A fuzzy rule-based colour image segmentation algorithm

Conference or Workshop Item

A FUZZY RULE-BASED COLOUR IMAGE SEGMENTATION ALGORITHM

Laurence S Dooley, Gour C Karmakar, and Manzur Murshed
Email: {Laurence.Dooley, Gour.Karmakar, Manzur.Murshed}@infotech.monash.edu.au

Gippsland School of Computing and Information Technology
Monash University, Churchill, Victoria, Australia - 3842

ABSTRACT

Most fuzzy rule-based image segmentation techniques to date have been primarily developed for gray level images. In this paper, a new algorithm called fuzzy rule-based colour image segmentation (FRCIS) is proposed by extending the generic fuzzy rule-based image segmentation (GFRIS) algorithm [2] and integrating a novel algorithm for averaging hue angles. Qualitative and quantitative analysis of the performance of FRCIS is examined and contrasted with the popular fuzzy c-means (FCM) and possibilistic c-means (PCM) algorithms for both the Hue-Saturation-Value (HSV) and RGB colour models. Overall, FRCIS provides considerable improvement for many different image types.

1. INTRODUCTION

One of the most intractable tasks in segmentation is to define the general properties of objects for perceptual grouping due to the potentially inordinate number of objects and the myriad of variations among them. Such a demand requires human expert and/or domain specific knowledge to be incorporated to achieve superior results. Fuzzy rule-based image segmentation systems can incorporate this expert knowledge, but they are very much application domain and image dependent. The structures of all of the membership functions are manually defined and their parameters are either manually or automatically derived [1]. Karmakar and Dooley [2] introduced a novel *generic fuzzy rule based image segmentation* (GFRIS) algorithm to address many of the aforementioned problems for gray level images.

The human eye is able to discern a large number of shades and intensities of colour but only around two-dozen shades of gray scale. By exploiting this additional information, objects that are unable to be segmented using gray level information, may potentially be able to be segmented using colour information [3]. Some existing fuzzy colour image segmentation techniques are described in [3-8]. This paper introduces a new colour image segmentation algorithm, called a *fuzzy rule-based colour image segmentation (FRCIS)* algorithm by extending the GFRIS algorithm [2], from gray level to colour and developing a new algorithm for averaging hue angles. The proposed FRCIS algorithm is both perceptually and numerically evaluated [9] and compared with the fuzzy c-means (FCM) [10] and possibilistic c-means (PCM) [11] using the HSV and RGB colour models.

This paper is organized as follows. Section 2 provides a brief overview of the techniques used to define the membership functions. The definition of the fuzzy rule and the automatic determining of the weighting factors and the threshold used are presented in Sections 3 and 4 respectively. The new algorithm for calculating the average of hue angles is described in Section 5, while an evaluation of the experimental results are discussed in Section 6. Section 7 provides some conclusions.

2. DEFINING MEMBERSHIP FUNCTIONS

The FRCIS algorithm uses three membership functions namely, the membership function for region pixel distributions, the closeness to their centres, and the spatial relations among the pixels in a particular region. These have already been fully described in [2] and are the bedrock of the GFRIS algorithm. However, all these membership functions have been defined for only gray level pixel intensity. In this section, these membership function definitions are extended for each colour component of each region.

2.1. Membership function for region pixel distributions

This membership function has already been fully described in [2]. The membership function for the pixel distribution of region R_j, $\mu_{D_iR_j}(P_{s,t})$ of a pixel with a value of $P_{s,t}$ at location (s,t) for the i^{th} colour component can be defined as: -

$$\mu_{D_iR_j}(P_{s,t}) = f_{iR_j}(P_{s,t}) \tag{1}$$

where $f_{iR_j}(P_{s,t})$ is the polynomial for the i^{th} colour component of region R_j and $i \in \{1,\ldots,\phi\}$ where ϕ is the number of colour components for a particular colour model, i.e. $\phi = 3$ for HSV.

2.2. Membership function to measure the closeness of a region

The definition of this particular membership function differs slightly from the original definition in [2]. This is because it uses a normalised difference with respect to the maximum value of the candidate pixel $P_{s,t}$ and the respective centre $C_i(R_j)$ of a region R_j, instead of fixed value $(2^b - 1)$ where b-bit gray levels or colour components are presumed. The membership function for the closeness to a region R_j, $\mu_{C_iR_j}(P_{s,t})$ of a candidate pixel $P_{s,t}$ for the i^{th} colour component is defined as: -

$$\mu_{C_iR_j}(P_{s,t}) = 1 - \left|C_i(R_j) - P_{s,t}\right| / \max\{C_i(R_j), P_{s,t}\} \tag{2}$$

where $C_i(R_j)$ is the centre of the i^{th} colour component of region R_j. This membership function considers more accurately the human visual perception than that of the GFRIS algorithm.

