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A Fusion Technique of Image Enhancement and Segmentation using Fuzzy Rule and Graph Cut Method

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Abstract: We have proposed image enhancement and segmentation based on fuzzy rule and graph cut method. A graph is constructed from the image using its intensity, texture and color profiles concurrently. A fuzzy rule based system is developed depending on the nature of image in order to find the weight which is required to develop feature for the specific image. The resulted weighted average of various image features is further used to frame normalized graph cuts. Further, the graph is bi-partitioned iteratively through the normalized graph cuts algorithm. As a result, we get optimum partitions which are the required segments of an image. We used the standard Berkeley segmentation database to test our algorithm and segmentation results are evaluated through index rand probabilistic, global consistency error, sensitivity, Dice similarity coefficient and positive predictive value. It is revealed that the proposed segmentation technique provides efficient results for different types of general images.

Key words: Image, enhancement, segmentation, noise, fuzzy, fuzzy c-means, graph cut

INTRODUCTION

Image segmentation is one of the basic problems in computer vision (Basavaprasad and Hegadi, 2014). Even after many years of research, broader purpose of image segmentation still remains a very exigent task as it is intrinsically ill-posed. Amongst different segmentation techniques, graph theoretical ones have several high-quality features in practical applications. It unambiguously categorizes the image elements into mathematical structures which are very sound and makes the formulation of the problem flexible and more skillful. In this study, we have proposed image enhancement and segmentation based on fuzzy rule and graph cut method to get an efficient segmentation of general images which can be used in the applications like machine vision, Iris recognition traffic control systems, locate tumors and other pathologies (Ravindra *et al*., 2011; Hegadi, 2010), brake light detection, pedestrian detection, medical imaging (Hegadi and Goudannavar, 2011), content-based image retrieval, measure tissue volumes, study of anatomical structure, objects locations from the satellite images (forests, roads, crops, etc.) (Ravindra *et al*., 2011), fingerprint recognition, diagnosis, surgery planning, intra-surgery navigation, virtual surgery simulation, video surveillance, recognition tasks, object detection, face detection, face recognition and much more. The study is based on the analysis of optimized fuzzy logic based segmentation for general images. In this research, we have used a FCM (Fuzzy C-Means) algorithm that integrates spatial information into the association function for clustering. The advantage of this method is that it is less responsive to noise than the other methods. This research is focused in developing the application for the analysis of general images by segmenting the images. The results show that this technique is effective for the segmentation of general images that can be used for analysis purpose. Image segmentation and consequent extraction from a which is affected by noise has been remained a difficult task in the image processing field. Improvement of image quality is also required by increasing the contrast and eliminating the noise. The most important idea of image enhancement is to fetch the details that are hidden in an image or to boost contrast in a low contrast image. We have proposed a novel adaptive fuzzy contrast enhancement method based on the fuzzy entropy standard which is followed by segmentation different types of generic images using the techniques of graph cuts. Thereafter, the graph is constructed from the image using its texture, intensity and color profiles concurrently. A fuzzy rule based structure is developed based on the nature of image in order to find the weight which is required to construct feature for the specific image. The graph is obtained from the fuzzy based rule. The weighted average of various image features is further used to frame normalized graph cuts. Then, the graph

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is bi-partitioned iteratively through the normalized graph cuts algorithm. As a result, we get best possible partitions which are the required segmented image. We have used the standard Berkeley segmentation database to test our proposed algorithm. The segmentation results are evaluated through global consistency error, index rand probabilistic, sensitivity, Dice similarity coefficient and positive predictive value. It is discovered that the proposed segmentation method gives skillful and useful results for different types of general images.

Literature review: We have reviewed many image segmentation algorithms from the literature using clustering and fuzzy rule based methods. Among them, we considered a very few as important for our proposed method (Majeed *et al*., 2010; Khokher *et al*., 2012a, b; Basavaprasad and Hegadi, 2014). We thoroughly surveyed fuzzy technique as well as graph based method and implemented them.

According to survey, an image segmentation and subsequent extraction from an image which is affected by noise in its background through the help of variety of soft computing techniques are somewhat new and somewhat popular due to several reasons. These techniques include different Genetic Algorithms (GA), Artificial Neural Network (ANN) representation dependent methods, histogram intensity based techniques, etc., giving an extraction result functioning in unsubstantiated form occurs to be still further attractive problem. According to survey, an attempt in this respect appears to be moderately basic where the image is considered as a fuzzy set notation (Zadeh, 1994; Majeed *et al*., 2010) then image is processed under fuzzification and finally resultant image is again processed under de-fuzzification to get the enhanced image.

A traditional Fuzzy C-Means (FCM) technique does not utilize the spatial information of the image. Gray image extraction is done using fuzzy logic. Fuzzy systems distress elementary methodology to characterize and process imprecision and uncertainty in the linguistic information. Fuzzy Rule Base Systems (FRBS) is defined as fuzzy based system which utilizes fuzzy rules to symbolize the field information of the problem.

