Intuitionistic Neutro Soft Rough Sets and Classical Regression Model for Brain Image Segmentation

Prasanthi Boyapati, N. Nagamalleswara Rao

Abstract: ***Magnetic resonance image (MRI) is one of major component in medical brain image, imaging technique and segmentation of brain medical image is a crucial & complex task in evaluation of MRI images. Conventionally, different types of fuzzy, soft set related approaches like intuitionistic, fuzzy c-means, fuzzy c-means were developed to segmentation of brain related image, but these approaches face accuracy loss in brain image segmentation. So we consider new segmentation approach i.e. Intuitionistic neutro soft based rough sets and Classical Regression model (INSRCRM) which is extension to Advanced machine learning approach i.e. Enhanced & Explored Intuitionistic FCM clustering (EEISFCM) for smoothness and to increase image accuracy and intensity. Proposed approach is applied to increase accuracy and intensity with respect to spatial data processing for medical brain image segmentation and evaluate histon and histogram based image smoothness. Proposed approach evaluated with lower and upper approximations for intensity based brain image segmentation. This approach mainly identifies real valleys to smooth measure to present brain image segmentation to reduce noise reduction based on threshold of image pixels with different image notations. Experimental results of proposed approach gives to find peaks and valleys to demonstrate better image segmentation results with respect to traditional approaches.***

Keywords: ***Medical image segmentation, regression model, Intuitionistic soft based rough sets, fuzzy c- means, Classification accuracy and spatial weighted data***

1. INTRODUCTION

In biomedical field, segmentation of image and exploration of contour are the most instinctive methodologies to define image in visualization. Segmentation of image is thought assignment for image identification and investigation based on image boundary representations, which are effected by noise. It is the crucial step to analyze images with respect to tissue classification and study analysis anatomical architecture and integrated surgery. Because of noise representation, variation of tissue, different partial volumes, non-uniformity image intensity and brain image segmentation is challenging task in present days. Traditionally different types of techniques are applied in different types scenarios like group based, based on region, image based histogram and combination of above representations. Because of simplicity of segmentation in image processing, it defines different types of static oriented approaches and describes image description based on image information. In brain image segmentation, white matter (WM), grey matter (GM) and (CSF) cerebro spinal fluid are the main basic regions to define tissue classification effectively. To process these parameters effectively, Different types of Intuitionistic fuzzy, soft and rough sets defined in related literature. These methods have some limitations to form cluster based on threshold values. Based on these limitations with rough set cluster representation is complex task in medical image segmentation. Fuzzy, rough sets applied for brain image segmentation based on accurate region selection to provide accurate image segmentation with better and efficient segmented results. Lower and upper boundary approximations if images to define soft, fuzzy sets involved classifying brain image segmentation images. To increase intensity of medical image advanced machine learning approach i.e. Enhanced and Explored Intuitionistic FCM (EEISFCMA) based on pixel weight of medical image segmentation, this method explores and identifies segmented results with comparison of existing methods based on fuzzy related image segmentation. This approach modify developed by complete classification with different regions based on brain image segmentation. This approach improves classification of region selection with different intuitionistic fuzzy, rough set related approaches based on bias field estimation to explore image intensity during image segmentation. These approaches were generalized from mathematical sets to improve image intensity with homogeneity during segmentation of image. Fuzzy related intuitionistic mathematical tools with their respective parameters evaluated based on membership and non-membership image pixel values. These methodologies are only based on intensity of image with different formations or relevant to similar elements. These approaches only consists weight based bias field and lower and upper approximation measures are considered to identify different regions in histogram based segmentation. However all these techniques constant types of images for processing image in different stages, it is difficult to identify appropriate constant relations for some input images. And also above approach is not smooth & peak level image segmentation is not suitable for histogram image religions. Another problem with above approach is, it is sensitive to remove noise of medical images.

