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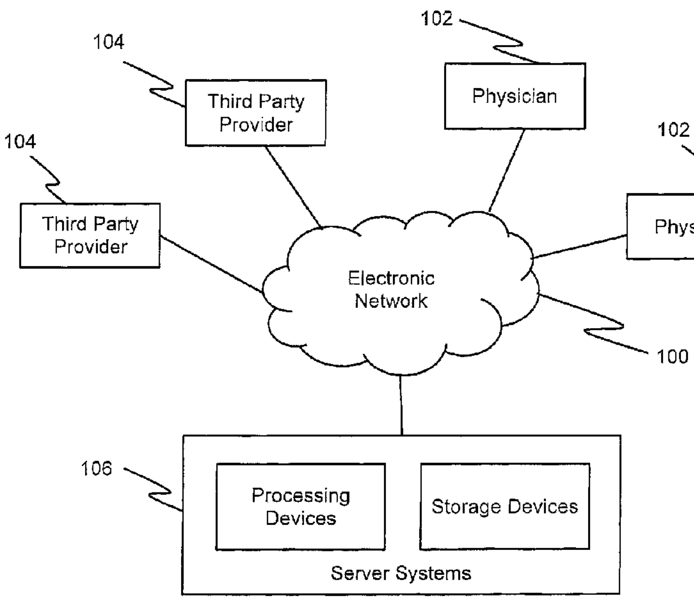

(57) Abrégé/Abstract:
Systems and methods are disclosed for estimating patient-specific blood flow characteristics. One method includes acquiring, for each of a plurality of individuals, a geometric model and estimated blood flow characteristics of at least part of the individual's vascular system; executing 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.

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.

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

RELATED APPLICATION

[001]

FIELD OF THE INVENTION

[002] Various embodiments of the present disclosure relate generally to medical imaging and related methods. More specifically, particular embodiments of the present disclosure relate to systems and methods for estimating patient-specific blood flow characteristics from vessel geometry and physiology.

BACKGROUND

[003] 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.

[004] 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

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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 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.

SUMMARY

[005] 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.

[006] According to one embodiment, a method is disclosed for determining patient-specific blood flow characteristics. The method includes 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, using at least one computer system, 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 for at least one point in the patient's geometric model.

[007] According to another embodiment, a system is disclosed 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 as disclosed herein.

[007a] According to another embodiment, a non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method as disclosed herein.

[007b] In one aspect, 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 an unsupervised machine learning algorithm on the geometric model and blood flow characteristics for each of the plurality of individuals; identifying, using the unsupervised 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 determine a blood flow characteristic of the patient for at least one point in the patient's geometric model.

[007c] In another aspect, there is provided 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 including the steps of: 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 an unsupervised machine learning algorithm on the geometric model and blood flow characteristics for each of the plurality of individuals; identifying, using the unsupervised 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 determine a blood flow characteristic of the patient for at least one point in the patient's geometric model.

[007d] In another aspect, there is provided a non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method including: 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 an unsupervised machine learning algorithm on the geometric model and blood flow characteristics for each of the plurality of individuals; identifying, using the unsupervised 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 determine a blood flow characteristic of the patient for at least one point in the patient's geometric model.

[007e] In another aspect, there is provided a computer-implemented method for determining individual-specific blood flow characteristics, the method comprising: obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data; one or more physiological parameters of the respective individual; and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data and the one or more physiological parameters having been non-invasively acquired; for each of a plurality of points in an individual-specific 3D model generated from the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of a geometry at the respective point and the one or more physiological parameters of the respective individual;

associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector; training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics; obtaining from server systems(s), for a patient, patient-specific imaging data of at least part of the patient's vascular system, the patient-specific imaging data, and one or more physiological parameters of the patient; the patient-specific imaging data and the one or more physiological parameters having been non-invasively acquired; and for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

[007f] In another aspect, there is provided a system for determining individual-specific blood flow characteristics, the system comprising: a data storage device storing instructions for estimating individual-specific blood flow characteristics; and a processor configured to execute the instructions to perform a method including the steps of: obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data, one or more physiological parameters of the respective individual, and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data and the one or more physiological parameters having been non-invasively acquired; for each of a

plurality of points in an individual-specific 3D model generated from the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of the geometry at the respective point and the one or more physiological parameters of the respective individual; associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector; training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics; obtaining from server systems(s), for a patient, patient-specific imaging data of at least part of the patient's vascular system and one or more physiological parameters of the patient, the patient-specific imaging data and the one or more physiological parameters having been non-invasively acquired; and for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

[007g] In another aspect, there is provided a non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method including: obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data, one or more physiological parameters of the respective individual, and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data

and the one or more physiological parameters having been non-invasively acquired; for each of a plurality of points in an individual-specific 3D model generated from in the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of the geometry at the respective point and the one or more physiological parameters of the respective individual; associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector; training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics; obtaining from server system(s) for a patient, patient-specific imaging data of at least part of the patient's vascular system and one or more physiological parameters of the patient, the patient-specific imaging data and the one or more physiological parameters having been non-invasively acquired; and for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

