

SYSTEMS AND METHODS FOR VASCULATURE CENTRELINE EXTRACTION**Technical Field**

[001] The present invention relates, in general terms, to the field of vascular disease, and more particularly, to systems and methods for vasculature centreline extraction. More particularly, the present invention relates to, but is not limited to, coronary artery or aortic centreline extraction.

Background

[002] Coronary arteries form an important part of the human heart. The myocardium of a human heart relies on the blood supplied from the coronary artery, and this provides energy for cardiac functions. Identifying the centreline of coronary arteries plays an important role in diagnosis of coronary artery diseases. Identification of the centreline of coronary arteries is also essential to automatically detect and quantify stenoses and plaques in coronary arteries. Similar importance can be placed on detection of centrelines of other parts of the vasculature.

[003] Conventionally, automatic quantification of stenoses and plaque has been done by an extraction of the curved Planar Reformatted (CPR) image from computed tomography coronary angiography (CTCA) using coronary artery centrelines, then training a model based on the CPR images to predict the presence of a stenosis or the extent of plaques. However, these methods tend to focus on the extraction of the full-length centrelines of four main arteries, i.e. the lines starting from the ostia to the end of the distal end of the vessel, without considering the branches and sub-vessels.

[004] There is hence a need for an automatic extraction of the centrelines of coronary arteries from CTCA images, for enabling cardiologists to accurately diagnose coronary artery diseases. Knowledge of the centrelines will then enable the cross section of arteries to be computed with the centreline information, revealing the presence of a stenoses or the extent of blockage to a user.

Summary

[005] Disclosed herein is a system for extracting, from an image, for each of one or more vessels of a vasculature shown in the image, the system comprising:

memory; and

at least one processor, the memory storing instructions that, when executed by the at least one processor, cause the system to:

receive, at a receiver system, a first mask of a portion of the vasculature;

identify seed points in the image, using a shape analysis model, based on a shape of the vasculature in the first mask;

generate, using a centreline tracing model, the centreline for each of the one or more vessels by:

tracing a traced centreline from each seed point;

selecting a candidate centreline from the traced centrelines, based on an anatomical feature of the portion of the vasculature;

and

filtering the candidate centrelines using one or more geometric shape filters to generate the centreline for each vessel; and

output the centreline for each vessel.

[006] Also disclosed is a method for extracting, from an image, a centreline for each of one or more vessels of a vasculature shown in the image, the method comprising:

receiving, at a receiver system, a first mask of a portion of the vasculature;

identifying seed points in the image, using a shape analysis model, based on a shape of the vasculature in the first mask;

generating, using a centreline tracing model, the centreline for each of the one or more vessels by:

tracing a traced centreline from each seed point;

selecting a candidate centreline from the traced centrelines, based on an anatomical feature of the portion of the vasculature; and

filtering the candidate centrelines using one or more geometric shape filters to generate the centreline for each vessel; and

outputting the centreline for each vessel.

Brief description of the drawings

- [007] Embodiments of the present invention relate to systems and methods for extracting, from an image, a centreline for each of one or more vessels of a vasculature, as well as systems and methods for training a model for extracting, from an image, a centreline for each of one or more vessels of a vasculature, and will now be described with reference to the following figures, in which:
- [008] Figure 1 illustrates a schematic of the anatomical relationship of the heart, aorta and coronary arteries. The coronary arteries appear as two free structures, each starting from the ostia connected to the aorta, and branches towards the vessel ends.
- [009] Figure 2 illustrates a workflow of the proposed coronary artery extraction method, according to an embodiment of the present invention.
- [010] Figure 3 shows a schematic of a CNN model for centreline patch orientation prediction.
- [011] Figure 4 illustrates two classes of input image patches for model training, the (a) on-the-line patch and (b) off-the-line patch.
- [012] Figure 5 illustrates the types of vessel mask image patches in 2D.
- [013] Figure 6 illustrates a plot of the calculation of the mean-shift line as the mean centreline of a bunch of candidate centrelines.
- [014] Figure 7 illustrates an example in centreline branch detection filtering. Branch points and sections between branches are detected, (a) in full-length centrelines after a geometric shape filter, (b) after branch detection and (c) after each section is merged.
- [015] Figure 8 illustrates a trace rate within distance limit (T_d), where given a distance d , T_d refers to the ratio of the length of a predicted centreline within a distance d from the annotated centreline over the length of the whole centreline.

