

## Chapter 9

# Optimization Techniques for the Multilevel Thresholding of the Medical Images

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### ABSTRACT

*Multilevel thresholding is segmenting the image into several distinct regions. Medical data like magnetic resonance images (MRI) contain important clinical information that is crucial for diagnosis. Hence, automatic segregation of tissue constituents is of key interest to clinician. In the chapter, standard entropies (i.e., Kapur and Tsallis) are explored for thresholding of brain MR images. The optimal thresholds are obtained by the maximization of these entropies using the particle swarm optimization (PSO) and the BAT optimization approach. The techniques are implemented for the segregation of various tissue constituents (i.e., cerebral spinal fluid [CSF], white matter [WM], and gray matter [GM]) from simulated images obtained from the brain web database. The efficacy of the thresholding technique is evaluated by the Dice coefficient (Dice). The results demonstrate that Tsallis' entropy is superior to the Kapur's entropy for the segmentation CSF and WM. Moreover, entropy maximization using BAT algorithm attains a higher Dice in contrast to PSO.*

## **INTRODUCTION**

Image segmentation is the process of extracting meaningful objects from the image. Computed tomography and MRI are the common imaging modalities that help physicians to non-invasively study the brain structures (Gondal and Khan, 2013). MRI is preferred modality of choice due to its higher soft tissue contrast and the availability of multispectral images. Upon careful analyzing these multiple images, a radiologist provides a decision about the lesion extent and the therapy treatment. Various tissue constituents in an MR image can be either manually marked by the radiologists (Georgiadis *et al.*, 2007, 2008; Zacharaki *et al.*, 2009) or they can make use of the semi-automatic or fully automatic computer-assisted approaches. Manual segmentation of MR image is both tedious and time-consuming due its 3D nature. Also, the outlined tissue constituent suffer from the effect of interobserver variability (Dou *et al.*, 2007; Corso *et al.*, 2008; Hemanth *et al.*, 2013). Though several segmentation methods have been presented in the past year's, thresholding is undoubtedly one of the most attractive technique due to its simplicity.

For the analysis of the medical images, many thresholding techniques have been developed in recent years which are either based on Kapur's entropy maximization (Kapur, Sahoo and Wong, 1985; Manikandan *et al.*, 2014) or the cross entropy minimization (Kaur, Saini and Gupta, 2016). The entropy criteria proposed by Kapur's and Otsu's based between class variance approach has been widely used to find the optimal thresholds in the case of images with bimodal histogram but for images with multimodal histogram, these approaches suffer from the drawback of an exponential surge in the computational time (Manikandan *et al.*, 2014). To overcome this problem heuristic based algorithms have been applied for dividing the image into several regions by obtaining the optimal set of threshold values.

Yin (Yin, 2007) presented a method that used particle swarm optimization (PSO) for finding of the optimal thresholds. The criteria employed for the multilevel thresholding was minimum cross entropy, and the efficacy of the method was validated by the measure of the computation time that was faster in than the exhaustive search methods. Nakib *et al.* (Nakib *et al.*, 2007) devised two-dimensional survival exponential entropy criteria based on PSO for MR image segmentation. The results were compared with those obtained using 2D Shannon entropy as the objective function in terms of the misclassification error.

Djerou *et al.* (Djerou *et al.*, 2009) proposed binary PSO for determining the optimum number and the corresponding values of the various thresholds. The Kapur's entropy and the Otsu's criteria were employed as objective function, uniformity measure, and computation time were used as a performance metric. The results illustrate that the Otsu's method was faster than the Kapur's method.

De *et al.* (De *et al.*, 2010) performed the segmentation of diseased MRI using PSO based Shannon entropy criteria. The segmented region was post-processed by applying masking operation. The method was based on the conception that diseased area would have different intensity level in contrast to the normal regions. Firstly, the normalized image histogram was obtained and then the entropy maximization was used to find the range of gray values for the diseased region using PSO. After that, region growing in the form of masking was also done to attain the final segmented image.

Gao *et al.* (Gao *et al.*, 2010) developed a multilevel thresholding technique based on quantum-behaved cooperative PSO (CQPSO). The proposed approach circumvented the problem of local trapping by preserving the fast convergence rate of basic PSO. The maximization of between class variance was used as an objective function. The experimental results indicate that, compared with the existing population-based thresholding methods, the CQPSO algorithm gets more effective and efficient results in terms of the objective function value and the computation time. Hongmei *et al.* (Hongmei *et al.*, 2010) devised a multilevel threshold image segmentation based upon improved PSO. The modified PSO used random

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