

Seeing Woods and Trees. A new Algorithm based on Unfocusing

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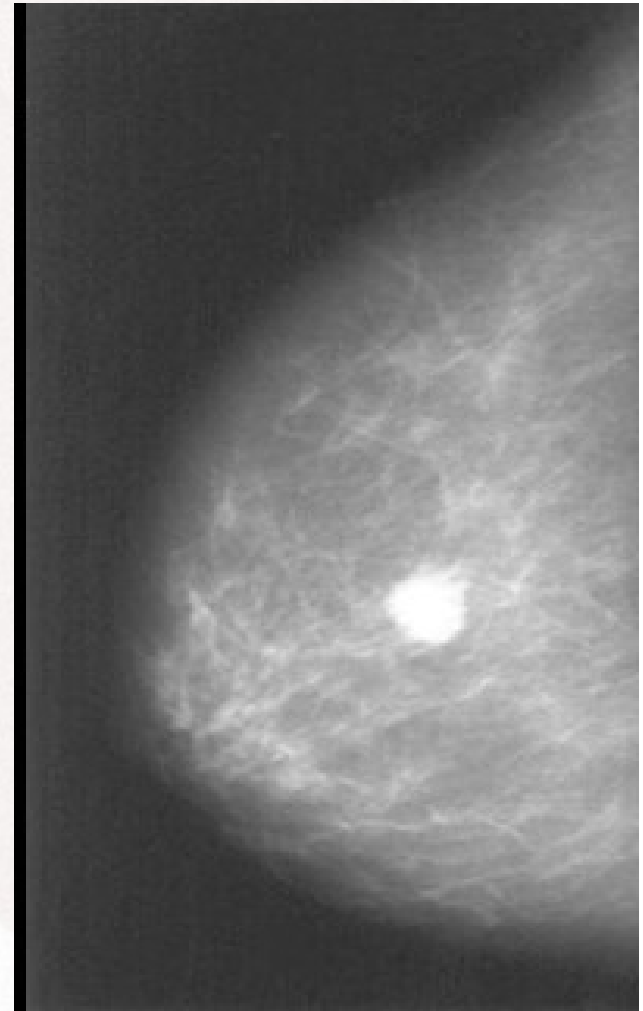
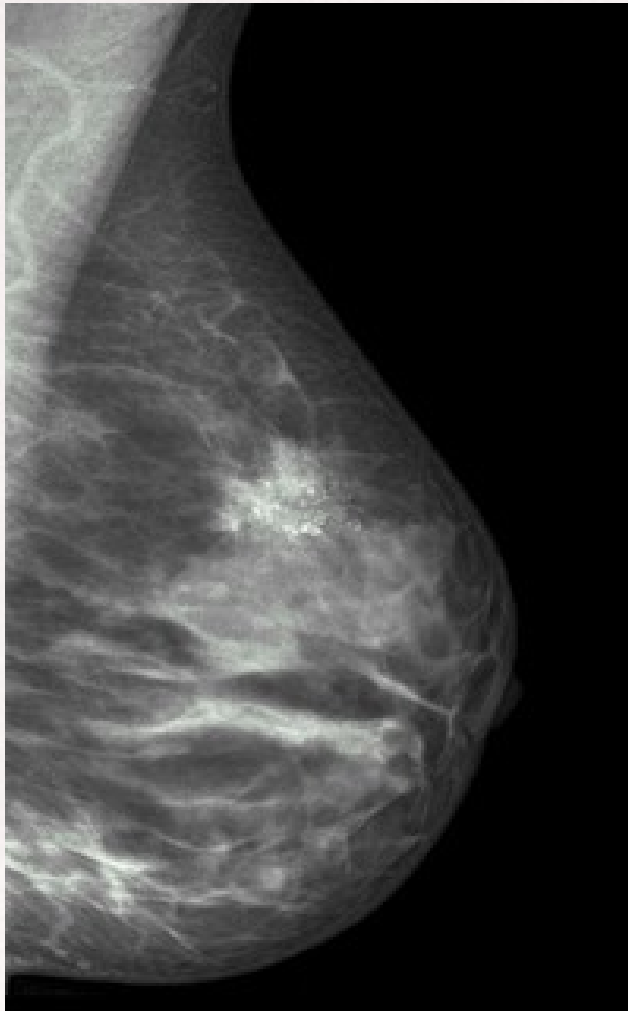
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Motivation