[016] Figure 9 illustrates the variable for computing overlap index within a distance d . The shadowed area represents the vessel mask input. C_e and C_r denote the evaluated and reference centrelines, respectively, and d is a given distance parameter.

[017] Figure 10 provides a rendered visual of coronary arteries with the predicted centrelines and annotated centrelines.

[018] Figure 11 is a schematic illustration of a system for implementing the workflow shown in Figure 2.

Detailed description

[019] The following detailed description is merely exemplary in nature and is not intended to limit the invention or the application and uses of the invention. Furthermore, there is no intention to be bound by any theory presented in the preceding background of the invention or the following detailed description.

[020] Disclosed herein are systems and methods for extracting, from an image, a centreline for each of one or more vessels of a vasculature. The following description will be made with reference to steps in the method. It will be apparent to the skilled person that the system disclosed herein, is configured to implement that method. The methods involve identifying a centrelines by detecting seed points and probabilistically extending from the seed points along the centreline to ascertain the trajectory, and thus the overall centreline, of an artery, for example.

[021] Figure 1 illustrates a schematic of the anatomical relationship of the heart, aorta and coronary arteries. The coronary arteries appear as two free structures, each starting from the ostia connected to the aorta and branching towards the vessel ends. It can be seen from Figure 1 that coronary arteries are intrinsically curved, making it difficult to visualise and determine the severity of blockages and stenoses (i.e. the abnormal narrowing of the blood vessel). Centreline extraction allows for the cross sections of arteries to be computed, based on the centreline information.

[022] With reference to Figure 2, a workflow 200 for implementing the present method is shown. In some embodiments, a first mask is received along with an input image, or only those parts of the input image within the first mask may be received. However, without loss of generality and for the sake of illustrating a most comprehensive embodiment, the workflow 200 involves received an image 202 of the vasculature of a patient. The image may be a raw CTCA image or it may have been pre-processed to remove noise, increase resolution or to enhance contrast to improve tissue differentiation. Other, or alternative, pre-processing steps may also be used.

[023] The image 202 is processed using a first machine learning model 204 that generates a first mask 206. Presently, the first machine learning model 204 is a lumen artificial intelligence (AI) model that generates a lumen mask 206, being a mask that retains features of the input image 202 corresponding to vascular lumens of the vasculature shown in the input image 202. The first machine learning model 204 may be trained on data tuples, each data tuple comprising an image of the vasculature of a patient and a mask that retains only features in the corresponding image that correspond to vessels in the vasculature. The first machine learning model 204 is therefore trained to identify the features in the mask from the corresponding original image, and to then use those features to identify vessels in new, subsequently received images. Thus, the first machine learning model 204 generates a lumen mask 206 corresponding to vessels (i.e., vascular lumens) in the input image 202.

[024] The image 202 is also processed using a second machine learning model 208 that generates a second mask 210. Presently, the second machine learning model 208 is a lumen artificial intelligence (AI) model that generates an aorta mask 210, being a mask that retains features of the aorta shown in the input image 202. Similar to the first machine learning model 204, the second machine learning model 208 may be trained on data tuples, each data tuple comprising an image of the vasculature of a patient and a mask that retains only features of the aorta in the corresponding image. The second machine learning model 208 is therefore trained to identify the features in the aorta mask from the corresponding original image, and to then use those features to identify the aorta in new, subsequently received images. Thus, the second machine learning model 208 generates an aorta mask 210 corresponding to aorta in the input image 202.

[025] Without loss of generality, the first mask 206 will herein after be referred to as the lumen mask 206, though it may mask other parts of the vasculature as required in a specific application, with the first machine learning model 204 therefore being configured to identify said other parts. Similarly, the second mask 210 will herein after be referred to as the aorta mask 210, though it may mask other parts of the vasculature or related organ as required in a specific application. Thus, the second machine learning model 208 will be configured to identify the relevant parts or organ as required.

[026] The lumen mask 206 and image 202 are processed by a shape analysis model 212, to identify seed points 214 in the image 202 (or in the portion of the image retained in the lumen mask 206). The seed points are identified based on the shape of the vasculature in the lumen mask – i.e., the portion of the vasculature retained by the lumen mask 205.

