US010702239B1

(12) **United States Patent**
McLane

(10) **Patent No.: US 10,702,239 B1**
(45) **Date of Patent: Jul. 7, 2020**

(54) **PREDICTING CHARACTERISTICS OF A FUTURE RESPIRATORY EVENT, AND APPLICATIONS THEREOF**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **16/659,392**

(22) Filed: **Oct. 21, 2019**

(51) **Int. Cl.**

A61B 5/08	(2006.01)
A61B 7/00	(2006.01)
G16H 50/20	(2018.01)
A61B 7/04	(2006.01)
A61B 5/00	(2006.01)

(52) **U.S. Cl.**
CPC ***A61B 7/003*** (2013.01); ***A61B 5/0823*** (2013.01); ***A61B 5/7267*** (2013.01); ***A61B 5/7275*** (2013.01); ***A61B 5/7425*** (2013.01); ***A61B 7/04*** (2013.01); ***G16H 50/20*** (2018.01)

(58) **Field of Classification Search**
CPC A61B 7/003; A61B 5/0823; A61B 5/7267; A61B 5/7275; A61B 5/7425; A61B 7/04; G16H 50/20
See application file for complete search history.

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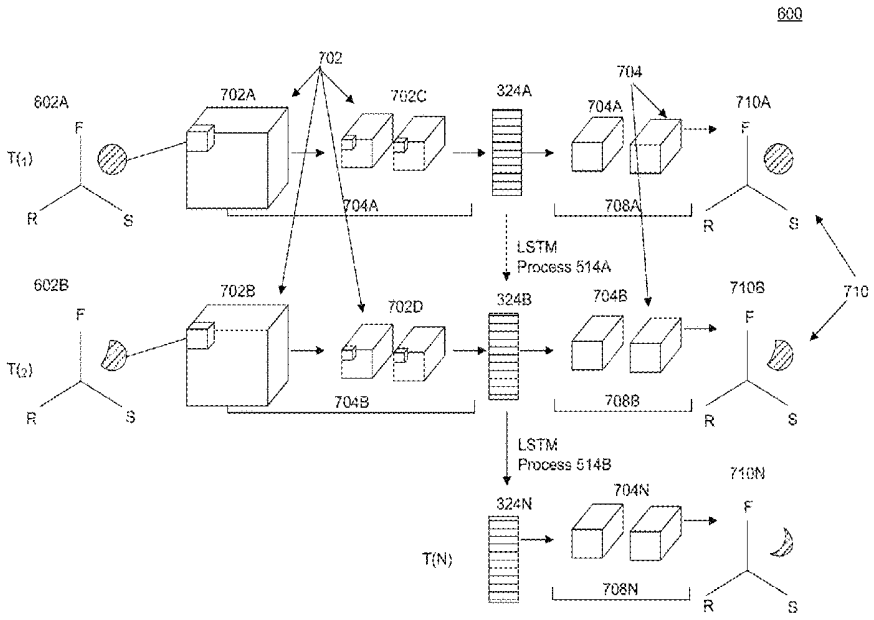
(57) **ABSTRACT**

Embodiments disclosed herein improve digital stethoscopes and their application and operation. A first method detects of a respiratory abnormality using a convolution. A second method counts coughs for a patient. A third method predicts a respiratory event based on a detected trend. A fourth method forecasts characteristics of a future respiratory event. In a fifth embodiment, a base station is provided for a digital stethoscope.

14 Claims, 21 Drawing Sheets



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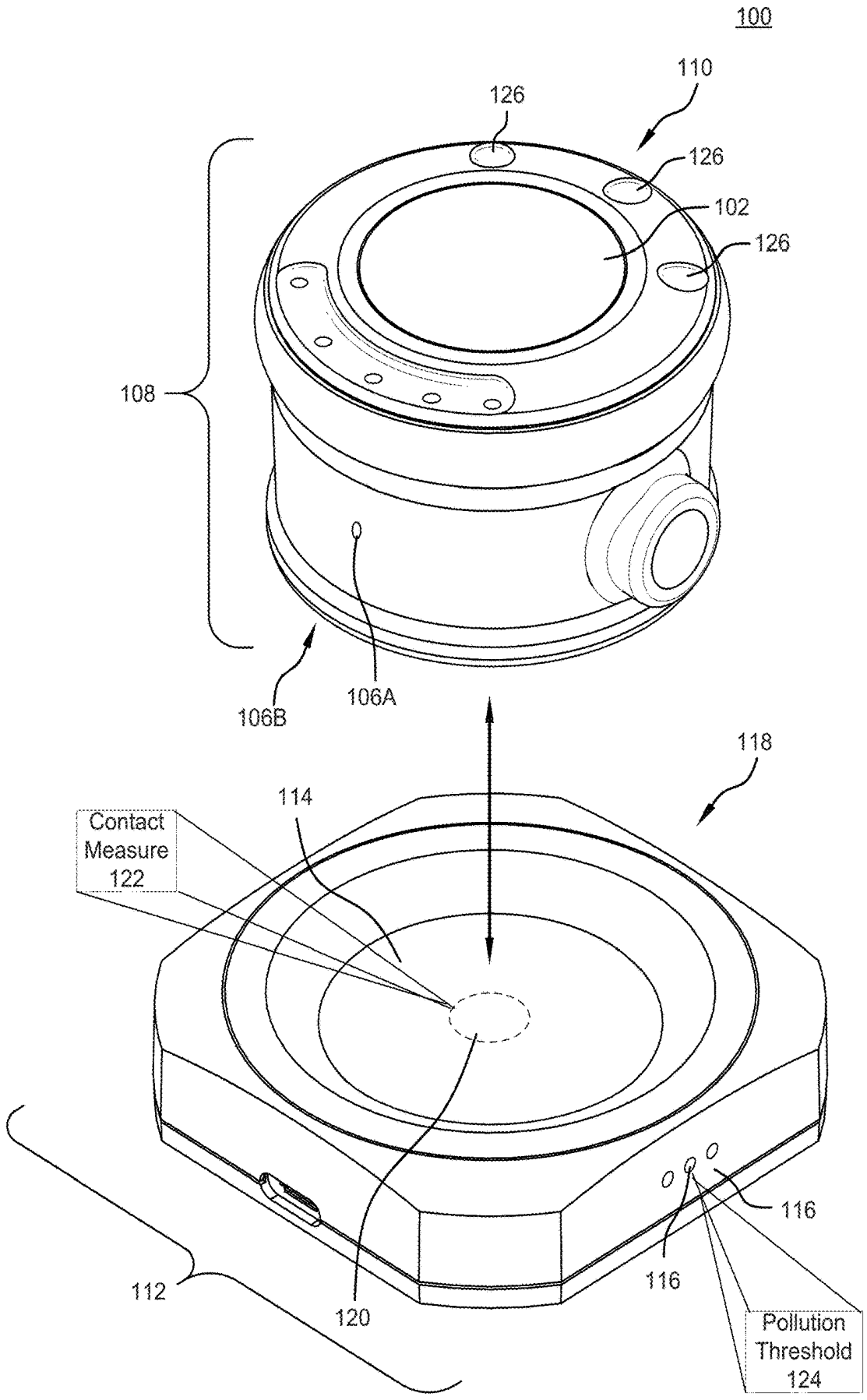
100
110
126
126
102
126
108
106B
106A
118
114
Contact Measure 122
112
120
116
116
Pollution Threshold 124

FIG. 1

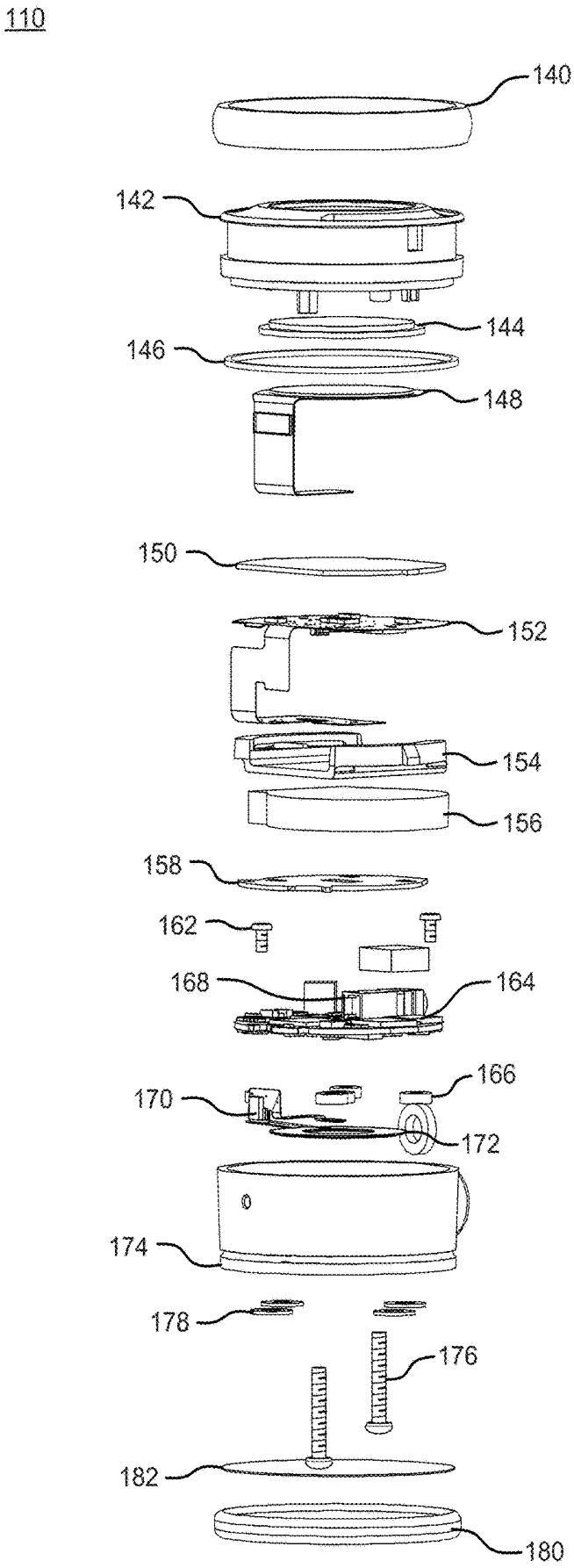
110
140
142
144
146
148
150
152
154
156
158
162
164
166
168
170
172
174
176
178
180
182

