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A Novel Medical Image Segmentation by Using Image Foresting Transform

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Abstract:

Seed-based methods for region-based image segmentation are known to provide satisfactory results for several applications, being usually easy to extend to multidimensional images. However, while boundary-based methods like live wire can easily incorporate a preferred boundary orientation, regionbased methods are usually conceived for undirected graphs, and do not resolve well between boundaries with opposite orientations. This motivated researchers to investigate extensions for some region-based frameworks, seeking to better solve oriented transitions. In this same spirit, we discuss how to incorporate this orientation information in a region-based approach called "IFT segmentation by seed competition" by exploring digraphs. We give direct proof for the optimality of the proposed extensions in terms of energy functions associated with the cuts. To stress these theoretical results, we also present an experimental evaluation that shows the obtained gains in accuracy for some 2D and 3D data sets of medical images.

Introduction:

Image segmentation, such as to extract an object from a background, is a well pursued topic in image processing and computer vision, that is useful for many applications such as medical and biological image analysis, and digital matting. However, in order to guarantee reliable and accurate results, user supervision is still required in several segmentation tasks, such as the extraction of poorly defined structures in medical imaging and arbitrary objects in natural images.

These problems motivated the development of several different methods for semi-automatic segmentation, aiming to minimize the user involvement and time required without compromising accuracy and precision. One important class of interactive segmentation comprises seed-based image segmentation methods, which adopt basically the following steps: The user provides a partial labeling of the image by placing hard region-based constraints (known as seeds).

After that, the seed's labels are propagated to all unlabeled regions by following some optimum criterion, such that a complete labeled image is constructed. Correction of wrongly segmented parts is accomplished by the addition and/or removal of seeds followed by the recomputation of the segmentation. This class encloses many of the most prominent methods for general purpose segmentation, which are usually easier to extend to multi-dimensional images, and that can also be adapted to automatic segmentation whenever the seeds can be automatically found.

Several seed-based image segmentation methods have been developed based on different theories, supposedly not related, leading to different frameworks, such as watershed, random walks, fuzzy connectedness, graph cuts, distance cut, image foresting transform, and grow cut. The study of the relations among different frameworks, including theoretical and empirical comparisons, has a vast literature. By ignoring some minor details, a diagram representation of these relations was also proposed, as shown in Figure 1.

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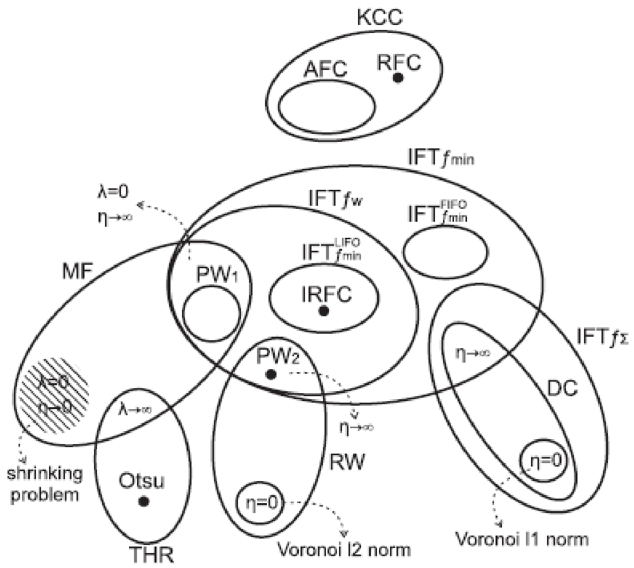

Fig.1. Schematic representation of the relations between methods

Where η is a power value applied to the arc weights, and λ ≥ 0 specifies the relative importance of object features.In this work we focus on developing extensions of a particular algorithm called IFT-SC -IFT segmentation by Seed Competition — which presents an excellent tradeoff between time efficiency and accuracy, as supported by earlier studies. In for instance, Iterative Relative Fuzzy Connectedness (IRFC) the top method from the fuzzy connectedness family — was implemented by using IFT-SC in linear time. IFT-SC provides optimum segmentation results from two points of view: as an optimum-path forest, as guaranteed by the image foresting transform (IFT); and as some optimum cut in the graph, according to the Generalize Graph Cut (GGC) segmentation algorithms framework. It can also be easily extended to multiple objects, but we will focus on binary image segmentation (object/background) for the sake of simplicity, and because it allows us to present in this work a novel formulation to IRFC, using a more elaborate connectivity function under the IFT framework. Despite the success of the region-based methods from seeds, many of them were conceived for undirected graphs and do not resolve well between boundaries with opposite orientations. On the other hand, boundary based methods, like live wire can easily incorporate boundary orientation to resolve between very similar nearby boundary segments (Figure 2), by favoring segmentation on a single orientation (e.g., counter-clockwise orientation).

