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Weighted kernel mapping model with spring simulation based watershed transformation for level set image segmentation

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ABSTRACT

This paper proposes a novel active contour model called weighted kernel mapping (WKM) model along with an extended watershed transformation (EWT) method for the level set image segmentation, which is a hybrid model based on the global and local intensity information. The proposed EWT method simulates a general spring on a hill with a fountain process and a rainfall process, which can be considered as an image pre-processing step for improving the image intensity homogeneity and providing the weighted information to the level set function. The WKM model involves two new energy functionals which are used to segment the image in the low dimensional observation space and the higher dimensional feature space respectively. The energy functional in the low dimensional space is used to demonstrate that the proposed WKM model is right in theory. The energy functional in the higher dimensional space obtains the region parameters through the weighted kernel function by utilising mean shift technique. Since the region parameters can better represent the values of the evolving regions due to the better image homogeneity, the proposed method can more accurately segment various types of images. Meanwhile, by adding the weighted information, the level set elements can be updated faster and the image segmentation can be achieved with fewer iterations. Experimental results on synthetic, medical and natural images show that the proposed method can increase the accuracy of image segmentation and reduce the iterations of level set evolution for image segmentation.

1. Introduction

Image segmentation is a fundamental concept in image processing and has been a main subject of many theoretical and practical studies [1–3]. Generally, the purpose of image segmentation is to split an image uniformly into intersected and non-overlapped regions through certain properties such as textures or colours. Therefore, image segmentation can simplify the image representation for image understanding and analysis. Active contour model introduced by Kass et al. [4] is one of the most successful methods for image segmentation. The basic idea is to represent a contour as the zero level set of the level set functionals, and evolve the curve under some constraints to extract the desired objects. Over the past few decades, the active contour models have shown promising results through using level set methods in image segmentation [5–12].

The active contour models by level set methods can be broadly categorised into two basic types: edge-based methods [5–9] and region-based methods [10–22]. The edge-based methods utilise image gradients to drive the level set evolution. For instance, the well-known geodesic active contour (GAC) model [5] uses an edge stopping function to lead the active contour to the object boundaries. The edge-based methods are suitable for the images with strong gradient or high contrast. However, these methods are susceptible to the environmental noises, the location of the initial curve as well as the weak edges [20]. To prevent these limitations, the region-based methods exploit the regional information such as intensities and textures inside and outside the evolving contour to guide the contour evolution.

The region-based active contour model assumes that the image in each region is statistically homogeneous [10–13]. In the early years, the most prominent representative of region-based models for image segmentation was Mumford–Shah (MS) model [23]. However, minimising the Mumford–Shah (MS) energy functional is arduous and time-consuming, and hence, some simplified versions of MS model have been proposed [12,13]. Among them, the

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Chan–Vese (CV) model is one of the most representative and popular region-based models, and has been extended in various ways [15–18]. Nowadays, the region-based models can be mainly classified into two groups: global region-based models [12–14,16] and local region-based models [15,17,18,22].

Intensity inhomogeneity occurs in many real-world images. The global region-based model may fail to handle the images with intensity inhomogeneity by only using global statistics. To solve this problem, the local region-based model assumes that an image with intensity inhomogeneity is intensity inhomogeneous in global region, but its each local region is approximated to be intensity homogeneous. In this way, the local region-based model can extract the local regional information to incorporate into the level set energy functional. The Local Binary Fitting (LBF) model [15] based on the kernel function utilises the averages of local intensities to approximate the image intensities inside and outside of the curve to guide the contour evolution. The Bias Correction based Local Binary Fitting (BCLBF) model [18] is an integration of the LBF model with multiplicative model of intensity inhomogeneity, and simultaneously uses the estimated bias field to correct the intensity inhomogeneity. The Local Images Fitting (LIF) model [17] introduces the local fitted image energy functional to extract the local information, then uses the Gaussian filtering to regularise the level set function. Huang and Zeng [22] proposed a modified BCLBF model (MBCLBF) to improve the segmentation results of the images with intensity inhomogeneity. Comparing with the global region-based models, the local region-based models are more complex and time-consuming [16].

