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# EXTENDED FUZZY RULES FOR IMAGE SEGMENTATION

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## ABSTRACT

The generic fuzzy rule-based image segmentation technique (GFRIS) does not produce good results for non-homogeneous regions that possess abrupt changes in pixel intensity, because it fails to consider two important properties of perceptual grouping, namely surroundedness and connectedness. In this paper a new technique called extended fuzzy rules for image segmentation (EFRIS) is proposed, which includes a second rule to that defined already in GFRIS, that incorporates both the surroundedness and connectedness properties of a region's pixels. This additional rule is based on a split and merge algorithm and refines the output from the GFRIS technique. Two different classes of image, namely light intensity and medical X rays are empirically used to assess the performance of the new technique. Quantitative evaluation of the performance of EFRIS is discussed and contrasted with GFRIS using one of the standard segmentation evaluation methods. Overall, EFRIS exhibits significantly improved results compared with the GFRIS approach.

## 1. INTRODUCTION

Image segmentation is the most important and difficult task of digital image processing and analysis systems, due to the potentially inordinate number of objects and the myriad of variations among them. The most intractable task is to define their properties for perceptual grouping, a demand that requires human expert knowledge be incorporated to achieve a superior segmentation result. Fuzzy rule-based image segmentation systems can incorporate this expert knowledge, but 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 [1-5]. Karmakar and Dooley [6-8] proposed a novel generic fuzzy rule based technique for image segmentation (GFRIS) by addressing these aforementioned problems. The technique however, does not work very well for image regions that are non-homogeneous and have sharp variations in pixel intensity. The eminent psychologist Gestalt stated that visual elements are grouped perceptually upon the principles of: proximity, closure, similarity, good continuation, common fate, surroundedness, relative size and symmetry [9]. The proximity, similarity and good continuation elements are all reflected in GFRIS. In this paper an extended fuzzy rule-based image segmentation (EFRIS) technique is proposed by integrating a rule, based upon the

surroundedness and connectedness properties of region's pixels in combination with the GFRIS rule. The performance analysis of both methods is conducted by applying a superior objective segmentation evaluation technique called the "discrepancy based on the number of mis-segmented pixels", which is one of the powerful empirical discrepancy methods [10]. This method is subsequently applied to two different classes of image: light intensity and medical x-ray of the human vocal tract.

Section 2 provides a brief overview of the technique used to define the fuzzy rules. The processing steps of the proposed methods are presented in sections 3. The evaluation and experimental results are discussed in section 4, with conclusions provided in section 5.

## 2. FUZZY RULES

Two fuzzy rules are used for two different purposes. The first represents the similarity, proximity, good continuation and spatial information of a region, while the second considers the surroundedness and connectedness of a region's pixels. Both rules are described in the following sections.

### 2.1. First Rule

Full details of this rule and its membership functions are given in [6-8]. It uses three membership functions to represent the region pixel distribution ( $\mu_{DR_j}(P_{s,t})$ ), closeness of a region ( $\mu_{CR_j}(P_{s,t})$ ), and spatial information among region pixels ( $\mu_{NR_j}(P_{s,t})$ ). Here  $\mu$ ,  $R_j$ , and  $P_{s,t}$  are the membership function,  $j^{\text{th}}$  region and the pixel at location  $(s,t)$  respectively. The two membership functions  $\mu_{DR_j}(P_{s,t})$  and  $\mu_{CR_j}(P_{s,t})$  represent the similarity based on gray level pixel distribution and intensity respectively, while the third  $\mu_{NR_j}(P_{s,t})$  characterizes the proximity, good continuation and spatial information of a region. The overall membership value  $\mu_{AR_j}(P_{s,t})$  of a pixel  $P_{s,t}$  for the region  $R_j$ , which represents the overall degree of belonging to the region  $R_j$ , is defined by the weighted average of the values of the three membership functions  $\mu_{DR_j}(P_{s,t})$ ,  $\mu_{CR_j}(P_{s,t})$ , and  $\mu_{NR_j}(P_{s,t})$ .

$$\mu_{AR_j}(P_{s,t}) = \frac{W_1\mu_{DR_j}(P_{s,t}) + W_2\mu_{CR_j}(P_{s,t}) + W_3\mu_{NR_j}(P_{s,t})}{W_1 + W_2 + W_3} \quad (1)$$

where  $W_1$ ,  $W_2$  and  $W_3$  represent the weightings given to the respective membership values for pixel distribution, closeness to the cluster centres and neighborhood relation. The rule is defined as:-

**Definition 1 (First Rule)** IF  $\mu_{AR_j}(P_{s,t})$  supports region  $R_j$  THEN pixel  $P_{s,t}$  belongs to region  $R_j$ .

