

Extremity bones segmentation in cone beam computed tomography, a novel approach

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Abstract. Bone segmentation in Cone Beam Computed Tomography (CBCT) may appear as a simple and efficient task. Unfortunately, this is not true for complex areas such as the hand, wrist or feet, where there are many small and thin bones that are very difficult to distinguish. In this article an efficient graph cut method to segment complex districts in CBCT has been developed.

A graph cut approach is initialized with an automatic "background" and "object" evaluation, carried out with pixel-based techniques, such as Otsu and Yen thresholding.

Segmentation result is post-processed with morphological operation, then connected components with 26-connectivity are evaluated to separate the different bone. Finally, the user can isolate the bone (or bones) of interest and display a 3D model.

The approach is compared with a standard graph cut approach which requires user scribbles to segment a single bone, both in terms of accuracy and usability.

Keywords: Segmentation, Computed Tomography, Bones, Foot and Ankle, Joints, Hand and Wrist, Graph Cut, Connected Component, User Interaction

1 Introduction

Cone-beam computed tomography (CBCT), an established imaging modality, is discovering new uses in the orthopedic field. The main benefit of CBCT scanners over spiral computed tomography is the capability to obtain 3D images more quickly, accurately, and with less radiation exposure, using smaller imaging devices [1]. That last point has made CBCT an effective imaging technique in emergency department and surgical rooms, specially for the diagnosis and treatment planning in extremities [2].

Clinical applications of this imaging modality will benefit from the development of more complex image analysis tools. In this sense, 3D models of bones

are of great interest in the orthopedic field, for intra operative guidance, reconstructive surgery and implant design. Moreover, new technologies such as augmented reality or 3D printing rely on the accuracy of 3D models. An accurate bone segmentation of CBCT volume is a crucial step to create three-dimensional models for orthopedics field.

A long bone's center section, also known as the shaft or diaphyses, is made up of hard, strongly attenuating, and thick cortical tissue that has higher values on tomographic scans. Segmenting the shaft of a long bone is a reasonably easy task because of the smooth bone borders and strong contrast between the cortical layer and the surrounding low-intensity soft tissue. Global thresholding, followed by fundamental morphological operations, can produce effective outcomes [3]. In contrast, short bones (cube-shaped with roughly equal vertical and horizontal dimensions) are made of spongy bone, covered with a very thin layer of compact bone. The wrist and ankle bones are examples of this kind of hard tissues. As Sebastian et al. [4] listed, there are manifold challenges regarding the segmentation of these kind of hard (shorts bones and epiphyses) tissues from tomography volumes:

Low-contrast and weak bone boundaries: thickness of the cortical shell is lower than in long bones.

Varying density of cancellous tissues: cancellous bone tissue is vascular and spongy, giving the appearance of textured and inhomogeneous bone. Thus, bone tissues density characteristics cannot be uniformly described. Hence, simple segmentation methods such as region growing or thresholding unavoidably produce inadequate results [4].

Narrow inter-bone spacing: the articular space between adjacent bones is extremely narrow. The inter-bone zones are diffused and brighter due to the partial volumetric effect, which is a characteristic of the CT modality and makes the bones appear to be in close proximity.

Bone segmentation in the extremities can be recognized as a challenging task. Moreover, extremities such as foot, ankle, hand and wrist, are characterized by a huge number of small, asymmetrical-shaped structures and densities.

Image processing solutions must be designed to facilitate and expedite this work while minimizing manual interaction and inter-operator variability [5]. The application of graph cut for user-friendly single bone segmentation and labeling in CBCT of extremities is discussed in this work.

Graph cut is a well known approach, Boykov et al.[6] applied it to image segmentation for the first time. In the past years, many researchers have applied this method to bone segmentation. Aslan et al. [7] use this approach to segment a single vertebra in CBCT scan. Liu et al. [8] interactively separate bones in CT scans, applying graph cut to segmented images. Pauchard et al. [9] use graph cut to compute a femur finite element model from clinical computed tomography scan for hip fracture prediction.

In conventional graph cut algorithm, the user makes scribbles on the input image to select background and object [10]. In this work an automatically seeded algorithm is presented, in which the initialization has been done with a mask

obtained through automatic thresholding. This allows to have a larger number of seeds pixels and results in an improved accuracy of segmentation. Moreover, this novel approach reduces user interaction to segment a single bone, as no background scribble from the user is required. Once all the bones were segmented, they are labelled via a connected component algorithm, then the bones of interest are extracted through a user interaction.

In this article, the overall approach is illustrated and some results are reported. Then, these results are compared with the traditional graph cut approach in the aim of extract a single bone, in term of accuracy and usability.

