A STUDY APPROACH THROUGH SEGMENTATION BY USING ROUGHNESS INDEX AND MRI

Mr. Athar Hussain*
M.E. Student, Department of
Computer Science and Information Technology,
H.V.P.M's College of Engineering & Technology,
Amravati.(M.S)-India
athar1357@gmail.com

Prof. Anjali B. Raut
Head of Department of
Computer Science and Engg,
H.V.P.M's College of Engineering & Technology,
Amravati.(M.S)-India
anjali_dahake@rediffmail.com

***ABSTRACT*— The paper presents the color image segmentation based on rough-set approach has been proposed. The color image segmentation is one of the most challenging tasks particularly in the area of image analysis, computer vision, and pattern recognition. In this paper, the proposed algorithm based on roughness index to calculate the peaks and valleys values. Based on peak and valley values to achieve better segmentation, Experimental results shows the roughness index theory to achieve better color image segmentation results and shows the graphs of roughness measurement versus intensities and compare to histogram and histon techniques. We propose a color image segmentation approach based on rough set theory elements. Main contributions of the proposed approach are twofold. First, by using an adaptive threshold selection, the approach is automatically adjustable according to the image content. Second, a region-merging process, which takes into account both features and spatial relations of the resulting segments, lets us minimize over-segmentation issues. These two proposals allow our method to overcome some performance issues shown by previous rough set theory-based approaches.**

Keywords*— *Rough Set Theory, The Histon, The Roughness Index, Region Merging, Segmentation

I. INTRODUCTION

Color image segmentation has been a central problem in computer vision and pattern recognition systems for many years. Its importance relies on its use as a pre analysis step for images in many applications such as object recognition, tracking, scene understanding, and image retrieval, among others. Segmentation refers to the process of partitioning a digital image into multiple regions that are assumed to correspond to significant objects in the scene. The partition consists of assigning a working label to every pixel within an image, in such a way that pixels with the same label share a set of particular features 1 and, in addition, are spatially connected. The concept of rough set was originally proposed by Pawlak as a mathematical approach to handle imprecision, vagueness, and uncertainty in data analysis. This theory has amply been demonstrated to have its usefulness and versatility by successful applications in a variety of problems. The theory of rough sets deals with the approximation of an arbitrary subset of a universe by two definable or observable subsets called lower and upper approximations. By using the concepts of lower and upper approximations in rough set theory, knowledge hidden in information systems may be unraveled and expressed in the form of decision rules. Another particular use of rough set theory is that of attribute reduction in databases. Given a dataset with discretized attribute values, it is possible to find a subset of the original attributes that are the most informative. This leads to the concept of attributes reduction which can be viewed as the strongest and most characteristic results in rough set theory to distinguish itself from other theories. However, in the existing databases the values of attributes could be both of symbolic and real-valued. The traditional rough set (TRS) theory will have difficulty in handling such values.

There is a need for some methods which have the capability of utilizing set approximations and attributes reduction for crisp and real-values attributed datasets, and making use of the degree of similarity of values. This could be accomplished by combining fuzzy sets and rough sets, i.e., fuzzy rough sets. On one hand, the main idea of the spatially guided methods is that pixels that are neighbors may have features in common. Their main drawback is that, even when the resulting regions in the segmentation are spatially well connected and compact, there is no guarantee that the segments are homogeneous in a specific feature space. Moreover, sequential design (pixel-by-pixel agglomeration) of these procedures often results in intensive computational schemes with significant memory requirements. Among these approaches, the quality of the segmentation is dependent on the initial seeds selection and homogeneity criteria used. On the other hand, we have the spatially blind algorithms. These methods assume that the color on the surface of an object is unvarying and, therefore, the object will be represented as a cluster of points in a given color space. Because of their simplicity and low computational cost, this kind of method has been widely adopted in the development of segmentation algorithms. Examples of these approaches include clustering and histogram-based approximations. In comparison with the spatially guided techniques, the spatially blind methods present some advantages. For example, comparing with the region-growing approaches, in the spatially blind techniques, there is no need to define the number and placement of the initial seeds. The advantage over the split-and-merge methods is that such methods require a post processing refinement in order to accurately capture the shape of the objects.

