US 20200138321A1

(19) **United States**

(12) **Patent Application Publication** (10) **Pub. No.: US 2020/0138321 A1**

Niebauer (43) **Pub. Date: May 7, 2020**

(54) **FREQUENCY ANALYSIS FOR PREDICTING LEFT VENTRICULAR DYSFUNCTION**

(71) Applicant: **THE CLEVELAND CLINIC FOUNDATION**, Cleveland, OH (US)

(72) Inventor: **Mark J. Niebauer**, Mayfield Heights, OH (US)

(21) Appl. No.: **16/676,997**

(22) Filed: **Nov. 7, 2019**

Related U.S. Application Data

(60) Provisional application No. 62/756,944, filed on Nov. 7, 2018.

Publication Classification

(51) **Int. Cl.**

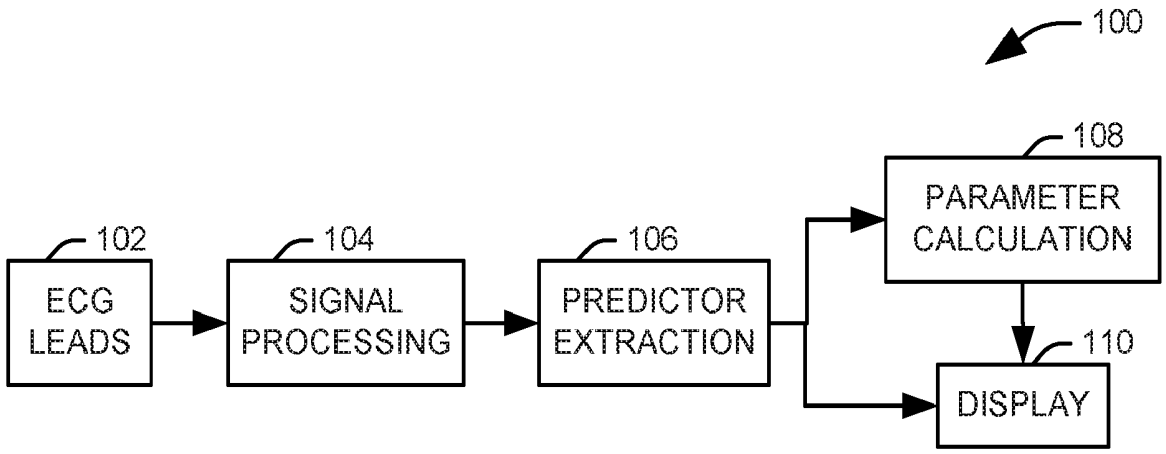
A61B 5/0452	(2006.01)
A61B 5/0408	(2006.01)
A61B 5/00	(2006.01)
G06N 20/20	(2006.01)

(52) **U.S. Cl.**

CPC ***A61B 5/0452*** (2013.01); ***A61B 5/0408*** (2013.01); ***G06N 20/20*** (2019.01); ***A61B 5/7225*** (2013.01); ***A61B 5/7275*** (2013.01)

(57) **ABSTRACT**

Systems and methods are provided for evaluating infranodal pacing is applied to a patient. Electrocardiogram (ECG) data representing the pacing is obtained from a set of electrodes as an ECG lead. A predictor value representing a frequency content a portion of the ECG lead is extracted. A fitness parameter is determined for the pacing from at least the predictor value. The fitness parameter represents a likelihood that the applied infranodal pacing will induce left ventricular dysfunction in the patient. The fitness parameter is displayed to a user at an associated display.



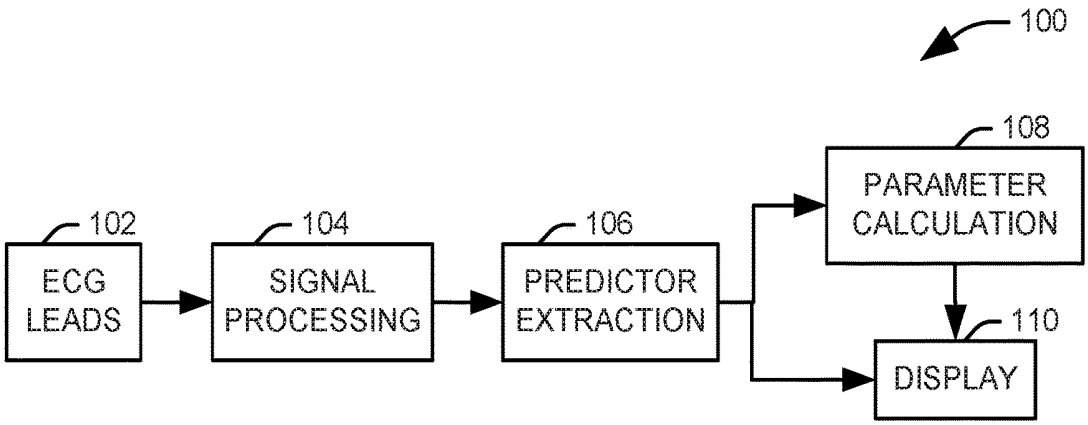

100
108
PARAMETER CALCULATION
102
ECG LEADS
104
SIGNAL PROCESSING
106
PREDICTOR EXTRACTION
110
DISPLAY

FIG. 1

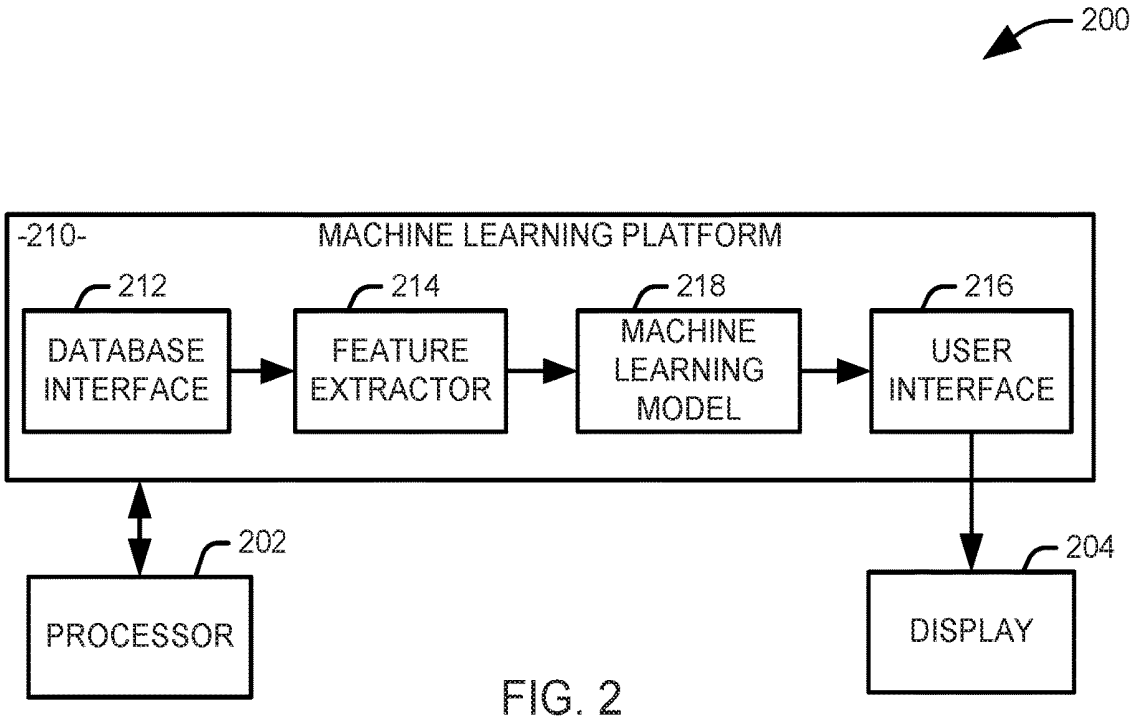

200
-210-
MACHINE LEARNING PLATFORM
212
DATABASE INTERFACE
214
FEATURE EXTRACTOR
218
MACHINE LEARNING MODEL
216
USER INTERFACE
202
PROCESSOR
204
DISPLAY

