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(54) **MATRIX-BASED PATIENT SIGNAL ANALYSIS**

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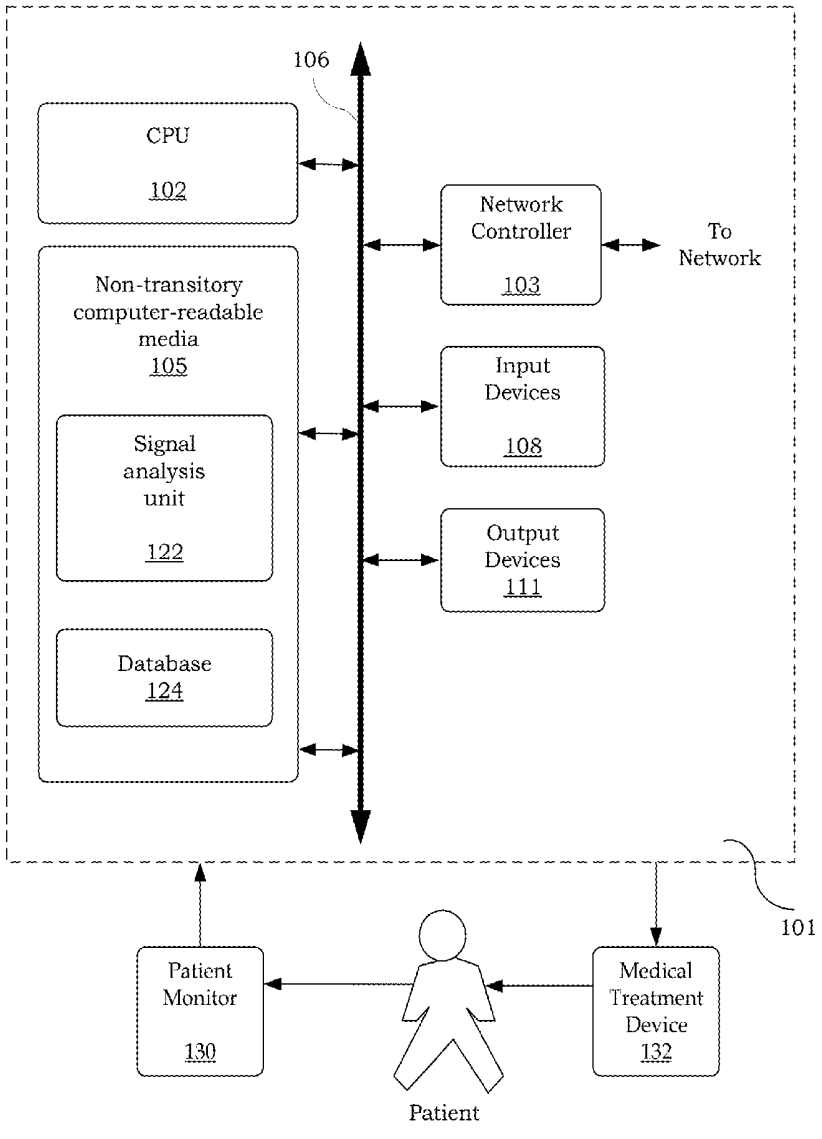
(57) **ABSTRACT**

Disclosed herein is a framework for facilitating patient signal analysis. In accordance with one aspect, the framework generates a signature cycle matrix corresponding to a single cycle of the patient signal data by segmenting the patient signal data into multiple portions. The signature cycle matrix may further be segmented into sub-matrices corresponding to different levels. Properties of the sub-matrices may then be determined to generate diagnostic results.



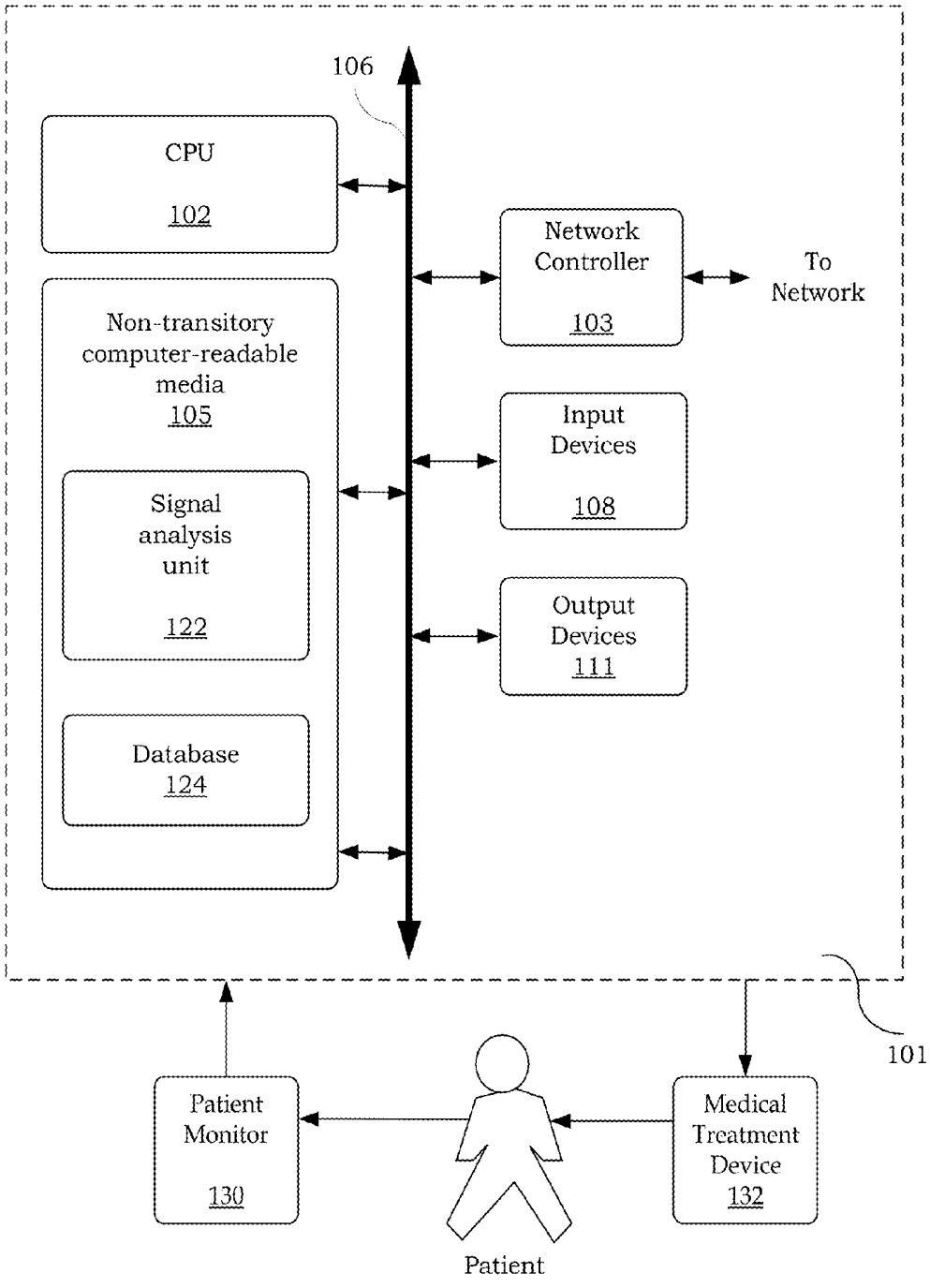

106
CPU
102
Network Controller
103
To Network
Non-transitory computer-readable media
105
Input Devices
108
Signal analysis unit
122
Output Devices
111
Database
124
101
Patient Monitor
130
Medical Treatment Device
132
Patient
100

