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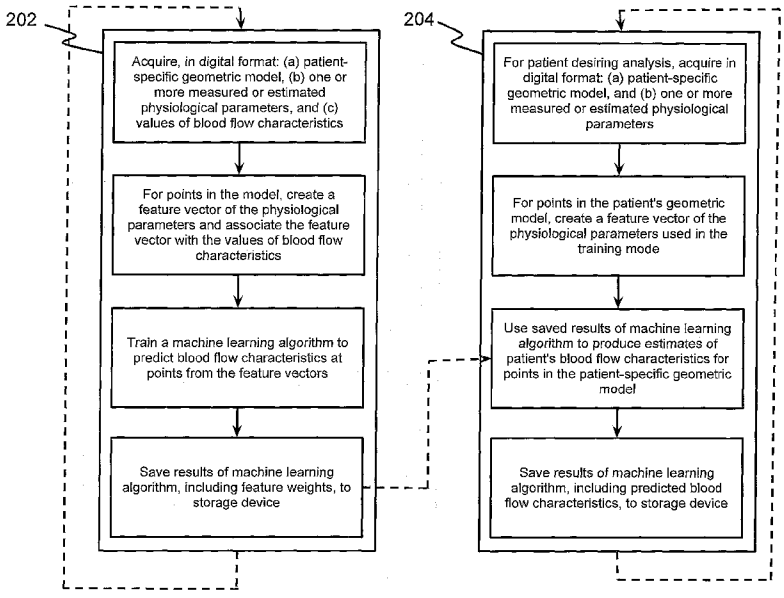

FIG. 2

(57) Abstract: Systems and methods are disclosed for estimating patient-specific blood flow characteristics. One method includes acquiring, for each of a plurality of individuals, a geometric model and estimated blood flow characteristics of at least part of the individual's vascular system; executing a machine learning algorithm on the geometric model and estimated blood flow characteristics for each of the plurality of individuals; identifying, using the machine learning algorithm, features predictive of blood flow characteristics corresponding to a plurality of points in the geometric models; acquiring, for a patient, a geometric model of at least part of the patient's vascular system; and using the identified features to produce estimates of the patient's blood flow characteristic for each of a plurality of points in the patient's geometric model.

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SYSTEMS AND METHODS FOR ESTIMATING BLOOD FLOW CHARACTERISTICS FROM VESSEL GEOMETRY AND PHYSIOLOGY

RELATED APPLICATION

This application is related to U.S. Patent Application No. 13/895,893, filed May 16, 2013, and U.S. Provisional Application No. 61/700,213, filed September 12, 2012, the entire disclosures of which are hereby incorporated by reference in their entirety.

TECHNICAL FIELD

Various embodiments of the present disclosure relate generally to medical imaging and related methods, e.g., systems and methods for estimating patient-specific blood flow characteristics from vessel geometry and physiology.

BACKGROUND

A functional assessment of arterial capacity is important for treatment planning to address patient needs. Recent studies have demonstrated that hemodynamic characteristics, such as Fractional Flow Reserve (FFR), are important indicators to determine the optimal treatment for a patient with arterial disease. Conventional assessments of these hemodynamic characteristics use invasive catheterizations to directly measure blood flow characteristics, such as pressure and flow velocity. However, despite the important clinical information that is gathered, these invasive measurement techniques present severe risks to the patient and significant costs to the healthcare system.

To address the risks and costs associated with invasive measurement, a new generation of noninvasive tests have been developed to assess blood flow characteristics. These noninvasive tests use patient imaging (such as computed tomography (CT)) to determine a patient-specific geometric model of the blood vessels and this model is used computationally to simulate the blood flow using computational fluid dynamics (CFD) with appropriate physiological boundary conditions and parameters. Examples of inputs to these patient-specific boundary conditions include the patient's blood pressure, blood viscosity and the expected demand of blood from the supplied tissue (derived from scaling laws and a mass estimation of the supplied tissue from the patient imaging). Although

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these simulation-based estimations of blood flow characteristics have demonstrated a level of fidelity comparable to direct (invasive) measurements of the same quantity of interest, physical simulations demand a substantial computational burden that can make these virtual, noninvasive tests difficult to execute in a real-time clinical environment. Consequently, the present disclosure describes new approaches for performing rapid, noninvasive estimations of blood flow characteristics that are computationally inexpensive.

It is desired to address or ameliorate one or more disadvantages or limitations associated with the prior art, or to at least provide a useful alternative.

SUMMARY

In accordance with the present invention there is provided a method for determining patient-specific blood flow characteristics, the method comprising:

acquiring, for each of a plurality of individuals, a geometric model and blood flow characteristics of at least part of the individual's vascular system;

executing a machine learning algorithm on the geometric model and blood flow characteristics for each of the plurality of individuals;

identifying, using the machine learning algorithm, for each of the plurality of individuals, a plurality of points in the geometric model of the individual that correspond to features predictive of blood flow characteristics of the individual;

acquiring, for a patient, a geometric model of at least part of the patient's vascular system; and

using the identified features to determine a blood flow characteristic of the patient for at least one point in the patient's geometric model.

