US 20180206797A1

(54) **METHODS AND SYSTEMS FOR PATIENT MONITORING**

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(57) **ABSTRACT**

Systems and methods are provided for false alarm suppression in patient monitoring systems. In one embodiment, a method comprises inputting each electronic signal of a plurality of electronic signals into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network, and responsive to an alarm generated based on at least one of the plurality of electronic signals, suppressing the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false. In this way, patient monitors may be more reliable with fewer false alarms.
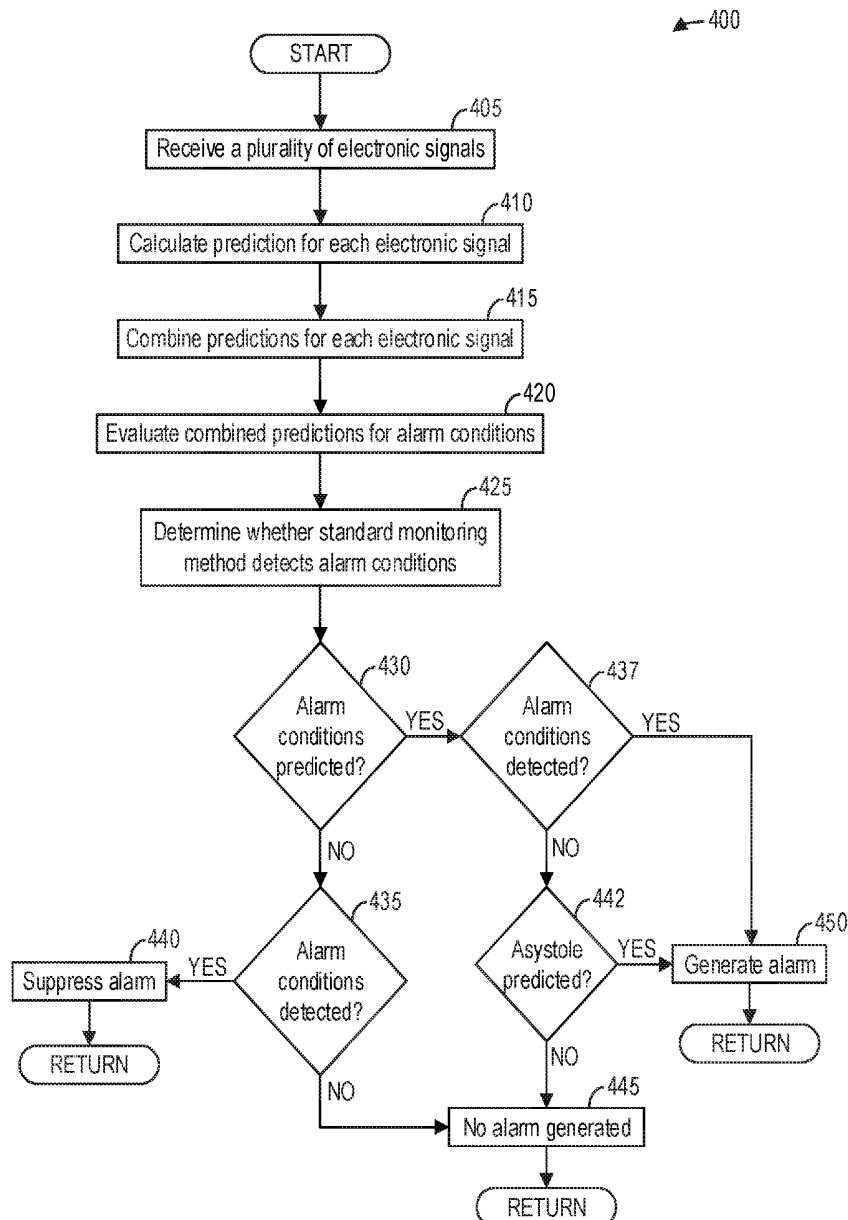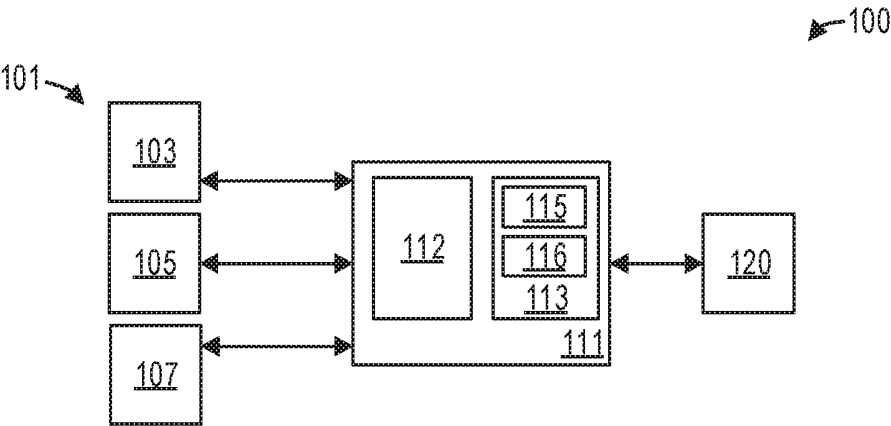
FIG. 1
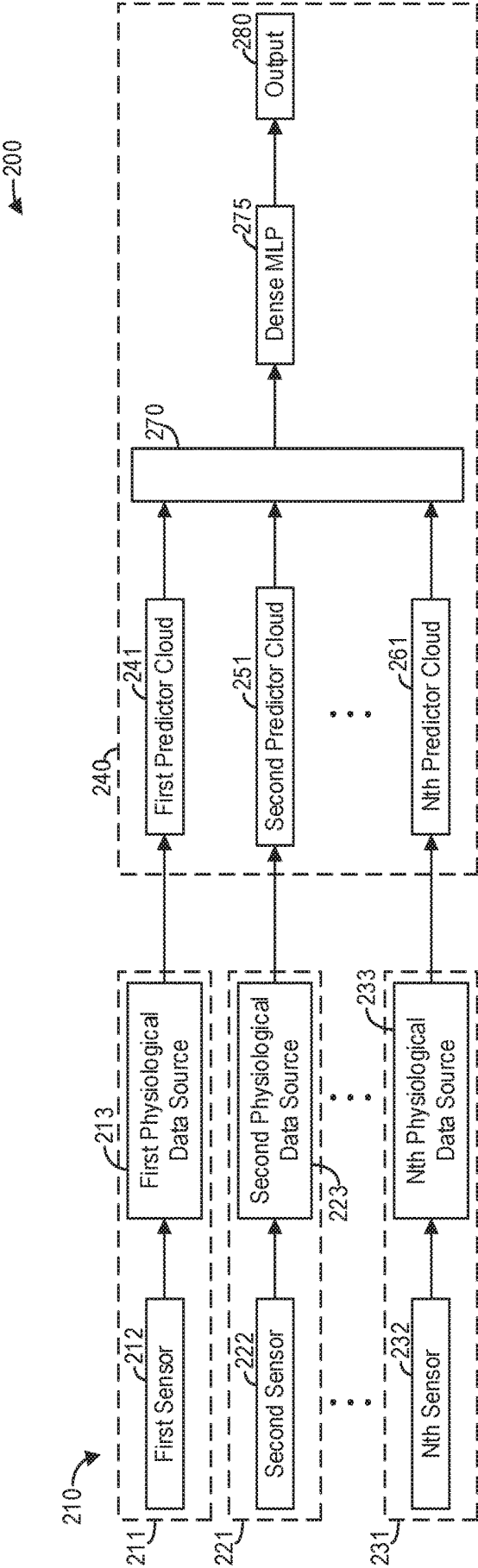
FIG. 2
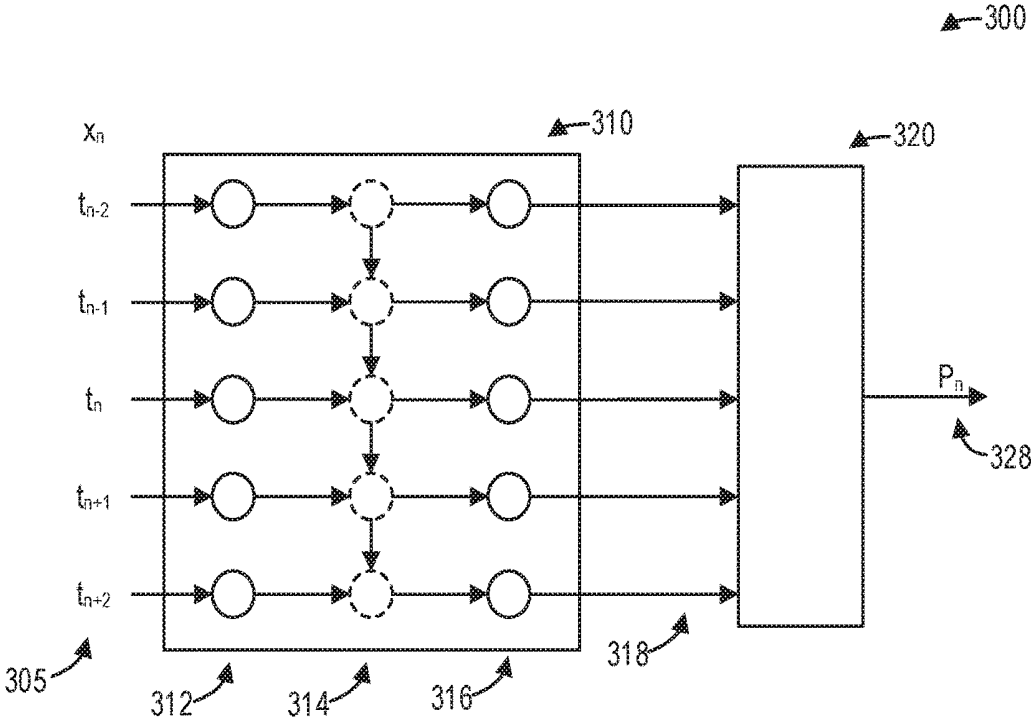
FIG. 3
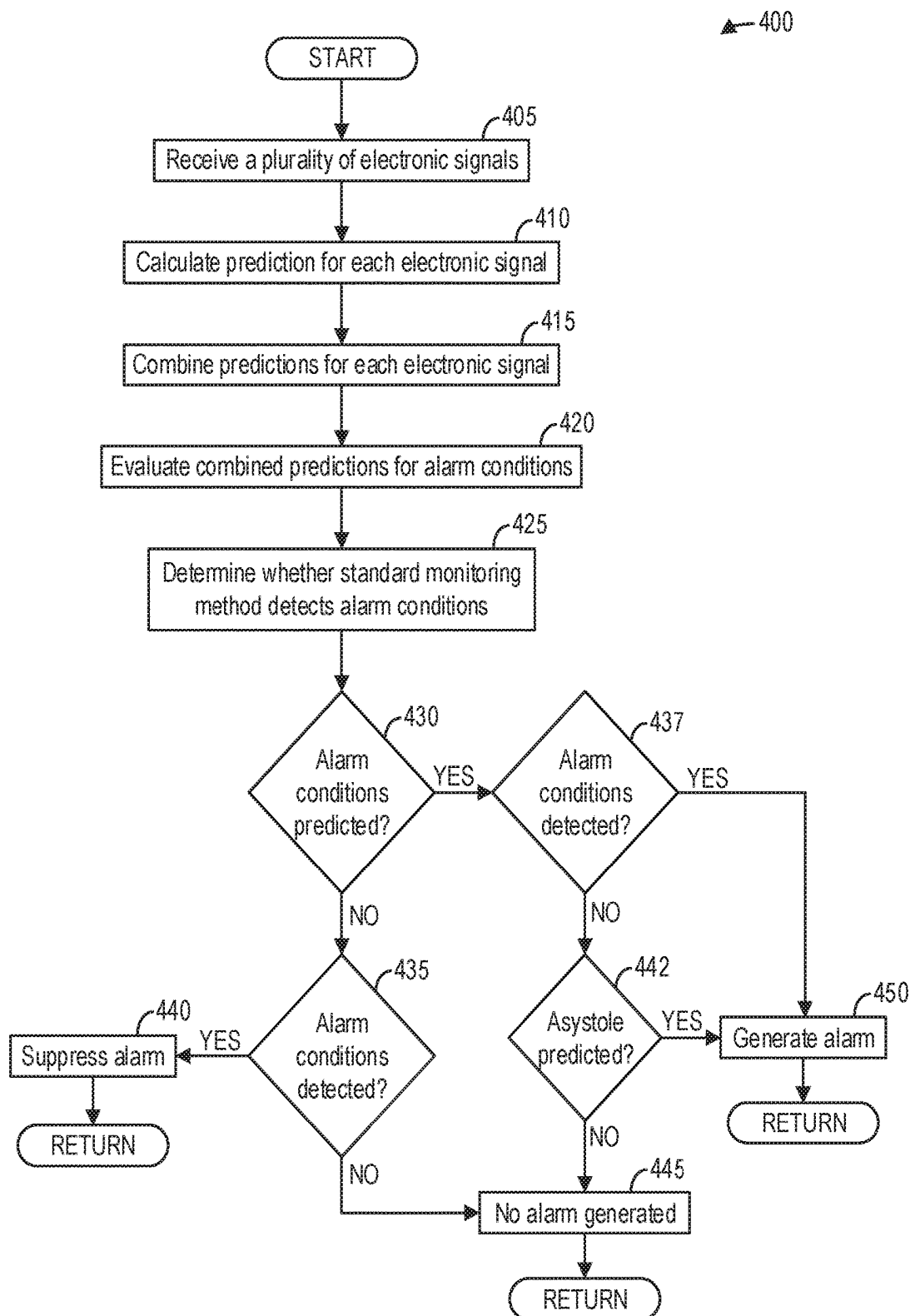
FIG. 4