FIG. 1A

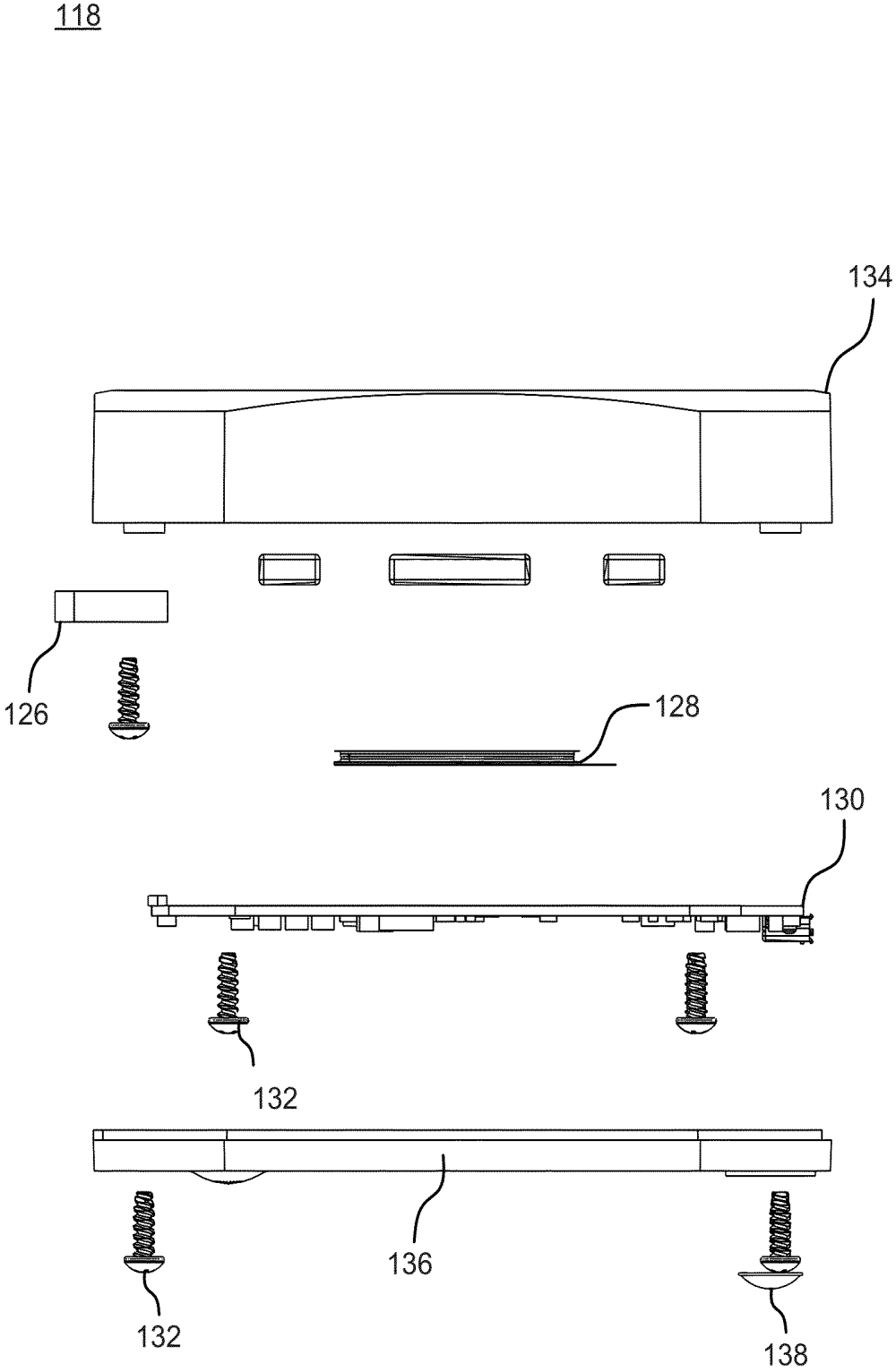

FIG. 1B

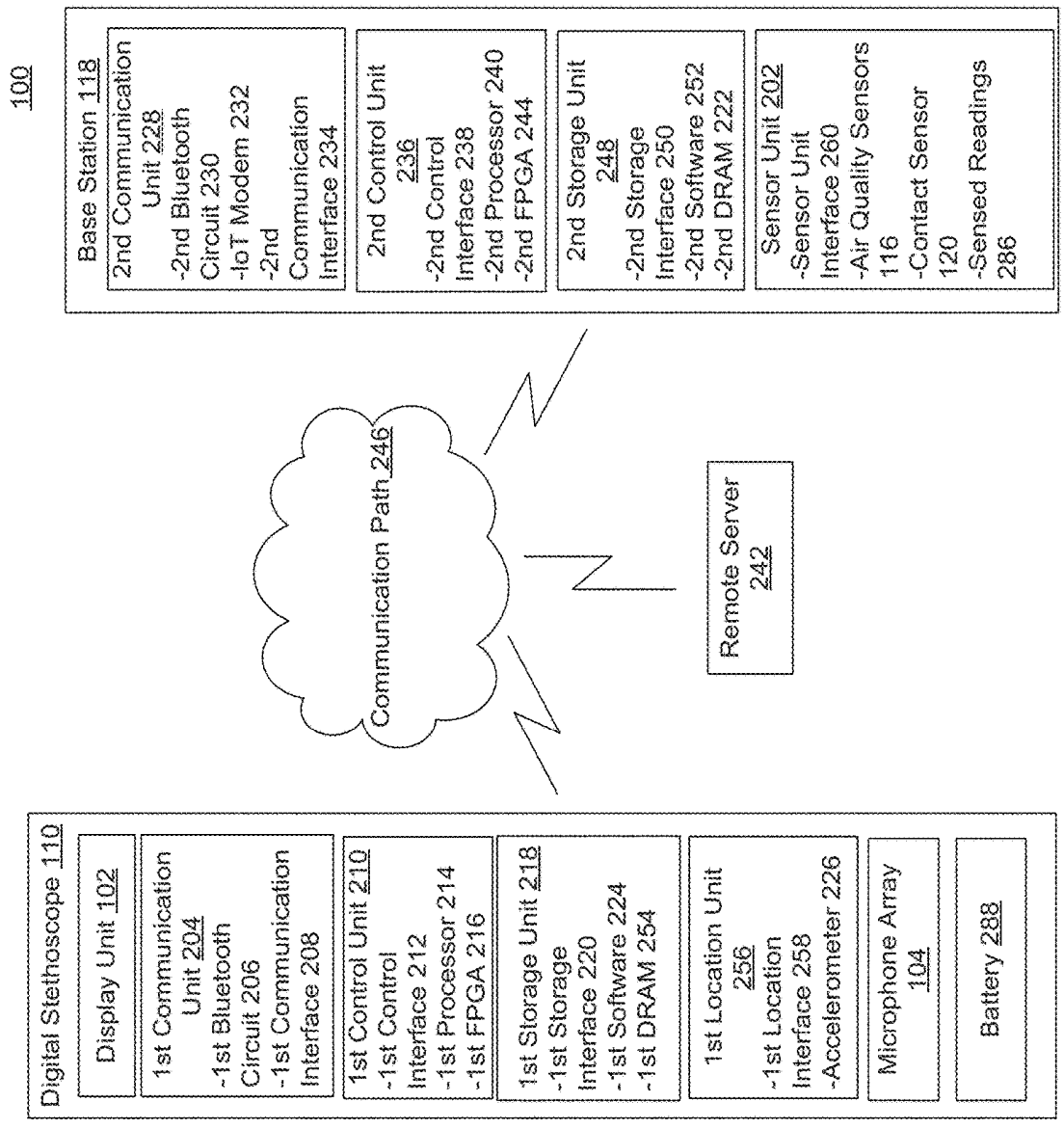
100
Digital Stethoscope 110
Display Unit 102
1st Communication Unit 204
-1st Bluetooth Circuit 206
-1st Communication Interface 208
1st Control Unit 210
-1st Control Interface 212
-1st Processor 214
-1st FPGA 216
1st Storage Unit 218
-1st Storage Interface 220
-1st Software 224
-1st DRAM 254
1st Location Unit 256
-1st Location Interface 258
-Accelerometer 226
Microphone Array 104
Battery 288
Communication Path 246
Remote Server 242
Base Station 118
2nd Communication Unit 228
-2nd Bluetooth Circuit 230
-IoT Modem 232
-2nd Communication Interface 234
2nd Control Unit 236
-2nd Control Interface 238
-2nd Processor 240
-2nd FPGA 244
2nd Storage Unit 248
-2nd Storage Interface 250
-2nd Software 252
-2nd DRAM 222
Sensor Unit 202
-Sensor Unit Interface 260
-Air Quality Sensors 116
-Contact Sensor 120
-Sensed Readings 286

FIG. 2A

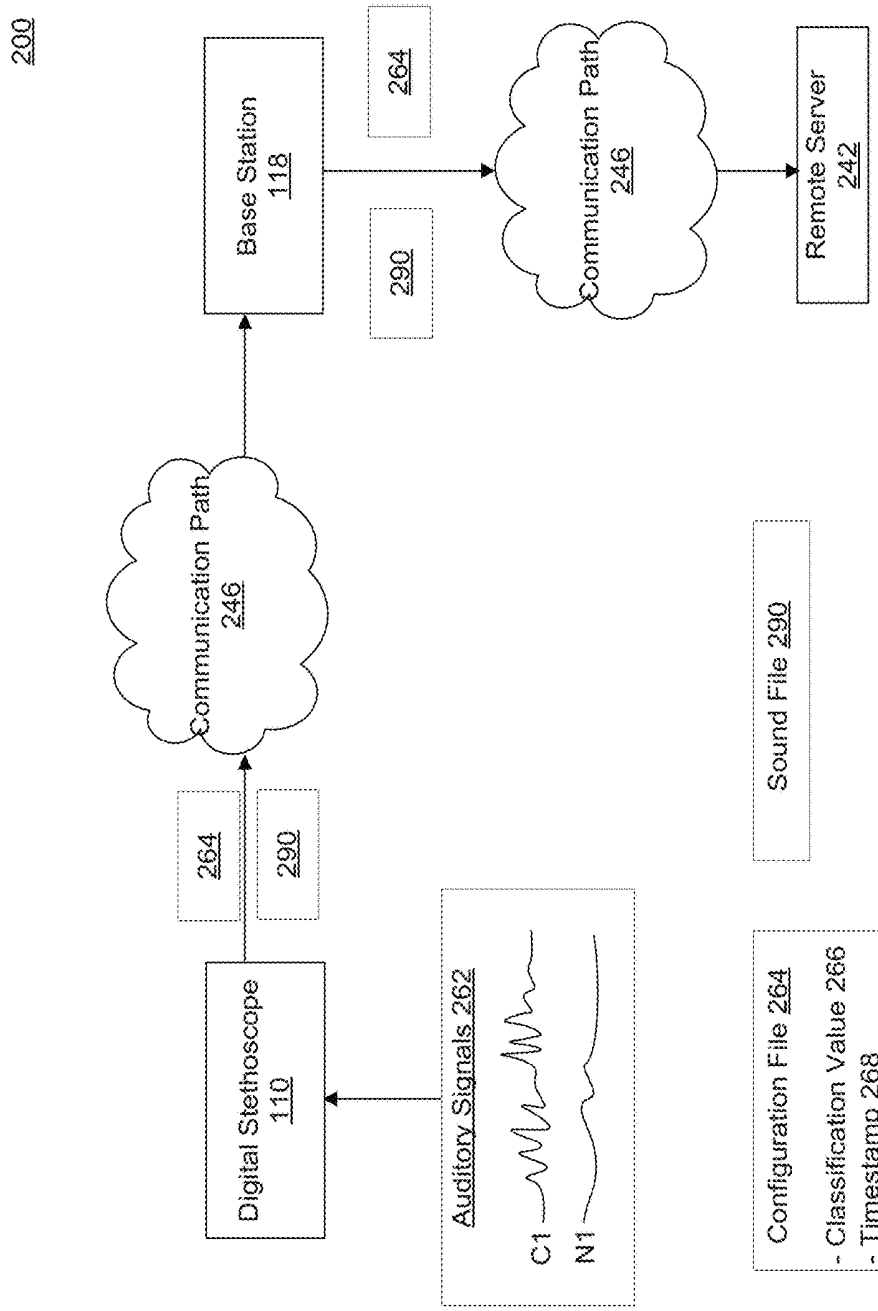
200
Digital Stethoscope 110
Auditory Signals 262
C1
N1
264
290
Communication Path 246
Base Station 118
264
290
Communication Path 246
Remote Server 242
Sound File 290
Configuration File 264
- Classification Value 266
- Timestamp 268
- Serial Number 270
- Accelerometer Data 272
- Cough Count 274