One of the aims of the AI scientific community nowadays is to achieve automatized medical diagnose (better than human). It can be said that this goal is actually not achieved and several challenges and problems remain yet unsolved

An important issue is how to diagnose with medical images. In this field clustering, and more specifically image segmentation, techniques play a key role

Motivation



Motivation

- There are lots of clustering methods
- Some of the most used are Expectation Maximization and Fuzzy c-Means
 - Problem: *These methods require to be given a priori the number of cluster to find!*
- In the literature there are methods to overcome this problem, but there are computationally very costly

WAT Algorithm

IDEA: Unfocus the image

- *Sometimes an unfocused image provides more structural information than the original image*
- *Excess of details can become noise*
- *Unfocusing means loss of accuracy but allows to see the general patterns and structures*

“You can't see the woods for the trees!”

WAT Algorithm

- In the WAT algorithm the main concept is SPOT
- Def: Pixel p defines spot if and only if
$$d(p,p') < r \leftrightarrow E(p,p') > h$$
- This means that if a neighborhood of a pixel p has a similar gray-level then p defines a spot
- In order to reduce computatona cost we will take random pixels p,p'

WAT Algorithm

Algorithm 2.2 *INPUT: A $N \times M$ image and values of the parameters r, h, k, l, ϵ*

1. Calculate the number n of pixels
2. Choose randomly n pixels p_1, \dots, p_n in the image
3. For each p_i
 - (a) Choose k random pixels p'_1, \dots, p'_k in a squared neighborhood of radius r around p_i
 - (b) Compare the gray-level between p_i and p'_j for $j = 1, \dots, k$ using the fuzzy relation E
 - (c) If l pixels among p'_1, \dots, p'_k verify $E(p_i, p'_j) \geq h$ then p_i defines a spot
4. Denote s_1, \dots, s_m the pixels defining spots
5. For each s_i
 - (a) For $j=1, \dots, n$ if $d(s_i, s_j) < 2r$ and $E(s_i, s_j) \geq h$ then t_i and t_j belong to the same cluster
6. Denote c_1, \dots, c_p spots defining different clusters

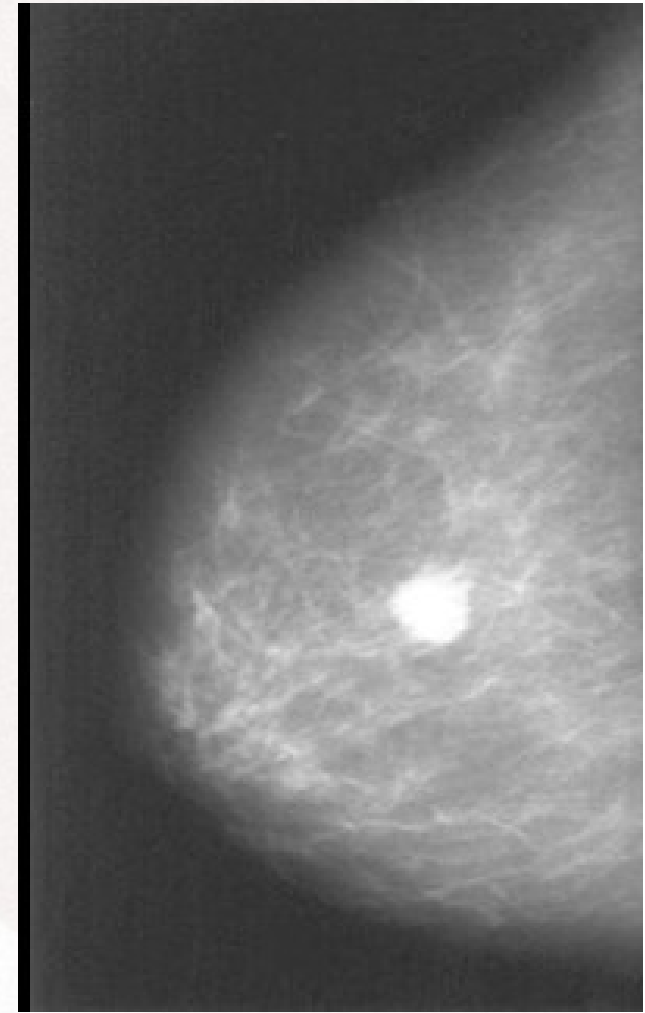
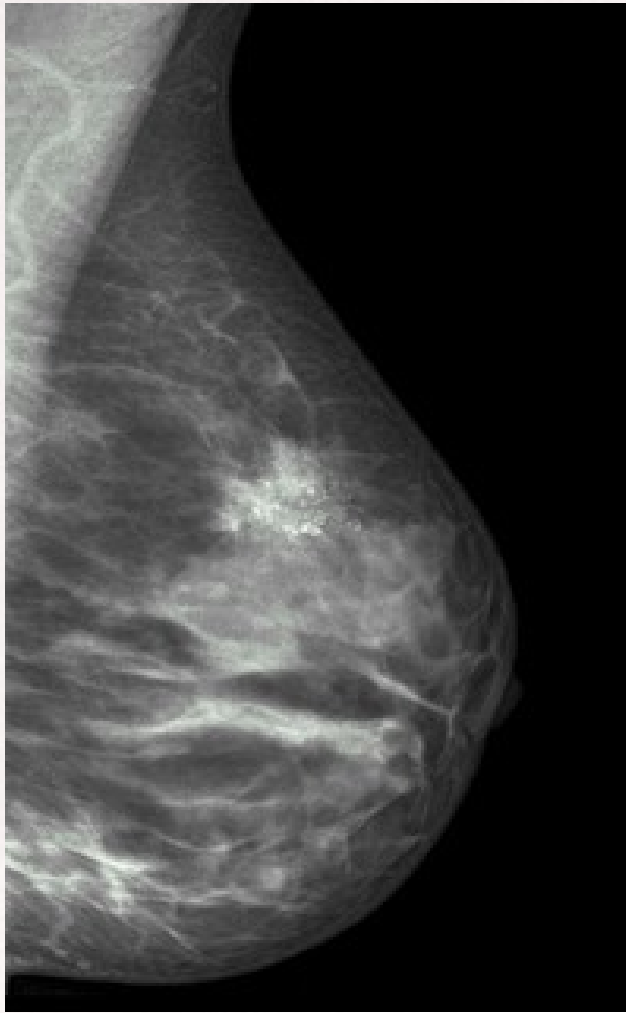
OUTPUT: c_1, \dots, c_p

