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VASCULAR IMAGING AND SEGMENTATION WITH REFERENCE TO DIABETIC RETINOPATHY : A BRIEF SURVEY

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ABSTRACT

In this paper we are discussing about the detection methods of retinal blood vessels and various retinal imaging techniques . In this paper we are also providing the comprehensive list of work carried by various Authors/Researchers till today with the methods adopted by them for segmenting blood vessels in tabular form. we know that the list is not complete by its mean but definitely will give the direction for new researchers . The Detection of blood vessels in retinal images is an important step in the predictions and diagnosis of cardio-vascular diseases, such as hypertension and diabetes, that are known to affect the appearance of the blood vessels in the retina. We Survey the current image processing techniques for segmenting blood vessels from other features in retinal photographs. The Paper focus on the importance of work in terms of identification of various disease to Diabetic retinopathy, Hypertension, ,cardiovascular and its relation to vessels structure.. Paper also focus on how the vessels width, vessel thickness, turtosity, and vessel junction separation changes as disease grade changes and therefore how it is important to detect vessel tree structure for early diagnosis and prevention of various disease.
Key words: vascular, segmentation, turtosity, retinopathy

Introduction

Examination of the vasculature of the human eye can predict the onset, aid in the diagnosis and track the passage of numerous diseases and conditions afflicting the circulatory system. However, direct viewing of the eye or manual analysis of retinal photographs is time-consuming, expensive and requires trained ophthalmologists and specialized equipment.An accurate method of mapping the retinal vasculature using commonly available digital cameras and off-the-shelf computing equipment would allow automated analysis and diagnostic tools be used, greatly enhancing the speed and availability of these tests,while significantly reducing the costs involved. Any automated method of retinal image segmentation must have the ability to accurately determine the location, size and boundaries of veins, arteries and capillaries within the eye and to track their passage across the image. This can then enable the use of automated diagnostic tools that provide valuable information on the many health problems that can be foreseen or monitored through retinal examination. This paper will examine the relationship between observations of the eye and a range of health problems, and go on to look at current methods used in automated retinal image segmentation. We then attempt to incorporate wavelet transforms of retinal images into a segmentation algorithm to detect features that may be extremely variable in size within images. We will elaborate on these experiments, including a brief introduction to wavelets, and ultimately produce a series of segmentation algorithms analysis of the retina is reliably able to indicate problems in other parts of the circulatory system, the brain and kidneys aswell as disorders within the eye itself. Hypertension has been shown by Hansen et al [4] to be directly related to mortality over a 10-year study period, and evidence of hypertension,or the prediction of its onset, and T. Wong et al[16] proved that this evidence can be obtained from vascular examination.In addition, owing to the similarities between the circulatory system of the eye and that of the brain, abnormalities within the retina have been shown by T. Wong et al in[15]to be correlated with an increased risk of stroke. In another study performed by T. Wong et al retinopathy has been conclusively shown to be linked to ventricular enlargement and sulcal widening, these being objectively measurable indices of brain atrophy, as explained by Wong et al in [17]. This same study shows evidence of other brain degeneration, such as lesions upon the white matter of the brain, being related to the severity and extent of the retinopathy.Examination of the circulatory system is a powerful tool in aiding the prediction, diagnosis and treatment of many life-threatening