Fig. 1

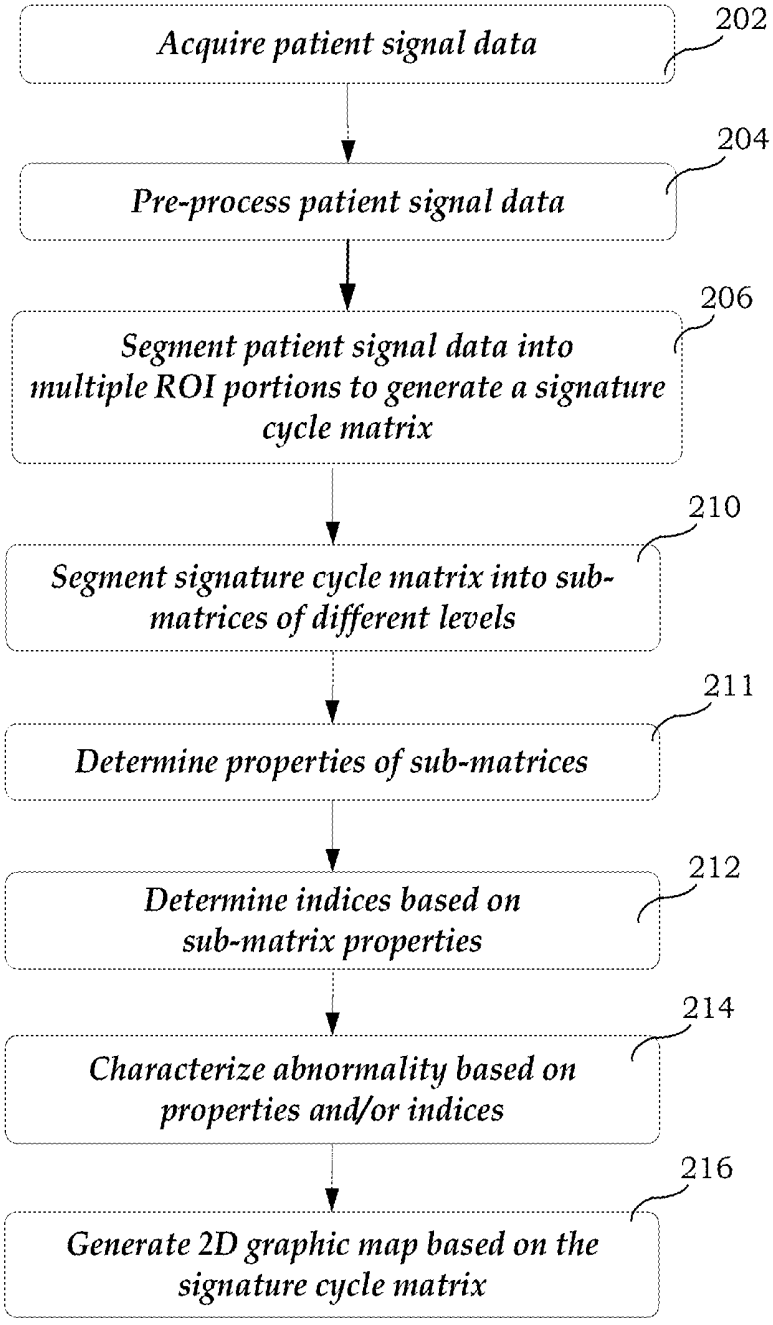

Acquire patient signal data
202
Pre-process patient signal data
204
Segment patient signal data into multiple ROI portions to generate a signature cycle matrix
206
Segment signature cycle matrix into sub-matrices of different levels
210
Determine properties of sub-matrices
211
Determine indices based on sub-matrix properties
212
Characterize abnormality based on properties and/or indices
214
Generate 2D graphic map based on the signature cycle matrix
216
200

Fig. 2

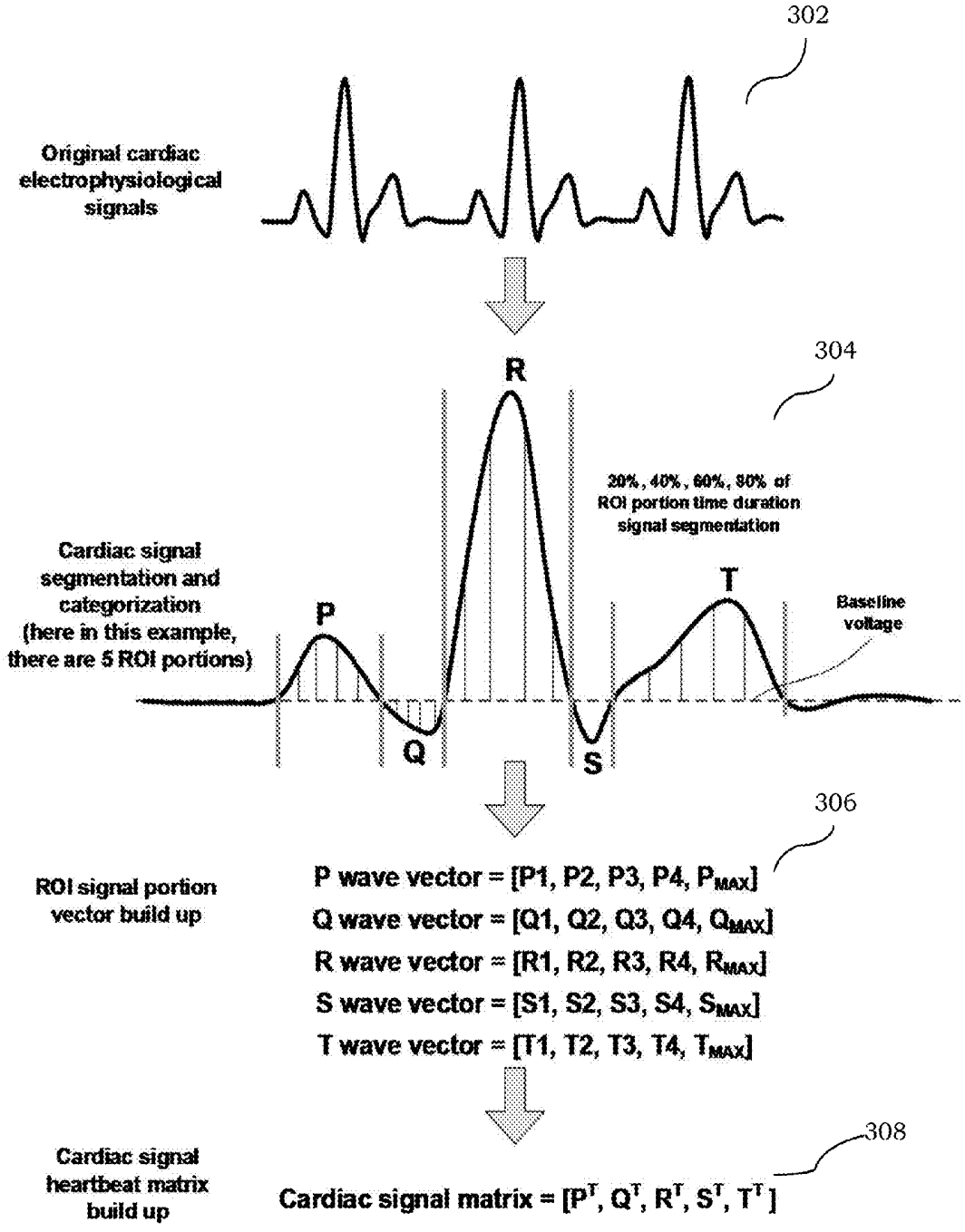

302
Original cardiac electrophysiological signals
304
R
20%, 40%, 60%, 80% of ROI portion time duration signal segmentation
Cardiac signal segmentation and categorization (here in this example, there are 5 ROI portions)
P
Q
S
T
Baseline voltage
306
ROI signal portion vector build up
P wave vector = [P1, P2, P3, P4, P_MAX]
Q wave vector = [Q1, Q2, Q3, Q4, Q_MAX]
R wave vector = [R1, R2, R3, R4, R_MAX]
S wave vector = [S1, S2, S3, S4, S_MAX]
T wave vector = [T1, T2, T3, T4, T_MAX]
308
Cardiac signal heartbeat matrix build up
Cardiac signal matrix = [P^T, Q^T, R^T, S^T, T^T]
300

