Image Threshold Using A-IFSs Based on Bounded Histograms

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Abstract. Atanassov's intuitionistic fuzzy sets (A-IFSs) have been used recently to determine the optimal threshold value for gray-level image segmentation [1]. Atanassov's intuitionistic fuzzy index values are used for representing the unknowledge/ignorance of an expert on determining whether a pixel of the image belongs to the background or the object of the image. This optimal global threshold of the image is computed automatically, regardless of the actual image analysis process.

Although global optimal thresholding techniques give good results under experimental conditions, when dealing with real images having several objects and the segmentation purpose is to point out some application-specific information, one should use heuristic techniques in order to obtain better thresholding results.

This paper introduces an evolution of the above mentioned technique intended for use with such images. The proposed approach takes into account the image and segmentation specificities by using a two-step procedure, with a restricted set of the image gray-levels.

Preliminary experimental results and comparison with other methods are presented.

Keywords: Fuzzy Sets Theory Applications, Atanassov's Intuitionistic Fuzzy Sets (A-IFSs), computer Vision, Pattern Recognition, Digital Image Processing.

1 Introduction

Many image analysis techniques take as starting point a segmentation of the image, that is, the image is decomposed into meaningful parts for further analysis, resulting in the partition of the set of pixels in the image into a finite set of regions (subsets) according to a certain criterion.

In reality, the segmentation of digital images is the process of dividing an image into disjoined parts, regions or subsets so that each one must satisfy a distinct and well-defined property or attribute.

The most commonly used strategy for segmenting images is global thresholding that refers to the process of partitioning the pixels in an image into object

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and background regions on the basis of the different intensity levels of gray of the pixels in the image. This partition is made by establishing a threshold, in such a way that all the pixels with intensity greater or equal than the threshold belong to the background (or to the object) and all the pixels with intensity lower than the threshold belong to the object (or to the background).

Extensive research has been conducted in this research field over the last years, and many types of segmentation techniques have been proposed in the literature, each one of them based on a certain methodology to classify the regions [2,3,4,5,6].

The proposed approach is an evolution/extension of the methodology, based on Atanassov's intuitionistic fuzzy sets (A-IFSs), presented in [1] intended for use with specific images within a particular image analysis process. This approach uses a two-step procedure, applying the methodology presented in [1] first to all the image pixels and then to a restricted set of the original image gray-levels' set.

2 Image Threshold Computation by Modelizing Knowledge/Unknowledge by Means of A-IFSs

Being (x, y) the coordinates of each pixel on the image Q, and being $q(x, y)$ the gray level of the pixel (x, y) so that $0 \leq q(x, y) \leq L-1$ for each $(x, y) \in Q$ where L is the image grayscale, many methods have been proposed for determining the threshold t of an image considering fuzzy set theory as an efficient tool in order to obtain a good segmentation of the image considered. The most commonly algorithm used to obtain the threshold is the one that uses the concept of fuzzy entropy and its main steps are the following:

(a) Assign L fuzzy sets Q_t to each image Q. Each one is associated to a level of intensity t, $(t = 0, 1, \cdots, L-1)$, of the grayscale L used.
(b) Calculate the entropy of each one of the L fuzzy sets Q_t associated with Q.
(c) Take, as the *best threshold* gray level t, associated with the fuzzy set corresponding to the lowest entropy.

The main problem of this algorithm is the step (a). In [1] this problem is solved using A-IFSs in the following way: In order to choose/construct the membership function of each pixel of the image to the associated fuzzy set, three numerical values are assigned to each one of them.

- A value for representing the expert knowledge of the membership of the pixel to the background. A membership function, constructed by the expert using dissimilarity functions, is used to obtain this value (see [7]).
- Dissimilarity functions are also used by the expert to construct a membership function to retrieve a value for representing the expert knowledge of the membership of the pixel to the object.
- The expert knowledge/ignorance, in determining the above mentioned membership functions, is represented by a third value obtained trough Atanassov's intuitionistic index.

The value represented by Atanassov's intuitionistic index indicates the knowledge/ignorance of the expert when assigning a pixel either to the background or the object, so that, when the expert is absolutely sure that a pixel belongs either to the background or the object the Atanassov's intuitionistic index associated with that pixel has the value of zero. This value increases with respect to the unknowledge/ignorance of the expert as to whether the pixel belongs to the background or the object. So, if the expert doesn't know if a pixel belongs to the background or the object, its membership to both must be represented with the value 0.5, and in such conditions, it is said that the expert used the greatest unknowledge/ignorance/intuition allowed in the construction of the membership functions, of the set associated with that pixel, to the background and the object resulting in a Atanassov's Intuitionistic Fuzzy Index maximum value. For this reason, A-IFSs (Atanassov's Intuitionistic Fuzzy Set [9,10]) are used.

