# Soft thresholding for medical image segmentation

S. Aja-Fernández, G. Vegas-Sánchez-Ferrero, M.A. Martín Fernández

Laboratory of Image Processing. Universidad de Valladolid. Spain

Universidad de Valladolid

Laboratorio de Procesado de Imagen

## Abstract

**A new soft thresholding method is presented. The method is based on relating each pixel in the image to the different regions via a membership function, rather than through hard decisions. The membership function of each of the regions is derived from the histogram of the image. As a consequence, each pixel will belong to different regions with a different level of membership. This feature is exploited through spatial processing to make the thresholding robust to noisy environments.**

## A New Fuzzy Thresholding Algorithm

We propose a new fast thresholding algorithm that makes a *soft* segmentation of the tissues for different modalities of medical images. *Soft thresholding* assigns a membership function to every pixel to each of the output classes, rather to a traditional hard thresholding.

1. Calculate the normalized $\overline{h(I)}$ histogram of the image $I(\mathbf{x})$.

2. Maxima search: The number of maxima will correspond to the number of classes in the image. To avoid local values, the histogram of the image is low pass filtered: $h_f(I) = h(I) * K_\sigma$.

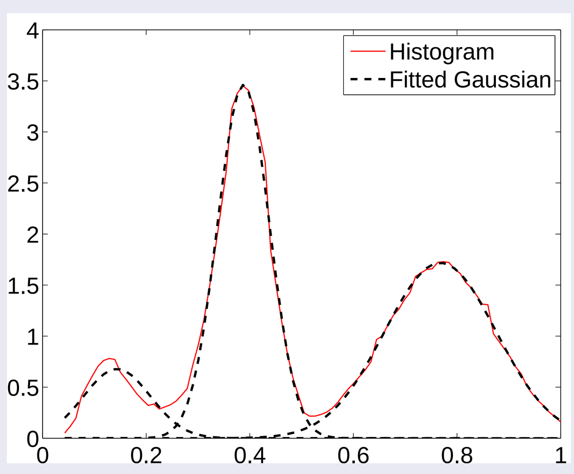
3. Fit a sum of known distributions (tipically Gaussians) to the histogram:
$$h_f(I) \approx \sum_{i=1}^{L} \omega_i \cdot p_i(x)$$
with $p_i(x)$ a probability distribution and $\omega_i$ some weights.

4. From probability to membership: Distributions $p_i(\mathbf{x})$ are transforemed into membership functions. We ask the fuzzy sets to be: (1) a complete Partition; (2) consistent; (3) normal; and (4) the intersection between adjacent fuzzy sets is $\mu_i(x_0) = \mu_{i+1}(x_0) = 0.5$. We propose to use Pseudo Trapezoid-Shaped (PTS)membership functions.

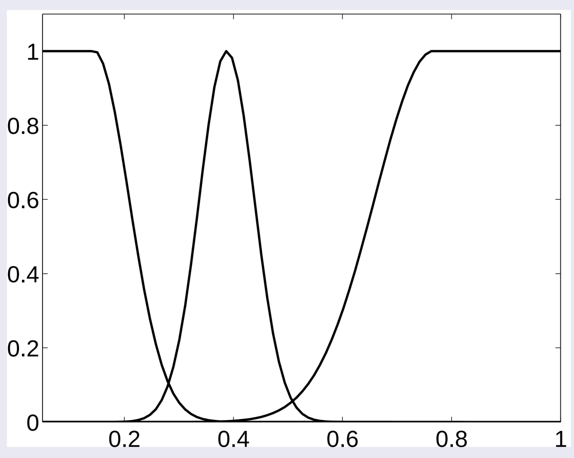
5. Membership to the regions: The membership of the image $I(\mathbf{x})$ to the region $R_i$ is defined by $\mu_i(I(\mathbf{x}))$. Using PTS MF defined as before, note that
$$\sum_{i=1}^{L} \mu_i(I(\mathbf{x})) = 1$$
A first segmentation of the image could be done:
$$M(\mathbf{x}) = \arg\max_i \mu_i(I(\mathbf{x})) \quad (1)$$

6. Adding local information: non-linear processing using the median in each channel:
$$\mu_i^{\mathcal{S}}(I(\mathbf{x})) = \text{med}_\eta(\mu_i(I(\mathbf{x}))) \quad (2)$$

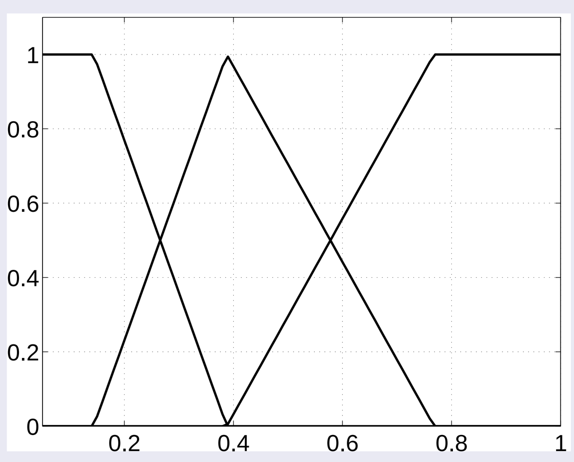
7. The thresholded image can be obtained using a maximum operator:
$$M(\mathbf{x}) = \arg\max_i \mu_i^{\mathcal{S}}(I(\mathbf{x})) \quad (3)$$