Fig. 3

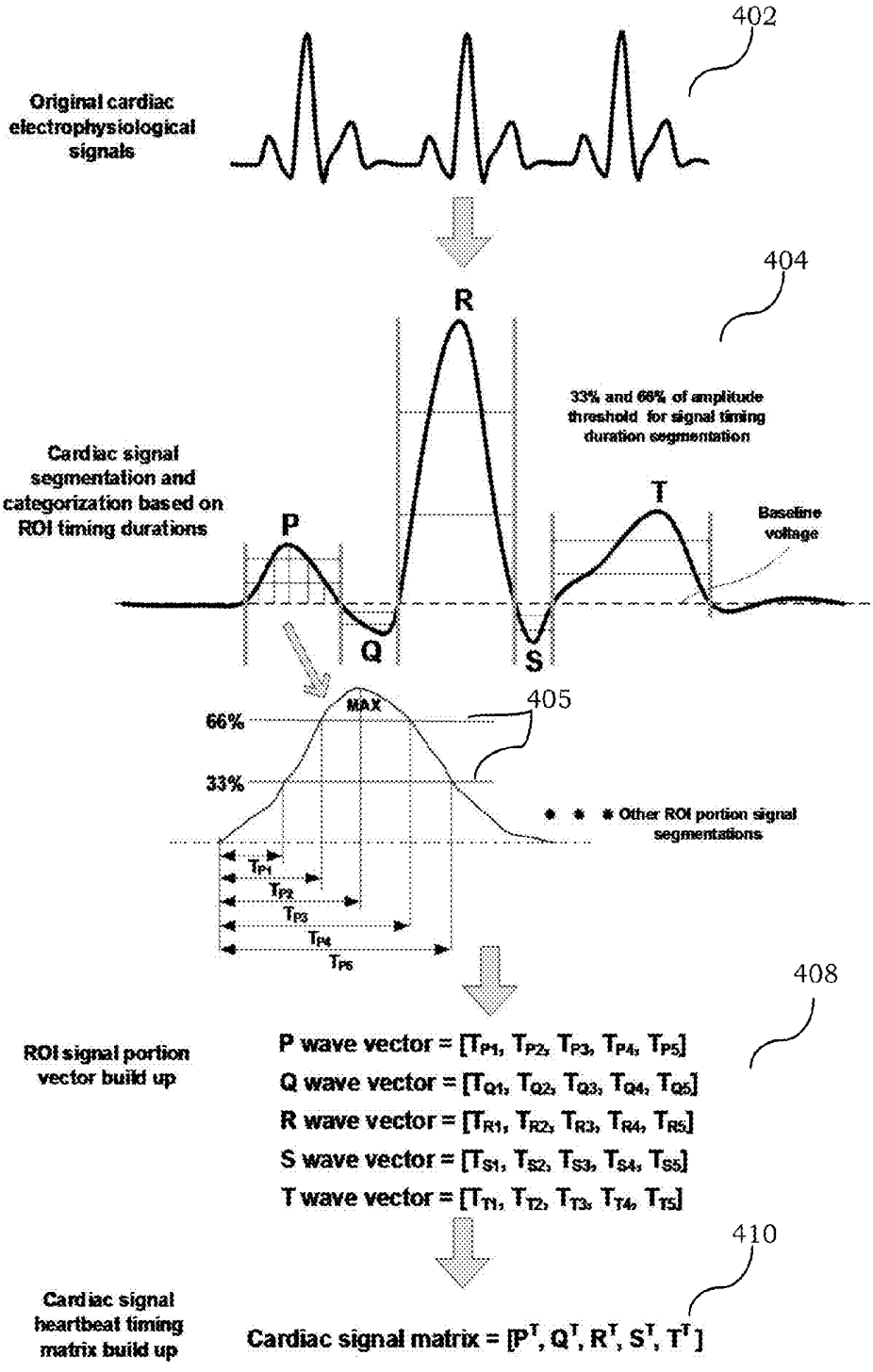

402
Original cardiac electrophysiological signals
404
R
33% and 66% of amplitude threshold for signal timing duration segmentation
Cardiac signal segmentation and categorization based on ROI timing durations
P
T
Baseline voltage
Q
S
405
MAX
66%
33%
* * * Other ROI portion signal segmentations
T_{P1}
T_{P2}
T_{P3}
T_{P4}
T_{P5}
408
ROI signal portion vector build up
P wave vector = [T_{P1}, T_{P2}, T_{P3}, T_{P4}, T_{P5}]
Q wave vector = [T_{Q1}, T_{Q2}, T_{Q3}, T_{Q4}, T_{Q5}]
R wave vector = [T_{R1}, T_{R2}, T_{R3}, T_{R4}, T_{R5}]
S wave vector = [T_{S1}, T_{S2}, T_{S3}, T_{S4}, T_{S5}]
T wave vector = [T_{T1}, T_{T2}, T_{T3}, T_{T4}, T_{T5}]
410
Cardiac signal heartbeat timing matrix build up
Cardiac signal matrix = [P^T, Q^T, R^T, S^T, T^T]
400

Fig. 4

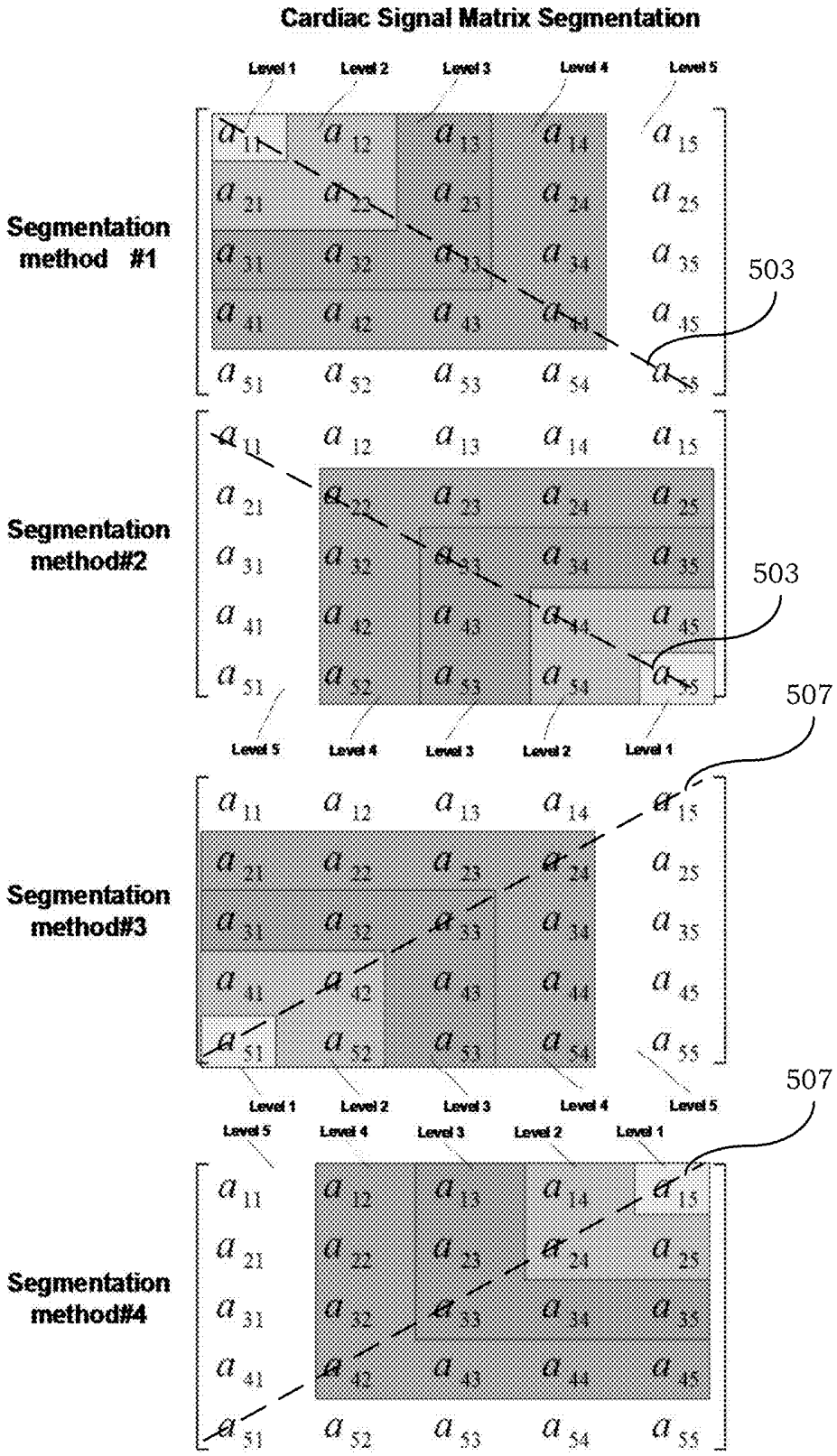

Cardiac Signal Matrix Segmentation
Segmentation method #1
Segmentation method#2
Segmentation method#3
Segmentation method#4
503
503
507
507
Level 1
Level 2
Level 3
Level 4
Level 5

