A Performance Study of Image Segmentation Techniques

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***Abstract*— Image based applications such as target tracking, tumor detection, texture extraction requires an efficient image segmentation process. The partitioning of image into various non- overlapping distinct regions refers the image segmentation. Various segmentation techniques like edge, threshold, region, clustering and neural network are involved in the effective image analysis. The efficiency of the segmentation process improved with the help of several algorithms, namely, active contour, level set, Fuzzy clustering and K-means clustering. This paper analyses the performance of algorithms for image segmentation in detail. Intensity and texture based image segmentation is the two levels of the level set method. The combination of both intensity and texture based image segmentation provides better results than the traditional methods. The detailed survey of segmentation techniques provides the requirement of the suitable enhancement method that supports both intensity and texture based segmentation for better results. The comparison between the traditional image segmentation techniques are illustrated.**

***Index Terms*— Active Contour Model, Fuzzy-C-Means (FCM), Image Segmentation, Gaussian Mixture Model (GMM), K-Means Clustering, Level Set methods.**

I. INTRODUCTION

Computer vision applications require an image segmentation to extract the meaningful regions of the image. The objective of efficient image segmentation is independent partitioning of regions that are visually different, meaningful to image characteristics and properties. The classification of image segmentation techniques [1] based on the detection performance are edge, threshold, region, fuzzy and neural network based. The edge detection [2] based recognition of real images reduces the false hit ratio. Threshold based techniques [3] such as mean, p-tile, edge maximization and visual applied to improve the performance of image segmentation. The region based [4], fuzzy based Gaussian Mixture Model (GMM) [5] and neural network [6] applied to segmentation in order to analyze the curvature regularity, energy function and noise effects in the image. The detailed description of image segmentation techniques based on the various factors discussed in this paper.

The refinement of boundary is an important requirement in image segmentation. Contour based approaches [7-9] applied on various images in order to handle the topology changes, noise, streaks and faint spots. The active contour segmentation extends into morphological nature for accurate refinement of boundary with more energy consumption. The split Bergman method efficiently minimizes the energy function. Contour based approaches ignores the spatial relationship between the colors of images, thereby segmented regions are fragmented. Fuzzy based clustering approaches are used for improvement in compactness that effectively reduces the limitation of fragmentation. Histogram Thresholding Fuzzy-C-Means (HTFCM) [10], adaptive FCM [11] and improved FCM [12] algorithms are used to improve the compactness of clusters.

The evolution of clustering algorithms provides the parameters such as the number of clusters and the location of cluster centroid, which plays the major role in image segmentation. Hence, image segmentation involves K-means clustering algorithms [13-15] to predict the number of clusters and location of cluster centroid. The accuracy and reproducibility are enhanced with minimum execution time by using K-means approaches. Level set methods [16-21] involves the combination of discriminative classification models and distance transforms to predict the snap closest to true object with less local minima.

The preliminary stage at diagnosis and brain image segmentation depends upon various factors such as homogeneity, contrast, noise and inequality content. The GMM reviews the factors on brain MRI image segmentation. The multi-scale graph cut approach and Maximum a Posteriori (MAP) principles are applied to image segmentation with pixel density functions. Multimodal image registration processing speed improved by multi-atlas based methods [22-27]. The textural analysis enhanced the object recognition system with sensing and collaborative information. Texture descriptors analyze the filter responses for effective discrimination. The texture based image segmentation utilizes the Convolutional Neural network (CNN) to recover the 3 D scene layout of the road scene image. The deformable models used both intensity and edge based feature traditionally. The inclusion of texture information increases the effectiveness of proposed image segmentation [28-35]. This paper presents the detailed analysis of the techniques involved in image segmentation and the performance parameters predicted in the traditional research works.

The paper is organized as follows. Section 2 describes the overview of major categories of an image segmentation. Section 3 presents various image segmentation techniques. Section 4 describes results and discussion about the traditional segmentation techniques. Section 5 provides proposed work and section 6 discusses conclusions.

