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IMPROVED SEGMENTATION OF RETINAL IMAGES TO DIAGNOSE VASCULAR DISEASE USING CHARGED FLUID METHOD

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ABSTRACT

Vessel segmentation still remains a challenging medical image analysis problem despite considerable effort in research. Many factors come together to make this problem difficult to be addressed. The images under consideration often come with noise and blur, and suffer from uneven illumination (or biased field in magnetic resonance imaging [MRI]) problems. In addition, although vessels in an image are similar to each other in general, they have different widths and orientations and sometimes different appearances in terms of intensity, color or local shape, which may become more complicated when disease is present. The application will develop a new deformable model, the charged fluid model (CFM) that uses the simulation of a charged fluid to segment anatomic structures in magnetic resonance images of the retinal. Conceptually, the charged fluid behaves like a liquid such that it flows through and around different obstacles. The simulation evolves in two steps governed by Poisson's equation. The first step distributes the elements of the charged fluid within the propagating interface until an electrostatic equilibrium is achieved. The second step advances the propagating front of the charged fluid such that it deforms into a new shape in response to the image gradient. The improved image is used for further analysis of vascular diseases

Keywords—Charged Fluid Method, Bias field, Magnetic Resonance Images, Image segmentation.

1. INTRODUCTION

Blood vessels can be conceptualized anatomically as an intricate network, or tree-like structure (or vasculature), of hollow tubes of different sizes and compositions including arteries, arterioles, capillaries, venules, and veins. Their continuing integrity is vital to nurture life: any damage to them could lead to profound complications, including stroke, diabetes, arteriosclerosis, cardiovascular diseases and hypertension, to name only the most obvious. Vascular diseases are often life-critical for individuals, and present a challenging public health problem for society. The drive for better understanding and management of these conditions naturally motivates the need for improved imaging techniques. The detection and analysis of the vessels in medical images is a fundamental task in many clinical applications to support early detection, diagnosis and optimal treatment. In line with the proliferation of imaging modalities, there is an ever-increasing demand for automated vessel analysis systems for which where blood vessel segmentation is the first and most important step.

As blood vessels can be seen as linear structures distributed at different orientations and scales in an image, various kernels (or enhancement filters) have been proposed to enhance them in order to ease the segmentation problem [1]–[11]. The main disadvantage of morphological methods is that they do not consider the known vessel cross-sectional shape information, and the use of an overly long structuring element may cause difficulty in detecting highly tortuous vessels [12].

2. RELATED WORK

Recent years have witnessed the rapid development of methods for vessel segmentation [12]–[14]. Broadly speaking, all of the established segmentation techniques may be categorized as either supervised [8] or unsupervised segmentation [6], [10], [15], [16] with respect to the overall system design and architecture. Supervised segmentation methods use training data to train a classifier (e.g., k-nearest neighbors [17], support vector machine (SVM) [18], [19], artificial neural networks (ANN) [20], Gaussian mixture models (GMM) [8], [21], AdaBoost [22], or conditional random fields (CRFs) [23]) so that it can be used for the classification of image pixels as either vessel or not in a new, previously unseen image. As such this approach requires hand-labelled gold standard images for training, and discriminative features, such as Gabor features [8], to be extracted for each pixel of an image. In contrast, unsupervised segmentation refers to methods that achieve the segmentation of blood vessels without using training data, or explicitly using any classification techniques. The lower requirement on the data and training makes unsupervised segmentation methods more applicable to a wider range of imaging modalities. This category encapsulates most vessel segmentation techniques inthe literature, such as and our model as described in this paper.For unsupervised segmentation, different segmentation models have been proposed ranging from the primitive thresholding technique [6], morphological path opening followed by thresholding and fusion [9], to elegant approaches such as active contour models [10], [15], [16], [29], [30]. In general, the main limitations of thresholding based methods [6], [9] are that it is difficult (or impossible) to determine optimum threshold values and one is unable to take into account the geometry information of the objects to be segmented, which limit its potential to be generalizable to wider applications.