FIG. 2

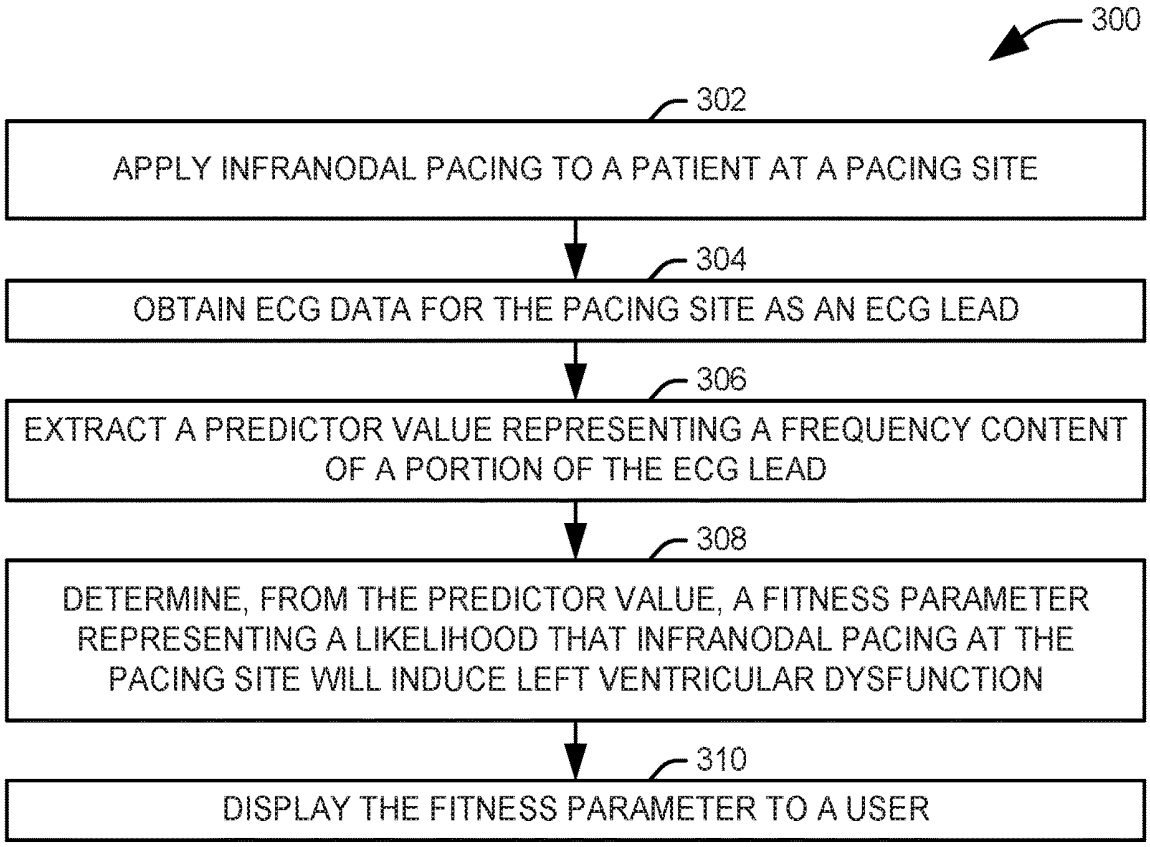

300
302
APPLY INFRANODAL PACING TO A PATIENT AT A PACING SITE
304
OBTAIN ECG DATA FOR THE PACING SITE AS AN ECG LEAD
306
EXTRACT A PREDICTOR VALUE REPRESENTING A FREQUENCY CONTENT OF A PORTION OF THE ECG LEAD
308
DETERMINE, FROM THE PREDICTOR VALUE, A FITNESS PARAMETER REPRESENTING A LIKELIHOOD THAT INFRANODAL PACING AT THE PACING SITE WILL INDUCE LEFT VENTRICULAR DYSFUNCTION
310
DISPLAY THE FITNESS PARAMETER TO A USER

FIG. 3

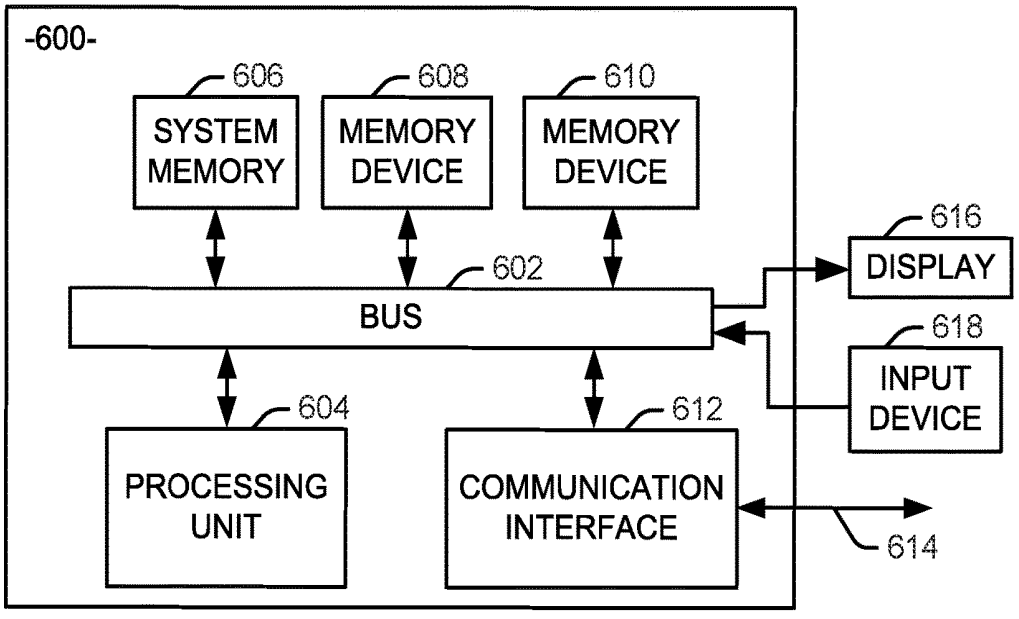

-600-
606
SYSTEM MEMORY
608
MEMORY DEVICE
610
MEMORY DEVICE
602
BUS
616
DISPLAY
618
INPUT DEVICE
604
PROCESSING UNIT
612
COMMUNICATION INTERFACE
614