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disorders. Current non-invasive methods such as Magnetic Resonance Imaging, Doppler Ultrasonography and Computed Tomography all require expensive and complex equipment and highly trained technical and medical staff to perform examinations and interpret the results. Even the most basic tests of the circulatory system, performed with standard surgical equipment to determine blood pressure at various parts of the body, are time consuming, require specialist training and do not necessarily produce repeatable results from one observation to the next. Due to the imprecision of manual observation and interpretation, measurements made by one clinician can vary substantially from those made by another, or even those made on other occasions by the same clinician. Because of the high cost of the technology and training involved in performing these tests they are not available to many people, particularly those in developing countries. Owing to these limitations, many disorders may go untreated or undiagnosed, and large-scale studies of population bodies remain very difficult to perform in a manner that provides quantitative data. Automated tools have the potential to improvement the reliability and repeatability of many forms of testing while reducing the costs involved. While there are numerous techniques for examining the circulatory system, the majority of these are expensive, invasive, time-consuming and technically complex. This makes them unsuited to repeated applications, or they may not be performed in many parts of the world where patients or the healthcare
system may be unable to afford the cost of what may well be a precautionary test. However, retinal imaging and observation of problems and changes within the blood vessels can perform many predictive and diagnostic tests on the circulatory system that would not otherwise be ossible. Compared to many ways of examining the circulatory system, retinal imaging is ideal because it is relatively non-invasive, easily repeatable and the circulatory system can be examined "in-situ" without interrupting its functions. Measurement of certain attributes of the eye has been shown by Wong et al in [15] to be related to hypertension and the likely onset of diabetes, in particular characteristic ranges of the arteriole-to-venule ratio, or AVR. This ratio, comparing the retinal arteriole widths and retinal vein widths, is readily measured from photographs of the retina, but performing the measurements is a tedious task that requires a substantial amount of effort by a human observer. Automating the segmentation of retinal images would allow the measurement of arteriole and vein widths to be performed electronically and almost instantaneously, making the diagnostic process faster, cheaper and more reliable. In the Beaver Dam Eye Study, each 10 mmHg increase in mean arterial blood pressure was associated with a 6 mm (or 3%) decrease in retinal arteriolar diameter, even after adjusting for age, gender, diabetes, smoking, and other vascular risk factors .The retinal and cerebral vasculature share similar embryological origin, anatomical features, and physiological properties This concept provides strong biological rationale for the use of retinal image analysis to indirectly study the cerebral microvasculature and related diseases. (ref :Beaver Dam, Rotterdam, and the Blue Mountains Eye studies)

1 Current Techniques of Retinal Imaging

Traditionally the retina has been observed either directly via an ophthalmoscope or similar optical devices such as the fundus camera. These are both visible-light devices that allow the user to view the rear surface of the eye, either directly via a series of lenses, mirrors and a light source, or through taking photographs which can then be examined in detail. The field of ophthalmology was revolutionized in 1851 with the invention of the ophthalmoscope by Hermann von Helmholtz[1] as for the first time detailed examinations of the interior of the eye could be made in living patients. The ophthalmoscope and later the fundus camera remained the primary methods of ocular examination into the 1960's, and they are standard tools still effective and in use today, although they are not without limitations, and both require trained users to operate and make diagnoses. With advances in medical technology, more powerful techniques were introduced. In 1961 fluorescein angiography was developed by Novotny and Alvis[12] , a procedure in which sodium fluorescein is injected into a vein, and under filtered light the sodium fluorescein within the blood fluoresces, glowing brightly and providing easily observed patterns of blood flow within the eye. This allows the arteries, capillaries and veins to be easily identified and photographed, and from this, large amounts of information concerning the health or otherwise of the circulatory system can be determined. Once the dye is adminis-tered the speed with which passages fill with marked blood, the rate at which this marked blood spreads through the eye and the time taken for the dyed blood to pass out of the eye are observed. These then provide valuable data about the effectiveness and degree of degeneration of the circulatory system of the eye, which has been shown to be indicative of the greater circulatory system of the entire body. During the 1990's the indocyanine green dye angiography technique was developed; similarly to the flourescein angiography a dye is injected into the bloodstream, however the indocyanine green dye glows in the infra-red section of the spectrum. The indocyanine green dye approach only came into widespread use when digital cameras sensitive into the infra-red became commonly available, and it complements fluorescein angiography by highlighting different aspects of the vasculature of the eye. In particular it enhances the structure of the choroid, which is the layer of blood vessels beneath the retina. These two techniques can be used together to gain a more thorough understanding of the structure and pathologies affecting an eye. They can illustrate patterns of blood flow, haemorraging and obstructions within the vascular system, but, like the ophthalmoscope, both require trained medical staff to perform the procedure, and a clinical environment where the images can be taken and analysed. In addition to these methods for observing the vasculature of the eye there are a range of other, more advanced, methods of mapping structures and changes within the eye, including ultrasound and laser tomography and laser-based blood flowmeters in development and in use. All of these can be used to scan the eye and make observations and diagnoses on the eye and circulatory system.While this is just a brief introduction to some of the diagnostic tools available, all of them suffer to some degree the problems of requiring technically complex and expensive equipment, highly trained specialists to operate the equipment and the risks involved with invasive procedures such as injecting dyes into the bloodstream. While retinal images themselves are relatively easily obtained with minimal equipment and training, to draw diagnoses from these images requires specialist training, and to adequately extract and track the vasculature from the images often takes techniques such as fluorescein angiography or indocyanine green dye. A method of processing visible-light images of the retina, such that the vasculature was able to be segmented from the remainder of the retinal image, and one which did not require the subject to undergo any form of medical procedure beforehand,would allow automated diagnostic tools to be used. Once automatic image analysis is possible, those at risk of numerous diseases and problems of the circulatory system can be rapidly and cheaply identified and referred for further treatment.The development of this method would also allow automated tracking of the progress of such health problems as diabetic retinopathy, and track changes in the eyes and circulatory system as the subject ages. This would have numerous health benefits, including providing an early warning on such diseases as hypertension, renal dysfunction and the risk of stroke or cerebral atrophy, again shown by Wong et al[15],[17]. There would also be substantial public health benefits to widespread precautionary scanning, in that resources could be more appropriately targeted to sections of the population found to be at greatest risk, and the prevalence of many illnesses could be more accurately determined. By allowing the use of automated analysis of easily and cheaply obtained images, retinal image segmentation can bring the advantages of retinal imaging as a diagnostic tool to those who would not have access to the technology or clinicians necessary to acquire and interpret the results of other forms of tests.

