RELAXED ORIENTED IMAGE FORESTING TRANSFORM FOR SEEDED IMAGE SEGMENTATION

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INTRODUCTION

In graph-based and seeded methods for image segmentation:

- A provided partial labeling of the image is propagated to all unlabeled pixels to obtain an optimal partition of an image graph.
- There is no unique method that performs best in all applications and rating criteria.
- Hybrid methods combine them in order to achieve a compromise between robustness, accuracy, shape regularity and efficiency.
- In this work, we intend to extend Relaxed IFT by Malmberg et al. to directed graphs, to properly incorporate the boundary polarity constraint, by proposing a novel hybrid method: Relaxed OIFT.
- Relaxed OIFT lies between the pure OIFT at one end and the extension of Random Walks (RW) to digraphs by Singaraju et al.

BACKGROUND: RELAXED IFT

- As proposed by [Malmberg et al., 2010], for an initial computed segmentation by Image Foresting Transform (IFT), a sequence of fuzzy segmentations by iterative relaxation is obtained as follows:

$$\mathcal{L}^{i+1}(s) = \begin{cases} \frac{\sum_{t \in \mathcal{N}(s)} \omega_{st} \cdot \mathcal{L}^i(t)}{\sum_{t \in \mathcal{N}(s)} \omega_{st}} & if\, s \notin \mathcal{S}_o \cup \mathcal{S}_b \\ \mathcal{L}^i(s) & otherwise \end{cases}$$

The final crisp $\mathcal{L}$ is then obtained, by assigning $\mathcal{L}(s) = 1$ to all $s \in \mathcal{V}$ with $\mathcal{L}^N(s) \geq 0.5$ and $\mathcal{L}(s) = 0$ otherwise.

BACKGROUND: OIFT

- OIFT [Miranda and Mansilla, 2014] lies in the intersection of the frameworks of IFT and Generalized GC (GGC). It considers the following energy for a crisp segmentation in a symmetric digraph:

$$E_2(\mathcal{L}) = \max_{\langle s,t \rangle \in \mathcal{A}:\, \mathcal{L}(s)=1} \omega_{st} \cdot |\mathcal{L}(s) - \mathcal{L}(t)|$$

Let $\mathcal{U} = \{\chi_P : \mathcal{S}_o \subseteq P \subseteq \mathcal{V} \setminus \mathcal{S}_b\}$ denote the universe of all possible segmentations separating $\mathcal{S}_o$ from $\mathcal{S}_b$. OIFT computes an optimum partition $\mathcal{L}'_{opt} \in \mathcal{U}$ by minimizing E_2 in a symmetric digraph, that is, $E_2(\mathcal{L}'_{opt}) = \min_{\mathcal{L} \in \mathcal{U}} E_2(\mathcal{L})$.

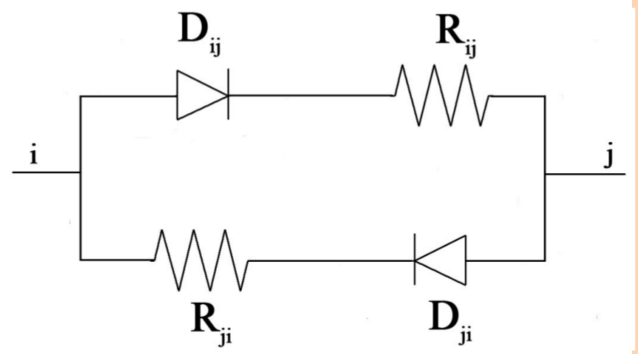
- To exploit the boundary polarity, we use the arc weights by:

$$\omega_{st} = \begin{cases} [\kappa_{st} \times (1-\alpha)]^\beta & \text{if } I(s) > I(t) \\ [\kappa_{st} \times (1+\alpha)]^\beta & \text{if } I(s) < I(t) \\ [\kappa_{st}]^\beta & \text{otherwise} \end{cases}$$

where the weights ω_{st} are a combination of an undirected affinity function κ_{st} between neighboring nodes s and t, multiplied by an orientation factor for $\alpha \in [-1, 1]$.

METHOD: RELAXED OIFT

- To extend Relaxed IFT to directed graphs, we consider OIFT and an energy function for the relaxation procedure, which has an equivalent electrical network problem with diodes and resistors [Singaraju et al., 2008].

