A FUZZY RULE-BASED COLOUR IMAGE SEGMENTATION ALGORITHM

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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 compared 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 potential 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].

2. DEFINING MEMBERSHIP FUNCTIONS

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 $R_i$, $\mu_{\text{FRCIS}}(P_a)$ of a pixel with a value of $P_a$ at location $(x,y)$ for the $i^{th}$ colour component can be defined as:

$$\mu_{\text{FRCIS}}(P_a) = f_{\text{FRCIS}}(P_a)$$

where $f_{\text{FRCIS}}(P_a)$ is the polynomial for the $i^{th}$ colour component of region $R_i$ and $i \in \{1, \ldots, 4\}$ where 4 is the number of colour components for a particular colour model, i.e. 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 $P_a$ 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 assumed. The membership function for the closeness to a region $R_j$, $\mu_{\text{FRCIS}}(P_a)$ of a candidate pixel $P_a$ for the $i^{th}$ colour component is defined as:

$$\mu_{\text{FRCIS}}(P_a) = 1 - \frac{C_i(R_j) - P_a}{\max C_i(R_j), P_a}$$

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 \(R_j\), \(\mu_{aa}(P_{ij},r)\) for the neighbourhood radius \(r\) is defined as:

\[
\mu_{aa}(P_{ij},r) = \left( \sum_{n=1}^{N} \frac{G_{nj} \times w_i}{C_{nj} \times G_{nj}} \right) \sum_{j=1}^{N} w_j \times G_{nj} \times w_i
\]

where \(N\) and \(G_{nj}\) 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 \(P_{ij}\); \(N\) is the number of segmented regions.

3. DEFINING THE FUZZY RULE

In contrast to the fuzzy rule \cite{2} for gray level intensity, in this section a fuzzy rule is heuristically defined for all three colour components. The overall membership value \(\mu_{aa}(P_{ij},r)\) of a pixel \(P_{ij}\) 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., \(\mu_{aa}(P_{ij},r)\), \(\mu_{pp}(P_{ij},r)\), and \(\mu_{pp}(P_{ij},r)\).

\[
\mu_{aa}(P_{ij},r) = \sum_{i=1}^{N} w_i \mu_{aa}(P_{ij},r) + \sum_{j=1}^{N} w_j \mu_{pp}(P_{ij},r) + \sum_{k=1}^{N} w_k \mu_{pp}(P_{ij},r)
\]

where \(w_i, w_j, \) and \(w_k\) 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 \(\mu_{aa}(P_{ij},r) = \max_{i=1}^{N} \mu_{aa}(P_{ij},r)\) THEN pixel \(P_{ij}\) 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 \cite{2}, is extended to incorporate colour components and determine the weighting factors \(w_i, w_j, \) and \(w_k\), and threshold \(T_i\). The spatial relationship weighting factors \(w_i, w_j, \) and \(w_k\) 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 \cite{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 \cite{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:

\[
\text{Definition 2—Difference Between Two Angles: The difference between two hue angles } h_1 \text{ and } h_2, \text{ } d(h_1, h_2) \text{ is defined as:}
\]

\[
d(h_1, h_2) = \min(|h_1 - h_2|, 2\pi - |h_1 - h_2|)
\]

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 \(h_i\) shown in Fig. 1. If the situation is assumed as 1, this can be considered a unit force \(F_i\) with direction \(h_i\). If a candidate pixel \(h_i\) joins this region, this can be regarded as a unit force \(F_i\) with direction \(h_i\). The resultant force of \(F_i\) and \(F_j\), namely \(R_i\) and resultant hue angle \(\psi_i\) of \(h_i\) and \(h_j\) shown in Fig. 1 may be computed using the force analysis technique, which will be formalised in Algorithm 1. Note, that the magnitude of \(R_i\) may not be unity. If another candidate pixel \(h_j\) with unit force \(F_j\) joins this region, the resultant force of \(R_i\) and \(F_j\), namely \(R_j\) and resultant hue angle \(\psi_j\) of \(\psi_i\) and \(h_j\) can also be calculated in exactly the same way. Therefore, \(\psi_j\) is the average angle of \(h_j\), \(h_j\), and \(h_i\). 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 \(\pi\) 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.
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 \( h_i \) and \( h_j \) with magnitudes \( F_i \) and \( F_j \) of the forces \( F_i \) and \( F_j \) respectively.

Postcondition: Resultant direction \( \psi \) (average angle) and magnitude \( R \) of the force \( R \).

1. Calculate the X and Y components of the resultant force \( R \):
   \[ R_x = F_i \cos(h_i) + F_j \cos(h_j) \]
   \[ R_y = F_i \sin(h_i) + F_j \sin(h_j) \]

2. Compute the magnitude of the resultant force \( R \). If it is zero, mark the resultant angle \( \psi \) 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 \( R_x > 0 \) 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](image)

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](image)

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 \( R_2 \) regions of the image in Fig. 2(a) and Fig. 2(c) respectively using the HSV and RGB
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.

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 ($R_h$) (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 ($R_g$) and fish ($R_f$) regions for the fish image (Fig. 4(j) - 4(n)). PCM could not separate at all the fish ($R_f$) from ground and trees ($R_g$) 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