FIG. 6

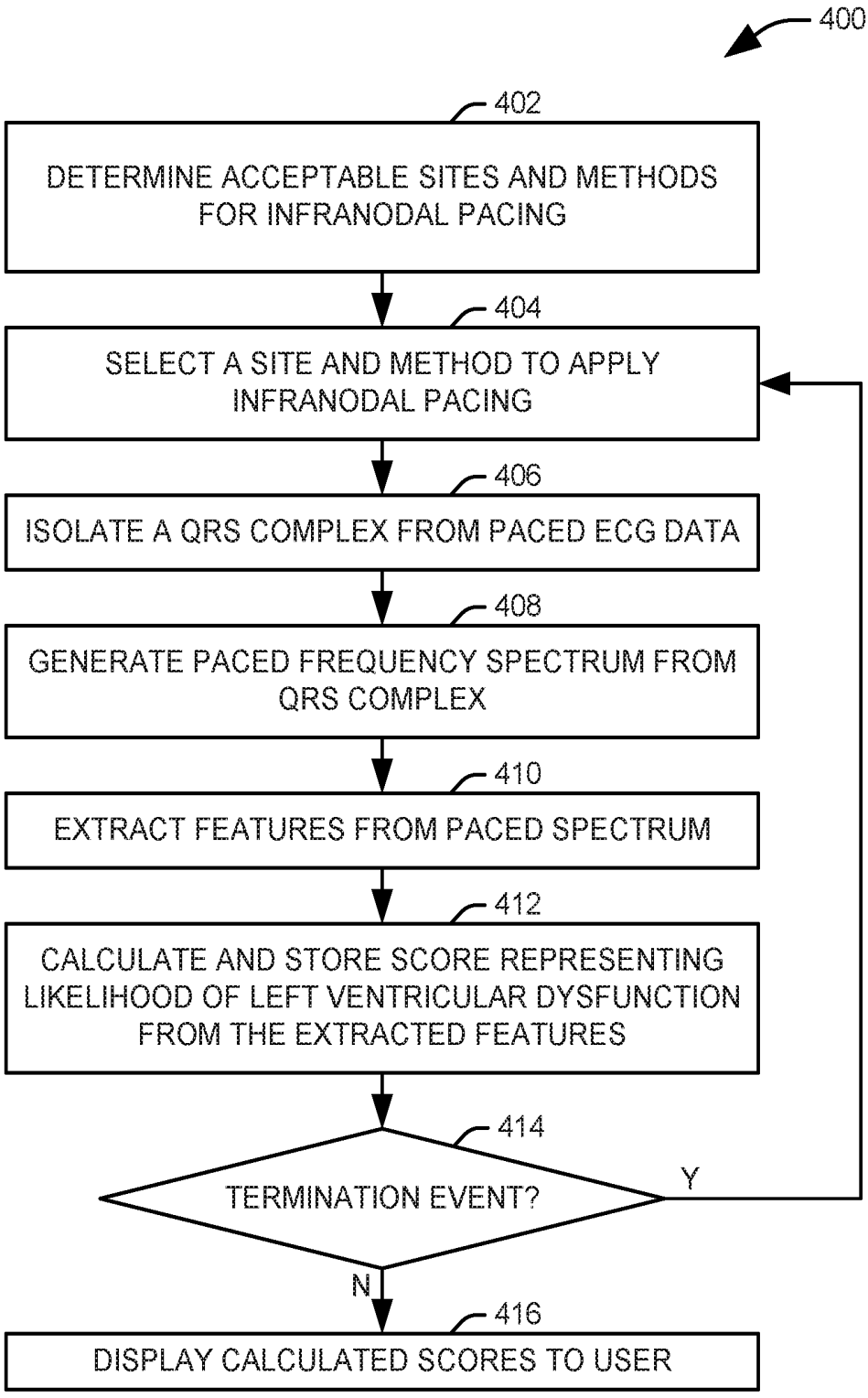

400
402
DETERMINE ACCEPTABLE SITES AND METHODS FOR INFRANODAL PACING
404
SELECT A SITE AND METHOD TO APPLY INFRANODAL PACING
406
ISOLATE A QRS COMPLEX FROM PACED ECG DATA
408
GENERATE PACED FREQUENCY SPECTRUM FROM QRS COMPLEX
410
EXTRACT FEATURES FROM PACED SPECTRUM
412
CALCULATE AND STORE SCORE REPRESENTING LIKELIHOOD OF LEFT VENTRICULAR DYSFUNCTION FROM THE EXTRACTED FEATURES
414
TERMINATION EVENT?
Y
N
416
DISPLAY CALCULATED SCORES TO USER

FIG. 4

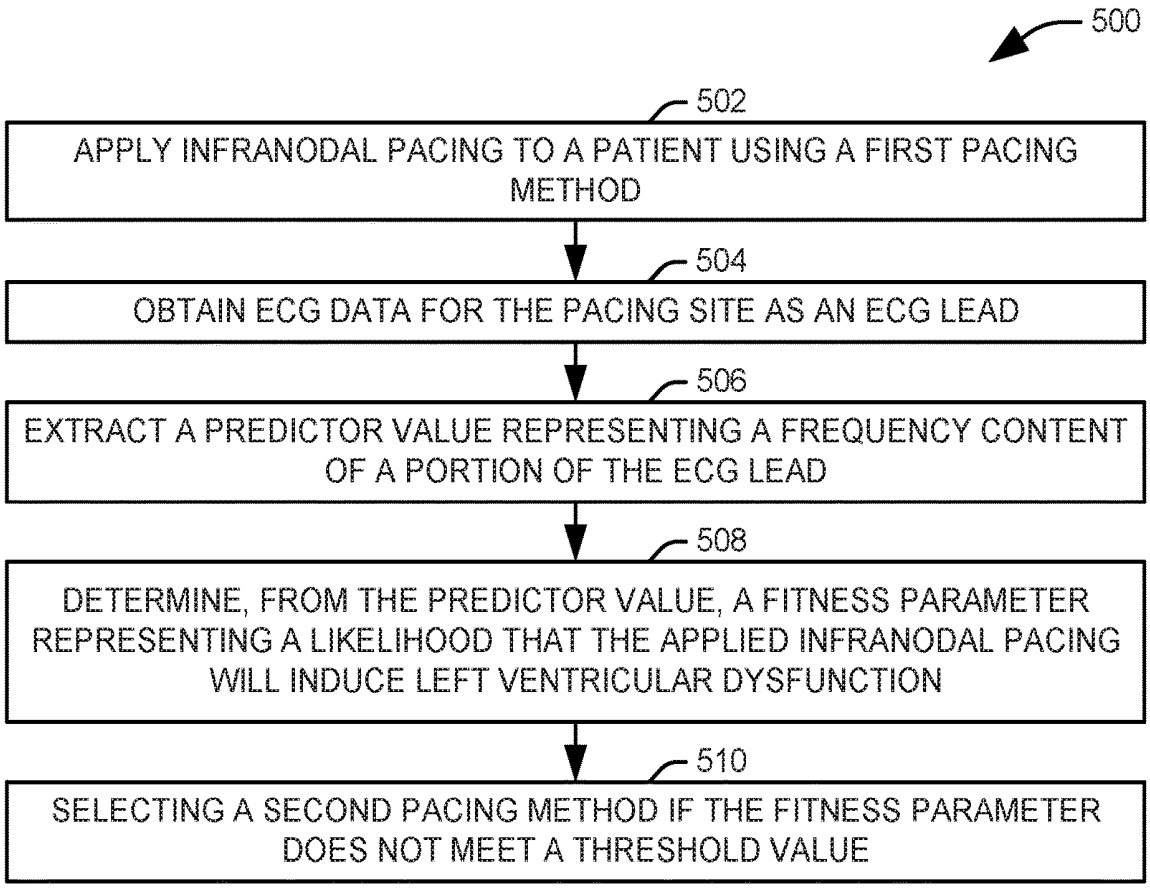

500
502
APPLY INFRANODAL PACING TO A PATIENT USING A FIRST PACING METHOD
504
OBTAIN ECG DATA FOR THE PACING SITE AS AN ECG LEAD
506
EXTRACT A PREDICTOR VALUE REPRESENTING A FREQUENCY CONTENT OF A PORTION OF THE ECG LEAD
508
DETERMINE, FROM THE PREDICTOR VALUE, A FITNESS PARAMETER REPRESENTING A LIKELIHOOD THAT THE APPLIED INFRANODAL PACING WILL INDUCE LEFT VENTRICULAR DYSFUNCTION
510
SELECTING A SECOND PACING METHOD IF THE FITNESS PARAMETER DOES NOT MEET A THRESHOLD VALUE