FIG. 2B

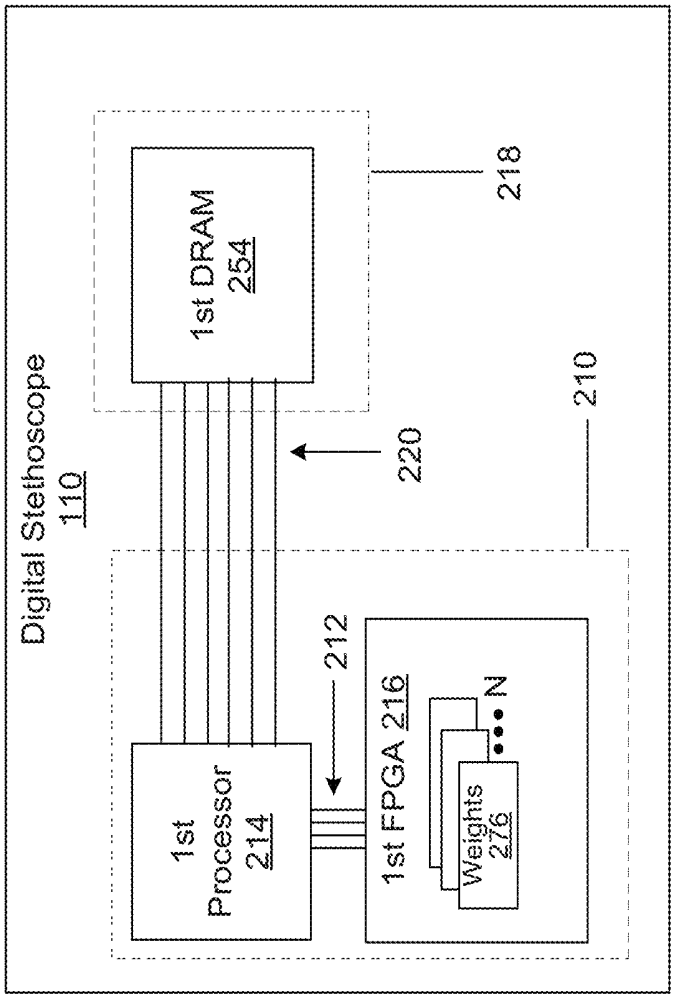
Digital Stethoscope
110
1st DRAM
254
218
220
210
212
1st
Processor
214
1st FPGA 216
Weights
276
N

FIG. 2C

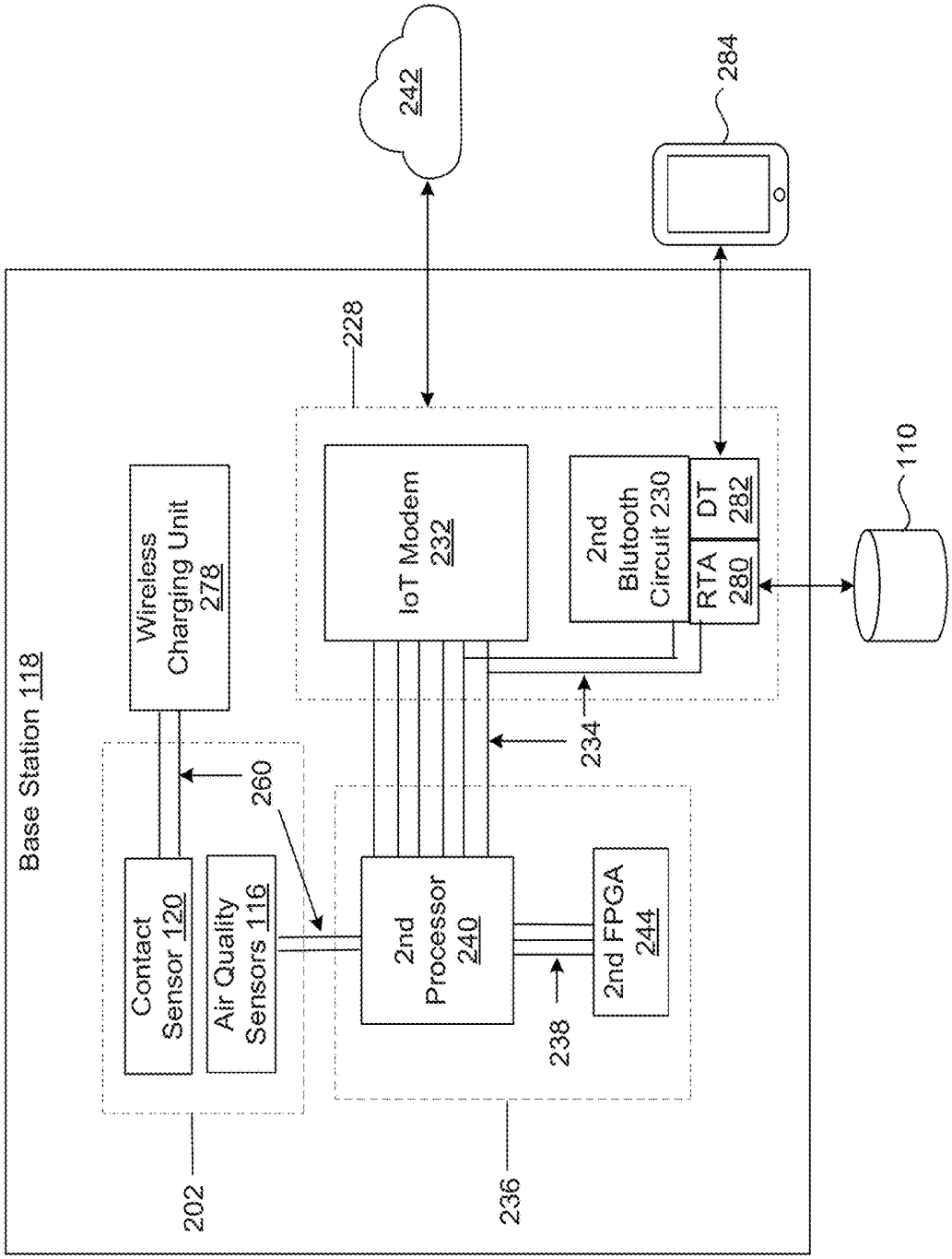
242
284
228
Base Station 118
Wireless Charging Unit 278
IoT Modem 232
2nd Blutooth Circuit 230
DT 282
RTA 280
110
234
260
Contact Sensor 120
Air Quality Sensors 116
2nd Processor 240
2nd FPGA 244
238
202
236

FIG. 2D

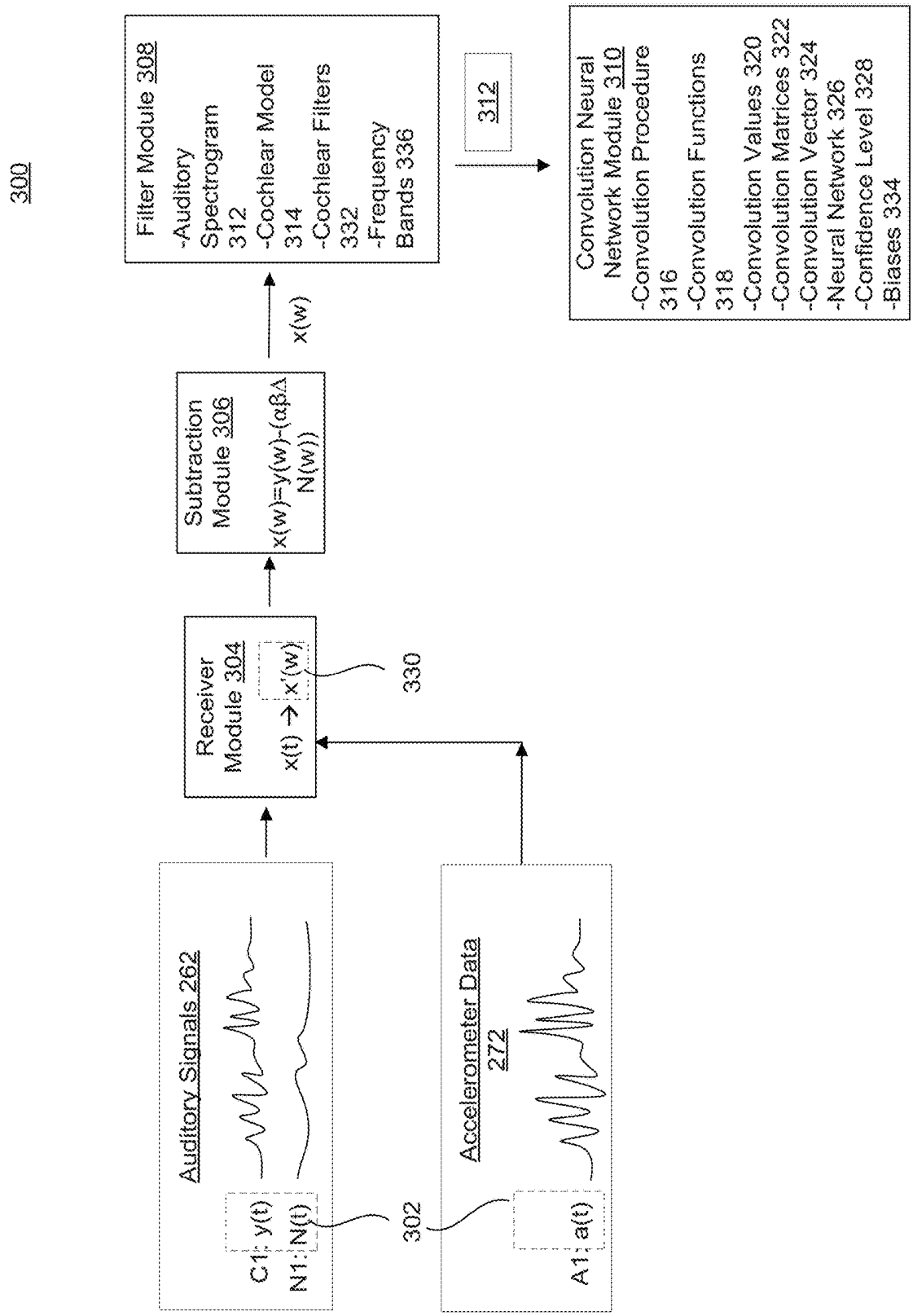
300
Auditory Signals 262
C1: y(t)
N1: N(t)
302
Accelerometer Data 272
A1: a(t)
Receiver Module 304
x(t) → x'(w)
330
Subtraction Module 306
x(w)=y(w)-(αβΔ N(w))
x(w)
Filter Module 308
-Auditory Spectrogram 312
-Cochlear Model 314
-Cochlear Filters 332
-Frequency Bands 336
312
Convolution Neural Network Module 310
-Convolution Procedure 316
-Convolution Functions 318
-Convolution Values 320
-Convolution Matrices 322
-Convolution Vector 324
-Neural Network 326
-Confidence Level 328
-Biases 334