In view of this, some region-based frameworks were later extended in order to incorporate the boundary orientation (boundary polarity), sometimes requiring a different algorithm to handle a more complex optimization problem.

Image Graphs:

In image processing Montanari and Martelli were the first to formulate a boundary finding problem as a shortest – path problem in a graph. Montanari required the boundary to be star-shaped. Martelli considered only a selected subset of the arcs and therefore, the algorithm failed in some situations. in region-based image segmentation, Udupa and Samarasekara and Saha and Udupa proposed the fuzzy connectedness theory for object definition, which was efficiently implemented by Nyul et al using Dial's bucket queue. Sharaiaha and Christofides used the Dial's algorithm to compute weighted distance and Chamfer distance transforms. Mayor extended the above work to some variations of the watershed transform based on the eikonal equation. Dial's bucket queue became the core of fast ordered propagation algorithms for various applications, including Euclidian distance transform, watershed transforms and morphological reconstructions.

A multi-dimensional and multi-spectral image Iˆ is a pair(I, Ɩ) where I Zn is the image domain and I (t) assigns a set of m scalars Ii (t), i = 1, 2, . . . ,m, to each pixel t I. The subindex 'i' is removed when m = 1.An adjacency relation A is a binary relation on I. Use t A(s) and (s, t) A to indicate that t is adjacent to s. Once the adjacency relation A has been fixed, the image Ɩ can be interpreted as a graph (I,A) whose nodes (or vertices) are the image pixels in I and whose arcs are the pixel pairs (s, t) in A. In this interested in irreflexive and symmetric relations. For example, one can take A to consist of all pairs of pixels (s, t) in the Cartesian product I ×I such that d(s, t) ≤ ρ and s = t, where d(s, t) denotes the Euclidean distance and ρ is a specified constant (e.g., 4-neighborhood, when ρ = 1, and 8-neighborhood, when ρ =√2, in case of 2D images). Each arc (s, t) A has a fixed weight w(s, t) ≥ 0 which may be computed from local image and object properties extracted from I . In this higher arc weights across the object's boundary should be considered, such as a dissimilarity measure between pixels s and t (e.g., w(s, t) = |I (t) − I (s)| for a single channel image Ɩ).

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The graph is undirected weighted if w(s, t) = w(t, s) for all (s, t) ⍰ A, otherwise we have a directed weighted graph. For a given image graph (I,A), a path πt = (t1, t2, . . . , t) is a sequence of adjacent pixels with terminus at a pixel t. A path is trivial when πt = (t). A path πt = πs •(s, t) indicates the extension of a path πs by an arc (s, t) (Figure). All paths considered in this work are simple paths, that is, paths with no repeated vertices (pixels). A predecessor map is a function P that assigns to each pixel t in I either some other adjacent pixel in I, or a distinctive marker nil not in I — in which case t is said to be a root of the map. A spanning forest is a predecessor map which contains no cycles - i.e., one which takes every pixel to nil in a finite number of iterations (Figures b and c, where R(πt) is a root node and P(t) is the predecessor node of t in the path πt). For any pixel t ⍰ I, a spanning forest P defines a path πt recursively as (t) if P(t) = nil, and πs •(s, t) if P(t) = s ≠ nil.

