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Hans Harley Ccacyahuillca Bejar. Relative Fuzzy Connectedness on Directed Graphs and its Application in a Hybrid Method for Interactive Image Segmentation. LatinX in AI Research at ICML 2019, Jun 2019, Long Beach, California, United States. hal-02244966

HAL Id: hal-02244966

<https://hal.archives-ouvertes.fr/hal-02244966>

Submitted on 1 Aug 2019

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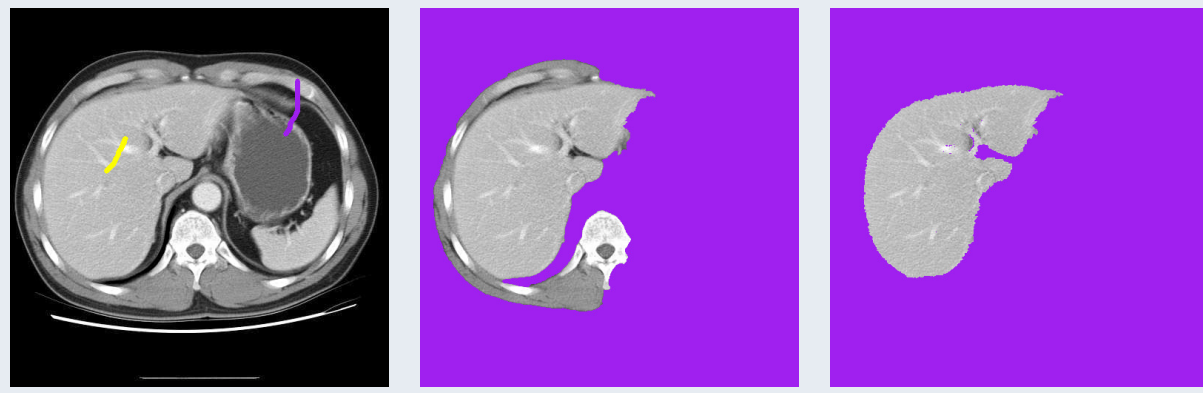
Relative Fuzzy Connectedness on Directed Graphs and its Application in a Hybrid Method for Interactive Image Segmentation

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Abstract



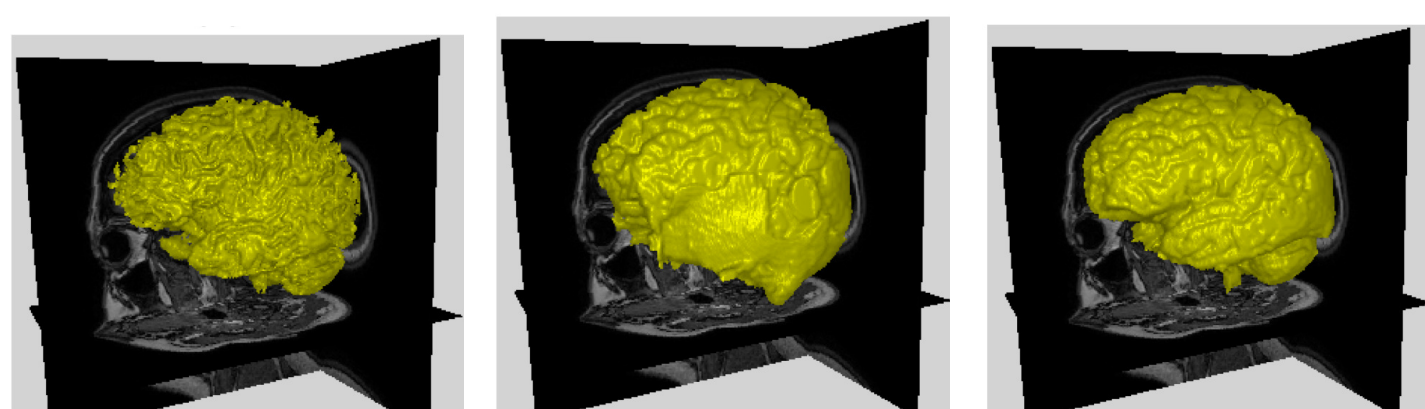
Original OIFT ORFC

Image segmentation consists of dividing an image into its composing regions or objects, for example, to isolate the pixels of a target object of a given application. In segmentation of medical images, the object of interest commonly presents transitions at its border predominantly from bright to dark or dark to bright. Traditional region-based methods of image segmentation, such as Relative Fuzzy Connectedness (**RFC**), do not distinguish well between similar boundaries with opposite orientations. The specification of the **boundary polarity** can help to alleviate this problem but this requires a mathematical formulation on **directed graphs**. A discussion on how to incorporate this property in the RFC framework is presented in this work. A theoretical proof of the optimality of the new algorithm, called Oriented Relative Fuzzy Connectedness (**ORFC**), in terms of an **energy function** on directed graphs subject to **seed constraints** is presented, and its application in powerful **hybrid** segmentation methods. The hybrid method proposed **ORFC & Graph Cut** preserves the **robustness** of ORFC respect to the seed choice, avoiding the shrinking problem of Graph Cut (GC), and keeps the strong control of the GC in the **contour delineation** of irregular image boundaries. The proposed methods are evaluated using **medical images** of MRI and CT images of the human brain and thoracic studies.