Fig. 5

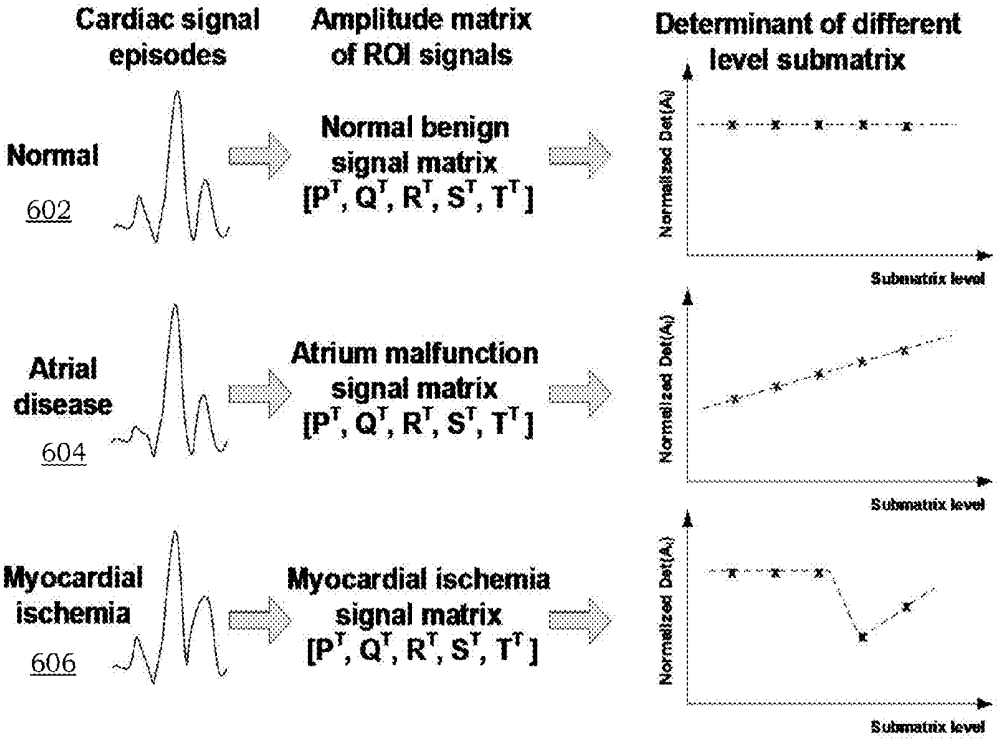

Cardiac signal episodes
Amplitude matrix of ROI signals
Determinant of different level submatrix
Normal
602
Normal benign signal matrix
[P^T, Q^T, R^T, S^T, T^T]
Atrial disease
604
Atrium malfunction signal matrix
[P^T, Q^T, R^T, S^T, T^T]
Myocardial ischemia
606
Myocardial ischemia signal matrix
[P^T, Q^T, R^T, S^T, T^T]
Normalized Det(A_i)
Submatrix level

Fig. 6

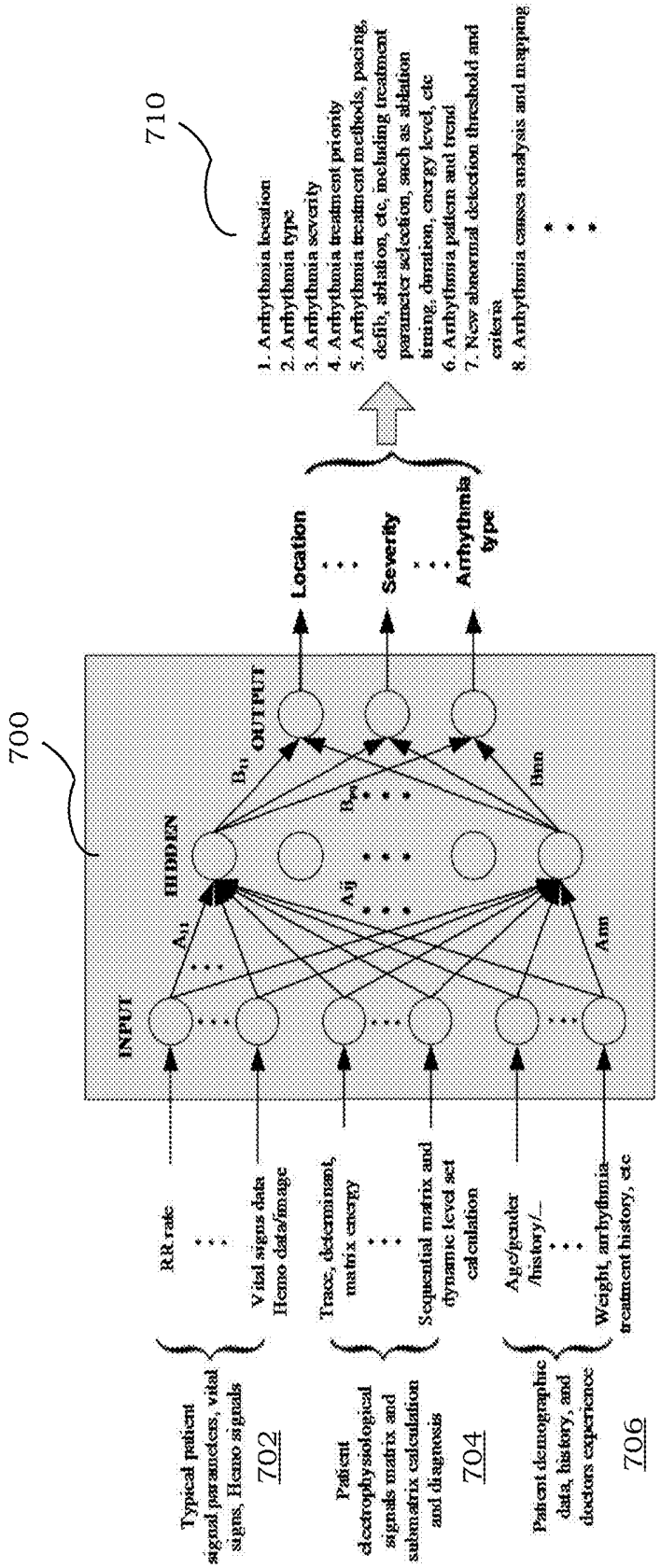

700
710
INPUT
HIDDEN
OUTPUT
Location
Severity
Arrhythmia type
1. Arrhythmia location
2. Arrhythmia type
3. Arrhythmia severity
4. Arrhythmia treatment priority
5. Arrhythmia treatment methods, pacing, defib, ablation, etc, including treatment parameter selection, such as ablation timing, duration, energy level, etc
6. Arrhythmia pattern and trend
7. New abnormal detection threshold and criteria
8. Arrhythmia causes analysis and mapping
RR rate
Vital signs data
Hemo data/image
Trace, determinant, matrix energy
Sequential matrix and dynamic level set calculation
Age/gender /history/...
Weight, arrhythmia treatment history, etc
Typical patient signal parameters, vital signs, Hemo signals
702
Patient electrophysiological signals matrix and submatrix calculation and diagnosis
704
Patient demographic data, history, and doctors experience
706

Fig. 7

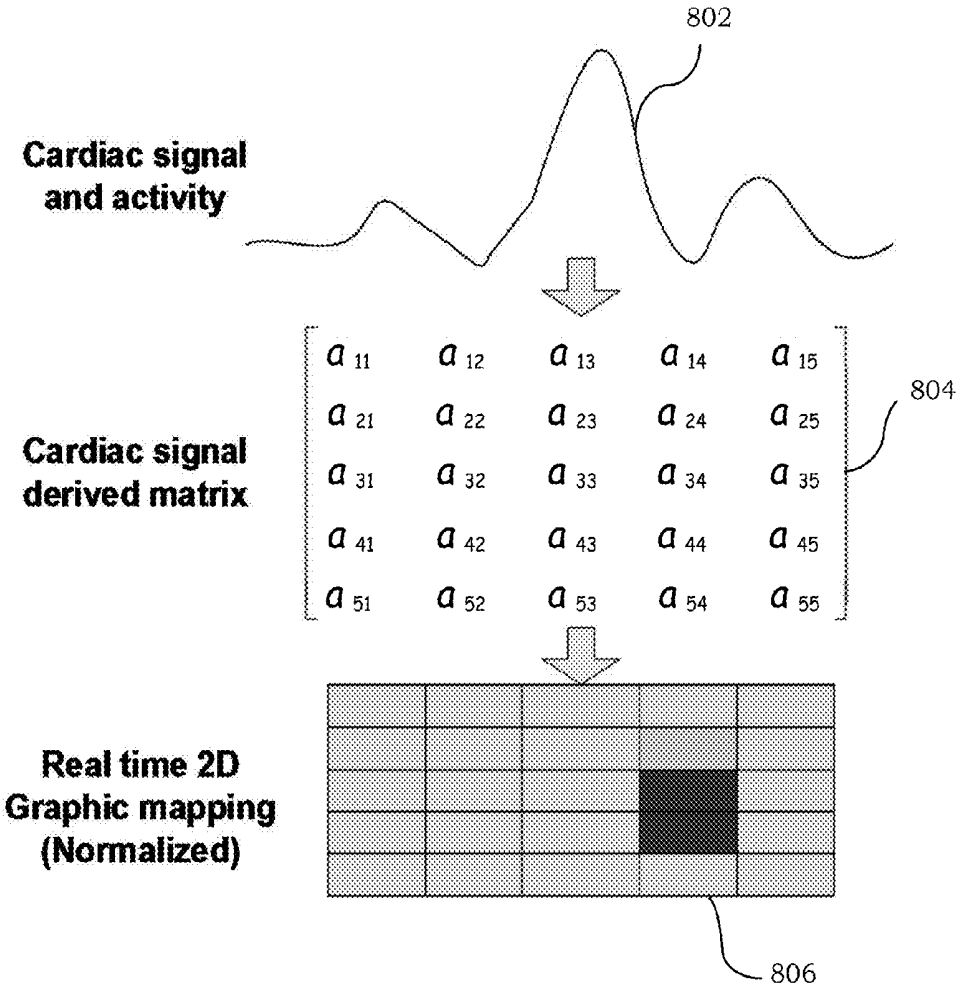

802
Cardiac signal and activity
Cardiac signal derived matrix
804
Real time 2D Graphic mapping (Normalized)
806

Fig. 8

MATRIX-BASED PATIENT SIGNAL ANALYSIS

TECHNICAL FIELD

[0001] The present disclosure generally relates to systems and methods for matrix-based patient signal analysis.