Because of its vigorous distinctiveness for data categorization (Khokher *et al*., 2012a, b) Fuzzy C-Means (FCM) clustering is one of the main open reach clustering method for image segmentation. To address the drawbacks of traditional FCM all these methods have customized the intensive function of traditional FCM and have integrated spatial information in the intensive function of the typical FCM. The methods that have been appraised in this survey are segmentation for general images with full of noise and medical images in the midst of spatial prospect, C-Means Clustering (NFCM), novel fuzzy, improved spatial fuzzy c-means clustering procedure. These techniques consist of various, Genetic Algorithm (GA) based methods, Artificial Neural Network (ANN) models and intensity histogram based methods and many other methods which affords an extraction details working in unsubstantiated form. Fuzzy Rule Base Systems (FRBS) are the fuzzy rules of fuzzy systems which use rules to correspond to the field information of the problem. Fuzzy Rule Base Systems (FRBS) are the fuzzy rules of fuzzy systems which use rules to correspond to the field information of the problem. Literature suggests that effort in this respect appears to be relatively elementary. In one more survey study, we have noticed that, we can get efficient results for the segmentation of images (Khokher *et al*., 2012a, b).

The results of experiments advise that their method is a proficient one in assessment to diverse further methods broadly addressed in survey. To validate the preeminence of performance of their proposed technique in respect of its contestants, they used recourse to valuable metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR).

In combination of fuzzy with graph theory, the image is represented as a graph using fuzzy based system. Then image feature model is developed using color, texture and intensity properties of an image. Next weighted average of image features is calculated. Followed by it fuzzy rule based constants and similarity or weight matrix are calculated. Finally, the graph is partitioned by normalized graph cuts process. The partitioned sub-graphs are the required segments of an input image.

After image enhancement, the graph is constructed from the image using its texture, intensity and color profiles concurrently. A fuzzy rule based structure is developed based on the nature of image in order to find the weight which is required to construct feature for the specific image. The graph is obtained from the fuzzy based rule. The weighted average of various image features is further used to frame normalized graph cuts. Then the graph is bi-partitioned iteratively through the normalized graph cuts algorithm. As a result, we get best possible partitions which are the required segmented images (Khokher *et al*., 2012a, b).

Construction of graph using fuzzy based system: The image is being undergone enhancement process, it is segmented based on graph cuts using the color, gray scale and texture properties. Based on the nature of image a fuzzy rule system is designed to find the weight which should be assigned to a particular image characteristic during development of graph. The input image is first transformed into a weighted undirected graph G(V, E) where $V = \{v_1, v_2, v_3, ..., v_{m \times n}\}$ is the set of nodes and the set of edges between nodes is represented by E. The graph G(V, E) is internally characterized by an affinity matrix or similarity matrix W that encompasses of all the weights of each edge in a particular graph. Different features of different images are useful in finding the degree of similarity among the neighboring pixels used to build the similarity matrix W.

Models of image feature: Next, we define the feature models of an image using brightness, color and texture for building the similarity matrix.

Brightness: Seeing the brightness feature of pixels, brightness similarity matrix W_b can be computed using Eq. 1. $\|S_{v_i}-S_{v_j}\|^2 \leq R$ for:

$$W_b(V_i, V_j) = \exp\left[-\left(\frac{I_{v_i}-I_{v_j}2}{\alpha}\right)^2 - \left(\frac{S_{v_i}-S_v2}{\beta}\right)^2\right] \quad (1)$$

Otherwise, $W_b(v_i, v_j) = 0$. In Eq. 1, $\|I_{v_i}-I_{v_j}\|^2$ and $\|S_{v_i}-S_{v_j}\|^2$ are the spatial domains and the Euclidean distances in intensity and correspondingly. I_{vi} is the intensity value while S_{vi} is the spatial location of node v_i and $\|\cdot\|^2$ is the Euclidean norm. $\alpha, \beta \in (0, \infty)$ are the factors which are used to correct the gray level and position impression in calculating the weights. $\Re$ controls the influence of the number of local vertices taking part in weight calculation.

Color: The segmentation which has to be optimal, constructed based on the feature of color. The perceptual color differentiation and Euclidean distance. This is particularly considered to intensely estimated corresponding vision perception of human being. The intermediate color similarity matrix W_c using lab color space can be calculated as: for $\|S_{v_i}-S_{v_j}|2 \leq \Re$:

$$W_c(V_i, V_j) = \exp\left[-\left(\frac{Z_{v_i}-Z_{v_j}2}{\alpha}\right)^2 - \left(\frac{S_{v_i}-S_{v_j}2}{\beta}\right)^2\right] \quad (2)$$

otherwise, $W_c(V_i, V_j) = 0$. Here $Z_{vi} = \{L(v_i), a(v_i), b(v_i)\}$ is the color feature vector for node v_i where, the component L represents the lightness which equals the human perception in brightness a and bare the coordinates of chromaticity.