2 Materials and Methods

The aim of this work is to segment a single bone in Cone Beam-CT scan of the extremities, in an accurate and user-friendly manner. To develop and test our method ten Cone Beam CT scans of the extremities were available. In this section, a segmentation algorithm based on graph cut approach is presented. Graph cut is a segmentation approach that considers both regional and boundary characteristics of the volume, this makes it suitable for segmentation in our target area. In graph cut segmentation the volume is represented as a graph [11][12], a graph $G = (V, E)$ is a generic structure made up of a collection of nodes V that represent the original image's pixels or voxels and a set of arcs (or edges) E that connect the nodes. Two unique terminal nodes, source s and sink t , which stand in for "object" and "background," respectively, in biobject segmentation are present in addition to nodes set V . As shown in Figure 1 the graph has two different kinds of edges represented in yellow and in blue or red. The first form, called n-links, which connects nearby pixels, uses the prefix "n" for "neighbor." The second kind of t-links, where "t" stands for "terminal," joins terminals and pixels.

In a graph G , a s/t cut is the split of V into two disjoint subsets S and T , with all object voxels connected to an object terminal node S and all background voxels attached to a background terminal node T . The objective is to choose the appropriate cut that will produce the best results given the segmentation requirements. The cheapest cut is also the best cut because it is the least expensive. The following energy function, which takes into account both regional and boundary factors, can be minimized to get the best cut.

$$E(A) = \sum_{p \in P} R_p(A_p) + \sum_{(p,q) \in N} B_{p,q}(A_p, A_q) \quad (1)$$

A_p is the label of pixel p in an image P . The first term is a regional term and $R_p(A_p)$ is the penalty to assign label A_p to pixel p . The region energy function should reach the smallest value if labels are correctly assigned to all the pixels. The second term is a boundary term $B_{p,q}(A_p, A_q)$, which can be interpreted as a penalty for discontinuity between p and q . $B_{p,q}(A_p, A_q)$ is large when p and q are similar and near to zero when p and q are completely different. In another word, if p and q are similar, then the probability that they belong to the same

object is high. Otherwise, p and q may belong to different objects. Therefore, boundary energy is small if neighboring pixels p and q are different.

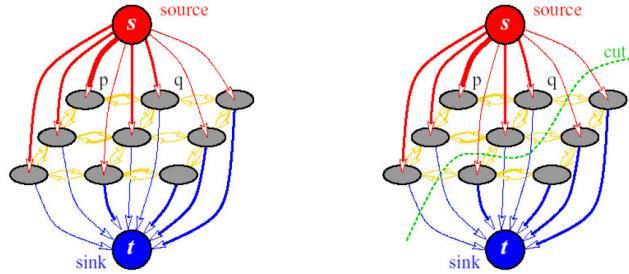


Fig. 1: Graph cut segmentation algorithm.

N-links (neighbor-links) connect (typically) two neighboring nodes and are associated with the boundary terms. In our implementation their cost is

$$w_{p,q} = f(|I_p - I_q|) \quad (2)$$

where I_p and I_q are intensities at pixels p and q and $f(x) = K * \exp(-x^2/\sigma^2)$

T-links (terminal-links) represent regional image properties and are connected to two terminals in the graph. For the smallest cost cut, inexpensive edges are attractive choices. The object and background model determines the weights of the T-links R_p to the object and the background vertex.

$$R_p(\text{obj}) = -\ln(\text{Pr} < I_p | O >) \quad (3)$$

$$R_p(\text{bkg}) = -\ln(\text{Pr} < I_p | B >) \quad (4)$$

where $\text{Pr} < I_p | O >$ and $\text{Pr} < I_p | B >$ represent likelihoods for object and background and are given by Gaussian mixture model.

These likelihoods for background and object are constructed based on an initialization mask, in which each pixel is marked as background object or probable background or object.

Accordingly with the characteristic of extremity bones in CBCT, an automatic labeling of volume data is performed. This is achieved using the well-known threshold techniques Yen and Otsu [13], [14]. With Yen algorithm, a threshold to identify sure foreground pixels is calculated.

Otsu method determines a threshold to identify sure background in the volume. All the pixels included in the range between these thresholds are labeled as uncertain pixels to be evaluated from the graph cut algorithm.

The segmented volume resulting from this algorithm is post processed with morphological operations. Bones making up extremities are separated via connected components labeling approach in three dimensions using a 26-connected neighborhood.

Ultimately, a Graphic User Interface (GUI) developed in Python allows the user to select the bone of interest. The segmented bones are rendered in 3D.

3 Results

Table 1: Comparison of the results on wrist and foot dataset. Dice Coefficient Score (DSC) is provided for both the proposed Graph Cut (GC) method and Graph Cut (GC) with user scribbles.

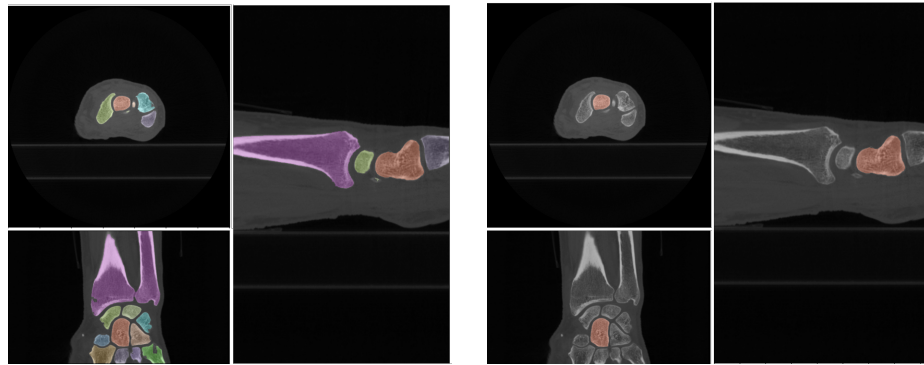
Target Bones	GC scribbles	GC threshold
Trapezium	0.867	0.896
Scafoïd	0.890	0.901
Lunate	0.823	0.896
Navicular	0.882	0.897
Talus	0.875	0.891
Medial Cuneiform	0.793	0.820
Proximal Falangis	0.784	0.882
Navicular	0.896	0.898

