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# Active contours driven by Cuckoo Search strategy for brain tumour images segmentation

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In this paper, an alternative Active Contour Model (ACM) driven by Multi-population Cuckoo Search (CS) algorithm is introduced. This strategy assists the converging of control points towards the global minimum of the energy function, unlike the traditional ACM version which is often trapped in a local minimum. In the proposed methodology, each control point is constrained in a local search window, and its energy minimisation is performed through a Cuckoo Search via Lévy flights paradigm. With respect to local search window, two shape approaches have been considered: rectangular shape and polar coordinates. Results showed that the CS method using polar coordinates is generally preferable to CS performed in rectangular shapes. Real medical and synthetic images were used to validate the proposed strategy, through three performance metrics as the Jaccard index, the Dice index and the Hausdorff distance. Applied specifically to Magnetic Resonance Imaging (MRI) images, the proposed method enables to reach better accuracy performance than the traditional ACM formulation, also known as Snakes and the use of Multi-population Particle Swarm Optimisation (PSO) algorithm.



## 1. Introduction

Image segmentation is a well-known and used task in several areas; some of them are related with clinical imaging applications. It consists in extracting a target region to be analysed instead of processing the entire image. In the particular case of brain tumour images the main goal is extract abnormal tissues to study its shape, volume and growth over the time. However, tumours delineation becomes an onerous task to perform manually due to the incremental amount of medical data generated in our days, disregarding the time consuming and the subjectivity of visual perception from specialised health professionals. In order to reduce this issues and the human interaction, computational methods are often used for segmentation tasks in order to achieve accurate, repetitive and faster results.

In recent years, many approaches have been proposed to improve quality and reliability of results obtained from segmentation processes. Image segmentation methods are generally classified into five categories: threshold-based, boundary based, region-based, learning-based and energy-based segmentation methods (Abdelsamea, Gnecco, Gaber, & Elyan, 2015). This last class of methods deals with the segmentation problem as a functional optimisation problem, whose energy contour interaction could be solved in a wide variety of approaches. The methodology proposed here using the Cuckoo Search strategy fulfils this last classification.

Active Contour Model (ACM) or Snake, proposed by Kass, Witkin, and Terzopoulos (1988), is an energy-based technique known as one of the most powerful image segmentation methods. This technique is defined as an optimisation problem, in which the total energy has to become minimal so as to ensure that the active contour is located on the object boundaries. ACM is applied in several areas such as, video tracking (Chen, Sun, Heng, & Xia, 2008), biology studies (Minervini, Abdelsamea, & Tsaftaris, 2014), surveillance systems, and extensively in medical images segmentation. Moreover, ACM is often used on Magnetic Resonance Imaging

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(MRI) and Computed Tomography (CT) for segmenting images e.g., human shin and womb fibroma (Tseng, Hsieh, & Jeng, 2009), brain tumour (Sachdeva, Kumar, Gupta, Khandelwal, & Ahuja, 2012) and left ventricle (Zhou et al., 2015). Nevertheless, the traditional formulation of ACM (Kass et al., 1988), which consist in an iterative gradient descent to solve the Euler equation, has two drawbacks. The first one is the stagnation tendency in a local solution (i.e., optimal contour) instead of converge towards the optimum contour. In order to avoid this inconvenience, ACM is often initialised as close as possible to the desired or expected contour. The second drawback is related to the difficulty to converge in non-convex shaped objects. The snakes convergence is considered as an optimisation problem, in which the total energy has to become minimal so as to ensure that snake is located on the object contour. Therefore, in order to solve this problem (and its drawbacks) and to improve its segmentation results, many contributions has been proposed in the literature, such as, the inclusion of the distance potential force model (Cohen & Cohen, 1993), of the gradient Vector Flow Field (Xu & Prince, 1998), of the boundary vector field (Sum & Cheung, 2007) and of solenoidal fields (Prince & Xu, 1996). Also, neural network models based on unsupervised learning and called Self-Organizing Maps techniques, have been widely used and incorporated in the ACM (Abdelsamea et al., 2015; Shah-Hosseini & Safabakhsh, 2003; Venkatesh & Rishikesh, 2000). On the other hand, functional energy minimisation was also proposed by using modern metaheuristic optimisation algorithms such as Genetic Algorithm (GA) by Xu et al. (2002), multi-population Particle Swarm Optimisation (PSO) by Tseng et al. (2009) and Honey Bee Mating Optimisation (HBMO) by Horng, Liou, and Wu (2010).

These nature-inspired techniques are extensively used in several applications (e.g., engineering problems, medical approaches and economic fields) due to their flexibility and simplicity of implementation and, certainly, because of their notable accuracy. One of these nature-inspired algorithms is Cuckoo Search (CS), proposed by Yang and Deb (2009), which exploits the brood parasitism behaviour of some species of cuckoos enhanced by Lévy flights instead random walks. CS has been applied in many areas and its popularity is increasing due to promising results outdoing those obtained with some metaheuristic techniques like PSO and GA, Yang and Deb (2014). Also, it is already used in image processing for multilevel thresholding (Bhandari, Singh, Kumar, & Singh, 2014; Brajevic & Tuba, 2014).

