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Incorporating priors for medical image segmentation using a genetic algorithm

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ABSTRACT

Medical image segmentation is typically performed manually by a physician to delineate gross tumor volumes for treatment planning and diagnosis. Manual segmentation is performed by medical experts using prior knowledge of organ shapes and locations but is prone to reader subjectivity and inconsistency. Automating the process is challenging due to poor tissue contrast and ill-defined organ/tissue boundaries in medical images. This paper presents a genetic algorithm for combining representations of learned information such as known shapes, regional properties and relative position of objects into a single framework to perform automated three-dimensional segmentation. The algorithm has been tested for prostate segmentation on pelvic computed tomography and magnetic resonance images.

1. Introduction

Target-volume and organ-at-risk delineation on medical images such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound is quite subjective. The uncertainty and variability in the definition of tumor margins results in suboptimal treatment of patients. The development of automated segmentation tools are therefore essential but remain a challenge for several reasons, such as the variability in organ shapes and tissue contrast on medical images. Despite advances in imaging for radiation-therapy treatment planning (RTP), most medical image segmentation algorithms require some form of human intervention to perform satisfactorily [2–4]. These segmentation algorithms do not incorporate the prior knowledge of human anatomy and representations of known shapes, relative positions of organs, and textures that a human observer uses to manually segment an image. This paper presents a genetic algorithm for combining known priors of shape, texture and relative positions of organs to perform automatic segmentation. Genetic algorithms (GAs) [5,6] simulate the learning process of biological evolution using selection, crossover and mutation. Genetic algorithms are blind optimization techniques that do not need derivatives to explore the search space; instead they use payoff values known as fitness to guide the search. This quality can make GAs more robust [7] than other local search procedures such as gradient descent or greedy techniques used for combinatorial optimization. GAs have been used for a variety of image processing applications, such as edge detection [8], image segmentation [9], image compression [10], feature extraction from remotely sensed images [11], and medical feature extraction [9]. The image processing problem that has been explored in this paper is image segmentation: a technique for delineating a region of interest on an image.

Level set methods are widely used in the field of medical image segmentation due to their ability to represent boundaries of objects that change with time or are ill-defined [12,13]. In the level set method, a deformable segmenting curve is associated with an energy function. The energy function may consist of region-based terms (such as pixel intensity values, edges, etc.) and contour-based terms (such as curvature and length of the curve). Here, we have used a genetic algorithm to perform level set curve evolution for performing segmentation. A genetic algorithm (GA) replaces the explicit energy function term used by the level set curve evolution with an implicit fitness function which indirectly correlates texture, relative position and shape information with the evolving curve. This provides a framework for incorporating high-level features and combining multiple priors for segmentation. The level set-based genetic algorithm (LSGA) (introduced by the authors in [1]) uses the learned shape, textural properties of a known object derived from training images to segment thermographic images. This paper presents an extension of the LSGA by incorporating spatial relationships between organs for segmenting images. The individuals of the GA are vectors of

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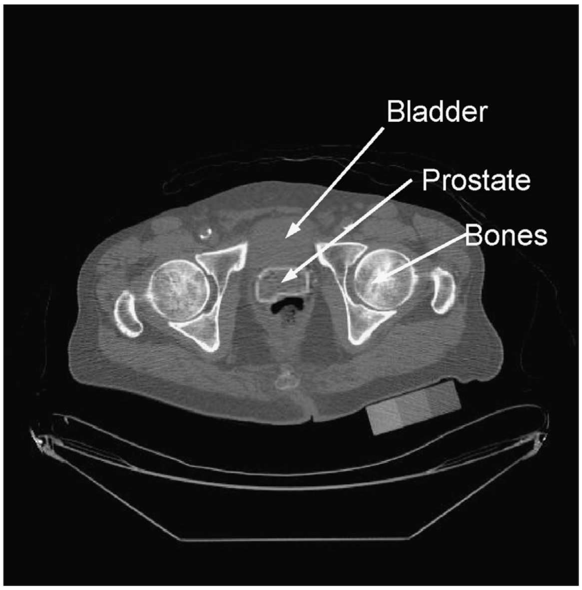

Fig. 1. A manually segmented prostate (shown as the white contour) from a single slice of a pelvic CT scan.

parameters of a level set function that the GA optimizes to produce *fit* individuals or good segmentations of a given image. The ability of the LSGA to combine multiple priors for segmentation is the main contribution of this paper. By incorporating derivative-free optimization for level set function optimization, the LSGA creates a framework for combining multiple features such as shape, texture, relative location information for segmentation. This allows the incorporation of several energy terms into the level set-based contour representation without increasing the computational complexity associated with computing derivatives in conventional curve evolution techniques.

