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(54) SYSTEM AND METHOD FOR PREDICTING NEAR-TERM PATIENT TRAJECTORIES

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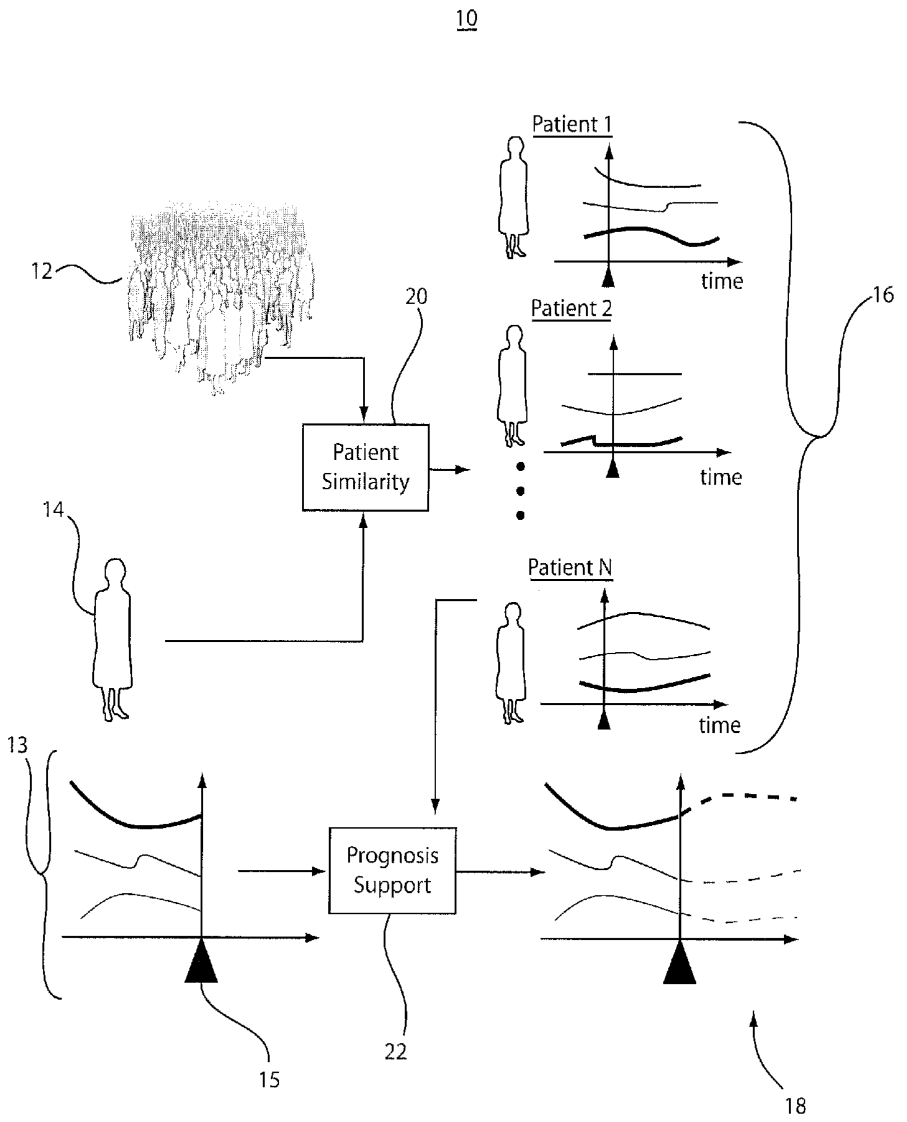
(57) **ABSTRACT**

A system and method for predicting near term measurements of a patient includes a stream processor configured to summarize raw measurements from patients into signatures and construct optimal prediction models based on previously obtained signatures. A similar patient tracker is configured to monitor similar patient information for a query patient. The similar patient information is determined based on a similarity between the query patient and signatures of other patients. A model analyzer is configured to employ retrofitted optimal prediction models from similar patients to predict near term measurements of the query patient.



