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A Novel Minimal Path Algorithm for the Extraction of Curve-Like Structures

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Abstract: Minimal path techniques can efficiently extract geometrically curve-like structures by finding the path with minimal accumulated cost between two given endpoints. The conventional minimal path techniques suffer from some notable problems such as endpoint problem, shortcut problem and accumulation problem. Here a Minimal path techniques that can efficiently extract geometrically curve-like structures is find out as a solution called Minimal Path Propagation with Backtracking (MPP-BT). The MPP-BT method first applies a minimal path propagation from one single starting point and then, at each reached point, traces certain steps back to the starting point. The backtracking in the proposed approach goes beyond the basic tracking backward operation by fully exploiting the information on visiting preference and cost increments during this backtracking process to give an overall effective structure extraction. A robust stopping strategy is built by evaluating the evolution of cost increments in backtracking during the propagation. It only requires a coarsely user-defined starting point for the whole structure extraction and is robust to parameter setting. The three problems can be well solved by the discriminative revisiting and the cost resetting scheme along the backtracking paths in the proposed MPP-BT method. This MPP-BT algorithm was tested on 2D crack images and 2D vessel images.

Keywords: Curve-like structure, centerline, minimal path tracking, backtracking, endpoint problem, shortcut problem, accumulation problem.

1. INTRODUCTION

Medical image segmentation is an essential, primary, and important step for clinical tasks such as 3-D organ visualization, disease diagnosis, and surgical planning. The extraction of vascular objects such as blood vessels, coronary arteries, and retinal blood vessels, has attracted the attention of more and more researchers. Extracting vessel structure remains a challenging problem because of a number of technical problems [2]. Due to partial volume, the intensity of small vessels become weaker or even completely disappears. Special image filtering is required to remove these artifacts from the data while preserving the details of small vessels. Even after these filtering, it is still not easy to extract the image structures which can be either the segmentation or the centreline of the object. A centreline is a continuous imaginary line through the centre of an object. Every point on the centreline must have more than one closest point to the boundary of the object [3] .

The importance of image processing for visual inspection has been increasing in various fields, especially in industrial production. As for the civil and construction engineering, visual inspection has been strongly required to examine and maintain the safety of structures. At present, the most popular method for inspection of concrete block structures depends on the specialists knowledge and experience by means of sketch of cracks which is manually produced. However, the method does not only required time and effort, but also lacks objectivity for quantitative analysis. An efficient and economical method is required in order to accomplish an efficient and accurate diagnosis of concrete structures.

The work focuses on extracting the topological structure of a 2D vessel images and 2D crack images. The proper vision and identification of CT (Computer Tomography) Coronary Angioplasty images, MRI (Magnetic Resonance Imaging) Angiography images and crack images are not possible. The retinal vessels and crack images are so minute that they cannot be extracted normally [4]. The project proposes a novel algorithm that can extract and analyses these images by employing minimal path techniques. Minimal path techniques can efficiently extract curve-like structures by optimally finding the integral minimal-cost path between two seed points. Successful applications of minimal path techniques have been found in contour completion, tubular surface segmentation, vascular centerline extraction, skeletonization and motion tracking. Minimal path techniques are fast and can avoid local minima by efficiently finding the global energy minima. As noted in, minimal path techniques can effectively locate tiny vessels and overcome vessel crossing and inhomogeneous intensity distribution in presence of stenoses or image degradations. However, some inherent problems should also be noticed for these minimal path based techniques:

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endpoint problem, shortcut problem and accumulation problem. Addressing these three issues is of major importance in dealing with complex topologies (i.e. multiple branches or lines), noise and inhomogeneous contrasts [5].

The paper proposes a novel algorithm that can extract and analyze Computer Tomography (CT) Coronary Angiography and crack images by employing minimal path techniques. The Computer Tomography(CT) Angiography images, Magnetic Resonance Imaging(MRI) Angiography images and crack images are been treated here as curve like structures. A semiautomatic method based on a minimum cost path approach has been evaluated based on frequently used vesselness measure and intensity information. User interaction should be minimized to one or two mouse clicks distally in the selected image. The study is very valuable for visualization and quantification of pathologies. The structure enables the clinician to make accurate measurements of the extent of pathologies and to visually inspect them at the same time. Those trajectories can also be the input to an endoscopic tool. And are applicable for the civil or safety engineers to identify and to find the extent of cracks in buildings, thereby they can execute necessary actions.

Here a solution termed Minimal Path Propagation with Backtracking (MPP-BT) is applied to face the three above problems. The MPP-BT method first applies minimal path propagation from one single starting point and then, at each reached point, traces certain steps back to the starting point. The Backtracking is the main techniques employed here and there by overall efficiency and performance could be improved. The backtracking in the proposed approach goes beyond the basic tracking backward operation by fully exploiting the information on visiting preference and cost increments during this backtracking process to give an overall effective structure extraction. A robust stopping strategy is built by evaluating the evolution of cost increments in backtracking during the propagation. It must be noticed that only a coarsely user-defined starting point is required for the whole structure extraction. The proposed method is applicable for subsequent analysis in clinical practice, research and for practical applications.