Segmentation with the Image Foresting Transform:

Image segmentation, i.e., the partitioning of an image into relevant regions, is a fundamental problem in image analysis. Accurate segmentation of objects of interest is often required before further analysis can be performed. Despite years of active research, fully automatic segmentation of arbitrary images is still seen as an unsolved problem. Semi-automatic, interactive segmentation methods use human expert knowledge as additional input, thereby making the segmentation problem more tractable.The segmentation process can be divided into two tasks: recognition and delineation. Recognition is the task of roughly determining where in the image an object is located, while delineation consists of determining the exact extent of the object. Human users outperform computers in most recognition tasks, while computers are often better at delineation. A successful semi-automatic method combines these abilities to minimize user interaction time, while maintaining tight user control to guarantee the correctness of the result.One popular paradigm for interactive segmentation is seeded region segmentation, where the user assigns labels (e.g., object and background) to a small subset of the image elements (known as seed-points). One popular paradigm for interactive segmentation is seeded region segmentation, where the user assigns labels (e.g., object and background) to a small subset of the image elements (known as seed-points).

An automatic algorithm then completes the labeling for all image elements. If the result is not satisfactory, the user can add or remove seed-points until a desired segmentation has been obtained. Many different algorithms have been proposed for performing the label completion, see, e.g. Here, we will focus on one such algorithm, the Image Foresting Transform (IFT). The IFT belongs to a family of graph-based methods, where the image is interpreted as a graph. Each image element corresponds to a node in the graph, and adjacent image elements are connected by edges. For each node in the graph, the minimum cost path from the node to the set of seed-points is computed.The cost of a path typically depends on local image features. By choosing an appropriate path cost function, popular image segmentation methods such as relative fuzzy-connectedness and watersheds can be implemented.The IFT can be computed efficiently using Dijkstra's algorithm, slightly modified to allow multiple seed-points. In interactive segmentation applications, a user often adds or removes seed-points to refine an existing segmentation. It was shown that seed-points can be added to, or removed from, an existing IFT solution, without recomputing the entire solution. This modified algorithm is called the differential IFT, and has been shown to give a significant reduction of the total time required for interactive segmentation.

In the original IFT, the resulting labels are crisp, i.e., each image element is assigned the label of exactly one seed-point. However, due to the finite resolution of digital images, an image element may be partially covered by more than one (continuous) object. By allowing mixed labels, it is possible to obtain segmentations with sub-pixel precision. Numerous studies have confirmed that pixel coverage segmentation outperforms crisp segmentation for subsequent measuring of object properties such as length and area/volume, see, e.g., it is shown that consequently misplacing the tissue borders, in a brain volume having voxels of size 1 mm3, by one voxel resulted in volume errors of approximately 30%, 40% and 60% for white matter, grey matter and cerebrospinal fluid, respectively. Segmentation methods with sub-pixel precision can also produce more visually pleasing results than their crisp counterparts. Surface extraction algorithms such as Marching Cubes can utilize sub-pixel precision to produce visually smoother surfaces. In the context of image compositing, sub-pixel segmentation is necessary to avoid aliasing artifacts.

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Here we propose a modified version of the IFT that computes labels with sub-pixel precision. In the following, we will refer to the original IFT method as crisp IFT, and the proposed method as sub-pixel IFT. Like the crisp IFT, the proposed method is defined on general graphs. Therefore, the method can be applied to higher-dimensional data without modification. Our method does not rely on any assumptions about the shape of the image elements. This makes the method more general, but also means that the output of the method is not strictly pixel coverage segmentation. Instead, we see the previously demonstrated advantages of pixel coverage segmentation as a motivation for including sub-pixel information in the IFT. We demonstrate that similar improvements in feature estimation can be achieved with the proposed sub-pixel IFT.

Proposed Segmentation Algorithm:

- Read the input MRI image.
- Initialize the region maximum distance and get the points for segmentation.
- Read the dimensions of input image and mean of the segmented region
- Free memory to store neighbours of the (segmented) region
- Start region growing until distance between region and possible new pixels become higher than a certain threshold
- Add new neighbors pixels and Calculate the neighbour coordinate
- Check if neighbour is inside or outside the image and Add neighbor if inside and not already part of the segmented area
- Add pixel with intensity nearest to the mean of the region, to the region
- Calculate the new mean of the region
- Save the x and y coordinates of the pixel (for the neighbour add process)
- Remove the pixel from the neighbour (check) list
- Return the segmented area as logical matrix.

Results and Discussion:

For validation of proposed segmentation algorithm several MRI brain images have been captured. Proposed segmentation algorithm is suitable for detecting cancer affected areas from a MRI images. Therefore all captured MRI images has fed to a proposed segmentation process to detect tumors and cancer affected area. The first MRI image input of the proposed algorithm is shown in below figure.