The present invention also provides a system for estimating patient-specific blood flow characteristics, the system comprising:

a data storage device storing instructions for determining patient-specific blood flow characteristics; and

a processor configured to execute the instructions to perform a method according to the above method.

The present invention also provides non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a

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method according to the above method.

BRIEF DESCRIPTION OF THE DRAWINGS

Some embodiments of the present invention are hereinafter described, by way of non-limiting example only, with reference to the accompanying drawings, in which:

FIG. 1 is a block diagram of an exemplary system and network for estimating patient-specific blood flow characteristics from vessel geometry and physiological information, according to an exemplary embodiment of the present disclosure.

FIG. 2 is a block diagram of an exemplary method for estimating patient-specific blood flow characteristics from vessel geometry and physiological information, according to an exemplary embodiment of the present disclosure.

DETAILED DESCRIPTION

Systems and methods are disclosed for deriving a patient-specific geometric model of a patient's blood vessels, and combining this geometry with the patient-specific physiological information and boundary conditions. Combined, these data may be used to estimate the patient's blood flow characteristics and predict clinically relevant quantities of interest (e.g., FFR). The presently disclosed systems and methods offer advantages over physics-based simulation of blood flow to compute the quantity of interest, such as by instead using machine learning to predict the results of a physics-based simulation. In one embodiment, disclosed systems and methods involve two phases: first, a training phase in which a machine learning system is trained to predict one or more blood flow characteristics; and second, a production phase in which the machine learning system is used to produce one or more blood flow characteristics and clinically relevant quantities of interest. In the case of predicting multiple blood flow characteristics, this machine learning system can be applied for each blood flow characteristic and quantity of interest.

According to one embodiment, a method is disclosed for estimating patient-specific blood flow characteristics. The method includes acquiring, for each of a plurality of individuals, a geometric model and estimated blood flow characteristics of at least part of the individual's vascular system; executing a machine learning algorithm on the geometric model and estimated blood flow characteristics for each of the plurality of individuals;

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identifying, using the machine learning algorithm, features predictive of blood flow characteristics corresponding to a plurality of points in the geometric models; acquiring, for a patient, a geometric model of at least part of the patient's vascular system; and using the identified features to produce estimates of the patient's blood flow characteristic for each of a plurality of points in the patient's geometric model.

According to another embodiment, a system is disclosed for estimating patient-specific blood flow characteristics. The system includes a data storage device storing instructions for estimating patient-specific blood flow characteristics; and a processor configured to execute the instructions to perform a method including the steps of: acquiring, for each of a plurality of individuals, a geometric model and estimated blood flow characteristics of at least part of the individual's vascular system; executing a machine learning algorithm on the geometric model and estimated blood flow characteristics for each of the plurality of individuals; identifying, using the machine learning algorithm, features predictive of blood flow characteristics corresponding to a plurality of points in the geometric models; acquiring, for a patient, a geometric model of at least part of the patient's vascular system; and using the identified features to produce estimates of the patient's blood flow characteristic for each of a plurality of points in the patient's geometric model.

Reference will now be made in detail to the exemplary embodiments of the disclosure, examples of which are illustrated in the accompanying drawings. Wherever possible, the same reference numbers will be used throughout the drawings to refer to the same or like parts.

The present disclosure describes certain principles and embodiments for providing advantages over physics-based simulation of blood flow to compute patient-specific blood flow characteristics and clinically relevant quantities of interest. Namely, the presently disclosed systems and methods may incorporate machine learning techniques to predict the results of a physics-based simulation. For example, the present disclosure describes an exemplary, less processing-intensive technique, which may involve modeling the fractional flow reserve (FFR) as a function of a patient's vascular cross-sectional area, diseased length, and boundary conditions. The cross-sectional area may be calculated based on lumen segment and plaque segment, among other things. The diseased length may be

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calculated based on plaque segment and stenosis location, among other things. The boundary conditions may reflect patient-specific physiology, such as coronary flow (estimated from myocardial mass), outlet area, and hyperemic assumptions, to reflect that different patients have different geometry and physiologic responses.

In one embodiment, fractional flow reserve may be modeled as a function of a patient's boundary conditions (f(BCs)), and a function of a patient's vascular geometry (g(areaReductions)). Although the patient's geometry may be described as a function of "areaReductions," it should be appreciated that this term refers, not just to changes in patient's vascular cross-sectional area, but to any physical or geometric characteristics affecting a patient's blood flow. In one

embodiment, FFR can be predicted by optimizing the functions "f" and "g" such that the difference between the estimated FFR ($FFR_{CT_ScalingLaw}$) and the measured FFR (mFFR) is minimized. In other words, machine learning techniques can be used to solve for the functions that cause the estimated FFR to approximate the measured FFR. In one embodiment, the measured FFR may be calculated by traditional catheterized methods or by modern, computational fluid dynamics (CFD) techniques. In one embodiment, one or more machine learning algorithms may be used to optimize the functions of boundary conditions and patient geometry for hundreds or even thousands of patients, such that estimates for FFR can reliably approximate measured FFR values. Thus, FFR values calculated by CFD techniques can be valuable for training the machine learning algorithms.