[007h] In another aspect, there is provided a computer-implemented method for determining individual specific blood flow characteristics, the method comprising: obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data, including individual-specific imaging data, and functional estimates of blood flow characteristics at one or more points of at least part of the individual's vascular system, the individual-specific imaging data and the

functional estimates of blood flow characteristics having been non-invasively acquired; creating a feature vector that comprises of the individual-specific imaging data, for each of the plurality of individuals;

associating the feature vectors with the functional estimates of blood flow characteristics, for each of the plurality of individuals; training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from the associated feature vectors, for each of the plurality of individuals; obtaining from server system(s), for an individual, individual-specific imaging data of at least part of the individual's vascular system, said individual-specific imaging data having been non-invasively acquired; and for at least one point in the patient-specific 3D model generated from the individual's vascular system, determining a blood flow characteristic of the individual, using the trained machine learning algorithm. A non-transitory computer-readable medium storing instructions to perform the method described above is also provided.

[007i] In another aspect, there is provided a system for determining individual-specific blood flow characteristics, the system comprising: a data storage device storing instructions for estimating individual-specific blood flow characteristics; and a processor configured to execute the instructions to perform a method including the steps of: obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data and functional estimates of blood flow characteristics at one or more points in individual-specific 3D models of at least part of the individual's vascular system, the individual-specific imaging data and the functional estimates of blood flow characteristics having been non-invasively acquired; creating a feature vector that comprises of the individual-specific imaging data, for each of the plurality of individuals; associating the feature vectors with the

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functional estimates of blood flow characteristics, for each of the plurality of individuals; training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from the associated feature vectors, for each of the plurality of individuals; obtaining from server system(s), for an individual, individual-specific imaging data of at least part of the individual's vascular system; said individual-specific imaging data having been non-invasively acquired; and for at least one point in a patient-specific 3D model generated from the individual's vascular system, determining a blood flow characteristic of the individual, using the trained machine learning algorithm.

[007j] In another aspect, there is provided a computer-implemented method for determining fractional flow reserve (FFR) for a plaque of interest for a patient, comprising: receiving a medical image of the patient including the plaque of interest; detecting image regions corresponding to the plaque of interest and a coronary artery tree of the patient; and determining an FFR value associated with the plaque of interest using a trained machine learning algorithm applied directly to the detected image regions.

[007k] In another aspect, there is provided an apparatus for determining fractional flow reserve (FFR) for a plaque of interest for a patient, comprising: means for receiving a medical image of the patient including the plaque of interest; means for detecting image regions corresponding to the plaque of interest and a coronary tree of the patient; and means for determining an FFR value for the plaque of interest using a trained machine learning algorithm applied directly to the detected image regions.

[007l] In another aspect, there is provided a non-transitory computer readable medium storing computer program instructions for determining fractional

flow reserve (FFR) for a plaque of interest for a patient, the computer program instructions when executed by a processor cause the processor to perform operations comprising: receiving a medical image of the patient including the plaque of interest; detecting image regions corresponding to the plaque of interest and a coronary tree of the patient; and determining an FFR value for the plaque of interest using a trained machine learning algorithm applied directly to the detected image regions.

[007m] In another aspect, there is provided a method for determining fractional flow reserve (FFR) for a stenosis of interest for a patient, comprising: receiving medical image data of the patient including the stenosis of interest; extracting a set of features for the stenosis of interest from the medical image data of the patient; and determining a FFR value for the stenosis of interest based on the extracted set of features using a trained machine-learning based mapping.

[007n] In another aspect, there is provided a non-transitory computer readable medium storing computer program instructions for determining fractional flow reserve (FFR) for a stenosis of interest for a patient, the computer program instructions when executed on a processor cause the processor to perform operations comprising: receiving medical image data of the patient including the stenosis of interest; extracting a set of features for the stenosis of interest from the medical image data of the patient; and determining a FFR value for the stenosis of interest based on the extracted set of features using a trained machine-learning based mapping.

[007o] In another aspect, there is provided a method for hemodynamic determination in medical imaging, the method comprising: acquiring medical scan data representing an anatomical structure of a patient; extracting a set of features

from the medical scan data; inputting, by a processor, the features to a machine-trained classifier, the machine trained classifier trained from synthetic data not specific to any patients; and outputting, by the processor with application of the machine-trained classifier to the features, a hemodynamic metric.

[007p] In another aspect, there is provided a method for hemodynamic determination in medical imaging, the method comprising: generating a plurality of examples of anatomical arrangements with computer modeling, physical modeling, or both computer and physical modeling; storing a value for a flow characteristic for each of the examples of the anatomical arrangements; and training, with machine learning, a classifier for predicting the flow characteristics for different anatomical arrangements.