A number of active contour models have been proposed for vessel segmentation problems, including the ribbon of twins (ROT) model [15], geodesic active contour (GAC) model [10], variations of the active contour without edge model (better known as the CV model [31]) [16], [29], [32], and the distance regularization level set evolution (DRLSE) model [33]. We only make briefly comments on these models and will review them in detail in the next section. As a parametric active contour model, the ROT model is difficult to formulate and optimize [15]. The GAC model requires careful good initialization [10]. The CV and DRLSE models are easy to formulate and optimize but the regularization term of the shortest smooth boundary length makes them not necessarily suitable for vessel segmentation problems. Of these models, only the ROT model and the DRLSE model have been evaluated against public datasets [15], [30]. As such, we propose a novel extension of the infinite perimeter active contour model so that the newly proposed model is able to take into account different types of image information. We also investigate its performance with three public retinal image datasets. The main reasons of using retinal images are twofold: first, there are well-established public datasets available for research and application purposes. These datasets are often used as benchmarks for developing new segmentation algorithms and for comparing them to state-of-the-art approaches. Secondly, retinal vessel analysis is important to the study of not only retinal diseases but also many systemic diseases (e.g., stroke and cardiovascular diseases) [12].

3. PROBLEM DESCRIPTION

Active contour models appear to be a natural choice as they can take into account the geometry information of the object as well as other useful information such as intensity linear. But delimits following factors.

- ✓ Active Contour Models is well perform the linear intensity images but error rate in in-homogeneities images like nonlinear retinal's .
- ✓ Nonlinear vessels segmentation will cost high energy variations.
- ✓ Not using vessels diseases.

OBJECTIVE

The various segmentation algorithm proposed earlier are threshold-based, region-based, statistics-based, deformable models, atlas guided technique and knowledge based approaches [9-11]. Among these, deformable models are the most popular models due to their ability to recover the shape of biological structures much more accurately in various segmentation applications [12-13]. The deformable models can be broadly classified into parametric and geometric models.

A moving equation should be defined to drive the initial contours to the structure boundaries due to which these algorithms are viewed as a modeling of curve evolution [14]. There are various algorithms proposed in these deformable models among which Charged Fluid Model (CFM) [15] is much accurate. But there are few limitations existing in this algorithm like, this algorithm requires initialization inside the region of interest and the algorithm also needs some improvisations for interactive segmentation.

4. PROPOSED SYSTEM

We developed a new deformable model, the charged fluid model (CFM), that uses the simulation of a charged fluid to segment anatomic structures in magnetic resonance images of the retinal. Conceptually, the charged fluid behaves like a liquid such that it flows through and around different obstacles. The simulation evolves in two steps governed by Poisson's equation.

The first step distributes the elements of the charged fluid within the propagating interface until an electrostatic equilibrium is achieved.

The second step advances the propagating front of the charged fluid such that it deforms into a new shape in response to the image gradient. We shows our system will effectively finds the vessels diseases.