[016] Referring now to the figures, FIG. 1 depicts a block diagram of an exemplary system and network for estimating patient-specific blood flow characteristics from vessel geometry and physiological information. Specifically, FIG. 1 depicts a plurality of physicians 102 and third party providers 104, any of whom may be connected to an electronic network 100, such as the Internet, through one or more computers, servers, and/or handheld mobile devices. Physicians 102 and/or third party providers 104 may create or otherwise obtain images of one or more patients' cardiac and/or vascular systems. The physicians 102 and/or third party providers 104 may also obtain any combination of patient-specific information, such as age, medical history, blood pressure, blood viscosity, etc. Physicians 102 and/or third party providers 104 may transmit the cardiac/vascular images and/or patient-specific information to server systems 106 over the electronic network 100. Server systems 106 may include storage devices for storing images and data received from physicians 102 and/or third party providers 104. Sever systems 106

may also include processing devices for processing images and data stored in the storage devices.

[017] FIG. 2 is a block diagram of an exemplary method for estimating patient-specific blood flow characteristics from vessel geometry and physiological information, according to an exemplary embodiment of the present disclosure. The method of FIG. 2 may be performed by server systems 106, based on information received from physicians 102 and/or third party providers 104 over electronic network 100.

[018] In one embodiment, the method of FIG. 2 may include a training method 202, for training one or more machine learning algorithms based on numerous patients' blood flow characteristic estimates, and a production method 204 for using the machine learning algorithm results to predict a particular patient's blood flow characteristics.

[019] In one embodiment, training method 202 may be performed based on FFR estimates generating using CFD techniques for hundreds of patients. Training method 202 may involve acquiring, for each of a plurality of individuals, e.g., in digital format: (a) a patient-specific geometric model, (b) one or more measured or estimated physiological parameters, and (c) values of blood flow characteristics. Training method 202 may then involve, for one or more points in each patient's model, creating a feature vector of the patients' physiological parameters and associating the feature vector with the values of blood flow characteristics. For example, training method 202 may associate an estimated FFR with every point in a patient's geometric model. Training method 202 may then train a machine learning algorithm (e.g., using processing devices of server systems 106) to predict blood flow characteristics at each point of a geometric model, based on the feature vectors

and blood flow characteristics. Training method 202 may then save the results of the machine learning algorithm, including feature weights, in a storage device of server systems 106. The stored feature weights may define the extent to which patient features or geometry are predictive of certain blood flow characteristics.

[020] In one embodiment, the production method 204 may involve estimating FFR values for a particular patient, based on results of executing training method 202. In one embodiment, production method 204 may include acquiring, e.g. in digital format: (a) a patient-specific geometric model, and (b) one or more measured or estimated physiological parameters. For multiple points in the patient's geometric model, production method 204 may involve creating a feature vector of the physiological parameters used in the training mode. Production method 204 may then use saved results of the machine learning algorithm to produce estimates of the patient's blood flow characteristics for each point in the patient-specific geometric model. Finally, production method 204 may include saving the results of the machine learning algorithm, including predicted blood flow characteristics, to a storage device of server systems 106.

[021] Described below are general and specific exemplary embodiments for implementing a training mode and a production mode of machine learning for predicting patient-specific blood flow characteristics, e.g. using server systems 106 based on images and data received from physicians 102 and/or third party providers 104 over electronic network 100.

GENERAL EMBODIMENT

[022] In a general embodiment, server systems 106 may perform a training mode based on images and data received from physicians 102 and/or third party providers 104 over electronic network 100. Specifically, for one or more patients,

server systems 106 may acquire a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.) of the following items: (a) a patient-specific model of the geometry for one or more of the patient's blood vessels; (b) a list of one or more measured or estimated physiological or phenotypic parameters of the patient; and/or (c) measurements, estimations or simulated values of all blood flow characteristic being targeted for prediction. In one embodiment, the patient-specific model of the geometry may be represented by a list of points in space (possibly with a list of neighbors for each point) in which the space can be mapped to spatial units between points (e.g., millimeters). In one embodiment, the list of one or more measured or estimated physiological or phenotypic parameters of the patient may include blood pressure, blood viscosity, patient age, patient gender, mass of the supplied tissue, etc. These patient-specific parameters may be global (e.g., blood pressure) or local (e.g., estimated density of the vessel wall at a particular location).

[023] For every point in the patient-specific geometric model for which there is a measured, estimated or simulated value of the blood flow characteristic, server systems 106 may then create a feature vector for that point. The feature vector may be a numerical description of the patient-specific geometry at that point and estimates of physiological or phenotypic parameters of the patient. The feature vector may contain both global and local physiological or phenotypic parameters, where: for global parameters, all points have the same numerical value; and for local parameters, the value(s) may change at different points in the feature vector. Server systems 106 may then associate this feature vector with the measured, estimated or simulated value of the blood flow characteristic at this point.

[024] Server systems 106 may then train a machine learning algorithm to predict the blood flow characteristics at the points from the feature vectors at the points. Examples of machine learning algorithms that can perform this task are support vector machines (SVMs), multi-layer perceptrons (MLPs), and multivariate regression (MVR) (e.g., weighted linear or logistic regression). Server systems 106 may then save the results of the machine learning algorithm (e.g., feature weights) to a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.).