BACKGROUND

[0002] The most predominant killers of Americans are Coronary Artery Disease (CAD), heart-related problems and cardiac disorders. Cardiac electrophysiological response and activity analysis are critical for the management of cardiac disorders in the heart tissue and cells, such as ventricular myocardial ischemia caused by a lack of blood oxygen. The clinical reference standard for evaluating cardiac rhythm and events is the 12-lead electrocardiogram (ECG) or multi-channel intra-cardiac electrograms (ICEG).

[0003] Currently, analysis of waveform morphologies and time-domain parameters, such as P wave, QRS complex, ST segment, T wave, etc., are used for identifying cardiac arrhythmia events, such as atrial fibrillation (AF), myocardial ischemia (MI), ventricular tachycardia/fibrillation (VT/VF), and so forth. However, the waveform morphologies and time domain parameter analysis are sometimes subjective and time-consuming, and requires extensive medical expertise and clinical experience for accurate interpretation and proper cardiac rhythm management.

[0004] Recent research efforts have started to apply more sophisticated mathematical theories to biomedical signal interpretation, such as frequency analysis, symbolic complexity analysis and signal entropy evaluation. However, cardiac electrophysiological (EP) signals (e.g., ECG and ICEG) vary with time and current signal analysis usually cannot localize the precise malfunction severity and trend of cardiac events (e.g. the myocardial ischemia and infarction), such as cardiac pathology irregularity stages, arrhythmia occurrence, drug delivery evaluation, etc.

[0005] Known clinical methods typically focus on overall EP signal voltage amplitude analysis for detecting arrhythmia. These methods may not use all the information provided by the EP signals, such as electrophysiological excitation and response activities during the tissue contraction (depolarization) and tissue reperfusion (repolarization). Cardiac abnormality and arrhythmia related information (e.g., timing, energy, etc.), especially in the early stage, may not be efficiently and effectively extracted and characterized by current clinical approaches.

[0006] Many traditional medical methods use signal morphology changes to track early cardiac pathologies. However, minute signal morphology changes may not be clearly visible and it is hard to quantitatively evaluate and quantify, for example, QR slope shape change without R peak and Q peak amplitude voltage changes. In addition, there is no known efficient approach to integrate all cardiac electrophysiological activities from different parts of the heart into one single mathematical calculation.

[0007] Further, known clinical evaluations may not be efficiently applicable in some cases. For example, myocardial ischemia (MI) detections usually use the golden standard based on ST segment voltage deviation (e.g., 0.1 mV elevation). There are at least two shortcomings with this golden standard for MI analysis: (A) This standard only works for surface ECG signals, but not for intra-cardiac electrogram (ICEG) signals; and (B) the ST segment deviation (voltage) cannot be utilized as a quantitative method for myocardial ischemia severity diagnosis and characterization.

[0008] Usually, surface ECG signal analysis based on multi-channel waveform time domain parameters are utilized for cardiac arrhythmia detection, such as heart rate variability (HRV), cardiac wave morphology, R wave, ST segment and T wave amplitudes, etc. However there are no efficient quantitative methods available for cardiac status detection and characterization (e.g., MI) such as quantitative characterization of severity of ongoing ischemia events with chest pain, discomfort, etc. Additionally, most clinical approaches for cardiac arrhythmia identification based on ECG signals are subjective and need extensive clinical expertise and knowledge for accurate pathology interpretation and proper cardiac rhythm management. Furthermore, current known ischemia event detection algorithms may cause false alarms due to single parameter analysis. For example, the amplitude voltage of the ST segment may not be able to provide the severity level of the ischemia event, and heart rate variability may not be able to provide the arrhythmia urgency level either.

SUMMARY

[0009] The present disclosure relates to a framework for facilitating patient signal analysis. In accordance with one aspect, the framework generates a signature cycle matrix corresponding to a single cycle of the patient signal data by segmenting the patient signal data into multiple portions. The signature cycle matrix may further be segmented into sub-matrices corresponding to different levels. Properties of the sub-matrices may then be determined to generate diagnostic results.

[0010] This summary is provided to introduce a selection of concepts in a simplified form that are further described below in the following detailed description. It is not intended to identify features or essential features of the claimed subject matter, nor is it intended that it be used to limit the scope of the claimed subject matter. Furthermore, the claimed subject matter is not limited to implementations that solve any or all disadvantages noted in any part of this disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

[0011] A more complete appreciation of the present disclosure and many of the attendant aspects thereof will be readily obtained as the same becomes better understood by reference to the following detailed description when considered in connection with the accompanying drawings. Furthermore, it should be noted that the same numbers are used throughout the drawings to reference like elements and features.

[0012] FIG. **1** shows an exemplary system;

[0013] FIG. **2** shows an exemplary method of analyzing patient signals;

[0014] FIG. **3** illustrates an exemplary method of amplitude segmentation;

[0015] FIG. **4** illustrates an exemplary method of timing duration segmentation;

[0016] FIG. **5** illustrates four exemplary methods of extracting sub-matrices;

[0017] FIG. **6** shows a computer simulation of three exemplary cardiac episodes for comparison;

[0018] FIG. **7** shows an exemplary artificial neural network (ANN) module; and

[0019] FIG. **8** illustrates the mapping of a cardiac signal to a two-dimensional (2D) graphic map.

DETAILED DESCRIPTION

[0020] In the following description, numerous specific details are set forth such as examples of specific components, devices, methods, etc., in order to provide a thorough understanding of embodiments of the present invention. It will be apparent, however, to one skilled in the art that these specific details need not be employed to practice embodiments of the present invention. In other instances, well-known materials or methods have not been described in detail in order to avoid unnecessarily obscuring embodiments of the present invention. While the invention is susceptible to various modifications and alternative forms, specific embodiments thereof are shown by way of example in the drawings and will herein be described in detail. It should be understood, however, that there is no intent to limit the invention to the particular forms disclosed, but on the contrary, the invention is to cover all modifications, equivalents, and alternatives falling within the spirit and scope of the invention.

[0021] It is to be understood that the system and methods described herein may be implemented in various forms of hardware, software, firmware, special purpose processors, or a combination thereof. Preferably, the present invention is implemented in software as an application (e.g., n-tier application) comprising program instructions that are tangibly embodied on one or more program storage devices (e.g., magnetic floppy disk, RAM, CD ROM, ROM, etc.), and executable by any device or machine comprising suitable architecture. If written in a programming language conforming to a recognized standard, sequences of instructions designed to implement the methods can be compiled for execution on a variety of hardware platforms and for interface to a variety of operating systems. In addition, embodiments of the present framework are not described with reference to any particular programming language. It will be appreciated that a variety of programming languages may be used to implement embodiments of the present invention.

[0022] The present framework provides a methodology to analyze patient signals. In accordance with one aspect, the framework analyzes the signature cycle vector (e.g., timing, amplitude, etc.) and matrix pattern generated from an electrophysiological (EP) patient signal. Such analysis may be used to more reliably and precisely characterize cardiac arrhythmia and heart tissue functionality, such as atrial or ventricular functions for detecting early stages of atrial fibrillation, myocardial ischemia-infarction, etc.

[0023] Cardiac functional abnormality or arrhythmia usually causes cardiac tissue performance (contracting and reperfusion) to be irregular and may reduce blood flow to regions of the heart, where cells respond by altering action potentials. The changes in these individual cells manifest in local electrograms during depolarization (action potential rising edge) and repolarization (action potential falling edge), reducing signal energy (hyperkalemia or anoxia) or creating multiphasic waveforms (decoupling). In some implementations, cardiac cycle signal vector and matrix-based pattern-mode analysis is provided to integrate characteristics of different cardiac functional modules (e.g., atrium, ventricle, any electrical potential pathway, etc.).

[0024] The framework described herein may generate various matrix properties and indices, such as matrix determinant, matrix trace, matrix-submatrix sequential index, etc., to characterize cardiac electrophysiological activities more accurately with better sensitivity and stability, especially in noisy conditions. The cardiac waveform signature vector and matrix pattern-mode evaluations may include characterization of critical ROI electrophysiological activity (e.g., R wave vector, T wave vector, etc.) within the same heartbeat. Such characterization may be used in real-time monitoring of cardiac tissue pathology (especially ventricular ischemia and infarction), such as in the application of implantable devices. The present framework may advantageously provide a more efficient, accurate and reliable method for identifying cardiac disorders, differentiating cardiac arrhythmias, characterizing pathological severities, predicting life-threatening events, and even evaluating drug delivery effects and providing treatment suggestions or evaluation.