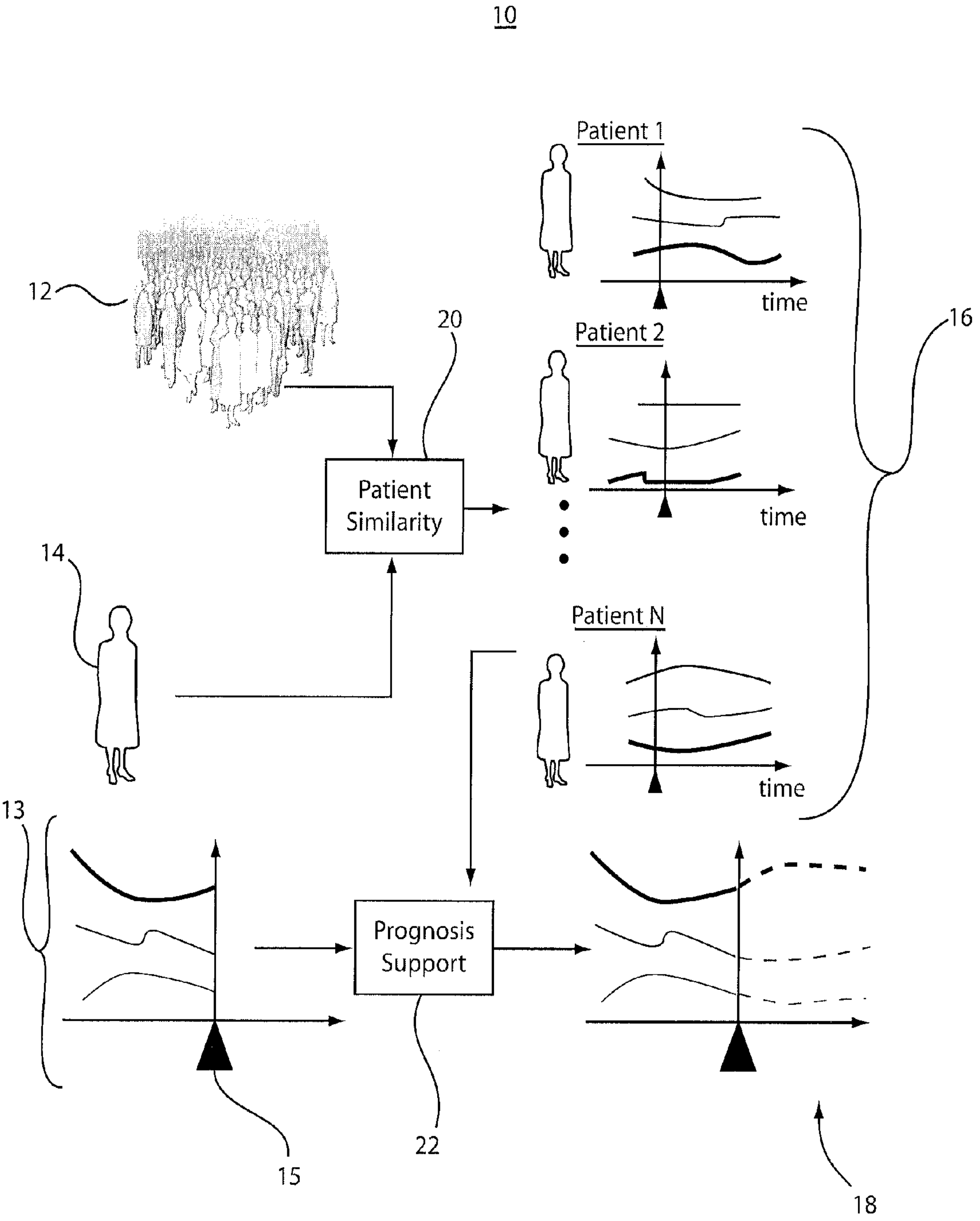

10
12
14
13
15
20
Patient Similarity
Patient 1
time
Patient 2
time
Patient N
time
16
Prognosis Support
22
18

FIG. 1

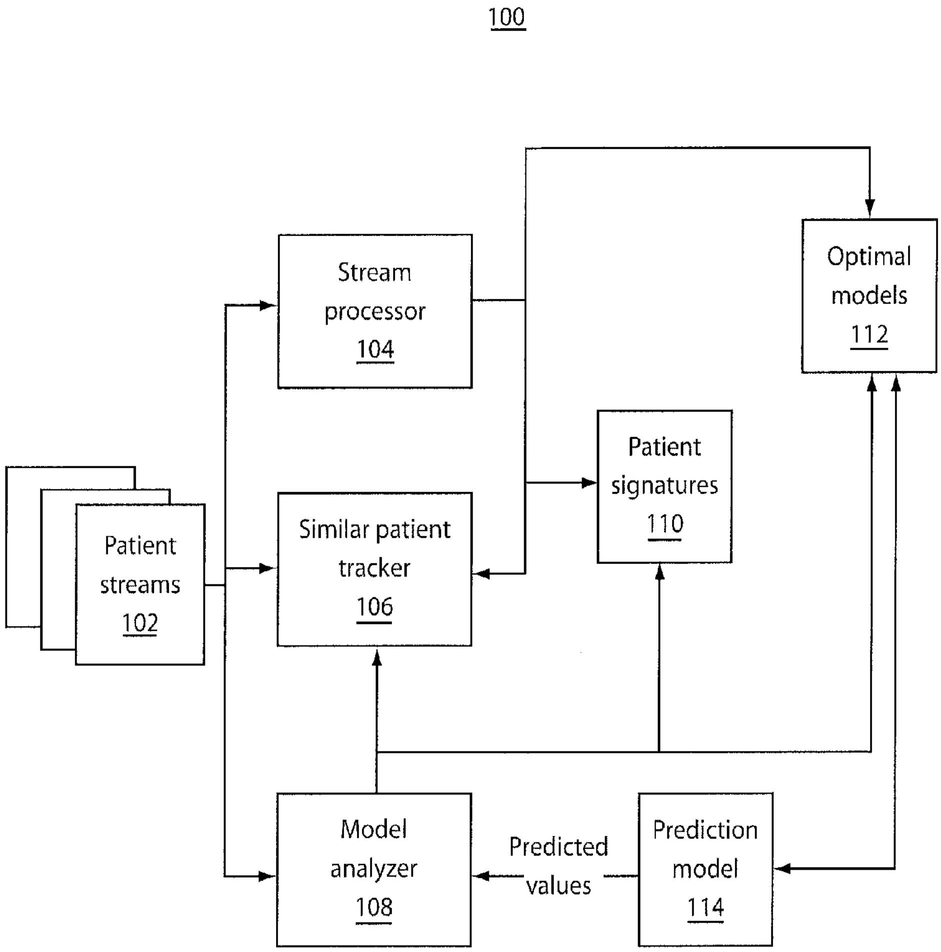

100
Stream processor 104
Optimal models 112
Patient signatures 110
Patient streams 102
Similar patient tracker 106
Model analyzer 108
Predicted values
Prediction model 114