FIG. 3

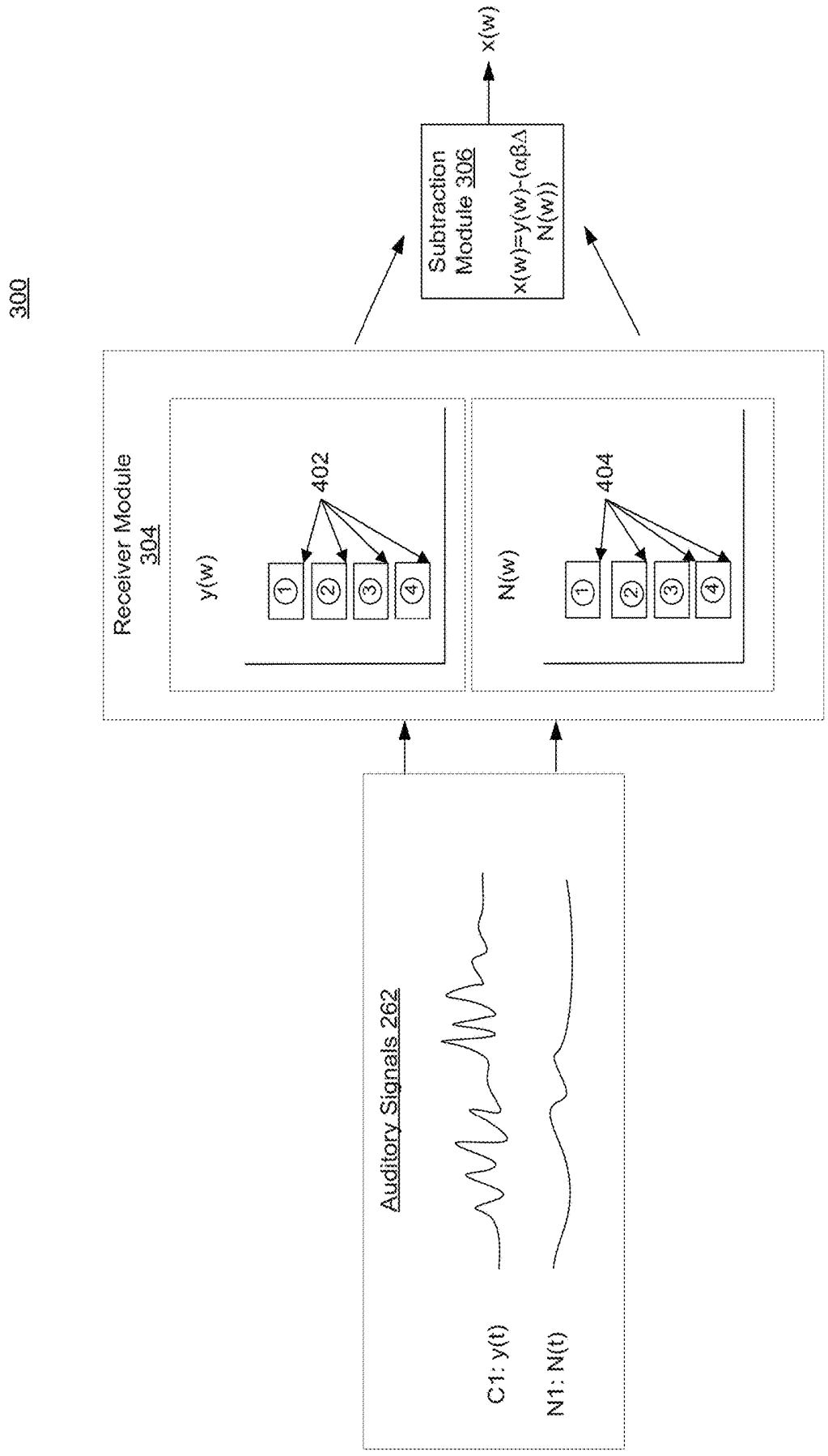
300
x(w)
Subtraction Module 306
x(w)=y(w)-(αβΔ N(w))
Receiver Module 304
y(w)
402
N(w)
404
Auditory Signals 262
C1: y(t)
N1: N(t)

FIG. 4A

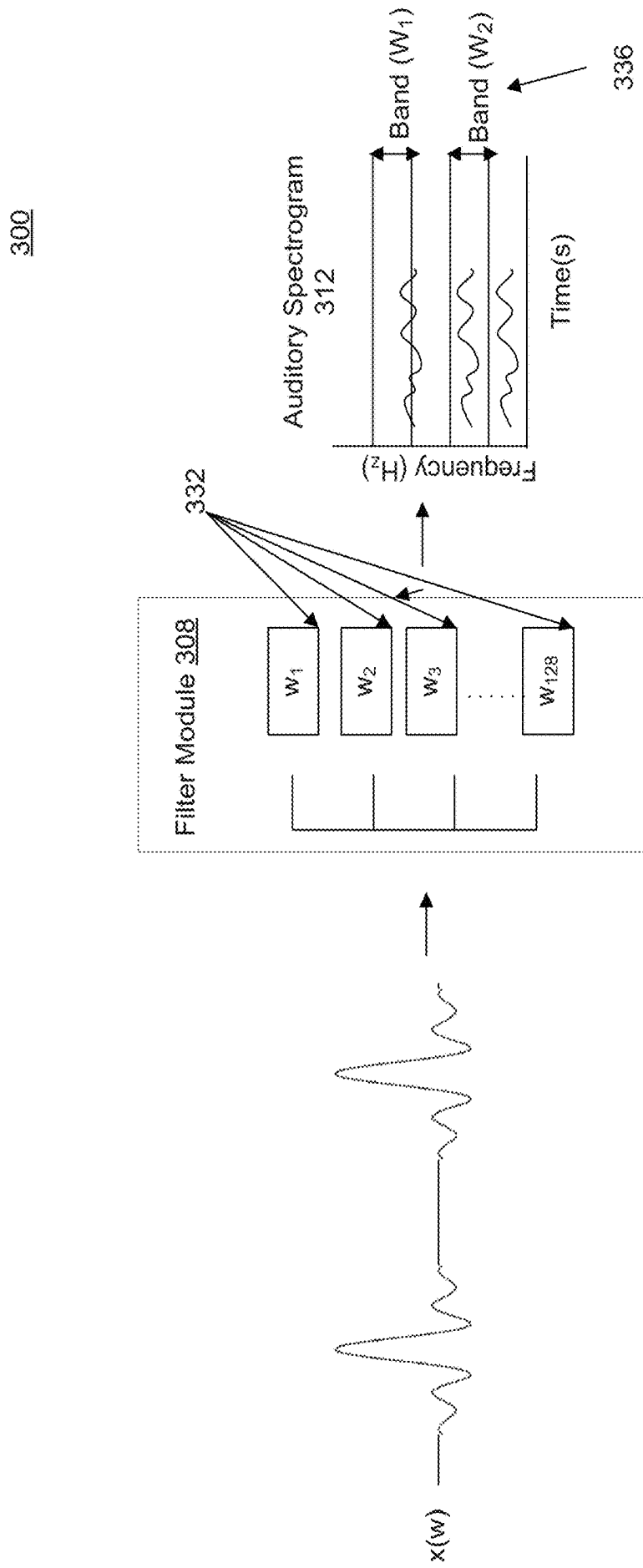
300
x(w)
Filter Module 308
w1
w2
w3
w128
332
Auditory Spectrogram
312
Frequency (Hz)
Time(s)
Band (W1)
Band (W2)
336

FIG. 4B

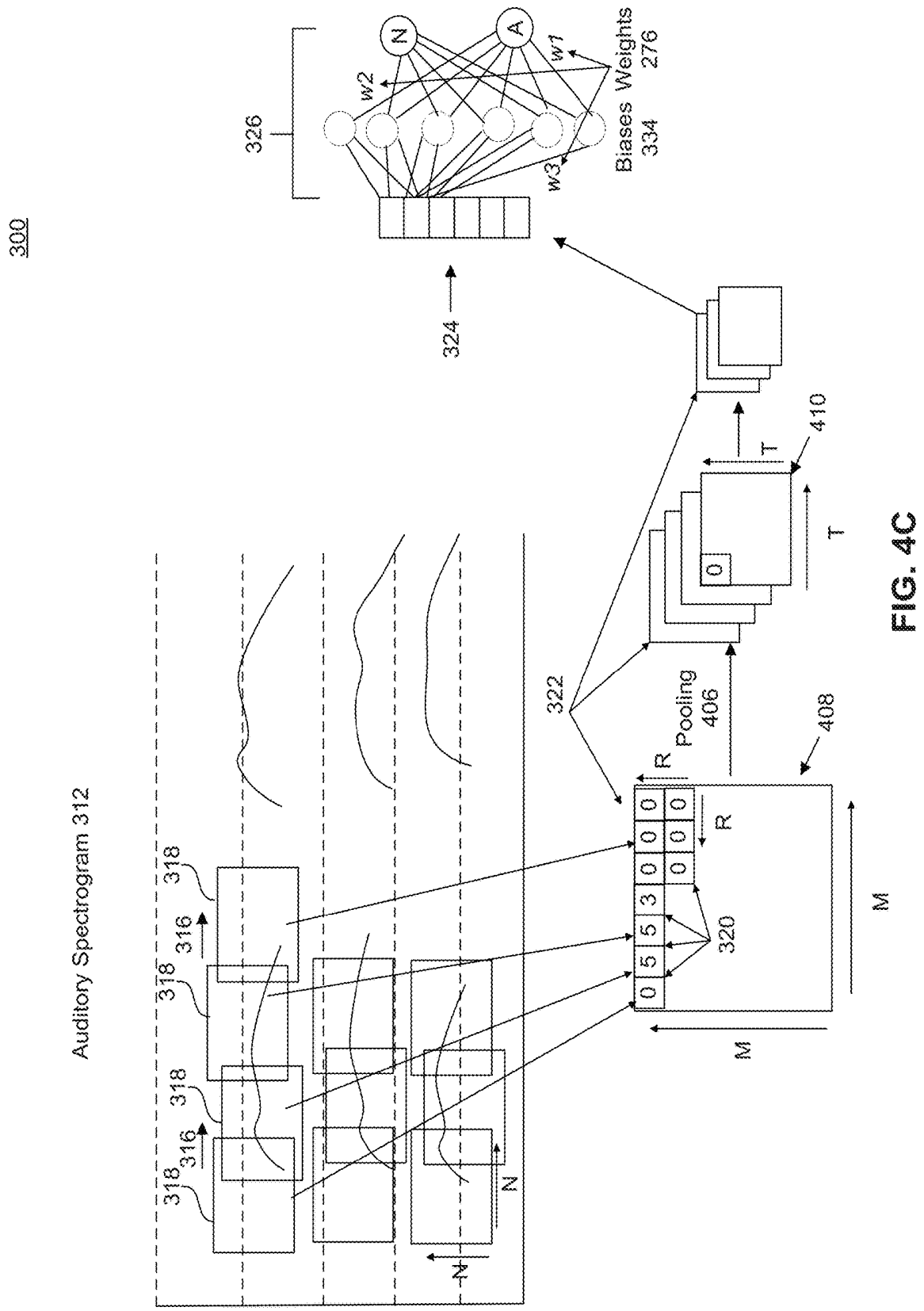
300
Auditory Spectrogram 312
318
316
N
326
N
A
w1
w2
w3
Biases Weights
334
276
324
322
Pooling
406
R
408
M
320
410
T
0