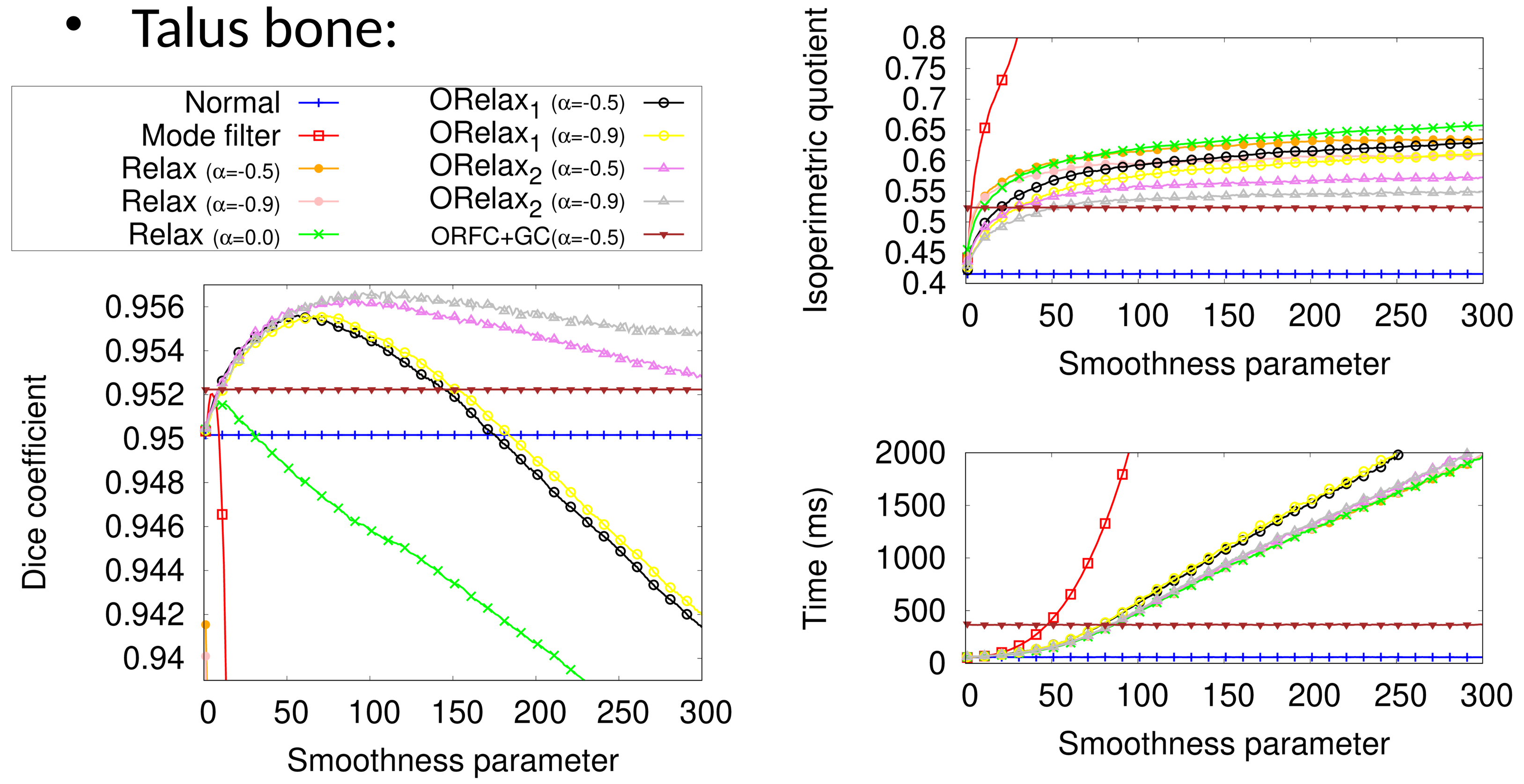


- In our solution, we perform a relaxation step, after setting the active diodes based on the potentials values from the previous iteration, by replacing the weights ωst of the ith iteration by:

