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Maximum Entropy Based Image Segmentation of Human Skin Lesion

Sheema Shuja Khattak, Gule Saman, Imran Khan, Abdus Salam

***Abstract*—**Image segmentation plays an important role in medical imaging applications. Therefore, accurate methods are needed for the successful segmentation of medical images for diagnosis and detection of various diseases. In this paper, we have used maximum entropy to achieve image segmentation. Maximum entropy has been calculated using Shannon, Renyi and Tsallis entropies. This work has novelty based on the detection of skin lesion caused by the bite of a parasite called Sand Fly causing the disease is called Cutaneous Leishmaniasis.

***Keywords*—**Shannon, Maximum entropy, Renyi, Tsallis entropy.

I. Introduction

IMAGE segmentation is a useful tool for image analysis. It is carried out on images to separate groups on the basis of similar characteristics. There are several methods and algorithms for segmentation e.g. region based, edge based [1] etc. and entropy being one of them.

Entropy is the measure of randomness or variance in an image. When the maximum of this variance is measured, it becomes Maximum Entropy. There are various theories regarding calculation of entropy which are Shannon, Tsallis, and Renyi etc.

Multilevel threshold is a method that segments a gray level image into a number of dissimilar portions. It establishes more than one threshold for the given image, which correspond to background and foreground. It works well for complex data because simple thresholding methods do not give satisfactory results on such data [2] because of the complexity of the input.

In this paper, image segmentation is performed using Shannon, Tsallis, Renyi and Maximum Entropy. The calculated entropies are used further for multilevel thresholding. The results are then compared on the basis of segmentation results.

The paper is arranged as follows: Section II gives the literature review in the field of image segmentation, Section III gives the methodology used for segmenting diseased skin tissue, Section IV gives the data set acquisition, Section V gives the results of the developed method and Section VI concludes the work.

II. Related Work

Image thresholding based on entropy is an influential method for image segmentation. Segmentation based on entropic methods can perform well [3] because it measures the randomness and variance within the input data.

Satorres Martínez et al. [4] have worked on defect detection using image segmentation based on entropy. The defects on transparent objects with irregular surface were detected through a special lighting system. Entropy calculation was performed to find the threshold value for segmentation.

Nguyen et al. [5] have proposed free form anisotropy for crack detection on pavement surface images. This method involves segmentation and entropy calculation.

Singh et al. [6] have studied different segmentation algorithms and have found computer vision to be an integrative area with application in medicine, remote sensing, electronics and so on. A suitable algorithm has to be adapted depending on the given problem and the type of input based on color, gray scale and text.

Cardenas et al. [7] used cerebral segmentation, comparing the children head sizes exposed to alcohol prenatally. The proposed method did not perform as well when applied to more than 300 scans having less than 5% of the images. Peng et al. [8] also used image segmentation and claim it to be a novel method for natural images. Balafar et al. [9] reviewed image segmentation methods based on brain Magnetic Resonance Imaging (MRI). The error free segmentation of such images plays a vital role for correct diagnosis. They have compiled a review of the trends applied in brain segmentation also covering the noise reduction and in homogeneity.

Liu et al. [10] proposed a method for sonar images. The existing level set segmentation method used for optical images do not segment the sonar images accurately because, such images have different properties. The main drawback of conventional segmentation for sonar images is the unhelpful effect of shadow in the image. Arora et al. [11] used Shannon entropy based on multilevel threshold segmentation. Multilevel threshold gives satisfactory results as compared to simple bi level-threshold when it comes to complex data. Horng [12] used maximum entropy in combination with multilevel threshold. Multilevel threshold is an important technique for image processing and pattern recognition. Yan et al. [13] have used entropy for segmentation and also computed maximal entropy to get sufficient pixel extraction. Entropy is considered to be effective as compared to gradient based methods which are sensitive to noise.

Yen et al. [14] describe that non-parametric methods have two main drawbacks that the selection of the number of gray levels is crucial and needs supervised strategy also the determination of threshold value for multilevel thresholding

Sheema Shuja Khattak, Imran Khan, and Abdus Salam are with the Abasyn University Peshawar, Peshawar, Pakistan (e-mail: shahkhn3@ gmail.com, imran.khan@abasyn.edu.pk, dr.salam@abasyn.edu.pk).
Gule Saman, is with the Shaheed Benazir Bhutto Women University, Peshawar, Pakistan (e-mail:gulesaman @sbbwu.edu.pk).

creates a computational over head while the proposed method is said to be computationally efficient while calculating the threshold automatically.

