A Review of Vessel Segmentation Techniques

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Abstract—**Due to the increasing demand for competent vessel segmentation techniques, it is important to review some of the available segmentation techniques. This paper presents a survey of the state-of-art vessel segmentation techniques. In this paper, vessel segmentation techniques are categorized into three classes. These are; Model based segmentation approaches, Tracking based segmentation approaches and Pattern recognition approaches. The three categories identified are never independent. Some of the methods are combined with others to aid segmentation. A contextual analysis is done exploring techniques in-terms of strengths and weaknesses. The summary highlights research gaps that need attention.**

Keywords—segmentation; vessels; heart

I. INTRODUCTION

Segmentation play an important role in medical imaging. Segmentation is used in several application such as study of anatomical structure, clinical diagnosis during quantification of tortuosity, stenosis and angiogenesis. In clinical diagnosis, segmentation helps to establish the patients' response to treatment and to determine the stage of the diseases.However, the above applications require a competent segmentation techniques that can not only segment different sizes of the vessels but can also detect abnormalities in vessels for better diagnosis.Some of the available techniques are manual based. Manual segmentation is tedious, complex and time consuming, especially during the analysis of large and complex datasets as compared to automated segmentation [16]. Although the automated techniques are considered to be accurate and fast, they still face challenges such as difficulty in distinguishing vessels from the non-vessels due to obstruction caused by conglutination tissues, difficulty in segmenting different sizes of vessels especially diseased vessels due to presence of artifacts in medical images (such as intensity inhomogeneity, noise and motion artifacts) which result in to false detection (non-vessels detected as vessels) and missed detection (vessels not detected by the detectors).

In this paper, a survey of the current segmentation techniques is presented. Segmentation techniques are classified into three categories. These are: (a) Model based segmentation approaches (b) Tracking based segmentation approaches and (c) Pattern recognition approaches. Strengths and weaknesses of each approach are mentioned.The rest of the paper is structured as follows: Section two presents three categories of segmentation approaches; Section three presents a contextual analysis of vessel segmentation techniques. The paper concludes with a highlight of opportunities for future research.

II. SEGMENTATION APPROACHES

The three segmentation approaches that have been employed to extract vessels from the heart include the model based segmentation methods [16] [18] [19] [21] [25] [26] [32] [52] [34] [35] [36] [37] [38] [39] [41] [42] [43] [44], Tracking method [24] [29] [30], and pattern recognition segmentation methods [1] [2] 20] [22] [23] [27] [28] [29] [49] [50] [51] [52] [55] [56] [58] [59] [60] [62] [63] [66] [67] [69] [75] [77] [76] [78] [79]. The next section presents the model based segmentation approach.

A. Model Based Segmentation Approaches

The approach involves matching a model which contains information about the expected shape and appearance of the structure of interest to new images, the segmentation is conducted in a top-down fashion [40]. Model based approaches face challenges such as difficulty in finding the model to fit the data [36], right parameters for model fitting [17] [31] [32] [52], segmenting the small vessels, detecting abnormalities in the diseased vessels. This is because model based segmentation approach is based on the assumption that structures of interest have a repetitive form of geometry. Methods that employ this approach can be divided in to three categories, namely; parametric model, deformable model-based segmentation, and statistical model. The three categories are described below:-

1. Parametric Model

In this approach, a part of a vessel is segmented by fitting the model to the image data within a 3-D Region of interest. Different schemes are applied in order to extract a full vasculature [17] [31] [32] [33]. For example in the incremental scheme, the parameters that are used for a model fitting are obtained from the results of the previous segment results which lead to inaccurate model fitting results due to wrong parameter setting especially in low contrast and noisy images [31] [32] [33]. Several attempts have been made to find accurate parameters for model fitting such as [20] proposed the use multiscale analysis and cylindrical elliptical model in finding of parameters for model fitting, however the method cannot detect edges of the vessels at the crossing point. Although elliptic parametric model can approximate healthy vessels and unhealthy vessels (such as vessels with stenosis) approximating pathological irregular shapes and vessel bifurcations.[17] Proposed the use of the kalman filter in finding the parameters for model fitting, the method can only detect the circular shaped vessels and cannot detect thin vessels. The model fitting results do not depend on the parameters but also the models such as the Gaussian smoothed cylinder model that is proposed in [17], The model can detect

vessels of particular shapes but cannot detect some abnormalities in vessels (such as detection of stenosis, tortuosity). Although cylindrical elliptical model, is capable of detecting healthy vessels and some abnormalities in vessels (such as narrowness in vessels), it doesnot detect vessels at the vessel junctions and tangent vessels.