[025] Also in a general embodiment, server systems 106 may perform a production mode based on images and data received from physicians 102 and/or third party providers 104 over electronic network 100. For a patient on whom a blood flow analysis is to be performed, server systems 106 may acquire a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.) of (a) a patient-specific model of the geometry for one or more of the patient's blood vessels; and (b) a list of one or more estimates of physiological or phenotypic parameters of the patient. In one embodiment, the patient-specific model of the geometry for one or more of the patient's blood vessels may be represented as a list of points in space (possibly with a list of neighbors for each point) in which the space can be mapped to spatial units between points (e.g., millimeters). The list of one or more estimates of physiological or phenotypic parameters of the patient, may include blood pressure, blood viscosity, patient age, patient gender, the mass of the supplied tissue, etc. These parameters may be global (e.g., blood pressure) or local (e.g., estimated density of the vessel wall at a location). This list of parameters must be the same as the list used in the training mode.

[026] For every point in the patient-specific geometric model, server systems 106 may create a feature vector that consists of a numerical description of the geometry and estimates of physiological or phenotypic parameters of the patient. Global physiological or phenotypic parameters can be used in the feature vector of all points and local physiological or phenotypic parameters can change in the feature vector of different points. These feature vectors may represent the same parameters used in the training mode. Server systems 106 may then use the saved results of the machine learning algorithm produced in the training mode (e.g., feature weights) to produce estimates of the blood flow characteristics at each point in the patient-specific geometric model. These estimates may be produced using the same machine learning algorithm technique used in the training mode (e.g., the SVM, MLP, MVR technique). Server systems 106 may also save the predicted blood flow characteristics for each point to a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.).

EXEMPLARY EMBODIMENT

[027] In one exemplary embodiment, server systems 106 may perform a training mode based on images and data received from physicians 102 and/or third party providers 104 over electronic network 100. Specifically, for one or more patients, server systems 106 may acquire a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.) of (a) a patient-specific model of the geometry for the patient's ascending aorta and coronary artery tree; (b) a list of measured or estimated physiological or phenotypic parameters of the patient; and (c) measurements of the FFR when available.

[028] In one embodiment, the patient-specific model of the geometry for the patient's ascending aorta and coronary artery tree may be represented as a list of points in space (possibly with a list of neighbors for each point) in which the space can be mapped to spatial units between points (e.g., millimeters). This model may be derived by performing a cardiac CT imaging study of the patient during the end diastole phase of the cardiac cycle. The resulting CT images may then be segmented manually or automatically to identify voxels belonging to the aorta and to the lumen of the coronary arteries. Once all relevant voxels are identified, the geometric model can be derived (e.g., using marching cubes).

[029] In one embodiment, the list of measured or estimated physiological or phenotypic parameters of the patient may be obtained and may include: (i) systolic and diastolic blood pressures; (ii) heart rate; (iii) hematocrit level; (iv) patient age, gender, height, weight, general health status (presence or absence of diabetes, current medications); (v) lifestyle characteristics: smoker/non-smoker; and/or (vi) myocardial mass (may be derived by segmenting the myocardium obtained during the CT imaging study and then calculating the volume in the image; the mass is then computed using the computed volume and an estimated density (1.05g/mL) of the myocardial mass.

[030] In one embodiment, measurements of the FFR may be obtained when available. If the measured FFR value is not available at a given spatial location in the patient-specific geometric model, then a numerically computed value of the FFR at the point may be used. The numerically computed values may be obtained from a previous CFD simulation using the same geometric model and patient-specific boundary conditions derived from the physiological and phenotypic parameters listed above.

[031] For every point in the patient-specific geometric model for which there is a measured, estimated or simulated value of the blood flow characteristics, server systems 106 may create a feature vector for that point that contains a numerical description of physiological or phenotypic parameters of the patient and a description of the local geometry. Specifically the feature vector may contain: (i) systolic and diastolic blood pressures; (ii) heart rate; (iii) blood properties including: plasma, red blood cells (erythrocytes), hematocrit, white blood cells (leukocytes) and platelets (thrombocytes), viscosity, yield stress; (iv) patient age, gender, height, weight, etc.; (v) diseases: presence or absence of diabetes, myocardial infarction, malignant and rheumatic conditions, peripheral vascular conditions, etc.; (vi) lifestyle characteristics: presence or absence of current medications/drugs, smoker/non-smoker; (vii) characteristics of the aortic geometry (Cross-sectional area of the aortic inlet and outlet, Surface area and volume of the aorta, Minimum, maximum, and average cross-sectional area, etc.); (viii) characteristics of the coronary branch geometry; and (ix) one or more feature sets.

[032] In one embodiment, the characteristics of the coronary branch geometry may include: (i) volumes of the aorta upstream/downstream of the coronary branch point; (ii) cross-sectional area of the coronary/aorta bifurcation point, i.e., inlet to the coronary branch; (iii) total number of vessel bifurcations, and the number of upstream/downstream vessel bifurcations; (iv) average, minimum, and maximum upstream/downstream cross-sectional areas; (v) distances (along the vessel centerline) to the centerline point of minimum and maximum upstream/downstream cross-sectional areas; (vi) cross-sectional of and distance (along the vessel centerline) to the nearest upstream/downstream vessel bifurcation; (vii) cross-sectional area of and distance (along the vessel centerline) to the nearest

coronary outlet and aortic inlet/outlet; (viii) cross-sectional areas and distances (along the vessel centerline) to the downstream coronary outlets with the smallest/largest cross-sectional areas; (ix) upstream/downstream volumes of the coronary vessels; and (x) upstream/downstream volume fractions of the coronary vessel with a cross-sectional area below a user-specified tolerance.

