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A Novel Approach for Solving Medical Image Segmentation Problems with ACM

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ABSTRACT
In this paper we proposed a novel segmentation algorithm for medical image segmentation that employs an active contour model (ACM) using level set method. This algorithm takes advantage of local edge feature algorithm for accurately drive the contour to required boundary region. The analysis and detection of any kind of brain tumors from magnetic resonance imaging (MRI) is very important for radiologists and image processing researchers. If objects of interest and their boundaries can be located correctly, meaningful visual information would be provided to the physicians, making the following analysis much easier. Within the numerous image segmentation algorithms, active contour model is widely used with its clear curve for the object. This algorithm measures the alignment between the evolving contour's normal direction of movement and the image's gradient in the adjacent region located inside and outside of the evolving contour and also considers the average edge intensity in the adjacent region located inside and outside of the evolving contour. This allows minimizing the negative effect of weak edges on the segmentation accuracy.
Keywords— Image segmentation, medical image analysis, active contour, region based, level set function.

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I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple regions. These regions are sometimes called region of interest (ROI). The goal of the image segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Medical image segmentation is an important task for identification and location of tumors, diagnosis, and computer guided surgery etc. Thus an effective image segmentation is utmost important not only in detecting the location of diseases in medical images but also equally imperative to observe the extent to which diseases spread across the ROI. The reason for segmenting the image into different regions is to identify the exact boundaries of the image for better visual interpretation. The segmentation is based on measurements taken from the image and might be gray level, color, texture, depth or motion. An important goal of medical image processing is to transform raw images into numerically allegorical anatomy for better representation, evaluation, and agreeable seek and mining. Computerized image analysis has played a more important role in medical imaging. Accurate Image segmentation is an essential difficulty of computer vision. The active contour models (ACM) are the most successful techniques in image segmentation along with the fundamental idea of ACM would be to evolve a new contour extract the necessary object. Region-based models tend to be preferred for image segmentation because they provide improvement more than edge based model inside a few aspects, it offers limitations. The organization of the paper as follows section I describes the basic introduction, section II will describe the problem statement and objective, related works are produced in section III and section IV respectively. Finally, Results and discussion followed by conclusion is shown in section V and VI.

II. PROBLEM DEFINITION

The correction of in-homogeneity artifact problems in MR images creates platform for different fields. The most important of these fields are: i.*Visualization*: After suppressing in-homogeneity problem and the brain image quality will enable the physician to study the required information for proper diagnosis.

ii.Segmentation: The algorithm used in this paper can be used to segment the MRI images.
iii. More accurate detection of brain activity: After correction in-homogeneity problem and extraction of required information with best segmentation algorithm will give more accurate brain activities.

Active contours are also known as snake's model it was first introduced by Kass .et.al in 1987. According to the curve representation, there are two main kinds of active contour models: parametric models and geometric models. Parametric active contour models use parameterized curves to represent the contours. Snake model, proposed by Kass et al. in [27], is a representative and popular one among parametric active contour models. In this model image boundary can be represented as parametric curve. Active contour is particularly well suited to segment an object instance in an image where the data are distorted by noise or artifacts. The problem of finding object boundary with less minimization of energy function E. Image segmentation is fundamental stage in medical image processing and machine vision applications. In segmentation phase, image in-homogeneity problem arises due to improper acquisition of image; variations in the image intensity level will leads to mis-interpretation by the doctors and radiologists. For instance, in medical image analysis, segmentation and registration stages are highly sensitive to spurious variations of image intensity.

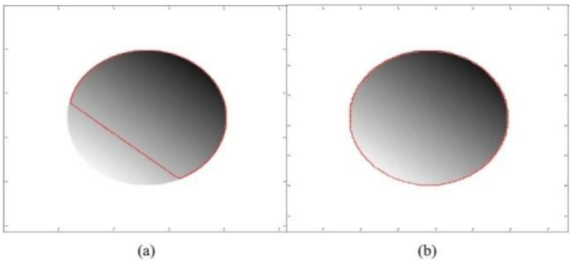


Fig. 1 Intensity in-homogeneity problem
(a) Basic Active contour (b) Proposed model.