Let denote a finite and nonempty set called the universe. Suppose is an equivalence relation on , i.e., is reflexive, symmetric, and transitive. The equivalence relation partitions the set into disjoint subsets. Elements in the same equivalence class are said to be indistinguishable. Equivalence classes of are called elementary sets. Every union of elementary sets is called a definable set. The empty set is considered to be a definable set, thus all the definable sets form an Boolean algebra. is called an approximation space.

II. ROUGH SET THEORY, THE HISTON, AND THE ROUGHNESS INDEX

Rough set theory is one of the most recent approaches for modeling imperfect knowledge. This theory was proposed by Pawlak as an alternative to fuzzy sets and tolerance theory. A rough set is a representation of a vague concept using a pair of precise concepts called lower and upper approximations. The lower approximation is a description of the universe of objects that are known with certainty, whereas the upper approximation is the description of the objects that possibly belong to the set. From this concept of a rough set and in the context of image segmentation with histogram-based methods, Mohabey and Ray have developed the idea of the histon which can be considered as the upper approximation of a rough set. In order to set the histon definition in the context of a histogram-based segmentation method, let us first define an image with M × N pixels size, where m and n are the image coordinates, $m \in [0, M-1]$ and $n \in [0, N-1]$.

The parameter $C = \{c_1, c_2, \ldots, c_j\}$ denotes the space in which the image is represented, and ci is the information channel used in such representation. Usually, for color images, but it may take any positive value. Let us also consider Li as the maximum number of intensity values in the given channel ci. Therefore, $I(m, n, c_i) \in [0, L_i - 1]$ is the intensity value for the component ci of the image at the coordinates (m,n). The histogram of an image I is a well-known representation of the frequency distribution of all the intensities that occur in the image. The histogram of a certain color channel i is computed as in Eq.(1).

$$h_i(g) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \delta[I(m,n,c_i) - g], \quad (1)$$

where δ(·) is the Dirac impulse, and g is a given intensity value $0 \leq g \leq Li - 1$.

Assuming that the features on the surface of the objects are unvarying, each object in the image may be identified as a peak in the histogram. The association of pixels with intensities related with such peaks leads to the segmentation of the relevant objects in the scene. Unfortunately, such an assumption is not always true and variations in the features on the surface of the objects are commonly found, making the identification of peaks a challenging task. Toward the solution of these uncertainties, the histon is a representation that associates pixels that are similar in features and may belong to one specific object in the image. Additionally, such association is not limited to similarity in features, but also includes the relationship of pixels with their neighbors.

Regarding the histon definition as the upper approximation of a rough set, we consider the similarity between a pixel $I(m,n,c_i)$ and its neighbors within a window W of P × Q pixels size. The similarity is computed as the Euclidean distance obtained using Eq.(2).

$$d(m,n) = \sum_{p,q \in W} \sqrt{\sum_{c_i \in C} [I(m,n,c_i) - I(p,q,c_i)]^2}. \quad (2)$$

The histon Hi, where i is a given color component in the color space, is computed as in Eq. (3).

$$H_i(g) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [1 + X(m,n)]\delta[I(m,n,c_i) - g], \quad (3)$$

where δ(·) is the Dirac impulse, g is the intensity value $0 \leq g \leq L - 1$, and X(·) is a matrix which records the pixels that are similar to its neighbors. X(·) is obtained as in Eq. (4).

$$X(m,n) = \begin{cases} 1, & d(m,n) < Ex \\ 0, & \text{otherwise} \end{cases}, \quad (4)$$

where Ex is the distance threshold for a pixel to be considered similar to its neighborhood. In order to process the pixels at the boundaries of the image in the matrix X, pixel values in the edge are mirrored outside the image instead of using zero values. This operation enables us to properly process the whole image under test. From the above definitions, we can say that the histon, in analogy to the histogram, registers the number of pixels that are similar to its neighbors. For each pixel that is similar in features to its neighbors, the corresponding bin in its intensity channel ci is incremented twice. This double increment in the histon results in the heightening of peaks, corresponding to locally uniform intensities. The main advantage of using the histon, instead of the regular histogram, is that the histon is able to capture the local similarity, resulting in a representation tolerant to small intensity variations and furthermore, since the peaks are heightened, their detection is easier.