[033] In one embodiment, a first feature set may define cross-sectional area features, such as a cross-sectional lumen area along the coronary centerline, a powered cross-sectional lumen area, a ratio of lumen cross-sectional area with respect to the main ostia (LM, RCA), a powered ratio of lumen cross-sectional area with respect to the main ostia, a degree of tapering in cross-sectional lumen area along the centerline, locations of stenotic lesions, lengths of stenotic lesions, location and number of lesions corresponding to 50%, 75%, 90% area reduction, distance from stenotic lesion to the main ostia, and/or irregularity (or circularity) of cross-sectional lumen boundary.

[034] In one embodiment, the cross-sectional lumen area along the coronary centerline may be calculated by extracting a centerline from constructed geometry, smoothing the centerline if necessary, and computing cross-sectional area at each centerline point and map it to corresponding surface and volume mesh points. In one embodiment, the powered cross-sectional lumen area can be determined from various source of scaling laws. In one embodiment, the ratio of lumen cross-sectional area with respect to the main ostia (LM, RCA) can be calculated by measuring cross-sectional area at the LM ostium, normalizing cross-sectional area of the left coronary by LM ostium area, measuring cross-sectional area at the RCA ostium, and normalizing cross-sectional area of the right coronary by RCA ostium area. In one embodiment, the powered ratio of lumen cross-sectional area with

respect to the main ostia can be determined from various source of scaling laws. In one embodiment, the degree of tapering in cross-sectional lumen area along the centerline can be calculated by sampling centerline points within a certain interval (e.g., twice the diameter of the vessel) and compute a slope of linearly-fitted cross-sectional area. In one embodiment, the location of stenotic lesions can be calculated by detecting minima of cross-sectional area curve, detecting locations where first derivative of area curve is zero and second derivative is positive, and computing distance (parametric arc length of centerline) from the main ostium. In one embodiment, the lengths of stenotic lesions can be calculated by computing the proximal and distal locations from the stenotic lesion, where cross-sectional area is recovered.

[035] In one embodiment, another feature set may include intensity features that define, for example, intensity change along the centerline (slope of linearly-fitted intensity variation). In one embodiment, another feature set may include surface features that define, for example, 3D surface curvature of geometry (Gaussian, maximum, minimum, mean). In one embodiment, another feature set may include volume features that define, for example, a ratio of total coronary volume compared to myocardial volume. In one embodiment, another feature set may include centerline features that define, for example, curvature (bending) of coronary centerline, e.g., by computing Frenet curvature:

[036] $\kappa = \frac{|p' \times p''|}{|p'|^3}$, where p is coordinate of centerline

[037] or by computing an inverse of the radius of circumscribed circle along the centerline points. Curvature (bending) of coronary centerline may also be calculated based on tortuosity (non-planarity) of coronary centerline, e.g., by computing Frenet torsion :

[038] $\tau = \frac{(p' \times p'') \cdot p'''}{|p' \times p''|^2}$, where p is coordinate of centerline

[039] In one embodiment, another feature set may include a SYNTAX scoring feature, including, for example, an existence of aorto ostial lesion, detection of a lesion located at the origin of the coronary from the aorta; and/or dominance (left or right).

[040] In one embodiment, another feature set may include a simplified physics feature, e.g., including a fractional flow reserve value derived from Hagen-Poisseille flow assumption ($Resistance \sim Area^{-2}$). For example, in one embodiment, server systems 106 may compute the cross-sectional area of the origin (LM ostium or RCA ostium) of the coronary from the aorta (A_0) with aortic pressure (P_0); compute cross-sectional area of coronary vessel (A_i) at each sampled interval (L_i); determine the amount of coronary flow in each segment of vessel using resistance boundary condition under hyperemic assumption (Q_i); estimate resistance at each sampled location (R_i) based on:

[041] $R_i = \alpha_i \frac{8\mu L_i}{\pi A_i^{\gamma_i}} + \beta_i$, where:

[042] Nominal value $\mu = \text{dynamic viscosiy of blood}$, $\alpha_i = 1.0$, $\beta_i = 0$, $\gamma_i = 2.0\ (\text{Hagen} - \text{Poisseille})$.