METHODS AND SYSTEMS FOR PATIENT MONITORING

FIELD

[0001] Embodiments of the subject matter disclosed herein relate to patient monitoring, and more particularly, to false alarm suppression in patient monitoring systems.

BACKGROUND

[0002] Patient monitors routinely process signals acquired from patients and provide a caregiver or clinician with computed estimates of features contained within those signals. In the case of ECG (electrocardiogram) signals, those features include heart rate and arrhythmias (i.e., disturbances in the normal cardiac rhythm).

[0003] One function of a patient monitor is to provide alarm mechanisms to alert the user when the patient's heart rate is outside of prescribed limits, or when arrhythmias occur. However, the presence of noise in the acquired ECG signal, due to a multiplicity of causes, results in a significant false positive alarm rate for these alarm conditions. Such false alarm rates decrease clinician productivity and satisfaction, and decrease the effectiveness of clinical alarm mechanisms.

BRIEF DESCRIPTION

[0004] In one embodiment, a method comprises inputting each electronic signal of a plurality of electronic signals into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network, and responsive to an alarm generated based on at least one of the plurality of electronic signals, suppressing the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false. In this way, patient monitors may be more reliable with fewer false alarms.

[0005] It should be understood that the brief description above is provided to introduce in simplified form a selection of concepts that are further described in the detailed description. It is not meant to identify key or essential features of the claimed subject matter, the scope of which is defined uniquely by the claims that follow the detailed description. Furthermore, the claimed subject matter is not limited to implementations that solve any disadvantages noted above or in any part of this disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

[0006] The present invention will be better understood from reading the following description of non-limiting embodiments, with reference to the attached drawings, wherein below:

[0007] FIG. 1 shows a block diagram illustrating an example patient monitoring system;

[0008] FIG. 2 shows a block diagram illustrating an example system for suppressing false alarms according to an embodiment;

[0009] FIG. 3 shows a block diagram illustrating an example predictor cloud for analyzing an electronic signal from a patient monitoring device according to an embodiment; and

[0010] FIG. 4 shows a high-level flow chart illustrating an example method for suppressing false alarms according to an embodiment.

DETAILED DESCRIPTION

[0011] The following description relates to various embodiments of patient monitors. In particular, systems and methods are provided for false alarm suppression in patient monitoring systems. A patient monitoring system, such as the system depicted in FIGS. 1 and 2, may monitor various physiological traits of a patient in a health care facility such as, for example, an intensive care unit (ICU). A plurality of predictor clouds, such as the predictor cloud depicted in FIG. 3, are configured to predict the expected value of each monitored physiological trait. Since a low signal quality or environmental interference may degrade the confidence of an alarm generated based on one or more of the monitored physiological traits, the use of deep learning techniques to predict what the monitored traits should be enables the suppression of false alarms caused by said signal quality or interference. A method for utilizing the false alarm suppression system in conjunction with a standard alarm method is depicted in FIG. 4.

[0012] FIG. 1 shows a block diagram illustrating an example patient monitoring system 100 for use in health care facilities. System 100 may comprise at least part of a patient monitor for monitoring one or more physiological traits (e.g., heart rate, respiratory rate, blood sugar levels, blood cell count, etc.) of a patient (not shown).

[0013] To that end, patient monitoring system 100 includes a plurality of patient monitoring devices 101, including a first monitoring device 103, a second monitoring device 105, and a third monitoring device 107. Each monitoring device of the plurality of patient monitoring devices 101 may be configured to monitor a different physiological trait of the patient. The patient monitoring devices may include, but are not limited to, an invasive and/or non-invasive blood pressure monitoring device, a pulse-oximetry monitoring device, a temperature monitoring device, a carbon dioxide monitoring device, a respiration monitoring device, a cardiac output monitoring device, and so on.

[0014] Patient monitoring system 100 further includes a computing device 111 communicatively coupled to each of the plurality of patient monitoring devices 101. The plurality of patient monitoring devices 101 provide measurements of physiological characteristics of a patient to a computing device 111.

[0015] Computing device 111 includes a processor 112 and non-transitory memory or storage device 113. The various methods and processes described further herein may be stored as executable instructions in the non-transitory memory 113 of the computing device 111 in system 100. For example, a standard monitoring module 115 and a predictor cloud monitoring module 116 may be stored as executable instructions in the non-transitory memory 113 that when executed cause the processor 112 to carry out specific methods and processes as described further herein.

[0016] Computing device 111 is also communicatively coupled to a display device 120. Display device 120 may be configured to display an alarm, in some examples, generated by the computing device 111.

[0017] The number of monitoring devices depicted is exemplary and non-limiting, as it should be appreciated that in some examples the plurality of patient monitoring devices 101 may include a number of monitoring devices greater than three or fewer than three.

[0018] FIG. 2 shows a block diagram illustrating an example system 200 for suppressing false alarms according

to an embodiment. System **200** includes a plurality of patient monitoring devices **210**, specifically N patient monitoring devices, where N is an integer greater than or equal to one. Each patient monitoring device of the plurality of patient monitoring devices **210** includes a sensor and a physiological data source. Specifically, first patient monitoring device **211** includes a first sensor **212** and a first physiological data source **213**; second patient monitoring device **221** includes a second sensor **222** and a second physiological data source **223**; the Nth patient monitoring device **231** includes an Nth sensor **232** and an Nth physiological data source **233**, and so on.

[0019] The sensors are placed on or in the vicinity of a patient to be monitored and are configured to read different physiological characteristics of the patient. For example, first sensor **212** may measure the patient's electrocardiogram (ECG), the second sensor **222** may measure the patient's invasive arterial blood pressure (IBP), the Nth sensor **232** may measure the patient's pulse oximetry (SpO_2), and so on. Alternatively, the sensors **212**, **222**, and **232** can monitor other physiological characteristics of a patient. In one embodiment, the same physiological trait (e.g., heart rate) can be determined based on sensing different physiological characteristics (ECG, IBP, SpO_2) of the patient, making at least some of the data from the sensors redundant.

[0020] The physiological data sources **213**, **223**, and **233** include software algorithms operable on a computer processing circuit or device (e.g., a microprocessor, a microcontroller, an application-specific integrated circuit (ASIC), etc.) including sufficient memory and interface circuitry to interface with the sensors **212**, **222**, and **232**. Physiological data sources **213**, **223**, and **233** preferably include algorithms which are operable independent of each other to arrive at one or more physiological data based on signals from respective sensors. The physiological data provided by each of physiological data sources **213**, **223**, and **233** may include raw data from sensors

[0021] **212**, **222**, and **232**, filtered data, statistical derivations of data from the sensors **212**, **222**, and **232**, binary flags indicating predetermined conditions are met, or other events or conditions based on signals from the sensors **212**, **222**, and **232**.

