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# Interactive segmentation of lumen border in OCT

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**SUMMARY**

In this paper, we present an approach for user assisted segmentation of lumen border in OCT images. This interactive segmentation is performed by a combination of point based soft constraint on object boundary and stroke based regional constraint. The edge based boundary constraint is imposed through searching the shortest path in a three-dimensional graph, derived from a multi-layer image representation. The user points act as attraction points and are treated as soft constraints, rather than hard constraints that the segmented boundary has to pass through the user specified points. User can also use strokes to specify foreground (region of interest). The probabilities of region of interest for each pixel are then calculated and their discontinuity is used to indicate object boundary. This combined approach is formulated as an energy minimization problem that is solved using a shortest path search algorithm.

**Key Words:** *Image segmentation, graph segmentation, Dijkstra shortest path, OCT segmentation, lumen border.*

## 1 INTRODUCTION

Optical Coherence Tomography (OCT) imaging technique is a catheter based technology, used in cardiology diagnosis. This catheter based approach is widely used to assess the severity of any stenosis present and to categorize their morphology. It also allows for the measurement of vessel diameter the location of any lesions, as well as many other clinical and therapeutic studies. In most OCT images, a cross-section of the arterial wall is proceeded, with three regions: the lumen, the vessel (made up of the intima and media layers), and the adventitia surrounding the vessel wall. The media-adventitia border is the dividing layer representing the outer arterial wall.

There have been many different approaches to the problem of segmenting medical images, such as IVUS images, e.g. [12, 11, 6, 5, 7, 15, 2, 10, 9]. These can be broadly categorized into fully automatic methods, or methods that allow user interactions, which can act as a basis for segmenting the similar images produced by OCT. Methods incorporating user prior knowledge into segmentation hence is often necessary and has been shown to be an effective approach [3, 7]. For instance, in [7] Ehab *et al.* incorporated a shape prior into graph cut construction to regularize segmentation of media-adventitia border. However, these approaches generally require significant amount of training data and model re-training is often necessary in order to adapt to new dataset. User initialization is an alternative approach to transfer expert knowledge into segmentation, e.g. [1, 13, 14, 16, 4, 8, 17, 18, 19, 20]. However, most user interactions are limited to either boundary based landmark placement or strokes indicating foreground and background regions. in this work, we propose an approach to combine these two different types of user interactions, i.e. boudary based and region based, to segment lumen border in OCT. The user points, are treated as soft constraint, instead of hard constraint in most interactive segmentation methods. We show that this soft user constraint allows effective combination of boundary and region based features. The method is compared on an OCT dataset with manually labelled "ground-truth" and compared against state-of-the-art techniques.

# 2 METHOD AND RESULTS

The proposed method involves the user selecting a series of points on the image and in order to enhance the image segmentation, the user can also select areas for foreground using strokes. These then form the basis of the energy function.

By assuming the user points are in a sequential order, we construct a multi-layer graph with each layer encapsulating a single individual user point. The segmentation problem is then transformed into searching the shortest path in this layered graph.

Conventionally, user input to segmentation is focused on foreground and background specification [1, 13, 14, 16]. For example, in [13], the user interaction consists of dragging a rectangle around the object of interest and in doing so the user specifies a region of background that is modeled in separating the foreground object. Several other methods require user to specify points on the object boundaries instead [4, 8, 17]. However, more often than not, these boundary based user points are treated as anchor points and the segmentation path has to go through them. This kind of hard constraint is not always desirable. It does not allow imprecise user input, and it can lead to difficulties in combining region based and boundary based approaches as discrepancy between different object descriptions is generally expected. Notably, in [17] the authors introduced soft constraint user point by embedding the user constraint in distance functions. The segmentation result is considered to be the shortest path to loosely connect the user points. In this work, we follow this approach to treat boundary based user points. However, we also allow user to place region based strokes. These strokes are used to model foreground probability, and the discontinuity in foreground probability indicates the presence of object boundary. We combine these two types user input with image features in an energy functional which is then optimized using graph partitioning through finding the shortest path from the first to last user points.

We construct a layered graph from the set of user points. The user points are assumed to be placed in a sequential order, which reduces the complexity from NP-hard to polynomial time.