2.3. Membership functions for spatial relation

The membership function for spatial relation between the pixels of the i^{th} colour component of a region R_j, $\mu_{N_iR_j}(P_{s,t},r)$ for the neighbourhood radius r is defined as: -

$$\mu_{N_iR_j}(P_{s,t}) = (N_{ij} \times G_{iR_j}) / \sum_{i=1}^{\phi}\sum_{j=1}^{\Re}(N_{ij} \times G_{iR_j}) \tag{3}$$

where N_{ij} and G_{iR_j} are respectively the number of neighbours and the sum of the inverse distances of the i^{th} colour component of a region R_j from the candidate pixel $P_{s,t}$. $\Re$ is the number of segmented regions.

3. DEFINING THE FUZZY RULE

In contrast to the fuzzy rule [2] for gray level intensity, in this section a fuzzy rule is heuristically defined for all three colour components. The overall membership value $\mu_{AR_j}(P_{s,t},r)$ of a pixel $P_{s,t}$ for a region R_j represents the overall degree of belonging to that region for all colour components. This is defined by the weighted average of all membership functions for each component, i.e. $\mu_{D_iR_j}(P_{s,t})$, $\mu_{C_iR_j}(P_{s,t})$, and $\mu_{N_iR_j}(P_{s,t},r)$.

$$\mu_{AR_j}(P_{s,t},r) = \frac{\sum_{i=1}^{\phi} w_{1i}\mu_{D_iR_j}(P_{s,t}) + \sum_{i=1}^{\phi} w_{2i}\mu_{C_iR_j}(P_{s,t}) + \sum_{i=1}^{\phi} w_{3i}\mu_{N_iR_j}(P_{s,t},r)}{\sum_{\kappa=1}^{3}\sum_{i=1}^{\phi} w_{\kappa i}} \tag{4}$$

where w_{1i}, w_{2i}, and w_{3i} are the weightings of the membership values of i^{th} colour component for pixel distribution, closeness to the cluster centres, and neighbourhood relations respectively.

Definition 1—Rule: IF $\mu_{AR_j}(P_{s,t},r) = \max_{1\le i\le \Re}\{\mu_{AR_i}(P_{s,t},r)\}$ THEN pixel $P_{s,t}$ belongs to region R_j.

It is important to note that this rule is generic enough to ensure the FRCIS algorithm is both application and image independent.

4. DETERMINING THE WEIGHTING FACTORS AND THE THRESHOLD

The data mining algorithm for the weighting factors and the threshold used by GFRIS [2], is extended to incorporate colour components and determine the weighting factors w_{1i}, w_{2i}, and w_{3i}, and threshold T_i. The spatial relationship weighting factors w_{31} and w_{32} for the hue and saturation colour components of the HSV colour model were empirically chosen as 0.2. The reason for the low value of both parameters is that hue denotes the dominant colour and already represents spatial relations by suppressing the minor variations of a colour, while saturation represents the relative colour purity, that is the whiteness of hue [12].

5. ARITHMETIC OPERATORS FOR HUE IN THE HSV COLOUR MODEL

The hue in the HSV colour model represents the dominant wavelength of the colour stimulus. The HSV colour model is represented by a cone, where the hue is the angle of each colour within the cone starting from 0 point on the x-axis [13]. Hue angles are used in calculating the membership functions defined in Sections 2.2 and 2.3 and automatically deriving the key weighting factors and thresholds described in Section 4 for the hue component of the HSV colour model. Since hue is expressed in angles, the arithmetic operations for Cartesian coordinates are not suitable for hue this leads to some difficulties when applying certain arithmetic operations on hue angles e.g. averaging. The definition of the difference between two hue angles h_1 and h_2 where both h_1 and h_2 are bounded in the range the $[0, 2\pi]$ and the formula for calculating the average of n hue angles are given as follows: -

Definition 2—Difference Between Two Angles: The difference between two hue angles h_1 and h_2, $diff(h_1,h_2)$ is defined as: -

$$diff(h_1,h_2) = \min(|h_1 - h_2|, 2\pi - |h_1 - h_2|) \tag{5}$$

When a candidate pixel joins its nearest region, the centre of that particular region is recomputed. The rationale behind recomputing the centre of a region, which considers the previous values of the centre and its candidate pixels, is best understood using an analogy from basic force analysis.