[0022] In some examples, the physiological data sources **213**, **223**, and **233** may be implemented as hardware and/or software in the corresponding patient monitoring device **211**, **221**, or **231** as depicted. However, in other examples, it should be appreciated that one or more of the physiological data source **213**, **223**, and **233** may be implemented away from the corresponding patient monitoring device **211**, **221**, or **231**. For example, one or more of the physiological data sources **213**, **223**, and **233** may be implemented in the computing device **240**.

[0023] Further, in some examples, one or more of the physiological data sources **213**, **223**, and **233** may be distributed across the corresponding patient monitoring device and the computing device **240** to perform some tasks separately in the patient monitoring device and the computing device. As an illustrative example, a first portion of the first physiological data source **213** may perform pre-processing and encoding in the patient monitoring device **211** while a second portion of the first physiological data source **213** may perform resource-intensive computations in the computing device **240**.

[0024] The physiological data sources may provide physiological data to the computing device **240** as depicted. Specifically, the computing device **240** may include a plurality of predictor clouds, including a first predictor cloud **241**, a second predictor cloud **251**, and so on, up to and including an Nth predictor cloud **261**. The computing device **240** may include a predictor cloud for each patient monitoring device. For example, first physiological data source **213** is configured to provide a first measurement of a first physiological trait based on a first physiological characteristic to a first predictor cloud **241**. Similarly, second physiological data source **223** is configured to provide a second measurement of a second physiological trait based on a second physiological characteristic of the patient to a second predictor cloud **251**, while the Nth physiological data source **233** is configured to provide an Nth measurement of an Nth physiological trait based on an Nth physiological characteristic of the patient to a corresponding Nth predictor cloud **261**. As described further herein with regard to FIG. **3**, each predictor cloud **241**, **251**, and **261** may include multiple neural networks, specifically a long short-term memory (LSTM) neural network and a recurrent neural network (RNN) stacked in series for estimating or predicting the expected value of a physiological trait responsive to measurements input to the predictor cloud.

[0025] The estimates or predictions output by each predictor cloud **241**, **251**, and **261** are concatenated or otherwise merged into a combined prediction **270**. The combined prediction **270** is then input to a dense multilayer perceptron (MLP) **275**. In a dense MLP, each node of a hidden layer of the dense MLP is connected to every other node in the next layer.

[0026] The output **280** of the MLP **275** may comprise a binary value, for example, true or false, 0 or 1, and so on. Depending on how the MLP **275** is configured, the output **280** determines whether an alarm should be generated or suppressed. In this way, the prediction of physiological parameters of a patient can aid clinicians to achieve better care. An example method for using the output **280** to allow or suppress an alarm generated by a standard alarm method is described further herein with regard to FIG. **4**.

[0027] FIG. **3** shows a block diagram illustrating an example predictor cloud **300** for analyzing an electronic signal from a patient monitoring device according to an embodiment. More specifically, the time series **305** of an electronic signal x_n is input to a long short-term memory (LSTM) neural network **310** and a recurrent neural network (RNN) **320** to generate a prediction **328**.

[0028] As noted above, predictor cloud **300** comprises a long short-term memory (LSTM) neural network **310** and a recurrent neural network (RNN) **320** stacked in series. LSTM neural network **310** includes an input layer **312**, at least one hidden layer **314**, and an output layer **316**. The LSTM neural network **310** overcomes the vanishing gradient problem experienced by recurrent neural networks by employing multiplicative gates that enforce constant error flow through the internal states of special units called memory cells. The LSTM neural network **310** thus has the ability to learn the long term correlations in a sequence.

[0029] The outputs **318** of the LSTM neural network **310** are input to the RNN **320**. RNN **320** may comprise, as a non-limiting example, a gated recurrent neural network. RNN **320** merges the outputs **318** of the LSTM neural network **310** in order to learn and fuse their patterns in

3

longer time slices. In some examples, the RNN **320** may include a pooling and a softmax function. The prediction output **328** output by the RNN **320** comprises a prediction of the electronic signal x_n at the time t_n.

[0030] FIG. **4** shows a high-level flow chart illustrating an example method **400** for suppressing false alarms according to an embodiment. Method **400** is described herein with reference to the systems and components depicted in FIGS. **1**-**3**, though it should be understood that the method may be implemented with other systems and components without departing from the scope of the present disclosure. For example, method **400** may be implemented as executable instructions in the non-transitory memory of computing device **111**.

[0031] Method **400** begins at **405**. At **405**, method **400** receives a plurality of electronic signals corresponding to a measured physiological parameter of a patient. Each electronic signal of the plurality of electronic signals is generated by a patient monitoring device, such as one of the plurality of patient monitoring devices **101**.