2. Deformable Model-Based Segmentation

Deformable models are curves used during segmentation. Vessels are segmented by the curve that move within the medical image under the influence of the internal forces, external forces, and the user constraint [82]. The internal and external forces are defined in order to preserve the smoothness of the object and to drive the model towards the desired position respectively. This is because such images have stacks of images that deform under the influence of the internal, external forces and user defined constraint. Deformable models enable the incorporation of information about the image structures [44]. The deformable model based segmentation approach can be divided in to two classes that include parametric model based segmentation and geometric model based approaches. The two classes of deformable models are described below [42]:-

2.1. Parametric Deformable Models

Parametric models are active curves whose deformations are determined by the displacement of a discrete number of control points along the curve [42]. The operation of parametric deformable model is based on either energy minimizing formulation or dynamic force formulation. Both of formulations lead to the same result and each of them of has an advantage over the other for example the energy minimizing formulation has an advantage of producing a solution that satisfies a minimum principle whereas the second formulation is flexible that is, One can use more general types of external forces. The main advantage of parametric deformable models is that they are fast in terms of convergence as compared to the geometric models. However parametric model require dynamic re-parameterization in cases where the initial model and the desired object boundary differs in size and shape in order to recover the object boundary in order to recover the object boundary. Re-parameterization is complicated and computationally expensive especially in 3D segmentation [81]. Parametric deformable models also are topological dependent, as a model can only be applied on one region of interest meaning that if the image has many regions of interest, a model will be applied sequentially on each of the region of Interest. The parametric deformable model cannot handle topological changes during deformations as compared to geometric deformable model [82]. The geometric deformable models are designed to handle topological changes [82].The next section presents the Geometric deformable model.

2.2. Geometric Deformable Model

Geometric deformable model was proposed by Malladi et.al [84] and Caselles et.al. [83]. the model is based on theory of curve evolution, where the evolving curve are implicitly represented as a level set of higher dimensional scalar function [82]. Geometric deformable model are also referred to as level set models [82].A geometric model based segmentation utilizes a distance transformation to define the shape. Transformationenables us to define a mode in a domain with dimensionality similar to the dataset space which provides a more mathematically straightforward integration of shape and image features in the model definition.The shape can be implicitly defined, with the control/deformation points being at the image pixels' positions by using transformation. Transformation also enable us to capture multiple ROIs with a single model, and therefore they can be robust to initializations [49].

2.2.1. Level set segmentation method

Level set method was first introduced by [49] in 1988. Level set methods aims at representing interfaces of surfaces through using a higher dimension. Meaning a 2D interface would be represented as a 3D level set function and a 3D interface as a 4D [49].The additional dimension represents time. During segmentation, the evolving surface is representedas a closed curve by the boundary of the level set at that iteration. The speed function is used to describe how each point in the boundary of the surface evolves. The speed function is a combination of both data term and the mean curvature of the surface. The mean curvature term is used to keep the level set function smooth, while the data function is used to force the model towards desirable features in the input data. The free weighting parameter $\alpha \in [0,1]$, is used to control the level of smoothness [68, 99, 98]. The smoothing term restricts how much the curve can bend and thus avoiding the effect of noise in the data, hence preventing the model from leaking into unwanted areas [68].This is one of the bigadvantage that level set method has over classical flood fill, region grow and similar algorithms that do not have a constraint on the smoothness of the curve.However, level-set methods is slow [57], involves large number of computations,lack an efficient representation of the surface during deformation,level-set models are also limited by resolution rather than shape and they fail to work well on images with intensity variation [62] [63], Meaning they are cannot work on images that suffer from intensity inhomogeneity.Researchers have tried to handle these problems, literature shows there is need for improvement such as in 1994, [66] proposed the narrow band method in order to decrease computational labour of the standard level set.In this method, only points within a narrow band are considered. Points that are far away from the zero level set are ignored at each iteration. This is because points far away from the zero level set do not have any influence on the result. The points within the band is used to calculate the distance function and then to initialize to the signed distance.A given band is used for several iterations with the same initialization. And when the interface gets close to the band it has to be reset from the current position of the zero level set and reinitialized. However the re-Initialization at every iteration and the procedure of finding out whether a pixel in level set is approaching the edge of the band consumes a lot of time. The narrow band method also faces a problem of keeping the boundaries of the band stable. Meaning that as other points are undergoing evolution, the neighbouring points remain fixed.In [67] introduced a sparse field method that uses a fast approximation of the