2. MINIMAL PATH THEORY IN CURVE-LIKE STRUCTURE EXTRACTION

In graph theory, the shortest path problem is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized. The problem of finding the shortest path between two intersections on a road map (the graph's vertices correspond to intersections and the edges correspond to road segments, each weighted by the length of its road segment) may be modelled by a special case of the shortest path problem in graphs. If one represents a non deterministic abstract machine as a graph where vertices describe states and edges describe possible transitions, shortest path algorithms can be used to find an optimal sequence of choices to reach a certain goal state, or to establish lower bounds on the time needed to reach a given state. Here the same minimal path technique is used for extraction of curve-like structures.

A. Limitations

In most applications of minimal path techniques, the question is mainly to find a way to reduce the user interaction when the target objects of interest have complicated topologies. The minimal path techniques suffer from some notable problems such as : endpoint problem, shortcut problem and accumulation problem.

Endpoint problem states that the requirement of setting two endpoints for each line to be extracted. The endpoints may be the starting point and the endpoint. But in most of the complex topologies that we are considered as the curve-like structures, it is not easy to predetermine the endpoint prior to the proper extraction. This would create false results than the actual result , making them insufficient for practical applications. The shortcut and accumulation (leakage) problems may be exemplified with Fig. 1 and Fig.2 (simulated images from [4]). Shortcut problem states that the connection might fail when the geodesic distance between the two points is much shorter than the desirable minimal path. In Fig. 1, depicting the shortcut problem, the line is open and the starting point is very close to the end point. Instead of extracting the desirable line in Fig. 1(c), the Dijkstra algorithm often tends to output the near shortest line corresponding to the shortest distance between the two endpoints, as seen in Fig. 1 (b). The Fig. 1 and Fig. 2, in which the simulated images were generated by adding a closed curve with low intensity contrast on a noisy stationary background. Image intensities are used in building the potential map P. In the Fig. 1(a) is the original curve image with the starting point (red) and end point (green); (b) and (c) illustrate respectively the wrong connection due to the shortcut problem and the desired connection (in red).

Accumulation problem states when connecting two distant points, the minimal path connection might become inefficient as the accumulated cost increases over the propagation and results in leakage into some non-feature regions near the starting point. In Fig. 2.3 (from [4]) shows that, as the minimal path tracking proceeds, more and more nonrelevant points near the starting point are traversed before the end point is reached to give the desirable minimal path connection (overlaid in red line). It is recorded from [4] that 7708 points needed to be traversed before the specified end point was reached. As the cost accumulates, the minimal path tracking becomes less efficient as the inclusion of more nonrelevant points. This problem is termed accumulation problem (or leakage problem). In Fig.2 Image intensities are used in building the potential map P.

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B. Applications in curve-like structures

Minimal path methods extract curve-like structure in an image by searching the connected path with a contour dependent minimum integrated energy between two user preset points, a starting point and an end point. Let f be the image. Here initially define E(C) as the integrated energy along a path C according to a given cost function:

$$E(C) = \int_{\Omega} \{w_1 \|\dot{c}(s)\|^2 + w_2 \|\ddot{c}(s)\|^2 + P(C(s))\}\, ds \qquad (1)$$

where C(s) represents a curve drawn on a 2D or 3D image, Ω its domain of definition, and P the potential function or penalty image term, being small where the curve should be attracted. Dismissing the second derivative term and using the arc-length s parameterization in the energy leads to the expression

$$E(C) = \int_{\Omega} \{w + P(C(s))\} ds \qquad (2)$$

where, Ω is the data space, and E(C) represents the energy along the path C; ω is the regularization term (often a real positive constant) and $C(s) \epsilon (\mathcal{R})^n$ is a parametrized curve with the arc lengths, that means $\|C(S)\|^2 = 1$. P(C(s)) in Eq.(2) denotes the cost (or potential) values for the points in the path C. P can be practically considered a pixel-wise cost map, whose values are calculated assuming that feature points have smaller values than non-feature points in image f . Thus, the map P should be built according to the specific properties of the target images. Given a potential $P \geq 0$ that takes lower values near the desired boundary, the objective of the minimal path technique is to look for a path (connecting two user-supplied end points) along which the integral of $\widehat{P} = P + \omega$ is minimal. Simple or more sophisticated information like the image intensity, the medialness measures or the sphere-based 4D curves can be used.