[0025] FIG. **1** shows an exemplary system **100** for implementing a method and system of the present disclosure. It is to be understood that, because some of the constituent system components and method steps depicted in the accompanying figures can be implemented in software, the actual connections between the systems components (or the process steps) may differ depending upon the manner in which the present framework is programmed For example, the system **100** may be implemented in a client-server, peer-to-peer (P2P) or master/slave configuration. In such configurations, the system **100** may be communicatively coupled to other systems or components via a network, such as an Intranet, a local area network (LAN), a wide area network (WAN), a P2P network, a global computer network (e.g., Internet), a wireless communications network, or any combination thereof. Given the teachings of the present invention provided herein, one of ordinary skill in the related art will be able to contemplate these and similar implementations or configurations of the present invention.

[0026] As shown in FIG. **1**, the system **100** may include a computer system **101**, a patient monitor **130** and a medical treatment device **132**. The computer system **101** may include, inter alia, a central processing unit (CPU) or processor device **102**, a non-transitory computer-readable media **105**, one or more output devices **111** (e.g., printer, display monitor, projector, speaker, etc.), a network controller **103**, an internal bus **106** and one or more input devices **108**, for example, a keyboard, mouse, touch screen, gesture and/or voice recognition module, etc. Computer system **101** may further include support circuits such as a cache, a power supply, clock circuits and a communications bus. Various other peripheral devices, such as additional data storage devices and printing devices, may also be connected to the computer system **101**.

[0027] The present technology may be implemented in various forms of hardware, software, firmware, special purpose processors, or a combination thereof, either as part of the microinstruction code or as part of an application program or software product, or a combination thereof, which is executed via the operating system. In one implementation, the techniques described herein may be implemented as computer-readable program code tangibly embodied in non-transitory computer-readable media **105**. Non-transitory computer-readable media or memory device **105** may include random access memory (RAM), read only memory (ROM), magnetic floppy disk, flash memory, and other types of memories, or a combination thereof. The present techniques may be implemented by patient signal analysis unit **122** that is stored in computer-readable media **105**. As such, the computer system

101 is a general-purpose computer system that becomes a specific-purpose computer system when executing the computer-readable program code.

[0028] The same or different computer-readable media **105** may be used for storing a database **124**. Database **124** may include a repository of determined parameters and ratios, selectable predetermined functions, patient signal data (e.g., electrophysiological, ECG, ICEG, respiration signal data, other hemodynamic or vital sign data, etc.), patient data (e.g., demographic data, pathology history, etc.), other input data and/or other derived output parameters. Patient signal data may be provided by a patient monitor **130** that is communicatively coupled to the computer system **101**.

[0029] Patient monitor **130** may be used to acquire various types of patient biometric or electrophysiological signal information for monitoring the patient. For example, the monitoring information may include, but is not limited to, electrophysiological signal data (e.g., ECG, ICEG, etc.), oximetric or SPO2 signal data, respiration signal data, blood pressure, temperature and/or other patient biometric, physiological, hemodynamic, vital sign or medical parameter information. The patient monitor **130** may include appropriate biometric sensors (e.g., leads for surface ECG and basket catheter for intra-cardiac electrographic signal data) for acquiring the monitoring patient signals. Implementations of the present framework provide parameters to detect, diagnose and quantify such patient signals.

[0030] Medical treatment device **132** may be automatically and adaptively controlled by the computer system **101** in a closed-loop feedback control system. Medical treatment device **132** may include, but are not limited to, a pacing device, ablator, cardioverter, defibrillator, and so forth. Control parameters of the medical treatment device **132**, such as the pacing parameter, ablation energy control, etc., may be automatically determined by computer system **101**.

[0031] FIG. **2** shows an exemplary method **200** of analyzing patient signals. The steps of the method **200** may be performed in the order shown or a different order. Additional, different, or fewer steps may be provided. Further, the method **200** may be implemented with the system **100** of FIG. **1**, a different system, or a combination thereof.

[0032] At **202**, patient monitor **130** acquires patient signal data from a current patient. In some implementations, the patient signal data comprises cardiac electrophysiological signal data, such as intra-cardiac electrographic (ICEG) data, surface ECG data, etc. The cardiac electrophysiological signal data may be acquired by multiple channels connected to, for example, an intra-cardiac basket catheter placed into the heart. Alternatively, or additionally, other types of electrophysiological signal data, such as hemodynamic (HEMO) signal data, respiration (or capnographic) signal data, blood pressure data, oximetric (SPO2) data, and/or other vital sign signal data, other measurable patient biometric, physiological or medical signals, may also be acquired. In addition, other patient information, such as demographic data, clinical application and patient status, including, but not limited to, weight, height, gender, age, allergies, medications, pathology history, pathology treatment history, etc., may also be acquired.

[0033] At **204**, the patient signal data is pre-processed. The patient signal data may be pre-processed by conditioning, filtering, amplification, digitization and/or buffering. For example, the patient signal data may be pre-filtered and amplified for display as a waveform on, for instance, patient monitor **130**. The patient signal data may be filtered to remove unwanted patient movement and respiratory artifacts, as well as power line noise. The filter may be adaptively selected in response to data indicating clinical application (e.g., ischemia detection application, rhythm analysis application). The patient signal data may be conditioned, amplified, buffered, filtered and/or digitized to produce a continuous stream of digitized samples.

[0034] In some implementations, a baseline value or signal is automatically extracted from the digitized patient signal data. The baseline value (or signal) generally refers to a known threshold value (or benign signal) with which an unknown value (e.g., amplitude) is compared when measured or assessed. The baseline value may be used in, for example, threshold determination. The baseline value may comprise a zero voltage line if a static (DC) voltage signal component is filtered out from the signal. The baseline value may be adaptively adjusted according to the current application and clinical requirements. Alternatively, if the value is not to be automatically determined, the user may manually select it via, for example, a user interface.

[0035] At **206**, patient signal analysis unit **122** segments the patient signal data into multiple portions to generate a signature cycle matrix. The signature cycle matrix corresponds to a single signal cycle (e.g., heartbeat). Each row or column of the signature cycle matrix represents signal data values (e.g., amplitude or time duration values) corresponding to a particular portion of the signal cycle. Each portion represents a region of interest (ROI) identified for further analysis. Based on the clinical application, different methods may be used to segment the patient signal waveform (e.g., amplitude, timing, frequency, energy, signal slope speed, etc.) at different levels to capture small signal changes in, for example, morphology, amplitude, timing, latency, energy, etc. A signature cycle matrix may then be constructed based on wave vectors derived from the segmented ROI portions.

[0036] FIG. **3** illustrates an exemplary method **300** of amplitude segmentation. At **302**, the original cardiac electrophysiological signal data is received. At **304**, the signal data is segmented into various ROI portions. More particularly, a whole heart beat is vertically segmented into several timing slices based on the cardiac waveform function peak and valley distribution. In this example, 5 ROI portions are selected: P, Q, R, S, and T waveform portions which are segmented by the reference or baseline voltage line (voltage of cardiac rest portion). Each ROI portion is further segmented into four sub-portions. For example, each waveform of the ROI portions is vertically segmented into four levels by using 20%, 40% 60%, and 80% points of the respective timing slice or duration. Hence, by using four-level timing categorization, each ROI signal portion may be segmented to derive 4 corresponding amplitude values. It should be appreciated, however, that any other number of levels or sub-portions may be used.

[0037] At **306**, these 5 segmented ROI signal portions are all utilized to construct the cardiac signature wave vectors. Each wave vector may include values extracted from the sub-portions of the respective ROI signal portion. In this example, each vector includes five voltage amplitude values corresponding to a particular ROI signal portion. For example, P**1**, P**2**, P**3** and P**4** are the segmented amplitudes in the P wave ROI portion. The wave vector may further include the maximum amplitude value of the associated ROI portion (e.g., P_{max}, Q_{max} R_{max}, S_{max} or T_{max}). The number of amplitude value points (e.g., 5) may be selected to match the total

number of the ROI portions (here in this example, there are 5 ROI portions) so as to create a square matrix at step **308**. Based on the clinical application and user preference, clinical users or computer software algorithms may adaptively select the number and locations of the ROI signal portions, modify the size of the segmentation point series, and/or update the size of the signal vector and matrix. At **308**, a 5×5 cardiac signature cycle matrix is constructed based on the transpose of the wave vectors (e.g., P^T, Q^T, R^T, S^T and T^T), which may be used for further calculation and diagnosis.