distance transform that makes it feasible to compute the neighbourhood of the level set model. The sparse field method ensures that no point enter or leave the active set unless it is adjacent to the model. As the model evolves, points that are no longer adjacent to the model are removed from the active set. The sparse-field algorithm overcome the aliasing artefacts associated with other level-set approaches however the method is slow and is associated with errors.[63] Introduced a constraint factor into the classical level set curve evolution to solve the problem of intensity variations. In order to solve difficulty of segmentation of closely touching objects in level set, a multiple level sets scheme was proposed by [64] [65]. Although level set methods produce better results, it still face vessel leakage, it is computationally expensive and highly time consuming making it unsuitable for practical application.[44] Utilized the geometric model to address the leakage problem faced by level set method. In this method, the location of the medial axis and the parameters are obtained through aligning the parametric elliptic model with the vessel cross section in order to obtain best fit. The position of each elliptical model for each vessel is determined according to medial axis. Level set did not lead to better results without further information.[18] Used multi-linear transformations to model bending and diameter variations of large vessels. The shape of these tubular segments is defined by the internal energy and their orientation is defined via multi-linear transformation. The parameters used depend on the number of iterations and different parameters are used during each iteration. However the parameters used in this algorithm aren't tested to select appropriate parameters which minimize the segmentation accuracy as used during validation.In order to model vessel bifurcation, [36] proposed a tracking algorithm, in this algorithm continuous model of a segmented vessel is generated. The parameters for model fitting are obtained through fitting the synthetic model on to the actual image. The right generalized cylinder state model includes a curvilinear axis associated to a stack of contours extracted by the fast marching level set algorithm. The kalman state estimator is used to describe the axis. However the model could not detect some abnormalities in the diseased vessels such stenosis.In order to model vessel bifurcation, [34] introduced a model-based tracing algorithm. In this algorithm a geometric parametric vessel model is used in the estimation of the vessel diameter at each central axis pixel with a measure of match used to determine how well the vessel model matches a given image with the assumption that vessels pixels have greater values than the background. The method focusses on vessel bifurcation.[35] Used 3D geometric model of Thoracic aorta obtained from 3D cine phase contrast MRI (Magnetic ResonanceImaging) acquisitions. In this method, magnitude and phase information is used during segmentation, a fast matching level set algorithm is used to extract the rough surface and geodesc active contour is used to refine the surface. The vessel tract is chosen basing on the isosurface while moving and adjusting the cardinal cubic spline. The new spline is fitted on to points obtained until it completely fit on the vessel [35], however the surface is not able to reach the vessel edges due to insufficient velocity contrast meaning the method could not effectively discriminate the vessel from the background and guide the algorithm evolution.