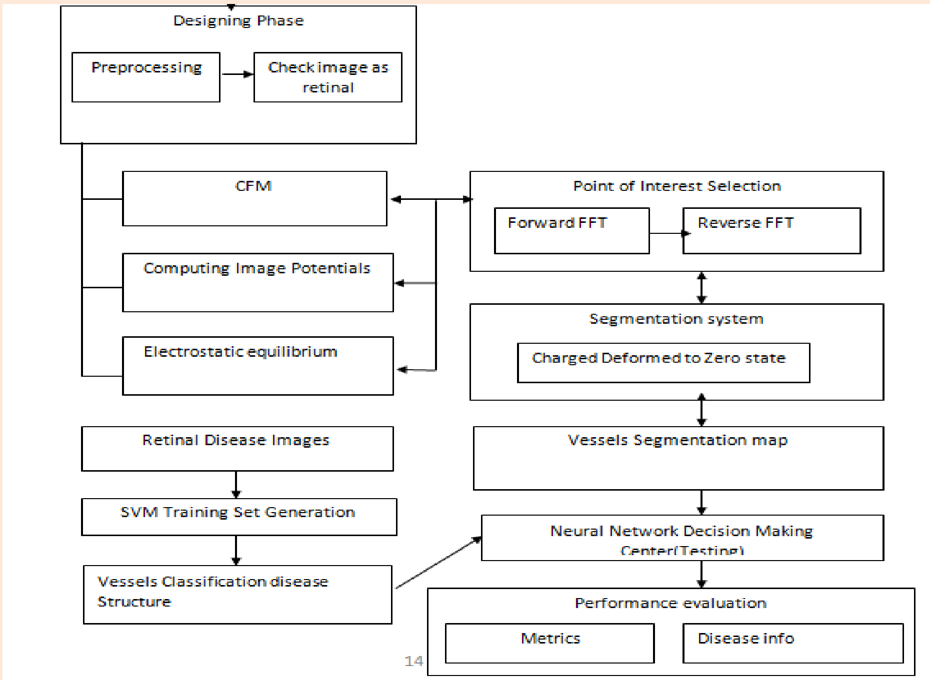


Fig.1.System Design.

Design is a meaningful engineering representation of something that is to be built. It is the most crucial phase in the developments of a system. Software design is a process through which the requirements are translated into a representation of software. Based on the user requirements and the detailed analysis of the existing system, the new system must be designed. This is the phase of system designing. Design is the perfect way to accurately translate a customer's requirement in the finished software product. Design creates a representation or model, provides details about software data structure, architecture, interfaces and components that are necessary to implement a system. The logical system design arrived at as a result of systems analysis is converted into physical system design.

4.1 DESIGN & SYSTEM MODEL

Physics-based probabilistic systems were being used to investigate and analyze the biological models. In charged fluid models, each fluid element has its own charge as if it has been calculated by interpolating the charges of the covered particles [15]. As there are few drawbacks in the CFM model stated in [15] like there should be an effective technique which can automatically segment the image, in this paper we introduce a new approach by including Otsu's algorithm to effectively segment the image for extracting the region of interest which in turn can help the medical practitioners to identify the deformity and its density for pre-surgery and post-surgery treatment. In this technique, the Otsu is used to automatically perform the histogram shape-based image thresholding. The advantage of using Otsu algorithm is that, the set of thresholds is selected automatically and stably based on integration of the histogram. The segmentation of the medical image involves 3 algorithms which are demonstrated below and the numbers specified in the brackets refer to the equations derived in paper [15].

4.3 CHARGED FLUID MODEL

To investigate and analyze the biological models physics-based probabilistic systems were being used. In charged fluid models, each fluid element has its own charge as if it has been calculated by interpolating the charges of the enclosed particles. Now, assume that a system of charged particles is initialized inside a region of interest (ROI) in an image. The particles will continue advancing apparent until they encounter a balancing inner force related to features in the image . However, it is confused to arrange and direct the particles toward the boundary of interest such that the final contour corresponding to the particle positions can exactly and properly represent the ROI.

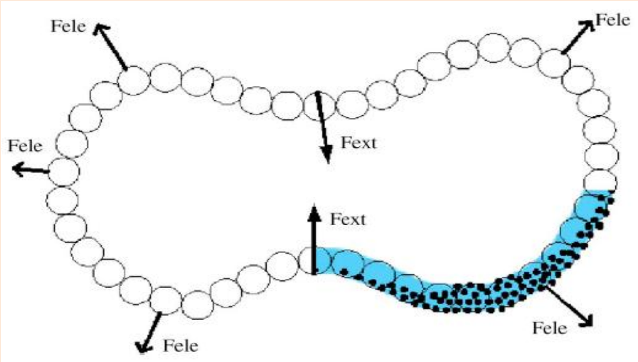


Fig 2. Concept of a charged fluid

A charged fluid theoretically consists of charged elements i.e., the large circles, each of which exerts a repelling electric force on the others. The fluid elements, as if they were consisted of different amounts of charged particles (the solid dots), are connected to one another by 8-connectivity when they advance. The charged fluid, behaving like a liquid, can be influenced by internal electric forces Fele of revulsion as well as external forces Fext from the image data. As there are few drawbacks in the CFM model stated in like there should be a valuable technique which can automatically segment the image, in this paper we propose an extended CFM for retinals MRI image segmentation by region based approach, which is able to deal with intensity inhomogeneities in the segmentation.