II. IMAGE SEGMENTATION TECHNIQUES

The detailed analysis of image segmentation categories [1-5] presented in the literature works to identify edge, region

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depends upon pixel and grouping of pixels with improved processing speed. The image segmentation techniques and associated equations are described as follows:

A. Active Contour model

Image segmentation utilizes the contour models to describe the boundary regions and improve the accuracy. The boundary refinement is an important process in contour model. Three techniques used for boundary refinement analysis as follows:

1. Constrained active contour

The convex active contour model with an edge detection function [7] g on image domain Ω described by

$$\min_{0\le u\le 1}\left(\int g_b \left|\nabla u\right| dx + \lambda \int h_r\, u dx\right) \tag{1}$$

Initially, probabilistic function $P(x)$ and Euclidean distance d are used for contour initialization. The formulation of regional term with the probabilistic method of foreground ($P_F(x)$) and background ($P_B(x)$)

$$h_r(x) = P_F(x) - P_B(x) \tag{2}$$

Finally, the boundary term described by equation (1) weighed by the function u and the weight g_b as follows:

$$g_b(x) = \frac{1}{1 + \left|\nabla I(x)\right|^2} \tag{3}$$

Here, I*(x)* describe the intensity of image pixels. The incorporation of probability function into the edge detection function improve the performance. The new weight function comprises trade off factor (β) and weight function of edge and contour (g_c, g_e) described as,

$$g_b = \beta . g_c + (1-\beta). g_e \tag{4}$$

The equation (4) returns the values from 0 to 1 for most likely edges. The image analysis based on edge detection model in (4) effectively performs without consideration of noise effects.

2. Convex energy function

The weight total variation of constrained active contour incorporates the energy model to detect the boundaries easily on the presence of small amount of Gaussian noise. The Local Gaussian Distributing Fitting (LGDF) analyzes the Gaussian noise effectively. The LGDF is pre based new energy function $E(\varphi)$ with the difference of gradient flow coefficients $r(x)$ described as

$$E(\varphi) = \int \left|\nabla(\varphi)\right| dx + \int \varphi(x)\, r(x) dx \tag{5}$$

The segmentation model based on equation (5) extracts the boundaries of an image with Gaussian noise.

3. Unsupervised segmentation

The Chan-Vese (CV) model [8] for local intensity analysis describes the region of an image expressed by the partial differential equation as follows:

$$\frac{\partial \varphi}{\partial t} = \delta(\varphi)\left[\mu div\left(\frac{\nabla \varphi}{\left|\nabla \varphi\right|}\right) - \lambda_1^+\left(u_1 - c_1^+\right)^2 + \lambda_1^-\left(u_1 - c_1^-\right)^2\right] \tag{6}$$

Here, c_1^+ c_1^- describes the average intensities of image described by the level set function $\varphi(x,y)$ with Dirac delta function. The abnormalities in group of image regions severely affects the quality of segmentation.

B. Fuzzy Clustering

The Fuzzy C-means clustering methods enhances the compactness of regions to separate the similar and dissimilar regions of an image. The FCM [10] based image analysis classified into three categories as follows:

1. Histogram thresholding

The objective function W_{ij} contains membership degree u_{ij}^m and distance between pixels in cluster d_{ij}^2 for FCM expressed as

$$W_{ij} = \sum_{i=1}^{N}\sum_{j=1}^{M} u_{ij}^m d_{ij}^2 \tag{7}$$

The intensity inhomogeneities introduced in micro imaging system affect the segmentation quality. Hence, the improvement in FCM needed to improve the quality.

2. Adaptive FCM

The objective function [11] comprises observed image intensities y_i, cluster centers c_k and weighing function u_{ik} required to improve the quality of an image expressed as follows:

$$J_{IAFCM} = \sum_{i\in D}\sum_{k=1}^{NC} u_{ik}^q \left\|y_i - g_i c_k\right\|^2 + \lambda \sum_{i\in D}\left(g_i - (H * g)_i\right)^2 \tag{8}$$

The membership function and cluster center are expressed as follows:

$$u_{ik} = \frac{\left\|y_i - g_i c_k\right\|^{-\frac{2}{q-1}}}{\sum_{l=1}^{NC}\left\|y_i - g_i c_l\right\|^{-\frac{2}{q-1}}} \tag{9}$$

$$c_k = \frac{\sum_{i\in D} u_{ik}^q G_i y_i}{\sum_{i\in D} u_{ik}^q G_i^2} \tag{10}$$

The relationship between gain field and convolution kernel defined by

$$g_i = (H * g)_i, i \in D \tag{11}$$

The gain field in terms of membership function represented as

$$g_i = \frac{\sum_{k=1}^{NC} u_{ik}^q \left\langle y_i, c_k\right\rangle}{\sum_{k=1}^{NC} u_{ik}^q \left\langle c_k, c_k\right\rangle} \tag{12}$$

The image segmentation based on AFCM improves the classification accuracy by detecting the intensity inhomogeneities. The robustness to noise and outliers is poor by using AFCM algorithm.