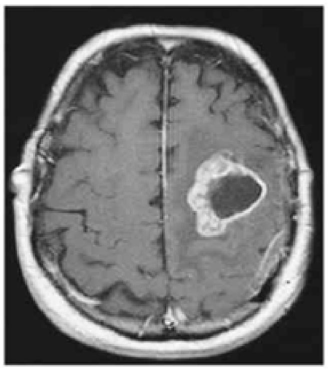

Fig: Input image

The result of proposed segmentation algorithm for first MRI input image is clearly segmented the affected area of brain. In proposed algorithm result the affected areas is easily identified and monitored for diseases diagnosis system. But for validating proposed algorithm one MRI input image is not enough. Therefore many other MRI images have fed to proposed algorithm.

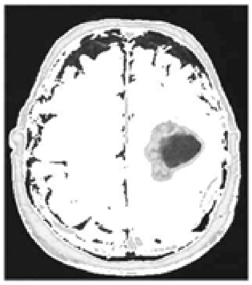

Fig: Output image

Proposed segmentation algorithm is applied for second MRI image to detect the tumors and cancer affected areas in the brain.

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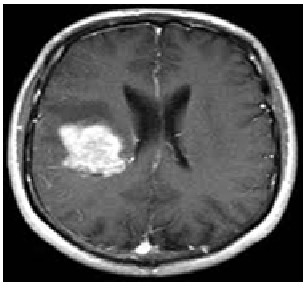

Fig: Input image

The result of proposed segmentation algorithm for second MRI input image is clearly segmented the affected area of brain. In proposed algorithm result the affected areas is easily identified and monitored for diseases diagnosis system.

Fig: Output image

Proposed segmentation algorithm is applied for third MRI image to detect the tumors and cancer affected areas in the brain.

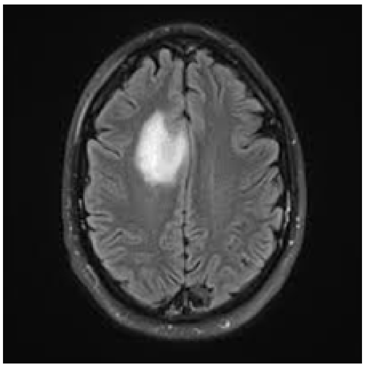

Fig: Input image

The result of proposed segmentation algorithm for third MRI input image is clearly segmented the affected area of brain. In proposed algorithm result the affected areas is easily identified and monitored for diseases diagnosis system.

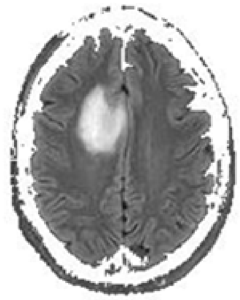

Fig: Output image

Proposed segmentation algorithm is applied for fourth MRI image to detect the tumors and cancer affected areas in the brain.

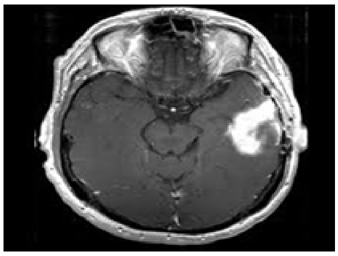

Fig: Input image

The result of proposed segmentation algorithm for fourth MRI input image is clearly segmented the affected area of brain. In proposed algorithm result the affected areas is easily identified and monitored for diseases diagnosis system.

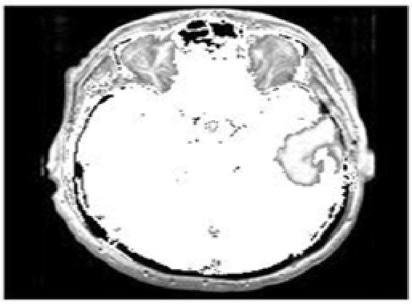

Fig: Output image.

Conclusion:

In existing the IFT-SC algorithm (IFT segmentation by Seed Competition), showing the importance of nonsmooth connectivity functions under the framework of the image foresting transform (IFT).

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The proposed segmentation algorithm accuracy has been verified with various MRI images the results are helpful for tumor detection and cancer affected area identification in different parts of the body in MRI images.

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