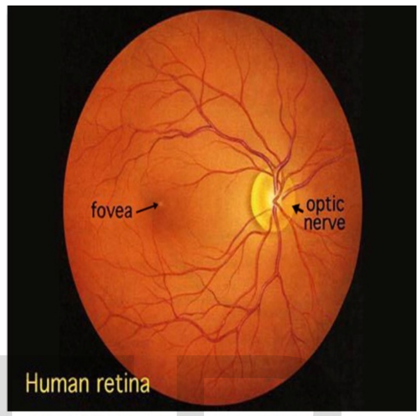


Figure 1. A view of the retina seen though an ophthalmoscope.

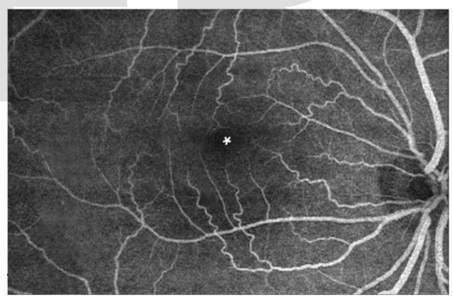


Fig. 17. Fundus photograph showing flourescein imaging of the major arteries and veins in a normal human right eye retina. The vessels emerge from the optic nerve head and run in a radial fashion curving towards and around the fovea (asterisk in photograph). (Image courtesy of Isabel Pinilla, Spain).

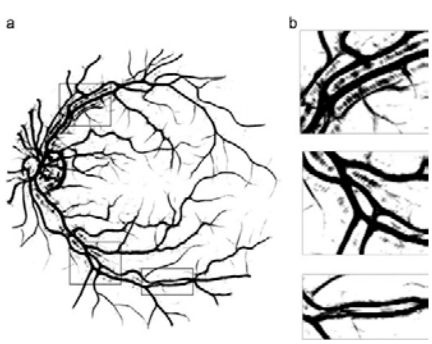
Fig(a)

2 Current Automated Vessel Segmentation Methods

There are a range of techniques that have been examined in order to produce an algorithm that can efficiently segment an image and handle the wide range of variations and features found within healthy and diseased eyes. These range from straightforward image processing techniques that will be familiar to those who have experience with computer graphics or vision, to more complex procedures that look at a range of attributes of a neighbourhood of pixels in an image, and try to determine some characteristic property that allows a decision to be made, classifiying a pixel as either “vessel” or “non-vessel”.