[0032] At **410**, method **400** calculates a prediction for each electronic signal. Specifically, each electronic signal of the plurality of electronic signals received at **405** is input to a corresponding predictor cloud configured to predict and estimate the physiological parameter. As described hereinabove with regard to FIGS. **2** and **3**, a predictor cloud comprises an LSTM neural network and a recurrent neural network stacked in series. Thus, each of the electronic signals or parameters may be fed simultaneously into a plurality of predictor clouds with different activation and hyper parameter settings in order to learn and predict the physiological parameters.

[0033] At **415**, method **400** combines the predictions for each electronic signal. In some examples, the predictions output by each predictor cloud may be concatenated or otherwise merged.

[0034] At **420**, method **400** evaluates the combined predictions for alarm conditions. As an illustrative and non-limiting example, the method may input the combined predictions into a multilayer perceptron (MLP) that determines whether an alarm should be generated based on a model learned from an input vector obtained by concatenation of the predictor clouds' outputs. While an MLP may be preferable in comparison to other types of neural networks due to the relatively higher number of degrees of freedom of the MLP, it should be appreciated that one or more neural networks other than an MLP may be used to evaluated the combined predictions for alarm conditions. Thus, at **420**, method **400** evaluates whether alarm conditions are predicted based on the combined predictions from the plurality of predictor clouds.

[0035] Continuing at **425**, method **400** determines whether a standard monitoring method detects alarm conditions. The standard monitoring method may comprise any suitable method for detecting alarm conditions known in the art; the method described herein of detecting alarm conditions via a plurality of predictor clouds operates in parallel to such a standard monitoring method in order to reduce the number of false positive alarms generated by the standard monitoring method. As an exemplary and non-limiting example, a standard monitoring method may comprise a threshold-based method wherein an alarm is generated responsive to measurements of one or more physiological parameters exceeding threshold limits. Such a method may additionally

or alternatively generate an alarm responsive to, as an example, a rate of change of a measurement of a physiological parameter exceeding threshold limits.

[0036] Continuing at **430**, method **400** determines whether alarm conditions are predicted at **420**. If alarm conditions are not predicted ("NO"), method **400** proceeds to **435**. At **435**, method **400** determines whether alarm conditions are detected by the standard monitoring method at **425**. If alarm conditions are detected ("YES"), method **400** continues to **440**. At **440**, method **400** suppresses the alarm generated by the standard monitoring method. Thus, even though the standard monitoring method detects alarm conditions, an alarm is not generated because the alarm conditions are not predicted. Method **400** then returns.

[0037] However, referring again to **435**, if alarm conditions are not detected ("NO"), method **400** proceeds to **445**. At **445**, no alarm is generated, since alarm conditions are neither predicted nor detected. Method **400** then returns.

[0038] Referring again to **430**, if alarm conditions are predicted based on the combined predictions at **420** ("YES"), method **400** continues to **437**. At **437**, method **400** determines whether alarm conditions are detected by the standard monitoring method at **425**. If alarm conditions are detected ("YES"), method **400** proceeds to **450**. At **450**, method **400** generates an alarm. In this instance, the alarm is generated because alarm conditions are both predicted and detected. The generated alarm may take on any form including, but not limited to, an audible sound, a visual indicator, and/or a vibrating or otherwise tactile alert. The alarm may include a message indicating the reason for the alarm. The alarm may also be differentiated based on a number of criteria including the type and severity of the event causing the alarm. Method **400** then returns.

[0039] However, referring again to **437**, if alarm conditions are not detected ("NO"), method **400** continues to **442**. At **442**, method **400** determines whether an asystole is predicted. Asystole, also referred to as flatline, comprises a state of no electrical activity from the heart and therefore no blood flow. If an asystole is not predicted ("NO"), method **400** proceeds to **445**, wherein no alarm is generated and the method returns. Thus, even though alarm conditions are predicted based on the combined predictions from the plurality of predictor clouds, since alarm conditions are not detected by the standard monitoring method and the prediction does not predict an asystole, method **400** does not generate an alarm. However, if an asystole is predicted ("YES"), method **400** proceeds to **450**, wherein method **400** generates an alarm. Method **400** thus generates an alarm responsive to an asystole prediction despite the standard monitoring method not detecting alarm conditions. In this instance, the predicted alarm conditions are considered severe enough to override the lack of an alarm generated by the standard monitoring method. Method **400** then returns.

[0040] The system architecture described hereinabove consists of different layers of abstraction for each modality or patient monitor. Namely, an LSTM neural network is provided for each channel of each modality. A subsequent layer comprises a gated recurrent neural network that merges outputs of the LSTM in order to learn and fuse their patterns in longer time slices. The last layer of the network comprises a pooling and a softmax function. While such a network is trained in a patient-specific manner, to avoid over-fitting and improve generalization of the model, a cloud of such networks trained individually may then be used to

4

merge and fuse all network outputs. The proposed architecture is thus modular and flexible, and can be adjusted according to the available modalities by fine-tuning the cloud after fixing the inputs.

[0041] The systems and methods described herein may be used for different clinical applications, including but not limited to epilepsy prediction and detection, patient activity and state recognition, false alarm suppression and assertion in ICU monitors, and so on. In some examples, the hyper parameters of each predictor cloud may be adjusted and the network architecture adapted for the specific purpose. With supervised learning, the neural networks described herein should learn the underlying model and distribution of inputs according to the annotated ground truth or training data. The methods described herein address major limitations of conventional and classical heuristic-based solutions which are no longer feasible for tackling big data.

