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Deformable models direct supervised guidance: A novel paradigm for automatic image segmentation

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ABSTRACT

Deformable models are a well-established and vigorously researched approach to tackle a large variety of image segmentation problems. However, they generally use a set of weighting parameters that need to be manually tuned, a task that is both hard and time consuming. More importantly, these techniques assume that the global minimum of the energy functional corresponds to the optimum segmentation result. However, it is difficult to model this condition a priori with a robust mathematical formulation, in particular when high precision of the segmentation results is required.

This contribution aims to establish an alternative approach for traditional optimization-based deformable model adjustment. This involves a general purpose, machine learning-based image segmentation framework that translates the available information into a different type of decision process. An automatically derived model is used to directly drive the deformable model evolution. In particular, we exploit ground truth information represented in a training image set by forcing the deformable model to evolve in a way that, in its final state, will make it perfectly cover the target object. This is done with the generation of a proper dataset of vector-label pairs, which we called the Image Vector-Label Dataset, the key element responsible of the integration of the different components in the framework: the deformable model, the term set, the driver, and the localizer. As opposed to classical optimization approaches, this framework gives the opportunity to automatically generate complex, nonlinear, and data-driven relationships among different sources of information, without any human intervention.

To prove the feasibility of our novel approach, we provide an effective reference implementation of our framework, tailored to the medical imaging field. We test it against a large set of state-of-the-art segmentation algorithms over two well-known image datasets with different image modalities and target structures. Although the proposed framework is not intended for a specific segmentation problem, its implementation is competitive or even outperforms most of the state-of-the-art algorithms specifically designed for the segmentation tasks at hand.

1. Introduction

Image segmentation is one of the most important image processing tasks and is a crucial step in many real world problems such as computer-assisted medical image analysis. Deformable models (DMs) [53,57,40] are promising and actively researched model-based approaches to tackle a huge variety of image segmentation problems. The widely recognized potency of DMs stems from their ability to segment, match, and track images by exploiting (bottom-up) constraints derived from the image data together with (top-down) *a priori* knowledge about the location, size, and shape of these structures.

From the classic snake model [43] to hybrid approaches using gradient vector flows [62] or watersheds [90], DMs have always involved an optimization process. Different families of optimization methods have been developed along the years. However, the requirements of many real image segmentation tasks are difficult to model with a robust mathematical formulation.

In particular, the energy minimization methods are often too generic to lead to a fine segmentation of thin structures, and when

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they give satisfactory results, they generally use weighting parameters that need to be manually tuned. Often these numerical parameters are obscure and their refinement time consuming. As pointed out by [68]: "the weighting coefficients are difficult to find especially when contours to be identified vary from one image to another".

There are many image segmentation problems where the numerical optimization process finds problems due to the non-homogeneous intensities within the same class of objects and the high complexity of their shape. This is, for example, the case of many medical images which involve high complexity of anatomical structures as well as large tissue variability [53,34].

Some of these problems can be solved by incorporating prior knowledge to the model [89]. In fact, well-known approaches [61,81] generally use energy minimization techniques to define the additional terms of the force from prior information. However, in fields such us medical imaging, the structures of interest are often very small compared to the image resolution and may have complex shapes with a significant variability. This makes it difficult to define energy constraints that remain both general and adapted to specific structures and pathologies [40].

Another important drawback of DMs is that the formulated minimization problem is difficult to solve due to the presence of numerous local minima and a large number of variables. On the one hand, this difficulty may lead to sensitivity to the initialization, complicating the unsupervised use of DMs. As images are assumed to be noisy, the external energy term is most probably multimodal. Hence, algorithms aimed at local optimization have problems optimizing deformable surface meshes. On the other hand, the global minimum of the energy function does not correspond to the best segmentation results in most of the cases. This makes the optimization task following a global approach harder, since in contrast to local approaches, it is really difficult to stop the model evolution at satisfactory local minima. In fact, the assumption of these techniques is that the global minimum of the energy function corresponds to the optimum segmentation result. However, modeling the segmentation problem with a mathematical formulation able to express such a function is a very difficult task, if not impossible, when a high precision of the segmentation results is mandatory.