III. OBJECTIVE OF THE WORK

Consider an image I we need to estimate the intensity level along the contour of the image. Hence in order to trace the contour first select two boundary points at starting and ending of the contour that is r(0) and r(1) and select some intermediate points between boundary such as r(s1),r(s2),r(s3) and r(s4) as shown in below fig. The selected contour can move iteratively according to the edges of the image hence the name is given.

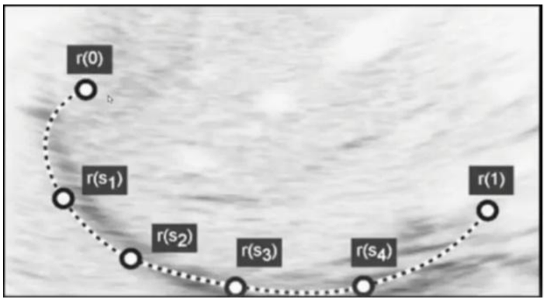


Fig.2 Active contour model representation

Mathematical Descrpition

From the fig.2 the external and internal energy function algon the contour can be represented as

$$E_{external}\ \big(r(s)\big) = -\|(\nabla f(r(s)))\| - -(1)$$

$$J(c) = \int_0^1 E_{internal}\ \big(r(s)\big) + E_{external}\ \big(r(s)\big)ds$$

For convergence it should be taken minimum values:

$$\min \text{of} \int_0^1 E_{external}\ \big(r(s)\big)ds - -2(a)$$

$$\min \text{of} \int_0^1 E_{internal}\ \big(r(s)\big)ds - -2(b)$$

$$\min \text{of}\ J(c) = \int_0^1 (E_{internal}\ \big(r(s)\big) + E_{external}\ \big(r(S)\big))\ ds$$

$$-w_1 \frac{1}{ds}\left(\frac{dr(s)}{ds}\right) + w_2 \frac{1}{ds^2}\left(\frac{d^2r(s)}{ds^2}\right) + \nabla E_{external}\ \big(r(s)\big) = 0$$

For solving, $h = \|r(s_i) - r(s_{i-1})\| - -(3)$

$$\frac{dr(s_i)}{ds} \cong \frac{r(s_{i-1}) - 2r(s_i) + r(s_{i-1})}{h^2}$$

Hence, finally from eq 1 and 2 and 3 along x and y-direction iterative values are

$$x^{(t+1)} = (A - \gamma I)^{-1}\left(x^{(t)} - \frac{dE(r(s^t))}{dx}\right)$$

$$y^{t+1)} = (A - \gamma I)^{-1}\left(y^{(t)} - \frac{dE(r(s^t))}{dy}\right)$$

Therefore according to Balloon Model final energy required is

finally, $$f_{external}\ \big(r(s)\big) = K_1 n\big(r(s)\big) - K_2 \frac{\nabla E_{external}\ (r(s))}{\|\nabla E_{external}\ (r(S))\|}$$

IV. LITERATURE REVIEW

In the literature on MR image segmentation can be roughly divided into two categories: a single image or gray scale segmentation where a single 2D or 3D image is used and multi-spectral image segmentation where multiple MR images with different gray scale contrasts are available. We define each method, provide an overview of its implementation, and discuss its advantages and disadvantages.

Thresholding approaches [1] segment the images by using some defined level as a predefined metric. Although it is simple but its main limitations are only two classes are generated, and it cannot be applied to multichannel images. In addition, thresholding typically does not take into account the spatial characteristics of an image. This causes it to be sensitive to noise and intensity in-homogeneities, which can occur in MR images. Both of these artifacts essentially corrupt the histogram of the image, making separation more difficult. Region growing [2] is a technique for extracting an image region that is connected based on some predefined criteria. Like thresholding, region growing is seldom used alone but usually within a set of image-processing operations, particularly for the delineation of small, simple structures such as tumors and lesions. The primary disadvantage of region growing is that it requires manual interaction to obtain the seed point. Thus, for each region that needs to be extracted, a seed must be planted. Split-and-merge is an algorithm related to region growing, but it does not require a seed point. Classifier methods [3] are pattern recognition techniques that seek to partition a feature space derived from the image by using data with known labels. There are a number of ways in which training data can be applied in classifier methods.