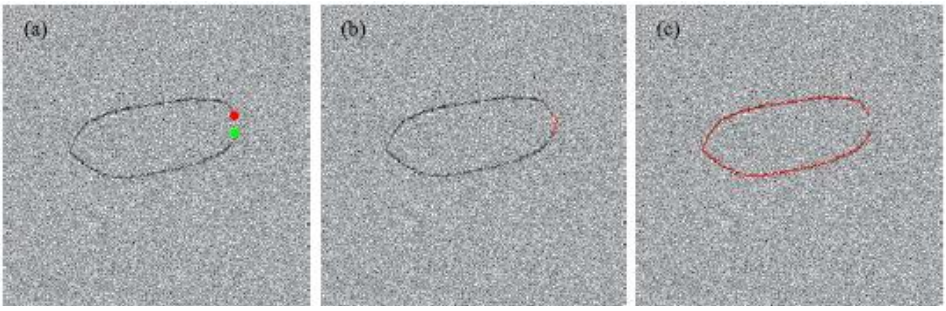

Fig. 1. Illustration of the shortcut problem for minimal path tracking

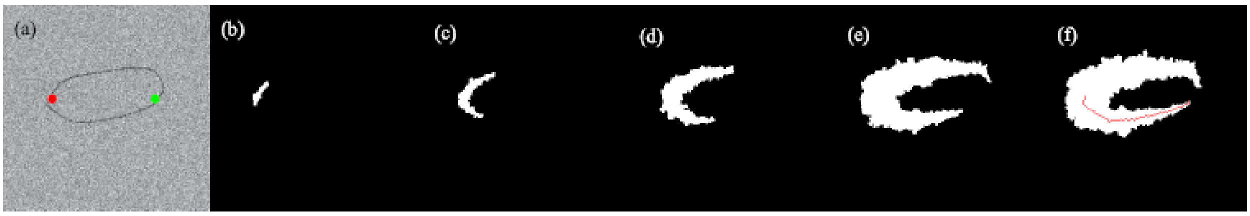

Fig 2. Illustration of the accumulation problem for minimal path tracking

The minimal path cost U(P_s ; p) between the current point p and the starting point P_s is defined as the minimum integrated cost among all the possible paths between the two points:

$$U(p_s, p) = inf \; \{ E(C), C \in A\, (p_s, p)\} \qquad (3)$$

$$= inf \left\{ \int_{\Omega} \hat{P}\,(C) ds, \;\; C \in A\,(p_s, p) \right\}$$

where, A(P_s ; p) is the set possible paths linking P_s and p, from which the minimal path between P_s and p can be efficiently found by applying either the Dijkstra algorithm and fast marching algorithm.

The Dijkstra algorithm can be applied by first setting all the node costs to infinity and then using an explicit discrete front propagation with direction pointing from the current minima to its neighbouring nodes. If a small cost U accumulated from the starting node is found the cost for each reached points will be updated. At every steps a priority queue may be setup to find the next point with minimum accumulated cost U compared to other points. But the implementation of the Dijkstra algorithm alone will be time consuming and less efficient. Since the Dijkstra algorithm suffers from a strong metrication problem. The Fast Marching algorithm replaces the graph update by a local resolution of the Eikonal equation.

The fast marching method is a numerical minimal path technique for solving boundary value problems of the Eikonal equation. This reduces significantly the grid bias, and can be shown to converge to the underlying geodesic distance when the grid step size tends to zero. Fast

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marching method takes advantage of this optimal control interpretation of the problem in order to build a solution outwards starting from the "known information", i.e. the boundary values. The algorithm is similar to Dijkstra's algorithm and uses the fact that information only flows outward from the seeding area. This problem is a special case of level set methods.

3. THE MINIMAL PATH PROPAGATION WITH BACKTRACKING (MPP-BT) APPROCH

A. Backtracking

Backtracking is a method of solving problems by assigning values to variables, one variable at a time. After each variable is set, an intermediate test is done to determine whether there is any hope of a solution. So long as there is a hop, additional variables are assigned values. If there is no hope. The next value is tried for the most recently set variables and testing continues. In this way all possible assignments of values to variables are considered implicitly. The version of backtracking continues even after the first solution is found. By using intermediate tests backtracking can solve problems much rapidly than they can solve by explicit enumeration.

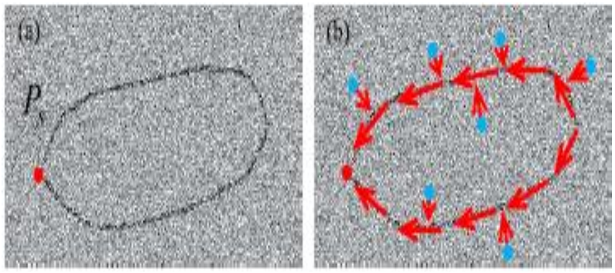

Fig. 3. Illustration of the backtracking operation in the minimal path propagation

As illustrated in Fig. 3, if there is a trace back from the minimal path each reached grid point p to the starting point ps, feature points (the points located inside the target curve like structures) will receive much more revisits than nonfeature points (the points located outside the target curve-like structures). This is due to the fact that feature points always have smaller cost values than non-feature points and the backtracked path is also the one with the minimal accumulated cost. In most time, such backtracking will reach feature points after some steps if the minimal path propagation is limited to the region around the target structures.

