Live-Wire Approach with FCM Clustering and Adaptive Filtering for Edge Detection in Medical Images

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Abstract

This paper presents a semiautomatic image edge segmentation method based on a modified Live-Wire algorithm. Main improvement of the presented algorithm, comparing to typical Live-Wire, is application of adaptive filtering of the input image and Fuzzy C-Means (FCM) clustering method to support the edge segmentation procedure. Thus possible edges are being searched in the proximity of boundaries between classes (regions) found by FCM method. Application of adaptive filtering improved the results of FCM clustering and cost map generation. The area searched for boundaries was vastly reduced thus significantly reducing computation time. Presented method was evaluated on magnetic resonance (MR) images of human neck, where soft tissue tumors were to be segmented. To contour the tumor using the presented method only a few points are required. This is large improvement comparing to manual tumor outlining still performed by many radiologists. Despite being in preliminary stage of development, obtained results encourage authors to further develop the method to be able to perform correct edge detection in various medical images, and to enable its operation in volumetric 3D data.

1. Introduction

During radiological diagnosis of soft tissue tumors it is important to determine tumor changes between patient's studies taken in some time intervals. According to found changes the radiologist can decide if the applied therapy is effective. Usually in radiological practice the largest diagonal of pathological tissue in selected transverse MR (magnetic resonance) slice is used to describe the tumor. This is not adequate, because tumor size can vary in each slice and its largest diameter can be perpendicular to the slices. Thus the volume of the tumor is more competent for this purpose. This unfortunately requires the radiologist to outline the tumor in each slice what is tedious and time consuming. For this reason there is a need for automatic or semiautomatic image processing tools to help the radiologists in their daily tasks.

One of methods suitable for finding boundaries of objects in an image is Live-Wire (LW) algorithm [1,2,3]. However, in its basic form it requires to perform a graph search on the whole image. This significantly increases calculation time and memory usage.

Development of Live-Wire methods is quite commonly found in the literature [4,5,6]. The main author also continues research in this field and proposed several approaches [7,8,9,10,11], this paper presents a preliminary step towards an another one.

The paper is organized as follows: the next section briefly describes the Live-Wire algorithm and its current modifications, section 3 shows the influence of an additional adaptive filtering using anisotropic diffusion of the input image on the edge segmentation process and results. The paper ends with a short summary in section 4.

2. Live-Wire edge segmentation

Live-Wire (LW) algorithm is an semiautomatic edge-based segmentation technique. It requires user interaction for providing characteristic points. Selected points are used to trace the boundary of a structure during the segmentation process. Image boundaries are represented by optimal paths linking the graph vertices (i.e. points) indicated by the user. Hence in the LW algorithm the image is seen as a weighted, undirected graph. Each graph vertex corresponds to a single image pixel and is connected with its eight neighbors. Additionally, a suitable weight assigned to each graph vertex describes the edge properties of the image pixel corresponding to this vertex. The full set of weights creates a matrix called an image cost map.

For each image pixel a weight describing its boundary properties has to be calculated. For this purpose various methods can be applied. In traditional LW method [1,2,3] image gradient features are adapted. Among them are: image gradient magnitude, image gradient direction, and laplacian zero-crossing. Other solutions employ the Fourier transform [12,13] or wavelet image decomposition [7,8,9]. The way the cost map is defined influences the final segmentation quality and precision of boundaries delineation.

Detection of the entire border in the image is carried out in several steps. In each step only a single border segment, limited by the pair of user selected points (the seed – starting – and the free – ending – point), is found. Every part of the boundary structure corresponds with the optimal path in the image graph, which connects vertices representing the seed and the free point.

To find a single border segment (optimal path) a graph searching algorithm is required. For this purpose the Dijkstra algorithm [14] has been used. It analyzes vertices and their neighborhood step by step, starting from the seed point manually selected by the user. As a result a tree rooted at this point is obtained. This tree constitutes a set of optimal paths that connect each image pixel with the seed point. In order to select exclusively one path the user has to specified a free (ending) point.