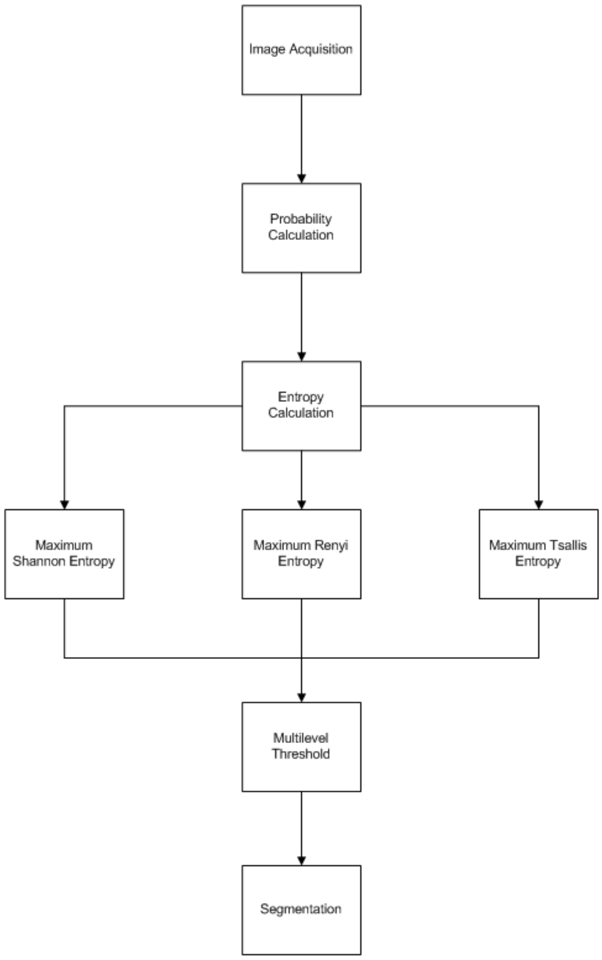

Fig. 1 Flowchart for segmentation

The method proposed by [15] uses histograms, histogram quantization, maximum entropy and multilevel threshold based segmentation for transplanted heart patient biopsies using myocardial images. Mahore et al. [16] have also used histograms, filtering for noise removal and maximum entropy for segmentation of medical images to be used by medical practitioners for different disease detection purposes.

Wang et.al [17] have used OTSU's algorithm to find the threshold for segmentation purposes. This method works for detecting vegetable disease and insect using smart devices for capturing the images.

III. Methodology

This paper is based on segmenting the diseased skin lesion from healthy skin. This research can be used to assist medical practitioners; effort has been made to develop an improved method to get the optimum value for threshold T using maximum entropy based image segmentation. However, in the proposed method histogram calculation is used to get statistical texture measures i.e. probability, which is an important element for computing maximum entropy. After the calculation of maximum entropy for each image in the acquired data set, maximum entropy is computed resulting in multilevel threshold, on the basis of which segmentation takes place. The maximum entropy calculation is based on Shannon, Renyi and Tsallis entropy. The flow chart of the developed method is given in Fig. 1.

The histograms were used for the acquired diseased skin images to compute the probability to find the pixel randomness in the image which is the essential element for computing entropy. Three maximum entropy based methods have been used for this work i.e. i. Shannon ii. Tsallis and iii. Renyi entropy.

The purpose of using these entropies as maximum entropy was to assess which of these perform well for medical images of the given problem to identify diseased skin lesions.

A. Shannon Entropy

There are various theories of entropy among which Shannon is considered the classic method which is considered to be the basis for other entropy based methods. Basic Shannon entropy has been used which is given as,

$$SE= - \sum_{i=0}^{n} p_i \log_2 p_i \tag{1}$$

Multi levels were obtained on the basis of the three values computed from the three entropy based methods.

B. Tsallis Entropy

Tsallis entropy, S_q, is stated as useful when the system has distinct microstates with strong correlation amongst them. Tsallis entropy can be defined as,

$$S_q=1/q\text{-}1(1\text{-}\sum p^q_i) \tag{2}$$

where, q is a parameter measuring how strong the correlations are. When q approaches the value 1, it becomes Boltzmann–Gibbs entropy. The parameter q is known as the Tsallis index [18] where, i is the number of states.

C. Renyi Entropy

The Renyi entropy is given by,

$$H_q(P)=1/1\text{-}q \ln\left(\sum_{i=1}^{N} p_i^{\,q}\right) \tag{3}$$

When q approaches the value 1, it becomes Shannon entropy [19]. Renyi entropy has Shannon entropy as a special case.

