ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, *Vol 9(48), DOI: 10.17485/ijst/2016/v9i48/105794, December 2016* ISSN (Online) : 0974-5645

Multilevel Thresholding for Image Segmentation based on Similarity Filtering

Antariksha Kar, Sidharth Bhatia and Gaurav Gupta*

School of Engineering and Technology, The Northcap University, Gurugram – 122017, Haryana, India; antarikshak@gmail.com, sidharthbhatia@ncuindia.edu, gauravgupta@ncuindia.edu

Abstract

Objective: In this paper, an effective and fast multi-threshold image segmentation method is proposed based on similarity filtering. **Method:** The image histogram peaks and the valley can be used to locate the clusters in the image. The idea of the proposed research is to fit the Gaussian distribution to the histogram of the image. Dominant peaks are selected from the input image histogram near to its Gaussian distribution. Then for each element of the peaks, peak's valleys are obtained in the left (low) and right (high) side. **Findings:** Experiments on a variety of images from Berkeley Segmentation Dataset (BSD) show that the new algorithm effectively segments the image in a computationally efficient manner. **Comparison/ Performance evaluation:** On comparison, proposed approach is found to be better than other existing methods. Peak Signal to Noise Ratio (PSNR) and time are used to evaluate the performance. The proposed algorithm tries to fit Gaussian curves on the dominant peaks and thus find the valleys which are used as thresholds. **Novelty:** This is always a quicker process as there is a predefined model which only needs to be fit for the given data set.

Keywords: Gaussian Distribution, Image Segmentation, Multilevel Thresholding, Similarity Filtering

1. Introduction

Image segmentation is one of the most widely pursued problems in the domain image processing. Since segmenting an image in the best way possible is the first step in an innumerable number of techniques[1-3]. Some of the area where image segmentation has been applied popularly are content-based information retrieval[4], machine learning[5], medical imaging[6], object detection[7], iris recognition[8], video surveillance, etc. Image segmentation effectively assigns a label to each and every pixel in the region of application. This suggests that these pixels with the same label share on or the other common traits. This property of Image segmentation has a very popular application in the field of computer graphics by the name of 'Marching Cubes'[9]. Loosely speaking image segmentation is divided into three types namely region based segmentation, data clustering and edge based segmentation. region based segmentation algorithms consist of seeded, unseeded region growing algorithms and JSEG also and the fast scanning algorithms.

A very important aspect of image segmentation algorithms is the thresholding technique used. Thresholding can, in simple non-technical terms be explained as assigning one value to pixels that have values more than T and assigning another value to pixels that have values lower than T. This simple concept can in fact help a lot. It effectively reduces the size of the original image significantly. Also for further processing that is to be applied, a thresholded image can provide existing structures in an image that can then be worked on to create a number of applications. In data intensive applications such as robotic vision, character recognition and autonomous target acquisition where speed of execution is of prime importance thresholding can provide an effective solution.

Thresholding can be classified into bi-level and multi-level thresholding. Both of these methods attempt to reach the same goal, that is, effective binarization of an image. Lot of algorithms has been proposed in this area[10]. Otsu's method has been by far the most popular one[11]. The aim of Otsu's algorithm is to minimize the intra-class

** Author for correspondence*

variance. According to a study[12], Otsu's method is one of the best for real world images for selecting a threshold to segment an image with regard to uniformity and shape measures.

However the underlying issue with Otsu's method is it being too slow for real time applications when multi-level thresholding comes into the picture. This is because Otsu's method utilizes an exhaustive search to minimize intra-class variance.

Some thresholding techniques that are inherently 1D are enhance for multi-level thresholding[13,14]. The method proposed[15], explains a 2D thresholding method that considers the pixel intensity value as well as the local neighborhood. Another method is called entropic thresholding[16]. This paper proposes a multilevel thresholding method for unevenly lighted images using Lorentz information measure. Another paper utilizes the human visual system for edge detection and segmentation[17].