In order to compute the next edge segment the graph searching procedure is repeated. As the new starting point the ending point from the previous iteration is used, new ending point is provided interactively by the user. Usually, the analysis stops when the entire border of a structure is detected.

2.1 LW on-the-fly

In the traditional LW method even the detection of a short boundary part requires searching of the full graph (that is all image pixels). Thus the graph searching stage is the most time consuming. In order to decrease the size of the graph to be processed, the LW on-the-fly modification has been proposed [13,15,16]. This solution requires that the free point is specified before the graph searching procedure starts. The searching process stops when the free point is achieved. Therefore, the set of analyzed points grows around the seed point in each direction, until the free point is reached.

2.1 LW-FCM algorithm

Next improvement of the algorithm is also aimed at reducing the size of the graph to be processed [8,9,10,11]. Aforementioned solutions – the traditional LW method and the LW on-the-fly take into consideration each image pixel independent of its properties and context. From the edge-based image segmentation point of view pixels located in homogeneous area have no boundary features required by LW methodology and thus can be ignored.

To support the LW algorithm a Fuzzy C-Means clustering (FCM) algorithm is added in order to find image pixels of similar intensities. During FCM clustering the image pixels, described in terms of the gray level value, are classified into several classes (number of classes is a parameter that can be specified by the user). As a result, each image pixel obtains a class label, pixels located in homogeneous areas get the same class label, what indicates that no border appears in this region of the image. Only those pixels whose neighborhood belongs to a different class are considered to be located at or near a border and only those pixels are subjected to the graph search procedure. Additionally, the number of classes allows to change the sensitivity of the edge detection. For small number of classes only strong edges can be detected, whereas large number of classes enables a correct segmentation of structures surrounded even by weak and thin boundaries. However it also influences the numerical complexity of the LW-FCM method.

3. Adaptive filtering

The quality of edge segmentation results obtained using the LW method is mainly influenced by the image cost map describing edge properties of image pixels. Image artifacts and noise influence the cost map by injecting useless or troublesome information. In order to avoid such problems, the input image has to be initially preprocessed. The most commonly used method is image filtering. Conventional low pass filtering removes noise and most artifacts, however it also blurs the edges, what is an undesired effect for edge segmentation. Median filtering mainly removes the impulse noise from the image and has been still insufficient for application in our Live-Wire edge segmentation approach. Much better results have been obtained by adaptive filtering, in which the filtering kernel parameters are calculated for each image pixel separately. This way impulse or gaussian noise and small artifacts from the image can be removed without unnecessary blurring of relevant edges.

During adaptive filtering process the filter kernel and its parameters are calculated for each image pixel separately. The calculations are based on gradient amplitude between pixel and its neighbors. In our approach as an adaptive filter an anisotropic diffusion is used [17,18].

In figure (Fig.1a) an exemplary image from MR study of a patient with tumor in neck area is presented. The image is then filtered using aforementioned anisotropic diffusion (Fig.1c).

Both images are subject to FCM clustering and the results can be seen in figure (Fig.1b) and (Fig.1d). From the figures it can be seen that the clustering results in more homogeneous areas without considerable artifacts.

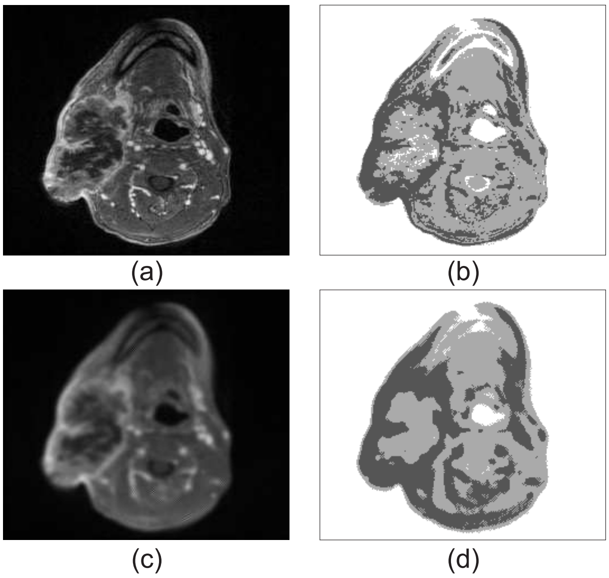

Fig.1. Original image (a), classes found by FCM clustering in the original image (b), filtered image (c), classes found by FCM clustering in the filtered image (d).

