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# Integration of fuzzy spatial relations in deformable models—Application to brain MRI segmentation

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**Abstract**

This paper presents a general framework to integrate a new type of constraints, based on spatial relations, in deformable models. In the proposed approach, spatial relations are represented as fuzzy subsets of the image space and incorporated in the deformable model as a new external force. Three methods to construct an external force from a fuzzy set representing a spatial relation are introduced and discussed. This framework is then used to segment brain subcortical structures in magnetic resonance images (MRI). A training step is proposed to estimate the main parameters defining the relations. The results demonstrate that the introduction of spatial relations in a deformable model can substantially improve the segmentation of structures with low contrast and ill-defined boundaries.

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## 1. Introduction

Spatial relations constitute the basic elements contained in linguistic descriptions of spatial configurations and describe the organization of the different objects in an image. These relations are usually classified into different types including topological, distance and directional relations [1]. Their importance has been highlighted in many domains related to computer science and engineering, such as artificial intelligence [1], computational linguistics [2], geographic information systems [3] or autonomous robotics [4].

In image analysis and pattern recognition, these relations provide structural knowledge by opposition to image features such as gray level or texture. Their ability to describe scenes [5,6] makes them potentially useful for a wide range of imaging applications including aerial imaging [5,7], face recognition [8] and medical imaging. Moreover, being close in essence to the natural language description, they can be easily understood and manipulated by a non-technical user who will then be able to interact more efficiently with image analysis procedures.

The analysis of brain magnetic resonance images (MRI) is a typical example of imaging application in which spatial relations can be useful. Indeed, the human brain is a structured scene and spatial relations are ubiquitous in natural language descriptions found in neuroanatomy textbooks [9]. Furthermore, relations between brain structures are more stable among individual subjects and less dependent on the acquisition parameters than the characteristics of the structures themselves. They can thus be a source a robustness for automated procedures.

Fuzzy sets constitute an appealing framework to represent spatial relations. Indeed, since they correspond to linguistic propositions, spatial relations are often intrinsically imprecise and fuzzy sets allow modeling this imprecision. The satisfaction of a given relation will then be defined as a matter of degree rather than in an "all-or-nothing" manner. Moreover, fuzzy sets provide a common framework to represent different types of individual spatial relations. In particular, the relations can be easily combined using fuzzy fusion operators. The fuzzy set framework has been used to represent different types of spatial relations including

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adjacencies [10], distances [11], directions [12], symmetries [13] and complex relationships such as “between” [14].

Spatial relations have been used in a relatively small number of pattern recognition applications. Keller and Wang [5] used spatial relations to automatically generate linguistic descriptions of images. Le Ber and Mangelinck [7] used topological relations to analyze satellite images. A handwritten recognition system based on directional relations has been proposed by Wang et al. [15]. Géraud et al. [16–18] have proposed to use fuzzy spatial relations for brain structure recognition on MRI. These relations were subsequently used for the same application in [19] in which they were combined to a possibilistic clustering method using a fusion framework. In all these applications, spatial relations were used for high-level tasks (i.e. recognition) and not directly integrated in the segmentation itself which was based only on image characteristics. However, spatial relations could be of great help to find the contours of poorly contrasted objects, with ill-defined boundaries or sharing similar intensities with their neighbors.

Several segmentation approaches implicitly integrate the spatial relationships between the objects of a scene. Atlas-based methods, e.g. [20,21], compute a nonlinear transformation between the target image and a labeled template. In such a way, the relations between the objects in the template are implicitly modeled. Point distribution models, which are used in active shape models [22], can infer not only the shape of individual objects but also the relations between them from a training set of instances. However, in these approaches, the spatial relations are defined implicitly in either the template or the training set and are not specified individually. We propose a different approach which aims at integrating explicitly individual spatial relations in the segmentation process. This should allow to model more directly expert knowledge expressed as linguistic descriptions and to explicitly choose the constraints which will be included in the segmentation, for example keeping only the relations which are anatomically meaningful.

Deformable models [23] refer to a large class of computer vision methods and have proved to be a successful segmentation technique [24] for a wide range of applications. Moreover, they constitute an appropriate framework for merging heterogeneous information such as image features and spatial relations. However, the accuracy of the segmentation results can be deteriorated when strong edges are lacking in the image. In those cases, the deformable model may leak through the boundaries of the objects. Spatial relations could help overcoming this difficulty by providing additional information about the spatial extension of the objects.

In this paper, we thus propose a methodology to introduce prior constraints based on fuzzy spatial relations in a deformable model. Spatial relations are represented as fuzzy subsets of the image space and are integrated in the deformable model as a new external force. The proposed framework is then used to segment brain subcortical structures in MRI. Our experiments show that adding spatial relations to a deformable model can prevent it from being attracted by contours of irrelevant objects and from progressing beyond the limits of structures with weak boundaries.

This paper is organized as follows. In Section 2, we briefly review the underlying principles of deformable models and present computational representations of spatial relations. Section 3 is devoted to the combination of spatial relations and deformable models. In Section 4, the proposed framework is applied to the segmentation of brain subcortical structures in MRI.

## 2. Background

### 2.1. Deformable models

Deformable models [23], also called active contours or snakes, are curves or surfaces evolving within an image from a starting point to a final state that should correspond to the target object (i.e. the object we want to segment). Two types of information drive the evolution: a data term that attracts the model towards the edges of the image and a regularization term that forces the model to stay smooth and regular. The evolution of a deformable model can be written as the minimization of the following energy [23]:

$$E(\mathbf{X}) = E_{int}(\mathbf{X}) + E_{ext}(\mathbf{X}), \tag{1}$$

where $\mathbf{X}$ is the deformable contour (or surface in 3D), $E_{int}$ is the internal energy that specifies the regularity of the contour and $E_{ext}$ is the external energy that drives the contour towards image edges. The external energy is computed by integrating on the contour a potential $P$ that should be minimum on image edges: $E_{ext}(\mathbf{X}) = \int_{[0,1]} P(\mathbf{X})\, \mathrm{d}s$. In the original formulation [23], the potential $P$ is derived from the image gradient.

The evolution can also be described by the following dynamic force equation [24]:

$$\gamma \frac{\partial \mathbf{X}}{\partial t} = \mathbf{F}_{int}(\mathbf{X}) + \mathbf{F}_{ext}(\mathbf{X}), \tag{2}$$

where $\mathbf{F}_{int}$ is the internal force and $\mathbf{F}_{ext}$ the external force. This expression is linked to the energetic formulation by $\mathbf{F}_{ext}(\mathbf{X}) = -\nabla P(\mathbf{X})$. However, this equation is more general since it allows using external forces that do not derive from an energy potential.

A considerable amount of research has been carried out on deformable models. Different external forces have been proposed to provide more robustness and a broader attraction range than the image gradient, e.g. [25,26]. Region-based forces have been designed and applied to the segmentation of textured images [27]. Furthermore, several authors have introduced prior shape constraints in deformable models, e.g. [22,28,29]. More details are beyond the scope of this paper and can be found in Refs. [24,29].

On the contrary, to our knowledge, fuzzy spatial relations have never been introduced in this context. Xu et al. [30] used

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