FIG. 2

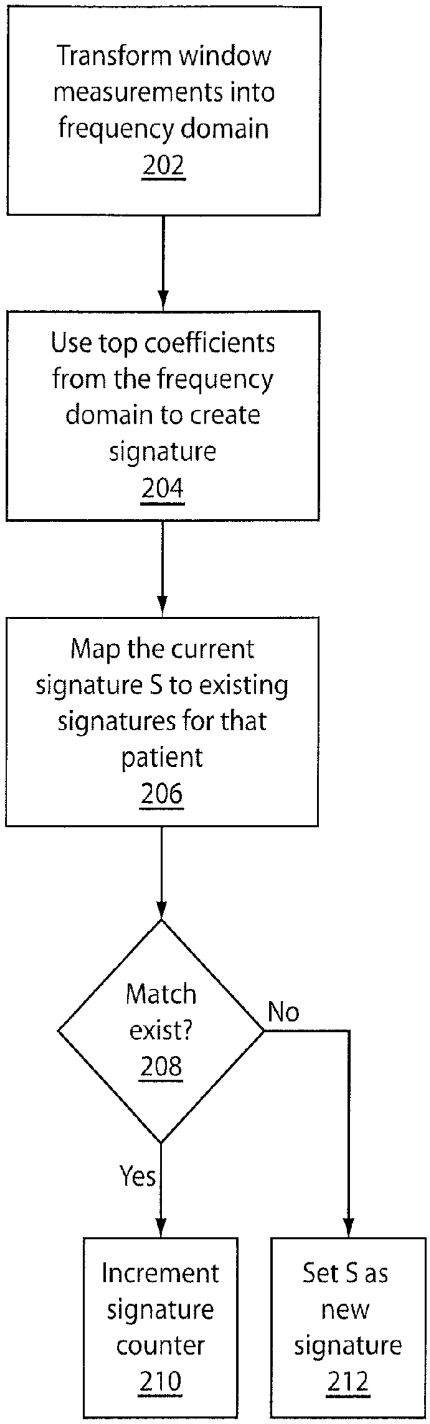

Transform window measurements into frequency domain 202
Use top coefficients from the frequency domain to create signature 204
Map the current signature S to existing signatures for that patient 206
Match exist? 208
No
Yes
Increment signature counter 210
Set S as new signature 212

FIG. 3

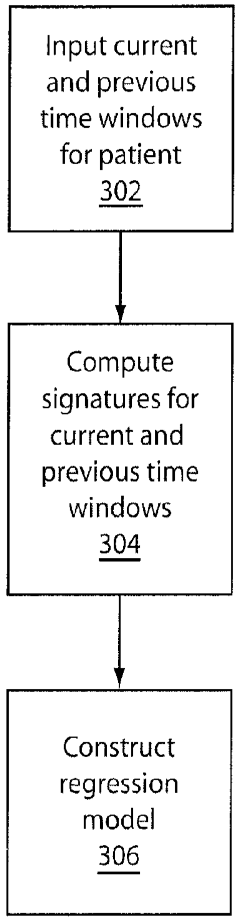

Input current and previous time windows for patient 302
Compute signatures for current and previous time windows 304
Construct regression model 306