In the rough set theory, the lower and upper sets can be correlated using the concept of roughness index. The roughness index is a representation of the granularity or accuracy of an approximation set. In our scope, the roughness index is the relationship of the histogram and the histon for each intensity level g. The roughness index is defined as in Eq. (5).

$$\rho_i(g) = 1 - \frac{|h_i(g)|}{|H_i(g)|}, \quad (5)$$

where i is the corresponding color component, h is the histogram, H is the histon, and j · j denotes the cardinality in each intensity level g. The value of roughness is close to 1 when the cardinality of the histon is large in comparison with the cardinality of the histogram in a given intensity value. This situation occurs when there is a high similarity in the features on a given region. If there is a small similarity and high feature variability in the neighborhood, the roughness index tend to be close to 0, because the histon and the histogram have the same, or almost the same, cardinality. In a general sense, the histon and the roughness index give a global distribution of the uniform and connected regions in the image, and each peak represents each one of such regions.

From the roughness index array, a multi thresholding method is applied for achieving the final image segmentation. Thresholds in each channel are automatically localized on the valleys between two significant peaks, which represent the meaningful objects in the scene. The final segmentation is the union of the segments for each channel. In this study, we use three color channels; however, it is worth to remark that it is possible to expand this approach for images that have more than three information channels. The proposed improvements in this article lead to the segmentation approach illustrated in Fig. 1. From now on, this method is referred to as PRM, for perceptual roughness index based method. In the beginning of the PRM, a color space transformation is applied to the input image, pursuing a representation closer to the human perception. Then the roughness index computation, a multithresholding method, and an adaptive peak selection are performed. The main improvement in this step is the adaptive peak selection, where the criteria used for choosing the significant peaks change in accordance with the image content. At the end, the segmented image is obtained after a region-merging process, which takes into account both feature similarity and spatial relationships. Each block of Fig. 1 is described in the following subsections.

Fig. 1.Roughness Index based Segmentation

III. REGION MERGING

A final point to consider is the region-merging procedure. The region merging is a common tool used to reduce over segmentation issues. The merging step broadly consists of fusing small regions with neighbor and bigger regions. For the region-merging step in our PRM, we take into account both the color similarity and the spatial relationship between regions. The strategy of our method first identifies the small regions whose number of pixels is less than a given threshold. From the experiments, detailed in the next section, we have found that a good minimum number of pixels in a given region to be considered is as small as 0.2% of the whole image size. Once we have identified all the small regions, they are fused with the most appropriate neighbor region. Such a region is one that minimizes the distance between the color components of the segments and maximizes the number of connected pixels between those two regions. Hence, a small region is merged with its neighbor that is more similar in features and has more connected pixels.