2.1Pixel Methods

The simplest methods of segmenting the vasculature of the eye rely on the observation that when the retina is photographed, and the green channel extracted from that image,the blood vessels appear to be darker than their surrounds. Simply stating that any pixel darker than some threshold is part of a blood vessel is the naive first approach, which will detect some blood vessels, but overall will perform extremely poorly. To improve this approach, the threshold is not based on some fixed global value, but the average brightness across the image is taken, and those pixels whose intensity is greater than the threshold from the overall average image intensity are deemed to be vessel. This method again performs poorly, as light levels and contrast will vary across the image due to initial lighting conditions, pathologies within the eye and artifacts related to the technique used to take the photograph, as well as the skill of the camera operator. Using some local intensity average based on a neighbourhood of pixels surrounding the one in question and then performing the thresholding operation on that pixel can give better results, but these are still less than ideal. However, when combined with further filtering and line detection as performed by Jiang et al [6], to extract only features that have the characteristics of vessels, very good results can be obtained, with Jiang et al [6] managing up to 92.12% accuracy for certain metrics according to a study by Niemeijer et al[11].



Fig(b)

2.2 Edge Detection Methods

A step up from pixel methods based solely on the intensity at a given point are edge detection algorithms. These use standard image-processing techniques such as the Canny, Sobel and Laplacian operators to extract lines from within the image. While they are appropriate for many applications in computer vision, generic edge detection operators are less appropriate for the task of retinal vessel segmentation due to the fact that most vessels have boundaries that are blurred or indistinct, and very fine vessels are often only two or three pixels wide, which are not picked up, instead being seen as part of the background. In addition to this, the edge detection operations do not distinguish between vasculature and pathologies within the eye. They can falsely despite the fact that in isolation they are not adequate for the entire task at hand.

2.3 Exploratory Algorithms

Exploratory algorithms, as demonstrated by Can et al in 1999 [2] and later by Grisan et al [3] in 2004 begin by sampling a large number of points within the image at regular intervals. They then perform operations on these sampled points to determine the likelihood that these pixels are within a blood vessel. Once some candidate seed points have been determined to be blood vessels, directional edge detection filters[2] are used to trace out the path of the blood vessel across the surface of the retina. Having acquired some candidate points that are likely to be vessels, antiparallel edges are searched for using directional templates similar to the edge detection templates of Sobel and Prewitt. Antiparallel edges are those that are in opposing directions on either side of the candidate vessel, of sufficient strength to indicate the presence of a legitimate edge. Once strong directional edges are detected, they must be filtered to determine the actual location of the blood vessel relative to the edges. Part of the filtering of the detected edges is that they are oriented at 180 degrees, ±22.5 degrees, in the case of [2]. This prevents edges that clearly belong to different vessels being grouped together as only those edges sufficiently parallel to belong to the same vessel are recorded as being potential edges to the section of vessel being traced.This has the advantage, as explained by Lin et al [9], of substantially reducing the processing required relative to pixel-based methods, as in the initial stage only some small number or pixels need be processed to determine whether or not they are likely to be vessel, and from this starting point only vessel pixels and a small boundary around them are processed. Pixels that represent vessels in an image consist of between 10% and 15% of the field of view, as has been shown in papers by Niemeijer et al [11], and Stall et al [14],and verified in the course of our experiments. Because of this exploratory algorithms can significantly cut down on the processing required per image. This is particularly relevant where vessel identification is being used to guide computer-controlled surgical equipment,as new images are typically provided to be processed at 30 or more frames per second from video equipment, and processing must be done in real

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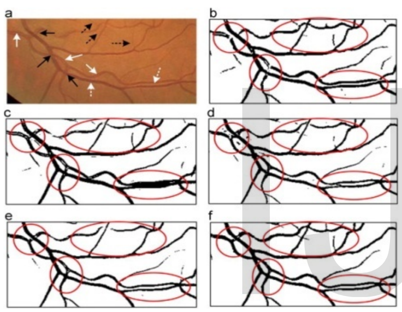
time to provide feedback and guidance to surgical tools