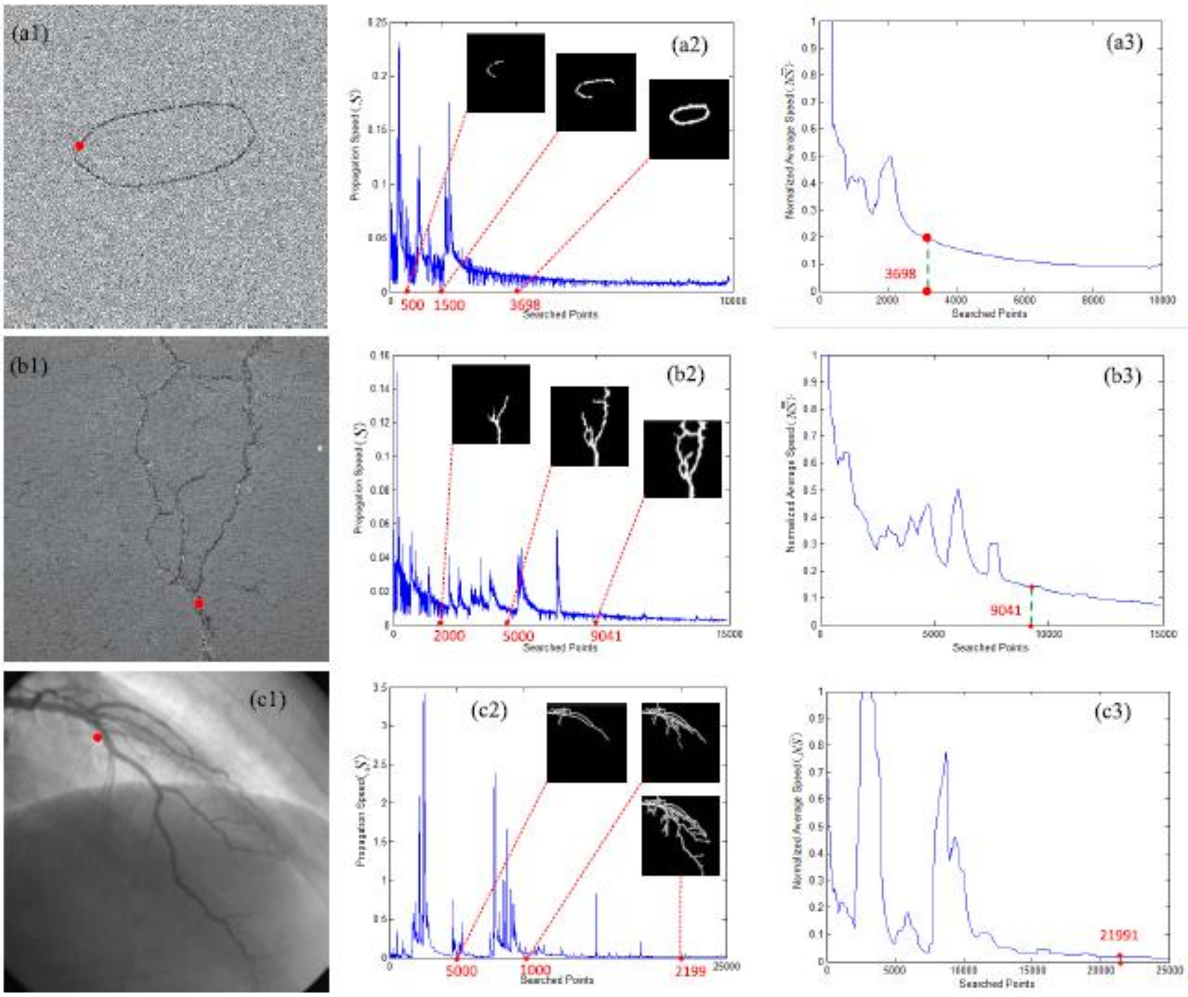

Fig. 5. Illustration of the MPP-BT stopping criterion

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The information of visiting preference and cost increments in such backtracking process can be exploited to overcome the problems mentioned earlier. This algorithm is termed Minimal Path Propagation with Back- tracking (**MPP-BT**), and this backtracking idea was first applied in our previous work in to build a centreline constraint for the region growing algorithm in vessel segmentation.

B. Overall Algorithm

a) Backtracking operation

First initiate the minimal path propagation with the Dijkstra algorithm and fast marching algorithm, from a starting point P_s . For each grid point P reached by the propagation front, calculate the cost value P(p) according to Eq. (2) and then track l_{bk} steps from point p backward to the starting point ps based on the connection information obtained from the previous minimal path propagation. The backtracking is stopped if the starting point ps is reached before l_{bk} steps. The minimal path propagation is controlled via a stopping strategy explained below to limit the propagation within the region around the target features. This implies that such backtracking always reaches a feature point after l_{bk} steps. For each last point (denoted by ${P_{bk}}^E$) in each backtracking path, then accumulate the reciprocal of its cost value P(${P_{bk}}^E$)) for the point ${P_{bk}}^E$ to form a feature map $\hat{I}_{BK}$:

$$\hat{I}_{BK} = \hat{I}_{BK} + \frac{1}{\eta + \hat{I}_{BK}} \qquad (4)$$

where η is a small positive constant to avoid a zero-valued denominator. Considering the fact that the feature points will get much more visits in the backtracking operations than nonfeature points, the feature points get much more accumulation in Eq. (3) than non-feature points.

b) Propagation stopping criterion

The MPP-BT algorithm is to be stopped when the target region of interest has been traversed, for which a proper stopping criterion is required. The stopping criterion is inevitable for reducing the computational cost and for avoiding the accumulation of wrong connections from non-feature points with the feature points. It is already been seen that always the feature points having the lower cost values will get the more revisit than the feature points with higher cost value and with the nonfeature points, during backtracking. Based on this fact the cost difference, (U(p)- U(${P_{bk}}^E$))along the backtracking path will significantly increase when the propagation starts to pick up non-feature points with much larger P values after the traversing of the feature region. A pixel-wise metric S(p) termed backtracking speed is used to quantify the backtracking distance over cost increment:

$$S(p) = \frac{l_{bk}}{(U(p) - U({P_{bk}}^E))} \qquad (5)$$

Where (${P_{bk}}^E$) is the point with l_{bk} steps back-traced from the current point p. There may be chances for some points near the starting point , may be reached before l_{bk} steps in backtracking, in this case simply reset the l_{bk} to the steps required to maintain the trace back from p to ps. Due to this the propagation speed will always has a higher value in feature region than in the non-feature region.