5. RESULTS AND DISCUSSION

In order to deal with intensity inhomogeneities in image segmentation, we formulate our method based on an image model that describes the composition of real-world images, in which intensity inhomogeneity is recognized to a component of an image. In this paper, we reflect on the following multiplicative model of intensity inhomogeneity. From the physics of imaging in a variety of modalities (e.g. camera and MRI), an observed image i can be modeled as

$$i=bT+n \qquad \text{------------------- (1)}$$

where T is the true image, is the factor that accounts for the intensity inhomogeneity, and n is additive noise. The component is referred to as a bias field. The true image T measures an intrinsic physical property of the objects being imaged, which is therefore assumed to be piecewise (approximately) constant. The bias field is assumed to be slowly changeable. The additive noise n can be assumed to be zero-mean Gaussian noise.

In this system, we consider the image i as a function $i:\Omega\rightarrow R$ defined on a continuous domain Ω. The assumptions about the true image T and the bias field b can be affirmed more specifically as follows:

(A) The bias field b is slowly varying, which implies that b can be well approximated by a constant in a neighborhood of each point in the image domain.

(B) The true image T approximately takes n distinct constant Values $c_1,\dots,c_n$ in disjoint regions $\Omega_1,\dots,\Omega_n$, respectively, Where $\{\Omega_i\}_{i=1}^n$ forms a partition of the image domain, i.e. $\Omega=\cup_{i=1}^n \Omega_i$ and $\Omega_i\cap\Omega_j=\emptyset$ for $i\neq j$

Based on the model in (7) and the assumptions A and B, we propose a method to estimate the regions $\{\Omega_i\}_{i=1}^n$, the constants $\{c_i\}_{i=1}^n$, and the bias field b . The obtained estimates of them are denoted by $\{\hat{\Omega}_i\}_{i=1}^n$, the constants $\{\hat{c}_i\}_{i=1}^n$, and the bias field $\hat{b}$, respectively. This criterion will be defined in terms of the regions Ω_i , constants c_i , and function b , as energy in a variational framework, which is minimized for finding the optimal regions $\{\hat{\Omega}_i\}_{i=1}^n$, constants $\{\hat{c}_i\}_{i=1}^n$, and bias field $\hat{b}$. As a result, image segmentation and bias field estimation are simultaneously accomplished. Our energy ∈ in (5) is expressed in terms of the regions $\Omega_1,\dots,\Omega_n$. It is difficult to derive a solution to the energy minimization problem from this expression of ∈. The energy ∈ is formulated by representing the disjoint regions $\Omega_1,\dots,\Omega_n$ and the energy minimization can be solved by using well-established variational methods [6].

The equation to find out the energy for the image is derived in paper (1). This is defined by

$$F(\emptyset.c,b)=\in(\emptyset,c,b)+vL(\emptyset)+\mu R_p(\emptyset) \quad \text{-------} (2)$$

Where the energy is $\in(\emptyset,c,b)$, with $L(\emptyset)$ and $R_p(\emptyset)$ being the regularization terms as defined below.

$$\in(\emptyset,c,b)=\int\sum_{i=1}^n [\![e_i(X)\, M_i(\emptyset(X))\, d_X]\!] \quad \text{--------} (3)$$

The energy term $L(\emptyset)$ is defined by

$$L(\emptyset)=\int|\nabla H(\emptyset)|dX \quad \text{-----------} (4)$$

which computes the arc length of the zero level contour of ∅ and therefore serves to smooth the contour by penalizing its arc length [5]. The energy term $R_p(\emptyset)$ is defined by

$$R_p(\emptyset)=\int [\![p(|\nabla\emptyset|)dX]\!] \quad \text{---------} (5)$$

with a potential (energy density) function $p:[0,\infty]\rightarrow R$ such that $p(s)\geq p(1)$ for all $s=1$, i.e. is a minimum point of p . By minimizing this energy, we achieve the result of image segmentation given by the level set function ∅ and the estimation of the bias field . The energy minimization is achieved by an iterative process: in each iteration, we minimize the energy

F(∅.c,b) with respect to each of its variables ∅, c, and b , given the other two updated in previous iteration. We provide the solution to the energy minimization with respect to b as follows.

