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# Example-guided segmentation

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ABSTRACT

In this paper, we propose a novel strategy to automatically segment volume data using a high-quality mesh segmentation of an "example" model as a guiding example. The example mesh is deformed until it matches the relevant volume features. The algorithm starts from a medical volume model (scalar field of densities) to be segmented, together with an already existing segmentation (polygonal mesh) of the same organ, usually from a different person. The pre-process step computes a suitable attracting scalar field in the volume model. After an approximate 3D registration between the example mesh and the volume (this is the only step requiring user intervention), the algorithm works by minimizing an energy and adapts the shape of the polygonal mesh to the volume features in order to segment the target organ. The resulting mesh adapts to the volume features in the areas which can be unambiguously segmented, while taking the shape of the example mesh in regions which lack relevant volume information. The paper discusses several examples involving human foot bones, with results that clearly outperform present segmentation schemes.



## 1. Introduction

The isolation of voxels in a three dimensional medical image that belong to an organ, called segmentation, is an important, challenging and current problem. It is of relevance for surgery planning, simulations, training and diagnosis. Despite great advances in the acquisition devices (CT, MRI, etc.), and the improvements in imaging techniques, problems still exist in connection with noise, artifacts, ill-defined boundaries, and distinct tissues with similar densities.

In consonance with the relevance of the problem, a very extensive literature exists, providing ever increasing fidelity of the results [1]. However, many established algorithms still involve a fair amount of direct help from a specialist. A current trend to improve this situation is to resort to model-based algorithms [2], but work remains to be done in some areas, as the reconstruction of bone joints. We explore in this paper the contribution to the robustness and to the minimization of operator intervention that we can achieve by using geometry processing techniques alongside the more established tools.

The main idea in the present paper is to use examples to drive the segmentation process. Segmentation will not only be based on the patient's captured volume information, but also on the geometric shape of the same organ from a different person.

The algorithm starts from a volume model (scalar field of densities) to be segmented, and an already existing segmentation (polygonal mesh) of the same organ in another dataset, usually from a different person. After an approximate 3D registration between the example mesh and the volume (this is the only step requiring user intervention), a pre-process step computes a suitable attracting field. The algorithm then adapts the shape of the polygonal mesh to the volume features in order to segment the target organ.

The main contributions of the algorithm we present include:

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- The formulation of an energy minimization problem that deforms the initial example mesh, trying to preserve its shape while adapting to the volume densities to be segmented. The algorithm maintains the topology and rough shape of the example mesh.
- An optimization algorithm based on iterating local operators, that succeeds in segmenting problematic cases with very limited user intervention: the initial coarse registration requires only the selection of four pairs of corresponding points.
- An adaptive algorithm that tends to use the volume information in the areas that can be unambiguously segmented, while importing the example shape in the areas with poor volume information.

Next section reviews the prior work, whereas Section 3 presents an overview of the algorithm, by formulating the segmentation problem as an energy minimization. Section 4 details the pre-process step and the computation of the driving scalar field and Section 5 presents the local operators that implement the optimization process. Section 6 presents and discusses the results on several case examples.

## 2. Previous work

Despite advances in medical imaging systems, the complexity of anatomical structures along with the lack of contrast, presence of artifacts, missing data and that densities do not map bijectively to tissues, make the automatic segmentation of medical images complex and challenging. No single segmentation technique may identify all anatomic structures and often medical experts must guide the segmentation given their knowledge about the shape of the anatomy.

A vast number of papers on image segmentation have been published in the last decades. Some of them focus on the segmentation of a specific structure. Hu et al. [1] present and discuss some general segmentation techniques categorized into four groups: region-based (thresholding, region growing, clustering, etc.), boundary-based (deformable models), hybrid and atlas-based. Region-based and boundary-based techniques exploit within-region similarities and between-regions differences, respectively, whereas hybrid techniques use both region and boundary features, and atlas-based techniques deform a template that reflects the anatomy of a specific structure to segment a new scan. Different authors provide other valid classifications [2,3].

Deformable models are curves or surfaces defined in an image domain that change their shape under the influence of forces. The forces are usually *internal*, from the curve or surface itself, and *external* from the image data. Deformable models were introduced by Kass et al. [4], as explicit deformable models and generalized to 3D by Terzopoulos et al. [5]. Since then, a number of papers have been published which propose new representations and deformation algorithms which allow the incorporation of changes to the topology of the initial shape, and offer improvements in the efficiency and robustness [6,7,1]. Although deformable models can be customized to segment specific structures, in the presence of missing data, fuzzy boundaries or artifacts, they require the help of a medical expert to complete the segmentation.

Deformable level set implicit surfaces provide a potential solution for the segmentation problem. Osher and Fedkiw [8] presented an algorithm based on dynamic implicit surfaces with evolving curves to solve the problem. Later, Chan and Vese [9] proposed to use the Mumford–Shah functional for 2D images without prominent edges. The minimization of the Mumford–Shah energy is known to produce better segmentation results than edge-based energy functionals, in regions with smooth boundaries. The Mumford–Shah energy of a certain temptative segmentation boundary $B$ is defined as a linear combination of the variances of the image values inside and outside $B$. Sharma et al. [10] use a modified Mumford–Shah energy with regularization which also includes terms depending on the surface area of $B$ and on the volume enclosed by $B$. They solve the variational problem by computing the steady state of a time-varying differential equation on a tri-cubic B-spline representation, for several segmentation sub-domains, using streaming-based algorithms [11] on 3D textures on the GPU.

Model-based (or atlas-based) methods aim to introduce medical knowledge into the segmentation algorithm. They usually consist of two steps. First the model is approximately located in the 3D image, then the shape (and appearance) of the model is optimized to perform the segmentation. The two best known general approaches are constrained deformable models which use a strong shape prior based on a simple example and point-based statistical models which store knowledge about the principal modes of variation of the template shape. The former could be considered hybrid methods [1] that use deformable models and regional information or a global transformation [12,2]. Heimann and Meinzer [13] present a complete survey of 3D statistical shape models. Probably the best-known methods in the area are Active Shape models [14] and Active Appearance models [15] by Cootes et al.

Model-based algorithms are the most robust methods when images are noisy or include artifacts. The major drawbacks are that statistical models require a large collection of training images, many shape parameters for complex structures and although additional constraints result in a higher robustness. They also limit the accuracy of the final result. Some recent approaches combine statistical and shape constrained approaches for the segmentation of specific structures (i.e. liver segmentation [16]).

Liu et al. [3] state that no segmentation framework (not even model-based) yield the level of precision, accuracy and efficiency that is required for some applications such as the segmentation of the bones at a joint in MR and CT images. The main problem is unclear boundaries between different tissues. They propose a strategy for intra-patient segmentation based on a segmentation of a bone in one position and using this model to segment the bone in other positions (images) by minimizing an energy function that utilizes both boundary and region-based information.

In our approach, the segmented shape of a known structure (bone) is deformed to identify the same bone in the CT