Results

In this work, we introduced the **ORFC** technique and showed that it can effectively exploit the boundary polarity improving the results in relation to its predecessor **RFC**. We also presented a powerful **hybrid approach**, which outperforms the previous works [KCC13, KCC12C]. A conference paper was published in SIBGRAPI [HHCB14], and one **journal paper** was published in the EURASIP Journal on Image and Video Processing [HHCB15].

ORFC algorithm



RFC RFC+GC ORFC+OGC

Algorithm to compute $A_{ORFC}^{in, \leq}(\{s_i\}, \mathcal{S}_b)$:

- 1 Compute the value of the map $V_b(s_i)$ for the function $f_{min}^{\mathcal{S}_b}$.
- 2 Remove from the graph G all edges with weight $\leq \varepsilon_{\infty \downarrow}^{in} = V_b(s_i)$, obtaining a new graph G_{\leq} .
- 3 Assign to the object the pixels that belong to the directed connected component of basepoint s_i in the transpose graph of G_{\leq} (i.e., $A_{ORFC}^{in, \leq}(\{s_i\}, \mathcal{S}_b) = \chi_O : O = DCC_{G_{\leq}^T}(s_i)$).

Algorithm to compute $A_{ORFC}^{out, \leq}(\{s_i\}, \mathcal{S}_b)$:

- 1 Compute the value of the map $V_b^{\parallel}(s_i)$ for the function $f_{min}^{\parallel \mathcal{S}_b}$.
- 2 Remove from the graph G all edges with weight $\leq \varepsilon_{\infty \downarrow}^{out} = V_b^{\parallel}(s_i)$, obtaining a new graph G_{\leq} .
- 3 Assign to the object the pixels that belong to the directed connected component of basepoint s_i in the graph G_{\leq} (i.e., $A_{ORFC}^{out, \leq}(\{s_i\}, \mathcal{S}_b) = \chi_O : O = DCC_{G_{\leq}}(s_i)$).

Theoretical definition of ORFC

ORFC as a directed cut in the digraph

ORFC is supported by a **graph cut optimality criterion**, which **encompasses RFC** as a particular case. In the case of directed graphs, we have two possible sets of **cuts (inner and outer)**. Let's consider the inner cut:

$$C_{in}(x) = \{ \langle a, b \rangle \in E : x(a) = 0 \wedge x(b) = 1 \}$$

So we have the following formulation for the **energy functional** of the ε_{∞} -minimizing problem.

$$\varepsilon_{\infty}^{in}(x) = \max_{\langle a, b \rangle \in C_{in}} w(a, b)$$

Let $\varepsilon_{\infty \downarrow}^{in}$ be the **minimum value** of the energy $\varepsilon_{\infty}^{in}(x)$, that is:

$$\varepsilon_{\infty \downarrow}^{in} = \min \{ \varepsilon_{\infty}^{in}(x) : x \in \mathcal{X}(\mathcal{S}_o, \mathcal{S}_b) \}$$

Therefore, we have the following **set of solutions**:

