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A local fuzzy thresholding methodology for multiregion image segmentation

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ABSTRACT

Thresholding is a direct and simple approach to extract different regions from an image. In its basic formulation, thresholding searches for a global value that maximizes the separation between output classes. The use of a single hard threshold value is precisely the source of important segmentation errors in many scenarios like noisy images or uneven illumination. If no connectivity or closed objects are considered, the method is prone to produce isolated pixels. In this paper a new multiregion thresholding methodology is presented to overcome the common drawbacks of thresholding methods when images are corrupted with artifacts and noise. It is based on relating each pixel in the image to different output centroids via a fuzzy membership function, avoiding any initial hard decision. The starting point of the technique is the definition of the output centroids using a clustering method compatible with most thresholding techniques in the literature. The method makes use of the spatial information through a local aggregation step where the membership degree of each pixel is modified by local information that takes into account the memberships of the surrounding pixels. This makes the method robust to noise and artifacts. The general formulation of the proposed methodology allows the design of spatial aggregations for multiple applications, including the possibility of including heuristic information via a fuzzy inference rule base.

1. Introduction

Thresholding is one of the most direct and simple approaches to image segmentation. It is an effective method as long as the image shows well defined areas and the gray levels are clustered around distant values with minimum overlap. It also has been used to provide an initial estimation or a prior to more complex segmentation methods (techniques based on snakes, level-sets or active contours need an initial segmentation, that can be manually done or obtained via thresholding [1,2]), to provide masks of regions of interest [3], or even as a technique to detect motion in surveillance environments [4,5]. Thresholding is also extensively used in the medical imaging field, where images are composed by several tissues, represented by their gray levels [6]. The arrangement of these tissues or organs inside the image is usually clearer than the arrangement of objects in a natural scene image, hence the using of specific thresholding techniques.

Image thresholding techniques are well known, and some of the most used methods date from the 70s, such as Otsu's method [7,8]. In its basic implementation, thresholding methods search for a global threshold value that somehow maximizes the separation between classes in the final result. However, regardless of the method chosen to find the separation between classes, the use of a single hard value is known to be the source of important segmentation errors when dealing with noisy images, uneven illumination and soft transitions between gray levels [9–11]. The main drawback of this global threshold approach is due to it being *pixel* oriented rather than *region* oriented, and therefore those pixels having the same gray level value will always be segmented into the same class. If no connectivity or closed objects are considered, the method is prone to produce isolated pixels.

Thus, despite being a long standing problem, these issues have not been resolved, and new approaches are required to solve different configuration of signal and images; see some surveys of them in [9,12–15]. In the first one [9], authors classify thresholding methods into six main categories:

1. Methods based on the shape of the histogram [7,8].
2. Clustering-based methods [16–21].
3. Entropy-based methods [22–24].
4. Local methods, that adapt the threshold value on each region based on local features [25,26].

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5. Object attribute-based methods that search a measure of similarity between gray-levels and objects, such as fuzzy shape similarity.
6. Spatial methods that use higher-order probability distribution and/or correlation between pixels [11].

The first three methodologies comprise the main *tradition* behind thresholding methods: the search for a global threshold that allows us to divide the image into two or more regions. Methods proposed in the literature can grow in complexity in the pursuit of the optimal threshold but ultimately, the final segmentation will only depend on the gray level of each particular pixel. The final classification is done pixelwise. Note that most of the algorithms based on fuzzy measures [27–33] fall into these categories. On the other hand, local methods assume that different areas in the image require different thresholds. This is the case for images with uneven illumination, in which objects are not totally represented by absolute gray values.

All these methodologies will fail in the case of images corrupted by noise, where the gray levels of each object are spread and merged due to the noisy distortions. Attribute-based methods are a good alternative, as long as we have key information about the objects in the scene. Finally, spatial methods take into account possible relations between pixels. The idea behind them is the fact that pixels belonging to the same object will have a certain degree of connectivity, i.e., the presence of isolated pixels is unlikely and there is a strong relation between a pixel and its neighborhood.

Note that these six categories can be merged into three practical methodologies:

1. Methods that calculate a global threshold for the whole image.
2. Methods that use an adaptive local threshold.
3. Methods that use spatial local information for classifying the pixels.