2.4 Ridge Detection

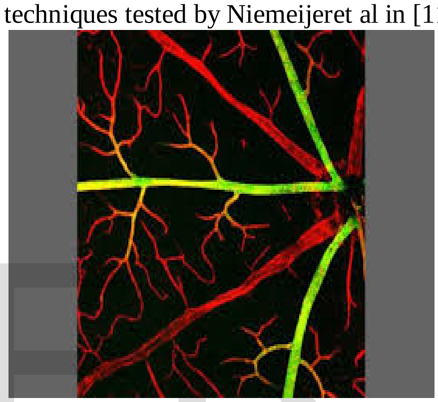
Ridge detection is based on the observation that the vessels can be modelled as ridges,where for each pixel a gradient is determined, based on the intensity of that pixel and surrounding pixels. Once a gradient is determined for each pixel the direction of maximum curvature can be determined along a line covering several pixels, and the peak of the ridge is that point at which the gradient is zero. Once the ridges have been highlighted further processing is done to link ridges and classify pixels based on their gradients and that of neighbouring vessel pixels. The effectiveness of one implementation of such an approach is shown in the paper published by Staal et al [14]. In this study the method was shown to perform fairly well, achieving a false positive rate of 1.9%, but a corresponding true positive rate of only 69.7%.



Fig(c)

2.5 Morphological Methods

The use of morphological operations in image segmentation typically uses combinations of the opening and closing operations to select for features, which may not necessarily be entire objects but components of the object being sought. These opening and closing operators are operations that can repeatedly enlarge and reduce the size of features, allowing the elimination of noise and smaller details by shrinking them to such a point that they are removed from the image, while simultaneously retaining and potentially emphasizing the larger elements. These openings and closings are built up from erosions and dilations,which are conceptually straightforward filters applied to an image that contract or expand the borders of regions, restricting their actions to those that are above or below some threshold of intensity or other criteria. The use of mathematical morphology is explained by Zana et al [18], with results obtained in [18] compared against other current image segmentation techniques by Niemeijer et al in [11] and against a wavelet-based image segmentation technique implemented by Leandro et al [2001] in [8]. Leandro et al [2001][8] showed that the morphological approach could extract fine details more reliably than the wavelet approach that they used, but that both approaches required post-processing with region-growing, Sobel edge detectors or adaptive thresholding used to produce the final image. Even following this processing the resulting outputs suffered from noise due to pathologies within the eye and an inability to pick up on very fine capillaries; however the work done by Zana et al was one of the better-performing techniques tested by Niemeijeret al in [11].



Fig(d)

3 Vessel Extraction Techniques

As wavelet transforms can be performed at multiple scales, it was intended that we would review some form of filter or operation that would be extremely accurate at detecting features within some specific range of sizes. Once such a filter was studied then it could be applied repeatedly to versions of the same target image at differing scales, detecting blood vessels of varying sizes. Each of the resulting series of images would then be rescaled to match the initial image size and they would be combined to produce the final segmented image. As part of this these investigations, two separate wavelet transforms were surveyed the Haar wavelet transform and the Daubechies transform.

3.1 Wavelets

Wavelets are a mathematical transform that can be performed on any quantifiable set of values over a finite range, so a wavelet transform can be applied to the pixel intensity values of an image. There are a large number of wavelet transforms of varying levels of complexity,from the most basic Haar transform to continuous Morlet transforms. Owing to the nature of the data, which is discrete, and the fact that we will be processing our data electronically,only discrete wavelet transforms were suited to the task. We investigated two families of wavelets to determine how they could be used as part of an image segmentation technique.. The two wavelets that were surveyed are the Haar wavelet transform,which is the simplest of the wavelets, and the Daubechies wavelet transform, which is a more complex wavelet that may have allowed us to focus on more specific aspects of the image. The Daubechies wavelet also helped to determine what could be gained from moving on to more complex wavelets and what direction our investigations should take.