In this work, a dataset of ten CBCT volumes is evaluated. The dataset consists of four feet scans, four wrist scans and two knee acquisitions. In Figure 2 and 3 the performances of the presented approach on foot and wrist are presented. The algorithm is capable to segment and labels all the bones in these districts and the user can easily select the bone of interest, quickly switching among adjacent bones.

The benchmark for testing our approach performances is the classical Graph Cut approach in which user makes a scribble to initialize the algorithm and to calculate object and foreground likelihood.

In term of usability, our approach requires less user interaction and provides more flexibility in segmenting adjacent bones. Because the user select bones after the entire district is segmented, this allows a faster selection of the desired bone.

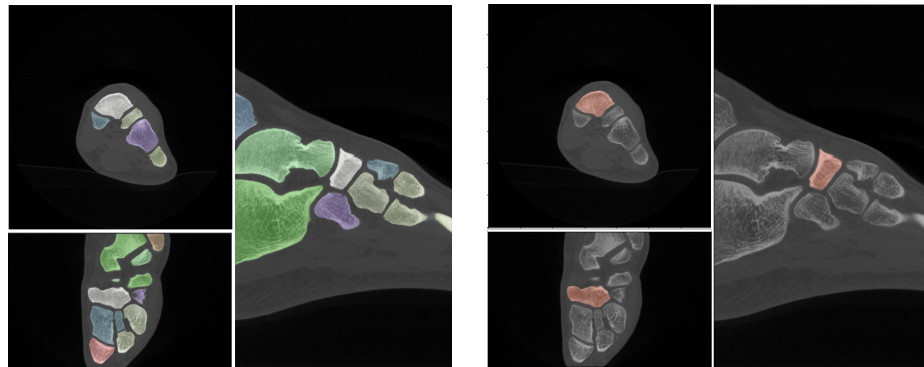
In quantitative terms, the well know metrics of Dice Score Coefficient (DSC) is used. A manual segmentation of specific wrist and foot bones is performed using 3D Slicer and then used as the ground truth for metrics evaluation. Table 1 reports performance in term of DSC between our approach and classical graph cut, in the segmentation of specific bone targets in wrist and foot.



(a) Graph cut segmentation and connected component labeling

(b) Capitate bone selection with a click on the corresponding label

Fig. 2: Wrist bones segmentation obtained with the proposed approach.



(a) Graph cut segmentation and connected component labeling

(b) Navicular bone selection with a click on the corresponding label

Fig. 3: Foot bones segmentation obtained with the proposed approach.

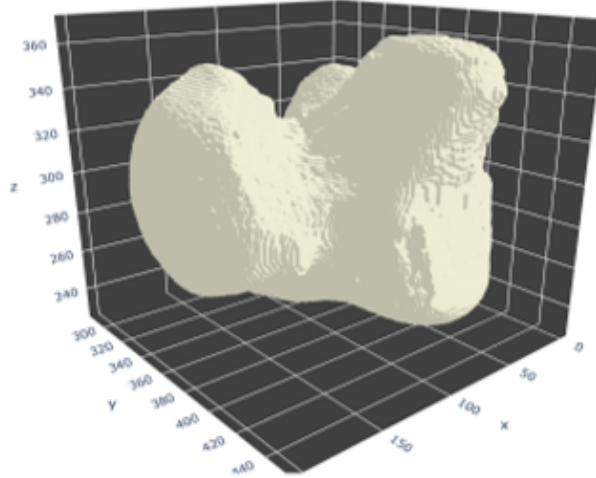


Fig. 4: 3D rendering of the Navicular bone obtained with the proposed approach

4 Conclusions

CBCT imaging modality is discovering new applications in orthopedics, especially in the extremities. In this work, a novel approach to fast and accurate segment single bone in the extremities is presented. Extremities 3D volume data obtained by the promising imaging techniques of CBCT has been used. First, the algorithm labels volume according to Yen and Otsu thresholding in order to create a map of pixel used to initialize Graph Cut. Then, the algorithm computes bone segmentation. Connected components are computed to label different bones. Finally, the user selects a single bone of interest (or several ones). A 3D rendering of bone is proposed.

This method has been compared with a standard graph cut approach in which the user has to labeling manually the bone of interest as "object" and the others as "background". Results demonstrate that our approach is more accurate, since it's better in term of the dice coefficient score. Regarding system usability allows less user interaction, resulting more user-friendly.

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