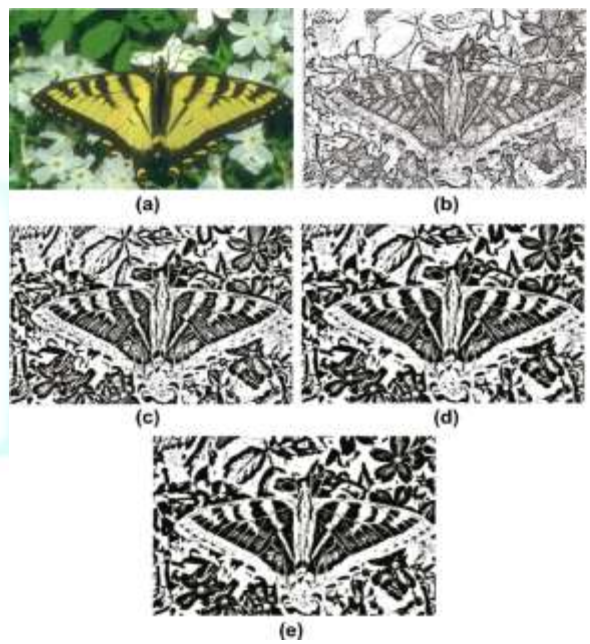

Fig. 2. Homogeneity distributions of image ‘Butterfly’ (a) original ‘Butterfly’ image, (b–e) homogeneous regions under different scales, (b) homogeneity under t = 1, (c) homogeneity under t = 10, (d) homogeneity under t = 20, (e) homogeneity under t = 30.

Illustrate the upper approximation and roughness on Red color component of image ‘Butterfly’ under multiple scales. It is obvious that the local homogeneity and roughness at most intensities will be generally enhanced as the scale decreasing. Under the large scales, almost all surrounding pixels in the neighborhood will be considered for measuring the color difference. Even the pixels far from the central position still play an important role in computing the local homogeneity, which may lead to the improper high color difference on small homogenous regions. Therefore the roughness measure with large scales tends to exhibit the homogeneity of large areas in color image, and the homogeneity of small regions will be neglected. On the other hand, when we construct the region roughness by small scales, only the pixels near the central element can cause influence to homogeneity measuring. Thus the roughness under small scales can reflect the homogeneity of small regions effectively. However, too small scales can make almost all image regions having the property of roughness. In that case, the roughness measurement cannot give the precise representation of homogeneity. Thus it should be known that seeking an optimal scale is the key to measure the roughness of color distribution.

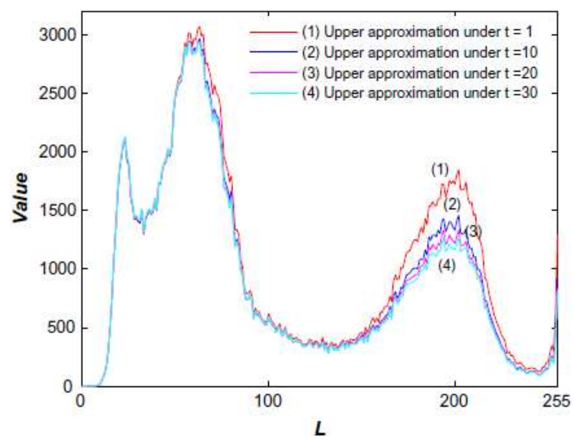

Fig. 3. Upper Approximations

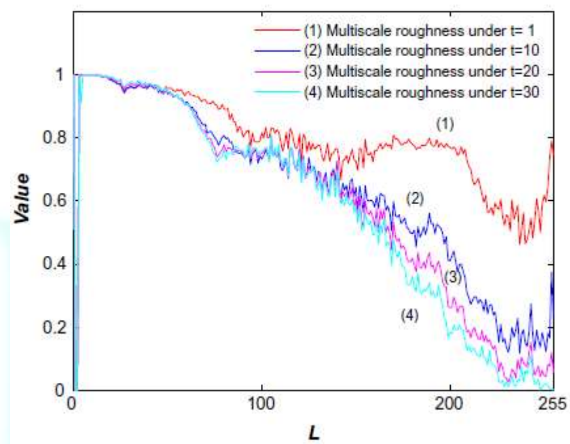

Fig. 4. Multiscale Roughness

The scale selection strategy will be further introduced in the following section. As mentioned above, given a proper scale t, the multiscale roughness can represent the color distribution more precisely and intuitively. First, because the homogeneity is computed from the surrounding elements in neighborhood and the influences of surrounding pixels are weighted based on the distance to the central pixel (i.e. reference point), the approximation induced from scale-space is more effective to represent the homogeneous regions and weaken the impact of noisy points. Secondly, besides the linear scale-space, the homogeneity function maps the local color difference into homogeneous degree, which can further quantify the roughness index. Finally, linear scale-space filtering can provide us an intuitive understanding on the roughness of color image. Like the human vision, multiscale roughness expresses the homogeneous regions from hierarchical views at different granular levels.