Histogram with fitted Sum of Gaussian



Gaussian membership functions



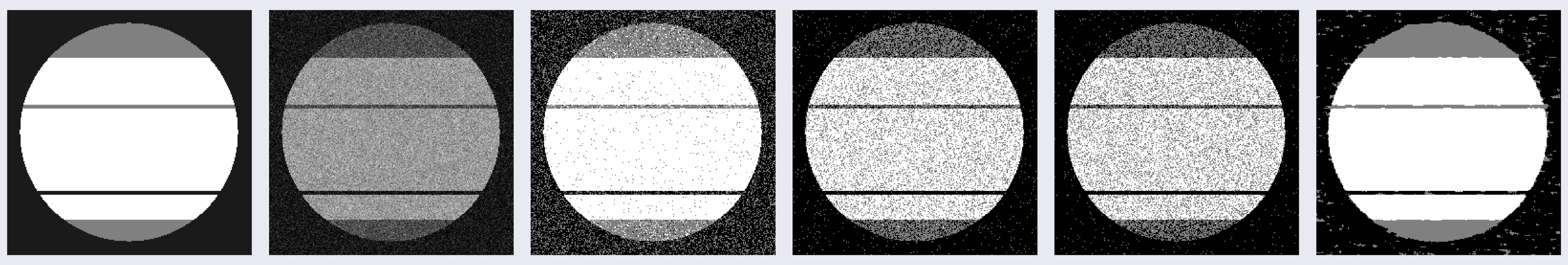
PTS membership functions

*From probability to membership: (a) (Normalized) histogram of the image $h_f(I)$, with three weighted Gaussian ($p_i(x)$) fitted using MMSE. (b) From $p_i(x)$ three fuzzy sets with Gaussian membership functions are created. (c) Alternatively, from $p_i(x)$ three fuzzy sets with PTS membership functions are created.*