Its behaviour can be represented by the illustrations in Fig. 5 (a1)-(c1) with four test images (two crack images in (a1) and (b1), and a vessel images in (c1) with the starting points in red.

By plotting the propagation speed S(p) for each reached point p in Fig. 5 (a2)-(c2), some ruptures of the propagation speed values are observed to be followed by decaying tails which often points to the end of the propagation in feature region, and the MPP-BT algorithm should be stopped at this time. It is also provide in Fig. 5 (a2)-(c2) the maps of the reached points for the different propagation phases (indicated by dotted red lines).

Based on the above observation, back tracking speed is a point based speed value, it is too sensitive to local fluctuations (especially points near P_s). So instead of using that the normal average speed, $N\bar{S}(P)$ is preffered:

$$N\bar{S}(p) = \frac{\bar{S}(P, l_{AVE})}{S_{max}(p)} \qquad (6)$$

where, $\bar{S}(P, l_{AVE})$ is the average of S values over the l_{AVE} points reached before the point p. Such averaging operation is used to smooth the local abrupt variations as it can be seen for propagation speed values in Fig. 5 (a2)-(c2). The propagation may be stopped when there are successive l_E points with lower values than $N\bar{S}^{min}$. $N\bar{S}^{min}$ is nothing but a dynamically varying parameter. At the begining of propagation $N\bar{S}^{min}$ may be initialized to a preset value ${N\bar{S}^{min}}_0$ (0< ${N\bar{S}^{min}}_0 < 1$). $N\bar{S}^{min}$ may be upadated minimum $N\bar{S}$ value among the already reached points. (ie, the newly reached point may have a smaller $N\bar{S}$ value than the current $N\bar{S}^{min}$.

4. RESULT ANALYSIS

A. Parameter Setting

The MPP-BT method involves six parameters to be set, namely, the l_{bk} to constrain the backtracking steps, the η in the Eq.(4). The propagation stopping mechanism includes the parameter l_{AVE} in computing the normalized average speed, the successive point number l_E and the initial value ${N\bar{S}^{min}}_0$ for $N\bar{S}^{min}$. The intensity values are directly used to calculate the pixel-wise cost map P. The Table 1 below shows the parameter settings of MPP-BT method, Most parameters in Table 1 were selected based on the information (e.g. the cost map values, the feature map values) collected in the minimal path propagation and backtracking, and choosing the one with the good results.

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Table 1

PARAMETER SETTING FOR THE MPP-BT METHOD	
Test Data	**Parameter Settings**
Simulated curve image in the Fig. 2(a) and the crack image in the Fig. 4(b1)	$l_{bk} = 15, \alpha = 0.7, \eta = 0.001$ $l_{AVE} = 1000, l_E = 1500, N\bar{S}^{min}{}_0 = .2$
Crack images	$l_{bk} = 15, \alpha = 0.7, \eta = 0.001$ $l_{AVE} = 1000, \quad l_E = 1500,$ $N\bar{S}^{min}{}_0 = 0.05$
2D Vessel data	$l_{bk} = 15, \quad \alpha = 0.7, \eta = 0.001$ $l_{AVE} = 1000, \quad l_E = 1500,$ $N\bar{S}^{min}{}_0 = 0.05$

B. Extraction Result

The 2D crack and 2D vessel (CTAG) images are considered for the analysis. Prior to the proper extraction the image need to be pre-processed for obtaining a preferable output. It helps to obtain better results by improving the image quality by suppressing noise and artefacts in the images. Here we there are two stages for pre-processing. The first stage is Gaussian blurring for establishing proper edge detection and the second stage is for intensity adjustments.

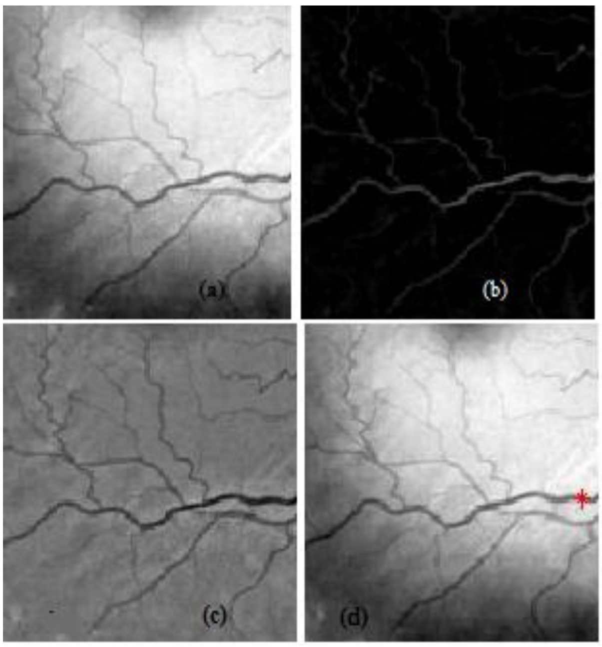

Fig.6. The Vessel Image (a) Gray Scaled input (b) Smoothed Image (c) Intensity Adjusted Image (d) Starting Point Initialized (Red star)