[027] A seed point is a point in the vessel centreline where a trace algorithm may begin. Hence, a seed point is often selected to be a point at the end of an artery vessel. This avoids issues associated with certain vessel shapes, in that a single aorta may branch into several vessels. Hence, by setting the seed point to be a point at the end of an artery (i.e., the end distal of the start of the artery, such as where the artery meets the aorta), it ensures that all arteries are covered. On the other hand, if a seed point were to be closer to the start of an artery (proximal relative to, for example, the aorta), not all branches may be covered, should the shape of the vessel be skewed.

[028] The shape analysis model 212 may be a 3D geometric shape analysis model, though in other embodiments it is a 2D shape analysis model. The shape analysis model 212 is applied by a computer system to detect objects similar to those described in a database (e.g. similarly shaped vessels), using a boundary representation to describe the vessels with its boundary, or it may involve using other volume-based analysis such as the constructive solid or point clouds. Such boundary representations can make use of changes in voxel (or “pixel” in 2D implementations) intensity or colour values relative to the values for neighbouring voxels. Such values can be used to infer edges, lines and other features in an image.

[029] A voxel is chosen at the end of each vessel as a candidate for the end of the respective vessel, the voxel corresponding to the seed point for the vessel. The vessel mask or lumen mask 206 (it will be understood that references to the mask refer to the portion of the vasculature shown within, and thus retained by, the mask) is divided into small patches, and if the said vessel terminates within a patch, the mass centre of the vessel may be used as the seed point – i.e., the mass centre is calculated for each patch having image features indicating a vessel enters the patch but does not exit the patch. Dividing the image into patches at the end point may comprise generating a single patch with the voxel at the centre, defining a box around the voxel (e.g., at a predetermined distance in each dimension or direction) and splitting the box up into patches (overlapping or non-overlapping) of fixed size, and other patchifying methodologies.

[030] Using the seed points, a centreline is then generated for each vessel. A pre-trained centreline direction classification model, also referred to as centreline tracing model 216, may be used to trace the potential centrelines. Figure 3 illustrates a model 300 for centreline patch orientation prediction. An input of a 3D image patch 302 is provided. The model maps the output to its orientation indicators – in the embodiment of a 500-element array output (or array output of some other size), one element will have a value of “1”, being the orientation indicator for that seed point or image patch, and all other elements in the array will be “0”. The centreline direction classification model 216 predicts the direction of a centreline 218 given a voxel in the lumen mask 206. For example, a set of direction vectors (stored in an array) may be evenly distributed on the circumference of a circle (for 2D implementations) or on the surface of a sphere (for 3D implementations) corresponding to an image voxel. The probability that the centreline extends along each direction vector can then be calculated. In one embodiment, 500 3D directional vectors are evenly distributed on a spherical surface, centred on a voxel. A 500 elements array is used as an indicator array to represent the 500 orientation vectors. Each centreline point (i.e., any point on a candidate centreline other than the seed point or point at the opposite, proximal end of the artery) generally has two direction vectors, pointing to a previous point and a next point along a candidate centreline. The first (seed) and the last point will have only one direction vector. The direction vectors are indexed in a 500-element array, and the nearest orientation vectors will have a respective indicator set to 1, with others set to 0. Thus, a centreline 218 of an artery or branch is detected generally along a line of successive orientation vectors with indicator “1”, through a

sequence of points (voxels or pixels) from the seed (distal end) to the proximal end, whether the proximal end is at the aorta or an intersection between vessels.

[031] The centreline direction classification model 216 may be a convolution neural network (CNN) model. An input data, defined as a binary image patch with a voxel size of $19 \times 19 \times 19$ may be used. The output may be 500 orientation vectors evenly distributed on a unit sphere – e.g. extending radially from a centre of the unit sphere. Each orientation vector is therefore considered as a class, and the output is an array of probabilities corresponding to each of the orientation classes. The parameters of this CNN structure may be as defined in Table 1, or assume any other appropriate structure.

Table 1: Parameters of the convolutional neural network model for orientation classification.

Layer	1	2	3	4	5	6	7
Kernel width	3	3	3	3	3	1	1
Dilation	1	1	2	4	1	1	1
Channels	32	32	32	32	64	64	500
Field width	3	5	9	17	19	19	19

[032] A CNN model may be used to predict the centreline. Given a first centreline point (a seed point), the model predicts a direction, the direction corresponding to a vector pointing from the first centreline point to the next centreline point. Then, for each successive point, a further direction to a subsequent point is predicted, and so on along the vessel until an ostium or other relevant vascular feature (discussed below) is reached.