In a second stage, the entropy values of each one of the L A-IFSs associated with the image are calculated. In this methodology, entropy on A-IFSs is interpreted as a measure of the degree of a A-IFS that a set has with respect to the fuzzyness of the said set (see [8]). Under these conditions the entropy will be null when the set is a FSs and will be maximum when the set is totally intuitionistic.

Finally, the gray level t associated with the fuzzy set with the lowest entropy is selected for the best threshold.

A possible implementation of this methodology [1], and the one used in this work, is now presented.

(Step A) - Construct L fuzzy sets Q_{Bt} associated with the background and L fuzzy sets Q_{Ot} associated with the object. Each one of these fuzzy sets is associated with a gray level t of the grayscale L used. The membership functions of these sets are defined by means of restricted dissimilarity functions and the expressions are:

$$\mu_{Q_{Bt}}(q) = F\left(d\left(\frac{q}{L-1}, \frac{m_{\mathrm{B}}(t)}{L-1}\right)\right)$$

$$\mu_{Q_{Ot}}(q) = F\left(d\left(\frac{q}{L-1}, \frac{m_{\mathrm{O}}(t)}{L-1}\right)\right)$$

where

$$m_{\mathrm{B}}(t) = \frac{\sum_{q=0}^{t} qh(q)}{\sum_{q=0}^{t} h(q)} \tag{1}$$

$$m_{\mathrm{O}}(t) = \frac{\sum_{q=t+1}^{L-1} qh(q)}{\sum_{q=t+1}^{L-1} h(q)} \tag{2}$$

and

$$F(x) = 1 - 0.5x$$

being $h(q)$ the number of pixels of the image with the gray level q.

Note that $F(x)$ is only one of the possible F functions that could be used (see [1]).

(*Step B*) - As it has been said before, the unknowledge/ignorance of the expert in the construction of the fuzzy sets (in *Step A*) is represented by means of Atanassov's intuitionistic fuzzy index (π), meaning that, it is considered that $\mu_{Q_{Bt}}$ ($\mu_{Q_{Ot}}$) indicates the expert's degree of knowledge of the pixel belonging to the background (object).

If the expert is certain of the pixel belonging to the background or the object, then the value of π must be zero. The value of π increases as the unknowledge/ignorance of the expert grows. However, the unknowledge/ignorance must have the least possible influence on the choice of the membership degree, so, in this implementation, in the worst case, the unknowledge will have a maximum influence of 25 percent.

Under these conditions, the following expression is used to calculate π:

$$\pi(q) = (1 - \mu_{Q_{Bt}}(q))(1 - \mu_{Q_{Ot}}(q)).$$

Again, this expression is only one of the possible ones (see [1]).

(*Step C*) - Construct an A-IFS, using π, with each one of the fuzzy sets Q_{Bt} and Q_{Ot}.

$$\begin{aligned} \tilde{Q}_{Bt} = \{(q, \mu_{\tilde{Q}_{Bt}}(q), \nu_{\tilde{Q}_{Bt}}(q)) | q = 0, 1, \cdots, L-1\}, &\text{ given by} \\ \mu_{\tilde{Q}_{Bt}}(q) = \mu_{Q_{Bt}}(q) & \\ \nu_{\tilde{Q}_{Bt}}(q) = 1 - \mu_{\tilde{Q}_{Bt}}(q) - \pi(q) = (1 - \mu_{Q_{Bt}}(q)) \cdot \mu_{Q_{Ot}}(q) & \end{aligned}$$

and

$$\begin{aligned} \tilde{Q}_{Ot} = \{(q, \mu_{\tilde{Q}_{Ot}}(q), \nu_{\tilde{Q}_{Ot}}(q)) | q = 0, 1, \cdots, L-1\}, &\text{ given by} \\ \mu_{\tilde{Q}_{Ot}}(q) = \mu_{Q_{Ot}}(q) & \\ \nu_{\tilde{Q}_{Ot}}(q) = 1 - \mu_{\tilde{Q}_{Ot}}(q) - \pi(q) = (1 - \mu_{Q_{Ot}}(q)) \cdot \mu_{Q_{Bt}}(q) & \end{aligned}$$

(*Step D*) - Calculate the entropy IE of each one of the L Atanassov's intuitionistic fuzzy sets, using the following expression, so that $0 \leq IE(\tilde{Q}_{Bt}) \leq 0.25$.

$$IE(\tilde{Q}_{Bt}) = \frac{1}{N \times M} \sum_{q=0}^{L-1} h(q)(1 - \mu_{Q_{Bt}}(q))(1 - \mu_{Q_{Ot}}(q)) \tag{3}$$

where $N \times M$ are the image dimensions in pixels.