3. *Statistical models*

The segmentation based on the statistical approach often rely on the intensity distribution in medical images. Segmentation solely depends on the image modality. For example in the MRA, two or three distributions are considered for anatomical structure, blood and the background. Distribution such as mixture of distribution, rician and uniform distribution [17], Gaussian distribution [86], exponential distributions [86], Maxwell-Gaussian-uniform mixtures for phase-contrast MRA are used to definedbasing on anatomical structure, blood and the background [85].Currently [86] segmented the vessels using the mixture models that consider of the statistical methods are constructed relaying on the characteristics of the image histograms. The problem faced by methods that adopt statistical techniques is the loss of data. This is because parameters used for model fitting are estimated from random variable whose distribution is a mixture of distribution [41].[39] Used rician and uniform distribution for background noise and vessel modelling and modified Expectation-Maximization algorithm for parameter estimation in order to segment the vessels. The two Statistical models were derived basing on the signal formation process and physical characteristics of the flow pattern. According to [39], rician distribution gives a better quality of fit to the observed background noise distribution than a Gaussian distribution. However the method over estimates the size of the vessels in the image.In 2012, [37] chose to track the centerline of the vessels. In this method, parameters are manually selected. The parameters (such as edge points, diameter, direction) used in the current iteration are obtained from the previous iteration using local grey level statistics and vessel's continuity. Statistical sampling scheme is applied in order to choose the most probable vessel configuration (such as normal, bifurcation). Local vessel's sectional intensity profiles are estimated by a Gaussian shaped curve. A Bayesian method is then used to identify local vessel's structure and find out the edge points from these candidates. The tracking of the previous vessel ends if the diameter of the vessel is less than one pixel. The tracking process continues until when the algorithm obtain information about all the branches in the network. The tracking process is stopped manually by the user. According to [37], the method is robust to noise as it utilizes both the grey level statistics in the local search area and the information from the previous iterations as compared to [38], where only pixels belonging to scanlines areutilized. However the method involve too much human intervention during parameter setting, model fitting, stopping of tracking process.Later in 2013, [43] proposed the graph-based method for 3D vessel tree structure segmentation based on a new tubularity Markov tree model. The method does not rely of region of interest and skeletonisation to obtain segmentation results. In order to construct a good vessel data fidelity, the tubularity markov tree model is proposed. The method made good use of the tubularity shape character of vessel structure with a Markov tree representation. In this method, a start seed node is manually set then the tubularity Markov tree is generated through adding the nodes with the highest weighted joint tubularity score iteratively until there is no node with the highest score in the stack using power-watershed implementation. Although the method produces promising

results, decisions contained in the decision tree are based on expectations, and irrational expectations can lead to flaws and errors in the decision tree [43].

Recently [86], proposed a hybrid method in order to deal with the problems (such as dependence of the image modality, uneven contrast media, bias field, and overlapping intensity distribution of the object and background) faced by statistical method. In this method a multi-scale filtering algorithm is applied on to the image in order to enhance vessels and deal with the noise, then a mixture model is formed out of the resulting image using the two exponential distributions and one Gaussian distribution. The mixture model is then fit to the histogram curve of the resulting image (image obtained after multiscale filtering), during the model fitting the expectation maximization algorithm is used to estimate the parameters. Then later markov random field is employed to improve accuracy and posterior probability estimation. However the method still face difficulty in distinguishing vessels from non-vessels. Another limitation is that the method can work on only angiographic images and the statistical method cannot work on angiographic images without the help of the multi-scale filter.

B. Tracking Based Segmentation Method

In this approach, vessel centerline is either chosen manually or automatically. In this research, we look at automated methods. Automated Algorithms that fall under this approach include a logic that enable the vessel tracker respond to the end points and the branching points. A function that estimates next vessel direction. Before the tracking process begin, one is required to choose the seed points on the edges, then vessel tracking process begins provided the location and direction of the vessel is known. The vessel tracker looks for closer vessel edge or centerline or both. An estimate of vessel direction is made and new step is made in a specified direction until the whole vessel tree is extracted. Several methods have been employed for-example [21], employed the two phase in the extraction vessels through using the balloon segmentation and snake segmentation during the first stage and second stage respectively. In this method, an initialization point in each of the slices is set before the tracking process to begin. The user also marks the beginning of the balloon segmentation (points in which segmentation start from). During the segmentation, initial points in all other slices are automatically obtained using the average position of a snake points only if the contour exceeds the number of iterations accepted for balloon. In cases where the contour exceeds the number of iterations, the initial point of the next slice is computed using the last regular snake. Segmentation is repeated for missed slices. The method does not detect small vessels and vessels placed parallel to the scan plane and it involve human intervention during parameter setting and adjustment.[29] Tracked the vessel axis using level set evolution. The evolution of the surface is guided by analyzing its skeleton topology during evolution, and imposing shape constraints on the topology to represent a single segment, a bifurcation or complex topology. The evolving surface is then reinitialized with the new topology. The new topology is obtained through analysing the previous results. After re-initialization a gradient based speed function is optimized to determine the strength of boundaries and how

hard the evolving surface is pushing against the boundaries for better segmentation results. However the method involves human intervention in setting the start and end point and it is computationally expensive.The next section presents some of the available pattern recognition based segmentation techniques.

