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Dynamic Programming Based Segmentation in Biomedical Imaging

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A B S T R A C T

Many applications in biomedical imaging have a demand on automatic detection of lines, contours, or boundaries of bones, organs, vessels, and cells. Aim is to support expert decisions in interactive applications or to include it as part of a processing pipeline for automatic image analysis. Biomedical images often suffer from noisy data and fuzzy edges. Therefore, there is a need for robust methods for contour and line detection. Dynamic programming is a popular technique that satisfies these requirements in many ways. This work gives a brief overview over approaches and applications that utilize dynamic programming to solve problems in the challenging field of biomedical imaging.

1. Introduction

Dynamic Programming (DP) introduced by Richard Bellman [1] is a widely used technique to solve optimization problems in a simple and efficient way. In computer vision, Amini et al. [2] showed on the example of active contours how DP can be utilized to perform energy minimization. Furthermore, DP was particularly used to detect lines in images [3] especially in the field of road detection in satellite images for example by Merlet and Zerubia [4], while Buckley and Yang [5] applied DP to solve a shortest path (SP) problem.

In biomedical imaging DP is a popular technique to find contours, lines and boundaries of organs, bones, vessels and cells. This survey focuses on applications in the field of biomedical imaging in particular on the detection and tracking of contours and structures by means of DP.

We organize our work as follows. In Section 2 we motivate this work by giving a short overview of issues in biomedical imaging. Then, in Section 3 we introduce common problems solved by DP and show examples of applications in Section 4. Finally, we conclude our work in Section 5.

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2. Motivation

In biomedical imaging many computer vision problems involve the detection of objects in pictures acquired through the various types of imaging techniques. A goal is to help physicians to automatically detect, track and analyze structures in biomedical images, to reduce the expert's workload, increase the productivity, and improve the accuracy of the diagnosis.

2.1. Application Overview

An example is the detection of the endocardial border of the heart [6–9] and its movement [10–12] that gives valuable knowledge (visually and quantitatively) about the heart function. Also artery and vessel boundary detection, e.g. presented in [13–21] is of great interest, where the detection and evaluation of vessel boundaries and vessel thickness (intima-media) is a marker to detect stenosis [16] or helps in the diagnosis of atherosclerosis [15,19]. The work in [22] proposes a technique to access the tree of fine vessels to determine their progress and density. Beside investigations in the field of blood supply, biomedical imaging is used to detect every kind of tumors, organs, bones, and even cells. The works in [23–26] propose methods to detect the ribs, spines and bones or specific parts of the spine, while [27,28] focus on tumor and cancer detection. The segmentation of microscopic cells includes approaches, where cell borders are detected fully automatically, e.g. [29–31], or where a single cell is

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segmented in a preselected ROI as done in [32,33]. Finally, there are various applications that utilize DP in ophthalmology to examine parts of the eye [34–36] and in the field of mammography to detect breast cancer [37–41].

2.2. Method Overview

Imaging modalities, e.g. MRI, ultrasound, X-ray, and microscopy, not only differ from their fundamental physical idea, but also in terms of usage (with contrast marker or without; invasive or not), application (2D or 3D; still images or image sequences), and the object or body part of interest. There exist a wide range of techniques and applications to detect and analyze their content. Some applications work totally automatically and some need user interaction. Most of these approaches have to deal with difficulties like inhomogeneities in the intensity of the targeted structures, strong noise or other artifacts depending on the acquisition system.

In terms of the described problems and the demand on a specific robustness, DP draws particular attention in biomedical imaging as it always finds a global optimum and it outputs a connected path despite of the presence of inhomogeneities and holes in the underlying image features. The various studies, introduced in this section, have in common to use DP in numerous ways.

Specific applications evoke specific questions. Most of the reviewed works try to find the shortest path to detect a contour or boundary in the image by minimizing some energy function by means of dynamic programming. Finding a contour or line by DP, for instance in ultrasonic data, demands techniques to properly carve out edges in the presence of noise and artifacts. This requires appropriate filtering and noise reduction such as proposed by Jia et al. and Lee et al. [26,27] or the integration of high-level information and prior knowledge to overcome uncertainties as approached by Oost et al., Koh et al. and Ungru et al. [9,23,42].