[033] The centreline tracing model 216 may be trained on two classes of image patches– the on-the-line patch and the off-the-line patch. Figure 4 illustrates these two classes of image input patches for training the model, with Figure 4(a) corresponding to the on-the-line patch, where the centrepoint of the patch is on the centreline 218, and Figure 4(b) corresponding to the off-the-line patch, where the centrepoint of the patch has a deviation from the centreline 218. For each patch, ground truth labels are provided corresponding to an indication of the centreline of each artery in the relevant patch, or an indication that the patch is off-the-line.

[034] A fixed radius (r) of 3 mm was used in training, though other radii may be used as appropriate. An on-the-line patch is used for training the model 216 to predict the previous or the next centreline point of a step r . This may be done by using a centreline point as the centre by cropping a patch, with a given size. The target orientation is then defined by a direction pointing to the previous centreline point and to the next centreline point.

[035] For example, a seed point is selected and used to generate a patch with the seed point at the centre. Direction vectors are generated from the seed point. The maximum direction feature is ascertained (i.e., the direction vector with highest probability of being on the centreline) and the algorithm moves by a pre-defined step size s , presently 3 mm, from the seed point along the direction vector of highest probability, to a new patch centre. The algorithm then repeats, from the new patch centre to find the next patch centre that is spaced a distance s from the new patch centre. In other words, the model may be implemented by using the initial given seed point p_0 as a centre, creating a patch from a vessel mask image, and feeding the input patch into an orientation classifier model. A list of directional probability values may be obtained and sorted. The probability value v_p may be obtained from the n maximum values, and the corresponding direction d of the directional vector may be obtained. If the previous direction exists, an angle is computed, the angle being between the previous and current directions. This may be repeated by moving each seed point by the pre-defined step size, until all the probability values are completed.

[036] An off-the-line patch is used for training a model 216 to predict the previous or the next centreline point, when the given first centreline point deviates from that of the centreline. The patch may be generated by applying a translation to a centreline, such as from points p_0 to p'_0 in Figure 4(b), then using p'_0 as the centre of the patch, and recalculating the direction of the next and previous points using the point p'_0 .

[037] The model 216 therefore indicates, for each vector in each patch, a likelihood of the vector extending along the centreline from the voxel corresponding to the respective patch. The likelihood, or probability, will be highest for a vector with least angular deviation between the voxel of the previous on-the-line patch and the voxel of the next on-the-line patch. In some embodiments, the centreline tracing model

identifies candidate directions from the plurality of directions by culling the directions based on an angle between each direction and a previous direction, wherein the direction of the next pixel is determined only from the candidate directions. The model 216 determines the centreline has ended when an anatomical feature has been detected – thus, anatomical features are incorporated into the assessment, per 220 (discussed below). An anatomical feature may be where the vessel reaches an intersection, or where there are no further on-the-line patches due to the vessel terminating at the aorta or an organ – these circumstances can be determined with reference to faces of patches, and geometric filters, as discussed below.

[038] The vessel regions in patches may fall within one of the following:

- no vessel regions fall within the patch;
- a vessel passes through the patch; and
- a vessel terminates within the patch.

[039] Vessel regions in patches may be classified in one of the above three categories, depending on an absence or presence of the vessel within the patch. A patch comprises six faces in the 3D embodiment, and four edges in the 2D embodiment. In a first scenario, none of the six faces of the patch coincide with the vessel mask voxel. The second scenario may correspond to a patch with two opposite faces (i.e. two distinct faces which are not touching each other) containing the vessel mask voxel. The third scenario may correspond to the patch having at least one and no more than four faces with vessel mask voxels, implying that the faces must be connected to each other. In this case, the vessel patch comprises both a vessel passing through the patch, and a vessel terminating within the patch.

[040] A vessel voxel with a patch (i.e., the patch is centred on the centre, where the patch may be 19x19x19 large, or another cube of odd side lengths to ensure a single, whole voxel is in the centre of the cube) may be defined as a positive face, and a patch without a vessel voxel may be defined as a negative face. If three negative faces are connected, a hinge vertex may be defined. Considering all scenarios possible due to rotation and reflection, it may be seen that 1, 2 and 4 hinge vertices are patches which contain a vessel terminator. These may be considered a positive patch, and all other scenarios may be considered a negative patch. Figure 5 illustrates the various types of vessel mask images in two-dimensions (2D). Positive edges refer to those with vessel pixels (i.e. the thin edges), while negative edges refer to those

without vessel pixels (i.e. the bold edges). When two negative edges are connected, a hinge vertex is assigned. If a patch has one or two hinges, it may be set as a positive patch and hence a seed point candidate. If a patch has 0 or 4 hinges, it may be set as a negative patch and hence not a seed point candidate.