[007q] In another aspect, there is provided a system for hemodynamic determination in medical imaging, the system comprising: a scanner configured to scan a vessel of a patient; a memory configured to store a plurality of features of the vessel of the patient, the features determined from the scan of the vessel; a processor configured to apply the features to a machine-trained predictor trained with training data of synthetic examples of vessels, and to output a prediction of a value of a hemodynamic variable based on the application of the features to the machine-trained predictor; and a display configured to indicate the value of the hemodynamic variable.

[008] Additional objects and advantages of the disclosed embodiments will be set forth in part in the description that follows, and in part will be apparent from the description, or may be learned by practice of the disclosed embodiments. The objects and advantages of the disclosed embodiments will be realized and attained

by means of the elements and combinations particularly pointed out in the description.

[009] It is to be understood that both the foregoing general description and the following detailed description are exemplary and explanatory only and are not restrictive of the disclosed embodiments.

BRIEF DESCRIPTION OF THE DRAWINGS

[010] The accompanying drawings, which are incorporated in and constitute a part of this specification, illustrate various exemplary embodiments and together with the description, serve to explain the principles of the disclosed embodiments.

[011] 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.

[012] 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.

DESCRIPTION OF THE EMBODIMENTS

[013] 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.

[014] 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 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.

[015] 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

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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

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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

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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 $\mathrm{FFR}_i = \frac{P_0 - \sum_{k=1}^{i} \Delta P_k}{P_0}$. 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.

[046] 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.

What is claimed is:

1. A computer-implemented method for determining individual-specific blood flow characteristics, the method comprising:

obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data; one or more physiological parameters of the respective individual; and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data and the one or more physiological parameters having been non-invasively acquired;

for each of a plurality of points in an individual-specific 3D model generated from the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of a geometry at the respective point and the one or more physiological parameters of the respective individuals;

associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector;

training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics;

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obtaining from server systems(s), for a patient, patient-specific imaging data of at least part of the patient's vascular system and one or more physiological parameters of the patient; the patient-specific imaging data and the one or more physiological parameters having been non-invasively acquired; and

for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

2. The computer-implemented method of claim 1 wherein the blood flow characteristics of the individuals include ischemia, blood flow, or fractional flow reserve.

3. The computer-implemented method of any one of claim 1 or 2, further comprising:

using the machine learning algorithm to weight an impact of features on the blood flow characteristic; and

using the machine learning algorithm to estimate a blood flow characteristic numerically, classify a vessel as ischemia positive or negative, or classify a respective individual as ischemia positive or negative.

4. The computer-implemented method of any one of claims 1 to 3, wherein the one or more physiological parameters include one or more of: heart rate, blood

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pressure, demographics such as age or sex, medication, disease states, including diabetes, hypertension, vessel dominance, and prior myocardial infarction (MI).

5. The computer-implemented method of any one of claims 1 to 4, further comprising: displaying or storing the estimated value of the blood flow characteristic of the patient in one or more of a media, including images, renderings, tables of values, or reports, or transferring the estimated value of the blood flow characteristic of the patient to a physician through other electronic or physical delivery methods.

6. The computer-implemented method of any one of claims 1 to 5, further comprising displaying along with each estimated value of the blood flow characteristic of the patient a confidence level or a positive, negative, or inconclusive indication.

7. The computer-implemented method of any one of claims 1 to 6, further comprising producing estimates of the blood flow characteristic of the patient based on one or more of analytical fluid dynamics equations and morphometry scaling laws.

8. The computer-implemented method any one of claims 1 to 7, wherein the individual-specific imaging data includes one or more of: vessel size, vessel size at ostium, vessel size at distal branches, reference and minimum vessel size at plaque, distance from ostium to plaque, length of plaque and length of minimum vessel size, myocardial volume, branches proximal/distal to measurement location, branches proximal/distal to plaque, and measurement location.

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9. The computer-implemented method any one of claims 1 to 8, further comprising:

compiling a library or database of individual-specific imaging data and physiological parameters along with FFR, ischemia test results, previous simulation results, and imaging data.

10. The computer-implemented method any one of claims 1 to 9, further comprising:

refining the machine learning algorithm based on additional data added to the library or database.

11. The computer-implemented method of any one of claims 1 to 10, wherein the individual-specific imaging data for the patient or the plurality of individuals is obtained from one or more of: medical image data, measurements, models, and segmentations.

12. A system for determining individual-specific blood flow characteristics, the system comprising:

a data storage device storing instructions for estimating individual-specific blood flow characteristics; and

a processor configured to execute the instructions to perform a method including the steps of:

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obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data, one or more physiological parameters of the respective individual, and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data and the one or more physiological parameters having been non-invasively acquired;

for each of a plurality of points in an individual-specific 3D model generated from the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of a geometry at the respective point and the one or more physiological parameters of the respective individual;

associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector;

training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics;

obtaining from server systems(s), for a patient, patient-specific imaging data of at least part of the patient's vascular system and one or more physiological parameters of the patient, the patient-specific anatomic data and the one or more physiological parameters having been non-invasively acquired; and

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for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

13. The system of claim 12, wherein the blood flow characteristics include ischemia, blood flow, or fractional flow reserve.