In this contribution, we propose an alternative approach involving a different type of decision process based on translating the available information into a Machine Learning (MLR) [6] model that is directly used to drive the DM evolution. This approach gives the opportunity to automatically generate complex, non-linear, and data-driven relationships among different sources of information (e.g. both global and local image cues, and shape-related prior knowledge). Thus, in our novel approach, the learning process is guided by the ground truth information represented in a training image set. This way, the problem is tackled from a different perspective; instead of designing a general-purpose energy function *a priori* (and setting the values of the associated parameters) that performs well with the problem at hand being optimized, our alternative solution procedure is to derive the model directly from the desired results themselves using a MLR method.

The key contribution of this paper is thus the introduction of a general MLR-based image segmentation framework. Given a dataset of training images, the framework will allow us to automatically design a model able to segment targets of the same type as the ones found in the training dataset, with minimal human intervention. For that aim, the framework is made up of four main components which can be customized to design different specific image segmentation methods: the *deformable model*, the *driver*, the *term set*, and the *localizer*. The driver is a general purpose machine learning tool whose output directly guides the selected DM evolution, on the basis on the available information contained in the term set. A serious limitation of existing DMs is that the final result is sensitive to the location of the initialization. To deal with this, we introduced the localizer. It aims at finding a rough location of the target object in the image area, providing a proper initialization for the DM. Finally, an additional transversal component, the *integration mechanism*, defines the way the framework components are connected to each other. This is a key component that clearly differentiates this proposal from the few similar ones. We generate a dataset of vector-label pairs, called the Image Vector-Label Dataset, exploiting ground truth information by forcing the DM to evolve in a way that, in its final state, will make it completely cover the target object.

To prove the feasibility of the proposed framework, we provide an effective implementation tailored to the medical imaging field. This implementation is based on the flexible and fast Shi Level Set (LS) [72], the accurate and easy to train Random Forest classifier [14], the effective object localizer introduced in [32], and a large set of extended image features described in Section 4.

The structure of this paper is as follows. Section 2 reviews the relevant proposals dealing with the application of MLR techniques to the adjustment of DMs for image segmentation. Section 3 introduces our general purpose, MLR-based image segmentation framework while Section 4 describes an implementation of our framework tailored to the medical imaging field. Finally, Section 5 is devoted to the evaluation of our proposal performance in comparison with other extended image segmentation methods while Section 6 summarizes some conclusions on the work carried out.

2. Survey of machine learning applications to deformable model-based image segmentation

In specialized literature, the typical image segmentation and recognition process employing DMs is organized as a pipeline comprising the following steps: initialization, evolution, and recognition (optional).

The application of MLR to image segmentation and, in particular, to DMs has seen widespread adoption in the last decade. After an extensive review of the literature, we defined a taxonomy recognizing four different categories and classifying the MLR-based strategies accordingly. The first category defines those works that use MLR to initialize DMs or to impose some constraints to their evolution (e.g. avoid further evolution if the DM is already far from the provided initialization), as in [48,79,75,49,33,47]. Apart from this characteristic, DMs evolve using standard energy minimization approaches in these works. We named this category *initialization*.

A different approach is to employ MLR in the generation of an external energy term to be used in the standard DM optimization procedure [64,50,87,22,56,70]. A popular choice consists of performing texture analysis. In this case, texture statistics are calculated in a small window centered at each pixel. A classifier is trained to distinguish between object and background on the basis of these statistics. Finally, a DM external energy term is generated to take into account the output of the classifier. We named this category *energy term generation*. Within this same category we can also include Active Appearance Models [23,24]. They are statistical models combining the shape and the texture information of a certain class of images. Its training requires the matching of a shape model over the training images. Automatic techniques usually employ an iterative optimization method that adjusts the model to the specific corresponding image features.

A very popular approach is to employ MLR in the recognition step only. In these works the segmentation is performed by the