3. Kernel metric

The inclusion of kernel metric in the objective function improves the robustness of image segmentation. The kernel measure (K) [12] depends upon the parameters of kernel bandwidth (σ) and dimension of image vectors (d)

$$t = -\left(\sum_{i=1}^{d}\left|x_i - y_i\right|^a\right)^b \tag{13}$$

$$K(x,y) = \exp\left(\frac{t}{\sigma}\right) \tag{14}$$

The cluster center function in (10) rewritten as by using kernel metric as

$$c_k = \frac{\sum_{i=1}^{N}\left(u_{ki}^m K(x_i, v_k) x_i\right)}{\sum_{i=1}^{N}\left(u_{ki}^m K(x_i, v_k)\right)} \tag{15}$$

The reconstruction of the original image at the point of convergence produces the accurate result.

C. K-means Clustering

The unsupervised learning algorithm for accurate extraction of tumor from an image is K-means clustering. In K-means process [14] , the distribution of vertices on K-means clusters on the basis of Poisson process refers to Prim's trajectory [13]. Prim's algorithm relates the k to Probability of False Alarm (PFA) in L-dimensional Euclidean space defined by

$$PFA\,(k,\in) = \left(1 - e^{-\lambda \in L}\right)^{k} \tag{16}$$

The matrix of labels are estimated by constructing minimum spanning tree using Prim's algorithm. An Automated 2-Dimensional K means algorithm (A2DKM) [15] eliminates the need of number of clusters.

D. Level Set Methods

Level set methods consider the topological changes to describe the curves. The deformation of the curve represented by Partial differential equation [16] as follows:

$$\frac{\partial \varphi(x,y,t)}{\partial t} = F\left|\nabla \varphi\right| \tag{17}$$

The evolving curve in image segmentation stopped at an object boundary by following two ways, namely, application of edge-stopping function and minimization of the energy function. Due to the presence of noise or insignificant image gradients in evolving curve, shrinking or growing based on the sign of F occur termed as one way curve evolution problem. To resolve this problem, the analysis of the curve based on an energy criterion introduced. The energy function depends upon the various parameters such as length(C) , area(C_{in}) , inside (C_{in}) and outside (C_{out}) region of curve represented as

$$E = \mu \cdot C + v \cdot C_{in} + F(C_{in}) + F(C_{out}) \tag{18}$$

The segmentation process involves the more than one two regions to be segmented. Hence, multilevel set multi-phase model [18] included in the level set energy function as

$$E(\varphi, c, b) = \int \sum_{i=1}^{N} e_i(x)\, M_i(\varphi(x))dx \tag{19}$$

$$e_i = \int K(y-x)\left|I(x) - b(y)c_i\right|^2 dy \tag{20}$$

Here K represents the kernel function defined by (14). The energy minimization with respect to φ, c and b carried out to predict the optimal cluster center and boundary. The level set function in (17) redefined by using the probabilistic parameters [19] to represent the region boundary and curvature as

$$\frac{\partial \varphi(x,y,t)}{\partial t} = -\left[\alpha \cdot R(x,t) + \beta \cdot B(x,t) + \gamma \cdot C(x,t)\right]\left|\nabla \varphi\right| \tag{21}$$

Gaussian filter effectively smoothens the initial pixel wise probabilistic values. Local classifiers and boundary refinement methods are used for effective refinement process. Level set formulation extends the segmentation application to localization of optical disk in retinal images [21], tracking of non-linear shapes [20] and liver tumor [17]segmentation. Level set models excludes the information other the boundary and the intensity inhomogeneity.

E. Intensity Based Segmentation

To analyze the inhomogeneity, the image can be modelled as normally distributed noise $b(x)$ with zero mean in intensity based image segmentation [27] as follows:

$$I(x) = b(x)\, I_o(x) + n(x) \tag{22}$$

The inclusion of density functions in the equation (22) to analyze the inhomogeneity provides the following model

$$p\left(I(x) \mid \{\chi, b, c, \sigma\} \quad \alpha \prod_{y \in W_x^{\rho}} p\left(I(x) \mid \{\chi, b, c, \sigma\}^{\pi_x(y)}\right)\right) \tag{23}$$

The adaptive weights depend upon the distance from y to x with the truncated kernel function as

$$\pi_x(y) = K(y-x) \tag{24}$$

Based on the density function and the adaptive weights, the intensity based image feature such as Discontinuity-Homogeneity (DH) ratio [24] of discontinuity descriptor to intensity defined by

$$DH = \frac{f_{s\left(\vec{x}, \vec{r}\right)}(I)}{\sqrt{\operatorname{var}_{s\left(\vec{x}, \vec{r}\right)}(I)}} \tag{25}$$