Texture: In both gray scale and natural color images, the feature texture, comprises the sufficient information which helps in the analysis of an image. Julesz introduced the term texton which is used to analyze thedifferent images. The histograms of windowed texton are related to calculate texture similarities. Window for pixel v_i is represented by $J(v_i)$ centered at pixel v_i. K number of bins per histogram exists for every channel texton. The texton containing K number of pixels that drop into the window $J(v_i)$ is used to compute the value of Kth histogram bin for pixel v_i. The equation for this is written as:

$$h_{v_i}(K) = \sum_{j \in J(v_i)} I\left[T(v_j) = K\right] \quad (3)$$

Where $T(v_j)$ gives the texton assigned to pixel v_j and $I[\cdot]$ is the indicator function. The pair-wise difference between two histograms h_{vi} and h_{vj} at pixels v_i and v_j, respectively is calculated as:

$$\aleph^2(h_{v_i} h_{v_j}) = \frac{1}{2}\sum_{k=1}^{K} \frac{\left[h_{v_i(k)} - h_{v_j(k)}\right]^2}{h_{v_i(k)} + h_{v_j(k)}} \quad (4)$$

Where h_{vi} and h_{vj} are the two histograms. Now the intermediate texture similarity matrix W_t can be calculated as:

$$W_t(v_i, v_j) = \exp[\aleph^2(h_{v_i, h_{v_j}})]/\gamma \quad (5)$$

Where $\gamma \in (0, \infty)$ is a parameter which adjusts the consequence of texture on computing the weights of each pixels. If the histograms h_{vi} and h_{vj} are very difficult, then weight $W_t(v_i, v_j)$ is small due to large value of $\aleph^2$.

Weighted average: The overhead model of feature provides the intermediate similarity matrices estimating the similarity among the neighboring pixels. Calculations of all models give precise projecting feature in the image however are not adequate enough which single handedly form an enhanced similarity matrix which is the groundwork of process of segmentation. The weighted average of intermediate matrices W_b, W_c and W_t (i.e., W_b and W_t for gray scale images and W_c and W_t for color images) are calculated to treasure the final similarity matrix W. It can be formulated as:

$$W(v_i, v_j) \sum_p c_p \times W_p, 0 \leq c_p \leq 1 \quad (6)$$

Where p = b, c and t are constants, c_b, c_c and c_t represent the weights to average out intermediate

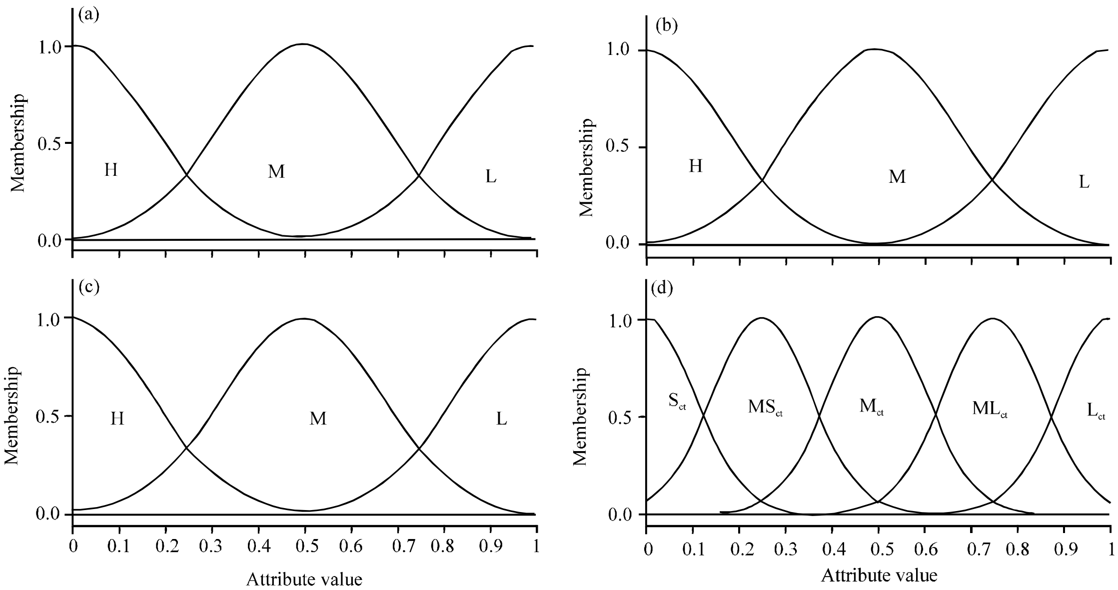


Fig. 1: a, b) Gaussian MFs; c) Gaussian MFs inputs and d) Corresponding output (Khokher *et al*., 2012a, b)

similarity matrices W_b, W_c and W_t, respectively. For gray scale images, constant $c_c = 0$ while for natural color images constant $c_b = 0$.

The transitional similarity matrices W_b, W_c and W_t can be examined to measure the that feature which will offer additional information about the image nature. This can be done by taking mean value of the intermediate similarity matrices. These mean value will be the closer to zero with the higher involvement of that specific feature. These values are the inputs of fuzzier where crisp values are transformed into fuzzy values. Gaussian Fuzzier (GF) is used as it has advantage over other fuzzier in terms of accuracy and efficiency. Membership function MF of GF which map x* to fuzzy set can be characterized using the mathematical equation:

$$\mu_F(x) = e^{-\left(\frac{x_1 - x_1^1}{\sigma_1}\right)^2} e^{-\left(\frac{x_N - x_N^1}{\sigma_N}\right)^2} \tag{7}$$

Where:
σ_i = The positive parameters
N = The number of linguistic terms and t-norm* is typically nominated as a product of algebra

A pool of linguistic values, i.e., H: High, M: Medium, L: Low, S: Small, MS: Medium Small, MH: Medium High and ML: Medium Low are given to each input and output variables. The Gaussian MFs is shown Fig. 1.