FIG. 5

FREQUENCY ANALYSIS FOR PREDICTING LEFT VENTRICULAR DYSFUNCTION

[0001] This application claims priority from U.S. Provisional Patent Application Ser. No. 62/756,944, filed 7 Nov. 2018 and titled "FREQUENCY ANALYSIS TOOL FOR PREDICTING PATIENTS WHO ARE LIKELY TO DEVELOP LEFT VENTRICULAR DYSFUNCTION AFTER RIGHT VENTRICULAR PACEMAKER", the subject matter of which is incorporated hereby incorporated by reference in its entirety.

FIELD OF THE INVENTION

[0002] The present invention relates to systems and methods for regulating the function of a heart in a living being and, in particular, is directed to systems and methods utilizing frequency analysis of an ECG lead to predict which patients are likely to experience left ventricular dysfunction during infranodal cardiac pacing.

BACKGROUND OF THE INVENTION

[0003] Pacing-induced cardiomyopathy can occur in patients receiving right ventricular (RV) pacing that have preserved left ventricle ejection fraction (LVEF) at the time of implant due to the high pacing percentage necessary to address conditions such as a left bundle block. The introduction of right ventricular (RV) pacing has been found to produce some degree of left ventricular (LV) dysfunction in between twelve and seventeen percent of patients having a normal LVEF at baseline. For patients who are already experiencing some degree of LV dysfunction, the risk is significantly higher, and the introduction of RV pacing can result in further loss of LV function.

SUMMARY OF THE INVENTION

[0004] In accordance with an aspect of the present invention, a method includes applying infranodal pacing to a patient at a pacing site. Electrocardiogram (ECG) data representing the pacing site is obtained from a set of electrodes as an ECG lead. A predictor value representing a frequency content a portion of the ECG lead is extracted. A fitness parameter is determined for the pacing site from at least the predictor value. The fitness parameter represents a likelihood that the infranodal pacing applied at the pacing site will induce left ventricular dysfunction in the patient. The fitness parameter is displayed to a user at an associated display.

[0005] In accordance with another aspect of the present invention, a system includes a signal processor configured to receive an ECG lead and isolate a portion of interest from the ECG lead during infranodal pacing of a patient. A predictor extraction component is configured to extract a predictor value representing a frequency content of the portion of interest. A parameter calculation component is configured to determine a parameter representing the likelihood that the patient will experience left ventricular dysfunction induced by the infranodal pacing from at least the predictor value.

[0006] In accordance with yet another aspect of the present invention, a method is provided for evaluating an infranodal pacing method in accordance with an aspect of the present invention. Infranodal pacing is applied to a patient using a first pacing method. Electrocardiogram (ECG) data representing the first pacing method is obtained from a set of electrodes as a first ECG lead. A predictor value is extracted representing a frequency content of a QRS complex of the first ECG lead. A fitness parameter is determined for the first pacing method from at least the first predictor value. The fitness parameter represents a likelihood that the infranodal pacing using the first pacing method will induce left ventricular dysfunction in the patient. A second pacing method is selected for the patient if the fitness parameter does not meet a threshold value.

BRIEF DESCRIPTION OF THE DRAWINGS

[0007] The foregoing and other features of the present invention will become apparent to those skilled in the art to which the present invention relates upon reading the following description with reference to the accompanying drawings, in which:

[0008] FIG. **1** illustrates one example of a system for predicting the likelihood that infranodal pacing will induce left ventricular dysfunction in a patient in accordance with an aspect of the present invention;

[0009] FIG. **2** illustrates one implementation of a system for predicting the likelihood that infranodal pacing will induce left ventricular dysfunction in a patient in accordance with an aspect of the present invention;

[0010] FIG. **3** illustrates a method for determining the likelihood that a patient will develop left ventricular dysfunction in response to infranodal pacing in accordance with an aspect of the present invention;

[0011] FIG. **4** illustrates a method for determining a best site for infranodal pacing to minimize a risk of left ventricular dysfunction in accordance with an aspect of the present invention;

[0012] FIG. **5** illustrates a method for evaluating an infranodal pacing method in accordance with an aspect of the present invention; and

[0013] FIG. **6** is a schematic block diagram illustrating an exemplary system of hardware components capable of implementing examples of the systems and methods disclosed herein.

DETAILED DESCRIPTION OF THE INVENTION

[0014] Systems and methods are provided herein for the use of the frequency content of the QRS complex during infranodal pacing to predict the likelihood that the infranodal pacing will induce left ventricular dysfunction. By "infranodal pacing," it is meant any pacing that falls below the atrioventricular node and provides ventricular activation, including right ventricular pacing, left ventricular pacing, biventricular pacing, and His-bundle pacing. The frequency content of an electrocardiogram (ECG) signal, referred to as a lead, captured during infranodal pacing can be analyzed and used to predict if a patient is likely to develop left ventricular dysfunction given a infranodal pacing applied in a specific location. This can be used during implantation of the pacemaker as an objective aid to select the most effective infranodal pacing method and associated site of those available for the individual patient.

[0015] In one example, frequency analysis of the QRS complex in can be performed, for example, via a Fourier transform, time-frequency analysis, wavelet analysis, or a similar process, to determine one or more features that can

be used for predicting the response of a patient to infranodal pacing. Features determined from the frequency analysis can include, for example, a fundamental frequency of the QRS complex as well as a measure of change of a median frequency throughout the QRS complex. This can be performed for multiple locations to select an infranodel pacing location that minimizes the likelihood of left ventricular dysfunction.

[0016] FIG. **1** illustrates a system **100** for predicting the likelihood that infranodal pacing will induce left ventricular dysfunction in a patient in accordance with an aspect of the present invention. In the illustrated implementation, the system **100** is a stand-alone module that obtains electrocardiogram (ECG) signals through a set of ECG electrodes **102**. It will be appreciated, however, that the system **100** could be implemented as machine executable instructions provided to an existing ECG apparatus, and utilize electrodes and signal processing components (e.g., filtering components, etc.) associated with that apparatus. The system can also be implemented as executable instructions provided to a cardiac rhythm management device, such as a pacemaker. Regardless of the specific implementation, the electrodes **102** can be arranged with any standard or specialized surface lead position.