FIG. 4

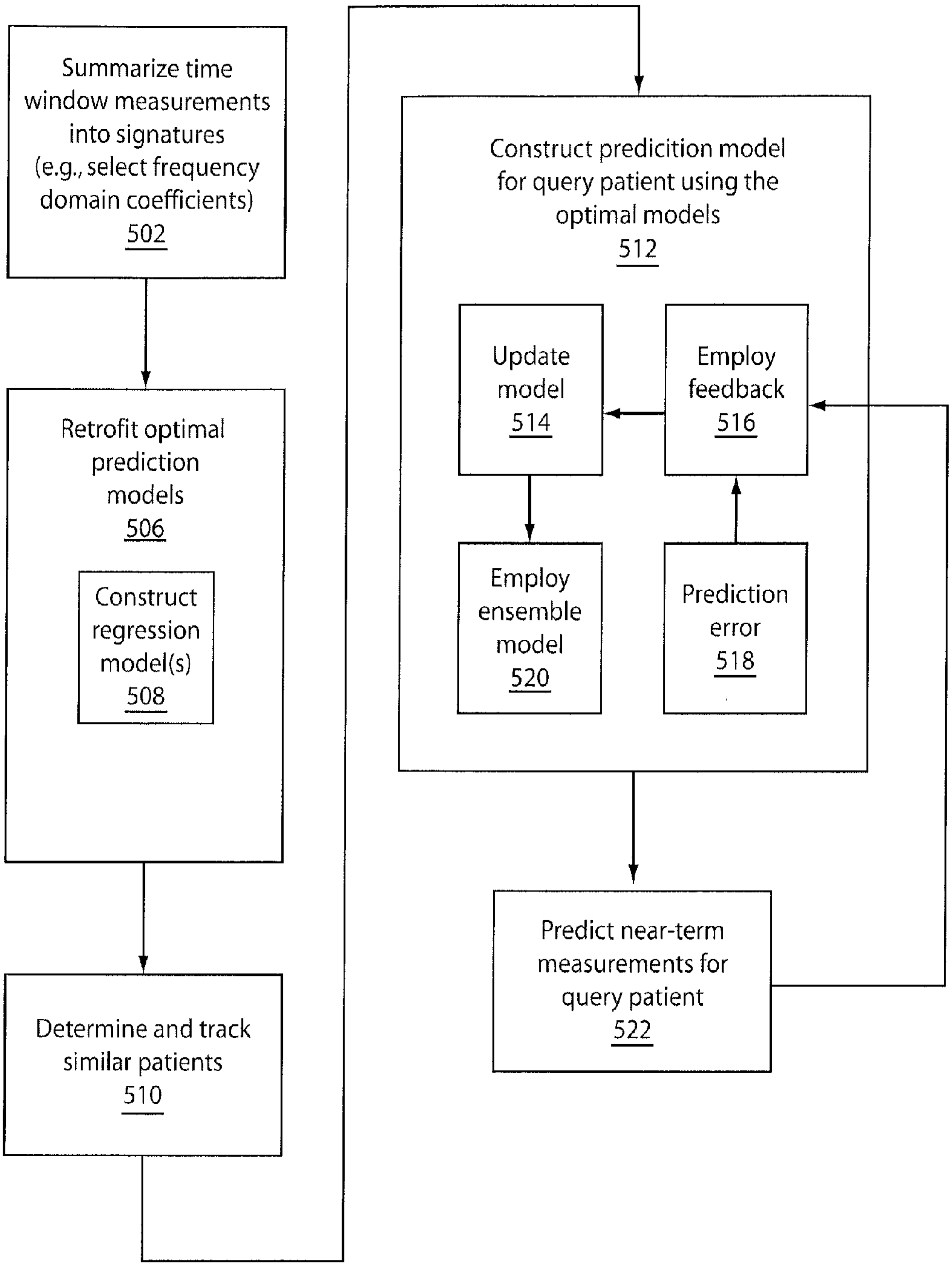

Summarize time window measurements into signatures (e.g., select frequency domain coefficients)
502
Retrofit optimal prediction models
506
Construct regression model(s)
508
Determine and track similar patients
510
Construct predicition model for query patient using the optimal models
512
Update model
514
Employ feedback
516
Employ ensemble model
520
Prediction error
518
Predict near-term measurements for query patient
522

FIG. 5

SYSTEM AND METHOD FOR PREDICTING NEAR-TERM PATIENT TRAJECTORIES

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is related to commonly assigned U.S. application Ser. No. [TBD], entitled "SYSTEM AND METHOD FOR PREDICTING LONG-TERM PATIENT OUTCOME", Attorney Docket Number YOR920100439US1(163-357), filed concurrently herewith, which is incorporated by reference herein in its entirety.

BACKGROUND

[0002] 1. Technical Field

[0003] The present invention relates to predicting of near term prognoses of patients and more particularly to systems and methods for near term prognosis using information about similar patients.

[0004] 2. Description of the Related Art

[0005] The task of prognosis is an important component of the process of clinical care. It is about predicting the future health status of the patient and the probable course of her health indicators. Oftentimes, clinicians are concerned about the near term potential trajectory of a number of Key Patient Indicators (KPIs) for a given patient such as echo cardiogram (ECG), blood pressure, heart rate, SpO_2. Accurately, predicting near term trajectories is needed to improve clinical effectiveness and efficiency. Usually, the prediction of trajectories of a patient is performed based on the data from that same patient, and predefined rules based on prior knowledge of clinicians and expert guidelines.

SUMMARY

[0006] A system and method for predicting near term measurements of a patient include a stream processor configured to summarize raw measurements from patients into signatures and construct optimal prediction models based on previously obtained signatures. A similar patient tracker is configured to monitor similar patient information for a query patient. The similar patient information is determined based on a similarity between the query patient and signatures of other patients. A model analyzer is configured to employ retrofitted optimal prediction models from similar patients to predict near term measurements of the query patient.

[0007] A method for predicting near term measurements of a patient includes summarizing time windows of patient measurements into signatures; retrofitting optimal prediction models based on historical measurements; tracking similar patients and signatures of the similar patients for a query patient; constructing a predictive model of the query patient using the optimal models from the similar patients; and predicting a near-term measurement for the query patient based on the predictive model.

[0008] These and other features and advantages will become apparent from the following detailed description of illustrative embodiments thereof, which is to be read in connection with the accompanying drawings.

BRIEF DESCRIPTION OF DRAWINGS

[0009] The disclosure will provide details in the following description of preferred embodiments with reference to the following figures wherein:

[0010] FIG. 1 is a block/flow diagram showing a system/method for retrieving patients with similarities for near term patient prognosis based on similar patients in accordance with one illustrative embodiment;

[0011] FIG. 2 is a block/flow diagram showing a system/method for near term patient prognosis in accordance with one illustrative embodiment;

[0012] FIG. 3 is a block/flow diagram showing a system/method for computing a patient signature in accordance with one illustrative embodiment;

[0013] FIG. 4 is a block/flow diagram showing a system/method for retrofitting models to form a prediction model in accordance with one illustrative embodiment; and

[0014] FIG. 5 is a block/flow diagram showing a system/method for near term patient prognosis based on similar patients in accordance with another illustrative embodiment.

DETAILED DESCRIPTION OF PREFERRED EMBODIMENTS

[0015] In accordance with the present principles, systems and methods for predicting near term prognosis of patients are provided. Current systems do not predict near term trajectories for a query patient using historical data or patterns from similar patients. Historical data from similar patients can help provide better estimate future events for the query patient, and can help determine different treatment options and their expected outcome. The method and infrastructure reliably and efficiently monitor and extract similar patient information in near real time.

[0016] In one embodiment, a compact summarization of longitudinal data streams of patient Key Patient Indicators (KPIs) is provided. An efficient similar patient matching method leverages compact summarization of patient KPIs, and a predictive model is updated and provides forecasts based on similar patients.

[0017] A stream processor summarizes the multiple longitudinal patient data streams into a small set of signature representations, and a similar patient tracker incrementally maintains the set of similar patients and reference timestamps. A predictive model leverages all the model parameters from similar patients to build a model for predicting the query patient.

[0018] Effective patient similarity assessment may be employed for clinical decision support. This similarity assessment enables the capture of past experience as manifested in the collective longitudinal medical records of patients and helps clinicians assess the likely outcomes resulting from their decisions and actions. A patient similarity metric is one that is clinically relevant and semantically sound. Patient similarity is highly context sensitive: it depends on factors such as the disease, the particular stage of the disease, and co-morbidities. One way to discern the semantics in a particular context is to take advantage of physicians' expert knowledge as reflected in labels assigned to some patients. A method that leverages localized supervised metric learning to effectively incorporate such expert knowledge to arrive at semantically sound patient similarity measures is disclosed.