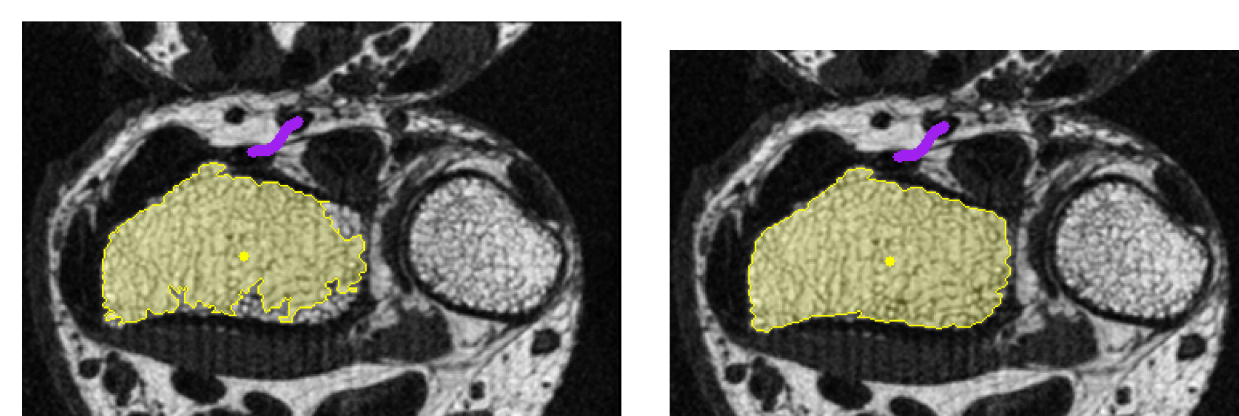
$$\mathcal{X}_{\infty}^{in}(\mathcal{S}_o, \mathcal{S}_b) = \{ x \in \mathcal{X}(\mathcal{S}_o, \mathcal{S}_b) : \varepsilon_{\infty}^{in}(x) = \varepsilon_{\infty \downarrow}^{in} \}$$

The **ORFC** algorithms on digraphs have the following definitions based on cut in graph:

For the **inner cut "in"** with one internal seed s_1 ,

$$A_{ORFC}^{in, \leq}(\{s_1\}, \mathcal{S}_b) = \chi_O \in \mathcal{X}_{\infty}^{in}(\{s_1\}, \mathcal{S}_b) : |O| = \min \{ |P| : \chi_P \in \mathcal{X}_{\infty}^{in}(\{s_1\}, \mathcal{S}_b) \}$$