D. Maximum Entropy

The other method used to calculate entropy is maximum entropy as given by [14],

$$TE(s') = \max_{s\varepsilon Gm} TE(s) \tag{4}$$

Multi levels were obtained on the basis of the two values computed from the two entropy based methods. Maximum entropy for Shannon entropy has been used for better comparison and a benchmark to be compared with.

The comparison has been carried out amongst the standard entropies. Where, there are several segmentation techniques but when it comes to medical diagnosis accurate and precise results are needed. The novelty of this paper comes from the fact that the data set used have originated from the images of the patients suffering from the disease causing skin damage known as Cutaneous Leishmaniasis. This disease is caused by the bite of a parasite called Sand Fly. The mentioned technique effectively detects the diseased part of the affected skin sample.

IV. Data Set Acquisition

Sony 8.1-megapixel Exmor R for low-light camera has been used for acquiring the image data set. The light-source was placed at 45˚ facing the diseased tissue and the camera was placed at the same distance as the light-source at 90˚ with respect to the diseased skin as shown in Fig. 2. All the variables are kept constant to ensure uniformity amongst the acquired data for effective experimentation.

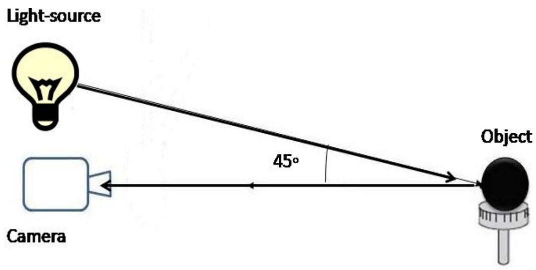

Fig. 2 Experimental Setup

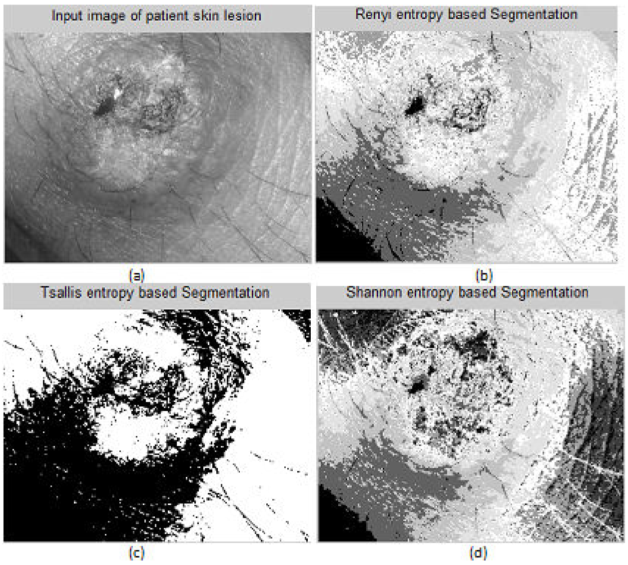

Fig. 3 (a) The input image, (b) the computed Maximum Renyi entropy, (c) the computed Maximum Tsallis entropy and (d) the computed Maximum Shannon entropy

V. Experimental Results

The segmentation was carried out on diseased skin tissue caused by Cutaneous Leishmaniasis. The method was tested on the data size of 45 image samples, out of which two samples of diseased skin images are given in this paper in Figs. 3 and 4. The results of segmentation based on Maximum Shannon, Maximum Tsallis and Maximum Renyi entropy are given in Fig. 3.

Fig. 4 shows different multilevels of intensity with the variation in intensity distinguishing the healthy and damaged skin.