[0019] Medical records capture both observations of patients' health status, and decisions and actions taken by clinicians and care providers. Buried inside these records are insights on temporal evolution patterns of patient health status, and the effects of different clinical decisions on the trajectory of a disease. Tapping into this source of insight can be achieved by developing techniques measuring cross patient similarities. These techniques can improve patients' clinical outcomes as tools for diagnostic and prognostic decision support.

[0020] As will be appreciated by one skilled in the art, aspects of the present invention may be embodied as a system, method or computer program product. Accordingly, aspects of the present invention may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "circuit," "module" or "system." Furthermore, aspects of the present invention may take the form of a computer program product embodied in one or more computer readable medium(s) having computer readable program code embodied thereon.

[0021] Any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium. A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any suitable combination of the foregoing. More specific examples (a non-exhaustive list) of the computer readable storage medium would include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain, or store a program for use by or in connection with an instruction execution system, apparatus, or device.

[0022] A computer readable signal medium may include a propagated data signal with computer readable program code embodied therein, for example, in baseband or as part of a carrier wave. Such a propagated signal may take any of a variety of forms, including, but not limited to, electro-magnetic, optical, or any suitable combination thereof. A computer readable signal medium may be any computer readable medium that is not a computer readable storage medium and that can communicate, propagate, or transport a program for use by or in connection with an instruction execution system, apparatus, or device.

[0023] Program code embodied on a computer readable medium may be transmitted using any appropriate medium, including but not limited to wireless, wireline, optical fiber cable, RF, etc., or any suitable combination of the foregoing. Computer program code for carrying out operations for aspects of the present invention may be written in any combination of one or more programming languages, including an object oriented programming language such as Java, Smalltalk, C++ or the like and conventional procedural programming languages, such as the "C" programming language or similar programming languages. The program code may execute entirely on the user's computer, partly on the user's computer, as a stand-alone software package, partly on the user's computer and partly on a remote computer or entirely on the remote computer or server. In the latter scenario, the remote computer may be connected to the user's computer through any type of network, including a local area network (LAN) or a wide area network (WAN), or the connection may be made to an external computer (for example, through the Internet using an Internet Service Provider).

[0024] Aspects of the present invention are described below with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems) and computer program products according to embodiments of the invention. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine, such that the instructions, which execute via the processor of the computer or other programmable data processing apparatus, create means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

[0025] These computer program instructions may also be stored in a computer readable medium that can direct a computer, other programmable data processing apparatus, or other devices to function in a particular manner, such that the instructions stored in the computer readable medium produce an article of manufacture including instructions which implement the function/act specified in the flowchart and/or block diagram block or blocks. The computer program instructions may also be loaded onto a computer, other programmable data processing apparatus, or other devices to cause a series of operational steps to be performed on the computer, other programmable apparatus or other devices to produce a computer implemented process such that the instructions which execute on the computer or other programmable apparatus provide processes for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

[0026] The flowchart and block diagrams in the Figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods and computer program products according to various embodiments of the present invention. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function (s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

[0027] Referring now to the drawings in which like numerals represent the same or similar elements and initially to FIG. **1**, a diagram illustratively shows a system **10** where a patient **14** with available observations **13** comes to a decision point **15**. Patients **12** who are clinically similar to a query patient **14** are retrieved. The system **10** is provided with decisions and actions **16** for a plurality of similar patients (patient **1**, patient **2**, etc.) and their consequences and decides on a best course of action for the current patient **14**. In addition, the system **10** can project a trajectory **18** of patient's health status, as captured by the patient's clinical factors and biomarkers, under the regime of any particular decision made.

[0028] The system **10** provides an alignment of the trajectories of patients' temporal characteristics to make the records amenable to semantically and clinically sound comparison. The system **10** devises similarity measures **20** that can reflect the clinical proximity or disparity between different patients. The system **10** couples decisions and their consequences using patient prognosis support **22**.

[0029] Different methods for feature generation over multi-dimensional temporal patient data may be employed. In one embodiment, a localized supervised metric learning approach can be adopted to arrive at a semantically sound similarity measure for retrieving patients represented in the multi-dimensional feature space.

[0030] Referring to FIG. **2**, a system **100** provides for predictions of near term prognosis of patients. System **100** may include on a single processing device such as a computer, a personal digital assistant or other computing device, or may include a plurality of distributed computers in a network environment or the like. Patient data streams **102** are input to the system **100**. The input data streams **102** provide patient vital signs, such as, e.g., Key Patient Indicators (KPIs) or other relevant patient information. A stream processor **104** performs a compact summarization of longitudinal data streams of the patient KPIs. The stream processor **104** summarizes the multiple longitudinal patient data streams into a small set of signature representations stored in a patient signature database **110**. The signatures may include a multidimensional vector that includes relevant information for that patient for a particular time window. For example, features may include heart rate, blood oxygen, temperature, etc.

[0031] A similar patient tracker **106** performs an efficient similar patient matching method that leverages the compact summarization of patient KPIs. The similar patient tracker **106** incrementally maintains the set of similar patients and a reference timestamp.

[0032] Updates and forecasting based on similar patients is performed using a model analyzer **108**. A predictive model **114** leverages all the model parameters from similar patients stored in optimal model storage **112** to build the model for predicting a query patient. Models may take many forms, but may be constructed using the relevant medical factors in the particular instance, e.g., for that disease, for that treatment program, etc.

[0033] The stream processor **104**, in real-time, summarizes raw input streams **102** such as ECG, blood pressure, SpO2 measures to extract representative signatures and store them in storage **110**. Stream processor **104** retrospectively constructs/updates the optimal predictive model **114** to predict the current measurements based on historical measurements. The similar patient tracker **106** updates the top similar patients (e.g., k patients) to each patient x based on the recent measurements from x. The similar patient tracker **106** constructs current signature based current measurements, and then searches the database **110** of existing patient signatures to find matching signatures of those existing patients. For each patient x, the similar patient tracker **106** can choose to maintain either a single set of similar patients to x, or different sets of similar patients for each type of measurement. For example, system **100** tracks two types of measurements ECG and SpO2. For patient x, the similar patient tracker **106** can choose to maintain either an overall set of similar patients to x, or two sets of similar patients, one set based on ECG and one set based on SpO2.