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So that, in this paper, we propose efficient image segmentation technique i.e. pattern extraction for pixel notation in segmentation of image into different regions, we propose Intuitionistic Neutro soft based rough sets and Classical Regression model which is extension to Enhanced and Explored Intuitionistic Soft based Fuzzy C-means (EEISFCM) for smoothness and increase image intensity and accuracy. We also obtain soft based rough measure of intuitionistic neutron soft based rough sets as basic representation to overcome above drawbacks. And this method is need not identify appropriate image peaks in identification of cluster with respect to spatial weight based on bias field to form different clusters. This proposed approach is insensitive to noise reduction for brain medical image segmentation. Experimental results give proposed approach can find tissue classification more easily and demonstrates better segmentation results with comparison of existing approaches.

II. PRELIMINARIES

2.1. Intuitionistic Neutro Soft Rough sets

Let us consider that A is the sub set of universal set U, with an equivalence relation R, then classification sub sets $U/R=\{A_1,A_2,\ldots\ldots,A_n\}$ (it satisfied different conditions)

$$A_i \subset U, A_i \neq \phi \forall i;$$
$$A_i \cap A_j \neq \phi \forall i, j;$$
$$A_1 U A_2, \ldots\ldots, U A_n = U; \qquad \text{.......... (1)}$$

For each sub set A_i i.e called as category with equivalence relationship R, Single attribute contain in R relation with an object $a_i \in U$ and it is identified by $[a_1]_R$ then internal relation for selected attributes

$$a_1 INT(R) a_2 = \{(a_1,a_2) \in U^2 \mid (a_1,a_2) \in P, P \in U/R\} \qquad \text{........... (2)}$$

With equivalence relations with respect to internal relation can be defined as

$$INT(P) = \bigcap_{R \in P} INT(R) \qquad \text{........ (3)}$$

Calculate the relation based on intuitionistic neutro soft based rough sets can be defined with lower and upper approximate of relation R with set relation A is

$$\overline{R}A = \cup\{Z \in U/R \mid Z \cap A \neq \phi\} \qquad \text{........... (4)}$$

A set of relations RA contains different attributes relates to A and upper and lower values with respect to different relations consists in A. Let I be the medical brain image then converted histogram is

$$t_1(g) = \sum_{n=1}^{N}\sum_{m=1}^{M} \beta\left(I(n,m)-g\right), \; for \quad 1 \leq g \leq L \qquad \text{........ (5)}$$

The histon of the brain medical image representation as follows:

$$t_2(g) = \sum_{n=1}^{N}\sum_{m=1}^{M} (1+I'(n,m))\,\beta\left(I(n,m)-g\right) \qquad \text{........ (6)}$$

Image histogram and histan are two representation of image in intuitionistic neutro soft rough sets, based on lower and upper histogram, histon image intensity can be calculated in intuitionistic soft rough sets is as follows

$$\rho(g) = 1 - \frac{t_1(g)}{t_2(g)} \; for \quad 1 \leq g \leq L \qquad \text{................... (7)}$$

Variance calculation for image segmentation using formula 10 at different noise level for brain medical images

III. PROPOSED METHOD IMPLEMENTATION

Basic image segmentation procedure of the proposed approach follows 3 different stages as show in architecture process. First, compute histon and histogram of the image according to above equations. Secondly, compute smoothness of the using classical regression methodology, based on weight measure function of image intensity, measure to segment medical image.

Classical regression for Image Smoothness

Histogram evaluation of gth grey level is t(g) and pair of literal observations of medical brain image $\{(1,t(1)),(2,t(2)),\ldots.,(L,t(L))\}$ model of the histogram of image is $t(g)=\mu(g)+\iota_g(1\leq g\leq L)$

$\mu(g)$ is unknown reliable function variable, ι_g is term of error. Error $\iota_g(1\leq g\leq L)$ is assumed variable with distributed and independent values in between 0-1 ideally.