Let the initial hue value of the centre of a particular region be h_1 shown in Fig. 1. If the saturation is assumed as 1, this can be considered a unit force F_1 with direction h_1. If a candidate pixel h_2 joins this region, this can be regarded as a unit force F_2 with direction h_2. The resultant force of F_1 and F_2, namely R_1 and resultant hue angle ψ_1 of h_1 and h_2 shown in Fig. 1 are computed using the force analysis technique, which will be formalised in Algorithm 1. Note, that the magnitude of R_1 may not be unity. If another candidate pixel h_3 with unit force F_3 joins this region, the resultant force of R_1 and F_3, namely R_2 and resultant hue angle ψ_2 of ψ_1 and h_3 can also be calculated in exactly the same way. Therefore, ψ_2 is the average angle of h_1, h_2, and h_3. A similar process is applied to recalculate the centre of this region for all candidate pixels that join this region.

This process can be formalised as follows: -

1. The initial value of the centre of a region and the first candidate pixel are considered two angles of unit force, since the respective saturation values are always one.
2. The resultant angle of the two forces (the initial value of the centre and the candidate pixel) is regarded as the current value of the centre.
3. When another candidate pixel joins this region, the resultant force (angle and magnitude) for the current centre and the force for the candidate pixel are used to recalculate the centre of this region. This process is repeated for all candidate pixels that join this particular region.

The actual magnitude of the resultant angle depends on the sign of both the X and Y components of the resultant force because of the π radians periodicity of the tangent function. This means that the resultant angle will be in first, second, third, and fourth quadrant depending on the respective signs of the X and Y components.

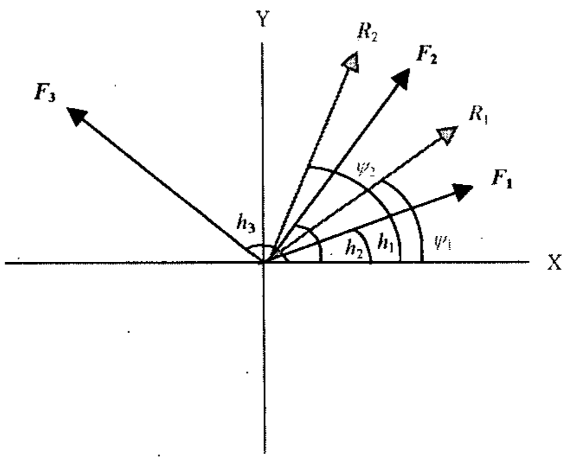

Fig. 1: Resultant (average) hue angle ψ_2 of h_1, h_2, and h_3.

The algorithm for calculating the average angle of two hue angles based on force analysis is formalised as follows: -

Algorithm 1 Calculation of the average of two hue angles

Precondition: Two hue angles h_1 and h_2 with magnitudes F_1 and F_2 of the forces $\boldsymbol{F_1}$ and $\boldsymbol{F_2}$ respectively.

Postcondition: Resultant direction ψ (average angle) and magnitude R of the force $\boldsymbol{R}$.

1. Calculate the X and Y components of the resultant force R.

   $R_x = F_1\cos(h_1) + F_2\cos(h_2)$

   $R_y = F_1\sin(h_1) + F_2\sin(h_2)$

2. Compute the magnitude of the resultant force R. If it is zero, mark the resultant angle ψ as undefined by setting its value as -1 and go to step 4.

   $R = \sqrt{R_x^{\,2} + R_y^{\,2}}$

   IF $(R = 0)$ THEN

   $\psi = -1$

   GOTO step 4

3. Determine the resultant direction (average angle).

   $$\psi = \tan^{-1}\left(\frac{|R_y|}{|R_x|}\right)$$

   IF $(R_x \geq 0)$ THEN

   IF $(R_y < 0)$ THEN

   $\psi = 2\pi - \psi$

   ELSE

   IF $(R_y > 0)$ THEN

   $\psi = \pi - \psi$

   ELSE

   $\psi = \pi + \psi$

4. STOP

All those pixel values, for which the average angle becomes undefined are blocked from the process for modification of each region centre in Section 2.2.

