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Robust noise region-based active contour model via local similarity factor for image segmentation

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ABSTRACT

Image segmentation using a region-based active contour model could present difficulties when its noise distribution is unknown. To overcome this problem, this paper proposes a novel region-based model for the segmentation of objects or structures in images by introducing a local similarity factor, which relies on the local spatial distance within a local window and local intensity difference to improve the segmentation results. By using this local similarity factor, the proposed method can accurately extract the object boundary while guaranteeing certain noise robustness. Furthermore, the proposed algorithm completely avoids the pre-processing steps typical of region-based contour model segmentation, resulting in a higher preservation of image details. Experiments performed on synthetic images and real word images demonstrate that the proposed algorithm, as compared with the state-of-art algorithms, is more efficient and robust to higher noise level manifestations in the images.

1. Introduction

Image segmentation plays a key role in both image understanding and computer vision. Numerous image segmentation methods have been proposed for different applications. Of special interest are those based on active contour models [1–5], which have been widely studied and used due to their ability to adaptively handle the changes of topological structure and smooth behavior. However, their methodology is normally adapted to a particular problem, and the robust and efficient application of a particular method to images of different complexity and unknown noise manifestations is still a challenging problem.

The principle of active contour model is based on the theory of contour evolution under given constraints to more accurately detect the object boundaries. As a consequence, depending on the kind of information used, existing active contour models are normally categorized into several types: edge-based models [1,3,4,6–11], global region-based models [5,12–16], edge/region-based active contour models [17], local region-based active contour models [18–29] and global/local region-based active contour models [30]. Edge-based models design a gradient stop function to accurately segment object boundaries in high quality images, while they are more sensitive to image noise and boundaries presenting weak gradient magnitude.

Global region-based models [5,12–16] attempt to solve the above problems by using the statistical information inside and outside active contour to guide the curve evolution. Although global region-based models have several advantages over edge-based models, including less sensitivity to noise and a better ability to detect weak boundaries, these models would fail to segment images having intensity inhomogeneity. Later, local region-based models [19,21–29] were presented to overcome this problem, using localized image information as constraints. The consideration of intensity statistics in localized regions instead of globally throughout the image improves segmentation performance on images with intensity inhomogeneity, but at the expense of a higher dependency on initialization parameters.

Although both global and local region-based models improve segmentation performance assuming weak to moderate Gaussian noise, these models still lack enough robustness to be applied to wider noise manifestations observed in real world applications, especially in cases with no a priori knowledge of noise characteristics.

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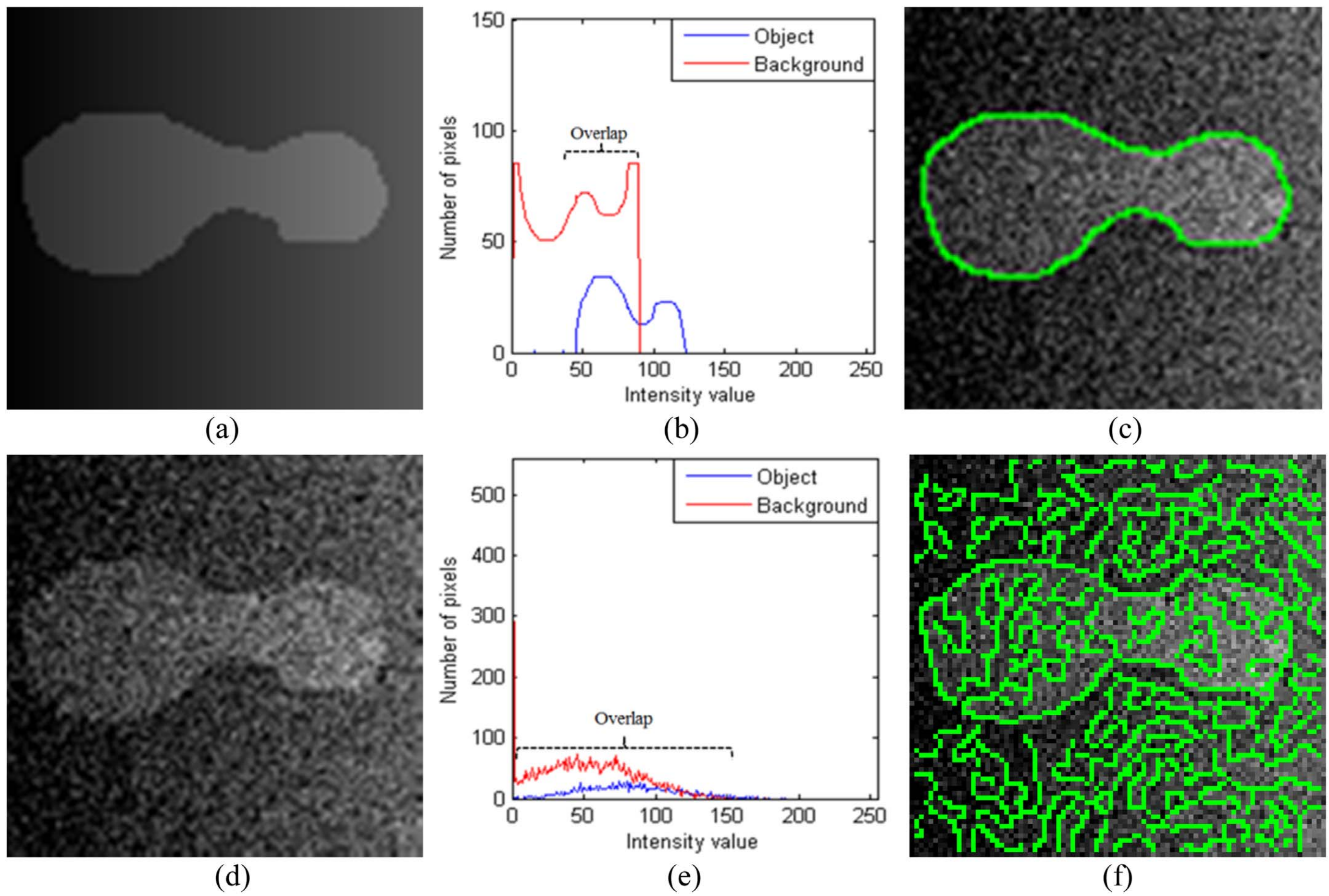