2. Proposed Work

In the proposed work, we focus on preserving the modality of the image and thus segmenting it using clustering-based thresholding techniques. The proposed algorithm is designed keeping in view the following points:

- A large number of images have been observed to have multiple modes where each mode has pixel values centered on or around the mean of that mode,
- A large variety of real world images are observed to have modes that are actually near Gaussian distributions centered on and around a peak (mostly the mean as said before). These peaks are surrounded by valleys on each side,
- The human visual system is such that for the pixel values contained in a given mode the system's attention is drawn mostly towards the mean values of that mode, and
- The PSNR value of the segmented image with respect to the original image usually gives a good indication of how well the segmentation has been done. Higher the PSNR higher is the segmentation quality. Here

$$\mathbf{PSNR} = 20\log_{10}\left(\frac{255}{\mathrm{RMSE}}\right) \tag{1}$$

Where,

$$RMSE = \sqrt{\frac{1}{MN}\sum_{I=1}^{M}\sum_{J=1}^{N}[I(i,j) - I'(i,j)]^2} \tag{2}$$

Here I and I' are the original and the segmented image respectively.

- The correct estimation of various modes of an image's histogram can be done by determining the peaks and valleys occurring in the histogram.

Algorithm: The steps given below describe the proposed algorithm

- If the image is a colored image then first convert it to a single channel grayscale image.
- Obtain the image histogram whose bins are in the range $R = [a, b]$; where $a = 0$ and $b = 255$.
- Smooth the histogram data to remove local noise using averaging filter (typical kernel size can be 5).
- Find the peaks array $P = [p_1, p_2, \ldots, p_n]$, from the histogram where $p_1, p_2, \ldots, p_n$ represent the locations of the dominant peaks for each near Gaussian distribution in the histogram.
- For each element of the peaks matrix P find the corresponding values of v_{low} and v_{high} which represent the corresponding peak's valleys on the left and on the right in the histogram respectively.
- Replace the image pixels in the range $[v_{low_n}, v_{high_n}]$ with the mean value of their intensities.

The steps 4 and 5 carried out very efficiently using a similarity filter[18]:

$$\mathbf{S}(\mathbf{p},\mathbf{q}) = \exp\left(\frac{-\frac{1}{2}(\mathbf{N_p} - \mathbf{I_q})^2}{\sigma_p^2}\right) \tag{3}$$

Where $\mathbf{S}$ is a Gaussian distribution centered at $\mathbf{N_p}$ and $\mathbf{I_q}$ is the histogram value at its bin location $\mathbf{q}$. $\sigma_\mathbf{p}$ in the above equation is half the distance (since 2 $\sigma_\mathbf{p}$ corresponds to a 95% confidence interval in a Guassian distribution) to valleys enclosing $\mathbf{N_p}$.

$$\sigma_p = \begin{cases} \dfrac{v_{high} - N_p}{2} & if\ I_q \geq N_p \\ \dfrac{N_{p - v_{low}}}{2} & if\ I_q < N_p \end{cases} \tag{4}$$

The idea of using a similarity filter comes from the background concept of bilateral filtering[19]. The bilateral filter is a low pass filter. It smoothes the image while preserving edge by means of a nonlinear combination of nearby pixel values. It combines gray levels or colors based on both their geometric closeness and their photometric similarity, and prefers near values to distant values in both domain and range.

3. Results and Discussions

The proposed algorithm is tested over a large number of images with varying range of complexity; here we show the experimental results for seven standard images only, due space limitation. We compared the proposed multilevel thresholding algorithm with another standard and recently developed multilevel thresholding algorithm[20].

In Figure 1 shows the obtained results with segmented image histogram. The PSNR value is widely regarded as an effective method for checking the image quality. The time and PSNR comparison for proposed algorithm with another standard and recently developed multilevel thresholding algorithm can be found in Table 1 and 2 respectively. As shown in Table 1 the time taken by our proposed algorithm is nearly half of Otsu's method takes in most of the cases. The algorithm was tested on a 3.5 GHz Intel Core i7 machine with 4GB of RAM. The time here depends on the number of peaks in an image's histogram. Even as the size of the image changes the time taken does not increase as the algorithm is not an exhaustive search algorithm like Otsu's. From Table 2, one can observed that the PSNR values are around or more than 30 dB which signifies a high similarity index between the original and the thresholded images from a viewer's perspective.

The accuracy and efficiency of the proposed algorithm becomes clear when, apart from application results, the algorithm is stacked up against Otsu's multilevel thresholding algorithm for theoretical evaluation of performance. Otsu's algorithm is an exhaustive search algorithm and thus searches $^{G-1}C_n$ combinations. Here G is the number of gray levels in an image and n is the number of thresholds.