[0038] FIG. **4** illustrates an exemplary method **400** of timing duration segmentation. At **402**, the original cardiac electrophysiological signal data is received. At **404**, the signal data is segmented into various ROI portions. In this exemplary timing duration segmentation, two voltage thresholds (**405**)—33% and 66% of the maximum voltage amplitude of the corresponding ROI portion—are used to separate the time duration of the corresponding ROI portion and derive five time points (T_{P1} to T_{P5}) that correspond to the voltage thresholds. At **408**, the time points (T_{P1} to T_{P5}) are used to generate wave vectors (e.g., P wave vector, Q wave vector, R wave vector, S wave vector and T wave vector) for the different ROI portions. For example, a P wave vector may include the time points T_{P1}, T_{P2}, T_{P3}, T_{P4} and T_{P5}. At **410**, a 5×5 cardiac signature cycle matrix is constructed based on the transpose of the wave vectors (e.g., P^T, Q^T, R^T, S^T and T^T), which may be used for further calculation and diagnosis.

[0039] Returning to FIG. **2**, at **210**, patient signal analysis unit **122** segments the signature cycle matrix into sub-matrices of different levels. In some implementations, a sequential sub-matrix extraction method is used to segment the signature cycle matrix into different level sub-matrices. Compared to the full signature cycle matrix, the sub-matrices characterize different features. The full matrix characterizes the entire waveform of the ROI signal portions, including the energy level and similarity, while the sub-matrices characterize similar waveform portions associated with different ROI signal portions.

[0040] FIG. **5** illustrates four exemplary methods of extracting sub-matrices. The sub-matrices are extracted from a square (N by N) signature cycle matrix (or mother matrix) along the diagonal or inverse diagonal of the mother matrix. In some implementations, five ROI signal portions and corresponding five parameters (e.g., amplitudes or timing durations) are categorized for each ROI area. In the example shown in FIG. **5**, the mother matrix is 5 by 5 and there are five levels of segmentation, including the mother matrix itself at level 5.

[0041] As illustrated by FIG. **5**, sub-matrix segmentation involves categorizing the mother matrix downwards or upwards along the normal diagonal **503** (upper left to lower right), or upwards or downwards along the inverse diagonal **507** (lower left to upper right) of the mother matrix. In addition, the four different matrix segmentation methods also have clinical signal value and meaning. For example, segmentation method #**1** shows a linear segmentation of the mother matrix downwards along the normal diagonal **503** of the mother matrix. The segmentation separates the mother matrix into five levels (from left to right) of sub-matrices. It should be appreciated, however, that other number of levels may also be defined.

[0042] Level 1 sub-matrix includes a single element (e.g., a_{11}) that represents the P wave existence. If the element's value is near zero, it means that P wave may be disappearing. The smaller the element's value is, the higher the severity of the P wave issue. Level 2 sub-matrix is two by two matrix that represents both rising edges of the P wave and Q wave, which can be utilized for rising edge correspondence of the rising speed for P and Q waves. Level 3 sub-matrix is a 3 by 3 matrix that represents the rising edges of the P, Q and R wave ROI portions, which can be utilized for determining rising edge mutual relations (e.g., rising speed and shape) for the P wave, Q wave and R wave ROI portions. Level 4 sub-matrix is a 4 by 4 matrix that includes a maximum value and information of 4 ROI portions (P, Q, R, S waves), which can be utilized for determining signal similarity relations of the signal shapes for the P wave, Q wave, R wave and S wave. Finally, level 5 sub-matrix is the 5 by 5 mother matrix of all ROI portions that includes information from all 5 ROI portions (P, Q, R, S and T waves), which can be utilized for determining signal shape and energy relations of all the ROI signal waveform portions. Accordingly, by using such matrix segmentation, different levels of sub-matrices can be generated, which may be used for further calculation and pattern-mode diagnosis and characterization, such as determining pathology severity, arrhythmia location, disease type, etc.

[0043] Returning to FIG. **2**, at **211**, patient signal analysis unit **122** determines properties of the sub-matrices. Such properties serve to show or detect any change in the entries (or elements) of the sub-matrices. In some implementations, two specific properties are utilized for cardiac cycle signal diagnosis: trace and determinant. Other properties, such as matrix rank, vector norm, matrix norm, etc., may also be used. The properties may also be combined to differentiate cardiac cycle signal changes in some clinical applications.

[0044] The trace (TR) of an N-by-N square sub-matrix A may be defined as a sum of the elements on the main diagonal (e.g., diagonal from the upper left to the lower right) of A, as follows:

$$\text{TRACE(cardiac signal matrix)} = TR(A) = \sum_{i=1 \text{ to } N} a_{ii} \tag{1}$$

$$|\text{TRACE(cardiac signal matrix)}| = |TR(A)| = \sum_{i=1 \text{ to } N} |a_{ii}| \tag{2}$$

wherein a_{ii} denotes the entry on the i-th row and i-th column of sub-matrix A.

[0045] The determinant (Det) of an N-by-N square sub-matrix A may be determined from entries of the matrix by a specific arithmetic expression (e.g., Leibniz formula or Laplace formula), such as follows:

$$\text{Det}(A) = \sum_{\sigma \in S_N} \text{SGN}(\sigma) \prod_{i=1}^{N} a_{i,\sigma_i} \tag{3}$$

wherein Det(A) is computed over all permutations σ of the set $S_N = \{1, 2, \ldots, N\}$. A permutation is a function that reorders this set of integers. The value in the i^{th} position after the reordering function a is denoted as σ_i. The set of all such permutations is denoted as S_N for each permutation σ; SGN (σ) denotes the signature of σ, a value that is +1 whenever the reordering given by a can be achieved by successively inter-

changing two entries an even number of times, and −1 whenever it can be achieved by an odd number of such interchanges.

[0046] At **212**, patient signal analysis unit **122** determines indices based on the properties of the sub-matrices. In order to more efficiently diagnose and characterize the ROI signal portion changes, a sequential energy index ($SMEI_{Trace}$) may be derived based on a sum of squared magnitudes of trace values corresponding to the sub-matrices as follows:

$$SMEI_{Trace} = \sum_{i \in Level_number} |TRACE_i|^2 \quad (4)$$

wherein Level_number is the total number of levels in the matrix segmentation, including the last level of segmentation that results in the mother matrix; $TRACE_i$ is the trace value of the level i sub-matrix.

[0047] A sequential energy index ($SMEI_{Determinant}$) may also be derived based on a sum of squared magnitudes of the determinant values corresponding to the sub-matrices as follows:

$$SMEI_{Determinant} = \sum_{i \in Level_number} |\mathrm{Det}(A_i)|^2 \quad (5)$$

wherein Level_number is the total number of levels in the matrix segmentation, including the last level of segmentation that results in the mother matrix; $\mathrm{Det}(A_i)$ is the determinant value of the level i sub-matrix.

[0048] At **214**, patient signal analysis unit **122** characterizes an abnormality based on the sub-matrix parameters and/or indices. The abnormality may include, for example, cardiac arrhythmia or myocardial ischemia. In some implementations, the location, severity, type and/or timing of cardiac pathologies are determined based on the sub-matrix parameters (e.g., determinant, trace, etc.) and/or indices (e.g., sequential energy index) derived therefrom. The working pattern and dynamic mode of the whole cardiac cycle may be derived for synchronizing multiple ROI signal portions and integrating data derived from different parts of the same cardiac cycle.

[0049] FIG. **6** shows a computer simulation of three exemplary cardiac episodes for comparison: normal (**602**), atrial disease (**604**) and myocardial ischemia (**606**). The normal episode refers to a benign cardiac cycle and the determinant values for amplitude sub-matrices of different levels are used as reference for normalizing the determinant values associated with the sub-matrices of corresponding levels. For example, the user or framework may divide a given determinant parameter value with the determinant parameter value of the benign reference sub-matrix at the same level.

[0050] If there is an atrial disease (**604**) that causes the signal amplitude to be smaller, all level determinant values become smaller. The sequential determinants of different levels shows a sloping trend. The slope degree and direction may also be used as quantitative parameters for detecting and characterizing cardiac arrhythmia. If there is myocardial ischemia event (**606**), which occurs at the T wave portion, the low level (e.g., 1-3) sub-matrix determinant values do not show any changes while the high level (e.g., 4-5) sub-matrix determinant values show drastic changes, especially in level 4 (>40% change). By using this simulation example, it can be shown that sub-matrix parameters can be used to monitor and characterize the location, type, severity and timing of cardiac signal changes.

[0051] For purposes of illustration, FIG. **6** shows three individual cardiac cycle diagnoses based on determinants derived from multi-level sub-matrices. It should be appreciated, however, that other sub-matrix properties and/or indices, such as trace, determinant and energy index, may also be used for diagnosis. In addition, this sub-matrix pattern diagnosis approach may be developed for continuous and real-time application, such as for real-time patient monitoring and health alarm system. The trace, determinant and energy index values derived from the different level sub-matrices may be re-organized for dynamic statistical analysis. For example, parameters and/or or indices derived from level 2 sub-matrices of a sequential cardiac cycles may be constructed into time series data. By extracting and reconstructing the dataset, parameters and indices, different kinds of methods, such as variation and variability, matrix entropy, hypothesis tests for qualitative and quantitative diagnosis, may be implemented.