6. EXPERIMENTAL RESULTS

The new FRCIS, FCM, and PCM algorithms were implemented using MATLAB 5.6 (The Mathworks, Inc.). Four different image types containing two and three real objects as regions were used in the experiments.

The results produced by the FRCIS, FCM, and PCM algorithms for the cloud (Fig. 2(a)) and crocodile (Fig. 2(c)) images based on the HSV colour model are presented in Fig. 2. FRCIS provided better results than FCM and PCM when the segmented results of the FRCIS are visually compared with the respective results of FCM and PCM.

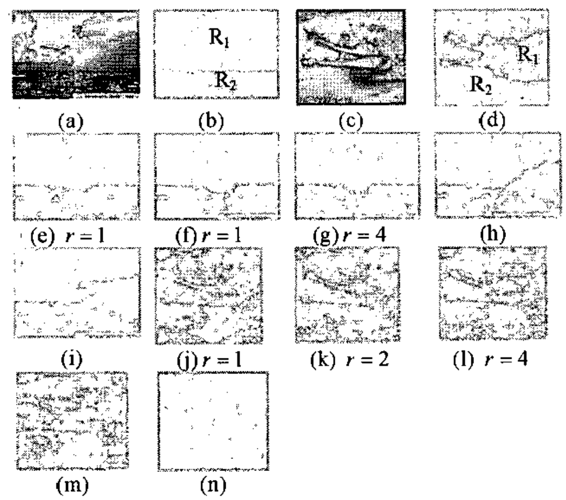

Fig. 2: (a) Cloud image, (b) Ref. image for cloud, (c) Crocodile image, (d) Ref. image for crocodile, The segmented results of the cloud and crocodile images into two regions by FRCIS (e) to (g) and (j) to (l), FCM (h) and (m), and PCM (i) and (n) respectively using the HSV colour model.

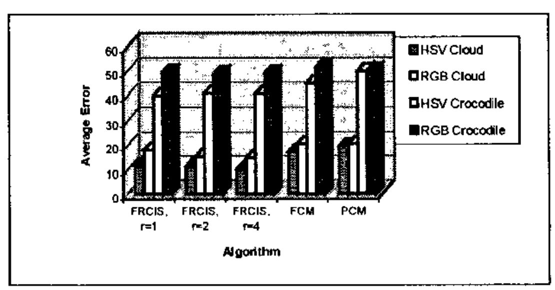

Fig. 3: Average percentages of error rates of the FRCIS, FCM, and PCM algorithms for the Fig. 2(a) and Fig. 2(c) image segmentations using the HSV and RGB colour models.

The average error percentages (average of Type I and II [9]) for the cloud (R_1) and crocodile (R_1) regions of the image in Fig. 2(a) and Fig. 2(c) respectively using the HSV and RGB colour models, and the FRCIS, FCM, and PCM algorithms are shown in Fig. 3. It can be seen that the error rates of FRCIS for all values of neighbourhood radius r are better than both FCM and PCM using both the HSV and RGB colour models.

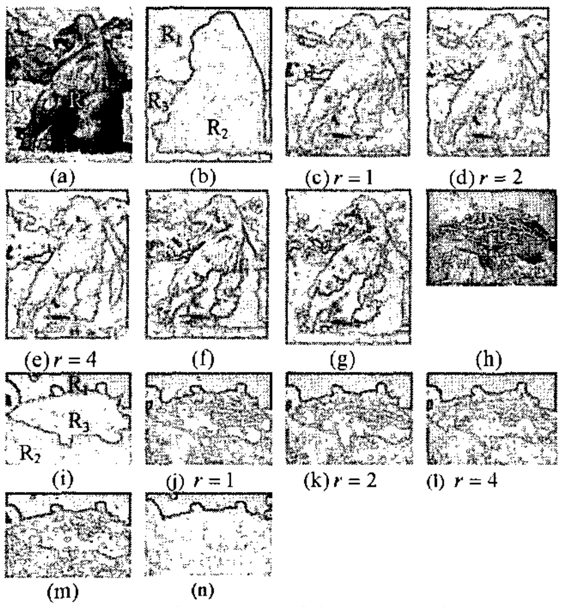

Fig. 4: (a) Gorilla image, (b) Ref. image for gorilla, (h) Fish image, (i) Ref. image for fish, The segmented results of the gorilla and fish images into two regions by FRCIS (c) to (e) and (j) to (l), FCM (f) and (m), and PCM (g) and (n) respectively using the HSV colour model. .