Hybrid segmentation: ORFC & GC

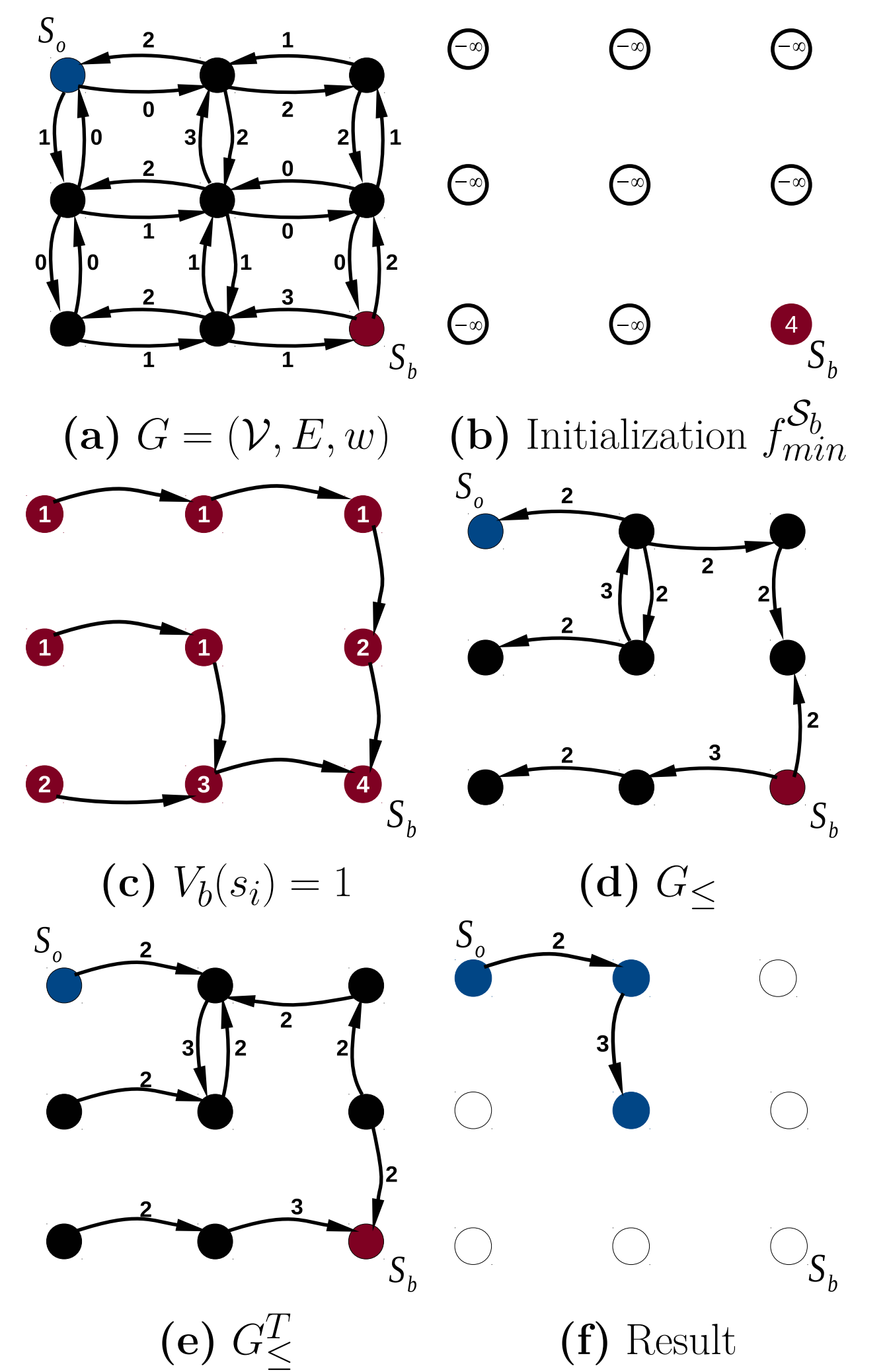


IRFC ORFC+GC

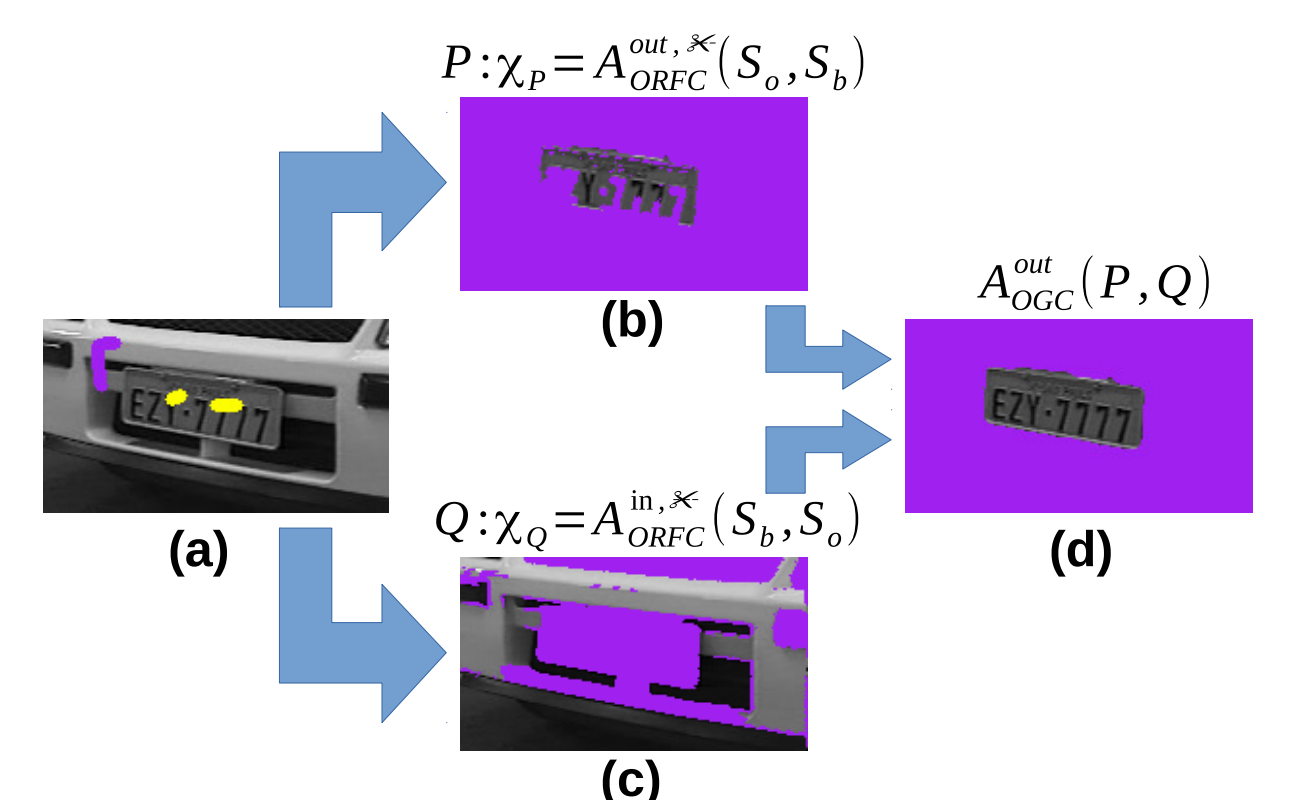
Algorithm to compute $A_{ORFC+GC}^{out, \leq}(\mathcal{S}_o, \mathcal{S}_b)$:

- 1 Compute $P : \chi_P = A_{ORFC}^{out, \leq}(\mathcal{S}_o, \mathcal{S}_b)$.
- 2 Compute $Q : \chi_Q = A_{ORFC}^{in, \leq}(\mathcal{S}_b, \mathcal{S}_o)$.
- 3 Compute and return $A_{OGC}^{out}(P, Q)$.