[041] While Figure 5 illustrates the types of vessel mask images in 2D, it shall be understood that the same may be applied to a three-dimensional (3D) setting.

[042] A seed point is designated by considering a positive patch and computing the mass centre of a voxel mask region. A positive patch may overlap another and may also overlap false seed points. Thus, not all seed points 214 are actually at the distal end of a lumen.

[043] The generation of centreline candidates may also result in false positives. Several geometric shape filters may be developed to reduce a redundancy of full-length centrelines. One or more geometric shape filters may therefore be used to filter candidate centrelines from those that are no longer candidates (i.e., are filtered out).

[044] The first filter is a mean-shift line filter, which is used to cluster and average a bunch of centrelines into a mean centreline 222. This may be determined by the overall distance of all the candidate centrelines. Centrelines belonging to the same vessel are identified by the distance between end points of those centrelines – e.g., the centrelines of the same vessel are those with closest end points. In such cases, when starting from the seed point, the locations and directions of subsequent points along the centreline are averaged to generate the mean-shift centreline.

[045] Variations are accounted for by averaging the various candidate centrelines into one, for computing the mean directions. Figure 6 shows a plot illustrating the mean-shift line generation.

[046] A second filter is the sharp angle filter 224. This seeks to eliminate crooked lines, arising from a distance variation of steps in different centrelines. While the steps have fixed length (3mm in some embodiments, though 1mm, 2mm, 4mm or another step length may be used), when the points defining candidate centrelines are merged or averaged, the resulting point may not be the exact fixed step length

from the voxel used as the seed or centre of a patch. An adaptive sharp angles filter may be applied to remove sharp angles, or U-turns of centrelines, to smoothen the centrelines.

[047] A third filter is an interval filter 226, which reduces an error arising from large point intervals between lines – the “interval” refers to the distance between points in the centreline developed by mean-shift merging or bifurcation, and a “large point interval” is thus a distance between points that is greater than the fixed length step used to generate the candidate centrelines. These may arise from a mean-shift merging procedure or a bifurcation detection procedure.

[048] A fourth filter 228 serves to detect bifurcation (i.e. branching). This may be done by beginning at an ostium (which applies to all ostia having been through the centreline tracing model), moving along the centreline in a pre-defined step for all centrelines, an examining the angles between any pair of lines. If an angle falling between any two lines is larger than a given threshold, the model detects a branch, and all lines up to the said point are cut off and designated as a trunk. A mean function is then applied to all lines leading up to the trunk, to produce the centreline of the trunk. All the remaining centreline sections form a sub-tree, and a similar bifurcation or branch filter is applied. Figure 7 illustrates an example of a centreline branch detection filtering, when branch points and sections are detected, for full-length centrelines after a geometric shape filtering, after a branch detection, and after each section is merged, for Figures 7(a), 7(b) and 7(c) respectively.

[049] Preferably, each of these filters are run more than once. This may be termed an iterative centreline extraction and seeks to eliminate the false positives and the redundancies. Preferably, these filters are run until the number of branch points, the position of the branch points, and the number of lines does not further change, and the results are said to be stable, per 232.

[050] A tree traversal algorithm may also be applied to re-connect the centreline sections to become full-length centrelines, per 230.

[051] In some embodiments, the anatomical features are derived from an ostium mask showing one or more ostia. Each, or at least one, candidate centreline extends from a respective said ostium. For example, a second mask 210 may be received

from model 208, each of the first mask 206 and second mask 210 being generated to mask respectively different portion of the vasculature. The ostium mask is then generated from the first mask 206 and second mask 210. The second mask 210 may be an aorta mask, showing the aorta in the original input image. The first mask 206 and the second mask 210 may be generated by known lumen mask segmentation methods.

[052] In some embodiments, the ostium mask is generated by applying a Boolean AND operation to the first mask and second mask. The ostium mask image may be generated by applying the Boolean AND operation between an aorta mask image (being the portion of the image 202 retained by the mask 210) and a coronary artery image (being the portion of the image 202 retained by the mask 206).

