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Extended Topological Active Nets☆

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ABSTRACT

Topological Active Nets are promising parametric deformable models that integrate features of region-based and boundary-based segmentation techniques. Problems associated with the complexity of the model, however, have limited their utility. This paper introduces an extension of the model, defining a new behavior for changing its topology, as well as a novel external force definition and a new local search optimization procedure. In particular, we propose a new automatic pre-processing phase, a new external energy term based on the Extended Vector Field Convolution, node movement constraints to avoid crossing links, and different procedures to perform link cuts and hole detection. Moreover, the new local search procedure also incorporates heuristics to correct the position of eventually misplaced nodes. The proposal has been tested on 18 synthetic images which present different segmentation difficulties along with 3 real medical images. Its performance has been compared with that of the original Topological Active Net optimization approach along with both state-of-the-art parametric and geometric active contours: two snakes (based on Gradient Vector Flow and Vector Field Convolution), and two level sets (Chan and Vese, and Geodesic Active Contour). Our new method outperforms all the others for the given image sets, in terms of segmentation accuracy measured by using four standard segmentation metrics.

1. Introduction

Deformable models [1] (DMs) are a promising and vigorously researched computer-assisted image segmentation technique. They have proven to be effective in segmenting digital images by exploiting features of the image data together with a priori knowledge about the structures of these images. Since the pioneering work of Kass et al. [2], a number of different kinds of deformable models have been proposed. They can be described by two different paradigms: *parametric deformable models*, which represent curves and surfaces explicitly in their parametric forms during deformation, and *geometric deformable models*, which represent curves and surfaces implicitly as level sets of a higher-dimensional scalar function [3]. There has been some discussion in the area to determine which of the two DM families provides better performance. However, experimental studies like [4] have shown that, as there are significant differences in the model principles, complexity and capabilities, this decision depends on the specific application tackled. In fact, it is said that existing DM methods are not mutually exclusive and that the proposal of new approaches combining features from different kinds of methods is a promising research line.

Among parametric DMs, the active net model is a discrete implementation of an elastic mesh with interrelated nodes [5]. It integrates features of region-based and boundary-based [6] segmentation techniques that could potentially lead to better segmentation results than those DMs based only on boundary information [4]. To this end, active nets distinguish two kinds of nodes: internal nodes, related to the region-based information, and external nodes, related to the boundary-based information. Since the model deformation is controlled by an energy functional in such a way that the mesh reaches a minimum when the model is over the objects, the segmentation process is tackled as a numerical optimization problem.

The Topological Active Net (TAN) model was developed as an extension of the original active net model [7,8]. It solves some intrinsic problems of deformable models such as the initialization problem. In addition, a TAN has a dynamic behavior that allows topological local

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changes to be performed in order to achieve accurate adjustments and to find all the objects of interest in the scene.

The advantage of this model is the capability of fitting the edges of the objects while at the same time detecting their inner topology. Given the dual nature of the nodes, the generic active net model can be easily customized to the specific segmentation problem by incorporating prior knowledge (such as texture, shape, or color information) [9]. Potential applications of TAN's special properties have not been explored yet. However, they have already been applied to different problems such as iris location [9], road sign detection [10], stereo matching [11], and segmentation of different structures in medical images [5,8,12] with successful results.

Despite the promising features of TANs, the complexity of the model and the difficult optimization task inherent to the segmentation process have limited their utility. In fact, only a few works [10,12–15] dealing with TANs have been developed during the last ten years. In addition, those works have mainly focused on the proposal of global optimization techniques without providing solutions to the main TAN drawbacks and limitations: topological changes, external energy definition, and local deformations.

In this paper, an Extended Topological Active Net (ETAN) model is presented. It aims at overcoming the limitations of TANs while keeping their promising features. Here, rather than introducing a model ready to be applied to a broad range of real world problems, we intend to provide a proof of concept to revive interest in a type of deformable model that did not receive much focus from the scientific community in the last few years. To do so, we combined the best capabilities of two different kinds of DMs, TANs and Extended Vector Field Convolution snakes [16,17], as well as we have designed some specific components. In particular, we have developed novel mechanisms tackling topological changes including external and internal link cuts, we propose a new external energy term to properly guide the model in the case of complex concavities and highly non-convex shapes, we introduce node movement constraints to avoid crossing links, and we design a new local search procedure including heuristics to correct the position of eventually misplaced nodes. Moreover, a new automatic pre-processing phase is employed.