C. Pattern Recognition Segmentation Method

Pattern recognition discriminate among data from different groups based on the morphological interrelationships within the data. The pattern recognition segmentation can be classified in to threshold based techniques, graph cuts and vesselness filters. The methods are described below:-

1. Threshold based segmentation

Among the edge based segmentation methods, thresholding method is the simplest and widely used method. The method uses a clip or threshold value to convert a gray-scale image into a binary image. A gray-scale image is converted by replacing the pixels in an image with a black pixel if the image intensity Iij is less than threshold value T (that is $I_{ij} < T$) or a white pixel if the image intensity I_{ij} is greater than that threshold value T (that is $I_{ij} < T$) using threshold method in order to separate the background from the foreground. The condition used during thresholding to obtain a segmented image is given as follows:-

$$g(x,y) = \begin{cases} 1 & if f(x,y) > T \\ 0 & if f(x,y) \le T \end{cases} \qquad (1)$$

Where (x, y) is the pixel value in the image g. T is the threshold.

[71] [72] categorized thresholding algorithms into global thresholding algorithms, Local thresholding, adaptive thresholding algorithms. Below are the some of the available thresholding techniques. In global thresholding, one threshold is used to separate background from the foreground. This type of thresholding is good in images where pixels intensity is consistent. In local thresholding, different threshold values are used to separate foreground from background. And In adaptive thresholding, allows the threshold value T to change basing on the slowly varying function of position in the image or on local neighbouring hood statistics. Methods that fall under each of the class are discussed below:-

1.1. Global thresholding

Global thresholding technique is a popular method used during segmentation because of its simplicity. However the method works well on pre-processed images or images whose pixel intensity is consistent. Inconsistency in the image pixels intensity may be as a result of noise, variation in illumination. Among the global thresholding methods, Otsu thresholding is a popular method because of its satisfactory results and easy of computation [14].

1.1.1. Otsu thresholding.

Otsu thresholding method was proposed by Otsu in 1979, Otsu method use the histogram of the image in order to identify

an optimal threshold [6]. Otsu thresholding method maximizes the between-class variance in order to choose an optimal threshold value for image segmentation. The method does not give better segmentation results if applied on one dimension and two dimension images because one dimension does not take in to consideration the spatial information between image pixels and it's difficult to obtain satisfactory segmentation results in the presence of noise [7] [8]. Two dimension does not utilize both spatial information (that is mean and median values). Although three dimension Otsu method utilize spatial information, detect and preserve regions of evident abnormalities in vessels, it is slow as compared to two dimension Otsu thresholding [3]. Its time complexity is O (L3). It also does not work well on noisy images [10].Some researchers have tried to reduce the computation time for example. [9] addressed the problem of redundant computation by computing look-up table in order to increase the speed of Otsu, the method is still O (L3). In 2011, [3] proposed to select each threshold component in the threshold vector independently instead of one threshold vector. The method calculates each optimal threshold from the original, mean-filtered, and median-filtered images independently and uses the most selected class by each threshold on the corresponding images as the thresholding result. The method is still not fast. Other researchers such as [10], proposed a multi-threshold Otsu to improve Otsu performance on noisy images. The method was applied in the segmentation of big vessels and 2D images, however it did not produce better results as it cuts vessels since image structure is segmented several times.

1.1.2. Isodata thresholding

In this method, the cluster centers are randomly placed. Then later standard deviation with each cluster and the distance between the cluster centers are calculated. Pixels are then assigned basing on the shortest distance to the Centre and the standard deviation. Cluster are split if one or more standard deviations is greater than the user defined threshold and clusters merged if one of the standard deviation is less than the threshold.Other iterations are performed with new cluster centers until the average change in the inter-center distance between iterations is less than a threshold or maximum number of iteration is reached.Clusters associated with fewer than the user-specified minimum number of pixels are eliminated.The method does not expert knowledge and requires less human intervention however as all other global thresholding methods, it works well on pre-processed images. Isodata is also time consuming especially if the data is unstructured [102] [103].

1.2. Local Thresholding

In local thresholding technique, the threshold value T does not only depend on gray levels of images but also on local image properties of neighbouring pixels such as mean or variance [73].Although Local thresholding works well in case of poorly illuminated images, it is region size dependent and time consuming [149].