[043] Server systems 106 may estimate pressure drop (ΔP_i) $as\ \Delta P_i = Q_i R_i$ and compute FFR at each sampled location as $\text{FFR}_i = \frac{P_0 - \sum_{k=1}^{i} \Delta P_k}{P_0}$. Locations of cross-sectional area minima or intervals smaller than vessel radius may be used for sampling locations. Server systems 106 may interpolate FFR along the centerline using FFR_i, project FFR values to 3D surface mesh node, and vary α_i, β_i, γ_i and obtain new sets of FFR estimation as necessary for training, such as by using the feature sets defined above to perturb parameters where α_i, β_i can be a function of

the diseased length, degree of stenosis and tapering ratio to account for tapered vessel; and Q_i can be determined by summing distributed flow of each outlet on the basis of the same scaling law as the resistance boundary condition ($outlet\ resistance \propto outlet\ area^{-1.35}$). However, a new scaling law and hyperemic assumption can be adopted, and this feature vector may be associated with the measurement or simulated value of the FFR at that point. Server systems 106 may also train a linear SVM to predict the blood flow characteristics at the points from the feature vectors at the points; and save the results of the SVM as a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.).

[044] In an exemplary production mode, servers systems 106 may , for a target patient, acquire in digital representation (e.g., the memory or digital storage (e.g., hard drive, network drive) of a computational device such as a computer, laptop, DSP, server, etc.): (a) a patient-specific model of the geometry for the patient's ascending aorta and coronary artery tree; and (b) a list of physiological and phenotypic parameters of the patient obtained during training mode. In one embodiment, the patient-specific model of the geometry for the patient's ascending aorta and coronary artery tree may be represented as a list of points in space (possibly with a list of neighbors for each point) in which the space can be mapped to spatial units between points (e.g., millimeters). This model may be derived by performing a cardiac CT imaging of the patient in the end diastole phase of the cardiac cycle. This image then may be segmented manually or automatically to identify voxels belonging to the aorta and the lumen of the coronary arteries. Once the voxels are identified, the geometric model can be derived (e.g., using marching cubes). The process for generating the patient-specific model of the geometry may

be the same as in the training mode. For every point in the patient-specific geometric model, the server systems 106 may create a feature vector for that point that consists of a numerical description of the geometry at that point and estimates of physiological or phenotypic parameters of the patient. These features may be the same as the quantities used in the training mode. The server systems 106 may then use the saved results of the machine learning algorithm produced in the training mode (e.g., feature weights) to produce estimates of the FFR at each point in the patient-specific geometric model. These estimates may be produced using the same linear SVM technique used in the training mode. The server systems 106 may save the predicted FFR values for each point to a digital representation (e.g., the memory or digital storage [e.g., hard drive, network drive] of a computational device such as a computer, laptop, DSP, server, etc.).

[045] In one embodiment, the above factors (i) thru (viii) ("Systolic and diastolic blood pressures" thru "Characteristics of the coronary branch geometry") may be considered global features, which are applicable to all points within a given patient's geometric model. Also, items (ix) thru (xv) ("Feature Set I: Cross-sectional area feature" thru "Feature Set VII: Simplified Physics feature") may be considered features that are local to specific points within a given patient's geometric model. In addition, features (i) thru (vi) may be considered variables within the function of boundary conditions, f(BCs), while features (vii) thru (xv) may be considered variables within the function of geometry, g(areaReductions), on that page. It will be appreciated that any combination of those features, modified by any desired weighting scheme, may be incorporated into a machine learning algorithm executed according to the disclosed embodiments.

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Other embodiments of the invention will be apparent to those skilled in the art from consideration of the specification and practice of the invention disclosed herein. It is intended that the specification and examples be considered as exemplary only, with a true scope and spirit of the invention being indicated by the following claims.

Many modifications will be apparent to those skilled in the art without departing from the scope of the present invention as hereinbefore described with reference to the accompanying drawings.

Throughout this specification and the claims which follow, 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.

The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived from it) or known matter forms part of the common general knowledge in the field of endeavour to which this specification relates.

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THE CLAIMS DEFINING THE INVENTION ARE AS FOLLOWS:

1. A method for determining patient-specific blood flow characteristics, the method comprising:

acquiring, for each of a plurality of individuals, a geometric model and blood flow characteristics of at least part of the individual's vascular system;

executing a machine learning algorithm on the geometric model and blood flow characteristics for each of the plurality of individuals;

identifying, using the machine learning algorithm, for each of the plurality of individuals, a plurality of points in the geometric model of the individual that correspond to features predictive of blood flow characteristics of the individual;

acquiring, for a patient, a geometric model of at least part of the patient's vascular system; and

using the identified features to determine a blood flow characteristic of the patient for at least one point in the patient's geometric model.

2. The method of claim 1, further comprising:

acquiring, for each of the plurality of individuals, one or more physiological parameters; and

executing the machine learning algorithm further based on the one or more physiological parameters.

3. The method of claim 2, wherein executing the machine learning algorithm comprises:

for a plurality of points in the geometric model for each of the plurality of individuals, creating a feature vector of the points or the physiological parameters; and

associating the feature vector for each of the plurality of individuals with the blood flow characteristics of the corresponding individual.

4. The method of claim 3, wherein executing the machine learning algorithm further comprises:

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training the machine learning algorithm to predict blood flow characteristics at various points based on the associated feature vectors.

5. The method of claim 3, wherein each feature vector includes one or more of:

systolic and diastolic blood pressures, heart rate, blood properties, individual age, individual gender, individual height, individual weight, presence or absence of disease, lifestyle characteristics, characteristics of aortic geometry, and characteristics of the coronary branch geometry.