This paper proposes a snake energy-minimisation type approach, but based on a Multi-population Cuckoo Search Strategy (MCSS), for the brain tumour images segmentation. MCSS aims to find accurately targeted object edges through a two non-sequential stages algorithm. In the first stage local search spaces (or windows) are set for each control point from the current contour (or initial contour, as the case may be). The second phase consists of placing randomly such control points inside each search window, in order to obtain new ones by the aid of the CS strategy. Moreover, two different search window geometries were considered: Rectangular Shaped Search Windows (RSSW) and Pizza-slice Shaped Search Windows (PSSW).

This document is organised as follows: In Section 2, ACM and CS are briefly described. The proposed scheme of cooperation between ACM and CS, ACM-MCSS, is introduced in Section 3. Some experimental results and their performance evaluation are discussed in Section 4. Finally, Section 5 presents the most relevant conclusions of this work.

## 2. Background

Relevant concepts of Active Contour Method and Cuckoo Search algorithm are described in this section.

### 2.1. Active Contour Model: Snake

The basic idea of Active Contour Model is the dynamic motion of a parametric curve under the action of certain control forces present in the image spatial domain, Kass et al. (1988). These forces are summarised in two types: internal and external forces. The internal force is responsible of the contour (or snake) smoothness, and the external one of pushing the snake towards the object boundary. According to the above mentioned, the ACM curve is described by $\mathbf{P}(s,t) = (x(s,t), y(s,t))^T$, where $s \in [0, 1]$ and $t$ is the discrete time between two consecutive steps. The cost function is the snake total energy, and its minimum is found when the snake evolves close to the desired contour, it is given by next equation

$$E_{snake} = \int_0^1 (E_{int}(\mathbf{P}(s,t)) + E_{ext}(\mathbf{P}(s,t)))ds, \tag{1}$$

since $E_{int}$ and $E_{ext}$ are respectively the internal and external energy terms. They are described as follows,

$$E_{int}(\mathbf{P}(s,t)) = \frac{1}{2}\left[\alpha(s,t)\left\|\frac{\partial \mathbf{P}(s,t)}{\partial s}\right\|^2 + \beta(s,t)\left\|\frac{\partial^2 \mathbf{P}(s,t)}{\partial s^2}\right\|^2\right], \tag{2}$$

$$\begin{aligned} E_{ext}(\mathbf{P}(s,t)) &= \gamma_{line}E_{line}(s,t) + \gamma_{edge}E_{edge}(s,t) + \gamma_{term}E_{term}(s,t), \\ &= \gamma_{line}C(s,t) - \gamma_{edge}|\nabla G * I(\mathbf{P}(s,t))|^2 \\ &\quad + \gamma_{term}\left.\frac{C_{yy}C_x^2 - 2C_{xy}C_xC_y + C_{xx}C_y^2}{(C_x^2 + C_y^2)^{3/2}}\right|_{(s,t)}, \end{aligned} \tag{3}$$

where the curve tension is controlled by the elasticity component $\alpha$, the bending by the rigidity component $\beta$ and, the external energy by the components $\gamma_{line}$, $\gamma_{edge}$ and $\gamma_{term}$. The external energy term is composed by line ($E_{line}$), edge ($E_{edge}$) and termination ($E_{term}$) energy functions, determined using $C(s,t) = G * I(\mathbf{P}(s,t))$ and its first and second order partial derivatives (i.e., $C_x$, $C_y$, $C_{xx}$, $C_{xy}$ and $C_{yy}$), where $G$ is the Gaussian function and $I$ is the image. The traditional solution of this problem consists on the numerical computing of the Euler equation in (4), until the equality is satisfied,

$$\nabla E_{ext} - \alpha(s,t)\frac{\partial^2 \mathbf{P}(s,t)}{\partial s^2} + \beta(s,t)\frac{\partial^4 \mathbf{P}(s,t)}{\partial s^4} = 0 \tag{4}$$

This condition corresponds to the minimum energy solution related with the energy stability state. In other words, the external energy component becomes equal to the internal one or *vice versa*.

### 2.2. Cuckoo Search algorithm

Cuckoo Search is a bio-inspired optimisation technique that mimics the brood parasitism behaviour of many species of cuckoos. CS was proposed by Yang and Deb (2009) as a way to exploit some features from swarm intelligence, such as diversification and intensification, through random walks and Lévy flights. The basic idea of CS consists in the laying of an egg by each cuckoo and hides it in an alien nest. At the beginning, a given number of nests are randomly chosen. Thereafter, only the best nest (with luckiest egg or best solution) shall prevail for next generation, $\mathbf{x}^*$. Nests with poorer solutions ($\mathbf{x}_i^t$) are replaced with new eggs, or with solutions from some available nests ($\mathbf{x}_i^{t+1}$) using a Lévy flight, as

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \zeta\,\nu(\mathbf{x}_i^t - \mathbf{x}^*), \tag{5}$$

where $\zeta > 0$ is the step size and its value is related to the size of the search space of the problem; $\mathbf{x}_i^t = (x_{i,1}^t, \ldots, x_{i,d}^t)^T$ is the $i$th solution at generation $t$ with $d$ components (or dimensions of the search space); and $\nu$ is a random number obtained from