1.3. Adaptive thresholding

Adaptive thresholding technique is used when images are captured under unknown lighting condition and it is required to segment a lighter foreground object from its background or whenever the background gray level is not constant and object contrast varies, within an image. This technique allows the threshold value T to change based on the slowly varying function of position in the image or on local neighbouring hood statistics. Threshold T depends on the spatial coordinated (x, y) themselves.Although the method is capable of identifying object region from background region very effectively in the boundary region, it still faces difficulty in obtaining a correct threshold value in images with the flat region [74].

1.4. Local adaptive thresholding

This segments the image with the assumption that all small regions have uniform illumination. In this method, adaptive thresholding is used to separate desirable foreground image objects from the background basing on the difference in the pixel intensities of each region in the image. The method is capable of retaining edges of the big vessels as compared to other sizes of vessels [88] [89]. Local adaptive thresholding is also computationally expensive as compared to other methods [75] [76] [77] [78].

2. Graph Cut Segmentation Method

In Graph cuts, a graph is defined as a set of nodes connected by a set of edges. Each edge in the graph is assigned weight [46]. In vessel segmentation, nodes represent pixels and edges represent neighbourhood representation between pixels. Graph cut involves binary labelling of the pixels of an image as belonging to the foreground or background class. A min-cut is used to partition the pixels into foreground and background [45] [46] [47]. White pixels in a binary image represent foreground ($x_i = 0$) and black pixels represent background($x_i = 1$) [45] basing on the prior knowledge about the objects and the background [45] [46] [47].The regional term is used to incorporate the regional information in to the segmentation. The boundary term is used to incorporate the boundary constraint in to segmentation. A relative importance factor is used to indicate whether the boundary information or and regional information is considered. The weights areused to indicate whether a particular pixel belongs to region of interest is obtained through comparing the intensity of pixel p with the given histogram (intensity model) of the object and background. When the intensity oftwo neighbouring pixel is very similar, the penalty is very high. Otherwise, it is low. Thus, when the energy function obtains Minimum value, it is more likely occurred at the object boundary.In order to get a reasonable segmentation result, the assignment of the weight in the graph is very important. In Boykov and Jolly's method, the weight of the graph between the pixel and the S-node is larger than the weight between the pixel and the T node if the pixel belongs to the object (foreground) meaning the cut will occur at the edge with a smaller weight. If the intensity of the neighbouring pixels is similar, the weight is big meaning that the cut won't be able to separate them. When the minimum cut is achieved from the graph the location of the cut is close to the object.

Graph cut method achieves an optimal result for the energy function and It doesnot require expert knowledge during segmentation [101].However the method is slow and is

associated with low accuracy as compared to other methods and it also incapable of detecting vessels in images with varying intensity. Several improvements have been made such as[57], introduced interactive graph cuts approach, this method utilized model-specific visual cues and contextual information in order to extract objects of interest from the binary image. According to [56], interactive graph cuts approach enable the user to extract information that he needs based on the problem and therefore [58] [55] [59] utilized geometric cues, [60] utilized the regional cues based on Gaussian mixture models, [61] utilized the high-level contextual information, and [48] [54] [53] used the Banded method, etc. however the method is slow and is not capable of separating touching vessels.In 2003, [48] introduced the Graph cuts–based active contours (GCBAC) method, the method is based on the same concept of [57]. Given an initial contour, the method iteratively search for the closest contour and then replaces it with a global minimum within the neighbourhood until the objective is achieved. The method is less time consuming but does not work well on images with intensity variations and it also involves human intervention during setting of the initial contour making which result in to difficulty in separating tight torching objects. In order to avoid human intervention during initial contour selection and also extract objects and separate tightly touching objects from images of varying intensity, [56]   introduced a constraint factor in Graph cuts–based active contours method. In this method, the objects are first of all extracted from the image and labelled. A novel scale-adaptive steerable filter is used to enhance the image. Then, morphological region growing algorithm uses each labelled object to determine its initial boundary. Constraint factor GCBAC uses initial boundaries to segment clustered objects. Morphological thinning algorithm is used to iteratively extract the touching edges. The method was compared to level set and watershed algorithm, segmentation produced by the methods are not better than segmentation results produced by level set. However the method has an advantage of producing results early as compared to level set but it still find hardship in separating tightly touching objects. It still find hardship in separating tightly touching objects and segmenting vessels in images that suffer from intensity inhomogeneity problem. The next section presents the vesselness filter method.