A simple classifier is the [4], in which each pixel is classified in the same class as the training datum with the closest intensity. The k-nearest-neighbor classifier is a generalization of this approach, in which the pixel is classified into the same class as the majority of the k-closest training data. A commonly used parametric classifier is the maximum-likelihood or Bayes classifier [5]. It assumes that the pixel intensities are independent samples from a mixture of probability distributions, usually Gaussian. A disadvantage of classifiers is that they generally do not perform any spatial modeling. This weakness has been addressed in recent work extending classifier methods to segmenting images that are corrupted by intensity in-homogeneities. Another disadvantage is the requirement of manual interaction to obtain training data.

Clustering algorithms [6] essentially perform the same function as classifier methods without the use of training data. Thus, they are termed unsupervised methods. To compensate for the lack of training data, clustering methods iteratatively alternate between segmenting the image and characterizing the properties of each class. Three commonly used clustering algorithms are the K -means algorithm, the fuzzy c-means algorithm, and the expectation-maximization (EM) algorithm. Like classifier methods, clustering algorithms do not directly incorporate spatial modeling and can therefore be sensitive to noise and intensity in-homogeneities. This lack of spatial modeling, however, can provide significant advantages for fast computation. Markov Random Field Model (MRF) itself is not a segmentation method but a statistical model that can be used within segmentation methods. MRFs model spatial interactions between neighboring or nearby pixels. A difficulty associated with MRF models is proper selection of the parameters controlling the strength of spatial interactions. A setting that is too high can result in an excessively smooth segmentation and a loss of important structural details. In addition, MRF methods usually require computationally intensive algorithms. Artificial neural networks (ANNs) are parallel networks of processing elements or nodes that simulate biological learning. Each node in an ANN is capable of performing elementary computations. Learning is achieved through the adaptation of weights assigned to the connections between nodes. ANNs represent a paradigm for machine learning and can be used in a variety of ways for image segmentation. Although ANNs are inherently parallel, their processing is usually simulated on a standard serial computer, thus reducing this potential computational advantage.

Deformable models [7] have been widely applied in the segmentation of medical images. Deformable models often used in restoration of cerebral cortex from MRI images. Deformable models have also been used in the segmentation of cardiac images bone in CT images and ultrasound. The dynamic nature of deformable models makes them especially well suited to motion-tracking tasks, which are common in ultrasound imaging. The main advantages of deformable models are their ability to directly generate closed parametric curves or surfaces from images and their incorporation of a smoothness constraint that provides robustness to noise and spurious edges. A disadvantage is that they require manual interaction to place an initial model and choose appropriate parameters.

From the literature, active contour methods are divided into two types these are region based and edge based. In edge based methods use image gradient as force to attract the contour with image edge boundaries. These models have been successfully used for general images with strong object boundaries, but they may suffer from boundary leakage problem for brain MR images, which typically contain weak boundaries between gray matter and white matter due to low contrast and partial volume effect. Region-based models have better performance than edge-based models in the presence of weak boundaries but region-based methods will suffer from image in homogeneity problems.

A major difficulty is that it is specific to the segmentation of MR images is the 'intensity in-homogeneity artifact' which causes a shading effect to appear over the image. The artifact can significantly degrade the performance of methods that assume that the intensity value of a tissue class is constant over the image. Although improvements in scanner technology have reduced this artifact somewhat, in-homogeneities remain a problem particularly in images acquired by using surface coils.

In fact, intensity in-homogeneity occurs in many real-world images from different modalities. In particular, it is often seen in medical images, such as X-ray radiography/tomography and magnetic resonance (MR) images. Segmentation is used to measure the size and shape of brain structures, to guide spatial normalization of anatomy between individuals and to plan medical intervention.