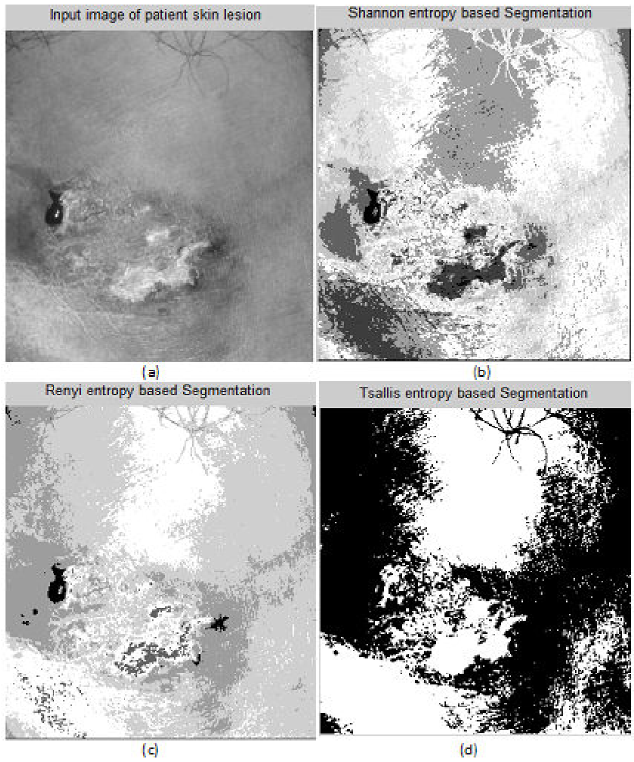

Fig. 4 (a) The input image, (b) the computed Maximum Shannon entropy, (c) the computed Maximum Renyi entropy and (d) the computed Maximum Tsallis entropy

It can be seen from Figs. 5 and 6 that light grey is assigned to the badly damaged part of the skin. The Maximum Renyi and Maximum Shannon entropy based segmentation has identified the skin as damaged and undamaged part while Tsallis entropy has identified only traces close to lesion. On the basis of the entropies calculated for multilevel threshold, segmentation helps in deciding which region belongs to which category. It can be concluded from the experimental results that Maximum Renyi and Maximum Shannon entropy have outperformed the other methods of entropy used. In order to support the results, histograms of segmented diseased skin images have been computed as given in Figs. 7-9 showing the division of regions based on the variation of intensity of the pixels in the image.

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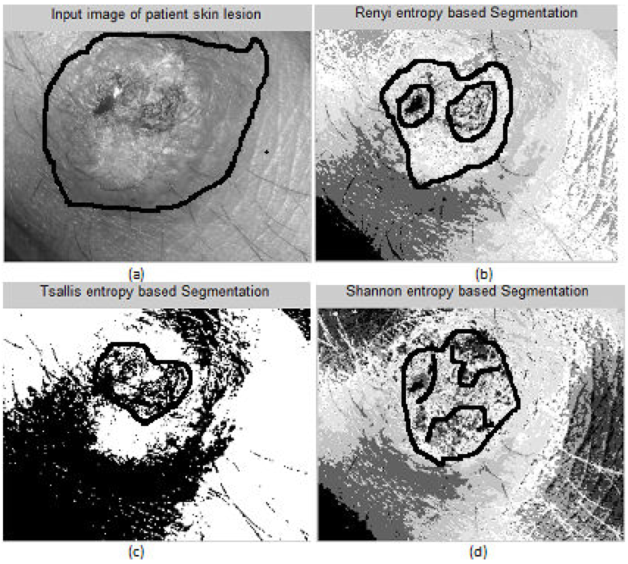

Fig. 5 Highlighted segments after Maximum entropy calculation of the samples given in Fig. 3

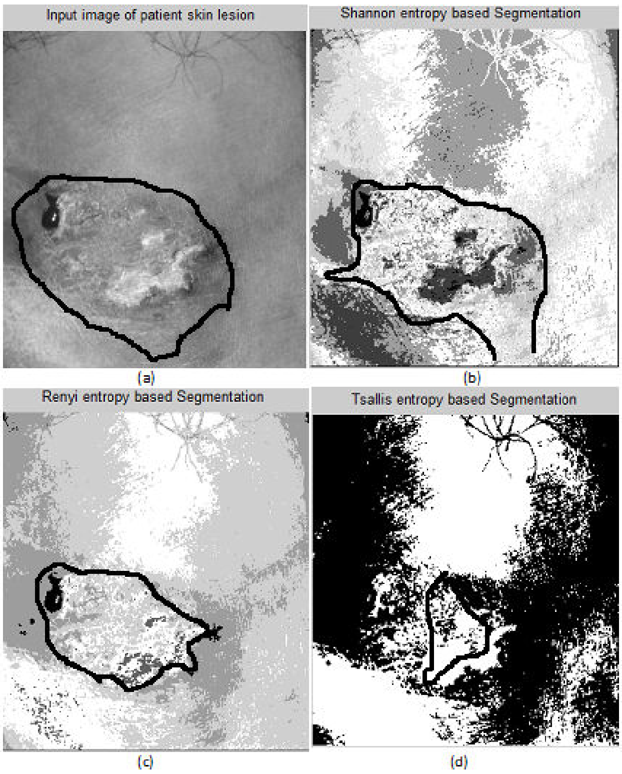

Fig. 6 Highlighted segments after Maximum entropy calculation of the samples given in Fig. 4

