An Automatic Transformation from Bimodal to Pseudo-Binary Images

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Abstract

In this paper a procedure is proposed to transform bimodal images into enhanced ones with unified properties. These (pseudo-binary) images keep valuable grey level information and can be easily segmented by a global thresholding technique, using always the same threshold in the middle of the grey scale. This transformation is automatically self-adjusted from the statistical characterization of the histogram modes. It can be useful for the automatic segmentation of bimodal images found in controlled illumination environments, dealing with possible uncontrolled light variations. In addition, the grey level values in the pseudo-binary image can be considered as occupation percentage of the pixels, so subpixel reasonings can be easily inferred from the data in this new image.

Key Words : Grey levels, Global thresholding techniques, Segmentation, Histogram Gaussian distributions, Subpixel precision.

1 Introduction

The method for segmenting a digital image is always closely related to the illumination scheme utilized. In certain environments, the digitization conditions (illumination technique, digitization process, etc.) are controlled. These conditions often provide well contrasted images in which segmentation is rather easy by means of global thresholding. These images present dark objects on a bright background or viceversa. But certain problems may arise such as presence of shadows, etc.^[1] A good segmentation preserving the object shape is the first step towards a reliable attribute measurement when a high standard of precision is needed, or in any case in which shape is an important issue. Complex schemes have been used^[2] for the automation of this process in non trivial images, with success only on specific conditions and with a high computational cost.

The information we "a priori" have about an image is its histogram, $H(z)$. A number of authors have used histogram characterization for image segmentation^[3-5] or for avoiding expensive computations on the image^[6]. This permits a fast processing procedure, because, once the histogram is computed, all operations are $O(N_z)$, where N_z is the number of grey levels. If the distributions of dark and bright pixels can be clearly identified, then the image histogram is said to be bimodal, and each mode may be assigned either to objects of interest or background. As the frequency distributions for the bright and dark models become increasingly overlapped, the choice of a threshold in the valley between both modes becomes more difficult.

The digital nature of the image introduces errors in object feature measurements due to the pixel quantization. Certain magnitudes like areas and centroids are

subjected to low precision when they are assessed using only the information contained in binary images. This is an important drawback when reliability in measurements with morphometric significance is needed^[7]. Such effects could be minimized using the information contained in the grey levels of the contour pixels and the adjacent ones. This would increase the precision and invariance of descriptors^[8].

In this work we propose to translate the global threshold determination problem in bimodal images into a transformation of the original image into an enhanced one that holds unified criteria. This new image is useful both to be easily thresholded always by the same threshold (to ease the segmentation problem) and for keeping grey levels in the transition zones (to deal with the subpixel approach). Due to the transformation definition, the grey level values in the transformed image can be considered as occupation percentage of the pixels, so subpixel reasonings can be inferred from the data in this new image. This transformation is self-adjusted from the analysis of the image histogram and implemented through a LUT. We name this procedure *pseudo-binarization*. The output images are then called *pseudo-binary* images.

This technique is useful in all situations in which the illumination conditions can be controlled enough to provide well contrasted images with objects and background that can be objectively isolated, like in many robotic applications^[9], but also if images are well contrasted in any context^[7,8]. Obviously, it is of interest when grey levels are wanted to be kept in transition zones.

2 The pseudo binarization procedure

2.1 Histogram analysis

One of the main issues of this procedure is its automatism. This automation comes from the analysis of the image histogram. But this image property is not usually suitable for the application of function analysis procedures, due to the stochastic component of its nature. A low-pass filtering of the histogram previous to its characterization, deletes unwanted "noise" letting the desired "signal" (the modes) arise. Let $H(z)$ the histogram of the original image. This discrete one-dimensional function will be filtered to produce a smooth reference histogram $H'(z)$ by means of a discrete convolution with a gaussian kernel,

$$G(z, w) = \frac{1}{\sqrt{2\pi}w} e^{-\frac{z^2}{2w^2}}$$

so the new histogram is expressed as $H'(z, w) = H(z) \otimes G(z, w)$.