(*Step E*) - Finally, the gray level associated with the Atanassov's intuitionistic fuzzy set $\tilde{Q}_{Bt}$ of lowest entropy IE is chosen as the best threshold.

3 Materials and Methods

In the image processing system boarded in this work, the main goal is to perform kinematic analysis for the left hindlimb in treadmill walking rats. The method used for the analysis of the hindlimb movement involved the placing of markers on the skin surface overlying joints under analysis. These markers are to be tracked by the system in order to characterize the hindlimb movement [11,12,13].

Image sequences acquired at the usual rate of 25 images per second are insufficient to characterize the rat's hindlimb movement, particularly due to aliasing phenomena's. In order to avoid this aliasing problem, a high-speed digital image camera (Redlake PCI 1000S, San Diego, USA) was used to record the rat gait at 125 frames per second, resulting in images of 480 $\times$ 420 pixels codified in 8 bits (256 gray levels).

Due to the high speed acquisition, other problems arise in contrast, noise, illumination, resolution, etc., resulting in noisy images with imprecision on the gray levels that conducts to fuzzy boundaries and ill defined regions, which makes the current approach to the segmentation of such images the natural approach.

4 Proposed Approach

4.1 First Step

In this step the pixels belonging to the background of the image are identified and withdraw from the image. In order to do so, the methodology presented in section 2 is applied to the image.

However, the threshold value th, computed at this point, is not used to segment the image, but to bind the original histogram of the image. Thus, all pixels below th value are "extracted" from the original histogram, hence their presence in the image will be ignored for further processing at step two. All other pixels (greater then th) will remain with their original gray level.

If we denote by P the number of pixels below threshold th, then

$$P = \sum_{q=0}^{th} h(q)$$

and the new image to be processed in step two is a $N \times M - P$ image with $L - th$ gray levels, where $q(x, y)$ is the gray level of the pixel (x, y) so that $th \leq q(x, y) \leq L - 1$ for each $(x, y) \in Q$, and where $[th + 1, \cdots, L - 1]$ is the image grayscale.

4.2 Second Step

At this stage, the same methodology is applied to image resulting from the *First Step*. In order to apply the section2 methodology, the following adjustments where made:

In *Step A*, $L - th$ fuzzy sets Q_{Bt} associated with the background and $L - th$ fuzzy sets Q_{Ot} associated with the object are constructed, instead of the original L fuzzy sets. Also, equations 2 and 2 become:

$$m_B(t) = \frac{\sum_{q=th}^{t} qh(q)}{\sum_{q=th}^{t} h(q)} \qquad m_O(t) = \frac{\sum_{q=th+t+1}^{L-1} qh(q)}{\sum_{q=th+t+1}^{L-1} h(q)}$$

respectively.