$\mu B(x)$, $\mu C(x)$ and $\mu T(x)$ is the input MFs and $\mu C_{t(x)}$ is the output MF. For color images $\mu C(x)$ and $\mu T(x)$ and for gray level images $\mu B(x)$ and $\mu T(x)$ are considered. One output MF is taken for calculation of constant C_t as rest of the constants can be calculated as $C_c = 1\text{-}C_t$ and $C_b = 1\text{-}C$ for the color and gray level images accordingly.

A fuzzy rule base comprises IF-THEN rules describing the relation between linguistic input and output values (Wang, 1997). Total there are nine cells produced by three precursor linguistic ideals (i.e., H: High, M: Medium, L: Low). Every cell of the nine cells constructsthe nine fuzzy IF-THEN rules. Figure 2 represents the decision table and IF-THEN rules. This can represented mathematically:

$$Q_M = \coprod_{r=1}^{M} Ru^{(r)} \tag{8}$$

Where:
Q_M = The resultant fuzzy relation
M = The number of rules to be followed

As fuzzy output set is union of M fuzzy sets can be computed using the following Eq. 9:

$$w_r C_t^* = \frac{\sum_{r=1}^{M} C_t^r \times w_r}{\sum_{r=1}^{M} w_r} \tag{9}$$

where, w_r represents the weights.

Partitioning of graph by normalized graph cuts process: After the graph obtained using the fuzzy rule based, the weighted average features of different images is further processed under normalized graph cuts framework to get optimal partitions through recursive bisections of the

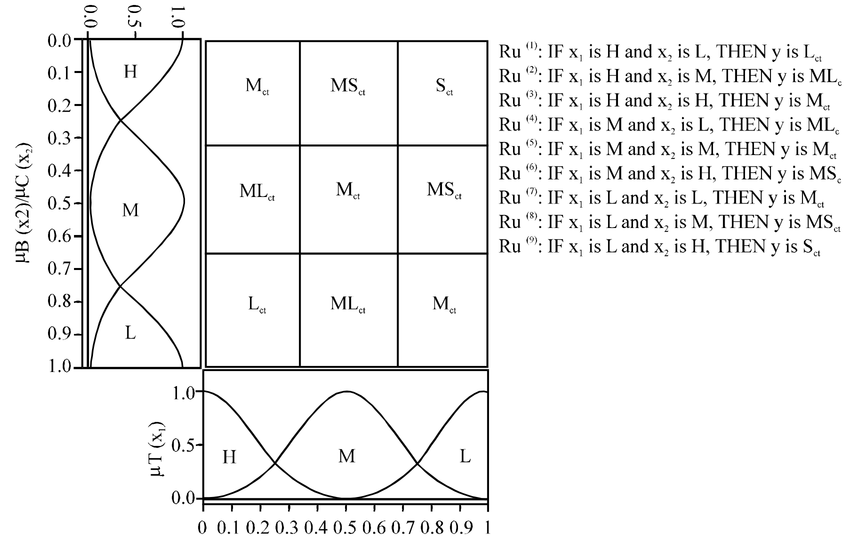


Fig. 2: Decision table and fuzzy IF-THEN rules (Khokher *et al*., 2012a, b)

graph G(V, E). The weight matrix W is used to find the different components of a comprehensive eigenvector system (Shi and Malik, 2000) can be formulated:

$$(D\text{-}W)y = \lambda D_y \tag{10}$$

where, D is the diagonal matrix calculated as D $(V_i, V_f) = \sum_{y} w(v_i, v_j)$ and $y = \{a, b\}^{m\times n}$ is an indicator vector to indicate the identity of pixels towards their group. Here if Y_{vi} =a and $v_i \in V_1$ and Y_{vj} = b if $v_j \in V_2$.λ. λ characterizes the eigen-values which results eigenvectors to partition the graph. The graph is bi-partitioned iteratively through the normalized graph cuts algorithm to obtain optimal segments resulting in image segmentation. For the segmentation, the standard Berkeley database is used to experiment our algorithm and then the segmentation outcomes are calculated through global consistency error, probabilistic rand index, positive predictive, Dice similarity coefficient and sensitivity value. It is revealed that the proposed segmentation technique gives effective results for most types of images. Extract the image features of the given imageas follows:

- Image intensity property is used to compute W_b
- Use lab color model to find W_c
- Texton based texture analysis technique is used to compute W_t
- Calculate the constants C_b, C_c and C_t using fuzzy rule Based system as follows
- Convert the crispy inputs into fuzzy inputs using GF with three linguistic terms
- Apply the fuzzy IF-THEN rules to get the output
- Merge the rules to be blazed using inference engine (Mamdani) to find a single fuzzy relation
- The fuzzy output is transformed into crispy output using center average defuzzifier
- Get the constants C_b, C_c and C_t
- Calculate the weighted average of W_b, W_c and W_t to obtain final similarity matrix W
- Divide the graph G(V, E) into number of sub-graphs by normalized cuts
- The matrix (similarity) W is used to compute the diagonal matrix D
- To get eigenvectors with smallest eigen-values, solve the generalized eigenvector system
- The graph is bi-partitioned through eigenvector with second smallest eigenvector
- Decide if current partition should be subdivided. If it is possible, repartition the segments iteratively to obtain the final result
- Using the partitioned graph, segmented image is obtained

