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An edge-based active contour model using an inflation/deflation force with a damping coefficient

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ABSTRACT

This publication presents an edge-based active contour model using the inflation/deflation force, allowing active contour nodes to be moved to find object boundaries in a digital image. The methods proposed in this study make it possible to keep a high value of the inflation/deflation force for each node until the node approaches the boundary of the analysed shape. After the boundary searched for is reached, the value of the inflation/deflation force for these nodes is automatically damped. The solutions used in this paper are of major practical significance if the analysed images contain weak boundaries and/or strong noise at the same time, and on top of that there are strictures of the shape which should be approximated. Experiments were carried out for artificial images as well as USG and MRI medical images, and have confirmed the suitability of the solutions used.

1. Introduction

Active contour methods are very frequently used in digital images for various applications, namely: shape recognition, segmentation, edge detection, and stereo matching. What is more, active contour models make it possible to locate the shape or shapes of interest, including frequently very complex ones, in a series of images, on the basis of as seed contour predefined by the user and a defined set of parameters, often in an automatic way, which makes this very convenient in practice. The existing active contour models can be divided into two main classes, namely: edge-based models and region-based models.

Edge-based models use local edge information to fit to the boundaries of the approximated shape (Caselles, Kimmel, & Sapiro, 1997; Kass, Witkin, & Terzopoulos, 1998; Li, Xu, Gui, & Fox, 2005; Xu & Prince, 1998; Zhou, Zhang, Zeng, & Wang, 2007). Methods using the gradient vector flow fields (GVF) are an important subgroup of edge-based models. Xu and Prince (1998) proposed using GVF to increase the capture range of the active contour, particularly to enable concavities to be segmented. Unfortunately, in a very noisy image, GVF determination may cause unsatisfactory segmentation results. What is more, the efficiency of the method (Xu & Prince, 1998) is greatly reduced by its high computation cost. Li and Acton (2007) and Kumar, Wong, Fieguth, and Clausi (2012) present solutions which improve segmentation results compared to the base model (Xu & Prince, 1998). The use of edge-based static forces referred to as vector field convolution (VFC) in Li and Acton (2007) allows good segmentation results to be obtained in images with impulse noise and also in concave surfaces. Kumar et al. (2012) in turn describe a solution using a tensor vector field and improving the segmentation of images with gaussian noise.

Popular edge-based models that need mentioning also include geodesic active contours (GAC) (Caselles et al., 1997; Paragios & Deriche, 2005; Shah & Ross, 2009), which use a defined edge-stopping function to stop the contour on the object boundary which is possible only close to this boundary as the function is computed based on the image gradient. In some edge-based models, a balloon force (or a pressure force) term was introduced (Cohen, 1991; Makowski, Sørensen, Therkildsen, Materka, Stødkilde-Jørgensen, & Pedersen, 2002; McInerney & Terzopoulos, 2000) to deflate or inflate the contour, which allows the contour to be initiated far from the boundary searched for. However, it is sometimes difficult to set the balloon force correctly, particularly if the analysed shape features concavities, strictures and, additionally, strong noise. These limitations are illustrated in Fig. 1(a) and (b). If the value of the balloon force is too small, the active contour may not approximate all areas in which there are strictures and, as a result, the further moving of the active contour will stop. On the other hand, an excessive balloon force value may cause the active contour to spill beyond the analysed boundary in areas where there are weak boundaries and/or strong noise. What is more, if the shapes are complex, the internal friction of individual parts of the active contour may be uneven, which can lead to the contour self-looping. Looping is illustrated by Fig. 1(c) and (d).

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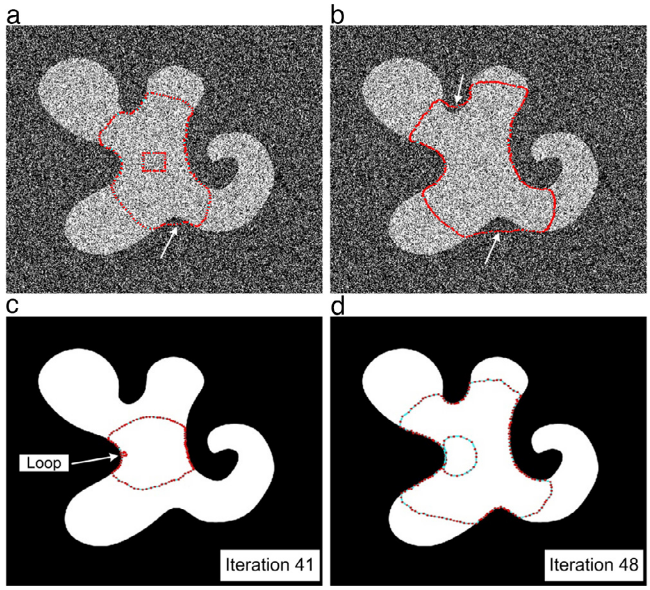

Fig. 1. Limitations of an edge-based active contour model using the balloon force when approximating a shape in an example artificial image 520 × 480 pixels in size. The initialisation of an active contour in the shape of a rectangle inside the analysed shape, as in example (a), is the same for all images. In images (a) and (b), white gaussian noise of the following parameters was added: $\mu = 0$ and $\sigma^2 = 0.9$. (a) Using an active contour in an image with major noise. Difficulties with determining the appropriate value of the balloon force which caused the contour to 'leak' beyond the approximated edge within the region marked with an arrow while at the same time the value of this force was too low for the contour to move through strictures and approximate the analysed shape in its entirety. (b) Increasing the balloon force. Fragments of narrowed areas have been approximated better than in example (a) but the contour 'leaks' beyond the analysed shape even more in the regions marked with arrows. (c) An active contour loop is forming at iteration number 41. (d) Iteration 48, the active contour loop is clearly bigger.