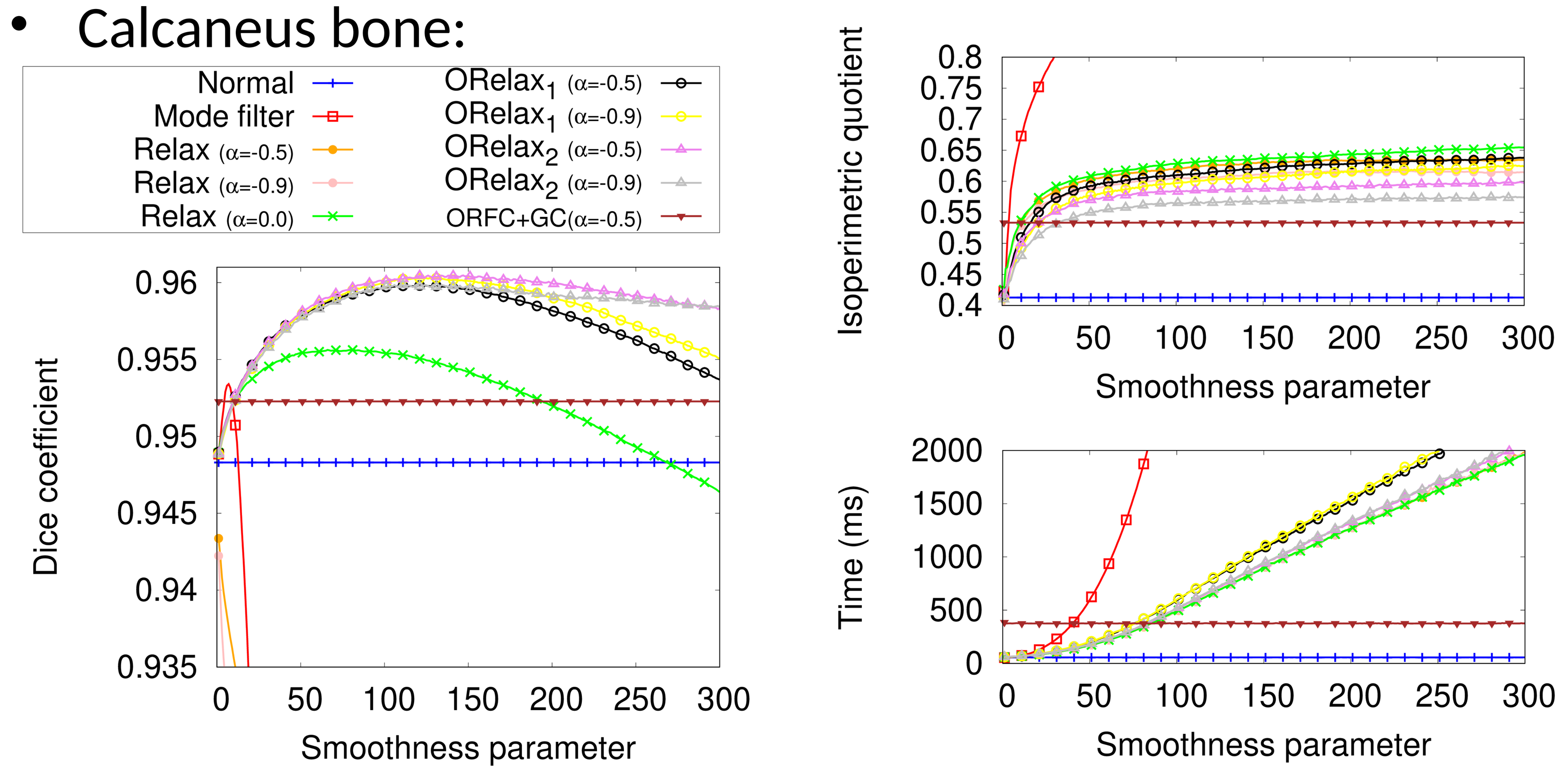
$$W^i(s,t) = \begin{cases} [\kappa_{st}]^\beta & \mathcal{L}^i(s) = \mathcal{L}^i(t) \\ \omega_{st} & \mathcal{L}^i(s) > \mathcal{L}^i(t) \\ \omega_{ts} & \mathcal{L}^i(s) < \mathcal{L}^i(t) \end{cases}$$