Fully automatic approaches usage gradually reduces due to insufficient reliability. In Semiautomatic methods require the user to specify various parameters. Mainly the objects in human body can vary with respect their size, shape and visualization so it makes difficult to segment the required objects such as bones and other organs . Basically two prevailing approaches for modeling in-homogeneities problems in medical images, one is based on tissue intensity level is spatially varied and mean intensities are independent to each other. Second approach use multiplicative gain field or additive bias field. Although the second approach has the advantage of being computationally less expensive. Second approach can give better results since the acquired image is simply multiplying the reciprocal of the gain field. [26] Level set methods have been widely used in image processing specially in image segmentation. The level set methods sometimes develop irregularities during its evolution state, which may cause numerical complexity and destroy the stability of evolution. This distance regularization function is able to maintain the desired shape of level set function smoothly and eliminates the need of re initialization of LSF. Shape based approach proposed by tsai.et.al [14]. The local clustering criterion function is defined for image intensities in neighborhood of each point. Now, this local clustering criterion of point is then integrated with respect to the neighborhood of entire points for global clustering criterion of image segmentation. In which bias function is also evaluated to intensity in-homogeneity correction. Implementation of our method shows that, it is more robust to initialization, and more accurate than conventional model. The accurate detection of boundaries of target regions by active contour models is ongoing research task and active contours have been widely used for object segmentation. Active contour models using level-set framework have various forms of expression, and they are divided into three major categories: edge-based, region-based [9] and hybrid level set models. In edge-based models, edges are usually generated firstly by an edge-detection algorithm and then using post processing to adjust to the final boundaries [12]. The Mumford-Shah (M-S) model [8] is the typical technique, and it depends on the defined edge function based on image gradient to stop the evolution process of active contour curves. The C-V model was proposed based on the M-S model and it can detect objects whose boundaries are not necessarily defined by gradient. Based on the C-V model, Tian et al. [9] proposed an active model by embedding the local intensity weighting and a vessel vector field into the energy function. However, those methods still trend to suffer from loss of small vessels caused by low intensity due to partial volume effects and noises. Combining region-based methods with other information. Jiang et al. [10] proposed a hybrid level-set method with a nonlinear speed function to extract brain from cerebral MRI volume. Zhao et al. [11] developed a MIP-guided approach for brain vessel segmentation. They first projected the volume onto the 2D plane, and applied an integrated active contour model to extract blood vessels [19] from MIP images, then projected back to the 3D volume. The proposed method showed satisfying segmenting results. However, their method is a little complicated with several projection and back projection operations. In [20] proposed a new hybrid level-set method integrating boundary and region information to avoid inaccurate segmentations for images. Based on that hybrid level-set model of Zhang et al [12], Hong et al. used a dynamic parameter to replace the presented value in the energy function to make segmentation more precisely. For images with weak boundaries, the energy functional of the edge-based active contour models will hardly approach zero on the boundaries of the objects and the evolving curve may pass through the true boundaries. Therefore, the edge-based active contour models [22] always fail to segment medical images properly, as blur or weak edge usually occur in the medical images, especially in MRI brain images, which typically contain large area of blur boundaries between gray matter and white matter .