For each user point, $X_i, i \in \{1, 2, ..., n\}$, we create a layer of directed graph. In that way we have a series of layers equal to the number of user points $n$, plus an additional layer to ensure a closed curve. This results in a multi-layer directed graph, $G = (V, E)$. For each pixel $p$, there exits an edge $e$ to each of its neighboring 8 pixels on the same layer. Therefore, a pair of neighboring pixels $(p, q) \in N$ with a corresponding edge $e = (v_p, v_q)$ also have an edge to the corresponding point on the superseding layer $e = (v_{p_n}, v_{p_{n+1}})$. For each edge, we assign a weight $w$ to build a weighted graph $(G, w)$. These weights are calculated based on whether the edge is internal to a layer ($w_i$) or trans-layer ($w_x$). By creating the graph in this way, an order is established with the user points.

The edges on the directed layered graph are categorized as internal edges $w_i$ within individual layers and interlayer edges $w_x$. The weighting for these two types edges is assigned differently.

The internal edges are assigned with two types of weights, i.e. boundary based edge weights and region based edge weights. The boundary based edge weights are calculated based on the magnitude of image gradients. The region based edge weights are computed from foreground probabilities, obtained from the user strokes and the attraction force imposed by user points and is materialized through the interlayer edge weights $w_x$.

The attraction force imposed by user points is materialized through the interlayer edge weights $w_x$.

Therefore, the energy function for any curve $C$ in our method is a combination of three terms, i.e.

$$\mathcal{E}(C, s_1, ..., s_n) = \alpha \sum_{i=1}^{n} ||C(s_i) - X_i|| + \beta \int_{0}^{L(C)} g(C(s))ds + \int_{0}^{L(C)} g_f(C(s))ds, \quad s.t. s_i < s_j, \forall i < j. \tag{1}$$

The first term is used to enforce the soft constraint by the user points, and it penalizes the path further away from the user points. The second term is the boundary based data term that prefers the path passing through strong edges, while the last term is the region based data term which prefers path traveling through abrupt changes in foreground probability. By using the layered graph construction, the minimization of the energy functional is achieved by finding the shortest path from the start point $r$ to the end point $t$. The Dijkstra's algorithm is used to calculate the shortest path in the layered directed graph.

We compare our method on example images against the recent star graph-cut method [16] which utilizes user input and a generic shape prior as a constraint. This star shape constraint requires the object boundary does not occlude itself from the center of the object, star point, which is very appropriate for OCT segmentation. We also show performance of the proposed method with user points alone, i.e. without user strokes. Fig. 1 shows our preliminary results.

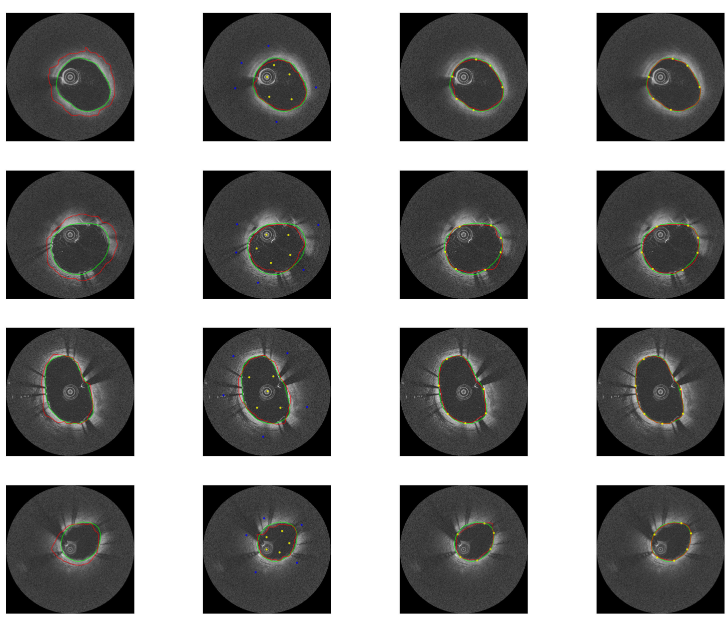

Figure 1: Comparison between groundtruth (green) and (from left to right) Star Graph Cut, Seeded Star Graph Cut, Single Method (no regional constraints), Proposed Method (red).

## 3 CONCLUSION

We present an interactive segmentation technique which combines boundary based and region based object representations, adopting a layered graph representation to simplify computation.

The proposed method was compared against a very recent graph cut technique that uses both implicit shape prior and user initialization, and shows very favourable results in the preliminary data.

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