The improvement in the cost map creation can also be seen. Cost map from the image not subjected to filtering contains information about irrelevant edges or lacking connections in anatomical boundaries (Fig.2b), while the cost map generated form the filtered image (Fig.2d) does not contain noise and anatomical boundaries start to be visible. Strength of filtering for the whole image is changeable as a user specified parameter.

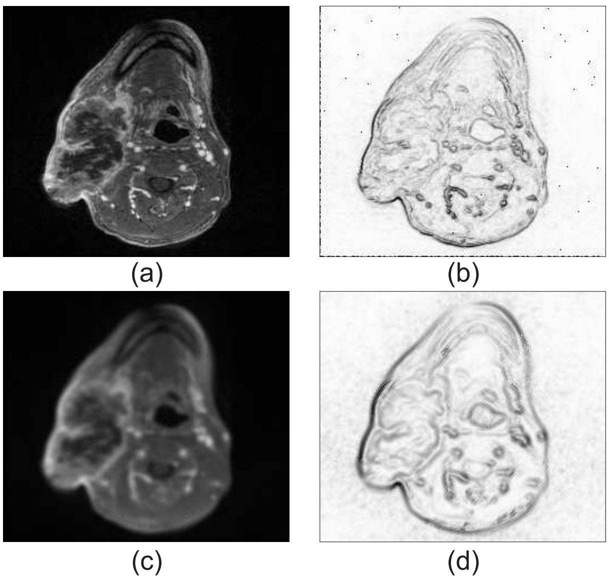

Fig.2. Original image (a), cost map from the original image (b), filtered image (c), cost map from the filtered image (d).

Final edge segmentation result is shown in figure (Fig.3). Main influence on decreasing the number of required control points has the FCM clustering step. This gives the possibility of smaller user interaction, but on demand the user can still place many points to ensure very precise edge segmentation if necessary. However even with a small number of selected points the segmentation results are more than satisfactory. In the figure the three manually selected points a marked with a thick short segment. Adaptive filtering allows to perform better quality of FCM clustering and thus smaller graph to be searched.

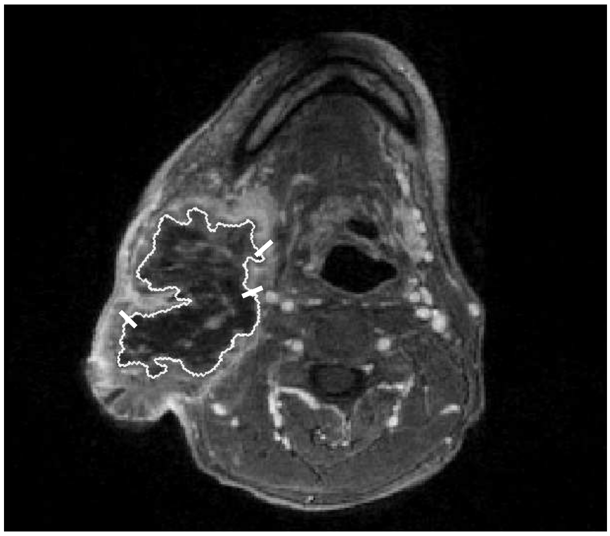

Fig.3. Segmentation results.

4. Summary

In this paper a preliminary step towards further improving edge segmentation methods based on Live-Wire algorithm (and its modifications) is presented. The improvement utilizes an application of an adaptive filtering by anisotropic diffusion of the input image. This step during the preprocessing stage allows a more precise generation of the image cost map. This gives better edge segmentation results. Promising results encourage authors to further develop the method to be able to perform edge detection in various medical images, and to enable its operation in volumetric 3D data.

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