[0042] A technical effect of the disclosure is the generation of an alarm based on physiological characteristics of a patient. Another technical effect of the disclosure includes the suppression of an alarm based on a deep neural network analysis of patient monitor data.

[0043] In one embodiment, a method comprises: inputting each electronic signal of a plurality of electronic signals into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network; and responsive to an alarm generated based on at least one of the plurality of electronic signals, suppressing the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false.

[0044] In a first example of the method, each electronic signal of the plurality of electronic signals corresponds to a physiological characteristic of a patient. In a second example of the method optionally including the first example, the physiological characteristic includes one of a heart rate, a blood pressure, peripheral oxygen saturation, blood glucose levels, and an electrocardiogram. In a third example of the method optionally including one or more of the first and second examples, the outputs of the plurality of predictor clouds comprise estimates of the plurality of electronic signals. In a fourth example of the method optionally including one or more of the first through third examples, the method further comprises combining the outputs of the plurality of predictor clouds. In a fifth example of the method optionally including one or more of the first through fourth examples, combining the outputs comprises concatenating the outputs of the plurality of predictor clouds. In a sixth example of the method optionally including one or more of the first through fifth examples, the method further comprises inputting the combined outputs into a multilayer perceptron trained to determine if the alarm should be generated based on the combined outputs. In a seventh example of the method optionally including one or more of the first through sixth examples, the method further comprises, responsive to the alarm not generated based on at least one of the plurality of electronic signals while the outputs of the plurality of predictor clouds indicates the alarm is true, generating the alarm. In an eighth example of the method optionally including one or more of the first through seventh examples, one or more electronic signals of the plurality of electronic signals may be added to or removed from the plurality of electronic signals. In a ninth example of the method optionally including one or more of

the first through eighth examples, the alarm comprises one or more of a visual alarm, an audio alarm, and a tactile alarm.

[0045] In another embodiment, a method comprises receiving a plurality of electronic signals, each electronic signal of the plurality of electronic signals corresponding to physiological measurements of a patient, predicting, for each electronic signal with a corresponding predictor cloud comprising a long short-term memory neural network and a recurrent neural network, an expected value for the electronic signal, concatenating the expected value for each electronic signal into a combined prediction, determining, with a multilayer perceptron, whether to generate an alarm based on the combined prediction, and generating the alarm responsive to output of the multilayer perceptron indicating to generate the alarm.

[0046] In a first example of the method, the plurality of electronic signals include one or more of a heart rate, a blood pressure, peripheral oxygen saturation, blood glucose levels, and an electrocardiogram. In a second example of the method optionally including the first example, the alarm comprises one or more of a visual alarm, an audio alarm, and a tactile alarm. In a third example of the method optionally including one or more of the first and second examples, the method further comprises generating a standard alarm responsive to one or more of the electronic signals deviating outside a threshold range, and suppressing the standard alarm responsive to the output of the multilayer perceptron indicating to suppress the alarm. In a fourth example of the method optionally including one or more of the first through third examples, one or more electronic signals of the plurality of electronic signals may be added to or removed from the plurality of electronic signals.

[0047] In yet another embodiment, a system comprises: a plurality of patient monitoring devices, each patient monitoring device of the plurality of monitoring devices configured to generate an electronic signal representing a measurement of a physiological parameter of a patient; and a processor communicatively coupled to the plurality of patient monitoring devices and the alarm device, the processor configured with instructions in non-transitory memory that when executed cause the processor to: input each electronic signal received from each of the plurality of patient monitoring devices into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network; and responsive to an alarm generated based on at least one of the electronic signals, suppress the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false.

[0048] In a first example of the system, the plurality of patient monitoring devices includes one or more of an electrocardiograph, a pulse oximeter, a glucose meter, and a temperature sensor. In a second example of the system optionally including the first example, the system further comprises a display device communicatively coupled to the processor, wherein the processor is further configured with instructions in the non-transitory memory that when executed cause the processor to display, via the display device, the alarm. In a third example of the system optionally including one or more of the first and second examples, the alarm is generated responsive to one or more of the electronic signals deviating outside a threshold range. In a fourth example of the system optionally including one or

more of the first through third examples, the processor is further configured with instructions in the non-transitory memory that when executed cause the processor to evaluate the outputs of the plurality of predictor clouds with a multilayer perceptron to determine whether the alarm is false.

[0049] As used herein, an element or step recited in the singular and proceeded with the word "a" or "an" should be understood as not excluding plural of said elements or steps, unless such exclusion is explicitly stated. Furthermore, references to "one embodiment" of the present invention are not intended to be interpreted as excluding the existence of additional embodiments that also incorporate the recited features. Moreover, unless explicitly stated to the contrary, embodiments "comprising," "including," or "having" an element or a plurality of elements having a particular property may include additional such elements not having that property. The terms "including" and "in which" are used as the plain-language equivalents of the respective terms "comprising" and "wherein." Moreover, the terms "first," "second," and "third," etc. are used merely as labels, and are not intended to impose numerical requirements or a particular positional order on their objects.