The segmentation results further improved by adding Image Derived Attributes (IDA) [26] in the intensity models. The performance measures to describe the IDA are Dice Similarity Coefficient (DSC) and Mean Absolute Distance (MAD). The maximal similarity from the Normalized Cross Correlation achieved in atlas based models [23] the ratio of NCC of the similarity measure of atlas defined by

$$r_i = \frac{NCC\,(T, A_i \circ M_i)}{\max_i NCC\,(T, A_i \circ M_i)} \tag{26}$$

The review of Gaussian Mixture Models (GMM) [22] based on similarity index presented on brain MRI images. The intensity based models laid a stone to reduce the coding length and accurate recognition of an object.

F. Texture Based Segmentation

The optimal segmentation based on textures efficiently reduces the coding length [30]. The total coding length of an image depends upon the length of particular region and the whole boundary of an image defined by

$$L_{w,e}^{S}(R) = \sum_{i=1}^{k} L_{w,e}(R_i) + \frac{1}{2} B(R_i) \tag{27}$$

The reduction of length defined by (23) performed by using agglomerative approximation. The uniformity nature of regions extends the segmentation approach into recognition of road sign image [28]. The histogram of uniformity U with each pixel and the corresponding intensity level y defined by,

$$U = \sum_{j=1}^{L} p^2(j) \tag{28}$$

$$y(i) = \sum_{j=1}^{N} w_j\, x_j(i) \tag{29}$$

An optimal solution corresponding to the estimating of minimum variance of weight for accurate road scene recognition is given by,

$$W = \Sigma^{-1} I \left(I^T \Sigma^{-1} I\right)^{-1} \tag{30}$$

Finally, higher value of likelihood road side areas is computed. The landmarks in target image represented by another texture based segmentation termed as game theoretic approach [29]. The intensity and shape likelihoods refers to payoff are maximal only for optimal candidate points by using Grey Level Co-occurrence Matrix (GLCM) [32] and data analysis [31]. The detailed survey presented that the suitable method required to improve the segmentation in retinal image scanning.