3. *Vesselness filter*

All vesselness filters aim at extracting tubular structures. Vesselness filters analyseimage behaviourby using the second order derivative of the Gaussian convolution [70]. The decomposition of the local second order structure of the image extracts the eigenvalues.The Eigen values of the hessian matrix are combined into vesselness measure to extract tubular structures although, however this is done in a different way. For example Sato's vesselness filter in [2], is designed for bright-vessel datasets.Sato's vesselness filter is based on only two eigenvalues of the hessian matrix. First, the eigenvalues are sorted in ascending order, then later two Eigen values are considered meaning that dark and bright lines are not treated in a similar manner [1]. Although Erdt's vesselness filter in [79] is based on all the three eigen values, it uses only one scale of Gaussian meaning it is not capable of extracting different sizes of vessels [1]. Frangi vesselness filter is one of the most widely used vesselness filters that was proposed by Frangi in 1998. This vesselness filter has the ability to enhance either dark vessels on a bright background or bright vessels on a dark background. It has a multi-scale feature which enables the extraction of vessels of various sizes. Unlike Sato's vesselness, Frangi is based on three Eigen values meaning that dark and bright regions are treated in the same manner. However Frangi vesselness filter is slow and does not work well on MRI images due to the nature of MRI images (MRI images suffer from problems such as noise, intensity inhomogeneity) [1] [11]. Most of the problems arise from MRI image acquisition caused by different lines in K-space measured with a different contrast with respect to T_2^*decay during MRI image acquisition. [13] [1], suggests that the number of lines in the K-space should be restricted during MRI Image acquisition in order to account for a reduction of the effective Fourier spectrum of a measured signal for faster segmentation process. However that takes place during image acquisition. Frangi vesselness filter also causes blurriness at the edges of the vessels in Medical images due to Gaussian convolution[11]. The Gaussian convolution does not only cause blurriness but it also make scale selection inaccurate.Another known problem of Frangi vesselness filter is that it cannot handle vessel crossings or bifurcations in medical images of different modalities since it only looks for line structures in the images [87].

4. *Morphological method*

In this method, the vessels in the image X are segmented using several operations that make use of the structuring element B of a particular size. The structuring element used depend on structure of interest for example in vessel segmentation, the commonly used structuring elements include the disc and square. Both the image X and B are represented as sets in the Euclidian bi-dimensional space. The morphological operations used during vessel segmentation include erosion, dilation, morphological opening, morphological closing, and top-hat morphological transform. Morphological opening and closing are built on erosions and dilations while Top-hat morphological transform is built on morphological opening and closing. Basically all operations are built on dilation and erosion operation because the two operations (dilation and erosion) consist of operations such as invariant, distributivity, local knowledge, increasing, duality which enable manipulation of image for further analysis.Among the operations, top-hat morphological transform operation is a popular tool that is widely used to extract the small or narrow or bright or dark tubular structures from the images with varying intensity due to its ability to correct illumination in order to uncover the objects rendered absent in the images and also get rid of the unwanted tissues in MRI image while enhancing the edges of the vessels at fast rate [4] [5]. Researchers [4] [5] [92] [93] [94] [95] [96] [97] [98] [99] are now combining top hat morphological operation with other methods in order to achieve better segmentation results however most of this research is 2D based and are to do with vessel segmentation in retina images. The few 2D and 3D vessel segmentations that focus on the heart vessels still need improvement such as [97] used mmorphological top-hat operator to enhance the contrast between the vessel and background, with fuzzy morphological opening used to denoise

the image. The resulting image is then thresholded in order to produce a segmented results.However, method is fast but it is not capable of detecting the entire vessel tree structure [144]. [90] Suggested the use of edge detection with top hat transformation in order to extract the entire vessel structure. In this method, with algebraic based algorithms is used to extract basic feature and remove undesired patterns, linear operators are used to compute shape properties in order to differentiate elements. And top-hat morphological transform used to denoise the image. The method mistake round linear bright structures for vessels. A combination of Top hat transform morphological operator would lead to better results since Frangi filter looks for tubular structures in the images. Recently, [92] introduced Top hat morphological transform operation in Frangi vesselness filter after the Hessian filter in order to deal with the noise problem in Frangi vesselness filter, The method achieve promising results. However it misses small vessel, leads to blurriness in the edges of the vessels due to the use of Gaussian convolution [10] [11], and does not maintain the edges of the small vessels as the vessels (especially small vessels) are split. Top hat morphological transforms face difficulty in segmenting vessels in image with much noise.Recently[91], improved top-hat transform morphological transform in order to deal with noise sensitivity problem. Improved top hat morphological operation is combined with CLAHE, Otsu thresholding and hessian matrix and eigenvalues transformation, with CLAHE and top-hat morphological transform used for vessel enhancement and low frequency noise or object removal, Otsu thresholding used to extract vessel attributes and region properties based thresholding and hessian matrix and eigenvalues transformation used to classify retinal image into wide and thin vessels enhanced images.The method is robust to noise but still has a problem of distinguishing vessels from non-vessels as the circular structures are detected as linear structures.