14. The system of claim 12 or 13, wherein the processor is further configured for:

using the machine learning algorithm to weight an impact of features on estimated blood flow characteristic; and

using the machine learning algorithm to estimate a blood flow characteristic numerically, classify a vessel as ischemia positive or negative, or classify a respective individual as ischemia positive or negative.

15. The system of claim 12, 13 or 14, wherein the one or more physiological parameters include one or more of: heart rate, blood pressure, demographics such as age or sex, medication, disease states, including diabetes, hypertension, vessel dominance, and prior myocardial infarction (MI).

16. The system of any one of claims 12 to 15, wherein the processor is further configured for:

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displaying or storing the estimated value of the blood flow characteristic of the patient in one or more of a media, including images, renderings, tables of values, or reports, or transferring the estimated value of the blood flow characteristic of the patient to a physician through other electronic or physical delivery methods.

17. The system of any one of claims 12 to 16, wherein the processor is further configured for:

displaying along with the estimated value of the determined blood flow characteristic of the patient a confidence level or a positive, negative, or inconclusive indication.

18. The system of any one of claims 12 to 17, further comprising producing estimates of the blood flow characteristic of the patient based on one or more of analytical fluid dynamics equations and morphometry scaling laws.

19. The system of any one of claims 12 to 18, wherein the individual-specific imaging data includes one or more of: vessel size, vessel size at ostium, vessel size at distal branches, reference and minimum vessel size at plaque, distance from ostium to plaque, length of plaque and length of minimum vessel size, myocardial volume, branches proximal/distal to measurement location, branches proximal/distal to plaque, and measurement location.

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20. The system of any one of claims 12 to 19, wherein the processor is further configured for:

compiling a library or database of individual-specific imaging data and physiological parameters along with FFR, ischemia test results, previous simulation results, and imaging data.

21. The system of any one of claims 12 to 20, wherein the individual-specific imaging data for the patient or the plurality of individuals is obtained from one or more of: medical image data, measurements, models, and segmentations.

22. A non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method including:

obtaining from server system(s), for each of a plurality of individuals, individual-specific imaging data, one or more physiological parameters of the respective individual, and one or more non-invasively computed blood flow characteristics of blood flow through at least part of each respective individual's vascular system, the individual-specific imaging data and the one or more physiological parameters having been non-invasively acquired;

for each of a plurality of points in an individual-specific 3D model generated from the individual-specific imaging data of each of the plurality of individuals, creating a feature vector of a geometry at the respective point and the one or more physiological parameters of the respective individual;

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associating each created feature vector with a non-invasively computed blood flow characteristic of blood flow through the part of the respective individual's vascular system at the respective point of the feature vector;

training a machine learning algorithm on the associated feature vectors and non-invasively computed blood flow characteristics of the plurality of points of the plurality of individuals' vascular systems to generate relations between each individual's individual-specific imaging data and the individual's non-invasively computed blood flow characteristics;

obtaining from server system(s) for a patient, patient-specific imaging data of at least part of the patient's vascular system and one or more physiological parameters of the patient, the patient-specific anatomic data and the one or more physiological parameters having been non-invasively acquired; and

for at least one point in a patient-specific 3D model generated from the patient's patient-specific imaging data, estimating one or more values of the blood flow characteristic at one or more points of the patient's vascular system, using the machine learning algorithm and the generated relations.

23. The computer-readable medium of claim 22, 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.

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24. The computer-readable medium of claim 22 or 23, wherein the one or more physiological parameters include one or more of systolic and diastolic blood pressures, heart rate, hematocrit level, blood pressure, blood viscosity, individual age, individual gender, individual height, individual weight, individual lifestyle characteristic, characteristics of aortic geometry, characteristics of the coronary branch geometry, and a mass of supplied tissue.

25. The computer-readable medium of claim 22, 23 or 24, wherein the machine learning algorithm includes one or more of: a support vector machine (SVM), a multi-layer perceptron (MLP), a multivariate regression (MVR), and a weighted linear or logistic regression.