[0017] The ECG leads from the electrodes is provided to a signal processing component **104** to condition the signal and isolate any portions of the signal of interest for the analysis. In one implementation, the signal processing component **104** can isolate a QRS complex from each of a proper subset of the ECG leads, for example, from leads I, AVF, and V3. The signal processing component **104** can include one or both of analog and digital filtering components to remove noise and/or pacing artifact from the ECG signals. The signal isolation process can be assisted by an operator or completely automated, depending on the implementation of the system.

[0018] A predictor extraction component **106** extracts a predictor value representing a frequency component of the ECG data from the processed data. For example, a frequency analysis of the ECG signal on one or more leads can be performed to provide a frequency domain representation of the signal, with the parameters drawn from the frequency domain representation. In one embodiment of the present invention, the frequency analysis is performed using a fast Fourier transform (FFT). In another embodiment of the present invention, the frequency analysis is performed using the Welch periodogram. In still another embodiment of the present invention, the frequency analysis is performed using autoregressive power spectrum (AR) analysis. In yet another embodiment, the frequency analysis is performed via a wavelet transformation of the ECG data. In still another embodiment, the frequency analysis is performed using time-frequency analysis. It will be appreciated that selected predictors can include, for example, a fundamental frequency in a selected portion of the ECG data, a change in the median frequency of the ECG data across the same or a different selected portion of the ECG data, or any other appropriate parameters representing the frequency.

[0019] In one example, the feature extractor **106** can include dedicated hardware or machine readable instructions stored on a non-transitory computer readable medium for performing a continuous or discrete Fourier transform. The inventors have determined that patients who are likely to experience LV dysfunction over time from RV pacing tend to have a paced QRS complex with a lower fundamental frequency than patients for whom LV dysfunction does not develop, and that the median frequency of the QRS complex decreases, as opposed to increases, during the QRS complex. Accordingly, the onset of LV dysfunction induced by RV pacing can be predicted from the spectral content of the QRS complex from a given patient. In this example, the fundamental frequency of the QRS complex, for example, from a V3 lead, along with a measure of the slope of the median frequency across the QRS complex can be extracted for the patient at each of a plurality of infranodal pacing sites.

[0020] The extracted predictors are provided to a parameter calculation component **108** which determines a parameter representing the likelihood that the patient will experience left ventricular dysfunction given infranodal pacing at a given pacing site. The parameter calculation component **108** can, for example, include an expert system or group of expert systems configurable to determine the effectiveness of a proposed infranodal pacing site for a patient. Examples of suitable systems can include artificial neural networks, support vector machines, Hidden Markov Models, rule based expert systems, and regression models, although any of a number of supervised or unsupervised learning algorithms can be used at the parameter calculation component **108**. Alternatively, the parameter calculation component **108** can simply calculate a function of the predictor value, such as a linear function or a step function, that provides a useful continuous or categorical metric for decision-making for a clinician. It will be appreciated that additional features unrelated to the frequency can be used for parameter calculation, including biometric parameters of the patient. It will be appreciated that data from the various leads can be used for extracting frequency spectra, such that features representing a given patient can be drawn from multiple frequency spectra representing multiple leads. In one implementation, information from different leads can be weighted differently. For example, the inventors have found information from lead V3 to be of particular value, and this increased value may be reflected in the operation of the parameter calculation component **108**.

[0021] The predictor values, along with an associated result from the parameter calculation component **108**, can be displayed at an associated display **110**. In one implementation, the frequency spectra associated with each of a plurality of pacing sites can be displayed along with associated metrics from the parameter calculation component **108** to allow a user to compare the values to select an optimum site for the application of infranodal pacing that minimizes the likelihood of left ventricular dysfunction. Accordingly, the determination of the optimal site can be made by the operator from the displayed frequency spectra, completely automated, or made by operator guided by results from the parameter calculation component **108**.

[0022] FIG. **2** illustrates another example of a system **200** for predicting the likelihood that infranodal pacing will induce left ventricular dysfunction in a patient in accordance with an aspect of the present invention. The system **200** includes a processor **202**, a display **204**, and a non-transitory computer readable medium **210** storing machine executable instructions for receiving and evaluating received ECG signals during infranodal pacing to determine the likelihood that the infranodal pacing at a selected site will induce left ventricular dysfunction in a patient. The executable instruc-

tions include a signal processor **212** to receive ECG data for the patient during infranodal pacing, condition the signal, and isolate any portions of the signal of interest for the analysis.

[0023] A feature extractor **214** extracts a set of at least one feature from the ECG signals representing the frequency content of the signals. For example, a frequency analysis of the ECG signal on one or more leads can be performed to provide a frequency domain representation of the ECG signal, with the parameters drawn from the frequency domain representation. It will be appreciated that selected features can include a median or fundamental frequency in a selected portion of the ECG data, a change in the median or fundamental frequency of the ECG data across the same or a different selected portion of the ECG data, or any other appropriate parameters representing the frequency. The change in the a given frequency can be determined, for example, by dividing the portion of the ECG into a plurality of subregions, and calculating a slope of the frequency across the subregions or a difference between the frequency for several regions. It will be appreciated that the difference calculation can be performed by providing median or fundamental frequencies for several subregions to a machine learning model. For example, in a regression analysis, the difference calculation can be implicit in the calculation of the regression coefficient.

[0024] The feature extractor **214** can also obtain one or more biometric parameters representing the patient, for example, an age of the patient, a sex of the patient, a duration of a QRS complex associated with the patient, a baseline left ventricle ejection fraction (LVEF), and an LVEF during pacing. The feature extractor **214** can, for example, retrieve the biometric parameters from an electronic health records database, receive them from a user via a user interface **216**, or obtain them from an imaging system (not shown) used to determine the LVEF prior to or during RV pacing.

[0025] The extracted features are provided to a machine learning model **218** that generates a clinical parameter representing a likelihood that the patient will develop LV dysfunction in response to RV pacing at a given site. The machine learning model **110** can utilize one or more pattern recognition algorithms, implemented, for example, as classification and regression models, each of which analyze the extracted feature vector to assign a clinical parameter to the user. It will be appreciated that the clinical parameter can be categorical or continuous. Where multiple classification and regression models are used, the machine learning model **218** can include an arbitration element can be utilized to provide a coherent result from the various algorithms. Depending on the outputs of the various models, the arbitration element can simply select a class from a model having a highest confidence, select a plurality of classes from all models meeting a threshold confidence, select a class via a voting process among the models, or assign a numerical parameter based on the outputs of the multiple models. Alternatively, the arbitration element can itself be implemented as a classification model that receives the outputs of the other models as features and generates one or more output classes for the patient.

[0026] A classification can also be performed across multiple stages. In one example, an a priori probability can be determined for a clinical parameter without the values representing the frequency content of a given site, for example, based upon the biometric parameters for the patient. A second stage of the model can use the values derived from the frequency content of the ECG signal, and, optionally, additional values, to generate a value for the clinical parameter. A known performance of the second stage of the machine learning model, for example, defined as values for the specificity and sensitivity of the model, can be used to update the a priori probability given the output of the second stage.

[0027] The machine learning model **218**, as well as any constituent models, can be trained on training data representing the various outcomes of interest. For example, each instance of training data can represent a given patient according to the set of extracted features and a categorical or continuous label. For example, each instance can be labeled with a class (e.g., an "experienced LV dysfunction" class or a "did not experience LV dysfunction" class) or a continuous value, such as a loss of LVEF from a baseline value prior to RV pacing. The training process of the machine learning model **218** will vary with its implementation, but training generally involves a statistical aggregation of training data into one or more parameters associated with the output classes. Any of a variety of techniques can be utilized for the models, including support vector machines, regression models, self-organized maps, k-nearest neighbor classification or regression, fuzzy logic systems, data fusion processes, boosting and bagging methods, rule-based systems, or artificial neural networks.