III. CONTEXTUAL ANALYSIS AND DISCUSSION

In this paper, segmentation methods are classified in to three categories namely: model based segmentation approaches, tracking based segmentation approaches and pattern recognition approaches.

Based on the contextual analysis of the reviewed papers, challenges still exist in segmenting vessels due toimage artifacts (such as intensity inhomogeneity, noise, motion artifacts). A few of these methods are capable of segmenting vessels in medical images of different modalities. Among the segmentation methods, techniques that employ model based segmentation approach depend on prior expert knowledge [30], as such they face difficulty in segmenting different sizes of vessels, especially diseased vessels. Model based segmentation techniques are also based on expectation and require human intervention during parameter setting, model fitting and vessel centerline tracking process. This leads to flaws and errors in the segmentation results. Although some of these model based segmentation techniques (such as the geometric deformable techniques) are parameter free, they are limited to resolution, slow and involve large computations during segmentation. On the other hand, although tracking techniques have the ability to estimate vessel diameter with a high performance, they are slow, encounter difficulties in segmenting small vessels. They also require human intervention in setting the start and end point of a single line, at the same time they are computationally expensive and cannot handle vessel crossover points [15] [30]. Pattern recognition techniques are widely known to be fast, easier to implement and involve higher accuracy. Pattern recognition techniques require no or minimal human intervention and are capable of segmenting and detecting abnormalities in both small and big vessels. Among the pattern recognition techniques, threshold based segmentation techniques are easy to implement. However, some of these techniques (such as global thresholding techniques) work well on pre-processed images. Local thresholding is capable of segmenting poorly illuminated images, however it depends on region size and is time consuming. Although Adaptive and Local adaptive thresholding are considered better in terms of dealing with varying intensity,Adaptive thresholding encounters difficulties in segmenting vessels in the flat regions.Moreover Local adaptive thresholding is not capable of maintaining the edges of small vessels and is computationally expensive. Other pattern recognition methods such as Graph cut, and Vessel filters have issues that need to be considered for future research. The Graph cut method is slow, finds hardships in separating tightly touching objects. It also has a bias towards cuts with short boundaries in small regions. Vessel filters is considered to be the best vessel segmentation technique as it is associated with high accuracy and is fast as compared to graph cut. Among the vesselness filters, Frangi hessian based vessel enhancement filter is widely used because it is capable of detecting different sizes of the vessels using the multiscale component with high accuracy. However, Frangi hessian based vessel enhancement filter is slow in 3D segmentationand causes blurriness around the boundaries of the vessels. It alsodoes not work well on images of some modalities such as MRI due to artifacts such as, intensity inhomogeneity, noise and motion artifacts. Moreover, it cannot handle vessel crossings or bifurcations in medical images.

IV. CONCLUSION

This paper presents a survey of vessel segmentation methods in medical imaging with emphasis on state-of-art vessel segmentation methods proposed for heart vessel segmentation. Our aim is to guide researchers to interesting research directions.Results of the overall contextual analysis reveal that Frangi vesselness filter technique may produce better results if the image is analyzed by using the second order derivative of the improved top-hat transform operation rather than Gaussian convolution so as to increase the speed of Frangi vesselness filter and at the same time deal with the vessel blurriness problem. A combination of improved Frangi vesselness filterwith other methods (such as 3D Otsu thresholding) that considers spatial information for better results, and at the same time detect and preserve regions of evident abnormalities in vessels, would lead to extraction of different sizes of both normal and abnormal vessels. These could be good pointers for future research.

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