PR (Probabilistic Random) index: It is a simplification to rand index. Randomindex (Rand, 1971) which measures the agreement of segmentation result with a given ground-truth. PR index compares the segmentations by considering pair wise label relationship. The 2 segments are represented by using the symbols S and S′ and with label assignment l_i and l'_i, correspondingly for N points $X = x_i$ where i = 1, 2, ..., N. Probabilistic random index is defined as fraction of number of pixel pairs overwhelming same label relationship in S and S'. It can be represented as:

$$R(S,S') = \frac{2}{N(N\text{-}1)}\sum_{i,j}\left[I(l_i = l_j \wedge l'_i = l'_j) + I(l_i \neq l_j \wedge l'_i \neq l'_j)\right] \tag{11}$$

In the above equation $i \neq j$ and 1 is the identity function whereas the denominator signifies all conceivable unique pixel pairs existing in a data set of N points.

GCE: This evaluation measure GCE (Global Consistency Error) (Khokher *et al*., 2012a, b) is related to consistency among segmentations. The parameters S and S′ are used to examine the segmentations by using consistency error measure. GCE exists in the range of 0-1 in which 0 represents that there is no error exists. The segments S and S′ are considered for a given pixel p_i. The pixel lies in the zone of enhancement if one of the segments is a proper subset of the other. Otherwise, if 2 regions overlap in an inconsistent way then corresponding error is calculated. Set difference is denoted by n and |x| for the cardinality of set x. For $R(S, p_i)$ presence a set of pixels that represents a region in the segmentation S which contains a pixel p_i, the native improvement error is computed using Eq. 12:

$$E(S,S',p_i) = \frac{|R(S,p_i) n R(S',p_i)|}{|R(S,p_i)|} \quad (12)$$

This local error measure is asymmetric. It encodes only one directional refinement measure. $E(S, S', p_i)$ is approximately zero when S is a refinement of S' but not vice versa. GCE is defined as:

$$GCE(S,S') = \frac{1}{N}\min\left\{\sum_i E(S,S',p_i),\ E(S',S,p_i)\right\} \quad (13)$$

where, N is the total number of pixels.

PPV, sensitivity and coefficient of dice similarity: Sensitivity S and PPV are the measures used to evaluate the segmentation results by calculating number of True Positive TP_n, False Positive FP_n and False Negative FN_n voxels. Using these voxels, S and PPV is given as:

$$S = \frac{TP_n}{TP_n + FN_n} \quad (14)$$

$$PPV = \frac{TP_n}{TP_n + FP_n} \quad (15)$$

Dice similarity coefficient D compares the two segments, i.e., the segment of test image and the segment from ground-truth or manual segmentation. Consider these 2 sub-sets be A and B, then D is computed by using Eq. 16:

$$D = \frac{2|A \wedge B|}{|A + B|} \quad (16)$$

The symbol ‖.‖ represents the function providing the segmented area.

MATERIALS AND METHODS

Proposed method: We have presented a hybrid method for the image segmentation process where in we have combined the fuzzy set theory based adaptive contrast image enhancement method with the image segmentation by fuzzy based system and graph cut technique (Khokher *et al*., 2012a, b). Firstly, the image is processed under the enhancement method in order to get the noise-free image. Then this noise-free image is processed under the fuzzy based system and graph cut method to get the required segmented image. During the process of hybridization, we not only combined the above mentioned two methods but also changed the values of the parameters that are used in fuzzy based system in order to get better enhancement and segmentation results. However, we have summarized the work of Richhariya and Srivastava.

Image enhancement process: Image segmentation and subsequent extraction from the image, affected by noise background has been a difficult task in the area of image analysis and processing. There exist several techniques accounted in the literature to this effect. Therefore, it is important improve the quality of an image by enhancing the contrast and remove the noise. The key reason behind the image enhancement is to fetch the details which are unseen in an image or to raise contrast in an image with low contrast. Firstly, the image is processed under the enhancement method in order to get the noise-free image. Image segmentation and subsequent extraction from the image, affected by noise background has been a difficult task in the area of image analysis and processing. There after, we offer an additional commanding and adaptive fuzzy contrast enhancement method that transforms image from fuzzy domain back to the spatial domain. We have implemented the work of Richhariya and Srivastava to achieve the image enhancement.

Image as fuzzy set notation: The original image of size M×N as intensity levels x_{ij} in range of [0, L-1] can be represented by array of fuzzy singleton in fuzzy set notation. Each element in the array corresponds to the degree of brightness of gray level. Its fuzzy notation is as follows:

$$X = \cup\left\{\mu\left(x_{i,j}\right)\right\} = \left\{\frac{\mu_{i,j}}{x_{i,j}} i = 1, 2, \ldots, M \text{ and } j = 1, 2, \ldots, N\right\} \tag{17}$$

where, $\mu(x_{i,j})$ denotes the degree of brightness processed by the gray level intensity of the (i, j) th pixel.