[0050] This written description uses examples to disclose the invention, including the best mode, and also to enable a person of ordinary skill in the relevant art to practice the invention, including making and using any devices or systems and performing any incorporated methods. The patentable scope of the invention is defined by the claims, and may include other examples that occur to those of ordinary skill in the art. Such other examples are intended to be within the scope of the claims if they have structural elements that do not differ from the literal language of the claims, or if they include equivalent structural elements with insubstantial differences from the literal languages of the claims.

1. A method, comprising:
inputting each electronic signal of a plurality of electronic signals into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network; and
responsive to an alarm generated based on at least one of the plurality of electronic signals, suppressing the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false.

2. The method of claim 1, wherein each electronic signal of the plurality of electronic signals corresponds to a physiological characteristic of a patient.

3. The method of claim 2, wherein the physiological characteristic includes one of a heart rate, a blood pressure, peripheral oxygen saturation, blood glucose levels, and an electrocardiogram.

4. The method of claim 1, wherein the outputs of the plurality of predictor clouds comprise estimates of the plurality of electronic signals.

5. The method of claim 1, further comprising combining the outputs.

6. The method of claim 5, wherein combining the outputs comprises concatenating the outputs of the plurality of predictor clouds.

7. The method of claim 5, further comprising inputting the combined outputs into a multilayer perceptron trained to determine if the alarm should be generated based on the combined outputs.

8. The method of claim 1, further comprising, responsive to the alarm not generated based on at least one of the plurality of electronic signals while the outputs of the plurality of predictor clouds indicates the alarm is true, generating the alarm.

9. The method of claim 1, wherein one or more electronic signals of the plurality of electronic signals may be added to or removed from the plurality of electronic signals.

10. The method of claim 1, wherein the alarm comprises one or more of a visual alarm, an audio alarm, and a tactile alarm.

11. A method, comprising:
receiving a plurality of electronic signals, each electronic signal of the plurality of electronic signals corresponding to physiological measurements of a patient;
predicting, for each electronic signal with a corresponding predictor cloud comprising a long short-term memory neural network and a recurrent neural network, an expected value for the electronic signal;
concatenating the expected value for each electronic signal into a combined prediction;
determining, with a multilayer perceptron, whether to generate an alarm based on the combined prediction; and
generating the alarm responsive to output of the multilayer perceptron indicating to generate the alarm.

12. The method of claim 11, wherein the plurality of electronic signals include one or more of a heart rate, a blood pressure, peripheral oxygen saturation, blood glucose levels, and an electrocardiogram.

13. The method of claim 11, wherein the alarm comprises one or more of a visual alarm, an audio alarm, and a tactile alarm.

14. The method of claim 11, further comprising generating a standard alarm responsive to one or more of the electronic signals deviating outside a threshold range, and suppressing the standard alarm responsive to the output of the multilayer perceptron indicating to suppress the alarm.

15. The method of claim 11, wherein one or more electronic signals of the plurality of electronic signals may be added to or removed from the plurality of electronic signals.

16. A system, comprising:
a plurality of patient monitoring devices, each patient monitoring device of the plurality of monitoring devices configured to generate an electronic signal representing a measurement of a physiological parameter of a patient; and
a processor communicatively coupled to the plurality of patient monitoring devices and the alarm device, the processor configured with instructions in non-transitory memory that when executed cause the processor to:
input each electronic signal received from each of the plurality of patient monitoring devices into a corresponding predictor cloud of a plurality of predictor clouds, each predictor cloud comprising a long short-term memory neural network and a recurrent neural network; and
responsive to an alarm generated based on at least one of the electronic signals, suppress the alarm responsive to outputs of the plurality of predictor clouds indicating the alarm is false.

17. The system of claim 16, wherein the plurality of patient monitoring devices includes one or more of an electrocardiograph, a pulse oximeter, a glucose meter, and a temperature sensor.

18. The system of claim 16, further comprising a display device communicatively coupled to the processor, wherein the processor is further configured with instructions in the non-transitory memory that when executed cause the processor to display, via the display device, the alarm.

19. The system of claim 18, wherein the alarm is generated responsive to one or more of the electronic signals deviating outside a threshold range.

20. The system of claim 16, wherein the processor is further configured with instructions in the non-transitory memory that when executed cause the processor to evaluate the outputs of the plurality of predictor clouds with a multilayer perceptron to determine whether the alarm is false.

* * * * *

专利名称(译)	用于患者监测的方法和系统		
公开(公告)号	US20180206797A1	公开(公告)日	2018-07-26
申请号	US15/413779	申请日	2017-01-24
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摘要(译)

提供了用于患者监测系统中的误报警抑制的系统和方法。在一个实施例中，一种方法包括将多个电子信号中的每个电子信号输入到多个预测器云的相应预测器云中，每个预测器云包括长短期记忆神经网络和递归神经网络，并且响应于基于多个电子信号中的至少一个产生的警报，响应于指示警报为假的多个预测器云的输出来抑制警报。通过这种方式，患者监护仪可以更可靠，具有更少的误报警。