3.2 The Haar Transform

The Haar wavelet transform was the first transform that was implemented,[19] and it was used to transform target images with minimal loss and in conjunction with a thresholding technique we were able to obtain initial results. The Haar transform is effectively an (averaging and differencing) operation. It operates by transforming a 1 × N array of values into a 1 × N array of results. The first [1...N2] elements of the array are the averages of pairs of the [1...N] original elements, and the following [N 2 + 1...N] elements in the array are the detail

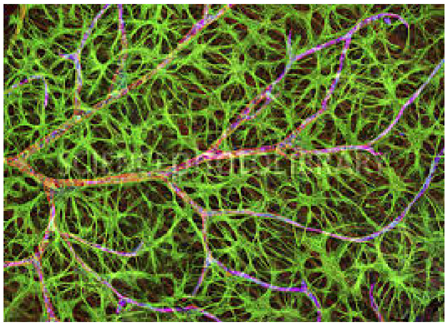
As the average element is equidistant from both x1 and x2, to restore the initial array we simply subtract the detail element from the average element, giving us x1 and add the detail element from the average to restore x2. For2–dimensional images the transform operation is performed on all rows of the image and then again on all columns of the output from the first application of the transform. In the typical transform upon images using standard inverted cartesian geometry the average elements are stored in the top left quadrant of the input image and detail elements stored in the remaining 3 quadrants of the image. The average elements from the top left corner are then processed in the same way as the entire image was to begin with to perform the second level of the transform. This process can be repeated as many times as is desired,each time further reducing the size and resolution of the output image.

3.3 The Daubechies Transform

The Daubechies Wavelet transform operates in a similar fashion to the Haar transform,however where the Haar transform averages two elements in the input array the Daubechies transform considers 4 or more elements, which may be pixels or groups of pixels from previous iterations of the transform. Variants of the Daubechies transform incorporate more coefficients, The transform then multiplies all the elements under consideration by a series of related coefficients to generate its output.The precise details of the Daubechies family of wavelets are too complex the transform involves a series of overlapping operations, as opposed to the Haar

3.4 Adaptive Thresholding

This method was introduced in [6]. From the observation that vessels are typically darker than their surrounds, we began surveying a series of vessel detection methods based upon this fact. These were based on tests of a 8–element neighbourhood at a variable distance around a central candidate pixel, where the central pixel was required to be at or above some threshold darker than the 8 comparison elements. This method is useful for detection of small darker regions entirely within a given area, but was found to fail where the aim was the detection of blood vessels, which typically traverse a large section of the image.The next stage in this process was to require that the candidate pixel was only some level darker than a number of the border pixels, to account for the fact that it was reasonable for a blood vessel to enter the field under consideration, pass through the central pixel and then pass out through the other side of the section being examined, which would mean that some of the border pixels of the region would have similar intensity levels to the central candidate pixel. This approach proved more successful, but is susceptible both to gradual changes of background intensity across the image and to noise. Slow changes in the intensity of the image are caused both by natural variation within the eye and variable illumination of the retina during the photographic process. As such, they are common to all of the retinal images, and there is no simple way of removing them without simultaneously removing large amounts of relevant information. By extending the range that the border pixels were displaced from the central pixel this method could be made less sensitive to minor artifacts and random noise within the image, but this proved to make the technique much more sensitive to the gradual changes of background colour. In brief Researcher **of** Lincoln university have worked on accurate methods for manually marking retinal vessel widths, validating retinal fundus image analysis algorithms: issues and a proposal, an active contour model for segmenting and measuring retinal vessels review **-** a reference data set for retinal vessel profiles, joining retinal vessel segments, a ribbon of twins for extracting vessel boundaries, automated measurements of retinal bifurcations, automated analysis of retinal vascular network connectivity, manual measurement of retinal bifurcation features



Fig(e)