[053] In some embodiments, if the ostium mask comprises more than two ostia, the centreline tracing model selects two ostia that are largest of the ostia in the ostium mask. In other embodiments, the ostium mask image comprises two ostia. These two ostia may be the ostia of the left coronary artery and right coronary artery.

[054] The tracking of centrelines generates a set of centrelines. This may include one of the following:

- from ostia to vessel ends;
- from vessel ends to ostia; and
- from one vessel end to another vessel end.

[055] With a given aorta structure, the ostia regions on the arteries may be determined, and the relevant centrelines of interest may be identified.

[056] In such cases, for centrelines which do not start or end at ostia regions (i.e. not centrelines of interest), such values may be discarded, leaving within the set only centrelines that start or end within the ostia regions. Centrelines terminating at an ostia region may be flipped such that they appear to begin with an ostium region. All centrelines hence appear to "begin" with an ostium region. Some vessels may contain more than one centreline. Further, centrelines may be broken into sections (per 234) corresponding to vessel sections, at their branching points.

[057] Each vessel section should hence contain a unique centreline.

[058] Once the centrelines are detected and, where appropriate, the mean is calculated such that there is a single centreline for each vessel, the centreline of each vessel is outputted (per 236).

[059] Figure 11 shows a computer system 1100 for implementing the method reflected in workflow 200. The system 1100 comprises memory 1102 and at least one processor (processor(s) 1104) that run instructions in the form of a program 1106 stored in memory 1102. Memory 1102 is therefore a non-volatile, computer readable storage medium storing instructions (program 1106) that, when executed by the processor(s) 1104 cause the system 1100 to executed the methods described herein.

[060] The system 1100 includes a receiver 1107 for receiving data such as input images, a filter module 1114 that stores the filters, such as centreline clustering and geometrical filters, applied to centrelines calculated from seed points, and an output 1109 for outputting centrelines detected by the system 1100.

[061] The system 1100 also includes a model repository 1108 for storing machine learning or AI models. The repository 1108 stores the shape analysis model 1110 that identifies seed points in the input images. The repository also stores the centreline tracing model 1112 that generates centrelines using one or more of the methods described above.

[062] The system 1100 may comprise a single server or distributed server system, and may be accessed through a smartphone laptop or any other device.

[063] The following examples are now provided to assist in detailing how the model was trained, according to various embodiments of the disclosure as defined by the claims. It includes various specific details which are to be regarded as merely exemplary.

Example 1: Model validation

[064] For validation of the trained model, a series of 41 clinical CTCA images were collected from a local hospital. The coronary arteries and centrelines are manually

annotated by clinical experts. The performance of centreline tracing may be quantified by the distance between the annotated centreline (C_a) and the predicted centrelines (C_p).

[065] The first performance index used here is the trace rate within a distance limit (T_d), defined as the percentage of predicted centreline points within a given distance d to the annotated centrelines, over the total number of points of predicted centrelines.

$$N_d = \text{Number of points } p \in C_p \text{ which } \min(\text{dist}(p, C_a)) < d$$

$$T_d = \frac{N_d}{(\text{Total number of points } p \in C_p)} * 100\%$$

[066] The number of points is used in place of length measurement. Alternatively, the length may be used. Here, the output centreline points have been normalised to ensure that all points are evenly distributed. Figure 8 illustrates the trace rate within distance limit (T_d), where given a distance d , T_d represents the ratio of the length of the predicted centreline within distance d from the annotated centreline over the length of the whole centreline.

[067] A well-trained model for a centreline trace method provides an output of the centrelines near the ground truth, or the manually annotated centrelines. The quantity T_d calculates the length of the extracted centreline within a given distance to the annotated centreline.

[068] The computed accuracy performance of the coronary arteries centrelines extracted from the test dataset ($n = 41$) as obtained from the trained model is shown in the table below. Table 1 below illustrates the results of the trace rate within distance limit (T_d) for the 41 test datasets. About 95% of centreline points are with 1 mm to the annotated centrelines. More than 97% of predicted centreline points are within 3 mm of the annotated centrelines points. Less than 3% of predicted centreline points are more than 3 mm away from annotations. This validates the trained model.

Table 2: Results of the trace rate within distance limit (T_d) for the 41 data sets

<i>d</i>	<i>Td</i> (%)
1.0mm	94.643
1.5mm	96.482
2.0mm	96.960
2.5mm	97.152
3.0mm	97.302

[069] The second performance index used here is the modified overlap evaluation index.