26. A computer-implemented method for determining individual-specific blood flow characteristics, the method comprising:

obtaining from server system(s), for each of a plurality of individuals, individual-specific anatomic data and functional estimates of blood flow characteristics at one or more points in individual-specific 3D models of at least part of the individual's vascular system, the individual-specific anatomic data and the functional estimates of blood flow characteristics having been non-invasively acquired;

creating a feature vector that comprises of the individual-specific anatomic data, for each of the plurality of individuals;

associating the feature vectors with the functional estimates of blood flow characteristics, for each of the plurality of individuals;

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training a machine learning algorithm that can determine blood flow characteristics at one or more points of a patient-specific 3D model generated from an individual's vascular system, from the associated feature vectors, for each of the plurality of individuals;

obtaining from server system(s), for an individual, individual-specific anatomic data including imaging data of at least part of the individual's vascular system, said individual-specific anatomic data having been non-invasively acquired; and

for at least one point in a patient-specific 3D model generated from the individual's vascular system, determining a blood flow characteristic of the individual, using the trained machine learning algorithm.

27. The computer-implemented method of claim 26, further comprising:

acquiring, for each of the plurality of individuals, one or more individual characteristics;

creating a feature vector that further comprises the individual characteristics, for each of the plurality of individuals;

training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from individual - specific anatomic data and individual characteristics, for each of the plurality of individuals; and

obtaining further, from server system(s), for the individual, one or more individual characteristics, said one or more individual characteristics having been non-invasively acquired.

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28. The computer-implemented method of claim 26 or 27, wherein the blood flow characteristics of the individuals include ischemia, blood flow, or fractional flow reserve.

29. The computer-implemented method of claim 26, 27 or 28, further comprising:

for each feature vector, using a regression or machine learning technique to weight an impact of the anatomic data on the blood flow characteristic; and

using the regression or machine learning technique to estimate a blood flow characteristic numerically, classify a vessel as ischemia positive or negative, or classify an individual as ischemia positive or negative.

30. The computer-implemented method of any one of claims 26 to 29, wherein the individual characteristics include one or more of: heart rate, blood pressure, demographics such as age or sex, medication, disease states, including diabetes, hypertension, vessel dominance, and prior myocardial infarction (MI).

31. The computer-implemented method of any one of claims 26 to 30, further comprising: displaying or storing the determined blood flow characteristic of the individual in one or more of a media, including images, renderings, tables of values, or reports, or transferring the determined blood flow characteristic of the individual to a physician through other electronic or physical delivery methods.

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32. The computer-implemented method of any one of claims 26 to 31, further comprising displaying along with each determined blood flow characteristic of the individual a confidence level or a positive, negative, or inconclusive indication.

33. The computer-implemented method of any one of claims 26 to 32, wherein the functional producing estimates of blood flow characteristics are based on one or more of analytical fluid dynamics equations and morphometry scaling laws.

34. The computer-implemented method of any one of claims 26 to 33, wherein the individual-specific anatomic data includes one or more of: vessel size, vessel size at ostium, vessel size at distal branches, reference and minimum vessel size at plaque, distance from ostium to plaque, length of plaque and length of minimum vessel size, myocardial volume, branches proximal/distal to measurement location, branches proximal/distal to plaque, and measurement location.

35. The computer-implemented method of claim 27, further comprising:

compiling a library or database of anatomic and individual characteristics along with FFR, ischemia test results, previous simulation results, and imaging data.

36. The computer-implemented method of claim 35, further comprising:

refining the machine learning algorithm based on additional data added to the library or database.

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37. The computer-implemented method of claim 35, wherein the individual-specific anatomic data for the individual or the plurality of individuals is obtained from one or more of: medical image data, measurements, models, and segmentations.

38. A system for determining individual-specific blood flow characteristics, the system comprising:

a data storage device storing instructions for estimating individual-specific blood flow characteristics; and

a processor configured to execute the instructions to perform a method including the steps of:

obtaining from server system(s), for each of a plurality of individuals, individual-specific anatomic data and functional estimates of blood flow characteristics at one or more points in individual-specific 3D models of at least part of the individual's vascular system, the individual-specific anatomic data and the functional estimates of blood flow characteristics having been non-invasively acquired;

creating a feature vector that comprises of the individual-specific anatomic data, for each of the plurality of individuals;

associating the feature vectors with the functional estimates of blood flow characteristics, for each of the plurality of individuals;

training a machine learning algorithm that can determine blood flow characteristics at one or more points of a patient-specific 3D model generated from an

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individual's vascular system, from the associated feature vectors, for each of the plurality of individuals;

obtaining from server system(s), for an individual, individual-specific anatomic data including imaging data of at least part of the individual's vascular system; said individual-specific anatomic data having been non-invasively acquired; and

for at least one point in a patient-specific 3D model generated from the individual's vascular system, determining a blood flow characteristic of the individual, using the trained machine learning algorithm.

39. The system of claim 38, wherein the system is further configured for:

acquiring, for each of the plurality of individuals, one or more individual characteristics;

creating a feature vector that further comprises the individual characteristics, for each of the plurality of individuals;

training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from individual - specific anatomic data and individual characteristics, for each of the plurality of individuals; and

obtaining from server system(s) further, for the individual, one or more individual characteristics, said individual characteristics having been non-invasively acquired.