FIG. 4C

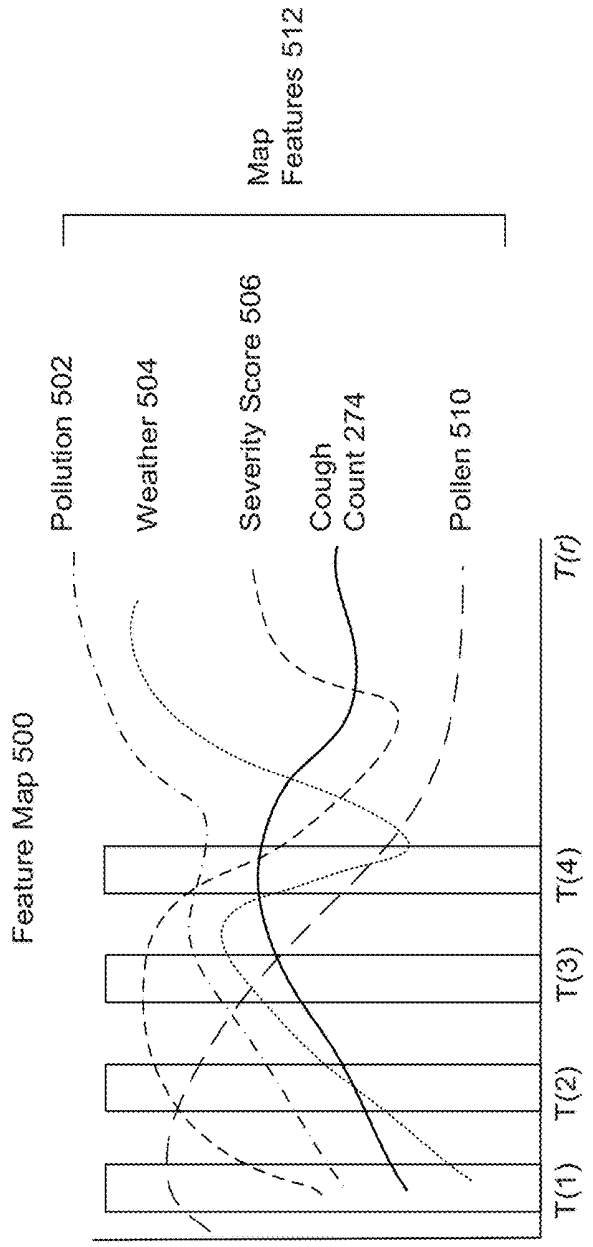
Feature Map 500
Pollution 502
Weather 504
Severity Score 506
Cough Count 274
Pollen 510
Map Features 512
T(1)
T(2)
T(3)
T(4)
T(r)

FIG. 5A

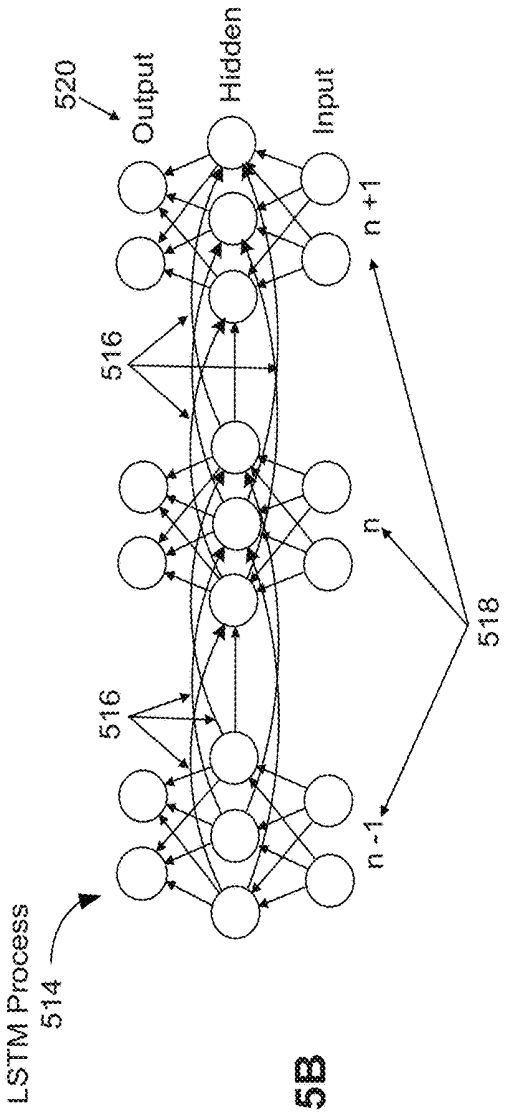
LSTM Process 514
520
Output
Hidden
Input
516
516
n +1
n
n -1
518

FIG. 5B

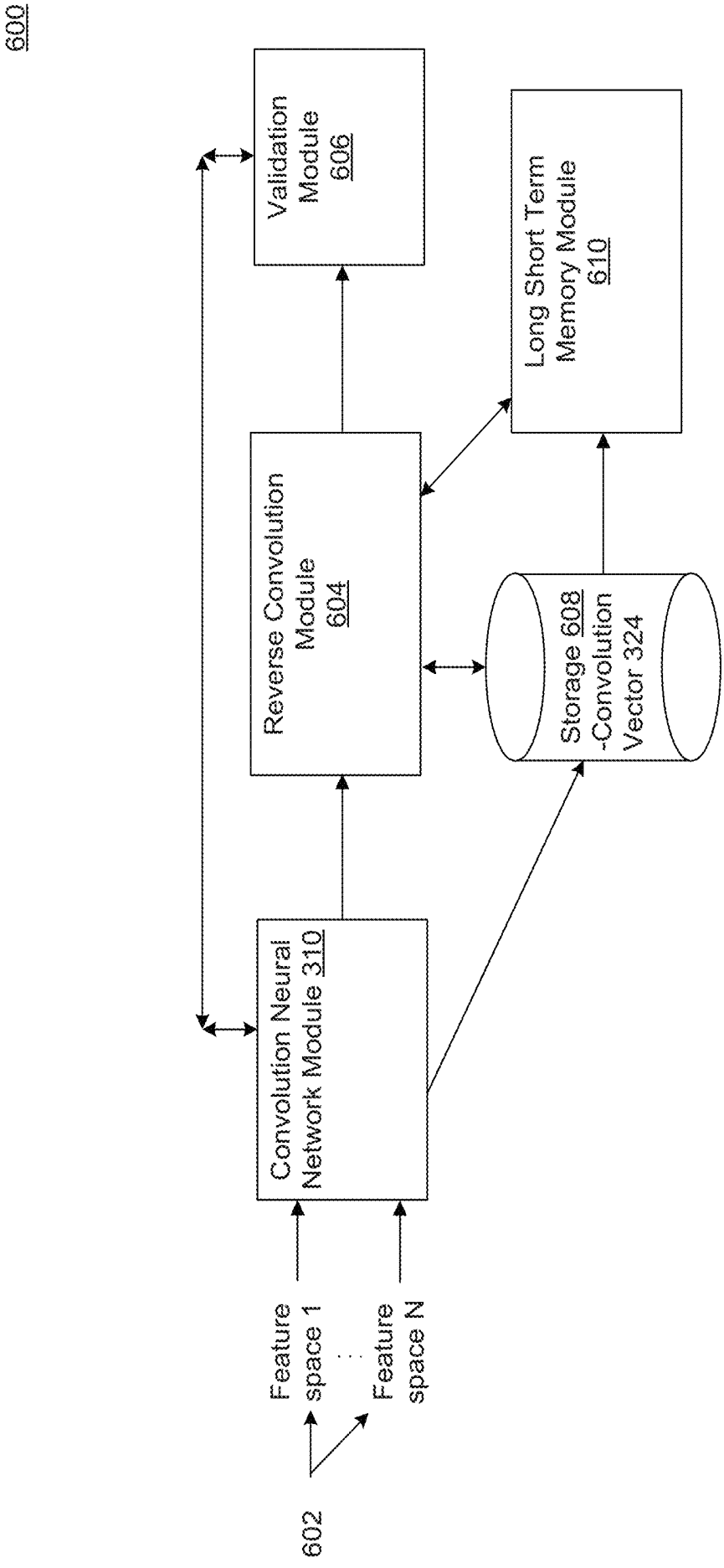
600
Validation Module 606
Long Short Term Memory Module 610
Reverse Convolution Module 604
Storage 608 -Convolution Vector 324
Convolution Neural Network Module 310
Feature space 1
Feature space N
602

