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 $h(l)$ histogram of the image $I(x)$.
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: $h(l) = h(l) + K_n$.
3. Fit a sum of known distributions (typically Gaussians) to the histogram:
   $$ h(l) = \sum_{i=1}^{k} \omega_i p_i(x) $$
   with $p_i(x)$ a probability distribution and $\omega_i$ some weights.
4. From probability to membership: Distributions $p_i(x)$ are transformed 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 membership functions. We ask the fuzzy sets to be: (1) a complete Partition; (2) consistent; (3) normal; and (4) the intersection between adjacent fuzzy membership functions. We propose to use Pseudo Trapezoid-Shaped (PTS) membership functions.
5. Membership to the regions: The membership of the image $I(x)$ to the region $R_i$ is defined by $\mu_i(I(x))$. Using PTS MF defined as before, note that
   $$ \sum_{i=1}^{k} \mu_i(I(x)) = 1 $$
   A first segmentation of the image could be done:
   $$ M(x) = \text{arg max}_i \mu_i(I(x)) $$
   (1)
6. Adding local information: non-linear processing using the median in each channel:
   $$ \mu_i^\sigma(I(x)) = \text{med}_\omega(\mu_i(I(x))) $$
   (2)
7. The thresholded image can be obtained using a maximum operator:
   $$ M(x) = \text{arg max}_i \mu_i^\sigma(I(x)) $$
   (3)

Experiments and Results

Methods:
1. Hard thresholding using Gaussian fit.
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.

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