40. The system of claim 38 or 39, wherein the blood flow characteristics include ischemia, blood flow, or fractional flow reserve.

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41. The system of claim 38, 39 or 40 wherein the processor is further configured for:

for each feature vector, using a regression or machine learning technique to weight an impact of the anatomic data on the blood flow characteristic; and

using the regression or machine learning technique to estimate a blood flow characteristic numerically, classify a vessel as ischemia positive or negative, or classify an individual as ischemia positive or negative.

42. The system of any one of claims 37 to 41, wherein the individual characteristics include one or more of: heart rate, blood pressure, demographics such as age or sex, medication, disease states, including diabetes, hypertension, vessel dominance, and prior myocardial infarction (MI).

43. The system of any one of claims 37 to 42, wherein the processor is further configured for:

displaying or storing the determined blood flow characteristic of the individual in one or more of a media, including images, renderings, tables of values, or reports, or transferring the determined blood flow characteristic of the individual to a physician through other electronic or physical delivery methods.

44. The system of any one of claims 37 to 43, wherein the processor is further configured for:

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displaying along with each determined blood flow characteristic of the individual a confidence level or a positive, negative, or inconclusive indication.

45. The system of any one of claims 37 to 44, wherein the functional estimates of blood flow characteristics are based on one or more of analytical fluid dynamics equations and morphometry scaling laws.

46. The system of any one of claims 37 to 45, wherein the individual-specific anatomic data includes one or more of: vessel size, vessel size at ostium, vessel size at distal branches, reference and minimum vessel size at plaque, distance from ostium to plaque, length of plaque and length of minimum vessel size, myocardial volume, branches proximal/distal to measurement location, branches proximal/distal to plaque, and measurement location.

47. The system of any one of claims 37 to 46, wherein the processor is further configured for:

compiling a library or database of anatomic and individual characteristics along with FFR, ischemia test results, previous simulation results, and imaging data.

48. The system of any one of claims 37 to 47, wherein the individual-specific anatomic data for the individual or the plurality of individuals is obtained from one or more of: medical image data, measurements, models, and segmentations.

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49. A non-transitory computer-readable medium storing instructions that, when executed by a computer, cause the computer to perform a method including:

obtaining from server system(s), for each of a plurality of individuals, individual-specific anatomic data and functional estimates of blood flow characteristics at one or more points in individual-specific 3D models of at least part of the individual's vascular system, the individual-specific anatomic data and the functional estimates of blood flow characteristics having been non-invasively acquired;

creating a feature vector that comprises of the individual-specific anatomic data, for each of the plurality of individuals;

associating the feature vectors with the functional estimates of blood flow characteristics, for each of the plurality of individuals;

training a machine learning algorithm that can determine blood flow characteristics at one or more points of a patient-specific 3D model generated from an individual's vascular system, from the associated feature vectors, for each of the plurality of individuals;

obtaining from server system(s), for an individual, individual-specific anatomic data including imaging data of at least part of the individual's vascular system; the individual-specific anatomic data having been non-invasively acquired; and

for at least one point in a patient-specific 3D model generated from the individual's vascular system, determining a blood flow characteristic of the individual, using the trained machine learning algorithm.

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50. The computer-readable medium of claim 49, wherein the method further comprises:

obtaining from server systems, for each of the plurality of individuals, one or more individual characteristics, said one or more individual characteristics having been non-invasively acquired;

creating a feature vector that further comprises the individual characteristics, for each of the plurality of individuals;

training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from individual - specific anatomic data and individual characteristics, for each of the plurality of individuals; and

obtaining further, from server system(s), for the individual, one or more individual characteristics, said one or more individual characteristics having been non-invasively acquired.

51. The computer-readable medium of claim 50, wherein training a machine learning algorithm that can determine blood flow characteristics at one or more points of an individual's vascular system, from individual-specific anatomic data and individual characteristics includes:

for a plurality of points in the vascular system of each of the plurality of individuals, creating a feature vector of the individual characteristics and individual-specific anatomic data; and

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

52. The computer-readable medium of claim 51, 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.

53. The computer-readable medium of claim 51, 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.

54. The computer-readable medium of claim 50, wherein the individual characteristics include one or more of heart rate, hematocrit level, blood pressure, blood viscosity, individual age, individual gender, individual weight, individual lifestyle characteristic, and a mass of supplied tissue.

55. The computer-readable medium of claim 48, wherein the machine learning algorithm includes one or more of: a support vector machine (SVM), a multi-layer

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perceptron (MLP), a multivariate regression (MVR), and a weighted linear or logistic regression.