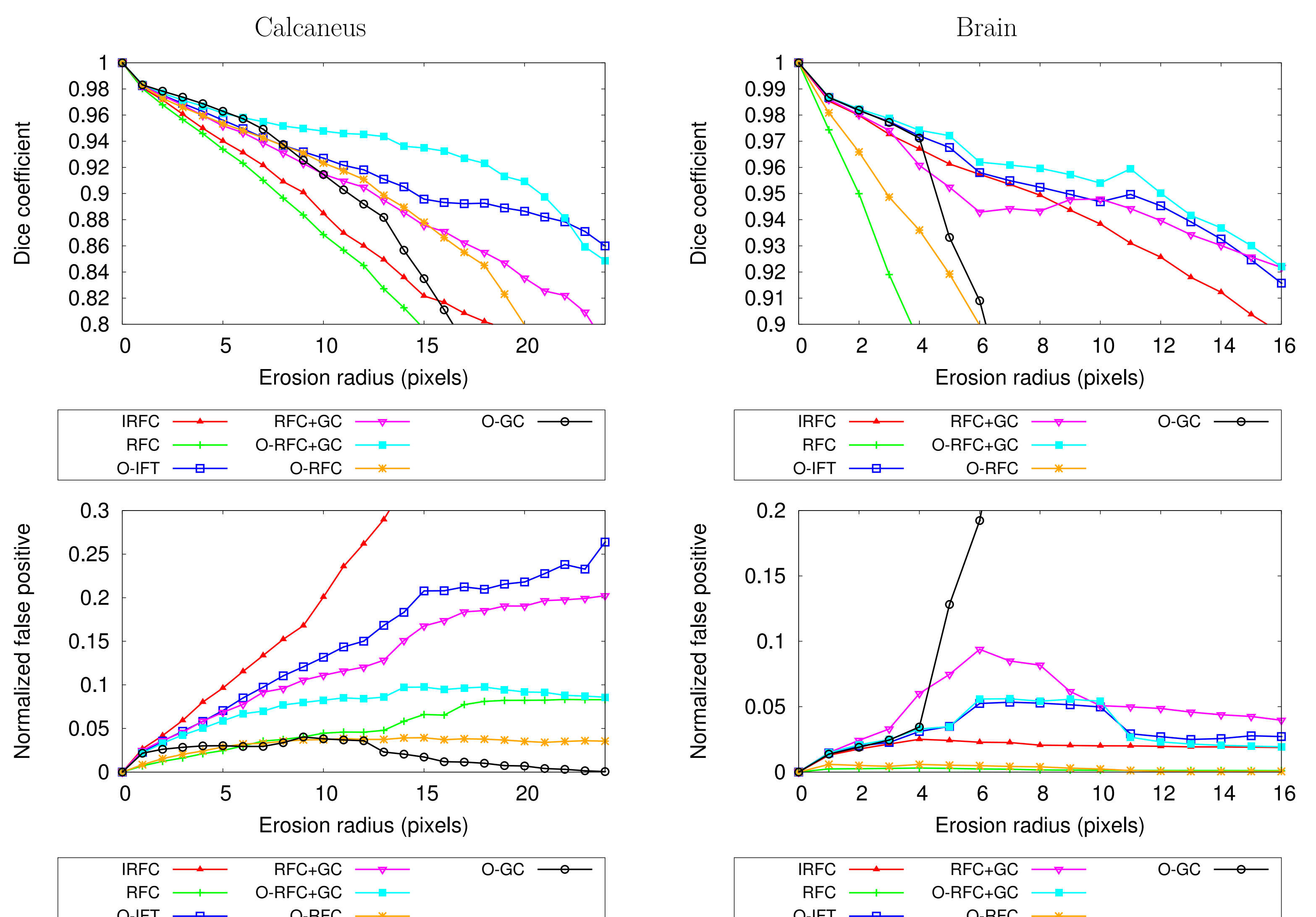
Example of $A_{ORFC}^{in, \leq}(\mathcal{S}_o = \{s_i\}, \mathcal{S}_b)$



Example of $A_{ORFC+GC}^{out, \leq}(\mathcal{S}_o, \mathcal{S}_b)$



Experimental Results



References