IV. SEGMENTATION METHOD

This paper proposes color (i.e. RGB) image segmentation based on multiscale roughness (MSR for short). The segmentation process is mainly divided into three stages. In the first stage, given a scale t, the approximations of each color component are computed, and then the roughness index under scale t is obtained using. For computing the multiscale roughness, we need to set two parameters. The first one is the size of the neighborhood, which is a window for scale-space filtering. A proper size is important to the quality of image segmentation. The third stage involves color merging as the post processing. Because the bands obtained from the roughness peaks and valleys usually cause over-segmentation, the color region merging is necessary to reduce the redundant color, which will merge the similar small segments together.

V. SIMULATION RESULTS

From the results, we observe that the different regions in the images are well segmented where the colors of the segmented regions match with those in the original image and all the important details in the images are preserved.

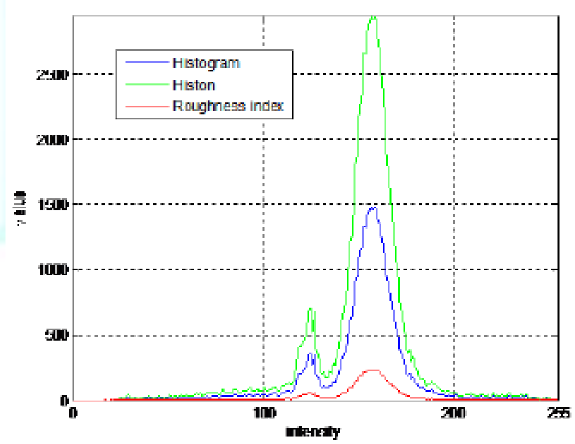

Fig. 5. Roughness index plot for ‘red’ component

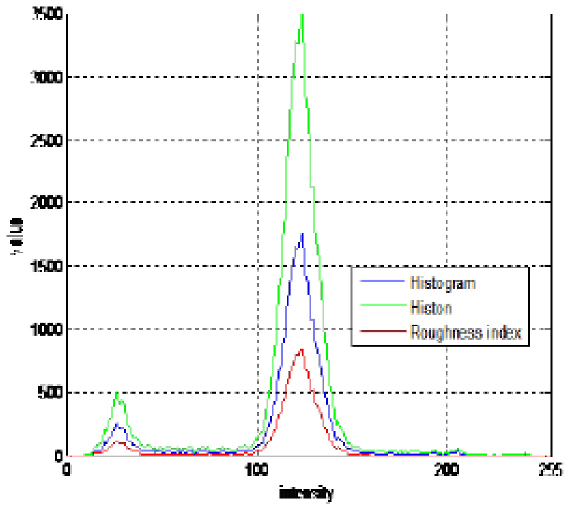

Fig. 6. Roughness index plot for 'green' component

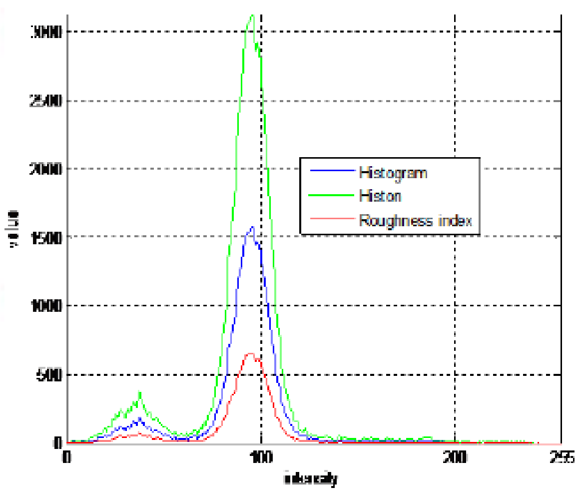

Fig. 7. Roughness index plot for 'blue' component

Shows the peaks occur at intensities in the graph of roughness index are 120 .140, 170 and valley values are 125,150,180. Which roughness is the maximum, the colors of the segmented regions are more close to the actual colors in the original image. This peaks and values represent in red component.