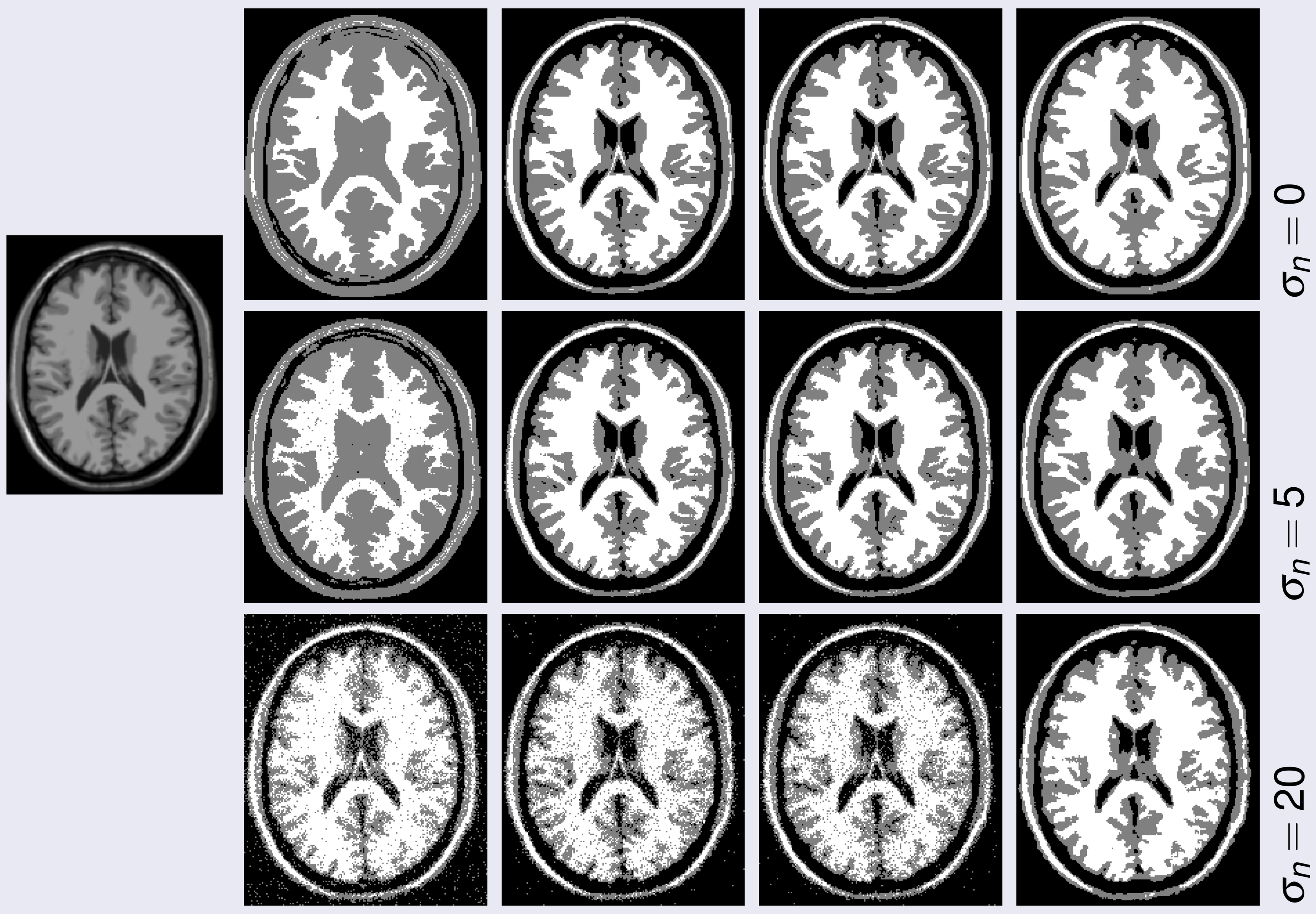
## Experiments and Results

### Methods:

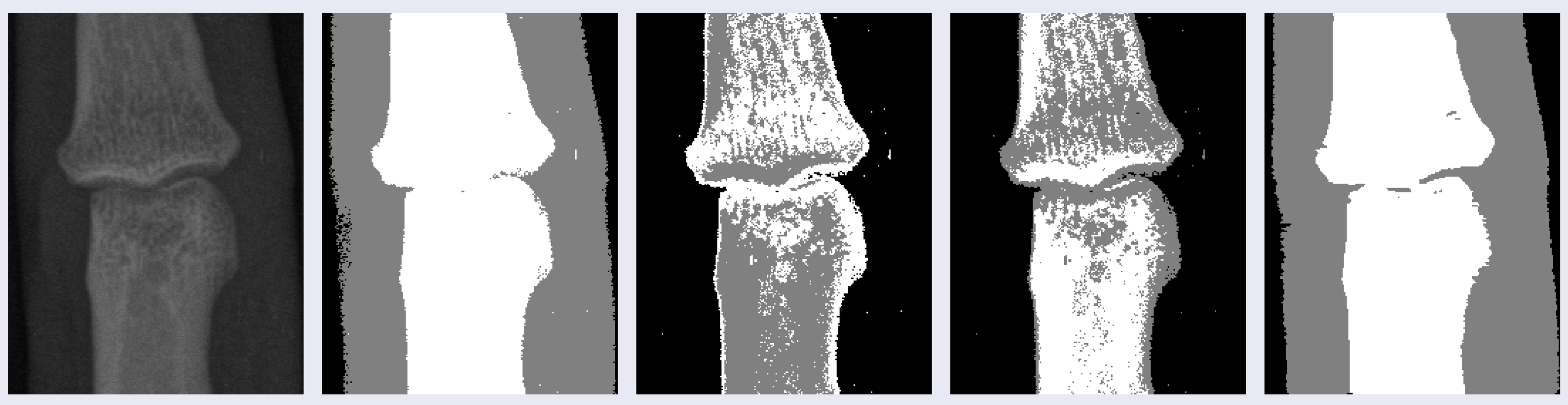
1. Hard thresholding using Gaussian fit.
2. K-means (KM).
3. Fuzzy c-means (FCM).
4. Fuzzy thresholding: Using PTS MF (from the same maxima used to fit the Gaussian) and spatial median filter.




*Experiment with synthetic phantom. (a) Original Phantom. (b) Phantom with Gaussian additive noise. (c) Hard Thresholding using 3 output sets. (d) K-means clustering with 3 centroids. (e) Fuzzy Thresholding using 3 output sets.*




*Experiment with MR data. Data from BrainWeb.*




*Experiment with radiograph data. A ROI of a larger radiograph image. 3 regions are considered.*

## Conclusions

- A new thresholding method is presented. It is based on changing the probabilistic point of view of the histogram of the image by a membership-related one. Each pixel is assigned to a region following a membership function. This way, the same pixel can belong to different regions with a different level of membership. This feature permits a further processing, as the spatial processing here presented.
- In this paper we have just presented the simplest configuration of a soft-decision thresholding method. The extention to other methods is straightforward.
- The method proposed has the following advantages: (1) It is totally automatic, and does not require human intervention, which makes it suitable for automatic processes; (2) the hard decision is postponed to the final stage. So, all the spatial operations done before taking into account the different memberships; (3) spatial operations make the thresholding more robust to noise and artifacts.

### Acknowledgements

The authors acknowledge the CICyT for research grant TEC 2007–67073/TCM, Junta de Castilla y León for grant SAN126/VA33/09 and Consejería de Sanidad de Castilla y León for grant GRS 292/A/08.


sanaja@tel.uva.es, gvegsan@lpi.tel.uva.es, migmar@tel.uva.es