Fuzzification: Membership function characterizes the fuzziness in the fuzzy set. The fuzzy function for gray level image is defined as:

$$\mu\left(x_{i,j}\right) = \begin{cases} 0 & \text{for } x_{ij} \le a \\ \dfrac{x_{ij}\text{-}a}{(b\text{-}a)(c\text{-}a)} & \text{for } a \le x_{ij} \le c \\ 1\text{-}\dfrac{\left(x_{ij}\text{-}c\right)^2}{(c\text{-}b)(c\text{-}a)} & \text{for } b \le x_{ij} \le c \\ 1 & \text{for } x_{ij} \ge c \end{cases} \tag{18}$$

Where:

$x_{i,j}$ = The intensity of an image
a, b, c = The parameters used to determined the shape of the function

The parameters a, b, c are calculated as follows:

- Assume that the image has gray levels from L_{min} to L_{max}
- Compute the histogram using the function Hist(x)
- Split the histogram into number of matrices each of size 16×16
- Find the maxima of the histogram column wise, Max (Hist(x_1)), Max (Hist(x_2)), …, Max (Hist(x_k))
- Compute the average height for local maxima:

$$\overline{\text{Hist}_{max}(X)} = \frac{1}{k}\sum_{i=1}^{K} \text{Hist}_{max}(x_i)$$

- Choose a local maximum as a peak if the height is greater than the average height $\overline{\text{Hist}_{max}(X)}$ otherwise, neglect it
- To determine the value of parameter a and c, select the gray level of the first peak P(x_i) and last peak P(x_k) that is a = P(x_1) and c = P(x_k)
- Determine the parameters b the midpoint of the interval [a, c]
- The membership function calculated is then transformed into the image intensity levels from the spatial domain to fuzzy domain

Defuzzification: To make the contrast enhancement more adaptive and more effective and to avoid over-enhancement/under-enhancement, adaptive fuzzy

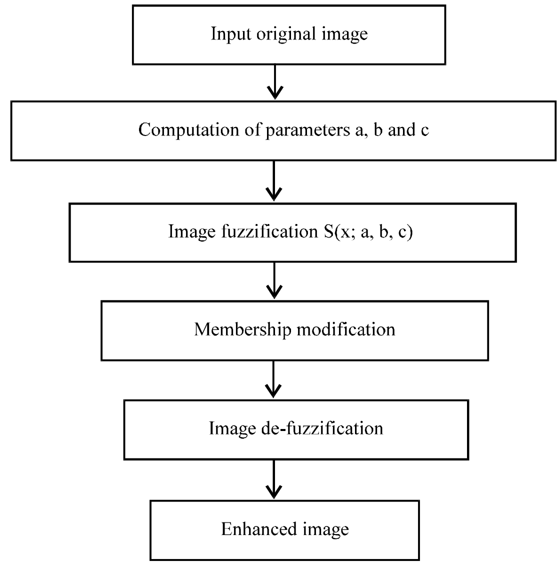


Fig. 3: Advanced contrast image enhancement

contrast enhancement, defuzzification is applied, that transforms the membership value μ ($x_{i,j}$) to the gray level by using Eq. 19:

$$x_{ij} = \begin{cases} L_{min}, & \mu\left(x_{i,j}\right) = 0 \\ L_{min} + \dfrac{L_{min}\text{-}L_{max}}{c\text{-}a}\sqrt{\mu\left(x_{i,j}\right)(b\text{-}a)(c\text{-}a)}, & 0 < \mu\left(x_{i,j}\right) \le \dfrac{(b\text{-}a)}{(c\text{-}a)} \\ L_{min} + \dfrac{L_{min}\text{-}L_{max}}{c\text{-}a}\sqrt{\left(c\text{-}a\text{-}1\text{-}\mu\left(x_{i,j}\right)\right)(b\text{-}a)(c\text{-}a)}, & \dfrac{(b\text{-}a)}{(c\text{-}a)} < \mu\left(x_{i,j}\right) < 1 \\ L_{max}, & \mu\left(x_{i,j}\right) = 1 \end{cases} \tag{19}$$

The overall image enhancement procedure explained above is shown in flow-chart which is as follows Fig. 3.

Image segmentation using fuzzy system and graph cut method: We have summarized the work by Khokher *et al.* (2012a, b) in this study.

Computation of constants using fuzzy rule: The computation of pixel's constants C_b, C_c and C_t be contingent on the participation of color, texture and brightness in an image consequently. The fuzzy rule based system provides high interpretability and also high accuracy. The process of constants calculation using fuzzy rule based system, feature extraction and weighted averaging is presented in Fig. 4.

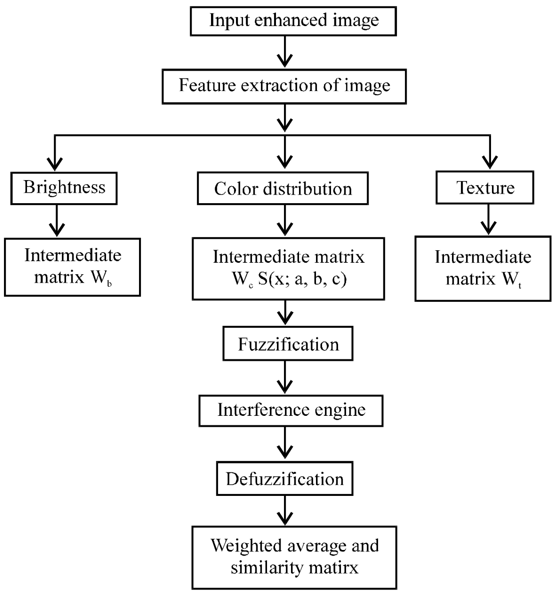


Fig. 4: Similarity or weight matrix calculation (Khokher *et al*., 2012a, b)