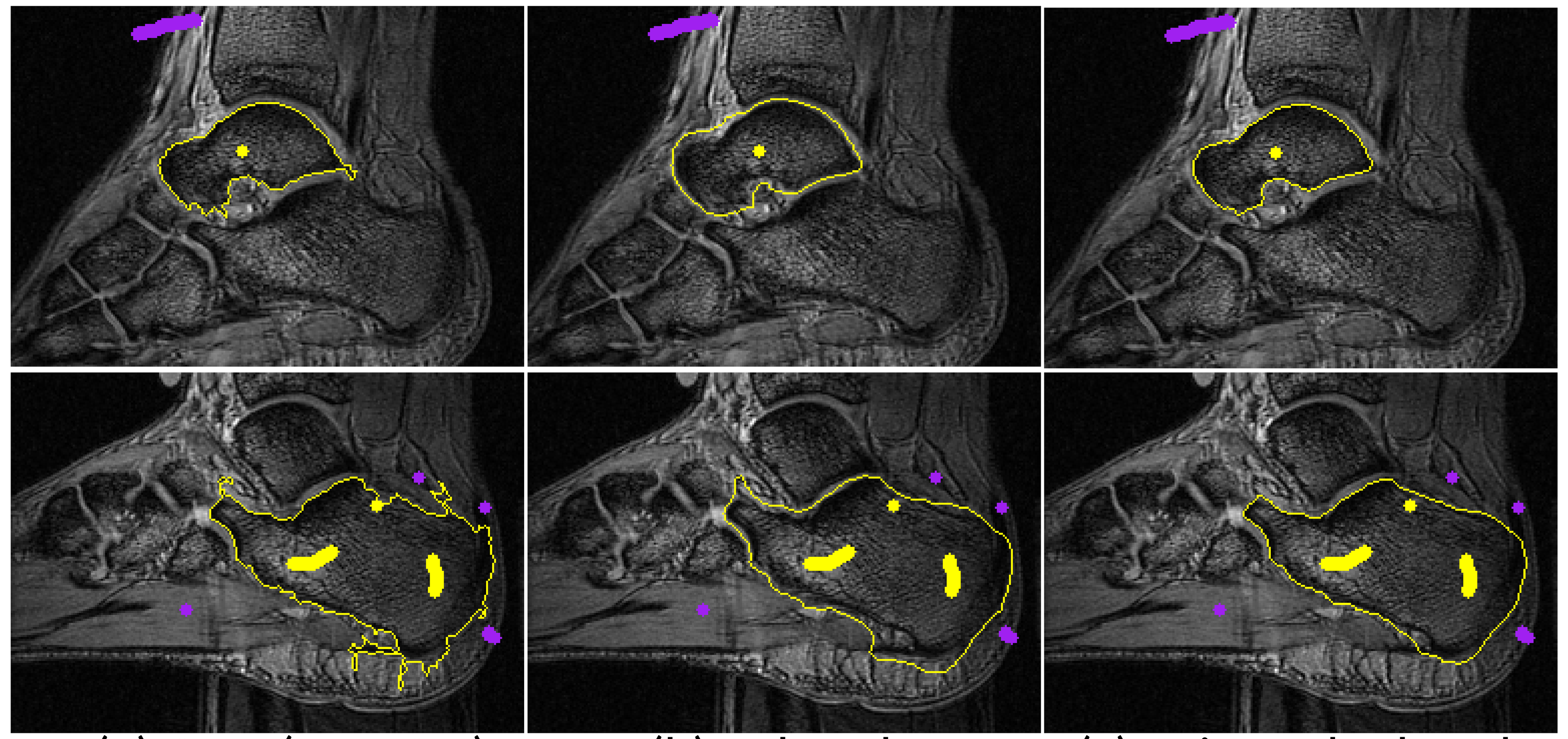
EXPERIMENTAL RESULTS

- Talus bone:



- Calcaneus bone:





(a) OIFT (α = −0.5) (b) Relaxed (c) Oriented relaxed

CONCLUSION

- Relaxed OIFT improved the perceived quality of the segmentation results, by increasing the circularity and accuracy in relation to OIFT, and with computational times close to ORFC+GC [Bejar and Miranda, 2015] for N < 100.
- As future work, we intend to correct imperfections in machine learning techniques, such as Deep Extreme Cut, by our relaxation procedure.

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