. Pixel q is in the neighborhood of pixel p, i.e., $q \in N(p)$.

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http://dx.doi.org/10.1016/j.bspc.2016.11.019
1746-8094/

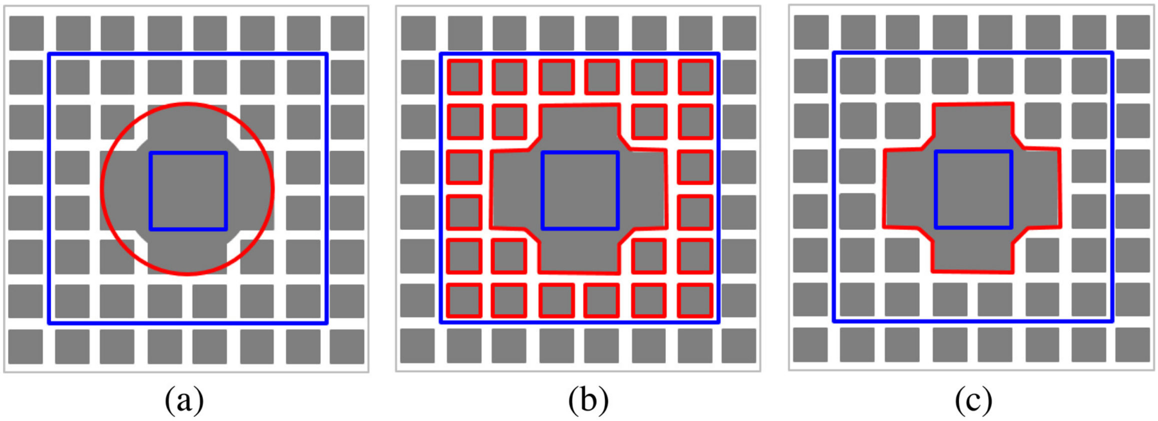

Fig. 1. Experiments on synthetic image. (a) Red curve is initialized curve, narrow band is built between blue curves, the narrow band should contain object boundary; (b) Result only utilizing t-links; (c) Result only utilizing n-links. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

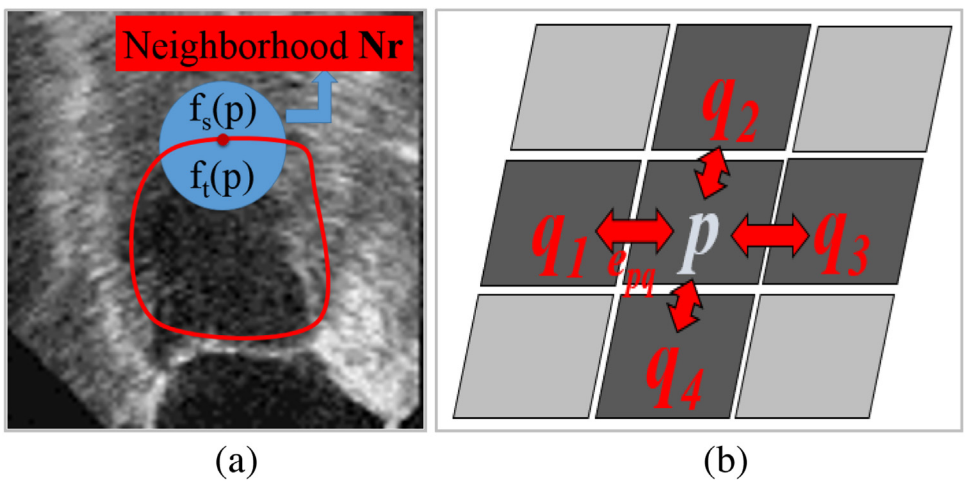

Fig. 2. Illustration of the neighborhood.

The GC formulation by Eq. (2) is an additive model, in which, the edge term $V_{p,q}(f_p, f_q)$ and the region term $D_p(f_p)$ are GC optimization formulations of image boundary function and region indicator function. The GC formulation by Eq. (3) is a multiplicative model, in which, the additive region term $D_p(f_p)$ has been modified into an edge-liked region term $B_{p,q}(f_p, f_q)$. In this case, the new region term can be multiplied with the edge term $V_{p,q}(f_p, f_q)$. In graph construction, n-links are used to connect neighboring pixels (p, q), and t-links are used to connect source terminal S and sink terminal T. Therefore, $V_{p,q}(f_p, f_q)$ and $D_p(f_p)$ in the additive GC formulation are weightings for n-links and t-links, while $V_{p,q}(f_p, f_q)$ and $B_{p,q}(f_p, f_q)$ are weightings for n-links in the multiplicative GC framework.

According to the differences of GC frameworks, GCACMs can be categorized into additive GCACMs (AGCACMs) [18–20] and multiplicative GCACMs (MGCACMs) [21–23]. For object segmentation, existing AGCACMs and MGCACMs are often reformulated in a narrow band, i.e., localized AGCACM (LA-GCACM) and localized MGCACM (LM-GCACM). Fig. 1(b) and (c) show experiments only utilizing t-links and n-links respectively. Experiments demonstrate that t-links will cause isolated segments (Fig. 1(b)), while the multiplicative GC framework can obtain more satisfying result when segmenting object in presence of surrounding clutters. Therefore, we only discuss the LM-GCACM in this paper.

In the following, we take [23] as an example to analyze drawbacks of the existing LM-GCACMs in object segmentation. In [23], Zheng et al. have proved that object segmentation will not be influenced even though the outer curve of narrow band is big due to min-cut property of GC based methods. For example, we use a big box as the outer curve of narrow band in Fig. 1, and the image bounding box can be used for simplicity. However, if the inner curve of narrow band is too small, the min-cut property of GC may make the segmentation fall into a local minimum. Therefore, it is difficult to be determined. For that reason, it is unpractical if the narrow band is updated along with the evolving curve at each iteration. Therefore, the narrow band scheme in the LM-GCACM in [23] is static. Once the narrow band is built before curve evolution, it will not be changed.

To sum up, though the static narrow band scheme needs to be built only once initially, there are two troublesome requirements: (1) The initialized curve should be located around the object boundary so that the local versions of intensities can characterize the local regions inside and outside object more accurately. (2) Although the outer curve of narrow band can be relaxed to the image bounding box, the inner curve is difficult to be determined.

Obviously, the static narrow band scheme in the LM-GCACM is inconvenient for object segmentation. In this paper, we propose a modified LM-GCACM based on a dynamic narrow band scheme for object segmentation. In the dynamic narrow band scheme, the initialized curve can be given with any location, size and shape as long as it is inside one object, and the narrow band is updated