Blood Vessel detection summary

1	2013	Lau PQ	Vessel segment graph
2	2013	Songhuo X	GA + FCM clustering
3	2013	Shanmugam	Extreme learning machine approach
4	2012	Tang y	Merging shape ,region edge information
5	2-12	Rattanapod	Multilevel line detection
6	2012	Chien chenhg	Counterlet transform
7	2012	Rouchdy	Geodesic voting methods
8	2012	Fraz	Ensemble classification
9	2012	Sumathy b	Morphological structur & entropy thresholding
10	2012	Vora R A	Wavelet energy entropy Kekre wavelet feature + Euclidian distance
11	2012	Kundu a	Morphological angular Scale space
12	2012	Holbura C	Supervised classifiers decision fusion
13	2012	Lazar Istavan	Directional height statistic
14	2012	Gegundez	Quality evaluation o vessel
15	2012	Cao	Patch based
16	2012	Ol vera w	Average of synthetic exact filters & hessian matrix
17	2012	Ahmed M B	Phase congruency
18	2012	Lin K	Anatomica realism
19	2012	Baishing	Geodesic time transform
20	2012	Vargaic	Committee of local expert
21	2012	Yu Honggang	Directional mathed filter & level set
22	2012	Hu zhihang	Multimodal 9SD OCT + Fundus)
23	2011	Yavuz	Gabor filter & top hat tranform
24	2011	Fraz	Line strength ,multiscale,gaborr ,morphological
25	2011	Selvathi d	Gabor wavelet & kernel classifiers
26	2011	Marin deigo	New supervised moment invariants based
27	2010	Salazar	Graph cut
28	2010	Paripurna S	Fractal dimension in spatial freq domain

29	2010	Akram M	Thresholding probing Wavelet
30	2010	Peng Q	Radial projection & supervised classification
31	2010	Polomera P	Parallel multiscale feature extraction & region growing
32	2010	Lu shijian	Iterative polynomial smoothing , bilateral filter
33	2010	Youj	2D matche d filter _ gabor filter Otsu _P tile thresholding
34	2010	Demir S	Multithresholding
35	2010	Du Xiaojun	Mumford Shah model gabor wavelet filter
36	2010	Adil Mouloud	Statistical base tracking technique
37	2010	Pourezza R	Radon transform & morphological reconstruction
38	2010	Lupassa	Using ad boost
39	2010	Moju s	Gabor & local binary pattern
40	2010	Palomera p	Parallel multiscale feature extraction & region growing
41	2010	Bhuiyan	Varying contrast & central reflex properties
42	2010	Shivram J	Knowledge based
43	2010	Moghimirad	Multiscale _ medialness function

44	2010	Lam B	Multi concavity modeling
45	2009	Chang Chin	Line operator & edge detector
46	2009	Rezatofighi	Polar run length features
47	2009	Akram M	2D gabor wavelet
48	2009	Akram M	Wavelet Tx ,gabor wavelet
49	2009	Hani a	ICA
50	2009	Parnama	Branches filtering
51	2009	Amin m	Phase congruency
52	2008	Rezatofiglu	Contourlet
53	2008	Salem nancy	Single parmeter ,eigen value of hessian matriix
54	2008	Kande G B	Histogram Matching + spatially weighted fuzzy C menas
55	2008	Espana	Deformable contour model
56	2008	Kande G B	Local relative entropy thresholding
57	2008	Narasimha	Generalized dual Gaussian model
58	2008	Yedidya T	Kalman Filter
59	2008	Fraz M	Center line & morphology
60	2008	Lam B	Divergence of vectors field Laplacian operators
62	2008	Basher al	Joining retinal vessel
63	2007	Martinez p	Insight segemnetation

			& registration tool kit
64	2007	Ricci E	Line operator &SVM
65	2007	Bhuiyan A	Unsupervised texture classification
66	2007	Supot s	Fuzzy K median clustering
67	2007	Li wang	Multiresolution Hermite model
68	2007	Wu Chang	Hybrid filtering
69	2007	Garg S C	Unsuoervised curvature based
70	2007	Zhang	Non linear projection
71	2007	Mac gillivray	Fractal analysis
72	2006	Salem N	Scale space features & k nearest neighbour
73	2004	Qing Z	2D entropies of gray level gradient co occurrence matrix

Conclusion;

Thus it becomes clear from various study that the vascular structure detection is important in diabetic retinopathy and the measurement of the parameter of vessel such as the width ,thickness,turtosisity ,junctions of vessel are of most important in early diagonosis of cardiovascular disease. The segmentation method and extraction methods are explained in brief ,this methods are applied to 2D images we want to see whether the above methods are suitable for 3D images .The paper also gives the comprehensive list of work done for the last decade.

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