[070] Conventionally, the overlap index (OV) requires the radius of artery vessels. Further, the conventional OV employs a standardised database which does not include data of small vessels, including those which are used in the training of the model. The conventional OV has hence been modified to compute a (modified) OV which does not make use of the radii of artery vessels, but instead, uses the centreline points in the mask. Since a ground truth mask is used, the centreline points must be within the vessel radius. Figure 9 illustrates the variable for computing overlap index within a distance *d*. The shadowed area represents the vessel mask input. *Ce* and *Cr* denote the evaluated and reference centrelines, respectively, and *d* is a given distance parameter.

[071] While some centreline points occur over different vessels, a mean vessel distance *dm* constraint is set when calculating the overlap index. Considering the reference (or annotated) centreline (*Cr*) and the evaluated (or predicted) centreline (*Ce*), a point of *Cr* is marked as a true positive *TPR_d* if its nearest point on *Ce* is vessel masked and the distance is less than *dm*, and false negative *FN_d* otherwise. A point on *Ce* is marked as true positive *TPM_d* if its nearest point on *Cr* is vessel masked and the distance is less than *dm*, and is marked as false positive *FP_d* otherwise.

[072] The modified overlap index *OVD* is hence calculated as follows:

$$OV_d = \frac{\|TPM_d\| + \|TPR_d\|}{\|TPM_d\| + \|TPR_d\| + \|FN_d\| + \|FP_d\|} \times 100\%$$

[073] Setting *dm* = 1.0, 2.0 and 3.0, the evaluated modified overlap index (*OVD*) for the test results were found to be:

Table 3: Performance of the model computed by the modified overlap index, in a similar method as a conventional evaluation methodology.

$d_m(\text{mm})$	$OV_d(\%)$
1.0	94.875
2.0	97.483
3.0	97.933

[074] The parameter d_m is introduced to avoid cross vessel errors of OVD. The value of d_m was set to be at 3.0 because the centreline tracking AI model is trained by the parameter radius = 3.0. For studying coronary arteries, it has also been found that 3 mm is sufficient to differentiate most vessels. Thus, an OVD value of $d_m = 3$ is found to accurately model most studies. Using $d_m = 1.5$ as a stricter constraint, the OVD value also shows the proposed method is reliable. Meanwhile, the OVD results also shown they are closely co-related to the Td measures computed for the trace rate within distance limit.

[075] Figure 10 provides a rendered visual of coronary arteries with the predicted centrelines and annotated centrelines, with 1000 indicating the annotated centrelines, and the 1002 indicating the predicted centreline formed by lines predicted by the model.

Example 2: Orientation classification model training

[076] 138 arteries mask images and their corresponding centrelines, as manually annotated, are used for model training. The training data was augmented using rigid transformation to the input data, to increase the size of the input data set. This may aid in obtaining a more robust model. After data augmentation, the model was trained on about 800,000 input patches.

[077] After 200 epochs, the trained model was found to have a good prediction of centreline orientations, for post-processing in subsequent steps.

[078] It will be appreciated that many further modifications and permutations of various aspects of the described embodiments are possible. Accordingly, the

described aspects are intended to embrace all such alterations, modifications, and variations that fall within the spirit and the scope of the appended claims.

[079] Throughout this disclosure, unless the context requires otherwise, the word “comprise”, and variations such as “comprises” and “comprising”, will be understood to imply the inclusion of a stated integer or step or group of integers or steps, but not the exclusion of any other integer or step or group of integers or steps.

[080] The reference to any prior art in this disclosure is not, and should not be taken as, an acknowledgement or any form of suggestion that the prior art forms part of the common general knowledge.

CLAIMS

1. A system for extracting, from an image, a centreline for each of one or more vessels of a vasculature shown in the image, the system comprising:
 - memory;
 - a model repository comprising a shape analysis model and centreline tracing model; and
 - at least one processor, the memory storing instructions that, when executed by the at least one processor, cause the system to:
 - receive, at a receiver system, the image and a first mask of a portion of the vasculature;
 - identify seed points in the image, using the shape analysis model, based on a shape of the vasculature in the first mask;
 - generate, using the centreline tracing model, the centreline for each of the one or more vessels by:
 - tracing a traced centreline from each seed point;
 - selecting a candidate centreline from the traced centrelines, based on an anatomical feature of the portion of the vasculature; and
 - filtering the candidate centrelines using one or more geometric shape filters to generate the centreline for each vessel; and
 - output the centreline for each vessel.
2. The system according to claim 1, wherein each seed point comprises a distal end of a respective said vessel.
3. The system according to claim 2, wherein the distal end of the respective vessel is identified by:
 - identifying candidate ends of vessels by applying shape analysis to the first mask;
 - dividing the image into patches at the candidate ends; and
 - identifying the seed points from the patches by calculating a mass centre of each patch having image features indicating a vessel enters the patch but does not exit the patch.