TABLE 1 INFORMATION ABOUT DIFFERENT IMAGE SEGMENTATION TECHNIQUES

Techniques	Author & Ref	Year	Performance	Images	Quality measurement
Active contour based image segmentation					
Unsupervised segmentation	Savelonas [8]	2011	A novel active contour based model segments the protein spots in two dimensional images with critical issues such as noise, streaks and multiplets.	Protein spots	Volumetric overlap Volumetric error
Convex energy function	Wu and Yang [9]	2012	A convex optimization function with local Gaussian distributing fitting term with spatially variations of means and variances presented and the energy function formulated.	Synthetic and real images	Influenze of weight function\ Segmentation level
Constrained Active contour	Anh et al [7]	2012	Boundary refinement tool presented in constrained active contour has the capability to produce the smooth and accurate boundary contour.	Buddhist image	Accuracy Speed
Fuzzy clustering					
Histogram Thresholding FCM	Tan et al [10]	2011	The histogram thresholding techniques extracts the uniform regions of an image and FCM used to evaluate the compactness of clustering of uniform regions.	Home Girl Capsicum	Algorithm Efficiency Intensity value
Adaptive FCM	Cao et al [11]	2012	Classical FCM employs the gain field model to correct the intensity in homogeneities by microscope imaging system. Gain field also regulates the center of cluster	M-Fish dataset	Correct detection rate False detection rate
Kernel measure+ FCM	Gong et al [12]	2013	Kernel distance measure and trade off fuzzy weight factor estimates the extent of neighboring pixels. The objective function incorporates the kernel distance measure to improve the robustness to noise.	Brain image Salt & pepper corrupted image	Entropy based evaluation function Layout entropy
K-means clustering					
Graph based K-Means clustering	Galluccio et al [13]	2012	The application Prim's algorithm and Lloyd algorithm constructs the Minimum Spanning Tree (MST) and generalized cluster centroids to determine the number of clusters and location of cluster centroids.	Mars hyper spectral image	Devis-Bouldin index
Advanced K means	Selvakumar et al [14]	2012	It detects the range and shape of Tumor in brain images and allows the accurate detection, reproducible and less execution time.	Brain MR image	Tumor shape Tumor position
Automated 2 Dimensional K means (A2DKM)	Yusoff et al [15]	2012	Local and spatial information includes in A2DKM to determine the number of clusters. The comparative analysis on memory consumption of AFKM and A2DKM provided.	Lake House Hut	Execution time Memory consumption
Level set based image segmentation					
Local clustering criterion	Li et al [18]	2011	Level set formulation utilizes the local criterion function that defines the partition energy for simultaneous image segmentation and analysis the performance with presence of intensity inhomogeneity	Limon Vessel MR breast image	Accuracy CPU time
Non-linear probabilistic method	Prisacariu et al [20]	2011	Elliptic Fourier descriptors represents the shape of the image. Segmentation carried out on nonlinear minimization of an energy function in latent space.	Kinematics of person	Accuracy
Discriminative classification	Liu and Yu [19]	2012	The elimination of local minima and prediction of snap close to object boundaries performed with the help of level set function.	Zebra Cheetah	Localized boundary Smoothness
Unified level set model	Li et al [17]	2012	It integrates the image gradient, region competition and prior information for CT liver tumor segmentation. the object indication improved by fuzzy clustering technique	LTSC dataset	Volume overlap error
Multiphase-multichannel	Kim and shan [16]	2011	The energy function minimization performed for each segment corresponds to roof plans. Based on the topological relations, the intersection of adjacent roof segments reconstructs the model.	Roof plan images	Convergence rate
Optical Disk (OD) localization and segmentation	Yu et al [21]	2012	Template matching identifies the Optical Disk location. Morphological filtering techniques eliminates the blood vessels and bright regions other than the OD.	MESSIDOR database	Mean Absolute Distance, Correlation factor
Intensity based image segmentation					
Atlas based approaches	Merida et al [23]	2012	Two atlas based models such as probabilistic model and multi atlas registration based models applied to breast MR dedicated strategies. The set of 27 manually segmented volumes are used for testing	Breast MR image	Dice coefficient
Multiscale graph cut approach	Mahapatra et al [25]	2012	Markov Random Field (MRF) models employs the multi-graph cut approach to achieve the sub-pixel registration and computation time reduction	Cine cardiac 3D liver perfusion	Computational complexity
MFLAAM	Toth et al [26]	2012	It utilizes the accurate algorithm for identification of Image Derived Attributes (IDA) offers effective segmentation and incorporates the level set implementation to overcome limitation in the specification of landmark and location of object interest in image.	T2 weighted prostate MRI	Mean dice coefficient Accuracy
Gaussian Mixture Model	Balafar [22]	2012	Presents a review of Gaussian Mixture Model (GMM) based image segmentation. The review of traditional works related to GMM based brain images also discussed.	T1 weighted MRI images	Jaccard Similarity Index Dic similarity index
Maximum-A-Posteriori (MAP)	Zhang et al [27]	2013	The nonsmooth nonconvex minimization problem investigated by MAP principle with relaxation in constraints of characteristic functions of partition regions	Brain MRI	Jaccard Similarity Coefficient CPU time

Detection filter	Law and Chung[24]	2013	A novel intensity based algorithm segments the intracranial vessels and the attached aneurysms. Based on the topology structure, detected turbulent flows affects the low intensity regions.	Vascular phantom	Discontinuity Homogeneity Ratio (DH)
Texture based mage segmentation					
Gaussian distribution	Sørensen et al [33]	2011	The textural dissimilarity between two Region of Interests (ROI) computed by k-NN classifiers and described by histogram of filter responses from the Gaussian filter bank	Lung cancer image	Histogram dissimilarity Rank correlation
	Mobahi et al [30]	2011	Homogeneous texture region modelled as Gaussian distribution and the boundary of image described buy adaptive chain code. An agglomerative clustering process applied to image segmentation	Berkeley Segmentation Data set (BSD)	Probabilistic Random Index(PRI),
Texture descriptor	Alvarez et al [28]	2012	It employs convolutional neural network to recover the 3D scene layout from road side images with the features from noisy labels. A novel texture descriptor used to predict the maximal uniformity	LabelMe dataset CamVid dataset	Average time for image Confusion matrix
Game theory	Ibragimov et al [29]	2012	Application of dynamic program to optimal search problem between the landmarks in target image. Segmentation problem modelled as game theory and solution is equilibrium of candidate points, represents the landmark.	Lung Chest Heart venticulars	Mean boundary distance Area overlap coefficient
Linear filters	Yuan et al [35]	2014	Remote sensing image segmentation incorporates the spatial and texture information. The employment of linear filters enhances the spatial features. The weight index describes the segment ownership of pixels	GeoEye-I satellite images	Correctness of segmentation Accuracy
High fidelity models	Tang et al [34]	2014	An object recognition system with sensing and collaboration information presented. The creation of high fidelity object models and the utilization in accurate detection and estimation provided.	Household objects	Confusion matrix Precision Recall
Grey Level Co-occurence Matrix (GLCM)	Reska et al [32]	2015	The integration of texture feature analysis with model evaluation analysis presented as two dimensional deformable model that uses edge and intensity based features.	Brodatz texture database	Texture orientation
Morphology and texture paradigm	Noor et al [31]	2015	Thresholding and morphological based segmentation module coupled with feedback detects large deviations. The feedback model allows the detection of abnormal lung disease.	High Resolution Computed Tomography	Similarity Jaccard Index Area Overlap Error