Fig. 1. Segmentation example in an image presenting intensity inhomogeneity corrupted by artificial noise. (a) and (d) are the inhomogeneity image and noise image, respectively, (b) and (e) indicate the intensity distribution of object and background in (a) and (d), respectively, (c) and (f) show a manually draw outline and unsuccessful segmentation results, as obtained using methods in [29].

Fig. 1 shows an example synthetic image showing intensity inhomogeneity in (a), and artificially corrupted by Gaussian noise with signal-to-noise ratio (SNR) of 4.2 dB in (d). We can observe the higher overlap in intensity values between object and background pixels after the image is corrupted by the Gaussian noise (compare Fig. 1(b)–(e)), which would make previous models [7,18,21,22,29] fail to accurately segment the object. Fig. 1(c) shows a manual outline drawn in the object to identify, while the state-of-art model [29] based on the local region has an unsuccessful segmentation result as shown in Fig. 1(f). For many types of images in real world applications, such as medical images or synthetic aperture radar (SAR) images, a successful segmentation algorithm needs to overcome wider manifestations of noise type and strength. Therefore, improving the robustness to noise of region-based active contour models is necessary.

We propose a novel region-based segmentation method that takes into account local similarity information in order to solve these limitations. The proposed method is able to segment objects from the image background with high noise levels as well as in images presenting intensity inhomogeneity. In this work we make three main contributions: first, we propose a local similarity factor to preserve noise robustness and outlier resistance, considering spatial distances and intensity differences in local regions. Second, our proposed algorithm was adapted to eliminate the necessity of pre-processing steps that frequently lead to loss of image details. Common pre-processing operations may blur object boundaries causing results that are too smooth or boundary leakage. Moreover, the proposed local similarity factor was designed to change from pixel-to-pixel and iteration-to-iteration. Therefore, the proposed method is expected to preserve more image details. Third, we present an extensive experimental analysis of both in our method and state-of-art models on synthetic images and real images, and show that the performance of our method was best providing more accurate segmentation results while also preserving edge information.

The rest of the paper is summarized as follows. We first review the previous work in Section 2. Then we describe the methodology of our proposed approach In Section 3. The experimental results and analysis are provided in Section 4, Section 5 summarizes conclusions.

2. Previous work

2.1. C–V model

For a given image $I(x)$ in the image domain $x \in \Omega$ and a closed contour curve C represented by level set function $\Phi(x)$ partitioning the image into object and background regions, the region-based model proposed by Chan and Vese [5] (C–V model) is formulated in terms of the level set function as follows:

$$\begin{aligned} E^{CV}(\Phi, c_1, c_2) = \mu \int_\Omega \delta\big(\Phi(x)\big)\big|\nabla\Phi(x)\big|dx \\ + \lambda_1 \int_\Omega \big|I(x) - c_1\big|^2 H\big(\Phi(x)\big)dx \\ + \lambda_2 \int_\Omega \big|I(x) - c_2\big|^2\Big(1 - H\big(\Phi(x)\big)\Big)dx \end{aligned} \tag{1}$$