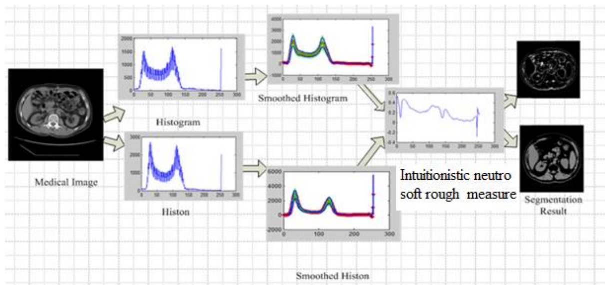

Figure 1. Sample procedure of proposed approach

Based on Taylor's theorem consideration for different pixel value presentation is shown in figure 2,

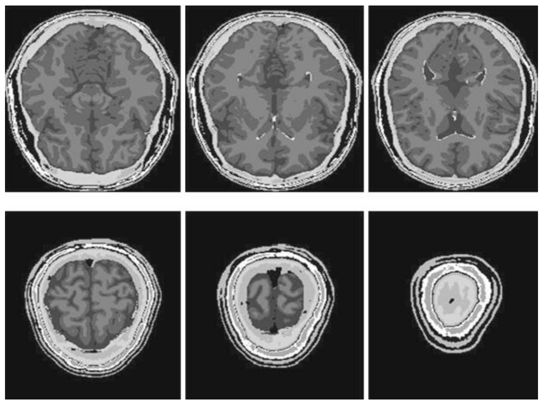

Figure 2. Different axial brain medical images

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Local image representation of different pixel values with different points can be represented with different approximated parametric functions. Bandwidth function b(a) and window smoothing is can be calculated $(a-b(a),a+b(a))$. Weight measure value for each parameter value is

$$\varpi_g(x)=K\left(\frac{g-a}{b(a)}\right) \qquad \text{............ (8)}$$

$\varpi_g(x)$ is the weight measure function for different weight measure values is observed in terms of kernel programming terminology with classical regression methodology with polynomial attribute relation is as follows:

$$\mu(v)\approx x_0+x_1(v-a)+\frac{1}{2}x_2(v-a)^2+....+\frac{x_r}{r!}(v-a)^r \qquad \text{..................... (9)}$$

Representation for component vector for local regression is

$$\mu(v)\approx x_0+x_1(v-a)+\frac{1}{2}x_2(v-a)^2+....+\frac{x_r}{r!}(v-a)^r =< x, X(v-a)> \qquad \text{.......... (10)}$$

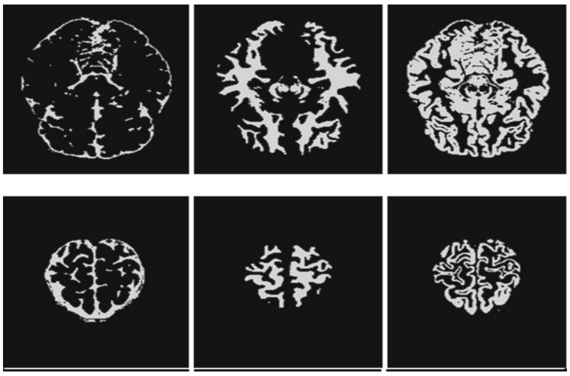

Figure 3. Brain medical image with respect to different weight measures

Where a is coefficient vector representation of relative function X (.), it is vector representations for different fitting functions, each fitting function attach with weighted values progressed with sum of squares is as follows:

$$\sum_{g=1}^{L}\varpi_g(a)\left(h(g)-< x, X(g-a)>\right)^2 \qquad \text{.............. (11)}$$

Based on weight squares, levels of different noise representations shown in figure 4 at different stages