[0028] For example, an SVM classifier can utilize a plurality of functions, referred to as hyperplanes, to conceptually divide boundaries in the N-dimensional feature space, where each of the N dimensions represents one associated feature of the feature vector. The boundaries define a range of feature values associated with each class. Accordingly, an output class and an associated confidence value can be determined for a given input feature vector according to its position in feature space relative to the boundaries. An SVM classifier utilizes a user-specified kernel function to organize training data within a defined feature space. In the most basic implementation, the kernel function can be a radial basis function, although the systems and methods described herein can utilize any of a number of linear or non-linear kernel functions.

[0029] An ANN classifier comprises a plurality of nodes having a plurality of interconnections. The values from the feature vector are provided to a plurality of input nodes. The input nodes each provide these input values to layers of one or more intermediate nodes. A given intermediate node receives one or more output values from previous nodes. The received values are weighted according to a series of weights established during the training of the classifier. An intermediate node translates its received values into a single output according to a transfer function at the node. For example, the intermediate node can sum the received values and subject the sum to a binary step function. A final layer of nodes provides the confidence values for the output classes of the ANN, with each node having an associated value representing a confidence for one of the associated output classes of the classifier.

[0030] A k-nearest neighbor model populates a feature space with labelled training samples, represented as feature vectors in the feature space. In a classifier model, the training samples are labelled with their associated class, and in a regression model, the training samples are labelled with a value for the dependent variable in the regression. When

a new feature vector is provided, a distance metric between the new feature vector and at least a subset of the feature vectors representing the labelled training samples is generated. The labelled training samples are then ranked according to the distance of their feature vectors from the new feature vector, and a number, k, of training samples having the smallest distance from the new feature vector are selected as the nearest neighbors to the new feature vector.

[0031] In one example of a classifier model, the class represented by the most labelled training samples in the k nearest neighbors is selected as the class for the new feature vector. In another example, each of the nearest neighbors can be represented by a weight assigned according to their distance from the new feature vector, with the class having the largest aggregate weight assigned to the new feature vector. In a regression model, the dependent variable for the new feature vector can be assigned as the average (e.g., arithmetic mean) of the dependent variables for the k nearest neighbors. As with the classification, this average can be a weighted average using weights assigned according to the distance of the nearest neighbors from the new feature vector. It will be appreciated that k is a metaparameter of the model that is selected according to the specific implementation. The distance metric used to select the nearest neighbors can include a Euclidean distance, a Manhattan distance, or a Mahalanobis distance.

[0032] A regression model applies a set of weights to various functions of the extracted features, most commonly linear functions, to provide a continuous result. In general, regression features can be categorical, represented, for example, as zero or one, or continuous. The machine learning model **218** can be implemented as a linear combination of the values of the extracted features. In a logistic regression, the output of the model represents the log odds that the source of the extracted features is a member of a given class. In a binary classification task, these log odds can be used directly as a confidence value for class membership or converted via the logistic function to a probability of class membership given the extracted features.

[0033] A rule-based classifier applies a set of logical rules to the extracted features to select an output class. Generally, the rules are applied in order, with the logical result at each step influencing the analysis at later steps. The specific rules and their sequence can be determined from any or all of training data, analogical reasoning from previous cases, or existing domain knowledge. One example of a rule-based classifier is a decision tree algorithm, in which the values of features in a feature set are compared to corresponding threshold in a hierarchical tree structure to select a class for the feature vector. A random forest classifier is a modification of the decision tree algorithm using a bootstrap aggregating, or "bagging" approach. In this approach, multiple decision trees are trained on random samples of the training set, and an average (e.g., mean, median, or mode) result across the plurality of decision trees is returned. For a classification task, the result from each tree would be categorical, and thus a modal outcome can be used, but a continuous parameter can be computed according to a number of decision trees that select a given task. Regardless of the specific model employed, the clinical parameter generated at the machine learning model **218** can be provided to a user at the display **204** via the user interface **216** or stored at the non-transitory computer readable medium **210**, for example, in an electronic medical record associated with the patient.

[0034] In one implementation, the machine learning model **218** can be applied to frequency data retrieved from each of a plurality of RV pacing sites to allow a user to compare the values to select an optimum site for the application of infranodal pacing or determine if a different method of infranodal pacing would be beneficial. Accordingly, the determination of the optimal site can be completely automated or made by an operator guided by results from the machine learning model. It will be appreciated that the machine learning model **218** can include multiple machine learning models that are selected according to a categorical feature of the patient, which may utilize different features from the feature extractor **214**. In one example, a first model can be selected if the patient has a LVEF in a first range, and a second model can be selected if the patient has an LVEF outside of the first range. Table 1 illustrates exemplary features that could be used for a first model, representing patients with an LVEF between fifty and sixty percent who are receiving right ventricular pacing, and Table 2 illustrates features for a second, more general, model that can be used for patients not falling within this range.

TABLE 1

	Normal (n = 41)	CM (n = 44)	Univariate P	Multivariate P	AUC
Age (y)	67.9 ± 11.4	72.5 ± 10.2	0.071	—	—
Gender (m/F)	21/20	25/19	0.605	—	—
QRSd (ms)	164.9 ± 27.6	172.7 ± 17.4	<0.05	0.078	0.644
Initial LVEF (%)	56.3 ± 3.0	54.5 ± 3.3	<0.01	0.051	0.663
Change in median QRS Frequency (Hz)*	0.208 ± 0.544	−0.199 ± 0.537	<0.001	<0.01	0.705

*Change in the median frequency of the second half of the QRS compared to the first half

TABLE 2

	Normal (n = 61)	CM (n = 49)	Univariate P	Multivariate P	AUC
Age (y)	70.1 ± 11.1	72.5 ± 10.2	0.242	—	—
Gender (m/F)	30/31	28/21	0.406	—	—
QRSd (ms)	164.4 ± 16.8	172.2 ± 16.6	<0.02	0.067	0.647
Initial LVEF (%)	59.2 ± 5.2	55.5 ± 4.5	<0.001	0.002	0.718

TABLE 2-continued

	Normal (n = 61)	CM (n = 49)	Univariate P	Multivariate P	AUC
Change in median QRS Frequency (Hz)*	0.139 ± 0.505	−0.193 ± 0.588	<0.002	<0.01	0.660

*Change in the median frequency of the second half of the QRS compared to the first half.

[0035] In view of the foregoing structural and functional features described above, methods in accordance with various aspects of the present invention will be better appreciated with reference to FIGS. **3-5**. While, for purposes of simplicity of explanation, the methods of FIGS. **3-5** are shown and described as executing serially, it is to be understood and appreciated that the present invention is not limited by the illustrated order, as some aspects could, in accordance with the present invention, occur in different orders and/or concurrently with other aspects from that shown and described herein. Moreover, not all illustrated features may be required to implement a method in accordance with an aspect of the present invention.