The intensity adjustment is mainly employed for making the intensity profile more evident, because intensity variation is mainly utilized in MPP-BT method for creating potential maps. The algorithm is programmed to work only in gray scale images so the colour input images are converted to gray scale format for the extraction. The input and smoothed version of 2D CT Scan vessel image and a 2D crack image are shown respectively in Fig. 6(a), 7(a) and Fig. 6(b), 7(b) and also intensity adjusted images of both the images are shown in the Fig. 6(c), 7(c). Using a Gaussian Blur filter before edge detection aims to reduce the level of noise in the image, which improves the result of the MPP-BT algorithm.

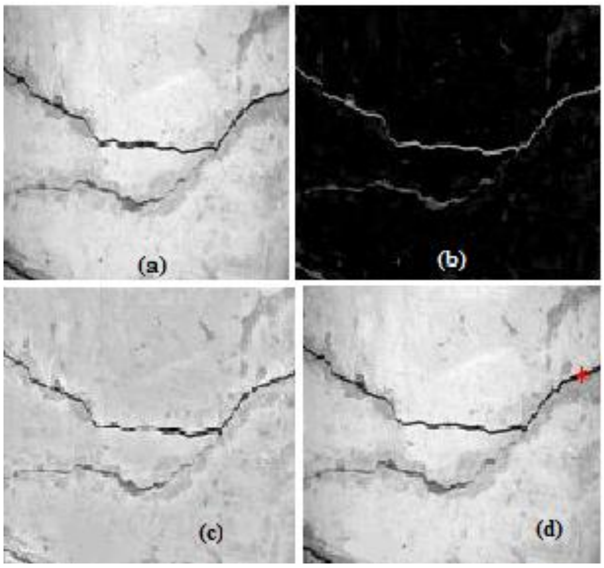

Fig.7. The Crack Image (a) Gray Scaled input (b) Smoothed Image (c) Intensity Adjusted Image (d) Starting Point Initialized (Red star)

The image is then intensity adjusted in which the user-defined starting point is initialized (indicated by red point). The actual algorithm will get executed after this step. The selected starting points in vessel and crack images respectively are shown in the Fig. 6(d) and Fig. 7(d).

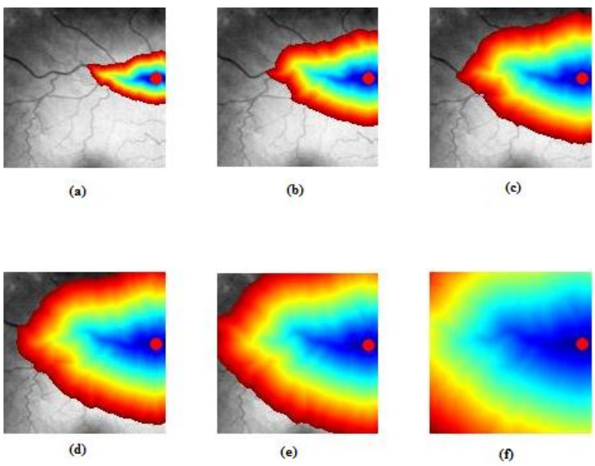

Fig. 8. The Gradient points in a Vessel image

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We need to represent the gradient points that are being generated and progressed as per the propagation of MPP-BT algorithm right from the user-defined starting point. Gradient points are nothing but a level surface, or isosurface, which includes a set of nodes (pixels) that may be having a definite cost value, obtained through minimal path technique . Here the cost values corresponds to those nodes having minimum intensity profile obtained through backtracking under minimal path propagation. The nodes may be divided into four profile zones - blue, green, yellow and red. The blue is the nodes which is in the nearest proximity of the starting node, the green and yellow are the intermediate points while red denotes the nodes that are at the farthest proximity of starting point. The stage by stage flourishing of gradients in the complete image (vessel image) is shown in the Fig. 8.

The final extracted image of vessel and crack images are shown in the Fig. 8 (a) and (b) respectively. Where the boundary points are denoted by blue points. The extracted image provides the information of all the curves associated with it.

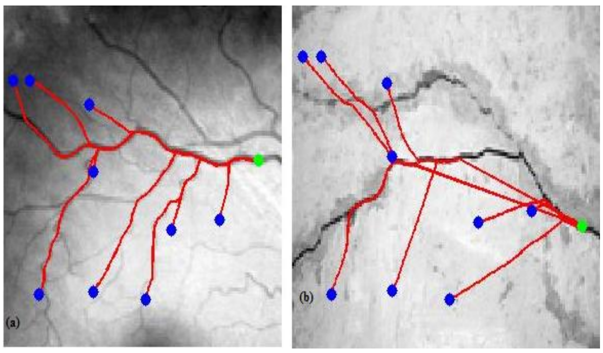

Fig. 8. Final extracted image of (a) Vessel (b) Crack image

But if the user wants to extract a particular region of interest among the total curve, then he may select the region of interest with a user defined starting point and with a user-defined end point. The image so extracted for the same vessel is also shown in the Fig. 9(b). This additional feature is incorporated to provide more flexible and viability to the user in analysing the extraction results