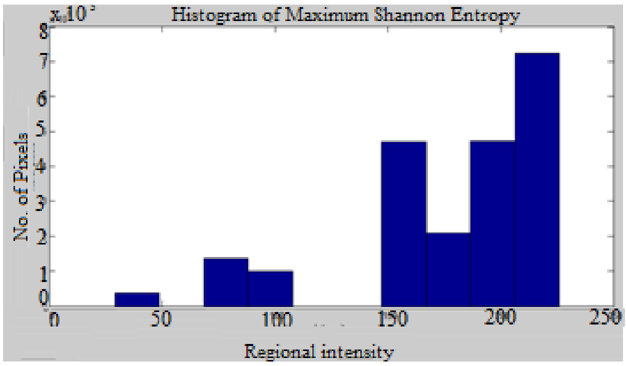

Fig. 7 Histogram for Maximum Shannon entropy in Fig. 4 (b)

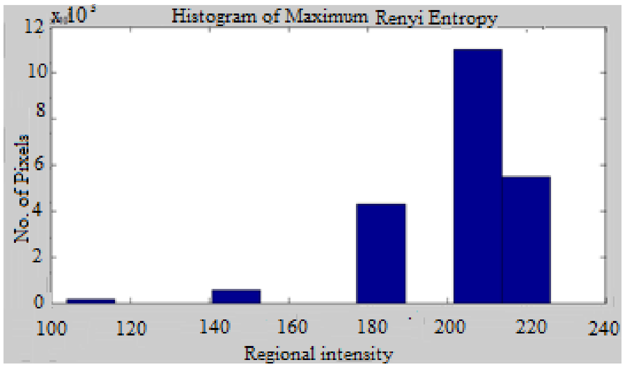

Fig. 8 Histogram for Maximum Renyi entropy in Fig. 4 (c)

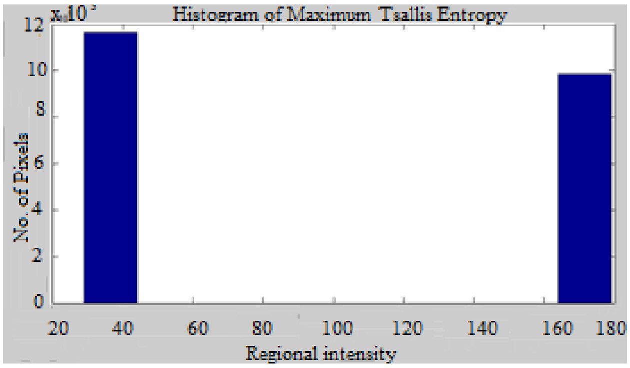

Fig. 9 Histogram for Maximum Tsallis entropy in Fig. 4 (d)

The clusters of data in the histograms using Figs. 7-9 represent the regions into which the diseased skin image has been divided. Furthermore, the peaks in the histogram depict the division of regions within the diseased skin image data set and which depends on the intensity variation of the lesion because the occurrence of the lesion is usually not uniform. The distinction of the diseased and non-diseased skin is a problem that can be best supported by using bi-modal histogram. Since, this research work involves multilevel threshold segmentation using maximum entropy which means that the regions are analyzed on more than one level of intensity and randomness because diseased skin lesion has variation e.g. some lesions are dark due to bleeding, some lesions are light in color and brittle, some skin lesions are hard and different texture. To overcome the complexity of the given problem multilevel threshold along with entropy has been used hence, measuring the multilevels of intensity and randomness of diseased skin lesion. Figs. 7-9 all support the hypothesis that the images would be divided into two regions depicting the healthy and unhealthy part of the skin. However, while examining the histograms it is evident that in some cases there are more than two peaks which show that the method is able to identify further categories in the diseased part of the skin. These might have been caused by advancement or an improvement of the disease as explained earlier. As some part of the affected tissue might be more damaged or healthier than the rest since exact progression cannot be determined in natural phenomenon as this.

VI. Conclusion

It can be concluded by analyzing the results qualitatively that Maximum Shannon entropy and Maximum Renyi entropy gives better segmentation output for diseased skin. The probability of image pixels was computed for maximum Shannon entropy, maximum Renyi entropy and maximum Tsallis maximum entropy and as an input. Multilevel threshold was adopted which transformed the image into various homogenous regions achieving the effective segmentation of skin lesions from healthy skin tissue.

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