Image Thresholding using 2D Tsallis-Havrda-Charvaat Entropy and Local Binary Pattern (LBP)

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Abstract

This paper proposes an automatic global thresholding method based on 2D Tsallis-Havrda-Charva+-t entropy and histogram of Local Binary Patterns (LBP). Tsalli-Havrda-Charvat entropy is obtained from 2D histogram, which has determined by using the LBP decimal value and the average decimal value of its neighborhood. Based on this entropy we obtain the optimal threshold pair by maximizing the criterion function. LBP histogram is adopted to capture the texture information. LBP's high performance for texture characterization helps to make our method more suitable for thresholding the images in problem. In this paper we report the effectiveness of our thresholding method when applied to some real-world and synthetic images, and experiments show that the performance of our proposed method is promising, robust and fast.

Keywords: Image Segmentation, 2D Histogram, Local Binary Pattern, Thresholding

1. Introduction

Image segmentation is one of the most difficult task in digital image processing. Image segmentation is the process of partitioning a digital image into multiple segments. It is used to locate object and boundaries in images. Segmentation is often considered to be the first step in image analysis. The purpose is to subdivide an image into meaningful non-overlapping regions and these regions are obtained corresponding to the physical parts or objects of a scene (3D) represented by the image (2D). It involves the assumption that intensity values are different in different regions. In each region, which represents the corresponding object in a scene, the intensity values are similar. The simplex method of image segmentation is called thresholding[1-14]. Thresholding is a technique, which is used to extract an object from its background by assigning an intensity value 't' for each pixel. Each pixel is either classified as an object point or a background point.This selection is grouped

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into two categories - Global and Local methods. Global method involves segmenting an entire image with a single value using the gray scale histogram. Local method partitioning an image into a group of sub-images and select a threshold point. For each sub-images, global is easy to implement.

In image segmentation, the texture image segmentation is the most difficult one. To solve the problems associated with texture images an entropy based thresholding method on 2D histogram of LBP domain is proposed. This new method extends the method proposed in[12]. This paper is organized as follows: In Section II, a brief description of the Tsallis-Havrda-Charvat entropy is given. In Section III, the experimental results are given. Finally, the paper concludes at Section IV.

2. Proposed Method

2.1 Tsallis-Havrda-Charvat Entropy

Image histogram holds an important property of the image and can be exploited to separate the object and the background. Normalized histogram can be realized as a probability distribution.

Let $P = (p_1, p_2, ..., p_n) \in \Delta_n$

Where

$$\Delta_n = \left\{ (p_1, p_2, \ldots, p_n) \mid p_i \geq 0, i = 1, 2, \ldots, n, n \geq 2, \sum_{i=1}^{n} p_i = 1 \right\}$$

Havrda and Charvat defined entropy of degree α as

$$H_n^{\alpha}(P) = \frac{1}{1-2^{1-}} \left[1 - \sum_{i=1}^{n} p_i^{-} \right] \quad (1)$$

Where, α is a real positive parameter and α≠1. Independently Tsallis[13] proposed a one parameter generalization of the Shannon entropy as

$$H_n^{\alpha}(P) = \frac{1}{\alpha - 1} \left[1 - \sum_{i=1}^{n} p_i^{\alpha} \right] \quad (2)$$

The same expressions are used for both these entropies except the normalizing factor. The Havrda and Charvat entropy is normalized to 1. That is, if P = (0.5, 0.5), then, $H_n^{\alpha}(P) = 1$ whereas the Tsallis entropy is not normalized. In this application both the entropies yield the same result and called as the Tsallis–Havrda–Charvat entropy, as proposed[12].

2.2 Local Binary Pattern (LBP)

Best and well known local texture capturing method is LBP (Local Binary Pattern).The LBP operator was introduced by Ojala et al.[24] for texture classification. Given a centre pixel in the image, the LBP value is computed by comparing its gray value with its neighbours, as shown in Figure 1, based on the following Equation:

$$LBP_{P,R} = \sum_{p=1}^{P} 2^{(p-1)} \times f_1(g_p - g_c) \quad (3)$$

$$f_1(x) = \begin{cases} 1, & x \geq 0 \\ 0, & \text{else} \end{cases}$$

Where g_c is the gray value of the center pixel, g_p is the gray value of its neighbours, P is the number of neighbours, and is the radius of the neighbourhood.

If the coordinates of g_c is (x,y), then the coordinates of g_p (X_p, Y_p) is given by:

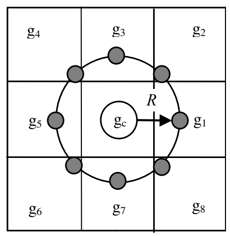

Figure 1. Local 8 neighbourhoods.

$$X_p = ipolate\left(x - R\sin\left(\frac{2\pi p}{P}\right)\right) \quad (4)$$

$$Y_p = ipolate\left(y + R\cos\left(\frac{2\pi p}{P}\right)\right) \quad (5)$$

Where p=(0,...,P-1) and ipolate() means interpolation must for those pixels which do not fall exactly in the centre of pixels. LBP represents local structure patterns in coded form. The decimal value of the binary code is set as the local micro-structure representation. So, they are useful in texture classification. Here, we have used the same LBP decimal values to generate the 2D histogram.