The proposed model will be tested over eighteen synthetic images categorized in six groups and three different levels of difficulty. The new model will be compared with the one designed by Ansia et al. [8] (also based on a local optimization of the TAN), including minor changes in the external energy term by Ibáñez et al. [13]. Besides, in order to increase the soundness of the experimental test and to show the advantages and disadvantages of ETANs for image segmentation, we also include widely employed parametric and geometric deformable models in the comparison. On the one hand, we compare against the Gradient Vector Flow (GVF) [18] and Vector Field Convolution (VFC) snake models [16], on the other hand, against the Chan and Vese (CaV) [19] and Geodesic Active Contour (GAC) [20] level set models.

The two snake models could be considered the state-of-the-art parametric deformable models. While the former is the most extended parametric model the latter has been recently proven to outperform it in several scenarios [16]. The CaV level set model can detect objects whose boundaries are not necessarily defined by the gradient as the level sets minimize an energy which can be seen as a particular case of the minimal partition problem. Finally, the GAC is based on the relation between active contours and the computation of geodesics or minimal distance curves.

The structure of this paper is the following: Section 2 introduces the TAN model and summarizes both the GVF- and VFC-snakes, as some of their components will be used in the ETAN design. Section 3 describes the proposed ETAN model, Section 4 explains the ETAN optimization process while Section 5 deals with some complementary tasks. Section 6 is devoted to the evaluation of the performance of our proposal and comparison with other methods. Finally, Section 7 summarizes some conclusions and future developments.

2. Background

2.1. Topological Active Nets

A TAN is a discrete implementation of an elastic two/dimensional mesh with interrelated nodes [5]. The structure of a small TAN is depicted in Fig. 1. As this figure shows, the model has two kinds of nodes: internal and external. Each kind of node represents different features of the objects: the external nodes fit the edges of the objects whereas the internal nodes model the internal topology of the object. Therefore, this model allows information based on discontinuities and information based on regions to be integrated in the segmentation process. The former is associated to external nodes and the latter to internal nodes.

A TAN is defined parametrically as $v(r,s) = (x(r,s), y(r,s))$ where $(r,s) \in ([0,1] \times [0,1])$. The mesh deformations are controlled by an energy functional defined as follows:

$$E(v(r,s)) = \int_0^1 \int_0^1 [E_{\text{int}}(v(r,s)) + E_{\text{ext}}(v(r,s))] drds$$

where E_{int} and E_{ext} are the internal and the external energies of the TAN, respectively. The internal energy controls the shape and the structure of the mesh whereas the external energy represents the external forces which govern the adjustment process.

The internal energy depends on the first and second order derivatives which control contraction and bending, respectively. The internal energy term is defined by the following equation:

$$E_{\text{int}}(v(r,s)) = \alpha\left(|v_r(r,s)|^2 + |v_s(r,s)|^2\right) + \beta\left(|v_{rr}(r,s)|^2\right) + |v_{rs}(r,s)|^2 + |v_{ss}(r,s)|^2)$$

where subscripts represent partial derivatives, and α and β are coefficients that control the first and second order smoothness of the net. In order to calculate the energy, the parameter domain $[0,1] \times [0,1]$ is discretized as a regular grid defined by the internode spacing (k,l) and the first and second derivatives are estimated using the finite difference technique. More details about the calculation of the terms of the previous equation are shown in [8].

The external energy represents the features of the scene that guide the adjustment process. It is defined by the following equation:

$$E_{\text{ext}}(v(r,s)) = \omega f[I(v(r,s))] + \frac{\rho}{|\aleph(r,s)|} \sum_{p \in \aleph(r,s)} \frac{1}{\|v(r,s) - v(p)\|} f[I(v(p))]$$

where ω and ρ are weights, $I(v(r,s))$ is the intensity value of the original image in position $v(r,s)$, $\aleph(r,s)$ is the neighborhood of node (r,s) and f is a functional, which is different for both types of nodes since the external nodes fit the edges whereas the internal nodes model the inner features of the objects. If the objects to detect are dark and the background is bright, the energy of an internal node will be minimum when it is on a point with a low gray level. On the other hand, the energy of an external node will be minimum when it is on a discontinuity and

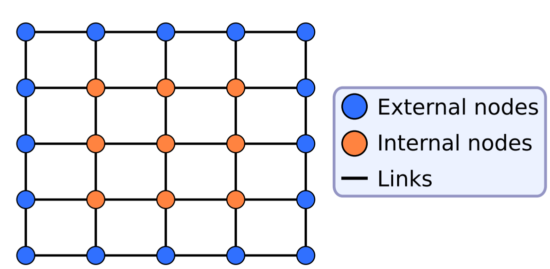

Fig. 1. A 5×5 example mesh.