[0034] The prediction model **114** may be refreshed periodically or may be refreshed in accordance with data characteristics. For example, as the SpO_2 reading changes, the model may be updated. The model analyzer **108** finds the optimal models **112** of the top "k" similar patients to each patient x, and then constructs a forecasting model or prediction model **114** based on the optimal models **112** and predicts the future measurement of x. A prediction error will be fed back to the similar patient tracker **106** to determine/update the top-k similar patients for x.

[0035] The patient signature database **110** includes patient signatures. A patient signature is a low-dimensional representation of the patient condition in a certain time window. Each patient can have multiple signatures based on the variation of his/her characteristics. Signature construction includes a time series of measurements as input, and a small set of signatures (low dimensional signatures) are output.

[0036] Referring to FIG. **3**, an illustrative method is described for generating a new patient signature in accordance with an exemplary embodiment. In block **202**, for each time window, W, over a time series, transform W into the frequency domain, e.g., using Fast Fourier Transformation (FFT) or Wavelets. In block **204**, use the top coefficients from the frequency domain as a current signature S. In block **206**, map S to existing signatures of this patient. In block **208**, determine if a match exits. In particular, we mark two signatures matched if the Euclidean distance of two signature vectors is small (e.g., within a threshold). In block **210**, if a match exists, then increment a counter of that signature by 1. Otherwise, in block **212**, insert S as a new signature.

[0037] A signature search is one method for tracking and finding similar patients. Since each signature may include a low-dimensional vector, a tree structure may be employed to index all the signatures to speed up any search.

[0038] Referring to FIG. **4**, the models are retrofitted to provide optimal models **112**. The optimal model retrofitting includes inputting for each patient x, a current time window W_t and previous time windows W_{t-1} in block **302**. In block **304**, signatures S_t and S_{t-1} are computed for current and previous windows for each patient x. In block **306**, a regression model of $S_t=f(S_{t-1})$ with parameter vector b, is constructed. Note that b_x is the model parameters of the regression model. The regression model may include any statistical function. In particular, the regression model may be employed in the prediction model for similar patients.

[0039] Referring to again to FIG. **2**, the prediction model **114** uses models from similar patients. The prediction model **114** receives as input, information on the query patient x and a previous time window W_{t-1} for query patient x. In block **110**, signatures for the query patient are computed. The similar patient tracker **106** employs the signatures to extract similar patients and their retrofitting model parameters (from optimal models **112**). An ensemble model or prediction model **114** is constructed from the retrofitted models of similar patients. For example, weighted averages may be computed for all the retrofitting models, where the weight of each patient may be proportional to a similarity score. The prediction model **114** is employed to predict near-term outcomes for the query patient based upon similar patients.

[0040] Patient similarity measures may be determined in a plurality of ways. In one particularly useful embodiment, similarity measures may be determined using localized supervised metric learning (LSML) to provide a patient similarity measure. When a physician looks for similar patients in a database, the similarity is often based not only on quantitative measurements such as lab results, sensor measurements, age and sex, but also on the physician's assessment of the disease type and stage. The assessment would potentially influence the relative importance a physician places on different measurements or groups of measurements. To compute this specific notion of similarity, a distance metric is needed that can automatically adjust the importance of each numeric feature by leveraging the physician's belief.

[0041] Formally, quantitative measurements of a patient are represented by an N-dimensional feature vector x. Examples of features are the mean and variance of the sensor measures, or Wavelet coefficients. The prior belief of physicians is captured as labels on some of the patients. With this formulation, one goal is to learn a generalized Mahalanobis distance between patient x_i and patient x_j defined as:

$$d_m(x_i,x_j)=\sqrt{(x_i-x_j)^T P(x_i-x_j)} \tag{1}$$

where $P \in \mathfrak{R}^{N\times N}$ is called the precision matrix. Matrix P is positive semi-definite and is used to incorporate the correlations between different feature dimensions. One aspect is to learn the optimal P such that the resulting distance metric has the following properties: 1) Within-class compactness: patients of the same label are close together; and 2) Between-class scatterness: patients of different labels are far away from each other. To formally measure these properties, we use two kinds of neighborhoods: 1) The homogeneous neighborhood of x_i, denoted as $\mathcal{N}_i^o$, is the k-nearest patients of x_i with the same label. 2) The heterogeneous neighborhood of x_i, denoted as $\mathcal{N}_i^e$, is the k-nearest patients of x_i with different labels.

[0042] Based on these two neighborhoods, we define the local compactness of point x_i as

$$C_i = \sum_{x_j \in N_i^o} d_m^2(x_i, x_j) \tag{2}$$

and the local scatterness of point x_i as

$$S_i = \sum_{x_k \in N_i^e} d_m^2(x_i, x_k) \tag{3}$$

The discriminability of the distance metric d_m is defined as

$$\mathcal{J} = \frac{\sum_i C_i}{\sum_i S_i} = \frac{\sum_i \sum_{x_j \in N_i^o} (x_i - x_j)^T P(x_i - x_j)}{\sum_i \sum_{x_k \in N_i^e} (x_i - x_k)^T P(x_i - x_k)} \tag{4}$$

The goal is to find a P that minimizes $\mathcal{J}$, which is equivalent to minimizing the local compactness and maximizing the local scatterness simultaneously. In contrast with linear discriminant analysis, which seeks a discriminant subspace in a global sense, the localized supervised metric aims to learn a distance metric with enhanced local discriminability. To minimize $\mathcal{J}$, we formulate the problem as a trace ratio minimization problem and use the decomposed Newton's method to find the solution.