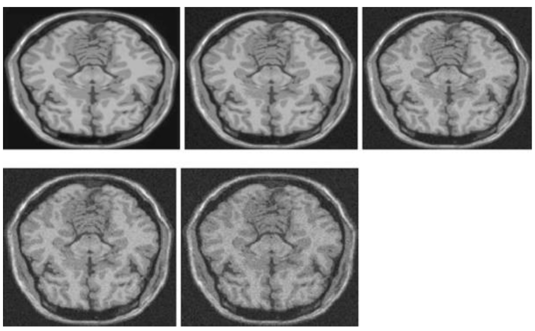

Figure 4. Image segmentation levels after smoothing with noise reduction

Noise reduction values for segmented image follows below equation

$$\Delta_a=\begin{pmatrix} 1 & 1-a & \frac{(1-a)^r}{r!} \\ 1 & 2-a & \frac{(2-a)^r}{r!} \\ 1 & L-a & \frac{(L-a)^r}{r!} \end{pmatrix} \qquad \text{...................... (12)}$$

All the noise values can be represented in LxL matrix with different diagonal values, based on these weight parameters intercept estimator with updated value noise function for image histogram and histon

$$\mu(a)=e_1^T\left(\Delta_a^T W_a \Delta_a\right)^{-1}\Delta_a^T W_a H \qquad \text{............ (13)}$$

Where $e_1^T=(1,0,......,0)$ based on above representation we have following scenario at different noise levels

$$\mu(a)=\sum_{i=1}^{L} l(a)h(i) \qquad \text{..................... (14)}$$

Based on above implementation, after noise reduction from overall image, overall intuitionistic neutro fuzzy soft rough sets measure for histogram and histon at different noise levels can be shown in figure 5.

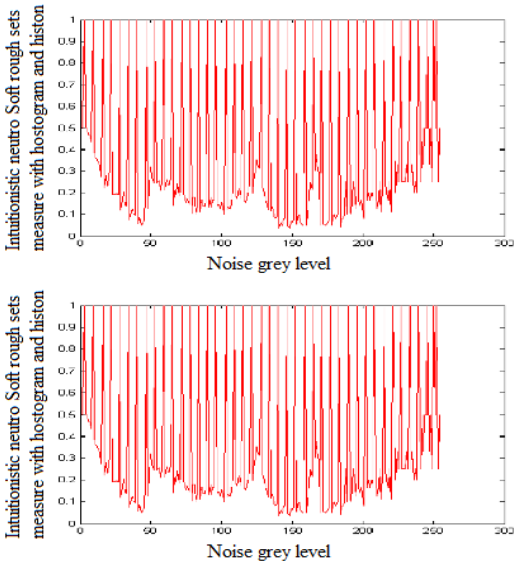

Figure 5. Intuitionistic neutro fuzzy soft rough set measures at different noise levels in image

This representation can be change whenever bandwidth values of classical regression, if bandwidth is small then data representation for image smooth is fall and noise is fix and variance of image is also large for image result. If bandwidth is large then no fixed value for different noise levels. Bandwidth selection for image at different noise levels as follows

$$y^*=\left(\frac{4}{3L}\right)^{1/4}\sigma \qquad \text{........... (15)}$$

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Where σ is the variance of smooth function at different noise levels, this classical regression for different noise image levels is computed using following algorithm.

I/P: Medical brain image i
O/P: Smoothed histogram/histon
Based on above equa 13,14. Compute histogram h
Calculate bandwidth of y* for h
Set classical regression value is 2.
Based on formula 10, compute W_x
Based on formula 12, compute Δ_x
$for(g=1; g \le L; g++)$
Based on formula 16, 17, calculate inspect estimator function μ_g with bandwidth and other parameter sequences.
Smoothed histogram/histon is $h1(g)=\mu(g);$

Algorithm 1. Classical regression for image histogram and histon for different images

Image segmentation with Intuitionistic Fuzzy Rough set Measure

Based on smoothing of the image computed in algorithm 1, compute smoothed intuitionistic neutro fuzzy soft rough set measure using variance of image

$$\widehat{\upsilon}(g)=1-\frac{h1(g)}{h2(g)} \; for(1 \le g \le L)$$

.... (16)