Energy Minimization With Respect to : For fixed ∅ and c , the optimal b that minimizes the energy ∈(∅,c,b) , denoted by , is given by

$$\hat{b}=(IT^{(1)}*K)/(T^{(2)}*K) \qquad \text{----------- (6)}$$

Where $T^{(1)}=\sum_{i=1}^{n} c_i u_i$ and $T^{(2)}=\sum_{i=1}^{n} c_i^2 u_i$. Note that the convolutions with a kernel function K confirms the slowly varying property of the derived optimal estimator $\hat{b}$ of the bias field.

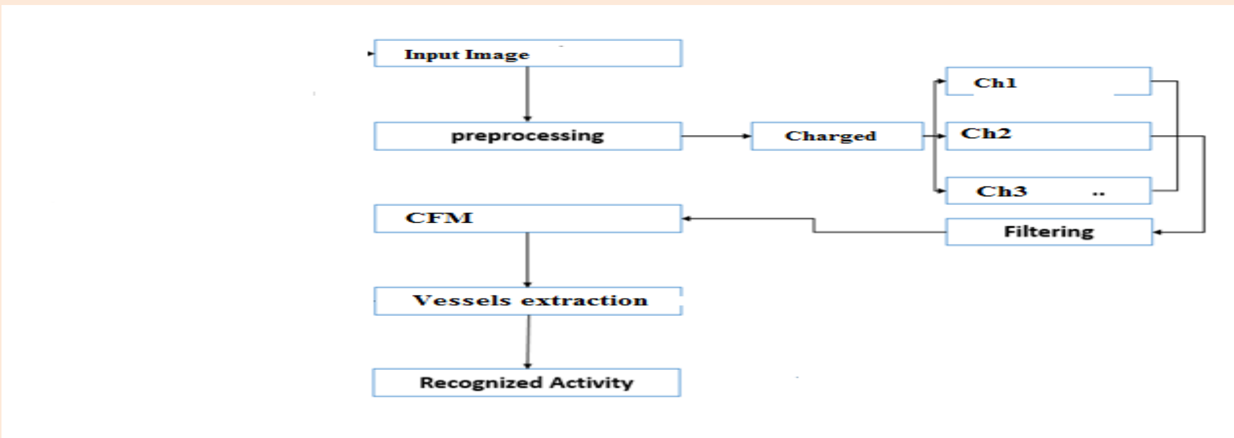
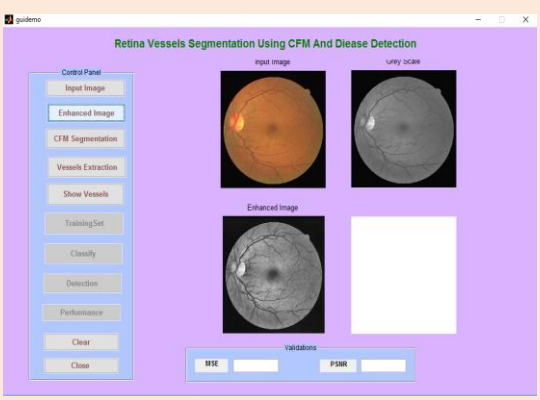


Fig 3. The Overall Process of CFM

3.2.4 SEGMENTATION SYSTEM

In charged fluid models, set the initial contours could fail due to the intensity inhomogeneity. In this paper we propose a region based approach for deal the intensity inhomogeneities i.e., extended CFM for retinal MRI retinal image segmentation. Our method is able to segment the image and estimate the bias field, and the estimated bias field can be used for intensity inhomogeneity correction (or bias correction). So, energy minimization is achieved by using this approach through getting the bias field $\hat{b}$ .The advantage of using the region based approach is that, we can set the accurate initial contours without impact of intensity inhomogeneities. The segmentation of the medical image involves 3 algorithms which are demonstrated below and the numbers specified in the brackets refer to the equations derived in paper [9].