[0052] Patient electrophysiological signal vector and matrix analysis may provide different kinds of information to the clinical users, such as amplitude change, timing changes, cardiac pathology severity, cardiac arrhythmia potential location, and/or treatment suggestions and methods. In order to more efficiently combine all patient data and associated parameters and/or indices, an artificial neural network (ANN) may be used. The ANN may non-linearly fuse all available data to provide a set of diagnostic results for use by a doctor to make informed decisions. Other types of methods, such as a fuzzy system or expert system, may also be used for data fusion. Statistical and hypothesis testing algorithms may also be fulfilled with ANN nonlinear data fusion and diagnosis.

[0053] FIG. **7** shows an exemplary ANN module **700**. The ANN module **700** includes 3 layers: (1) input layer, (2) hidden layer and (3) output layer. Weights (A_{11} to A_{mn} and B_{11} to B_{mn}) between the layers may be adaptively adjusted with a training data set. The ANN module **700** has a self-learning ability with new input data, which can increase the accuracy of the calculated results **710**. The ANN module **700** combines patient signal data **702** (e.g., vital sign, hemodynamic signal data, etc.), different sub-matrix parameters and indices **704** generated by the present framework (e.g., trace, determinant, energy, sequential matrix index, dynamic level set, etc.), patient data (e.g., demographic data, treatment history, etc.) and information derived from the doctor's experience **706** to generate quantitative and qualitative output results **710**. The output results **710** include detailed patient status and treatment parameters for optimized cardiac rhythm management (CRM), such as cardiac arrhythmia type, severity, location mapping, trend, etc., as well as suggestions for treatment, such as treatment location, priority, treatment control parameter (e.g., pacing parameter, ablation energy control, etc.), and so forth.

[0054] At **216**, patient signal analysis unit **122** generates a two-dimensional (2D) graphic map based on the signature cycle matrix. The signature cycle matrix clinically corresponds to a cardiac response signal cycle and can be graphically mapped to patient heart activities for visualization. Severity or deviation degrees of signal may also be color coded in the graphic map.

[0055] FIG. **8** illustrates the mapping of a cardiac signal **802** to a 2D graphic map **806** via its derived signature cycle

matrix **804**. Each entry in the derived signature cycle matrix **804** may be mapped to an element on the 2D graphic map **806**. Accordingly, all ROI signal portions (P wave, Q wave, R wave, etc.) are mapped and filled into the graph **806**. The color coding of the elements in the 2D graphic map **806** represents the severity or percentage change in the corresponding entry (e.g., amplitude or timing duration). This 2D graphic map may be rendered and presented on a display device in real-time for easy signal monitoring by a user. The 2D changes in color is advantageously more convenient and easier to detect than minute changes in the signal waveform or parameters in the one-dimensional domain.

[0056] While the present invention has been described in detail with reference to exemplary embodiments, those skilled in the art will appreciate that various modifications and substitutions can be made thereto without departing from the spirit and scope of the invention as set forth in the appended claims. For example, elements and/or features of different exemplary embodiments may be combined with each other and/or substituted for each other within the scope of this disclosure and appended claims.

1. A system for patient signal analysis, comprising:

a patient monitor configured to acquire a patient signal data from a patient; and

a computer system communicatively coupled to the patient monitor, wherein the computer system includes

a non-transitory memory device,

a processor device in communication with the memory device, and

a signal analysis unit stored in the memory device and operative with the processor device to perform steps including

generating a signature cycle matrix corresponding to a single cycle of the patient signal data by segmenting the patient signal data into multiple portions,

segmenting the signature cycle matrix into sub-matrices corresponding to different levels,

determining properties of the sub-matrices,

determining a sequential energy index based on the properties of the sub-matrices, and

characterizing an abnormality based on the properties and the sequential energy index.

2. The system of claim **1** wherein the signal analysis unit is further operative with the processor device to generate the signature cycle matrix by

segmenting each of the multiple portions into sub-portions,

generating wave vectors based on values extracted from the sub-portions, and

generating the signature cycle matrix based on the wave vectors.

3. The system of claim **2** wherein the values comprise voltage amplitude values.

4. The system of claim **3** wherein the voltage amplitude values comprise a maximum voltage amplitude value of a corresponding portion.

5. The system of claim **2** wherein the values comprise time durations.

6. The system of claim **1** wherein the sub-matrices comprise:

a first level sub-matrix that represents existence of a P wave in the cycle;

a second level sub-matrix that represents both rising edges of the P wave and a Q wave in the cycle;

a third level sub-matrix that represents rising edges of the P wave, the Q wave and an R wave in the cycle;

a fourth level sub-matrix that represents information from the P wave, the Q wave, the R wave and an S wave in the cycle; and

a fifth level sub-matrix that represents information from the P wave, the Q wave, the R wave, the S wave and a T wave in the cycle.

7. The system of claim **1** wherein the properties comprise trace or determinant values.

8. The system of claim **7** wherein the sequential energy index comprises a sum of squared magnitudes of trace values corresponding to the sub-matrices.

9. The system of claim **7** wherein the sequential energy index comprises a sum of squared magnitudes of determinant values corresponding to the sub-matrices.

10. The system of claim **1** wherein the abnormality comprises cardiac arrhythmia or myocardial ischemia.

11. A computer-implemented method of patient signal analysis, comprising:

receiving, from a patient monitor, patient signal data;

generating, by a processor device, a signature cycle matrix corresponding to a single cycle of the patient signal data by segmenting the patient signal data into multiple portions;

segmenting, by the processor device, the signature cycle matrix into sub-matrices corresponding to different levels;

determining, by the processor device, properties of the sub-matrices; and

generating, by the processor device, diagnostic results based on the properties.

12. The method of claim **11** wherein the multiple portions correspond to P, Q, R, S, and T waveform portions.

13. The method of claim **11** wherein generating the signature cycle matrix comprises:

segmenting each of the multiple portions into sub-portions,

generating wave vectors based on values extracted from the sub-portions, and

generating the signature cycle matrix based on the wave vectors.

14. The method of claim **13** wherein the values comprise voltage amplitude values or time durations.

15. The method of claim **11** wherein determining the properties comprises determining trace or determinant values of the sub-matrices.

16. The method of claim **11** wherein generating the diagnostic results comprises combining, via an artificial neural network, the properties and associated indices with other patient data.

17. The method of claim **11** wherein generating the diagnostic results comprises identifying the location, severity, type or timing of a cardiac pathology.

18. The method of claim **11** further comprising:

mapping each entry in the signature cycle matrix to an element on a two-dimensional graphic map; and

presenting, on a display device, the two-dimensional graphic map for a user to monitor the patient signal data.

19. A non-transitory computer readable medium embodying a program of instructions executable by machine to perform steps for patient signal analysis, the steps comprising:

receiving, from a patient monitor, patient signal data;

generating, by a processor device, a signature cycle matrix corresponding to a single cycle of the patient signal data by segmenting the patient signal data into multiple portions;

mapping each entry in the signature cycle matrix to an element on a two-dimensional graphic map; and

presenting, on a display device, the two-dimensional graphic map for a user to monitor the patient signal data.

20. The non-transitory computer readable medium of claim **19**, wherein the element is color coded to represent percentage change in the corresponding entry of the signature cycle matrix.

* * * * *

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申请(专利权)人(译)	西门子医疗解决方案USA，INC.		
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[标]发明人	ZHANG HONGXUAN		
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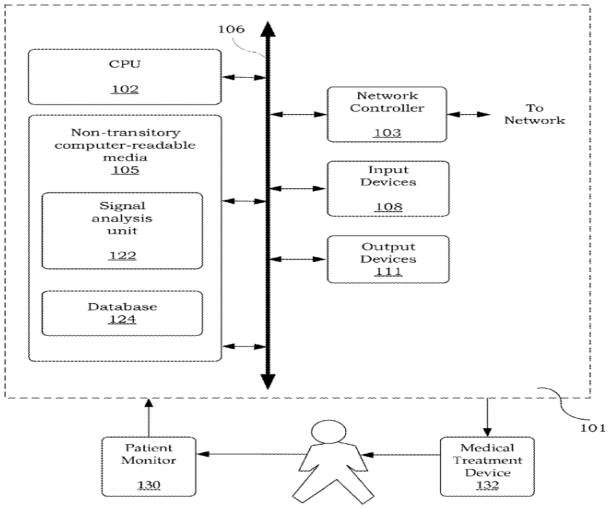
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