VI. CONCLUSION

In this article, a set of modifications was proposed in order to improve a rough set theory-based segmentation method. This methodology takes advantage of the integration of spatial information about the pixels and the association of similar colors. The spatial information is added in two places: (1) within the histon representation, through the similarity computation of neighbor pixels, and (2) in the region-merging process, in which not only the similarity in the feature space is taken into account, but also the connectivity between two segments is considered. A multiscale roughness measure has been proposed for color image segmentation. Aiming at the problems of existing histogram-based methods, we apply the linear scale-space theory into the traditional roughness measure to construct the multilevel representation of color homogeneity. For scale selection, we propose the roughness entropy to measure the information contained in roughness, and then decide the optimal scale for segmentation according to the entropy variation. Experimental results have shown that the segmentation based on multiscale roughness performs well on the natural images in the testing database. We have presented a rough-set theoretic approach for color image segmentation. The proposed algorithm is a variant of the histogram-based segmentation algorithm in which the graph of roughness measure verses intensity values has been used as the basis of segmentation. The computational complexity of the proposed method is slightly more than the conventional histogram-based thresholding algorithm, but the key point of our approach is that, using the roughness index for selection of peaks and valleys results in more realistic values and thus achieves better segmentation results. The experimental results show the superiority of the algorithm. The proposed approach may have many image processing applications and can be easily extended for the segmentation of multispectral images.

REFERENCES

[1] L. Shapiro and G. Stockman, Computer Vision, Prentice-Hall, Upper Saddle River, New Jersey (2001).

[2] K.-S. Fu and J. K. Mui, "A survey on image segmentation," Pattern Recognit. 13(1), 3–16 (1981).

[3] N. R. Pal and S. K. Pal, "A review on image segmentation techniques," Pattern Recognit. 26(9), 1277–1294 (1993).

[4] H. Cheng et al., "Color image segmentation: advances and prospects," Pattern Recognit. 34(12), 2259–2281 (2001).

[5] L. Lucchese and S. Mitra, "Color image segmentation: a state-of-the-art survey," Proc. Indian Natl. Sci. Acad. 67(2), 207–221 (2001).

[6] S. R. Vantaram and E. Saber, "Survey of contemporary trends in color image segmentation," J. Electron. Imaging 21(4), 040901 (2012).

[7] X. Wu, "Adaptive split-and-merge segmentation based on piecewise least-square approximation," IEEE Trans. Pattern Anal. Mach. Intell. 15(8), 808–815 (1993).

[8] H. Chang, D.Y. Yeung, Robust path-based spectral clustering, Pattern Recognition 41 (2008) 191–203.

[9] H.D. Cheng, Y. Sun, A hierarchical approach to color image segmentation using homogeneity, IEEE Transactions on Image Processing 9 (12) (2000) 2071–2082.

[10] Z. Pawlak, "Rough Set Approach to Knowledge-Based Decision Support," European J of Oper Res, vol. 99, pp. 48-57, 1997.

[11] Komorowski, J., Pawlak, Z., Polkowski, Skowron, A. Rough sets: A tutorial. In: S. K. Pal, A. Skowron (Ed.). Rough Fuzzy Hybridization: A new Trend in Decision-Making. Berlin: Springer-Verlag, 1999, 3–98 [KPP 99].

[12] Pawlak, Rough Sets: Theoretical Aspects of Reasoning About Data, Boston, MA, Kluwer Academic Publishers, 1991.

[13] Yao,Y.Y.,Wong, S. K. M. and Lin,T.Y. A Review of Rough Set Models in: LYN,T.Y; Cercone. N. (Eds.). Rough Sets and Data Mining: Analysis of Imprecise Data, Kluwer Academic Pub. 1997.