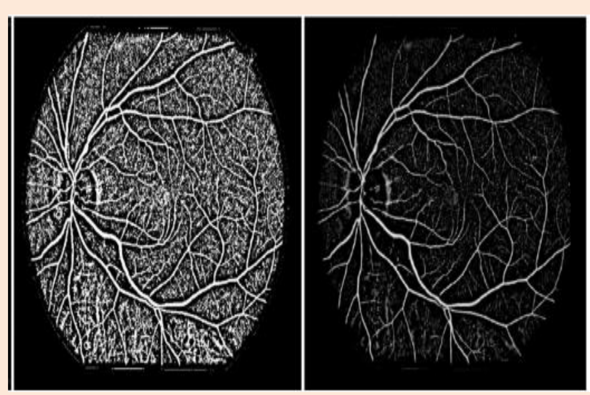


Fig 5.Vessel collection

Fig 6.Segmentation

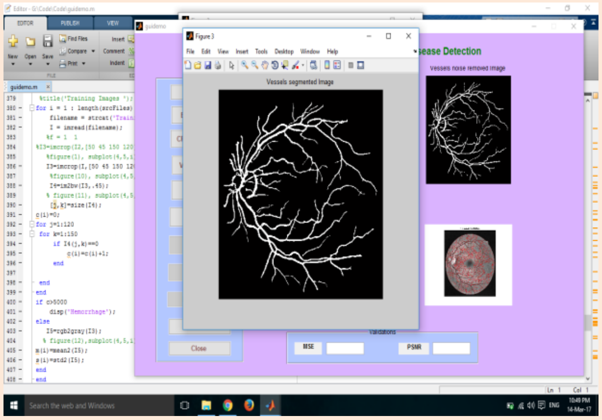


Fig 6.Segmentation

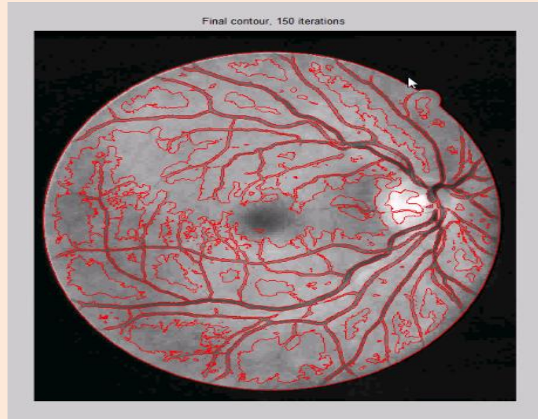


Fig 7.Flow of charged fluid

6. SUMMARY AND CONCLUSION

The segmentation has a vital role in the field of medical imaging for effective diagnosis of the patient having deformities help the medical practitioner in performing the pre-surgery and post-surgery process. Hence in this paper, we proposed an effective segmentation method based on CFM model to segment the medical image. Hence, our proposed method yields better results when compared to the existing method and is much faster when compared to the existing model. We have presented an Extended CFM work for segmentation and bias correction of images with intensity in homogeneities. Based on a generally accepted model of images with intensity in homogeneities and a derived local intensity bias filed property, we define an energy of the bias estimated that represent a partition of the image domain and a bias field that accounts for the intensity in homogeneity. Segmentation and bias field estimation are therefore jointly performed by CFM minimizing the proposed energy functional. The slowly varying property of the bias field derived from the projected energy is naturally ensured by the data term in our proposed CFM frame, without the need to inflict an explicit smoothing term on the bias field. Our method is much more robust to initialization than the wavelet based approaches. Further we reach the framework with retinal's vessels vascular wide information, that's the vascular future disease classification.

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