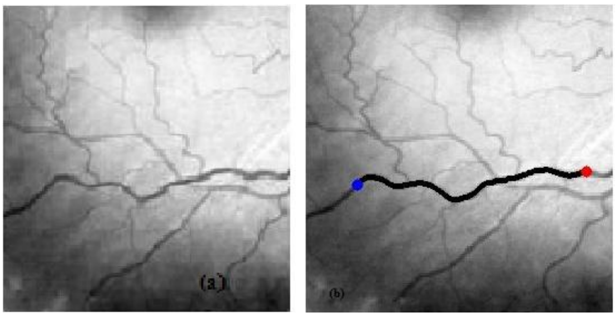

Fig. 9. The final extracted vessel images with a used defined end points

C. Qualitative Evaluation

The basic problems of extracting an image through minimal path technique that we had initially mentioned like shortcut and accumulation problems can be well solved by the cost resetting scheme based on the cost increments along the backtracking path. The MPP-BT method helps to reset the accumulated cost U(p) of each reached point p to the difference between the costs of the current point p and the last point P_{bk}^{E} in the path back-traced from poin p. In this way, it is possible to reduce the accumulated from the starting point to the accumulated cost last P_{bk}^{E} in the backtraced path. The cost so obtained may be used as minimal path cost for point p because the last back-traced path are feature points. Since the feature points may get more revisit than the non feature points.

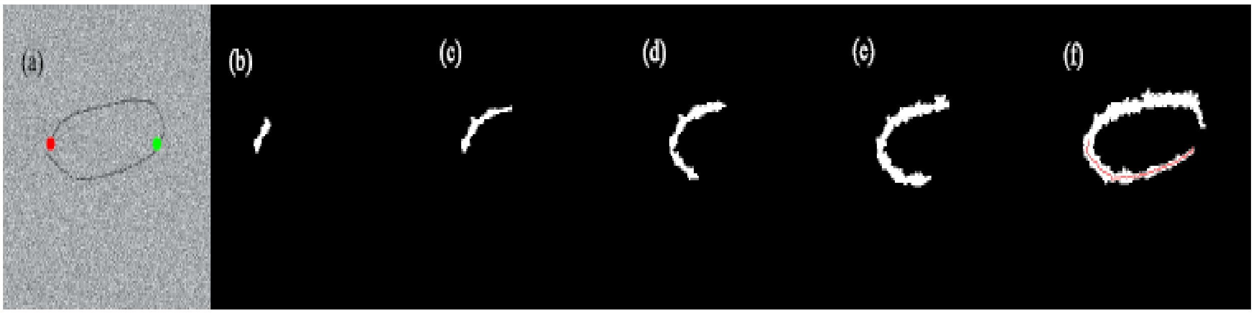

Fig. 10. Illustration of the reduction in accumulation problem achieved by using cost resetting scheme

Compared to the result in Fig. 2, we can see in Fig. 10 that this cost resetting scheme leads to improved tracking efficiency, in other words, the desirable connection can be obtained with much less points traversed than the result for the original minimal path tracking in Fig. 2 (1826 vs 7783). The accumulation problem can thus be overcome by this cost resetting scheme. It is also noted that accumulation is only imposed on the last points other than on all the points in backtracked paths, and this will lead to less computation cost than the method conventional method. The proposed method highlights the tracking trajectory by simply adding one count to each backtracked point. The normalized average speed based stopping strategy is crucial to the performance of the proposed method. Structure missing or wrong inclusion will result if the minimal path propagation stops too early or too late. The Fig. 5

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illustrates the evolution of the traversed regions as the propagation goes on for two typical crack images, one 2D vessel image and one 3D vessel image. It is seen that proposed stopping strategy is overall robust in limiting the propagation within the regions of the target structures.

5. APPLICATIONS OF THE PROPOSED SYSTEM

As it is already been seen the proposed work is mainly applicable in vascular centreline extraction and in crack detection. Coronary artery disease (CAD) is currently one of the main causes of death in the world. Computed tomography coronary angiography (CTCA) is a non-invasive technique that allows both the evaluation of the coronary lumen and vessel wall. It provides information regarding the presence, extent, and type (noncalcified or calcified) of coronary plaques. The project focuses on extracting the topological structure of a 2D vessel images and 2D crack images. The proper vision and identification of CTCA images and MRI (Magnetic Resonance Imaging) Angiography images are not possible. The retinal vessels and crack images are so minute that they cannot be extracted normally. The project proposes a novel algorithm that can extract and analyse these images by employing minimal path techniques.

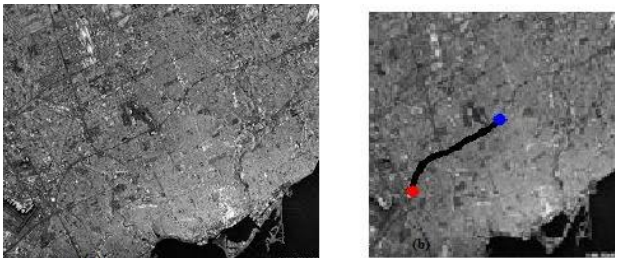

Fig. 11 Extraction of Space Image

Also the need of image processing for visual inspection has been increasing now days in various fields, especially in industrial production. As for the civil and construction engineering, visual inspection has been strongly required to examine and maintain the safety of structures. The conventional methods are time consuming and lack objectivity for quantitative analysis. Moreover the extent and severity of the crack cannot be obtained. There are several crack detection systems in the market but many of these systems are not fully developed. A system that can detect, measure and localise cracks is optimal. The proposed method finds a solution for these limitations.

