Image Segmentation by Local Entropy Methods

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ABSTRACT

This paper will briefly describe local entropy and local relative entropy thresholding methods and compare them to two studied methods from the literature, those of Kittler and Illingworth and of Otsu.

INTRODUCTION

Local segmentation or thresholding methods have often been found to perform better than global methods due to increased sensitivity to small area features[1]. The global threshold is based upon some metric computed over the entire image. A threshold derived from such an average response will often fail to segment small objects or objects with similar characteristics to the global background. In this paper we extend the entropy and relative entropy thresholding methods of Chang et. al.[2] to local computation. A more detailed explanation of the mathematics involved is given in Althouse[3]. The entropy and relative entropy thresholds are compared to those computed by the Otsu[4] and by the Kittler and Illingworth[5] methods. Some objective threshold measures are used in the comparison. Computing local thresholds for non-overlapping windows and using the thresholds to generate a binary image generally yields a visually displeasing checkerboard effect. That this can be alleviated in most images by spatial smoothing is demonstrated.

THRESHOLDING METHODS

We will not attempt here to explain the thresholding methods in any detail, referring the interested reader to the appropriate articles. Otsu considers the image histogram to consist of two gaussian populations representing the object and background. A threshold is selected to maximize the between class separation on the basis of the class variances. Using the same two gaussian classes assumption, Kittler and Illingworth select a threshold which is minimum error in the Bayes sense.

Entropy is the measure of the information content in a probability distribution. Relative entropy measures the discrepancy between two probability distributions on the same event space. To provide the probability distribution needed for the entropy measures, a co-occurrence matrix is generated from the input image. It is a mapping of the pixel to pixel greyscale transitions in the image between the neighboring pixel to the right and the pixel below each pixel in the image. From the co-occurrence matrix comes the distribution of greyscale transitions. The candidate threshold divides the co-occurrence matrix into four regions representing within object, within background, object to background, and background to object class transitions. Three entropies, called local, joint, and global, are computed by differing combinations[2] of the entropies of the four regions. Note that the name 'local entropy' does not refer to a locally generated threshold, but is the name originally given to the method. Optimal thresholds are found by maximizing the entropies as a function of threshold. The relative entropy is computed from the

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transition distributions of the original image and the segmented image. By minimizing the relative entropy as a function of threshold, the original image and segmented image transition distributions are most closely matched.

A commonly used test image, Lena, is shown for subjective comparison. In Figure 1 is the original image and Figures 2-5 are the Otsu, Kittler-Illingworth, 'local' entropy, and 'local' relative entropy results. For a portrait image such as this, the facial features are generally of primary importance, and we see that the 'local' relative result gives the best detail there.

The three entropy and three relative entropy thresholds are objectively compared with the thresholds from Otsu's and Kittler and Illingworth's methods by use of the Uniformity[6] and Shape[1] segmentation measures. These data are in Table 1. Thresholds optimal for each of the measures are included to give a sense of the measure's weight. That the measures do not agree very well is not surprising. Using a normalized average score from both measures, global entropy does best. One may be able to rely on measures to judge thresholds for a class of images, but it seems not in general.

LOCAL THRESHOLDING

For the local computation of thresholds, the thresholding algorithm in its entirety is executed on each sub-image or window of a chosen size of the original image to generate a threshold which is used to segment the greyscale sub-image into a binary sub-image. The subimages are the reassembled into a complete binary image. For the image of Lena, as in Figure 6, where the desired binary image should have as much spatial detail of the original image as possible, local thresholding provides some improvement. The windows are clearly evident in this image because no attempt has been made to smooth the window boundaries. In comparison with the globally applied threshold in Figure 5, the local threshold yields better spatial detail. Relative entropy methods seem to be more sensitive to variation as evident by the greater window edge discontinuities. The window size itself has considerable effect on the magnitude of edge discontinuities and should be chosen with some characteristic of the input image in mind. Here an 8x8 pixel window is used since the features of interest are quite small. Fitting characteristics could be the spatial size of variations in the image, general target size, or textural frequency.

The local implementation is most suitable when used with a smoothing algorithm which can either modify a window threshold by examining the thresholds generated in neighboring windows, or by setting individual pixel thresholds on the basis of neighboring pixel values. If one views the matrix of thresholds generated for each window of the image as an image itself and applied smoothing to it in the form of a low pass filter, window edge discontinuities should be reduced. A simple 3x3 low-pass filter of the form [1 1 1, 1 2 1, 1 1 1] was used. The filter was applied to all thresholds except those at the outside or edge of the matrix. The matrix edge thresholds are excluded since the eight neighbors of each threshold are needed for the filtering operation. An unsmoothed 'frame' of windows may be noticeable on images where the window size is large. This method of smoothing was selected for its simplicity and good result. Figure 7 is the smoothed image corresponding to the unsmoothed image in Figure 6.

Local application of spectral co-occurrence matrix methods to segment multispectral or hyperspectral images is introduced in Althouse and Chang[7].

CONCLUSION

Entropy and relative entropy segmentation methods are discussed and implemented both globally and locally. Local implementation is shown to yield improved detail to the segmented image.

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Table 1. Thresholds and measures for Lena image.

METHOD	THRESHOLD	SHAPE MEASURE	UNIFORMITY MEAS.
local entropy	160	.434	.879
joint entropy	125	.473	.756
global entropy	137	.483	.812
'local' relative	191	.323	.857
joint relative	204	.208	.768
global relative	193	.309	.847
Kittler-Illingworth	165	.417	.886
Otsu	162	.425	.883
shape	135	.484	
uniformity	163		.891

Figure 1. Original Lena image.

Figure 2. Otsu method, threshold at 162

Figure 3. Kittler-Illingworth method, threshold at 165.

Figure 4. 'Local' Entropy, threshold at 160.

Figure 5. 'Local' Relative Entropy, threshold at 191.

Figure 6. Locally applied 'local' relative entropy threshold, 8x8 window.

Figure 7. Spatially smoothed Figure 6.