FIG. 6

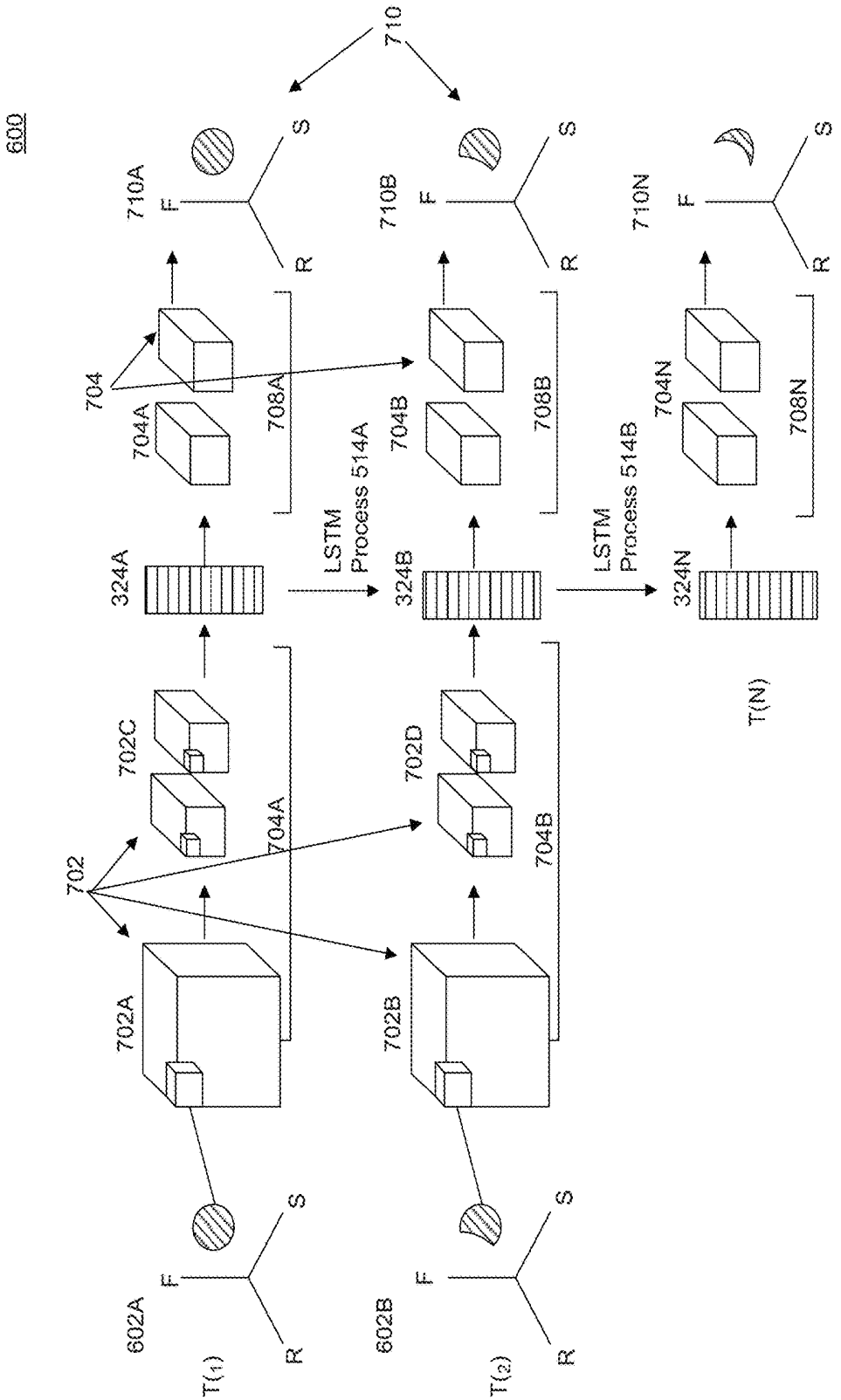
600
710
710A
710B
710N
F
S
R
704
704A
704B
704N
708A
708B
708N
LSTM Process 514A
LSTM Process 514B
324A
324B
324N
702
702A
702B
702C
702D
602A
602B
T(1)
T(2)
T(N)

FIG. 7

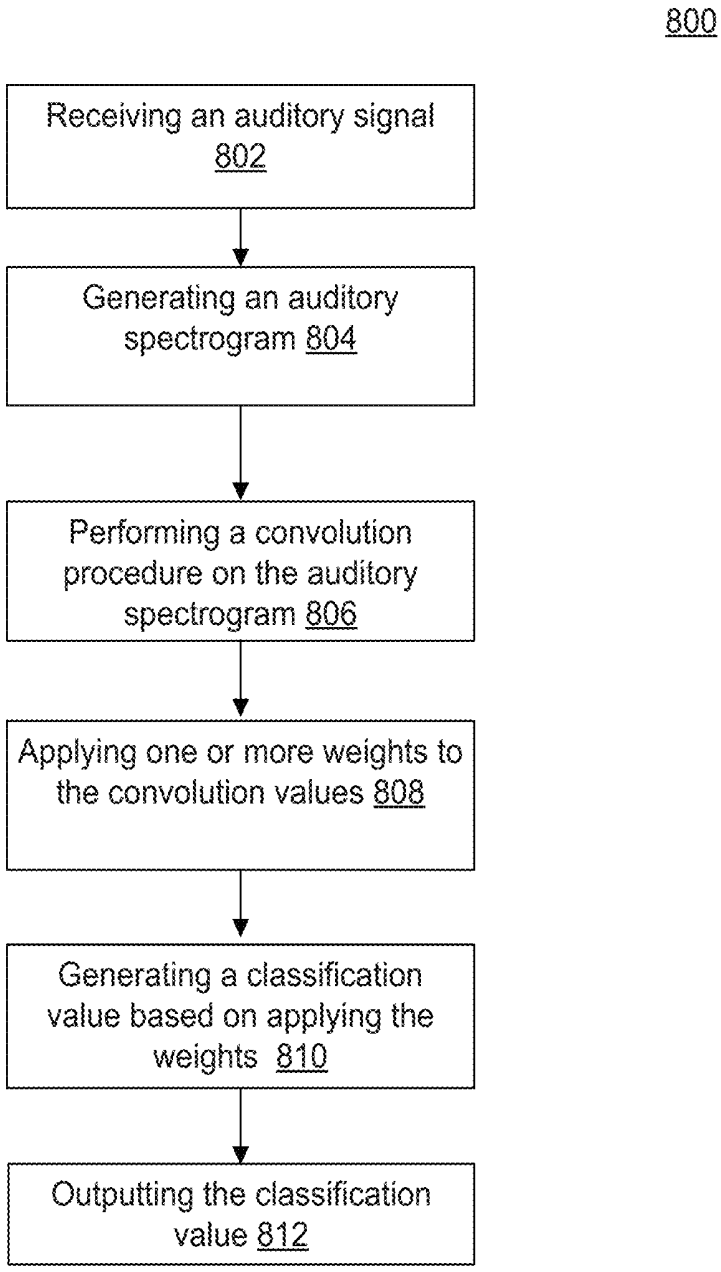
800
Receiving an auditory signal 802
Generating an auditory spectrogram 804
Performing a convolution procedure on the auditory spectrogram 806
Applying one or more weights to the convolution values 808
Generating a classification value based on applying the weights 810
Outputting the classification value 812

FIG. 8

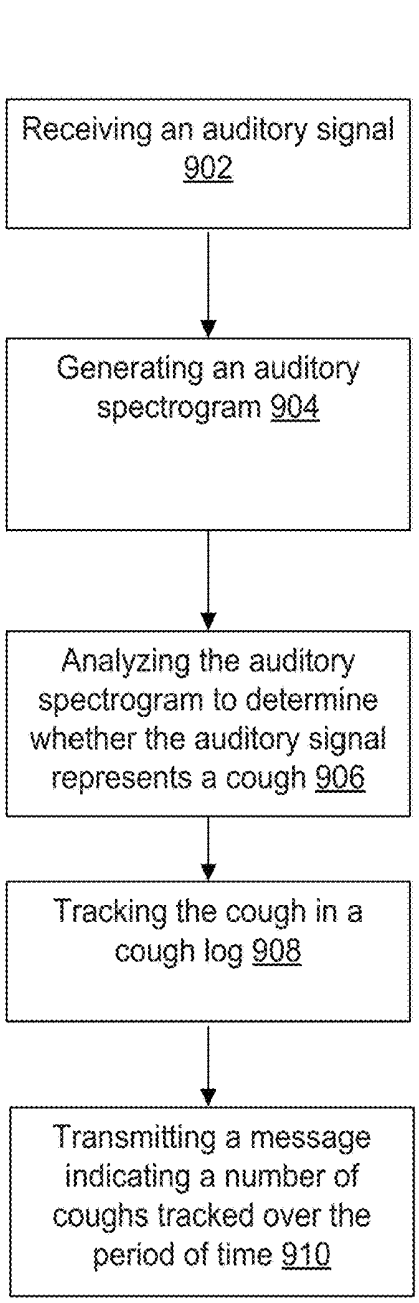
900
Receiving an auditory signal 902
Generating an auditory spectrogram 904
Analyzing the auditory spectrogram to determine whether the auditory signal represents a cough 906
Tracking the cough in a cough log 908
Transmitting a message indicating a number of coughs tracked over the period of time 910

FIG. 9

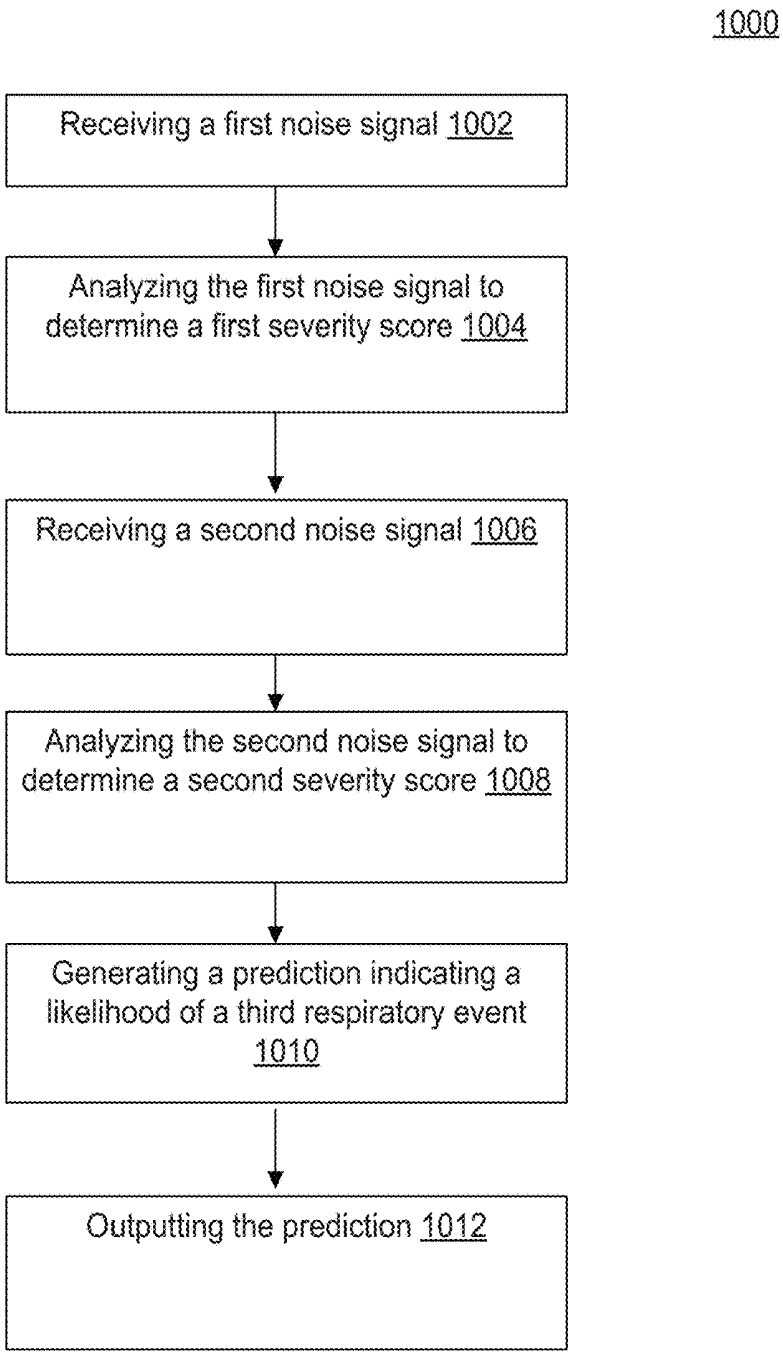
1000
Receiving a first noise signal 1002
Analyzing the first noise signal to determine a first severity score 1004
Receiving a second noise signal 1006
Analyzing the second noise signal to determine a second severity score 1008
Generating a prediction indicating a likelihood of a third respiratory event 1010
Outputting the prediction 1012