In this paper we propose a new thresholding methodology that takes advantage of the main features of the last two categories:

- The membership degree of a particular pixel in a class is spatially related with the membership of its surrounding neighbors.
- The final thresholding will take into account the local membership in each of the classes, which implicitly makes the threshold locally variant.

The main contribution of this paper relies on Fuzzy Sets Theory and Fuzzy Logic [34]. Fuzzy logic is known to be a very flexible tool in classification problems where imprecise knowledge or not-well-defined features have to be used. In addition, fuzzy logic is also a natural selection where information has to be retrieved from linguistic statements. It has been widely used in the field of systems control [35], but there are also a great amount of applications in the image processing field [36–38]. In the last 20 years, many methods based on fuzzy logic and fuzzy measures [39,40] have been proposed for image thresholding. They are mainly focused on the search for the optimum threshold using fuzzy measures, buy many times they do not take into account spatial information. Some of the techniques used comprised fuzzy clustering [41,42], modified versions of fuzzy clustering methods [19,21], fuzzy measures [27,43,30,44], optimization of fuzzy compactness [45], fuzzy entropy [46] and the interpretation of thresholds as type II fuzzy sets [33,32]. Parallel with fuzzy measures, other soft computing methods have arisen, such as the heuristic methods based on ant, bees and bacteria colonies [47–49].

In this paper we propose a new methodology which differs from those approaches in the literature. The starting point is the idea that the membership of a pixel in a particular class or object will be highly correlated with the membership in that class of the surrounding pixels. To take into account this local spatial information we propose the use of fuzzy sets: a pixel will be assigned to the different classes of a multiregion segmentation through a fuzzy membership function. The traditional hard assignment (i.e. a pixel belongs or does not belong to an output class) is replaced by a soft assignment, following the basic theory of fuzzy sets.

The paper is organized as follows: Section 2 presents the new thresholding methodology proposed. Results and comparison with another methodologies and methods are shown in Section 3. Conclusions are presented in Section 4.

2. Multiregion fuzzy thresholding

2.1. Motivation and purpose

The main limitation of global thresholds is that pixels having the same intensity levels will always be segmented into the same class. This may lead to misclassification in images corrupted by noise or uneven illumination. To overcome this problem, information about the behavior of the spatial surroundings of each pixel must be considered. This spatial information can be taken into account using very different methods, each one of them generating a different output segmentation. Most used methods are those we can call *blind methods*: methods that *clean* the segmented image using local processing but without any prior information of the image structure, object distribution, nature of noise, etc. These methods only make use of the segmented values. Some common examples are the median filtering and morphological operations to remove isolated pixels.

To motivate use of the local information, see for instance the image in Fig. 1. A pixel has been classified as belonging to the Class 3 (red). In a 3×3 neighborhood around the pixel we can check that this pixel is an isolated value, probably generated by noise. The *correction* to this misclassification can be done using information about the image (such as the model of noise, the classification probability, the distance to the centroid) or just using spatial or morphological operations. Note that if we use a median filter over that neighborhood, the pixel will now be classified as Class 1 (blue). Similar results can be found using a filling algorithm. In those cases, important information about the image is missing. If we check the distance to the centroids, we realize that the pixel is 0.52% Class 3 and 0.48% Class 2, and it has been classified as 3 by a small range. In a noisy image, it is very likely that this pixel belongs to Class 2, and is unlikely to belong to Class 1. In what follows we will be using this idea of taking into account the local properties to improve the classification methodology.

We propose a new thresholding methodology to make a multiregion segmentation of the different areas within an image. To that end, we will follow a fuzzy assignment classification that will follow the philosophy behind many fuzzy-based approaches in the literature [27–31], but it will be complemented with a spatial aggregation step that will take advantage of the soft classification and the spatial relations. Our *fuzzy thresholding* methodology will assign a membership degree to every pixel for each of the output classes, rather than to a traditional hard thresholding. The membership degree of each pixel is then modified using local information following some aggregation scheme and some fuzzy rules set beforehand. The aggregation method is to be specifically designed for each particular application, although some examples will be given. The inclusion of this aggregation step will be a great advantage when dealing with noisy images.

Finally, note that the methodology is compatible and complementary to some of the methods already proposed in the literature,