In order to make use of the advantages of both global and local models but overcome the disadvantages of them, some hybrid models have been proposed [24,25] by combining the global and local region-based information. Zhou et al. [24] adopted a weighting function to combine a global energy term and a local energy term so that the produced hybrid model could improve the efficiency and accuracy of medical image segmentation. This hybrid model could not handle various types of images. Wang et al. [25] utilised the global region-based model to preliminarily segment the image and get a coarse segmentation, and then used the local region-based model to further segment the image. This hybrid method could improve the accuracy of the segmentation, but could not improve the efficiency. Moreover, it could only be used for the two-phase segmentation.

The level set image segmentation by the kernel mapping (KM) model [16] is a global region-based model, which can segment various types of images, including images with slight intensity inhomogeneity. However, the KM model is not suitable for segmenting images with severe intensity inhomogeneity, such as computed tomography (CT) and magnetic resonance (MR) images. In other words, the KM model produces more inaccurate segmentation results than the local region-based models for images with severe intensity inhomogeneity.

Motivated by the problems mentioned above and inspired by hybrid models as well as kernel mapping method, a weighted kernel mapping (WKM) model along with a novel extended watershed transformation (EWT) method based on the spring simulation for the level set image segmentation is proposed in this research. Unlike the existing methods in the literature that the corrected image [18,22] can be obtained in the level set evolving process, the proposed approach utilises the EWT method to process the image with intensity inhomogeneity or noise before the level set evolution. The weighted information for performing the level set image segmentation will be prepared via the EWT process as well. The WKM model involves two new energy functionals in the low dimensional observation space and the higher dimensional feature space respectively. The energy functional in the low dimensional observation space is a new global region-based model, which can be used to demonstrate the correctness of the proposed WKM model in theory. The weighted information from the EWT process is used to construct a weighted kernel mapping function. The energy functional in the higher dimensional feature space is a new local region-based model by applying the weighted kernel mapping function onto the global region-based model, which can obtain the region parameters through the weighted kernel function and then guide the motion of the zero level set towards the object boundaries. Several popular kernel functions are capable of clustering the data of complex structure properly [26,27]. Namely, the image segmentation is spatially constrained clustering of image data. The weighted kernel mapping function can transform nonlinear separable data into linear separable data [28]. In this way, the image that cannot be accurately segmented in the low dimensional space can be accurately segmented in the higher dimensional space by applying the weighted kernel mapping function. Being a hybrid model, the proposed approach can effectively deal with various types of images. In this paper, some kinds of images including the natural images from Berkeley database, the brain images from Normal Brains Database, as well as some artificial images are tested and evaluated. In summary, the main contributions of this work are listed as follows:

a. An extended watershed transformation (EWT) based on spring simulation is proposed and its algorithm is presented. The extended watershed transformation manages to improve the image homogeneity and provide the weighted information for the level set function of the WKM model.
b. Two new energy functionals in the low dimensional observation space and the higher dimensional feature space are designed respectively. The theoretical proof based on the energy functional in the low dimensional space is given.
c. By combining the EWT method, a weighted kernel mapping (WKM) model for level set image segmentation is proposed, which leads to better segmentation accuracy and iterative efficiency. The main experiments for multi-phase image segmentation further demonstrate the desirable performance of the WKM model.

The remainder parts of this paper are organised as follows: Section 2 reviews the related work on level set image segmentation. Section 3 introduces traditional watershed transformation in image segmentation. Section 4 describes the proposed level set image segmentation approach and its implementations. The experimental results are evaluated in Section 5 and the conclusions are drawn in Section 6.

2. Relate work for level set image segmentation

In this section, three classical level set image segmentation models: KM, LIF and BCLBF [16–18] are reviewed and discussed. The LIF and BCLBF models are two popular local region-based level set image segmentation models, while the KM model is a global region-based level set image segmentation model. The discussion here focuses on the energy functionals and their time complexity.

2.1. The LIF model

For an image I in an image domain Ω, the energy functional of the LIF model is defined as follows:

$$E^{LIF}(u) = \frac{1}{2}\int_{\Omega} |I(x) - I^{LFI}(u(x))|^2 dx, x \in \Omega \quad (1)$$

$$I^{LFI} = m_1 H_\varepsilon(u) + m_2(1 - H_\varepsilon(u)) \quad (2)$$

where m_1 and m_2 meet the following conditions:

$$m_1 = mean(I(x) \in \{u(x) > 0, and, x \in W_k\}) \quad (3)$$