III. SURVEY DISCUSSION

Various techniques for image segmentation techniques are depicted. The results of the survey are shown in Table 1. The review of image segmentation techniques and classification emphasized that hierarchical framework in image segmentation techniques and how they are used to improve the quality of recognition. Segmentation based on active contour models conveyed that refinement of boundary was an important process in segmentation. Grouping of pixels of an image led the development of fuzzy based and K- means clustering process. The kernel metric approaches in addition to clustering eliminated the need of prediction of the number of clusters. K-means processes applied in various real world images such as brain MRI images, tumor segmentation for maximum accuracy.

The Texture Based Encoding Segmentation (TBES) models emphasized the reduction of coding length and the uniformity nature of maximum likelihood regions provide the way to use angular based texture pattern and intensity deviation matrix to improve the quality of segmentation in proposed work.

IV. PROPOSED WORK

The proposed multilevel set segmentation based on the combination of intensity and texture with level set functions consists of various processes. In the intensity analysis, extraction of threshold computes the edge intensity variation between the pixel and neighborhood pixels in matrix form. In the texture pattern analysis, angular texture pattern selects window coefficient by varying the angles for accurate image analysis. Based on intensity difference and texture pattern, the weight function is formed. The pixel matching process followed weight formation analyzes the matching of the pattern edge with the threshold value of the deviation matrix until the condition ($W_i > W_{i-1}$) is satisfied. The updated weight matrix computes the contour formation over an image. Finally, application of the label on the basis of layer separation provides the segmentation output. The comparative analysis between angular texture pattern and traditional level set method shows that the effectiveness of proposed segmentation. The flow diagram of proposed method as shown in fig. 1.

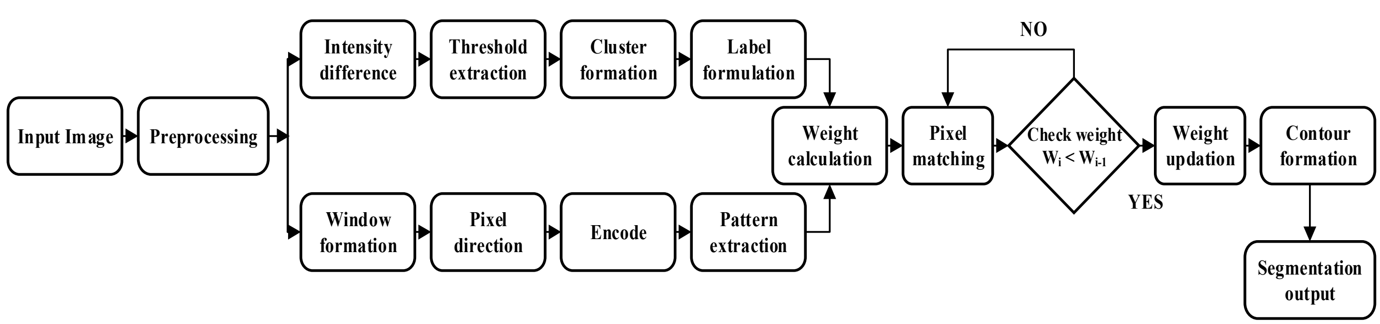

Fig. 1 Flow diagram of proposed method

V. CONCLUSION

In this paper, an overview of various image segmentation is presented. From the survey, it is find out that intensity and texture based methods based on level set function efficiently segment the image. The quality of the image with the presence of noise analyzed and improved on texture based methods. The analysis of the performance parameters such as accuracy, confusion matrix parameters, Kappa's coefficient on traditional methods showed the suitable methods were required for improvement. The effective refinement of boundary on Optical Disk (OD) in retinal images performed by the level set methods.

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