FIG. 10

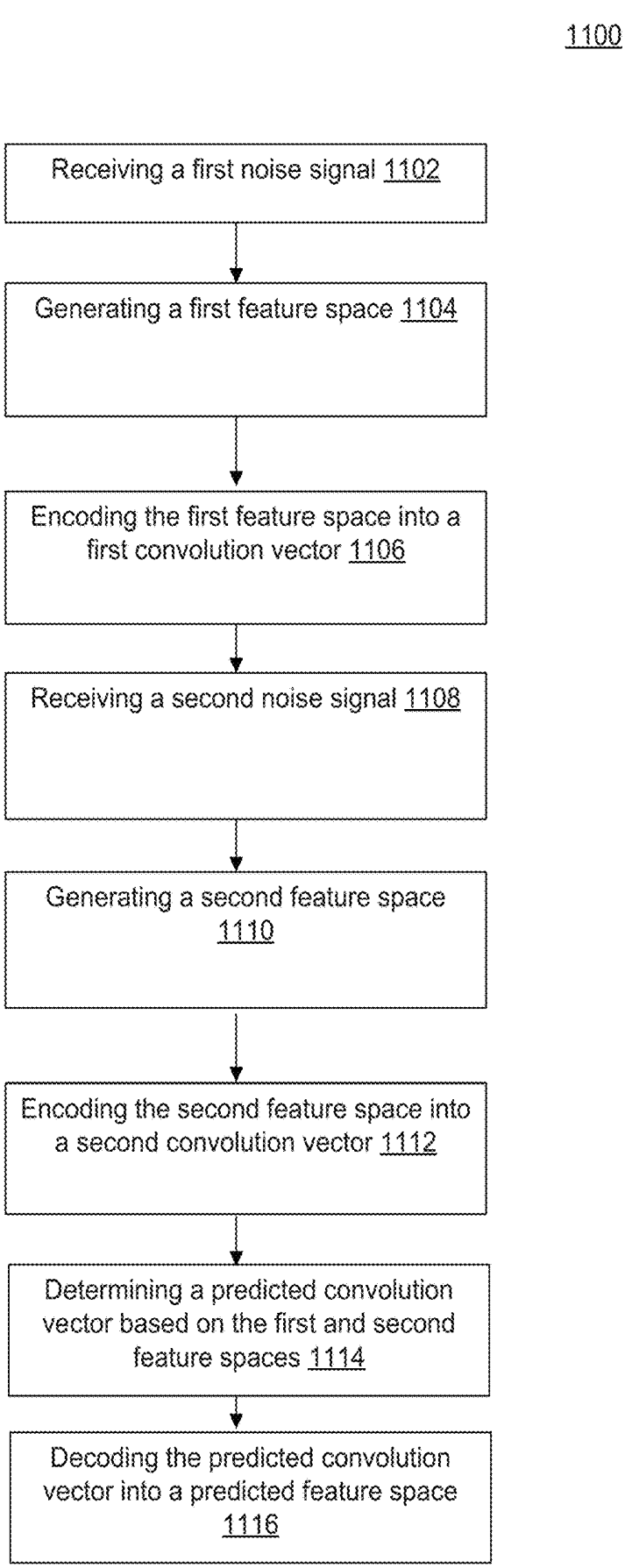
1100
Receiving a first noise signal 1102
Generating a first feature space 1104
Encoding the first feature space into a first convolution vector 1106
Receiving a second noise signal 1108
Generating a second feature space 1110
Encoding the second feature space into a second convolution vector 1112
Determining a predicted convolution vector based on the first and second feature spaces 1114
Decoding the predicted convolution vector into a predicted feature space 1116

FIG. 11

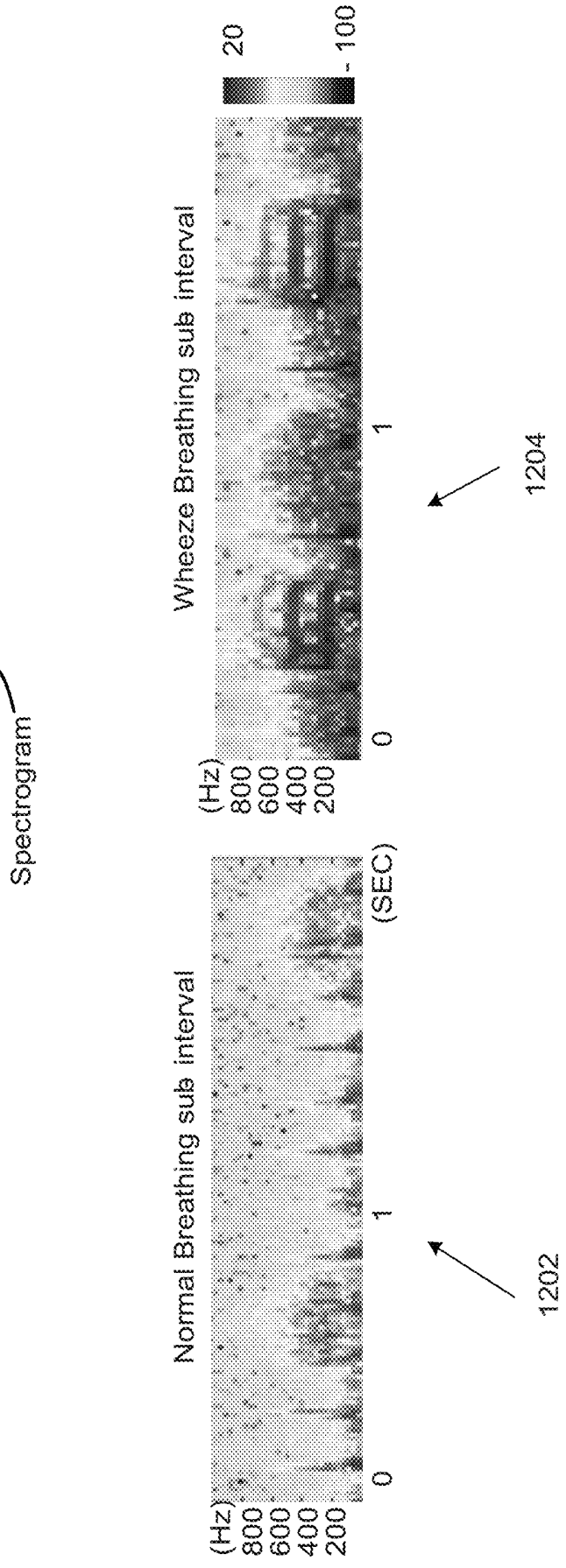
1200
Spectrogram
Wheeze Breathing sub interval
20
- 100
(Hz)
800
600
400
200
0
1
1204
(SEC)
Normal Breathing sub interval
(Hz)
800
600
400
200
0
1
1202

FIG. 12

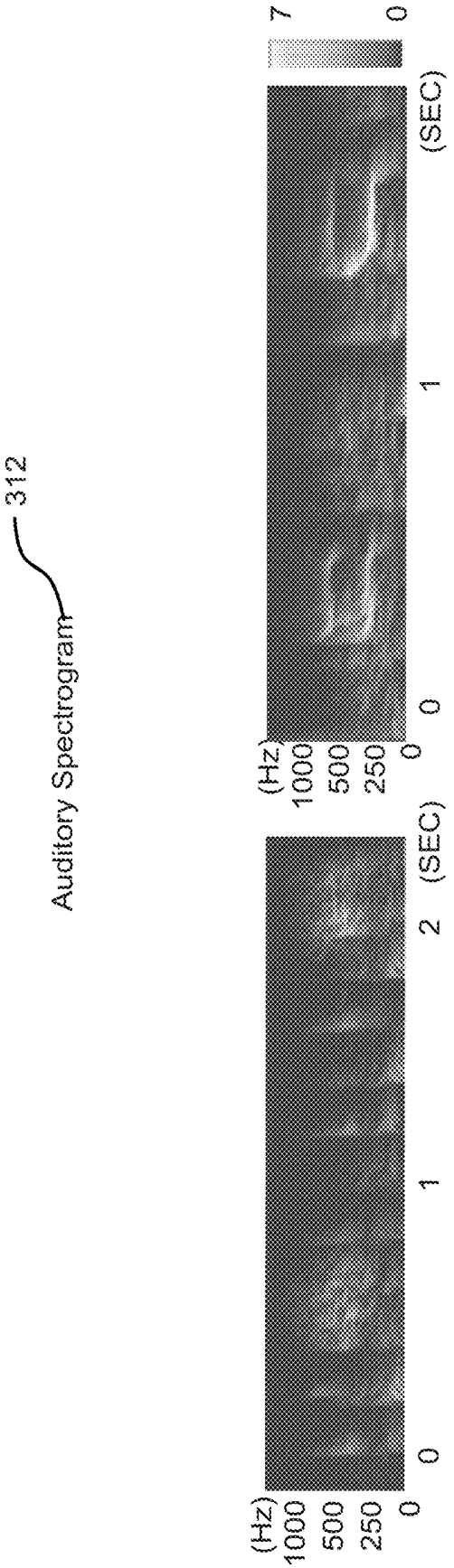
312
Auditory Spectrogram
7
0
(SEC)
(Hz)
1000
500
250
0
0
1
2
(SEC)
(Hz)
1000
500
250
0
0
1