$\mu_{AR_j}(P_{s,t})$  will give support to the region  $R_j$  if  $\mu_{AR_j}(P_{s,t}) = \max\{\mu_{AR_1}(P_{s,t}), \mu_{AR_2}(P_{s,t}), \dots, \mu_{AR_{\mathfrak{R}}}(P_{s,t})\}$  where  $\mathfrak{R}$  indicates the number of regions.

## 2.2. Second Rule

The second rule deals specifically with two perceptual properties of a region, namely surroundedness and connectedness. This rule is pipelined with the above rule, so that its output is refined using the surroundedness and connectivity properties of a region based on the split and merge algorithm. If the segmented regions produced by the first rule are denoted as  $R_j$  where  $j=1 \dots \mathfrak{R}$ , then all segmented regions (every  $R_j$ ) are split into a number of objects using 4-connected neighborhood property. Following the splitting, region  $R_j = \{O_{1j}, O_{2j}, \dots, O_{n_jj}\}$  is a set of objects where  $O_{1j} \cap O_{2j} \cap \dots \cap O_{n_jj} = 0$  and  $n_j$  represents the number of 4-connected neighborhood objects in region  $R_j$ . The main object of a region  $R_j$ ,  $O_{m_jj} = O_{ij}$  for  $|O_{ij}| = \max\{|O_{1j}|, |O_{2j}|, \dots, |O_{n_jj}|\}$  where  $| \cdot |$  is the cardinality of a set i.e. the number of pixels belonging to an object. The membership function for the surroundedness of an object ( $O_{ij}$ ) surrounded with a main object ( $O_{m_kk}$ ) is then defined as:-

$$\mu_{SO_{ij}}(O_{ij}, O_{m_kk}) = \frac{\eta_{ij}}{|O_{ij}|} \quad (2)$$

where  $\eta_{ij}$  is the number of pixels of an object  $O_{ij}$ , inside the main object  $O_{m_kk}$ . The contour of the main object is determined by constructing the convex hull for that object. The merging operation is performed by the following rule:-

**Definition 2 (Second Rule)** IF  $\mu_{SO_{ij}}(O_{ij}, \underbrace{O_{m_kk}}_{i \neq m_j \wedge k \neq j}) \geq \text{Th}$  AND  $O_{ij}$  is 8-connected neighborhood with  $\underbrace{O_{m_kk}}_{i \neq m_j \wedge k \neq j}$  THEN  $O_{ij}$

merges with  $\underbrace{O_{m_kk}}_{i \neq m_j \wedge k \neq j}$ .

Where  $i \neq m_j \wedge k \neq j$  ensures that an object  $O_{ij}$  is not a main object of its region  $R_j$  and merges with a main object of another region. Th is a threshold, which defines the degree of surroundedness used in the experiments.

## 3. SEGMENTATION STEPS

The segmentation consists of the following steps:-

- Step 1: The image is initially segmented using the first rule.
- Step 2: Each segmented region is spilt into a number of objects based upon 4- connected neighborhood. The main object, which is the object that contains the maximum number of pixels of each region, is then determined.
- Step 3: Objects are merged with a main object of other regions based on the second rule (see section 2.2). Once an object is merged, the merging algorithm repeats for all other objects belonging to the same region that were previously surrounded and not connected to the main region.

## 4. EXPERIMENTAL RESULTS

Both the new EFRIS and GFRIS systems were implemented using MATLAB 5.3.1 (The Mathworks, Inc.). Two different image types were used in the experiments, namely a light intensity gray-scale image shown in figure 1(a) which comprises one homogeneous and one non-homogeneous region, and a medical X-ray of the human vocal tract shown in figure 1(d), which contains two separate homogeneous regions.

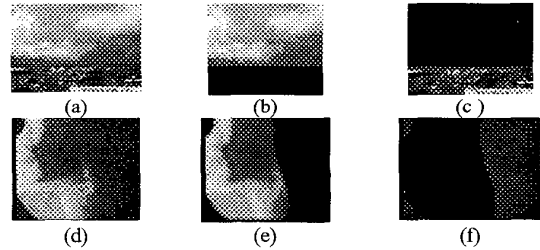


Figure 1: Original cloud scene, X-ray of the human vocal tract and their reference images: (a) Cloud image, (b) Ref: image for cloud, (c) Ref: image for urban scene, (d) Human vocal tract, (e) Ref: image for vocal tract, (f) Ref: image for the background