6. The method of claim 3, wherein each feature vector includes one or more of:

a cross-sectional area feature set, an intensity feature set, a surface feature set, a volume feature set, a centerline feature set, and a simplified physics feature set.

7. The method of claim 1, further comprising:

identifying, using the machine learning algorithm, weights of features predictive of blood flow characteristics corresponding to a plurality of points in the geometric models; and

storing the identified weights to a storage device.

8. The method of claim 2, wherein using the identified features to determine the patient's blood flow characteristic comprises:

for each of a plurality of points in the patient's geometric model, creating a feature vector of the patient's physiological parameters corresponding to feature vectors acquired for each of the plurality of individuals.

9. The method of claim 2, wherein the physiological parameters include one or more of a heart rate, a hematocrit level, a blood pressure, a blood viscosity, an individual's age, an individual's gender, an individual's weight, an individual lifestyle characteristic, and a mass of supplied tissue.

10. The method of claim 1, wherein the machine learning algorithm includes one or

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more of: a support vector machine (SVM), a multi-layer perceptron (MLP), a multivariate regression (MVR), a tree-based classifier, and a weighted linear or logistic regression.

11. The method of claim 1, further comprising:

displaying the determined blood flow characteristic of the patient for at least one point in the patient's geometric model to a physician or transmitting the determined blood flow characteristic over a network.

12. A system for estimating patient-specific blood flow characteristics, the system comprising:

a data storage device storing instructions for determining patient-specific blood flow characteristics; and

a processor configured to execute the instructions to perform a method according to any one of claims 1-11.