4. Conclusion

A multilevel thresholding method for image segmentation has been proposed that uses similarity filtering. This predefined model based method is quick and efficient and this has been validated by the PSNR results and running time of the algorithm. The algorithm could also be applied to real time operating systems using computer vision systems, specifically object detection by mobile robots. These further improvements and experimentation are left for future work.

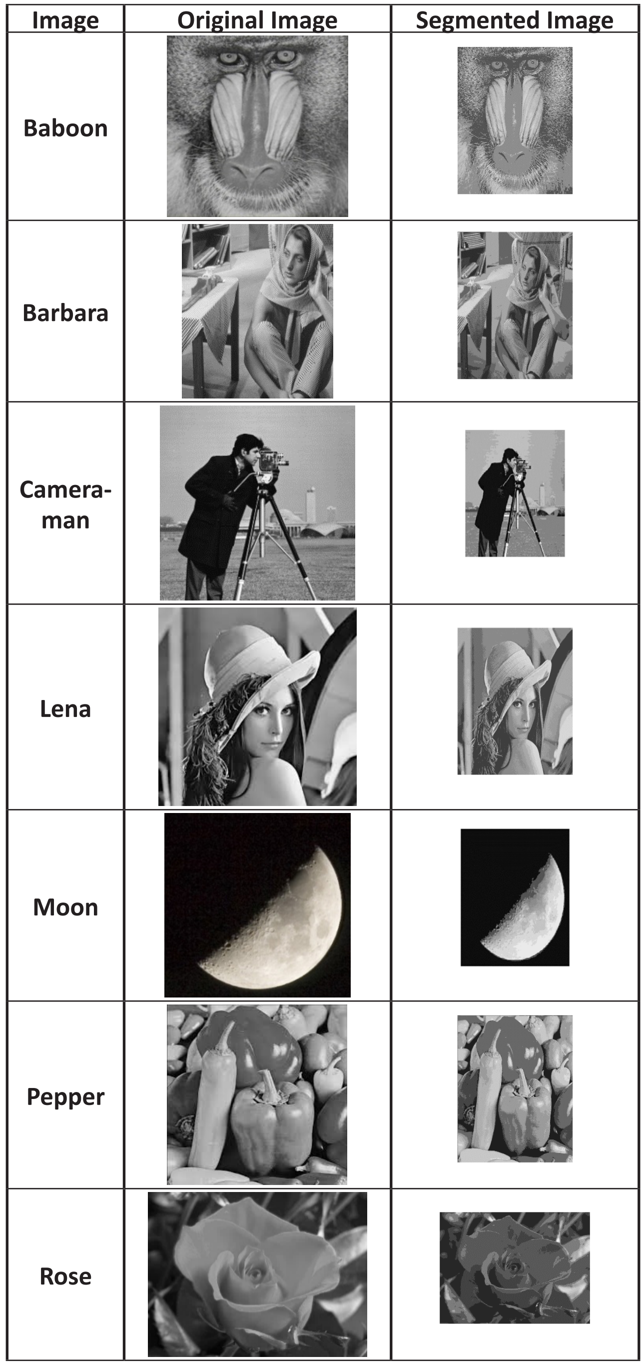

Figure 1. Original Image, histogram and segmented images using proposed method.

Table 1. Computational time comparison

Sl. No	Image	Size	Time(s)				
			Proposed	Otsu's time	Watershed algorithm	K means	S Arora [16]
1.	Baboon	512x512	0.038	0.062	0.058	0.151	0.09
2.	Barbara	512x512	0.039	0.061	0.060	0.154	0.089
3.	Cameraman	256x256	0.015	0.031	0.023	0.025	0.030
4.	Lena	512x512	0.040	0.060	0.059	0.385	0.086
5.	Moon	355x351	0.030	0.045	0.031	0.030	0.048
6.	Peppers	512x512	0.012	0.028	0.059	0.300	0.089
7.	Rose	480x361	0.034	0.051	0.041	0.089	0.061