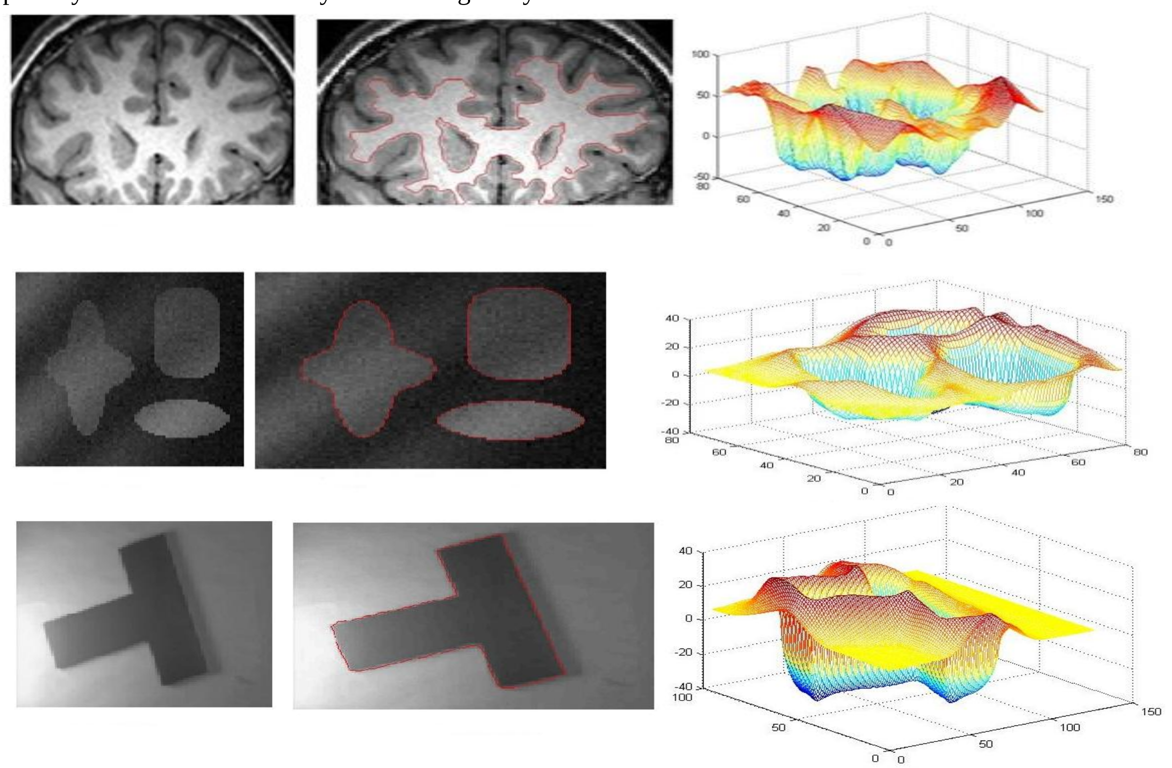
Many region-based active contour algorithms and modified region approaches [25] are based on the assumption that an image can be approximated by global intensity. For example, Chan [13],[24] and Vese proposed a famous Chan-Vese (CV) model in and Yezzi et al. proposed a fully global approach in [16], deriving a set of coupled curve evolution equations from a single global cost functional to promote multiple contours to segment multiple-region image.CV model, also known as PC (piecewise constant) model, proposed in [7], is a simplified Mumford-Shah function. The model utilizes the global mean intensities of the interior and exterior regions of images. Thus, it has good segmentation result for the objects with weak or discrete boundaries but often has erroneous segmentation for images with intensity in-homogeneity.

Lankton and Tannenbaum proposed localizing region-based active contours (LRBAC) in [15], allowing any region-based segmentation energy to be reformulated in a local way. The technique they proposed can be used with any global region-based [18] active contour energy, segmenting objects with heterogeneous statistics. However, they are computationally too expensive. One way to reduce the computational cost being proposed in [9] is to use a contour near the object boundaries as the initial contour. In local region-based active contour models are proposed to overcome the difficulty caused by intensity in homogeneity.

The local binary fitting (LBF) model [21] in and the region-scalable fitting (RSF) model [23] in being proposed by Li et al [16] are the most popular models. LBF model utilizes image information in local regions. RSF model draws upon intensity information in local regions at a controllable scale. These two models have similar capability to handle intensity in homogeneity. However, they are also sensitive to initialization. To make the segmentation efficient, Piovano et al. [17] used convolutions to quickly compute localized statistics and yield results similar to piecewise smooth segmentation.

V.RESULTS AND DISCUSSION

The performance of the algorithm is exactly determined and the same is produced in figure.3 from the existing works i.e. Basic CV and LBF model it is cleared that the problem of in-homogeneity due to intensity variations in the image boundaries can be solved .From the mathematical description, the problem of image in-homogeneity can be modelled combindly with active contour and level set function for various MRI image dataset. Increasing the no. of iterations the exact variations at the image edges can be predicted. Balloon force is an external force that will make the model to move inward or outward of the contour according to the image boundaries. Contour with iterations like 1000,200,300,150 and 220 and corresponding level set function is specified in fig.3. By increasing the number of iterations it is not guaranteed to achieve feasible results for better interpretation it is mainly depends on the type of image to process for a given application. After performing different iterations for all the input images and considering at 300 iterations, the time to execute the particular image shown below for all three models specified in table.1. and the same is produced using charts in fig.4.