RESULTS AND DISCUSSION

Using the proposed method, number of gray scale and color images are used to test. The standard Berkeley segmentation database (Martin, 2000) with 200 images and their respective ground-truth segmentation is used to test the proposed algorithm. Simulations are performed using C++ programming language and Matlab. To compute the intermediate weight matrices, Euclidean distance in spatial domain $\Re$ is taken as $\sqrt{2}$. Figure 5a, e, i and m are the sample test images used to experiment using the proposed algorithm. The enhanced images through proposed algorithm are shown in Fig. 5b, f, j and n. Segmented color images are shown in Fig. 5c, g, k and o. Figure 5d, h, l and p are the segmented images using proposed method. We have presented a hybrid method for the image segmentation process wherein we have combined the fuzzy set theory based adaptive contrast image enhancement method with the image segmentation by fuzzy based system and graph cut technique (Khokher *et al*., 2012a, b).

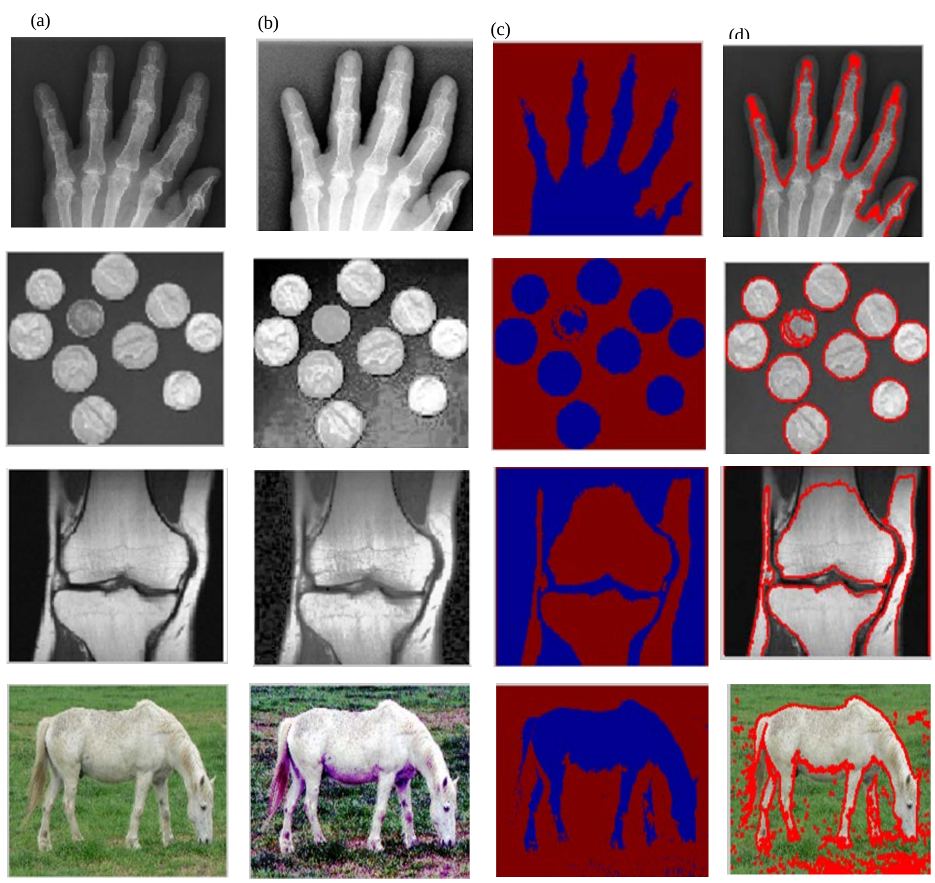


Fig. 5: Different images, showing the details of image segmentation using the proposed method: a) Original image; b) Enhanced image; c) Segmented color image and d) segmented plot image