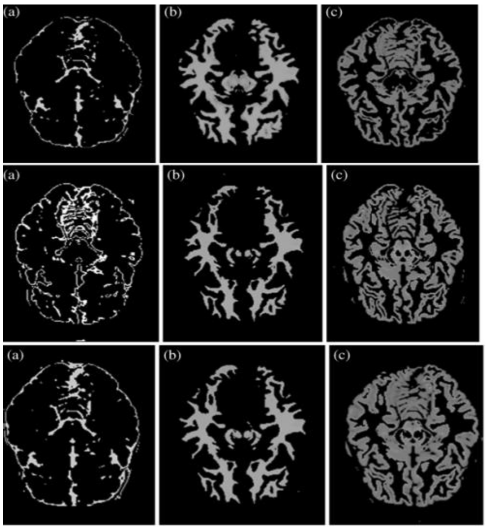

Figure 6. Segmented images represented at different noise grey levels

As shown in figure 6, it defines different image segmentation images at different noise levels associated with each grey level pixel values of brain image.

Our proposed segmentation algorithm as follows:

I/P: Smooth histogram $h1(g)$ and histon is $h2(g)$
O/P: Segmented regions $S_1, S_2 \ldots S_L$
Based on equa 17,18 calculate smoothed intuitionistic neutro fuzzy soft rough set measure $\widehat{\upsilon}(g)$
Calculate all levels using following formula:

$$L=\left\{g \mid \left(\widehat{\upsilon}(g)>\widehat{\upsilon}(g-1)\right) \& \left(\widehat{\upsilon}(g)>\widehat{\upsilon}(g+1)\right)\right\}$$

.... (20)
Identify all valleys using formula

$$K=\left\{g \mid \left(\widehat{\upsilon}(g)>\widehat{\upsilon}(g-1)\right) \& \& \left(\widehat{\upsilon}(g)>\widehat{\upsilon}(g+1)\right)\right\}$$

.... (21)
Remove all valleys if
$if\,(g...is...valley) \& \widehat{\upsilon}(g+1) \ne \widehat{\upsilon}(g-1)$
Arrange all the valley representations in ascending order
Segment brain image I integrated with grey levels, if it is matched with sorting condition,
$[1, j_1], [1, j_2], \ldots\ldots, \left[v_{|V|-1}, v_{|V|}\right]$
Output segmented image regions.

Algorithm 2. Brain image segmentation with intuitionistic neutro fuzzy rough soft measure

The value of robustness is high for particular image .i.e. closely related to 0-1, then histogram is larger with comparison of smoothed histon of brain medical image..

IV. RESULTS

In this section, we define experimental evaluation of proposed algorithm implementation with different brain image databases. Here we show simulated results with realistic brain Magnetic Resonance Image extracted from simulated brain data set. We apply our approach at single and multiple simulated at different dimensions based on following parameters like slice thicknesses (smoothness) , grey noise levels and intensity of image with uniformity and finally represent results with time for image segmentation of brain segmented images. For that, we are using latest Mat Lab with simulate function on Window 10 and Pentium processor for kernel programming in brain images. Sample abdomen images are shown in following figure.

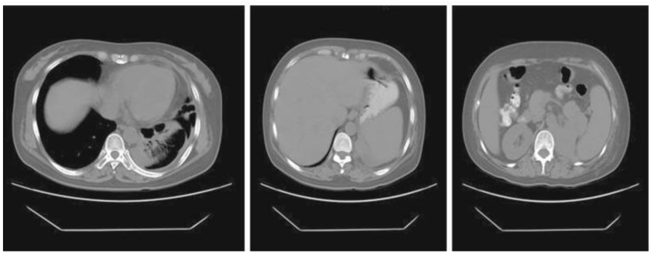

Figure 7. Sample image abdomen images from MRI brain images

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Using above image representations, we simulate brain image with modularity of modality= T1 at different noise levels 3%, 0%, and 9% and also take different image scaled range for segmentation is 0,1,....., 255 pixel values.