As alluded previously, quantitative evaluation of the segmentation process was achieved using discrepancy based on the number mis-segmented pixels [10]. The confusion matrix  $C$ , is an  $\mathfrak{R}$  by  $\mathfrak{R}$  square matrix where  $\mathfrak{R}$  represents the number of segmented regions and  $C_{ij}$  denotes the number of  $j^{\text{th}}$  region pixels classified as region  $i$  by the segmentation process. For the  $i^{\text{th}}$  region, type I error,  $\text{errorI}_i$  and type II error,  $\text{errorII}_i$ , are defined as:-

$$\text{errorI}_i = \frac{\left( \sum_{j=1}^{\mathfrak{R}} C_{ji} - C_{ii} \right)}{\sum_{j=1}^{\mathfrak{R}} C_{ji}} \times 100 \quad (3)$$

$$\text{errorII}_i = \frac{\left( \sum_{j=1}^R C_{ij} - C_{ii} \right)}{\left( \sum_{i=1}^R \sum_{j=1}^R C_{ij} - \sum_{j=1}^R C_{ji} \right)} \times 100 \quad (4)$$

For both GFRIS and EFRIS, the membership function for region pixel distribution  $\mu_{DR_j}(P_{s,i})$  was developed using the clusters produced by the fuzzy c-means (FCM) algorithm [11] and their centre values were used to initialize the centres of the clusters required to define the membership function for closeness of a region ( $\mu_{CR_j}(P_{s,i})$ ). The values of weights and the threshold were empirically determined as  $W_1 = 1, W_2 = 2, W_3 = 1, T=25$ , and  $W_1 = 1, W_2 = 1.5, W_3 = 1, T=30$  for the cloud and human vocal tract images respectively. The neighborhood radius ( $r$ ) was taken as 1, 2 and 4. The threshold  $Th$  was empirically selected as 0.8. The segmented results of the cloud image (figure 1(a)) into two regions namely, the homogenous clouds ( $R_1$ ) and non-homogenous urban scene ( $R_2$ ) produced by GFRIS and EFRIS are shown in figure 2.

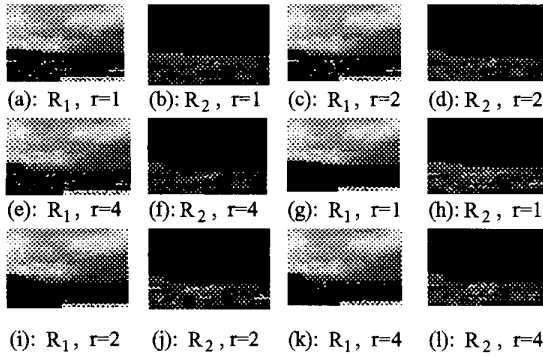


Figure 2: The segmented results of the cloud image into two regions by GFRIS (a) to (f) and EFRIS (g) to (l)

The numerical segmentation results of cloud image segmentation with respect to reference images (figures 1(b) and 1(c)) are shown in the following table 1.

Table 1: Error percentage for cloud (region  $R_1$ ) of cloud image segmentation

Method	Error I	Error II	Method	Error I	Error II
GFRIS $r=1$	8.8332	20.4783	EFRIS $r=1$	8.8332	12.9107
GFRIS $r=2$	1.9749	21.4497	EFRIS $r=2$	1.9749	13.4333
GFRIS $r=4$	2.0388	23.9742	EFRIS $r=4$	2.0308	17.7535

In table 1, only the error rates for region  $R_1$  are shown since the error rates of the other region  $R_2$  will simply be the reverse order of region  $R_1$ . The segmentation results for the

cloud image using GFRIS show that region  $R_1$  i.e. cloud (figures 2(a), 2(c) and 2(e)) contains a large number of misclassified pixels from region  $R_2$ , the non-homogeneous urban scene region, which has sharp variations in pixel intensity. Type II error rates for region  $R_1$  using GFRIS (Table 1) are higher than type I error rates. Almost all of the misclassified pixels, except the text caption were correctly classified using the second rule of EFRIS (figures 2(g)-2(l)). The type I errors of region  $R_1$  for EFRIS were caused almost exclusively by the text caption. The average error rates for both techniques are graphically shown in figure 3.