This H' is easier to be analyzed, but is also dependent on the width of the filter w . This parameter is not conditionant because it can be chosen within a wide range of values without important variations in the outcome. The filtering provides a reference histogram for further characterization of both modes, but this process does not affect the image, because H' is just a tool for mode extraction, while the pseudo-

binarization transformation is done on the original H . Thus, a reasonable wide gaussian is desirable: this way, only valid information survives. From these considerations, w has been heuristically set to 2.5 with good results in all images tested.

Once we have $H'(z, w)$ in which the two modes are hypothetically distinguishable, the aim is to extract the mode characterization through their approximation with two normal distributions; i.e. the means and standard deviations computed from the frequencies of H :

$$\mu_m = \frac{\sum_i z_i h(z_i)}{\sum_i h(z_i)} \quad \text{and} \quad \sigma_m^2 = \frac{\sum_i z_i^2 h(z_i)}{\sum_i h(z_i)} - \mu_m^2,$$

where $h(z_i)$ represent the frequencies for each grey level z_i , $i \in [z_{min}, z_{max}]$, and $m = \{0, 1\}$ for our problem (two modes: dark and bright). For isolating both modes, the bottom $h_0 = H'(z_0)$ of the valley between both modes in H' is sought, and only values of z $h(z_0) > h_0$ are considered, being z_0 level that separates the modes (see Fig. 1).

Fig. 1. Smoothed histogram and valley detection for mode characterization.

2.2 Image transformation

The pseudo-binarization method has been designed based on a contrast stretching procedure^[9]. Using the above described characterization, a classification of the image pixels into three sets is performed. We assume $z_{min} = 0$.

1. *Pixels clearly belonging to mode 0*: those with their grey levels between the minimum level (z_{min}) and the dark mode mean plus a given number of times, n , its standard deviation ($\mu_0 + n\sigma_0$). In the transformed image the grey level $z' = z_{min}$ will be assigned to these pixels.
2. *Pixels clearly belonging to mode 1*: those with their grey levels between the bright mode mean minus n times its standard deviation ($\mu_1 - n\sigma_1$) and the maximum level (z_{max}). In the transformed image the maximum grey level, $z' = z_{max}$, will be assigned to these pixels.
3. *Intermediate pixels*: those between $\mu_0 + n\sigma_0$ and $\mu_1 - n\sigma_1$. They will take grey level values linearly expanding the histogram to cover the whole grey level range. If the image assumptions are held, these pixels will be adjacent to boundary zones.

The implementation of this classification generates a look up table (LUT) for the transformation, as observed in Fig. 2, that produces a contrast stretching in the histogram. This way, the objects can be isolated from the background and furthermore the grey level values are preserved at the edge points (in which the

intermediate values in the grey scale are generated). This transformation can be analytically expressed as follows:

$$z' = T[H(z)] = \begin{cases} 0 & \text{if } z \leq \mu_0 + n\sigma_0 \\ \frac{z_{max}}{\mu_1 - n\sigma_1 - (\mu_0 + n\sigma_0)} z + \frac{z_{max}(\mu_0 + n\sigma_0)}{\mu_0 + n\sigma_0 - (\mu_1 - n\sigma_1)} & \text{if } \mu_1 - n\sigma_1 > z > \mu_0 + n\sigma_0 \\ z_{max} & \text{if } z \geq \mu_1 - n\sigma_1 \end{cases} \quad (1)$$

Fig. 2. Plot of the transference function used for the histogram transformation described in Eq. (1).

Only n remains to be selected to define the transformation. This n is also extracted from the characterization of both modes. For this, n is incremented, $n = 1, 2, 3, \dots$, and, for each n , $\mu_0 + n\sigma_0$ and $\mu_1 - n\sigma_1$ are computed until $\mu_0 + n\sigma_0 \geq \mu_1 - n\sigma_1$. Then, n is set one unity less in order to make room for the intermediate grey levels.