[0043] Since P is a low-rank positive semi-definite matrix, we can decompose the precision matrix as $P=WW^T$, where $W \in \mathfrak{R}^{N\times d}$ and $d \leqq N$. The distance metric can be rewritten as $d_m(x_i,x)=\|W^Tx_i-W^Tx_j\|$. Therefore, the distance metric is equivalent to Euclidean distance over the low-dimensional projection W^Tx.

[0044] Data Description and Feature Extraction: We have used the physiological data for 74 patients obtained from the MMIC II database in our experiments. Each patient is represented with 5 streams of sensor readings, sampled at 1 minute intervals: 1) Sp02, 2) heart rate (HR), 3) mean ABP (ABP-mean), (4) systolic ABP (ABPSys), and diastolic ABP (ABP-Dias). All patients belong to one of two groups H or C. Those in group H (36 patients) had experienced Arterial Hypotensive Episode (AHE) events during the forecast window, whereas those in group C (38 patients) did not experience any AHE within the forecast window. The start of the forecast window is timestamped in the data set (T_0) and its duration is 1 hour, in which an episode of AHE can occur. For this study, we focus on a 2-hour window around T_0 for each patient. The data samples from two patients in H group show higher variability than those in C group. Physicians actually use the variability level of ABP to diagnose AHE.

[0045] We have used two different schemes to represent the 2-hour temporal data for each patient: a statistical time domain method and a wavelet domain method. In the former, we compute the mean and variance of data from each sensor for each patient. Thus, each patient is represented in the time domain with a 10-dimensional vector. In the latter, the wavelet coefficients of the 2-hour window from each sensor are computed. We use Daubechies-4 Wavelet and keep the top-10 coefficients. Finally, the coefficients from all 5 sensors are vectorized into a 50-dimensional feature vector for each patient.

[0046] From the feature extraction step described, we obtain 74 N-dimensional feature vectors where N=10 for the statistic method and N=50 for the Wavelet method. We then compare the following three distance metrics using the leave-one-out paradigm:

A) Expert uses Euclidean distance of the variance of the mean ABP; B) PCA uses Euclidean distance over low-dimensional points after PCA (an unsupervised metric learning algorithm); and C) LSML using the localized supervised metric learning method.

[0047] The performance metrics include k-NN classification error rate and precision@10 retrieval results. The precision@10 of a query point is computed by retrieving 10-nearest points with a specific distance metric and then computing the percentage of those retrieved points having the same label as the query point.

[0048] To have a fair comparison, both PCA and LSML project data into 1-dimensional space since the Expert method only uses one feature, i.e., the variance of mean ABP. Table 1 shows the classification results using 3-NN classifier, and Table 2 shows the retrieval results. As can be observed in both tables, LSML out-performs both expert and PCA on both statistical and Wavelet features, which confirms the importance of leveraging label information into the distance metric. We also observe that Wavelet features improve the performance significantly for LSML, where the classification error drops by half (from about 15% to less than 7%).

TABLE 1

Classification error comparison			
	Expert	PCA	LSML
Statistic features	0.2295	0.2131	0.1475
Wavelet features	NA	0.2295	0.0656

TABLE 2

Precision@10 retrieval results			
	Expert	PCA	LSML
Statistic features	0.6120	0.5355	0.6557
Wavelet features	NA	0.5410	0.7869

[0049] A method for deriving semantically sound similarity measures for retrieving patients represented by multidimensional time series has been described. The present methods use both statistical and wavelet based features to capture the characteristics of patients, and leverage localized supervised metric learning to incorporate physicians' expert domain knowledge.

[0050] Referring to FIG. **5**, a system/method for predicting near term measurements of a patient is illustratively shown in accordance with one exemplary embodiment. In block **502**, time windows of patient measurements are summarized into signatures. This may be performed by converting raw data into the frequency domain (e.g., FFT, Wavelets, etc.) and selecting predetermined coefficients to comprise the signature. The frequency domain coefficients may represent time windows of a time series of measurements representing health status for a given patient. The time series of measurements may include one or more of heart rate, blood pressure, blood oxygen, electrocardiogram information, temperature, etc. The raw measurements are preferably summarized in real-time or near real-time (e.g., at the same time or within minutes or hours).

[0051] In block **506**, optimal prediction models are retrofitted based on historical measurements. That is that we learn a regression model using historical data as input and current data as output, and update the model as more recent data becomes available. The retrofitting of optimal prediction models may include constructing a regression model using patient signatures to construct the optimal prediction models in block **508**.

[0052] In block **510**, similar patients and the signatures of the similar patients are determined and tracked for a query patient. The similar patients are determined by comparing signatures and computing a similarity score between a query patient and other patients. The other patients may include historical data or may include patients being monitored contemporaneously with the query patient. In block **512**, a predictive model of the query patient is constructed using the optimal models from the similar patients. The predictive model can be updated by determining which of the optimal prediction models need to employed to predict near term measurements of the query patient based upon current conditions of the query patient in block **514**. In block **516**, feedback of a set of top similar patients is provided to enable updates to the optimal prediction models. In block **518**, the feedback may include prediction error for updating the optimal prediction models.

[0053] The predictive model may be constructed by employing an ensemble model from the retrofitted optimal prediction models. The ensemble model may include weighted averages of all the retrofitted optimal prediction models where weights are proportional to a similarity between the query patient signature and the other patient signatures in block **520**. In block **522**, a near-term measurement for the query patient is predicted based on the predictive model. The prediction may be output as part of a patient report or provided wherever a physician, nurse or technician would find them useful. In one embodiment, models can be tested over time using the wealth of collected data.