Table 2. PSNR values comparison

Sl. No	Image	Size	PSNR				
			Proposed	Otsu's time	Watershed algorithm	K means	S Arora (Reference paper)
1.	Baboon	512x512	32.45	8.44	20.02	19.03	15.82
2.	Barbara	512x512	32.56	8.68	14.80	15.90	16.67
3.	Cameraman	256x256	31.17	8.92	18.06	17.89	17.79
4.	Lena	512x512	31.79	8.46	17.93	18.09	18.78
5.	Moon	355x351	34.57	15.45	29.95	31.06	10.12
6.	Peppers	512x512	30.80	9.30	16.71	17.78	19.90
7.	Rose	480x361	33.45	11.07	19.63	20.34	10.93

5. References

1. Arora S, Hanmandlu M, Gupta G, Singh L. Enhancement of Overexposed Color Images. Proceedings of ICoICT, Malaysia; 2015, p. 207-11.
2. Gupta G, Kumar M. An Iterative Marching with Correctness Criterion Algorithm for Shape from Shading under Oblique Light Source. Proceedings SocProS, India; 2012. p. 28-30.
3. Hanmandlu M, Arora S, Gupta G, Singh L. A Novel Optimal Fuzzy Color Image Enhancement using Particle Swarm Optimization. Proceedings of IC3, India; 2013. p. 41-46.
4. Lew M. Content-based Multimedia Information Retrieval: State of the Art and Challenges, ACM Transactions on Multimedia Computing, Communications, and Applications. 2006 Feb; 2(1):1–19.
5. Graves, G. Batchelor MB. Machine Vision for the Inspection of Natural Products. Springer, 2003.
6. Wu W, Chen AYC, Zhao L, Corso JJ. Brain Tumor Detection and Segmentation in a CRF Framework with Pixel-Pairwise Affinity and Super Pixel-Level Features, International Journal of Computer Aided Radiology and Surgery. 2014 March; 9(2):241-53.
7. Delmerico JA, David P, Corso JJ. Building Façade Detection, Segmentation and Parameter Estimation for Mobile Robot Localization and Guidance. Proceedings of IROS: USA, 2011, p. 1632-39.
8. SRI International Sarnoff Launches Iris Biometric Vehicle Access Control System. Date accessed. 20/10/2015. Available at: http://www.biometricupdate.com/201401/sri-international-launches-new-iris-recognition-access-control-system.
9. Lorensen WE, Cline HE. Marching Cubes: A high Resolution 3D Surface Construction Algorithm. Computer Graphics. 1987 July; 21(4):163-69.
10. Sezgin M, Sankur B. Survey Over Image Thresholding Techniques and Quantitative Performance Evaluation, J. Electron. Imaging. 2004 Jan; 13(1):146–65.
11. Otsu N. A Threshold Selection Method from Gray-Level Histograms, IEEE Trans. Sys. Man. Cyber. 1979 Jan; 9(1):62–66.
12. Sahoo PK, Soltani S, Wong AKC. Survey: A Survey of Thresholding Techniques, Computer Vision Graphics Image Process. 1988 July; 41:233–60.
13. Tsai DM, Chen YH. A Fast Histogram-Clustering Approach for Multilevel Thresholding, Pattern Recognition Letters. 1992 April; 13(4):245-52.
14. Chen WT, Wen CH, Yang CW. A Fast Two-Dimensional Entropic Thresholding Algorithm, Pattern Recognition, 1994 July; 27(7):885-93.
15. Kirby RL, Rosenfeld A. A Note on the use of (Gray, Local Average Gray Level) Space as an Aid in Thresholding Selection, IEEE Transactions on System Man Cyber-Algorithm for Multilevel Thresholding. 1979; SMC-9(12):860-64.
16. Huang Q, Gai W, Cai W. Thresholding Technique with Adaptive Window Selection for Uneven Lighting Image, Pattern Recognition Letter. 2005 May; 26(6):801–08.

17. Tseng DA, Huang MY. Automatic Thresholding based on Human Visual Perception, Image Vision Computing. 1993 Nov; 11(9):539–58.
18. Silva DVS, Fernando WAC, Kodikaraarachchi H, Worrall ST, Kondoz AM. Adaptive Sharpening of Depth Maps for 3D-TV, Electronics Letters. 2010 Nov; 46(3):546-48.
19. Tomasi, Carlo, Manduchi R. Bilateral Filtering for Gray and Color Images. Proceedings of ICV. India, 1998.
20. Arora, Siddharth. Multilevel Thresholding for Image Segmentation through a Fast Statistical Recursive Algorithm, Pattern Recognition Letters. 2008 Jul; 29(2):119-25.