2.3 2D Histogram

In order to compute the 2D histogram of a given LBP image we precede as follows:

Calculate the average LBP decimal value of the neighborhood of each pixel. Let $g_{lbp}(x, y)$ be the average LBP decimal of the neighborhood of the pixel located at the point (x, y). The average LBP decimal value for the 3 × 3 neighborhood of each pixel is calculated as

$$g_{lbp}(x,y) = \left\lfloor \frac{1}{9}\sum_{i=-1}^{1}\sum_{j=-1}^{1} f_{lbp}(x+i, y+j) \right\rfloor \quad (6)$$

Where $[r]$ denotes the integer part of the number r. The pixel's LBP decimal value, $f_{lbp}(x,y)$, and the average of its neighborhood, $g_{lbp}(x,y)$, are used to construct a two-dimensional histogram using the following Equation.

$$h(m, n) = prob(f_{lbp}(x, y) = m \;\; AND \;\; g_{lbp}(x, y) = n) \quad (7)$$

The normalized histogram is approximated by using the formula

$$\hat{h}(m,n) = \frac{number\ of\ elements\ in\ the\ event\left(f_{lbp}(x,y)=m\right) AND \left(g_{lbp}(x,y)=n\right)}{number\ of\ elements\ in\ the\ sample\ space}$$

$$= \frac{number\ of\ pixels\ with\ LBP\ decimal\ value\ and\ average\ LBP\ decimal\ value\ n}{number\ of\ pixels\ in\ the\ image} \quad (8)$$

2.4 The Object and Background Probabilities Calculation

Through a vector (t, s), the threshold can be obtained where 't' represents the threshold of the gray level of the pixel for $f_{lbp}(x, y)$, and s, for $g_{lbp}(x, y)$, represents the threshold of the average gray level of the pixel's neighborhood. A surface can be drawn using the joint probability mass function p (m, n), which will have two peaks and one valley. The object and background correspond to the peaks. Selecting the vector (t, s), it can easily be separated. This vector maximizes a suitable criterion function $\varnothing_\alpha(t, s)$ and using this vector (t, s), the domain of the histogram is divided into four quadrants shown in Figure 2: the first quadrant by [t + 1, 255] × [0, s], the second quadrant by [0, t] × [0, s], the third quadrant by [0, t] × [s + 1, 255], and the fourth quadrant by [t + 1, 255] × [s + 1, 255]. Since first and third quadrants contain information about edges and noise alone, they are ignored in the calculation. Rest of the two quadrants i.e. second and fourth quadrants contain the object and the background. Therefore, the second and fourth quadrants are considered to be independent distributions and the probability values in each case must be normalized in order to have a total probability equal to 1. The normalization is done by using a posteriori class probabilities, (t, s) and (t, s), where:

$$P_2\left(t,s\right)=\sum_{i=0}^{t}\sum_{j=0}^{s}p\left(i,j\right)\ \text{ and }\ P_4\left(t,s\right)=\sum_{i=t+1}^{255}\sum_{j=s+1}^{255}p(i,j) \tag{9}$$

The contribution of the quadrants, which contains the edges and noise i.e. first and third quadrants, are considered as negligible. Therefore, we approximate $P_4\left(t,s\right)$ as $P_4\left(t,s\right)\approx 1-P_2\left(t,s\right)$

A threshold 't' is to be set to partition the image into two parts: object and background. This image thresholding can be thought as similar to partitioning the set '*G*' having values 0-255, into two disjoint subsets:

$G_0=\left\{0,1,2,\&\,,t\right\}$ and $G_1=\left\{t+1,\,t+2,\,t+3,...,255\right\}$.

The probability distribution associated with these two sets G_0 and G_1 are:

$$\left(\frac{p(0,0)}{P_2(t,s)},....,\frac{p\left(0,s\right)}{P_2\left(t,s\right)},\frac{p(1,0)}{P_2(t,s)},\cdots\frac{p(t,s)}{P_2\left(t,s\right)}\right)$$

and

$$\left(\frac{p(t+1,s+1}{P_4(t,s)},...,\frac{p(t+1,255)}{P_4(t,s)},.....\frac{p(255,255)}{P_{4(t,s)}}\right)$$

(0, 0) 2nd quadrant	(255, 0) 1st quadrant
3rd quadrant (0, 255)	4th quadrant (255, 255)

Figure 2. Quadrants in the 2D histogram due to thresholding at (t,s).