[0054] Having described preferred embodiments of a system and method (which are intended to be illustrative and not limiting), it is noted that modifications and variations can be made by persons skilled in the art in light of the above teachings. It is therefore to be understood that changes may be made in the particular embodiments disclosed which are within the scope of the invention as outlined by the appended claims. Having thus described aspects of the invention, with the details and particularity required by the patent laws, what is claimed and desired protected by Letters Patent is set forth in the appended claims.

What is claimed is:

1. A system to predict near term measurements of a patient, comprising:

a stream processor configured to summarize raw measurements from patients into signatures and construct optimal prediction models using previously obtained signatures;

a similar patient tracker configured to monitor similar patient information relative to a query patient, the similar patient information being determined based on a similarity between the query patient and the signatures of other patients; and

a model analyzer configured to employ retrofitted optimal prediction models from similar patients to predict near term measurements of the query patient.

2. The system as recited in claim **1**, wherein the stream processor summarizes raw measurements in real-time or near real-time.

3. The system as recited in claim **1**, wherein the signatures include frequency domain coefficients which represent time windows of a time series of measurements representing health status for a given patient.

4. The system as recited in claim **3**, wherein the time series of measurements includes one or more of heart rate, blood pressure, blood oxygen, electrocardiogram information and temperature.

5. The system as recited in claim **1**, wherein the similar patient tracker updates which optimal prediction models that are employed to predict near term measurements of the query patient based upon current conditions of the query patient.

6. The system as recited in claim **5**, wherein the model analyzer determines a set of top similar patients and feeds back this information to enable the similar patient tracker to update the optimal prediction models.

7. The system as recited in claim **6**, wherein the model analyzer employs prediction error as feedback for updating the optimal prediction models.

8. The system as recited in claim **1**, wherein the stream processor constructs a regression model using patient signatures to construct the optimal prediction models.

9. The system as recited in claim **1**, wherein the model analyzer employs an ensemble model from the retrofitted optimal prediction models to create the prediction model.

10. The system as recited in claim **1**, wherein the ensemble model includes weighted averages of all the retrofitted optimal prediction models where weights are proportional to a similarity between the query patient signature and the other patient signatures.

11. A method for predicting near term measurements of a patient, comprising:

summarizing time windows of patient measurements into signatures;

retrofitting optimal prediction models based on historical measurements;

tracking similar patients and signatures of the similar patients for a query patient;

constructing a predictive model of the query patient using the optimal models from the similar patients; and

predicting a near-term measurement for the query patient based on the predictive model.

12. The method as recited in claim **11**, wherein summarizing time windows includes summarizing raw measurements in real-time or near real-time.

13. The method as recited in claim **11**, wherein the signatures include frequency domain coefficients which represent the time windows of a time series of measurements representing health status for a given patient.

14. The method as recited in claim **13**, wherein the time series of measurements includes one or more of heart rate, blood pressure, blood oxygen, electrocardiogram information and temperature.

15. The method as recited in claim **11**, wherein constructing includes updating which of the optimal prediction models are employed to predict near term measurements of the query patient based upon current conditions of the query patient.

16. The method as recited in claim **15**, further comprising providing feedback of a set of top similar patients to enable updates to the optimal prediction models.

17. The method as recited in claim **16**, wherein the feedback includes prediction error for updating the optimal prediction models.

18. The method as recited in claim **11**, wherein retrofitting optimal prediction models includes constructing a regression model using patient signatures to construct the optimal prediction models.

19. The method as recited in claim **11**, wherein constructing a predictive model includes employing an ensemble model from the retrofitted optimal prediction models to create the prediction model.

20. The method as recited in claim **19**, wherein the ensemble model includes weighted averages of all the retrofitted optimal prediction models where weights are proportional to a similarity between the query patient signature and the other patient signatures.

21. A computer readable storage medium comprising a computer readable program for predicting near term measurements of a patient, wherein the computer readable program when executed on a computer causes the computer to perform the steps of:

summarizing time windows of patient measurements into signatures;

retrofitting optimal prediction models based on historical measurements;

tracking similar patients and signatures of the similar patients for a query patient;

constructing a predictive model of the query patient using the optimal models from the similar patients; and

predicting a near-term measurement for the query patient based on the predictive model.

22. The computer readable storage as recited in claim **21**, wherein summarizing time windows includes summarizing raw measurements in real-time or near real-time,

23. The computer readable storage as recited in claim **21**, wherein the signatures include frequency domain coefficients which represent the time windows of a time series of measurements representing health status for a given patient.

24. The computer readable storage as recited in claim **23**, wherein the time series of measurements includes one or more of heart rate, blood pressure, blood oxygen, electrocardiogram information and temperature.

25. The computer readable storage as recited in claim **21**, wherein constructing a predictive model includes employing an ensemble model from the retrofitted optimal prediction models to create the prediction model, wherein the ensemble model includes weighted averages of all the retrofitted optimal prediction models where weights are proportional to a similarity between the query patient signature and the other patient signatures.

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专利名称(译)	用于预测近期患者轨迹的系统和方法		
公开(公告)号	US20120041277A1	公开(公告)日	2012-02-16
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申请(专利权)人(译)	国际商业机器公司		
当前申请(专利权)人(译)	国际商业机器公司		
[标]发明人	EBADOLLAHI SHAHRAM HU JIANYING SORRENTINO ROBERT K SOW DABY M SUN JIMENG		
发明人	EBADOLLAHI, SHAHRAM HU, JIANYING SORRENTINO, ROBERT K. SOW, DABY M. SUN, JIMENG		
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外部链接	Espacenet USPTO		

摘要(译)

用于预测患者的近期测量的系统和方法包括流处理器，其被配置为将来自患者的原始测量值汇总成签名并基于先前获得的签名构建最佳预测模型。类似的患者跟踪器被配置为监视查询患者的类似患者信息。基于查询患者与其他患者的签名之间的相似性来确定类似的患者信息。模型分析器被配置为采用来自类似患者的改进的最佳预测模型来预测查询患者的近期测量。