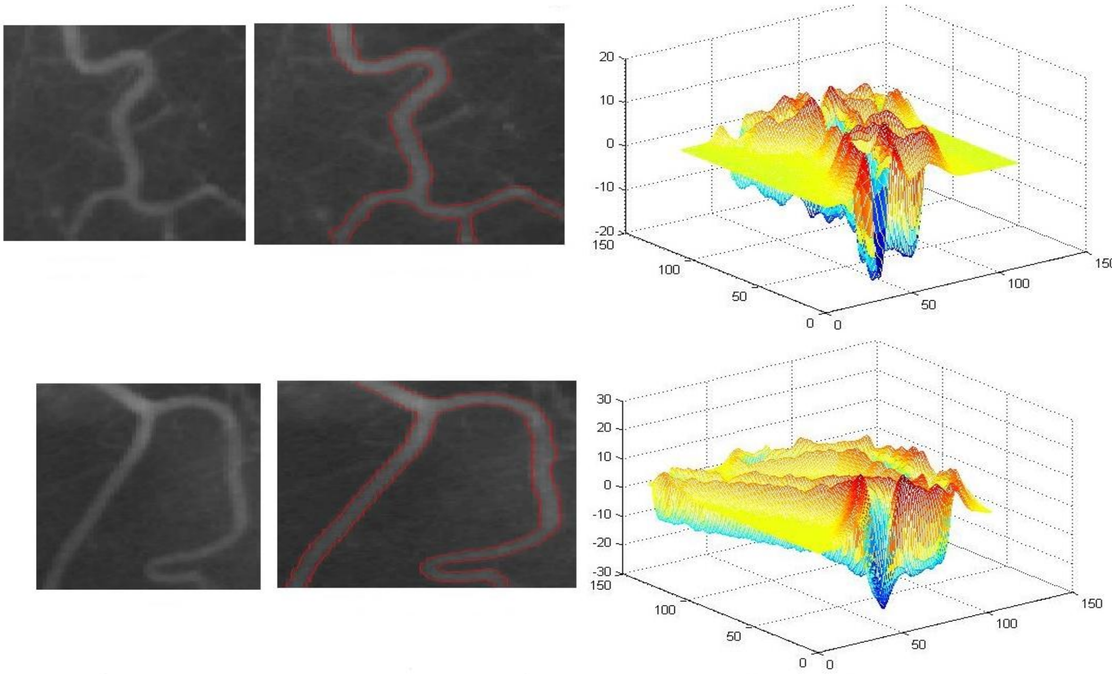


Fig.3 Analysis of various Images with different Iterations and corresponding level set function.

Table.1. Comparison of proposed method with CV and LBF.

	Time Elapsed (at 300 iterations per sec)		
Images	LBF Model	CV Model	Proposed ACM Model
Image1	44.996	44.257	38.593
Image2	435.773	278.051	267.238
Image3	44.679	32.148	31.313
Image4	176.875	130.756	115.051
Image5	154.235	145.746	124.145

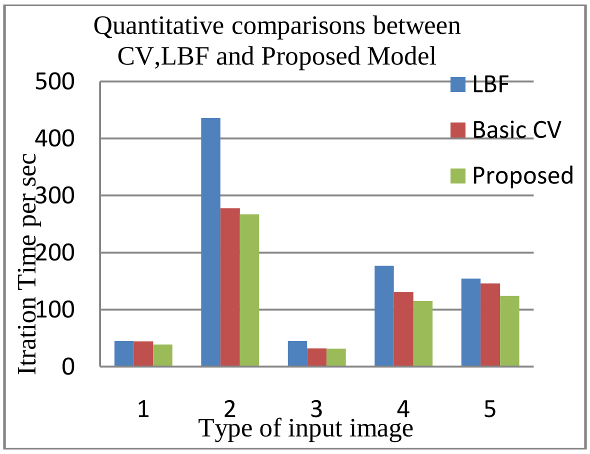


Fig.4 Qualitative Comparisons between Proposed method with CV and LBF

VI. CONCLUSION

In this paper we proposed Segmentation Algorithm with ACM to solve in-homogeneity problems during medical image segmentation. Intensity of the image is varies at the edges while taking MRI scanning from the patient. Due to these non uniform intensities accuracy of the detected organs will reduce, therefore radiologist not able to diagnose the problem of the patient. The experimental result shows that the proposed algorithm performed superior than the conventional segmentation algorithms in abnormal conditions. In this paper we provide an approach will segment MR images along with in homogeneity and to indicate the reliability, effectiveness, and robustness from the existing works. The extension of this work uses deep learning models to enhance the segmentation quality and reduces the no. of iterations required.

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