4. The system according to any one of claims 1 to 3, wherein the anatomical features are derived from an ostium mask showing one or more ostia, each candidate centreline extending from a respective said ostium.
5. The system according to claim 4, wherein the receiver receives a second mask, each mask being generated to mask a respectively different portion of the vasculature, the system generating the ostium mask from the first mask and second mask.
6. The system according to claim 5, wherein the ostium mask is generated by applying a Boolean AND operation to the first mask and second mask.
7. The system according to claim 5 or claim 6, wherein the second mask is an Aorta mask.
8. The system according to claim 7, wherein, if the ostium mask comprises more than two ostia, the centreline tracing model selects two ostia that are largest of the ostia in the ostium mask.
9. The system according to any one of claims 1 to 8, wherein the first mask is a coronary artery mask.
10. The system according to any one of claims 1 to 9, wherein, for each seed point, the centreline tracing model traces the respective traced centreline by:
 - determining and sorting direction probabilities for a plurality of directions the traced centreline may extend from the seed point;
 - determining, from the plurality of directions, a direction of a next pixel in the traced centreline; and
 - continuing to trace the traced centreline if the next pixel corresponds to a vessel voxel.
11. The system according to claim 10, wherein the centreline tracing model identifies candidate directions from the plurality of directions by culling the directions based on an angle between each direction and a previous direction, wherein the direction of the next pixel is determined only from the candidate directions.

12. A method for extracting, from an image, a centreline for each of one or more vessels of a vasculature shown in the image, the method comprising:
- receiving, at a receiver system, a first mask of a portion of the vasculature;
 - identifying seed points in the image, using a shape analysis model, based on a shape of the vasculature in the first mask;
 - generating, using a centreline tracing model, the centreline for each of the one or more vessels by:
 - tracing a traced centreline from each seed point;
 - selecting a candidate centreline from the traced centrelines, based on an anatomical feature of the portion of the vasculature;
 - and
 - filtering the candidate centrelines using one or more geometric shape filters to generate the centreline for each vessel; and
 - outputting the centreline for each vessel.
13. The method according to claim 12, wherein each seed point comprises a distal end of a respective said vessel.
14. The method according to claim 13, wherein identifying the distal end of the respective vessel comprises:
- applying shape analysis to the first mask to identify candidate ends of vessels;
 - dividing the image into patches at the candidate ends; and
 - identifying the seed points from the patches by calculating a mass centre of each patch having image features indicating a vessel enters the patch but does not exit the patch.
15. The method according to any one of claims 12 to 14, comprising deriving the anatomical features from an ostium mask showing one or more ostia, each candidate centreline extending from a respective said ostium.
16. The method according to claim 15, comprising:
- receiving a second mask at the receiver, each mask being generated to mask a respectively different portion of the vasculature; and

generating the ostium mask from the first mask and second mask.

17. The method according to claim 16, wherein the ostium mask is generated by applying a Boolean AND operation to the first mask and second mask.
18. The method according to claims 16 or 17, wherein the second mask is an Aorta mask.
19. The method according to claim 18, wherein, if the ostium mask comprises more than two ostia, the method comprises selecting, using the centreline tracing model, two ostia that are largest of the ostia in the ostium mask, the candidate centreline being a centreline extending from one of the two largest ostia.
20. The method according to any one of claims 12 to 19, wherein the first mask is a coronary artery mask.
21. The method according to any one of claims 12 to 20, wherein, for each seed point, the method comprises tracing the respective traced centreline, using the centreline tracing model, by:
 - determining and sorting direction probabilities for a plurality of directions the traced centreline may extend from the seed point;
 - determining, from the plurality of directions, a direction of a next pixel in the traced centreline; and
 - continuing to trace the traced centreline if the next pixel corresponds to a vessel voxel.
22. The method according to claim 21, comprising identifying candidate directions from the plurality of directions by culling the directions based on an angle between each direction and a previous direction, and determining the direction of the next pixel only from the candidate directions.