Another application with specific requirements are circular objects like cardiac and vascular borders in ultrasound and MRI [10,11,13] or cells in microscopic images [29,31-33]. Also the detection of the mammographic mass in a preselected ROI [37–41] or the segmentation of the optic disk in retinal fundus images of the eye as done in [36] aims to find circular structures by means of DP. These applications arise the need of finding a circular path with minimal cost: a circular shortest path (CSP). A CSP beside the optimality constraint demands the closedness of the contour as further restriction and is generally discussed by Sun and Pallottino [43] and Appleton and Sun [44] and applied on biomedical images among others in [8,10,11,13,24,29,33,37-39].

The evaluation of vessel border thickness [15,17-19], spine boundaries [25,45], ribs [24], or retinal [35] and corneal layers [34] necessitates to detect structures with two or more nearly parallel contours. In general, the set of simultaneous paths with the lowest cost in total is referred to as multiple shortest path (MSP). Nevertheless, it is important to note that not all of the works above search for an optimal solution for this problem.

A special type of shortest paths are active contours. Active contours are popular in biomedical imaging and can be implemented with DP as shown by Amini et al. [2]. Active contours usually need an initial contour, which is obtained by user interaction, random generation, or a contour of a previous frame (in image sequences). This initial contour is attracted iteratively through some forces to a local minimum as originally proposed by Kass et al. [46]. While active contours by Kass et al. are modeled as continuous curves, Amini et al. introduce a discrete DP-based optimization approach, where contours are represented by some control points connected via splines. A non-iterative approach of deformable contours is proposed in [10,11] to attract a contour (represented by a few control points) to the left ventricular border in MRI and track it over time. Other approaches like [19,25] mainly use shape constraints instead of initial points to diminish the search space to arrange the contour points and attract it to an object border. Deformation and tracking over time is also examined in the approach of Pham and Doncescu [28].

A further application of DP in biomedical imaging is proposed in [22], where a vascular tree is detected and represented as a graph by means of a region growing technique based on DP. This approach is the only reviewed approach that is not based on energy minimization (Table 1).

3. Problems and Solutions

As discussed in Section 2 the introduced applications can be categorized into a few problems. Most of them can be summarized as energy minimization tasks. A transfer of these problems into graphs allows us to simplify and generalize the description of the various reviewed approaches. An optimal path, hence the path with the lowest cost in a graph is also known as shortest path. This section gives a brief overview of shortest path problems solved by DP and introduces the most common methods.

3.1. Solving Shortest Path Problems by Dynamic Programming

A graph is a structure that contains nodes connected by edges. A path in a graph is a connection of several nodes via edges. Each edge can be associated with a specific weight, also known as cost. Then, finding the shortest path in a graph means finding the path with the lowest cost sum of all edges in the path. According to Felzenszwalb and Zabih [47] there are two forms of shortest path problems. The *single-source* type searches the shortest path from a source point s to each of the remaining nodes while the *all-pairs* search tries to find the shortest path between each possible pair of nodes in a graph. The mentioned shortest path problems can be solved by generic shortest path algorithms such as proposed by Dijkstra [48]. For an overview we refer to [49].

The single-source shortest path is the most frequently used type and can be efficiently solved by DP. Dynamic programming sequentially solves the shortest path problem by splitting it into simpler subproblems. Starting at node s, at each state $i = 1, \ldots, n$, the algorithm evaluates the shortest path back to s. Because DP works sequentially, it can only find shortest paths in a directed acyclic graph (DAG) that is exemplary illustrated in Fig. 1.

A shortest path search is often utilized for discrete energy minimization as shown in [5]. A common description of energy in computer vision consists of two terms: energy based on observations in some underlying data and energy of some prior, including constraints of smoothness:

$$E = E_{data} + E_{prior} \tag{1}$$

Table 1
Efficiency of the main methods.

Method	
SP	$\mathcal{O}(k^2 n)$
Matrix-based approaches	
– SP	$\mathcal{O}(kmn)$
– MSP	$\mathcal{O}(k^p m^p n)$
– CSP - MSA	$\mathcal{O}(km^2 n)$
– CSP - IPA	$\mathcal{O}(km\hat{n}), \hat{n} > n$
– CSP - MBTA	$\mathcal{O}(kmn)$
Active contours	
– ordinary approach	$\mathcal{O}(k^3 n)$
– circular contours, MSA	$\mathcal{O}(k^4 n)$
– circular contours, randomly fixed neighbors	$\mathcal{O}(k^3 n)$

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