Fig. 1 shows a typical pelvic CT scan from a patient suffering from prostate cancer and undergoing radiation therapy. Tumor delineation in the prostate is performed manually by a physician or a medical physicist for identifying treatment locations and determining radiation dosage as shown by the white contour in Fig. 1. The prostate is located between the bladder and the rectum, which are also labeled in the figure. Since the bladder and the rectum are more texturally prominent on these images; the radiologist uses the locations of these organs to approximately delineate the prostate on these images. Automating this task, therefore, involves incorporating the prior knowledge of shapes, textures and relative positions of organs present in a pelvic scan. The ability of the GA to combine multiple priors for segmentation is the main contribution of this paper. By incorporating derivative-free optimization for level set function optimization, the GA creates a framework for combining multiple features for segmentation. The paper is organized as follows: We first review the current methods and algorithms used for medical image segmentation and discuss the advantage of using a genetic algorithm over conventional optimization methods for level set curve evolution. The methodology is then described followed by the application for prostate segmentation on pelvic CT/MR scans. The strengths and limitations of the GA and future work are discussed at the end.

2. Literature review

Medical images are captured from parts of living organisms so that the structural information contained in them can be quantified and analyzed. They can be acquired in several modalities such as Computed Tomography (CT), Ultrasound (US), Magnetic Resonance Imaging (MRI), Spectroscopy and so on [16]. One of the main challenges of medical image processing is that the information present in these images is usually of a semantic nature. Therefore, an effective mechanism for mapping the pixel-based information to semantic information is needed before this information can be used for accurate diagnosis and treatment planning. Medical image analysis typically involves segmentation, recognition and classification. Here we describe the current state-of-the-art in medical image segmentation and discuss the need to incorporate unconventional optimization techniques such as genetic algorithms for image segmentation.

Segmentation is defined as the process of demarcating an object on an image with a contour. It is performed by determining properties of the object that differentiate it from the rest of the image. These properties can be image pixel-based properties such as edges, texture, pixel intensity variations inside the object, or object-level properties such as shape, size, orientation, location with respect to other objects, etc. The pixel-based features can be extracted using simple image processing routines on an image. For example, edges of an image can be derived using a gradient operator on the image. Texture is a pixel-level feature that quantifies the perceived physical appearance of a surface. Textural segmentation methods can be broadly classified into statistical, spectral and spatial filtering methods, and model-based methods. Statistical approaches such as moment-based methods [17], co-occurrence matrices [18] etc., quantify textures like coarse, grainy, smooth, etc. Spectral and spatial filtering methods try to simulate the human visual system [19] by performing local spectral frequency analysis [20–23]. Model-based methods such as Markov random fields (MRF) [24,25] and fractal-based modeling [26] have also been used for texture segmentation. One major drawback of all pixel-based segmentation algorithms is that there is no notion of shape in these methods and they can identify regions outside the object as being part of the object and. We demonstrate the outcome of using a texture-only approach on the problem of prostate segmentation using Gabor wavelets, described in the following section. Pixel-based operations are more suitable for problems where objects have prominent edges and markedly different textures inside and outside the object. Most medical images have noise and artifacts that appear during the image acquisition process and suffer from low contrast with broken/diffuse edges around regions of interest. Therefore, often an object-based approach or a combination of pixel and object-based techniques are more suitable for medical image segmentation.

Active-contour models are shape-based procedures where an energy function minimization drives contour deformation [12,27,28,29]. Leventon et al. [30] introduced statistical shape priors into their geodesic active-contour model to generate maximum *a posteriori* estimates of pose and shape. They segmented synthetic as well as medical images using their method and compared level-set evolution with and without shape influence. Tsai et al. [31] derived a shape-based level set function using statistics defined over local regions in a set of training images. They showed automatic segmentation results on several synthetic images and semi-automatic segmentation on cardiac and pelvic MRI images. Shape priors have also been used with active-contour-based image segmentation by Etyngier et al. [32]. They used diffusion maps to model shapes as finite-dimensional manifolds. Their segmentation results were accurate but the initial contour was placed manually in the images. Chan and Vese introduced a region-based energy function based on the piece-wise constant Mumford-Shah model [15], in order to detect features with diffuse boundaries. Their energy functional for curve evolution is given by:

$$\begin{aligned}F(c_1,c_2,C) &= \mu\cdot length(C)+\upsilon\cdot Area(inside(C))\\ &\quad+\lambda_1\int_{inside(C)}|u_0(x,y)-c_1|^2dxdy\\ &\quad+\lambda_2\int_{outside(C)}|u_0(x,y)-c_2|^2dxdy. \qquad (1)\end{aligned}$$