We choose 50-100 sample brain images (example brain images are shown in figure 2-3),for comparative (we compare existing approaches with proposed approach i.e. (INSRCRM) segmented methods. Based on three components i.e. Cerebro Spinal Fluid (CSF) Grey Matter (GM) and White Matter (WM) for above mentioned methods. Segmented images for above considerable methods shown in figure 8.

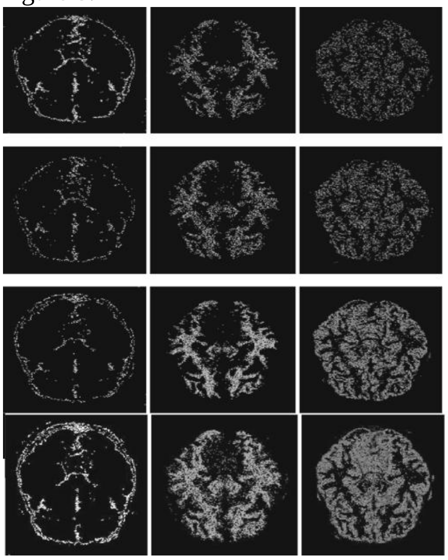

Figure 8. Brain image segmented results at different noise ranges at 0%, 3%, 9% and intensity at 21%

Different indices with respect to different components CSF, GM and WM for 50-100 images at different noise levels shown in figure 8. So those samples brain image histogram, histon and other features shown in below figures.

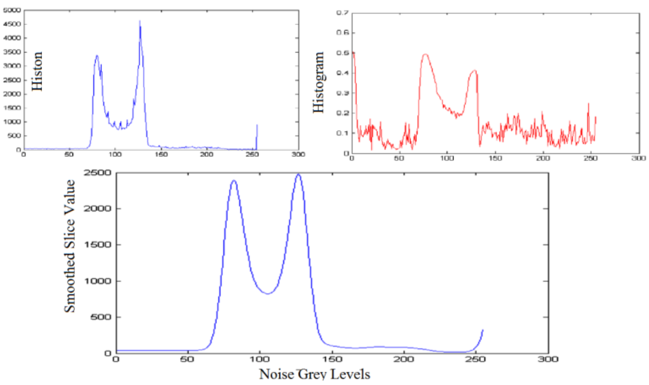

Figure 9. Performance of proposed approach in terms of histogram, histon and smoothness of image

Histon, histogram and intuitionistic neutro soft rough sets measure and their smoothed histogram/histon image representation shown in figure 9, intuitionistic neutro soft rough sets measure with histon and histogram for different noise levels, if intuitionistic neutro soft rough sets measure consists lot of valleys, then it is difficult to identify image segmentation based on weight measure representation. Based on results shown in figure 6 and figure 8, we compare above techniques in terms of segmentation accuracy, time, smoothness and intensity in terms of histogram, histon for different brain images.

V.CONCLUSION

In this paper, we propose and implement new segmentation method i.e. intuitionistic neutro soft based rough sets with classical regression model (INSRCRM) and rough set representations. This proposed approach is histogram based threshold segmentation method, this method consists classical regression for slice smoothing of image at different intuitionistic soft rough sets is histogram at lower approximation levels and histon at large approximation noise levels. Multiple image regression process can be applicable to classify image segmentation accurately based intuitionistic soft rough set measure. Our experimental results give most realistic and better segmented results than traditional methods and because of classical regression define smoothness for intuitionistic soft based rough set measure values to segmented brain medical images. Finally our proposed approach explores image intensity, spatial information and other parameters relates to brain image segmentation. Because of rough set semantic nature present in real time image processing applications, so we are going to develop this approach to support novel segmentation approach which is support to kernel based optimized parameters extraction in medical brain image segmentation.

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