[0036] FIG. **3** illustrates a method **300** for determining the likelihood that a patient will develop left ventricular dysfunction in response to infranodal pacing in accordance with an aspect of the present invention. At **302**, infranodal pacing is applied to a patient at a pacing site. At **304**, electrocardiogram (ECG) data representing the pacing site is obtained from a set of electrodes as an ECG lead. It will be appreciated that ECG data can be collected for multiple infranodal pacing sites, with the analysis steps at **306** and **308** performed for each pacing site to determine a pacing site with a lowest likelihood of inducing left ventricular dysfunction.

[0037] At **306**, a predictor value representing a frequency content of the ECG lead is extracted from the ECG data. In one example, a QRS complex is isolated as the portion of the ECG lead, and the predictor value is extracted to represent a frequency component of the isolated QRS complex. The predictor value can include any appropriate measure of the frequency content of the selected portion of the ECG lead, and can include, for example, a fundamental frequency of a portion of the ECG lead or a change in the median frequency across a portion of the ECG lead. In one implementation, the change in the median frequency across a portion of the ECG lead can be determined by dividing the portion of the ECG lead into a plurality of regions and calculating a slope of the median frequency across the QRS complex. Alternatively, the change in the median frequency can be determined as a difference between a median frequency of a second half of the portion of the ECG lead and a median frequency of a first half of the portion of the ECG lead.

[0038] At **308**, a fitness parameter is determined for the pacing site from at least the predictor value. The fitness parameter represents a likelihood that the infranodalpacing applied at the pacing site will induce left ventricular dysfunction in the patient. In one implementation, the fitness parameter for the pacing site is determined by providing the predictor value to a machine learning model. Alternatively, the predictor value or a function of the predictor can be used as extracted as a measure of the fitness of the pacing site. In one implementation, biometric parameters that do not represent a frequency component of the portion of the ECG lead, such as a QRS duration, a left ventricular ejection fraction, an age of the patient, or a similar value, can be used in addition to any extracted predictor values. These values can be used as additional features for a machine learning model or, in one example, to select among multiple machine learning models. For example, a first machine learning model when a given biometric parameter is within a first range, and a second machine learning model can be used when the biometric parameter is within a second range. At **310**, the fitness parameter is displayed to the user at an associated display.

[0039] FIG. **4** illustrates a method **400** for determining a best site for infranodal pacing to minimize a risk of left ventricular dysfunction in accordance with an aspect of the present invention. At **402**, a plurality of acceptable sites and methods for applying infranodal pacing to the ventricle are determined. A clinician can determine one or more types of infranodal pacing, such as left ventricular pacing, right ventricular pacing, biventricular pacing, and His-bundle pacing, that may be effective for a given patient. For each of these pacing methods, a number of anatomically available sites can be determined from imaging of the chest cavity. At **404**, a pacing method and associated site is selected and the selected pacing is applied to the patient at the selected site. At **406**, at least one QRS complex is isolated from ECG data from the patient. In one implementation, the QRS complex from the V3 lead is used, but it will be appreciated that information from different leads or multiple leads can be used.

[0040] At **408**, each QRS complex is converted into the frequency domain to produce respective frequency spectra. At **410**, one or more features are extracted from the frequency spectrum associated with the selected pacing site. For example, the one or more features can include a fundamental frequency associated with the QRS complex, a median power for the QRS complex, or a change in one of these values across various portions of the QRS complex. In one implementation, one feature can include a change in the median frequency across a frequency spectrum derived from the QRS complex on the V3 lead.

[0041] At **412**, a score representing the effectiveness of the selected pacing site and method is calculated from the extracted features and stored. For example, the features can be provided to an expert system, such as an artificial neural network, a statistical classifier, or a support vector machine, that provides a confidence value representing the likelihood that a patient will develop left ventricular dysfunction induced by pacing at the selected pacing site. At **414**, it is determined a termination condition has been achieved. For example, the method can be terminated if no additional pacing sites remain for evaluation or if the calculated score exceeds a threshold value. If not (N), the method returns to **402** to select a new pacing site and method. If so (Y), the calculated scores can be provided to a user at an associated display at **416**.

[0042] FIG. **5** illustrates a method **500** for evaluating an infranodal pacing method in accordance with an aspect of the present invention. At **502**, infranodal pacing is applied to a patient using a first pacing method, such as right ventricu-

lar pacing, left ventricular pacing, biventricular pacing, or His-bundle pacing. At **504**, electrocardiogram (ECG) data representing the first pacing method is obtained from a set of electrodes as a first ECG lead. At **506**, a predictor value is extracted representing a frequency content of a QRS complex of the first ECG lead. At **508**, a fitness parameter is determined for the first pacing method from at least the first predictor value. The fitness parameter represents a likelihood that the infranodal pacing using the first pacing method will induce left ventricular dysfunction in the patient. At **510**, a second pacing method is selected for the patient if the fitness parameter does not meet a threshold value.

[0043] FIG. **6** is a schematic block diagram illustrating an exemplary system **600** of hardware components capable of implementing examples of the systems and methods disclosed herein. The system **600** can include various systems and subsystems. The system **600** can be a personal computer, a laptop computer, a workstation, a computer system, an appliance, an application-specific integrated circuit (ASIC), a server, a server BladeCenter, a server farm, etc.

[0044] The system **600** can include a system bus **602**, a processing unit **604**, a system memory **606**, memory devices **608** and **610**, a communication interface **612** (e.g., a network interface), a communication link **614**, a display **616** (e.g., a video screen), and an input device **618** (e.g., a keyboard, touch screen, and/or a mouse). The system bus **602** can be in communication with the processing unit **604** and the system memory **606**. The additional memory devices **608** and **610**, such as a hard disk drive, server, standalone database, or other non-volatile memory, can also be in communication with the system bus **602**. The system bus **602** interconnects the processing unit **604**, the memory devices **606-610**, the communication interface **612**, the display **616**, and the input device **618**. In some examples, the system bus **602** also interconnects an additional port (not shown), such as a universal serial bus (USB) port.

[0045] The processing unit **604** can be a computing device and can include an application-specific integrated circuit (ASIC). The processing unit **604** executes a set of instructions to implement the operations of examples disclosed herein. The processing unit can include a processing core.

[0046] The additional memory devices **606**, **608**, and **610** can store data, programs, instructions, database queries in text or compiled form, and any other information that may be needed to operate a computer. The memories **606**, **608** and **610** can be implemented as computer-readable media (integrated or removable), such as a memory card, disk drive, compact disk (CD), or server accessible over a network. In certain examples, the memories **606**, **608** and **610** can comprise text, images, video, and/or audio, portions of which can be available in formats comprehensible to human beings. Additionally or alternatively, the system **600** can access an external data source or query source through the communication interface **612**, which can communicate with the system bus **602** and the communication link **614**.

[0047] In operation, the system **600** can be used to implement one or more parts of a system for evaluating the response of a patient to infranodal pacing in accordance with the present invention, in particular, the predictor extraction component **116** and the parameter calculation component **118**. Computer executable logic for implementing the system resides on one or more of the system memory **606**, and the memory devices **608** and **610** in accordance with certain examples. The processing unit **604** executes one or more computer executable instructions originating from the system memory **606** and the memory devices **608** and **610**. The term "computer readable medium" as used herein refers to a medium that participates in providing instructions to the processing unit **604** for execution. This medium may be distributed across multiple discrete assemblies all operatively connected to a common processor or set of related processors.