2.5 Entropic Criterion Function Generation

The following equations give the Tsallis–Havrda–Charvat entropies associated with object and background:

$$H_b^{\alpha}\left(t,s\right)=\frac{1}{\alpha-1}\left[1-\sum_{i=0}^{t}\sum_{j=0}^{s}\left(\frac{p(i,j)}{P_2(t,s)}\right)^{\alpha}\right] \tag{10}$$

and

$$H_w^{\alpha}(t,s)=\frac{1}{\alpha-1}\left[1-\sum_{i=t+1}^{255}\sum_{j=s+1}^{255}\left(\frac{p(i,j)}{1-P_2(t,s)}\right)^{\alpha}\right] \tag{11}$$

And priori Tsallis–Havrda–Charvat entropy of an image is given by

$$H_T^{\alpha}=\frac{1}{\alpha-1}\left[\sum_{i=0}^{255}\sum_{j=0}^{255}p(i,j)^{\alpha}\right] \tag{12}$$

Where $\alpha(\neq 1)$is a positive real parameter.

According to the consideration that, a physical system can be decomposed into two statistical independent subsystems *A* and *B*, the probability of the composite system is $p^{A+B}=p^{A}s^{B}$ then the Tsallis–Havrda–Charvat entropy of the system follows the non-additivity rule:

$$H_T^{\alpha}(A+B)=H_T^{\alpha}(A)+H_T^{\alpha}(B)+(1-\alpha)H_T^{\alpha}(A)H_T^{\alpha(B)} \tag{13}$$

Therefore, the criterion function is:

$$\phi_{\alpha}(t,s)=H_b^{\alpha}(t,s)+H_w^{\alpha}(t,s)+(1-\alpha)H_b^{\alpha}(t,s)H_w^{\alpha}(t,s) \tag{14}$$

By maximizing the above criterion function (Equation 14), the optimal threshold pair $(t^{*}(\alpha),s^{*}(\alpha))$ can be calculated. Thus

$$\left(t^{*}\left(\alpha\right),s^{*}\left(\alpha\right)\right)=Arg\max_{(t,s)\in G\times G}\phi_{\alpha}(t,s) \tag{15}$$

3. Test Results

In this section, we discuss the experimental results obtained using the proposed method. Our proposed method is compared with other two methods Otsu[16] and Sahoo[12]. Sample comparison results are shown in Figure 3. Our proposed method gives good results than the other two methods.

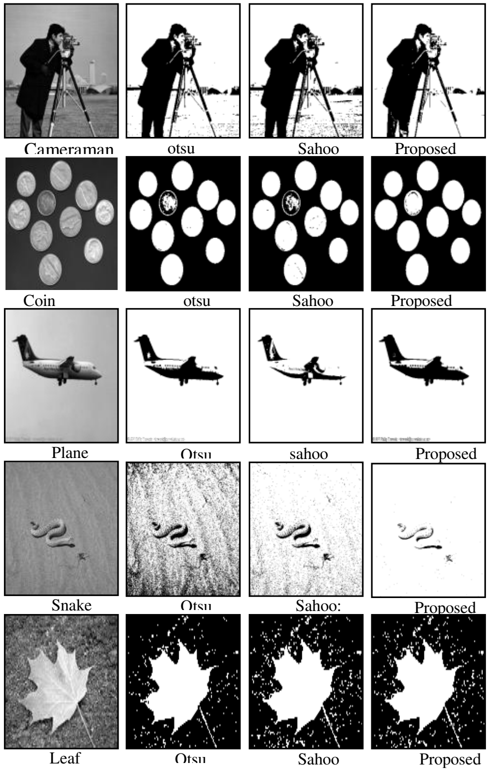

Figure 3. Visual comparison results on different images (α=0.8).

Table 1. Performance measurement on different images by proposed method and other two methods (Otsu and Sahoo)

Test image	Otsu	Sahoo	proposed
Cameraman	.61	.66	.52
Coin	.59	.60	.53
Plane	.61	.59	.42
Snake	.51	.55	.39
leaf	.53	.54	.52

We measure the performance of the proposed method and all other methods using the metric Misclassification Error (M.E.). It is defined as follows:

$$M.E. = 1 - \frac{|B_o + B_t| + |F_o + F_t|}{|B_o| + |B_t|} \tag{16}$$

Where, B_o and F_o are the background and foreground of original images and B_t and F_t are the test images, respectively. The performance measurement on different images is shown in Table 1. The misclassification error in our method is much lesser than the other two methods.

4. Conclusion

Using Tsallis–Havrda–Charvat's entropy of degree α and LBP based 2D histogram; we have developed a new method for thresholding of images. This method usage a 2D LBP histogram computed from the image. The 2D histogram was constructed using the LBP decimal value of a pixel and local average LBP decimal value to choose an optimal threshold value. The output result shows the superiority of the proposed method than other two methods. The values of α and average filter mask size control the thresholding result. Therefore, in future an optimum and adaptive measure of α and mask size can be thought to develop a fully automatic unsupervised thresholding technique.

5. References

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