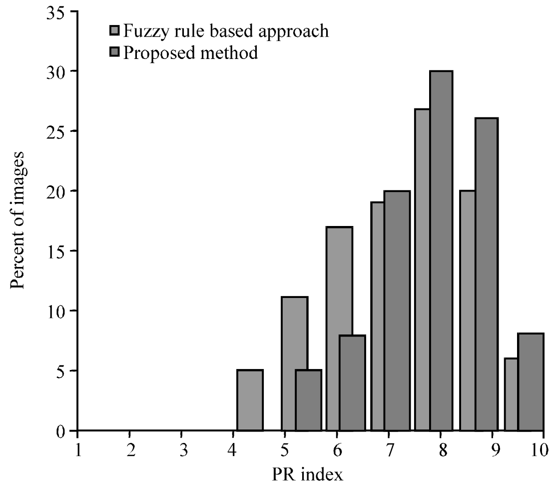


Fig. 6: Graph analysis showing the comparison of PR index distribution

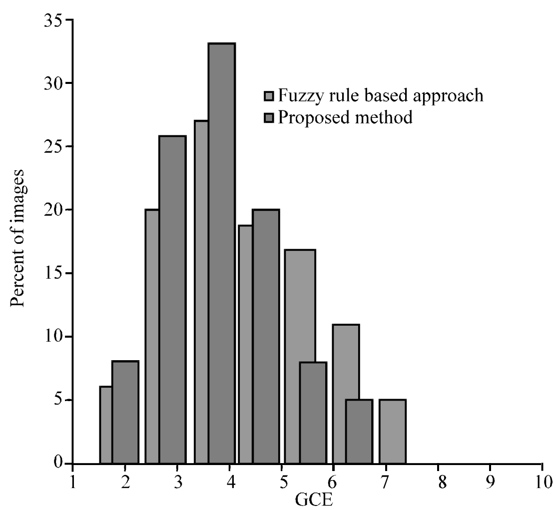


Fig. 7: Graph analysis showing the comparison of GCE distribution

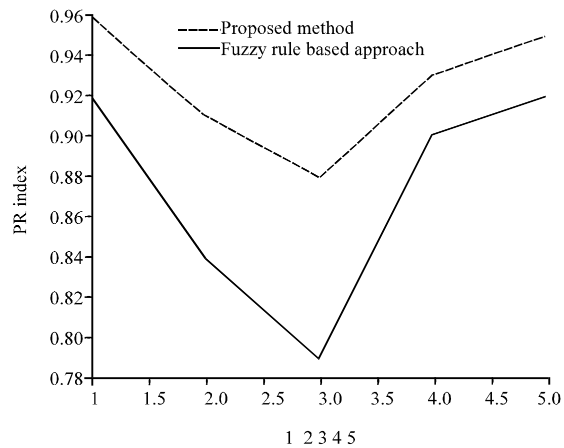


Fig. 8: Graph analysis showing the comparison of PR evolution

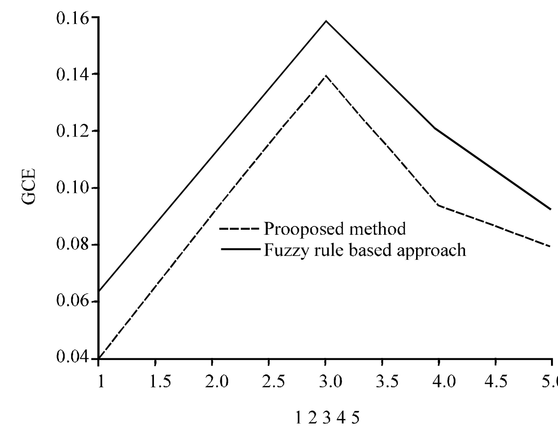


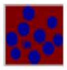
Fig. 9: Graph analysis showing the comparison of GCE Evolution

Firstly, the image is processed under the enhancement method in order to get the noise-free image. Then, this noise-free image is processed under the fuzzy based system and graph cut method to get the required segmented image. During the process of hybridization, we not only combined the above mentioned two methods but also changed the values of the parameters that are used in fuzzy based system in order to get better enhancement and segmentation results.

It is found that these results are improved as compared to the fuzzy rule based approach (Khokher *et al*., 2012a, b).

For the quantitative evaluation of our proposed algorithm, PR index (Unnikrishnan *et al*., 2005), GCE (Martin, 2000), sensitivity, PPV and Dice coefficient (Rand, 1971) are used. These techniques use the ground-truth segmentations to evaluate the segmentation outcomes. PR index and GCE distribution for proposed technique and its comparison with fuzzy rule based normalized cuts method using different image feature (i.e., gray level images, texture for texture images, color/brightness for color) are shown in Fig. 6-9. The segmented images are shown in Table 1. The proposed method finds the mean and standard deviation for S, PPV and D for each segment in the segmented image. We can clearly notice that maximum of the evaluation measures range between 0.91 and 0.97 for S, PPV and D which proves a good segmentation.

Table 1: Image segmentation results using sensitivity, positive predictive value anddice coefficient from the proposed method

Segmented image	Evaluation	Seg#1	Seg#2
	S	0.94±0.04	0.92±0.05
	PPV	0.96±0.04	0.94±0.03
	D	0.92±0.06	0.93±0.04
	S	0.95±0.03	0.95±0.05
	PPV	0.93±0.05	0.94±0.04
	D	0.91±0.06	0.93±0.03
	S	0.97±0.06	0.96±0.06
	PPV	0.93±0.04	0.93±0.03
	D	0.92±0.06	0.93±0.02
	S	0.93±0.02	0.93±0.07
	PPV	0.94±0.04	0.96±0.05
	D	0.96±0.06	0.94±0.02

CONCLUSION

It is revealed that there is no ideal technique for image segmentation, since the outcomes of image segmentation relies on many properties of pixel such as texture, color, intensity and image content and their problem area. Hence, it is not possible to judge on a single technique for every type of images and some techniques can execute fine for a specific type of image. Therefore, it is better to use combination of different methods particularly graph based technique as one of them for image segmentation process. In this proposed image enhancement and segmentation based on fuzzy rule and graph cut method, first, we have used the fuzzy based image enhancement technique for improving the quality of image by reducing noise in it. This step is very useful for segment the image and getting a better segmentation result. Then, we combined the fuzzy based rule with graph cut method to achieve the image segmentation. For our experiment, the standard Berkeley segmentation database is used to test the algorithm and finally segmentation results are evaluated through index rand probabilistic, global consistency error, positive predictive value, sensitivity and Dice similarity coefficient. The proposed segmentation technique provides efficient results for different types of general images.

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