The classic discretisation of the gradient in the GAC model may also lead to loops forming on the active contour as demonstrated in Guyader and Vese (2008). A solution to this is offered by a topology–constrained segmentation model based on the GACs in which a topological constraint is enforced. Makowski et al. (2002) and Nakhmani and Tannenbaum (2012) also present solutions that allow self-crossings and the looping of the active contour to be eliminated. The image gradient in Makowski et al. (2002) is used to stop the contour guided by the balloon force. Makowski et al. (2002) analyse only an inflating contour, i.e. one that is increasing its surface area. In Nakhmani and Tannenbaum (2012), a constant number of nodes is set, and the removed nodes are replaced but in the most sparse regions. When an active contour is used to approximate complex shapes, for instance the one presented in Fig. 1, it is difficult to assume a constant number of nodes. If the computer implementation uses nodes (or snaxels), then after the seed contour is initiated, it can consist of just a few nodes, whose number should be gradually increased at subsequent iterations. It is worth noting that ensuring the control of the correct number of nodes does not only apply to the subject of active contour. For instance, Crampton and Forbes (2007) present a solution that uses the parametrised nodal point density function for spline approximation.

Region-based active contour methods find the optimal energy for which the model fits the image best based on statistics calculated from subregions. The approach presented in Mumford and Shah (1989) enables the image to be approximated using a smooth function inside every analysed area. Chan and Vese (2001) present a solution in which every region in the image is approximated using a certain constant function. In region–based models there is no problem with self-crossings and loops of the contour (Cheung, Liu, & You, 2012; Liu & Peng, 2012; Talu, 2013). Some of the best known methods (Chan & Vese, 2001; Yezzi, Tsai, & Willsky, 2002) use the assumption that there are homogeneous regions of interest in the image. Unfortunately, in medical images, e.g. USG, there are usually statistically non–homogeneous regions.

Of course, there are also other classifications of different groups of active contour methods, including those that use machine learning techniques, for example Self-Organising Maps (SOMs) (Shah-Hosseini & Safabakhsh, 2003; Venkatesh & Rishikesh, 2000). These methods use SOM weights to ensure the stable control of the evolution, e.g. of an edge-based active contour. A more detailed review of papers on the classification of various active contour methods can be found in Osher and Paragios (2003), Abdelsamea, Gnecco, and Gaber (2014) and Abdelsamea, Gnecco, Gaber, and Elyan (2015).

In this paper, an edge-based active contour model was proposed in which, just like in Cohen (1991) and Makowski et al. (2002), a balloon force is employed, but in a more universal way, as in this paper an inflation/deflation force is introduced for individual nodes of the active contour. It is also worth noting that the proposed approach employing an inflation/deflation force allows the contour to deflate and inflate at the same time, thus helping initialise it. In contrast, in Cohen (1991), McInerney and Terzopoulos (2000), Park, McInerney, Terzopoulos, and Kim (2001) and Makowski et al. (2002) the active contour can only be either deflating or inflating at all iterations. The value of the balloon force in Cohen (1991), McInerney and Terzopoulos (2000), Park et al. (2001) and Makowski et al. (2002) is constant for all the iterations executed, while in this paper, the value of the inflation/deflation force for every node is kept high until the node reaches the boundary of the analysed shape. Then, after the nodes reach the boundary searched for, the inflation/deflation force for these nodes is damped. This solution is of major practical significance if the analysed image contains both weak edges and/or strong noise, and on top of that there are strictures of the shape which should be approximated. It is all about the active contour stopping at the weak edges (e.g. ones that are fuzzy as a result of noise in the image) but getting through the strictures of the shape, keeping a relatively high value of the inflation/deflation force in this image fragment to allow it to reach the edge being identified. The use of the automatic control of the inflation/deflation force for individual nodes raises the resistance to noise and thus ensures better segmentation results for noisy images compared to methods presented in Cohen (1991), Xu and Prince (1998), McInerney and Terzopoulos (2000) and Makowski et al. (2002). In addition, in this paper the active contour is protected from the formation of self-crossings and loops at all the iterations executed and no situation as shown in Fig. 1(c) and (d) occur in it. In addition, this paper made it possible to automatically add new nodes and remove superfluous ones in order to approximate the edge accurately. The solutions applied in this paper and used in the edge-based model were compared to a GAC model making use of a morphological approach (Alvarez, Baumela, Henriquez, & Marquez-Neila, 2010) to segment artificial images as well as medical USG and MRI images. The morphological active contour model can evolve thanks to the use of mathematical morphology operators. In this model there are no floating point operations which allow the contour to evolve fast. In addition, the morphological model does not have suffer from self-crossings and loops.

The contents of this article are as follows. Section 2 formulates an edge-based active contour model which uses the inflation/deflation force with the damping coefficient. Section 3 presents the computer implementation of the active contour model used to segment shapes in digital images. Section 4 describes the experiments completed. The last section contains summary and conclusions.

2. Formulating an edge-based active contour model using the inflation/deflation force

In a two-dimensional discrete domain of a digital image defined by the brightness function I, an active contour is composed of N