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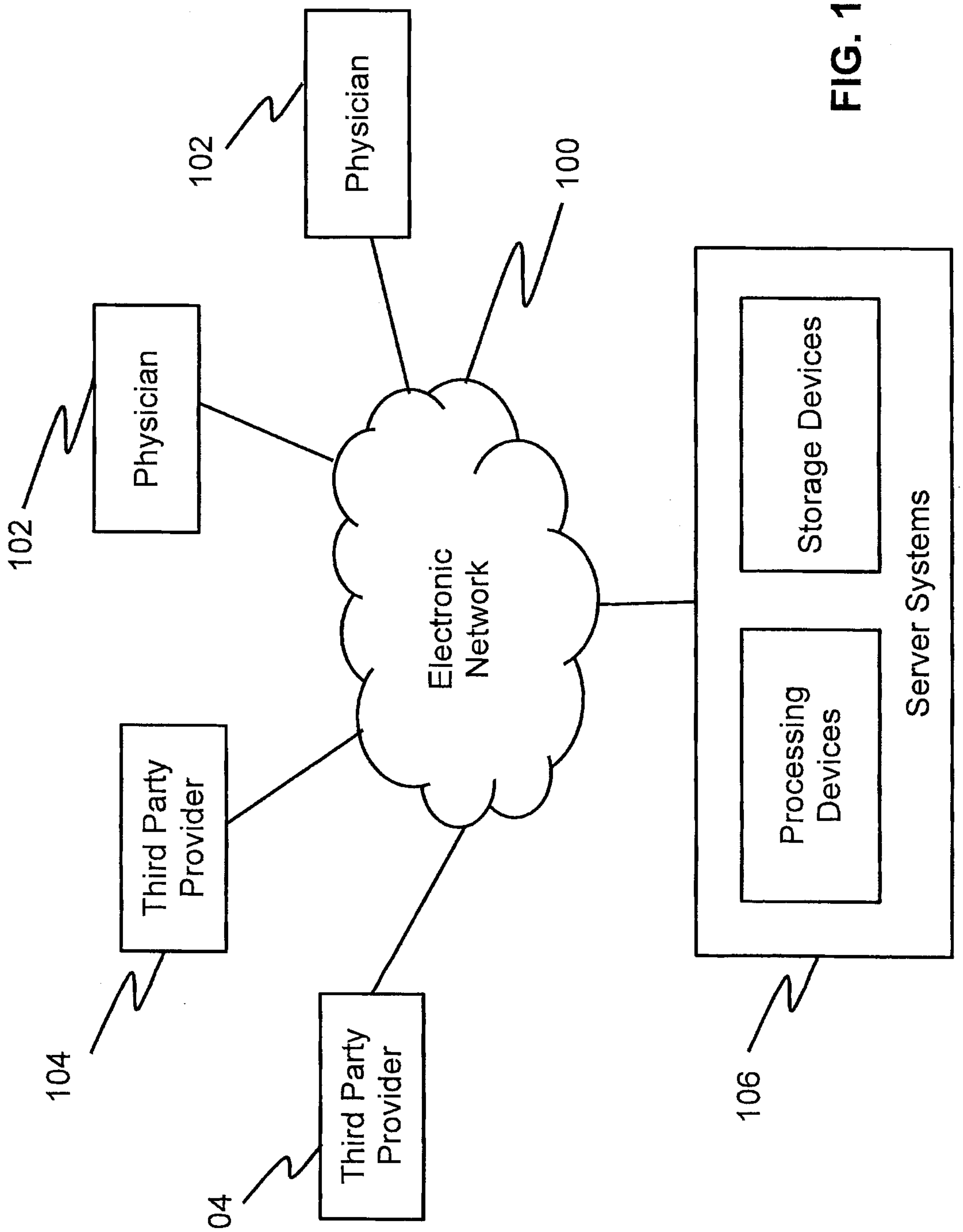