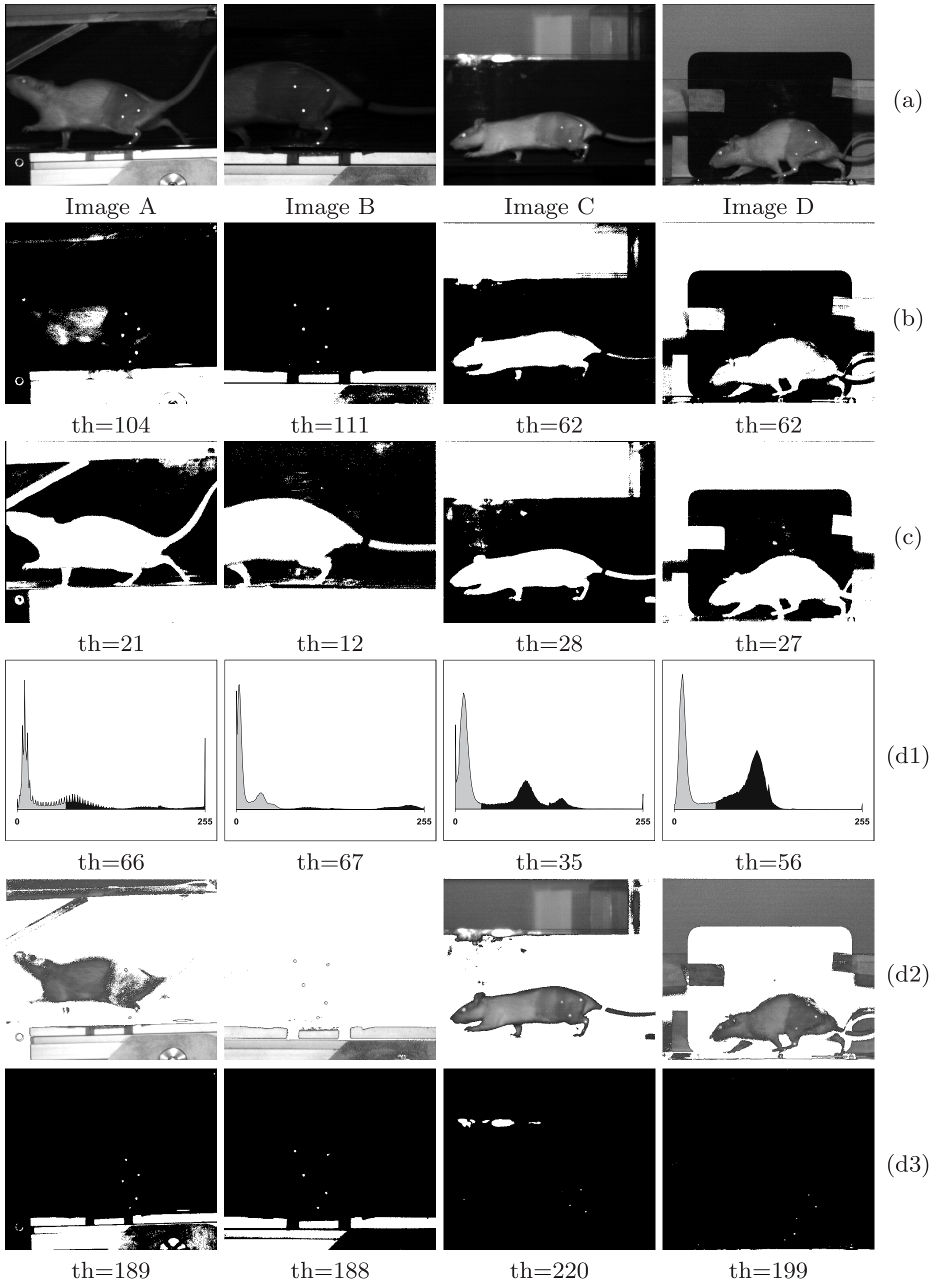

Fig. 1. (a) Original image (b) Binary image obtained with the Otsu algorithm (c) Binary image obtained with Kittlers algorithm (d1) Histogram of the original image, where the gray portion represents the gray level intensities that were "removed" from the image (d2) Resulting image after the *First Step* (d3) Binary image obtained with the proposed algorithm after the *Second Step*

In *Step B* and *Step C* although all expressions remain the same, note that $q \in [th+1, \cdots, L-1]$.

In *Step D* equation 3 become

$$IE(\tilde{Q}_{Bt}) = \frac{1}{N \times M} \sum_{q=th+1}^{L-1} h(q)(1 - \mu_{Q_{Bt}}(q))(1 - \mu_{Q_{Ot}}(q))$$

5 Experimental Results

In order to test the performance of the proposed approach, four images, presenting contrast problems (more prone to difficulties), from the walking rats' sequences were selected and used as test images. Each one of these images is part of a sequence of images where the rat gait is recorded and is analyzed by tracking the markers placed on the rats in each image. The purpose of the segmentation step in this process is to point out those markers.

We also compare the obtained results with non fuzzy well known methodologies, the Otsu technique [14] and the clustering-based Kittler method [15]. The original images and the results of the used techniques are illustrated in Fig. 1.

The results obtained with the Otsu (Fig.1b) and Kittler (Fig.1c) methodologies do not perform well in identifying the rats markers. Only in one situation (Image B with Otsu method) the markers are clearly identified for further processing. On the contrary, the proposed methodology (Fig.1d3) succeeds in identifying the markers for all the images and, thus, is more reliable for the necessary further processing in order to extract the markers position in the image.

6 Conclusions and Future Work

The problem of segmentation in spite of all the work over the last decades, is still an important research field in image processing mostly due to the fact that finding a global optimal threshold is not trivial, and is indeed a very difficult task. One of the most commonly used strategy for segmenting images is global thresholding that refers to the process of partitioning the pixels in an image into regions on the basis of the different intensity levels of gray of the pixels in the regions without distinguishing the pixels within a region, even if their gray values are significantly different in the original image. For this reason, finding an algorithm that can be successfully applied to all kinds of images is a difficult task that, probably, will never be accomplished. Thus, it is suitable to develop new threshold techniques, or new extensions to the existing ones, that can effectively lead us to an optimal threshold within the specificities of one's application.

Although the previous methods presented give good results under experimental conditions, they do not always take into account the specificities of the image analysis process in which it is going to be applied. The new approach presented, successfully intended to endow the algorithm with heuristic techniques that enable to adapt the algorithm with the particular image analysis process.

The preliminary results show that all of the tested images can be properly segmented according to our image analysis process needs and application purpose. Further work is intended, focusing on the adaptation of the proposed algorithm towards a multi-threshold approach and to color image segmentation.[9].

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