13. A non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method according to any one of claims 1-11.

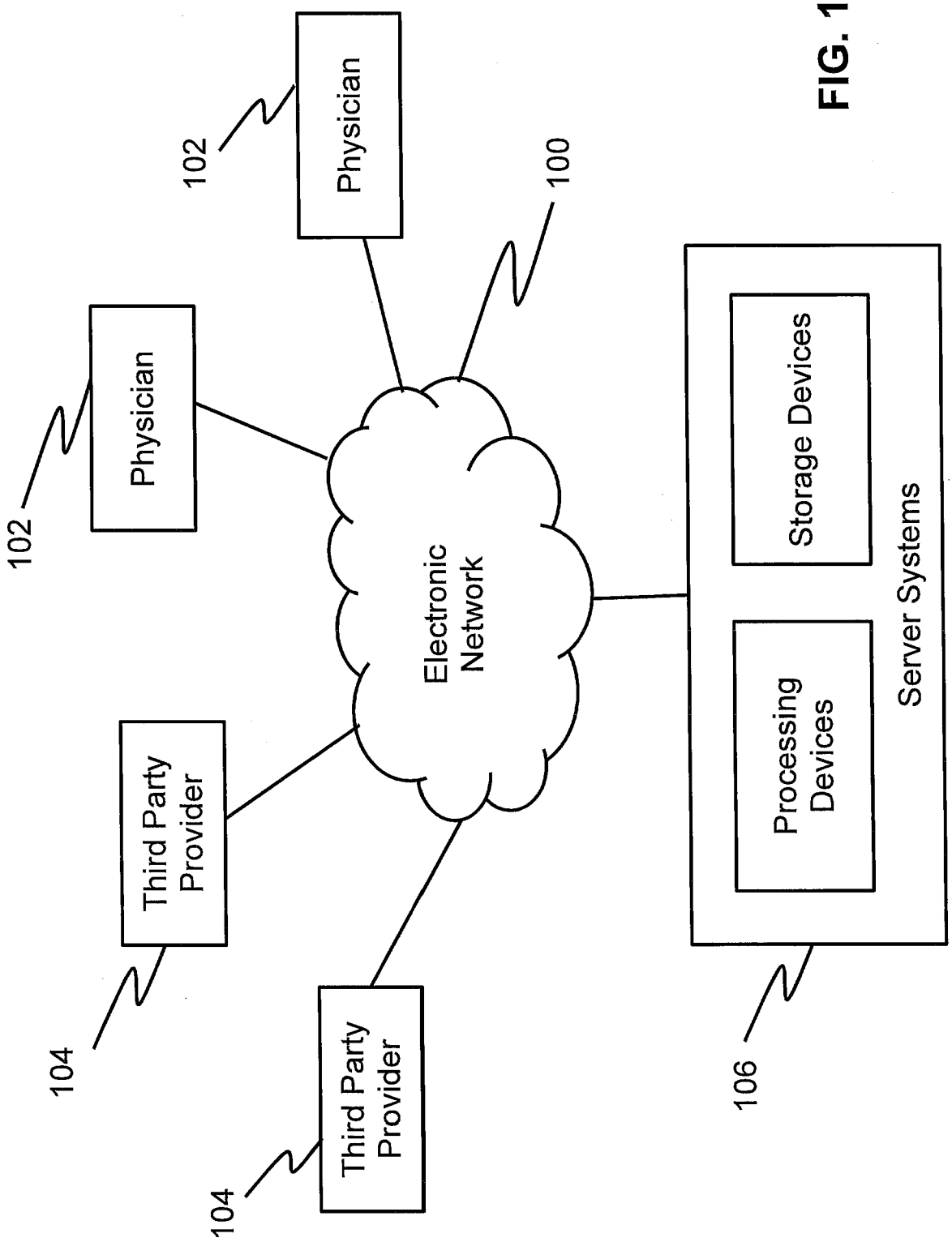
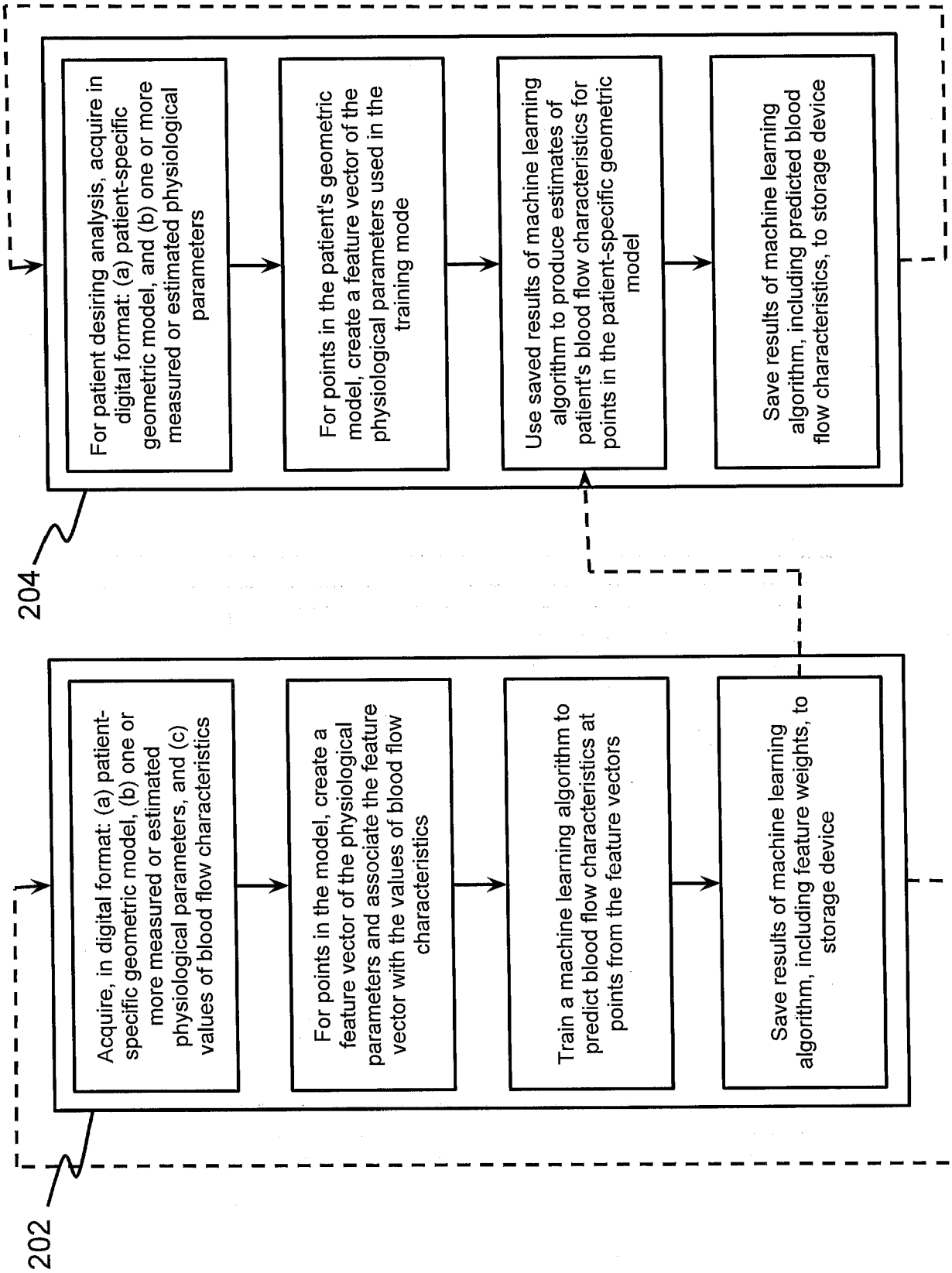

Physician
102
Physician
102
100
Electronic Network
Third Party Provider
104
Third Party Provider
104
Server Systems
Storage Devices
Processing Devices
106

FIG. 1


202
Acquire, in digital format: (a) patient-specific geometric model, (b) one or more measured or estimated physiological parameters, and (c) values of blood flow characteristics
For points in the model, create a feature vector of the physiological parameters and associate the feature vector with the values of blood flow characteristics
Train a machine learning algorithm to predict blood flow characteristics at points from the feature vectors
Save results of machine learning algorithm, including feature weights, to storage device
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For patient desiring analysis, acquire in digital format: (a) patient-specific geometric model, and (b) one or more measured or estimated physiological parameters
For points in the patient's geometric model, create a feature vector of the physiological parameters used in the training mode
Use saved results of machine learning algorithm to produce estimates of patient's blood flow characteristics for points in the patient-specific geometric model
Save results of machine learning algorithm, including predicted blood flow characteristics, to storage device

FIG. 2