FIG. 1

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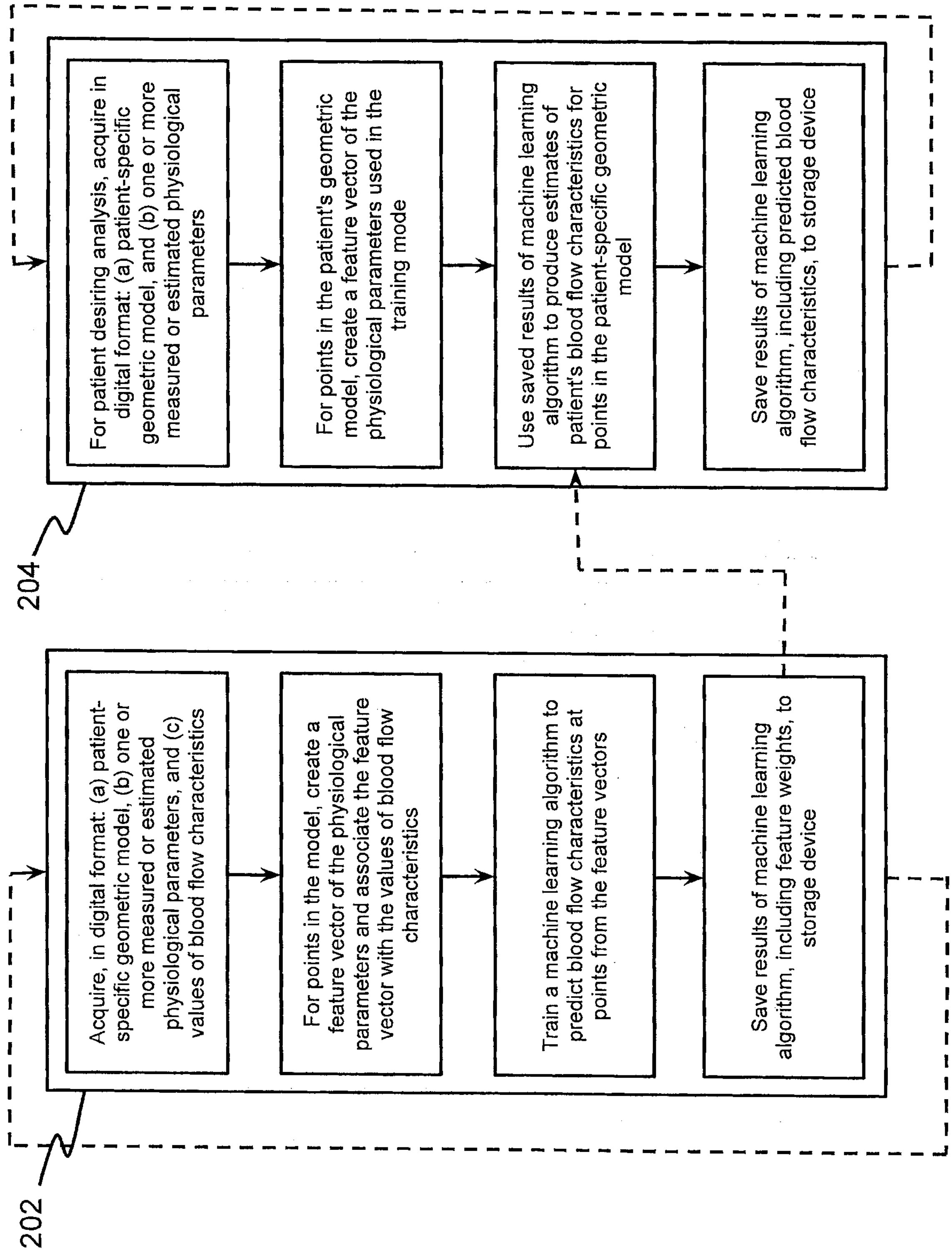
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Acquire, in digital format: (a) patient-specific geometric model, (b) one or more measured or estimated physiological parameters, and (c) values of blood flow characteristics
For points in the model, create a feature vector of the physiological parameters 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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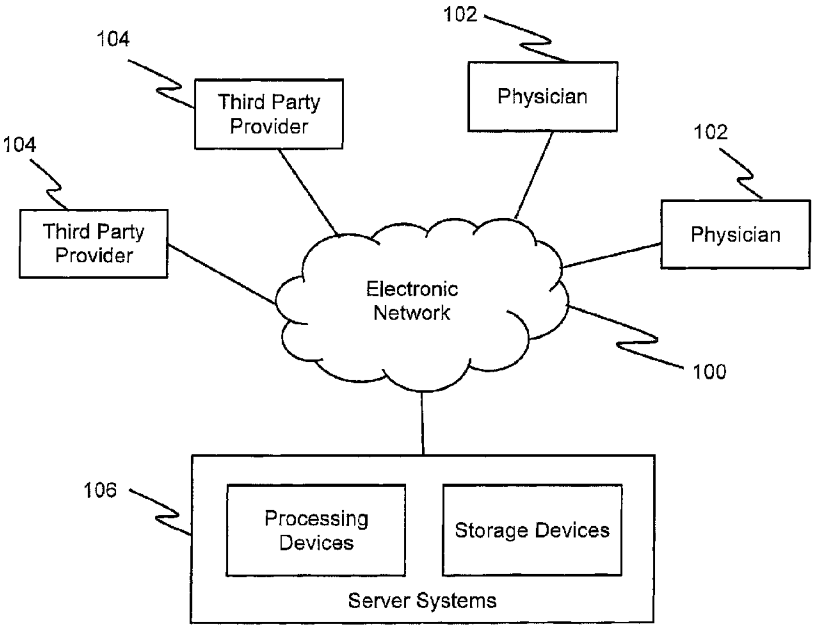
For patient desiring analysis, acquire in digital format: (a) patient-specific geometric model, and (b) one or more measured or estimated physiological parameters
For points in the patient's geometric model, create a feature vector of the physiological parameters used in the training mode
Use saved results 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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104
Third Party Provider
Third Party Provider
102
Physician
102
Physician
Electronic Network
100
106
Processing Devices
Storage Devices
Server Systems