- $r \in \mathbb{Z}^+$; $r \ll N, M$: Radius of granularity
- $h \in \mathbb{R}$; $h \in [0, 1]$: Similarity of gray-level to suppose common cluster
- $k \in \mathbb{Z}^+$; $k \in [1, (2r)^2]$: Number of pixels to evaluate in each neighborhood
- $l \in \mathbb{Z}^+$; $l \in [0, k]$: Threshold of similar pixels within a neighborhood to assume spot is defined
- $\epsilon \in \mathbb{R}$; $\epsilon \in (0, 1)$: Exhaustivity of search in the image

Comments on the WAT Algorithm

- Find n is non-trivial, a method is proposed in the work
- The rest of parameters measure the degree of “unfocusness”
- Joining spots can be seen as a Filtered Single Linkage
- It is the “eye” regarding the image which is unfocused, not the initial image

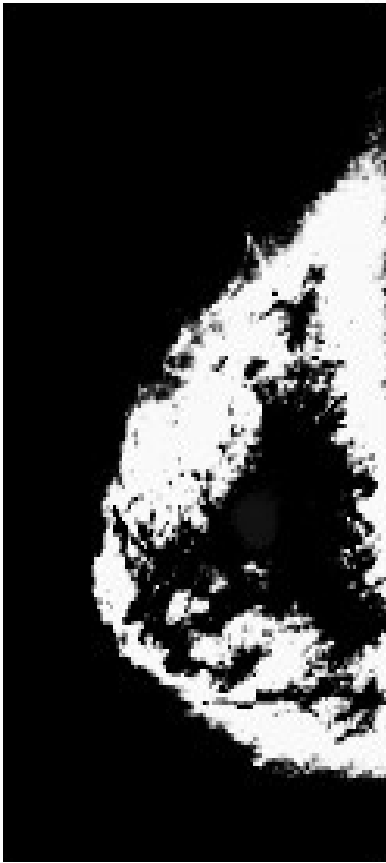
Application of the WAT Algorithm



Application of the WAT Algorithm



Application of the WAT Algorithm



Conclusions

- WAT is computationally no cost
- The output provided is quite accurate on the image tested
- Further work has to be done in order to verify that the results obtained with the images tested are preserved with other images
- WAT can be theoretically justified



***Thank you for your
attention!***