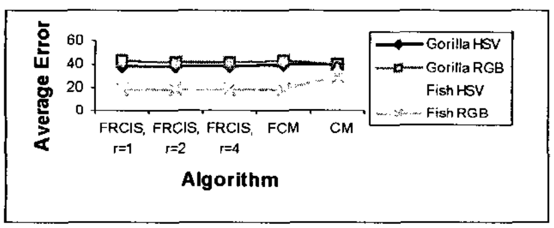

Fig. 5: Average percentages of error rates of the FRCIS, FCM, and PCM algorithms for the Fig. 4(a) and 4(c) image segmentations using the HSV and RGB colour models.

Further experiments were conducted using the gorilla (Fig. 4(a)) and fish (Fig. 4(h)) images consisting of three distinct regions. The segmented results of these two images produced by the FRCIS, FCM, and PCM algorithms using the HSV colour model are presented in Fig. 4, which clearly illustrates that FRCIS separated gorilla (R_2) (Fig. 4(c) - 4(e)) better for the HSV colour model and all values of r than FCM and PCM (Fig. 4(f) - 4(g)). FRCIS also outperformed both FCM and PCM especially for ground and trees (R_2) and fish (R_3) regions for the fish image (Fig. 4(j) - 4(n)). PCM could not separate at all the fish (R_3) from ground and trees (R_2) region shown in Fig. 4(n). The comparative average error rates are presented in Fig. 5. The FRCIS algorithm obtained 4.9% and 26.3% of the overall error improvements over FCM and PCM respectively for the gorilla and fish images using the HSV colour model, compared with corresponding values of 2.4% and 12.5% for the RGB colour model.

7. CONCLUSIONS

This paper has introduced a new algorithm called *fuzzy rule-based colour image segmentation* (FRCIS) by extending the original GFRIS algorithm and integrating a new approach for averaging hue angles. Both a quantitative and qualitative analysis have been undertaken to compare it with FCM and PCM. The experimental results have shown that FRCIS outperformed both FCM and PCM for both HSV and RGB colour models. Since the proposed technique is fuzzy rule based, it is capable of incorporating any type of attribute of any special application domain.

8. REFERENCES

[1] G. C. Karmakar, L. Dooley, and S. M. Rahman, "Review on fuzzy image segmentation techniques," in *Design and Management of Multimedia Information Systems: Opportunities and Challenges*: Idea Group Publishing, USA, pp. 282 -313, ISBN 1-930708-00-9, 2001 (a Book Chapter).

[2] G.C. Karmakar and L.S. Dooley, "A Generic fuzzy rule based image segmentation algorithm", *Pattern Recognition Letters*, vol. 23, pp. 1215-1227, 2002.

[3] H. D. Cheng, X. H. Jiang, Y. Sun, and J. L. Wang, "Colour Image Segmentation: Advances and Prospects," *Pattern Recognition Letters*, vol. 11, pp. 2259-2281, 2001.

[4] Y. W. Lim and S. U. Lee, "On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques," *Pattern Recognition Letters*, vol. 23, pp. 935-952, 1990.

[5] A. Moghaddamzadesh and N. Bourbakis, "A fuzzy region growing approach for segmentation of color images," *Pattern Recognition Letters*, vol. 30, pp. 935-952, 1997.

[6] B. C. Chien and M. C. Cheng, "A colour image segmentation approach based on fuzzy similarity measure," presented at FUZZ-IEEE'02, 2002.

[7] H. D. Cheng, X. H. Jiang, and J. Wang, "Color image segmentation based on homogram thresholding and region merging," *Pattern Recognition Letters*, vol. 35, pp. 373-393, 2002.

[8] T. D. Pham and H. Yan, "Color image segmentation using fuzzy integral and mountain clustering," *Fuzzy Sets and Systems*, vol. 107, pp. 121-130, 1999.

[9] Y.J. Zhang, "A survey on evaluation methods for image segmentation", Pattern Recognition, 29, 8, 1335-1346, 1996.

[10] J.C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", New York: Plenum, 1981.

[11] R. Krishnapuram and J. Keller, "A possibilistic approach to clustering," *IEEE Transactions on Fuzzy Systems*, vol. 1, pp. 98-110, 1993.

[12] S. J. Sangwine and R. E. N. Horne, "The colour Image Processing Handbook," first edition ed.: Chapman & Hall, 1998.

[13] D. Cardani, "Adventures in HSV Space," http://www.buena.com/articles/hsvspace.pdf, 2002.