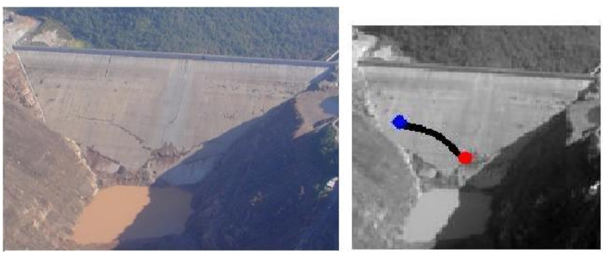

Fig. 12. Extraction of a crack in a dam

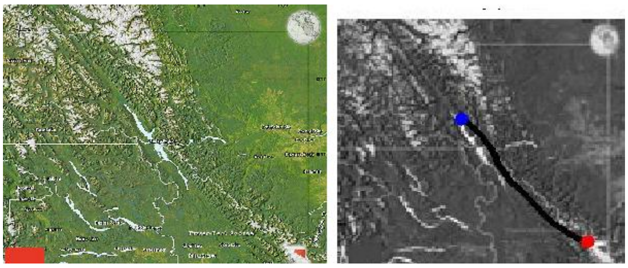

Fig. 13. Extraction of a River from the Satellite Image

Instead of these the proposed system can be applicable in some other areas as well. Such as in analysis of spacecraft images, Structural Health Monitoring (SHM) of bridges, dams and tunnels, for feature extraction of satellite images and so on. The spacecraft images unravel the geographical details and extraterrestrial life in space. The images so obtained may not be clear and requires proper techniques to segment the figure based on location of a particular features on the surface. If we wanted to segment the figure in between the impression, cracks or valleys on the surface of the planets, the proposed system may be used to track the corresponding physical feature from the figure. SHM of a structure performs structural characterization and damage detection over time in order to provide reliable information regarding the integrity of the structure. Prolonged periods of rainfall and flooding, Inadequate spillway capacity in dams, internal erosion and Earthquakes are the main reasons for the failure of a structure, which typically cause longitudinal cracks at the tops of the embankments and that leads to structural failure. These cracks can be extracted trough MPP-BT method and can be used as a best aid for SHM.

Satellite images are images of the Earth's surface. Although satellite imagery is very useful, it does have some downfalls. One of the most common types of satellite images is the Landsat image. Landsat satellites collect and transmit images which show both physical and cultural features on the Earth's surface. To create an adequate image from space, optimum conditions are also required. Weather patterns can be unpredictable and the sun, which is the major source of light, needs to be in an ideal position. The altitude at which satellite photographs are taken sometimes makes it difficult to distinguish ground features. The MPP-BT can be used as a solution to these problems. It helps to track the rivers, crevices etc. The corresponding extraction of a space image, crack in a dam and extraction of a river from satellite image on the earth surface are being respectively shown in the fig. 11, 12 and 13.

6. CONCLUSION AND FUTURE SCOPE

An approach termed MPP-BT is developed based on the intuitive observation that feature points with low cost value points will always receive much more revisits than non-feature points. Backtracking is the key feature of this work. The basic problems such as endpoint, shortcut and

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accumulation problems that are encountered when we are employing minimal path approaches can be rectified through MPP-BT algorithm through visiting preference and cost increments in the backtracking process. The discriminative revisit and the cost resetting scheme which is achieved through the backtracking in the proposed MPP-BT method is well used to solve the formatted issues. During backtracking the cost difference between two feature points may be calculated and whenever it crosses the non feature points this cost difference goes high and can be used as an indication of region outside our target zone. This reduces propagation of minimal path technique to nonrelavent points and thereby we can avoid the shortcut and accumulation issues. The endpoint problem is not an issue in MPP-BT since no user-defined end point is required for the execution of the algorithm. The data collected through the same backtracking technique is been utilized to a stopping criterion for the proposed algorithm. The MPP-BT algorithm was tested on 2D crack and 2D vessel images. The extraction result shows that the proposed algorithm can provide effective extraction of curve like structures with only one user-defined starting point. And moreover the whole algorithm is robust to parameter setting.

Though the proposed algorithm is advanced enough, it may fail in extracting some features when there is an obvious gap between them. This results in giving false curve-like structures in the extraction result. This necessitates the need of a break point connection algorithm to be in cooperated with the proposed algorithm. When the structure of interest includes a complex 3D topologies the extraction fails and early stopping of the propagation might have happen. Even if the extraction is possible it is will be a time consuming task. These issues should also be addressed in future development of algorithm. It is also required to make the proposed algorithm fully automatic, for which the starting point should also be initialized automatically, rather than the current user-defined scheme. And further-more it will be efficient enough, if it is possible to calculate the physical parameter such as area, radius and length of the extracted image.

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