[0048] What have been described above are examples. It is, of course, not possible to describe every conceivable combination of components or methodologies, but one of ordinary skill in the art will recognize that many further combinations and permutations are possible. Accordingly, the disclosure is intended to embrace all such alterations, modifications, and variations that fall within the scope of this application, including the appended claims. As used herein, the term "includes" means includes but not limited to, the term "including" means including but not limited to. The term "based on" means based at least in part on. Additionally, where the disclosure or claims recite "a," "an," "a first," or "another" element, or the equivalent thereof, it should be interpreted to include one or more than one such element, neither requiring nor excluding two or more such elements.

Having described the invention, the following is claimed:

1. A method comprising:

applying infranodal pacing to a patient at a pacing site;

obtaining electrocardiogram (ECG) data representing the pacing site from a set of electrodes as an ECG lead;

extracting a predictor value representing a frequency content a portion of the ECG lead;

determining a fitness parameter for the pacing site from at least the predictor value, the fitness parameter representing a likelihood that the infranodal pacing applied at the pacing site will induce left ventricular dysfunction in the patient; and

displaying the fitness parameter to a user at an associated display.

2. The method of claim **1**, wherein extracting a predictor value representing the frequency content of the ECG lead comprises:

isolating a QRS complex from the ECG lead; and

extracting the predictor value as to represent a frequency content of the isolated QRS complex.

3. The method of claim **1**, wherein the predictor value for the frequency content of the portion of the ECG lead is extracted as a fundamental frequency of the portion of the ECG lead.

4. The method of claim **1**, wherein the predictor value for the frequency content of the portion of the ECG lead is extracted as a change in the median frequency across the portion of the ECG lead.

5. The method of claim **4**, wherein the predictor value for the frequency content of the portion of the ECG lead is extracted as a difference between a median frequency of a first subregion of the portion of the ECG lead and a median frequency of a second subregion of the portion of the ECG lead.

6. The method of claim **1**, determining a fitness parameter for the pacing site from at least the predictor value comprises determining a fitness parameter for the pacing site from the predictor value and a biometric parameter that is not extracted from a frequency content of the ECG lead.

7. The method of claim 6, wherein the biometric parameter is a left ventricular ejection fraction of the patient.

8. The method of claim 1, wherein the ECG lead is a first ECG lead, the pacing site is a first pacing site, the predictor value is a first predictor, and the fitness parameter is a first fitness parameter and the method further comprising:

applying infranodal pacing to the patient at a second pacing site;

obtaining electrocardiogram (ECG) data representing the second pacing site from the set of electrodes as a second ECG lead;

extracting a second predictor value representing a frequency content of as portion of the second ECG lead;

determining a second fitness parameter for the second pacing site from at least the extracted second predictor value, the second fitness parameter representing a likelihood that the infranodal pacing applied at the second pacing site will induce left ventricular dysfunction in the patient;

selecting between the first pacing site and the second pacing site according to the first fitness parameter and the second fitness parameter.

9. The method of claim 1, wherein determining the fitness parameter for the pacing site from at least the extracted predictor value comprises providing the predictor value to a machine learning model.

10. The method of claim 9, wherein the predictor value is a first predictor and the method further comprising extracting a second predictor value, wherein providing the predictor value to the machine learning model comprises providing the first predictor value to a first machine learning model when the second predictor value is within a first range, and providing the second predictor value to a second machine learning model when the second predictor value is within a second range.

11. The method of claim 10, wherein the second predictor value is a left ventricular ejection fraction of the patient.

12. The method of claim 10, wherein applying infranodal pacing to the patient comprises applying right ventricular pacing to the patient.

13. A system comprising:

a signal processor configured to receive an ECG lead and isolate a portion of interest from the ECG lead during infranodal pacing of a patient;

a predictor extraction component configured to extract a predictor value representing a frequency content of the portion of interest; and

a parameter calculation component configured to determine a parameter representing the likelihood that the patient will experience left ventricular dysfunction induced by the infranodal pacing from at least the predictor value.

14. The system of claim 13, wherein the signal processor is configured to isolate a QRS complex as the portion of interest from the ECG lead.

15. The system of claim 14, wherein the prediction extraction component extracts a fundamental frequency of the QRS complex as the predictor value.

16. The system of claim 14, wherein the prediction extraction component extracts a value representing a change in the median frequency across the QRS complex as the predictor value.

17. The system of claim 14, wherein the parameter calculation component is configured to determine the parameter representing the likelihood that the patient will experience left ventricular dysfunction induced by the infranodal pacing from the predictor value and a biometric parameter that is not extracted from a frequency component of the QRS complex.

18. The system of claim 17, wherein the biometric parameter is duration of the QRS complex.

19. The system of claim 13, the parameter calculation component comprising a machine learning model trained on data from a plurality of previous patients.

20. A method comprising:

applying infranodal pacing to a patient using a first pacing method;

obtaining electrocardiogram (ECG) data representing the first pacing method from a set of electrodes as a first ECG lead;

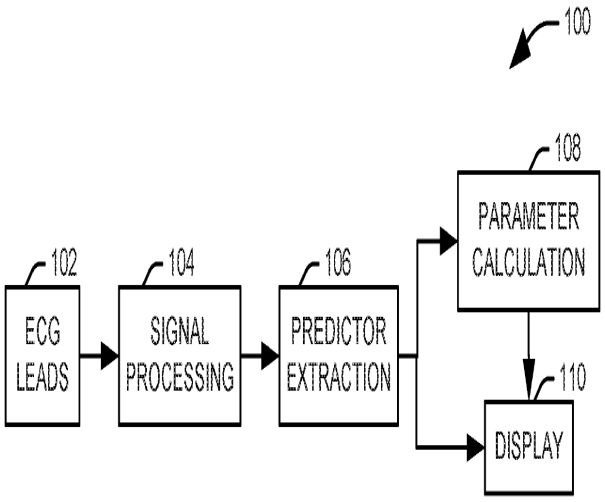
extracting a predictor value representing a frequency content of a QRS complex of the first ECG lead;

determining a fitness parameter for the first pacing method from at least the first predictor value, the fitness parameter representing a likelihood that the infranodal pacing using the first pacing method will induce left ventricular dysfunction in the patient; and

selecting a second pacing method for the patient if the fitness parameter does not meet a threshold value.

* * * * *

专利名称(译)	频率分析预测左心室功能障碍		
公开(公告)号	US20200138321A1	公开(公告)日	2020-05-07
申请号	US16/676997	申请日	2019-11-07
[标]申请(专利权)人(译)	克里夫兰诊所基金会		
申请(专利权)人(译)	克利夫兰诊所基金会		
当前申请(专利权)人(译)	克利夫兰诊所基金会		
发明人	NIEBAUER, MARK J.		
IPC分类号	A61B5/0452 A61B5/0408 A61B5/00 G06N20/20		
CPC分类号	A61B5/7275 A61B5/0452 A61B5/0408 A61B5/7225 G06N20/20 G06N20/00		
优先权	62/756944 2018-11-07 US		
外部链接	Espacenet USPTO		

摘要(译)

提供了用于评估将下节律应用于患者的系统和方法。 代表起搏的心电图（ECG）数据是从一组电极作为ECG导线获得的。 提取表示ECG导联的一部分的频率内容的预测值。 从至少预测值确定用于起搏的适合度参数。 适应性参数代表所应用的节律下起搏将在患者中诱发左心室功能障碍的可能性。 适应性参数在关联的显示器上显示给用户。