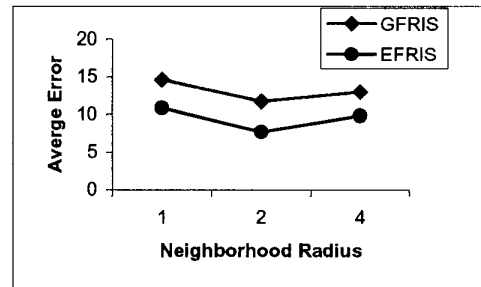


Figure 3: Average error rates of GFRIS and EFRIS for cloud image segmentation

From figures 2 and 3, it is clear that EFRIS achieved significant improvements over the GFRIS approach. The average error rates of both techniques for  $r=4$  are higher than that for  $r=2$  because there is no sharp boundary between cloud and urban scene. As a result, some portions of the urban scene have been interpreted as part of the cloud segment for higher orders ( $r=4$ ) of spatial information.

A second series of experiments was performed using a medical X-ray image of the human vocal tract (figure 1(d)). The segmentation results for the two separate regions namely, the human vocal tract  $R_1$ , figure 1(e) and background ( $R_2$ ), produced by both GFRIS and EFRIS are given in figure 4.

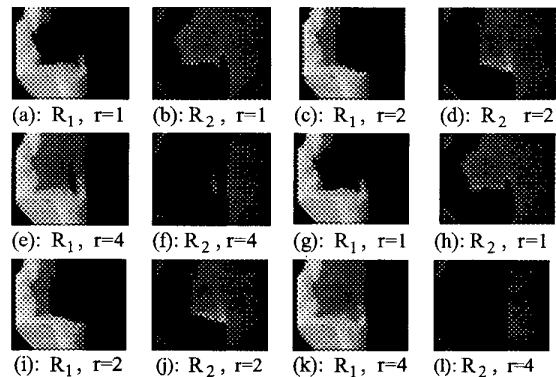


Figure 4: Segmented results of human vocal tract into two regions produced by GFRIS (a) to (f) and EFRIS (g) to (l)

The error and average error rates of human vocal tract segmentation with respect to the reference images (figures 1(e) and 1(f)) are shown in Table 2 and figure 5 respectively. The segmented results (figures 4(g)-4(j) and Table 2) using EFRIS for  $r=1$  and  $r=2$  are not significantly better compared with GFRIS, because there are no meaningful objects of a region that are surrounded and connected with other region and vice versa. EFRIS demonstrated superior performance compared with GFRIS for  $r=4$ , as depicted in figures 4(k), 4(l) and 5.

Table 2: Error percentage for human vocal tract (region  $R_1$ ) of x-ray of human vocal tract segmentation

Method	Error I	Error II	Method	Error I	Error II
GFRIS $r=1$	38.0529	7.477	EFRIS $r=1$	37.7601	7.4734
GFRIS $r=2$	30.1424	7.47776	EFRIS $r=2$	29.7274	7.4772
GFRIS $r=4$	3.903	14.5789	EFRIS $r=4$	1.9118	14.3982

GFRIS was unable to separate a small section of the human vocal tract (figures 4(e) and 4(f)) because of the very low pixel contrast, however EFRIS was able to successfully separate the entire human vocal tract (figure 4(k)).

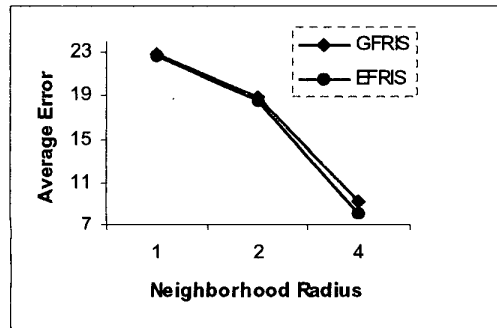


Figure 5: Average error rates of GFRIS and EFRIS for human vocal tract segmentation

Both the error and average error rates decrease rapidly for higher order of spatial information because the both regions are homogeneous.

## 5. CONCLUSIONS

This paper has outlined the development of a generic fuzzy rule-based image segmentation technique by incorporating two of the most important perceptual properties of region grouping namely, surroundedness and connectedness. A new technique called the extended fuzzy rules for image segmentation (EFRIS), has been proposed and both a quantitative and qualitative analysis undertaken to compare it with the generic approach (GFRIS). The experimental results have shown that EFRIS outperformed GFRIS, despite being more computationally expensive because of the additional rule integrated into the GFRIS model. The weighting factors and the thresholds were empirically determined, though a fully automated technique is currently being developed to determine these parameters. Since the

proposed technique is fuzzy rule based, it is capable of incorporating any type of attribute of any special application domain. It is possible to add membership functions for high level semantics of an object for object based image segmentation. More research however is required in order to automatically determine the explicit number of regions in an image.

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