The pseudo-binary image obtained this way is easily segmentable by means of an edge tracking algorithm that separates pixels over the central value of the grey intensity range ($z' = z_{max}/2$) from those under it. Moreover, since image has not been binarized, the grey levels at the edge-adjacent zones are kept and linearly expanded to a maximum range (see result section), so subpixel precision can be inferred from these values interpreted as percentage of occupation in order to compute precise shape descriptors^[7,8].

3 Results and Discussion

The behaviour of the proposed method is shown for images of real applications in different domains such as robotics^[9] and medical imaging^[7,8]. In Fig. 3, a number of images are presented: tools, CT scan, and a Moiré topography. The differences between dark and light modes have been maximized in the transformed image, and they can be segmented by a threshold $= z_{max}/2$. Note that, in the first example, false contours can be removed through morphological filters, if necessary. In spite of the trimodal character of the CT image, the transformation is able to separate bone from soft tissue. Working with the resulting image is much easier and morphological filters or edge detection algorithms can help the final segmentation of the objects of interest. The third image shows how the method cope with a wide range of variations in illumination conditions, resolving low contrasted images. Finally, in the Moiré topography, fringes become well contrasted for segmentation.

The histograms for the first and second examples in Fig. 3 show the three different regions of the histogram after the application of the transformation: two

single level modes at z_{min} and z_{max} , and some few intermediate levels (thick bars for the pseudo-binary image and thin bars for the original one). On the other hand, those of the third and fourth examples show the histograms H and H' , and the detection of the separation level, z_0 .

Fig. 3. (Left) Original images; (center) Pseudo-binary images; (right) Comparative histograms for the original (raw and smoothed) and transformed images. First row: scissors; Second row: CT scan of a human vertebra; Third row: low contrast image; Fourth row: Moiré topography.

Fig. 4. Numerical and grey values for pixels in an image window subjected to the transformation with different n values: (left) original image; (centre) using one standard deviation; (right) using five standard deviations.

Fig. 4 shows how the contrast is being improved as n is increased. The linear definition for the central zone of the transformation transference function, permits to map the grey level values of the pseudo-binary image into occupation percentages. This fact implies that a global threshold that preserves shape should be defined like the one that sets the edges at 50% of object occupation, so the enhanced image should be always thresholded by the central value of the grey level scale.

Once the image has been pseudo-binarized we can extract shape contours. Thus, the contours will be defined as the border points for the different 8-connected sets of pixels with grey values greater or less than $z_{max}/2$. Fig. 4 (left) shows the set of pixels that verify this condition. For locating the edges with subpixel precision, first the direction of the gradient vector at each border point is found. Then, the displacement of the center of the boundary pixel in the direction of the gradient is determined by the following equation:

$$\Delta = 1.5 - \frac{z + z_{+1}}{z_{max}} ; \quad (2)$$

where z is the grey level at the boundary pixel and z_{+1} that of the 8-neighbour in the gradient direction. See in Fig. 5 (right) the results of applying this method with the values displayed in Fig. 5 (left). This equation works regardless of dark and bright modes representing either objects and background or vice versa.

Fig. 5. (left) Boundary points. (right) Edge location with subpixel precision through the use of the grey level values in the pseudo-binary image. The circle represents orientation and position of the edge at each boundary point.

4 Conclusions

An efficient and simple procedure has been proposed to transform bimodal images into an enhanced one with unified criteria. This approach permits to translate the global threshold determination problem into an histogram analysis and characterization problem. In addition, this new image is useful either to be easily thresholded always by $z_{max}/2$ (to ease the segmentation problem) or to keep grey levels in the transition zones (to deal with the subpixel approach). Due to the transformation definition, the grey level values in the transformed image can be considered as occupation percentage of the pixels, so subpixel reasoning can be inferred from the data in this new image. Moreover, due to the linear expansion of the intermediate grey levels, the possible segmentation would be very respectful with the shapes in the image.

This method has been successfully utilized in robotics^[10] and in medical imaging^[7,8] applications.

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