FIG. 13

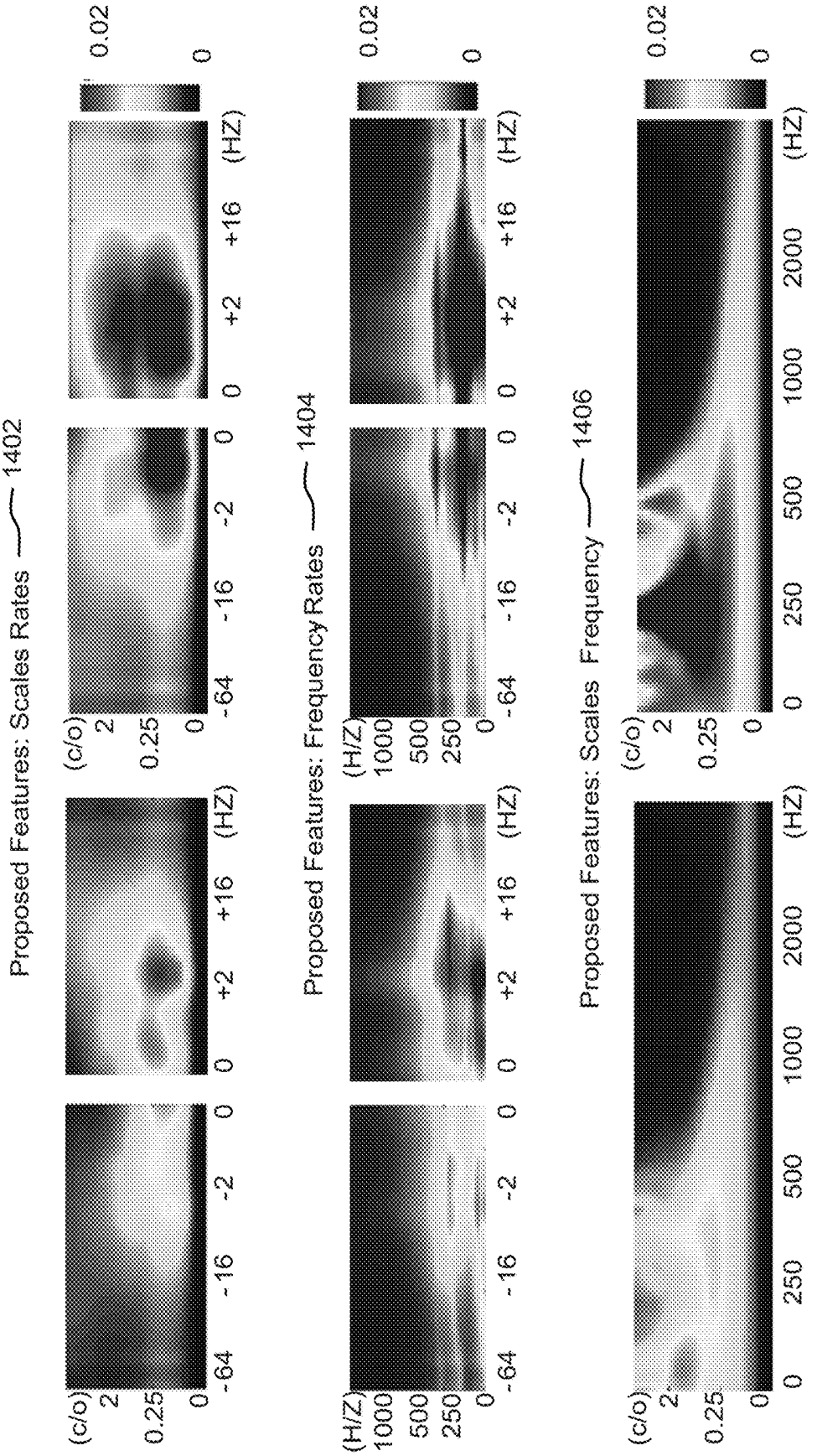
Proposed Features: Scales Rates
1402
Proposed Features: Frequency Rates
1404
Proposed Features: Scales Frequency
1406
(c/o)
(H/Z)
(HZ)
0.02
0

FIG. 14

PREDICTING CHARACTERISTICS OF A FUTURE RESPIRATORY EVENT, AND APPLICATIONS THEREOF

TECHNICAL FIELD

An embodiment relates generally to a digital stethoscope, and more specifically a digital stethoscope for detecting a respiratory abnormality and a method of operation thereof.

BACKGROUND

Respiratory illnesses such as asthma, chronic obstructive pulmonary disease (COPD), bronchitis, emphysema, and pneumonia affect many individuals. The ability to quickly detect and forecast the onset of these conditions, including possible life threatening events associated with these conditions, is of vital importance to those affected. Generally, diagnosis of these respiratory illnesses involves a doctor that listens to patient's breathing using a stethoscope. A stethoscope is an acoustic medical device for auscultation. It typically has a small disc-shaped resonator that is placed against the skin, and a tube connected to two earpieces. However, these traditional stethoscopes are prone to error and require a doctor to be present and to make the diagnosis. The need for a doctor makes daily monitoring for these conditions impractical.

A number of patents and applications have been filed that attempt to deal with these issues. U.S. Pat. No. 9,848,848 describes a digital stethoscope that uses a number of audio filters to control noise and reduce the possibility of error. U.S. Patent Pub. No. 2018/0317876 describes using a classification system, such as a binary support vector machine, to distinguish between those noises that are normal from those that are abnormal.

However, a number of limitations still exist in the art. For example, there is a need to improve real-time performance of the classification algorithm to allow it to be executed in real time and locally on a device that exists at the patient's home. There may be a need to improve the ability to forecast future respiratory future respiratory events. There may be a need to catalog data collected from in-home stethoscopes, while protecting a patient's privacy interest. Currently, a classification system may be able to predict whether a noise is normal or abnormal, but cannot predict a severity of a future respiratory event or the characteristics of that respiratory event. Methods, devices, and systems are needed to address these issues.

SUMMARY

Embodiments disclosed herein improve digital stethoscopes and their application and operation. In a first embodiment, a method detects of a respiratory abnormality using a convolution. The convolution may improve performance, particularly in situations where the detection should occur in real-time. The method involves receiving, from a microphone, an auditory signal. An auditory spectrogram is generated based on the auditory signal. A convolution procedure is performed on the auditory spectrogram to generate one or more convolution values. The convolution values represent a compressed version of a portion of the auditory spectrogram, and the convolution procedure is trained to generate one or more features for detecting the respiratory abnormality. One or more weights trained for detection of the respiratory abnormality are applied to the convolution values. A classification value is generated based on the application of the weights to the convolution values. The classification value indicates whether the auditory signal includes the respiratory abnormality.

In a second embodiment, a method counts coughs for a patient. The method involves receiving from a microphone of a digital stethoscope an auditory signal over a period of time. An auditory spectrogram is generated based on the auditory signal. A control unit of the digital stethoscope analyzes the auditory spectrogram to determine whether the auditory signal represents a cough. The control unit of the digital stethoscope tracks the cough in a cough log. Based on the cough log, a communication unit of the digital stethoscope transmits to a cloud-based service a message indicating a number of coughs tracked over the period of time for storage on a remote server.

In a third embodiment, a method predicts a respiratory event based on a detected trend. The method involves receiving, from a microphone of a digital stethoscope, a first noise signal at a first time. The first noise signal is analyzed to determine a first severity score indicating how severe a first respiratory event of a patient captured in the first noise signal is. A second noise signal captured at a second time is received from the microphone of the digital stethoscope. The second noise signal is analyzed to determine a second severity score indicating how severe a second respiratory event of the patient captured in the second noise signal is. Finally, a prediction is generated indicating a likelihood of a third respiratory event occurring for the patient at a future time based on applying a first weight to the first severity score and a second weight to the second severity score. The first and second weights are trained based on a history of respiratory events.

In a fourth embodiment, a method forecasts characteristics of a future respiratory event. The method involves receiving, from a microphone of a digital stethoscope, a first noise signal. The first noise signal captures a first respiratory event at a first time. A first feature space representing the first noise signal is generated. The first feature space is encoded into a first convolution vector using a convolution procedure. A second noise signal is received, from the microphone of the digital stethoscope. The second noise signal captures a second respiratory event at a second time. A second feature space representing the second noise signal is generated. The second feature space is encoded into a second convolution vector using the convolution procedure. A predicted convolution vector is generated based on the first and second feature spaces. Finally, the predicted convolution vector is decoded into a predicted feature space representing a sound made by the future respiratory event.

In a fifth embodiment, a base station is provided for a digital stethoscope. The base station includes a housing configured to accept the digital stethoscope. The base station includes a wireless charging unit, located within the housing, configured to charge the digital stethoscope when it rests on the exterior of the housing. The wireless charging unit is further configured to detect when the digital stethoscope becomes detached from the housing. A communication unit is coupled to the wireless charging unit. The communication unit is configured to receive a noise signal from the digital stethoscope when the wireless charging unit detects the digital stethoscope becoming detached from the housing and to communicate the respiratory event to a cloud-based service. Finally, a control unit is coupled to the communication unit and is configured to analyze the noise signal for a respiratory event.

Certain embodiments of the invention have other steps or elements in addition to or in place of those mentioned above.

The steps or elements will become apparent to those skilled in the art from a reading of the following detailed description when taken with reference to the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

The accompanying drawings, which are incorporated herein and form a part of the specification, illustrate embodiments of the present disclosure and, together with the description, further serve to explain the principles of the disclosure and to enable a person skilled in the arts to make and use the embodiments.

FIG. **1** is an exemplary digital stethoscope and base station of a system for detecting a respiratory abnormality in an embodiment of the present invention.

FIG. **1**A is an exemplary architecture of the digital stethoscope in an embodiment of the present invention.

FIG. **1**B is an exemplary architecture of the base station in an embodiment of the present invention.

FIG. **2**A is a network diagram of the system for detecting the respiratory abnormality including further components of the digital stethoscope and base station in an embodiment of the present invention.

FIG. **2**B is an exemplary control flow of the system for detecting the respiratory abnormality in an embodiment of the present invention.

FIG. **2**C is a further exemplary architecture of the digital stethoscope in an embodiment of the present invention.

FIG. **2**D is a further exemplary architecture of the base station in an embodiment of the present invention.

FIG. **3** is an exemplary second control flow for detection of the respiratory abnormality in an embodiment of the present invention.

FIG. **4**A is an exemplary depiction of the functioning of a receiver module and a subtraction module in an embodiment of the present invention.

FIG. **4**B is an exemplary depiction of the functioning of a filter module and the generation of an auditory spectrogram in an embodiment of the present invention.

FIG. **4**C is an exemplary depiction of the functioning of a convolution neural network module in an embodiment of the present invention.

FIG. **5**A is an exemplary feature map used to predict a respiratory event or respiratory condition in the future in an embodiment of the present invention.

FIG. **5**B is an exemplary depiction of an LSTM process used to predict a third respiratory event occurring for the patient at a future time in an embodiment of the present invention.

FIG. **6** is an exemplary third control flow for forecasting characteristics of a future respiratory event or respiratory condition in an embodiment of the present invention.

FIG. **7** is an exemplary depiction of the third control flow for forecasting characteristics of a future respiratory event or respiratory condition in an embodiment of the present invention.

FIG. **8** is an exemplary method of operating the computing system in an embodiment of the present invention.

FIG. **9** is a further exemplary method of operating the system in an embodiment of the present invention.

FIG. **10** is a further exemplary method of operating the system in an embodiment of the present invention.

FIG. **11** is a further exemplary method of operating the system in an embodiment of the present invention.

FIG. **12** depicts exemplary spectrograms representing breathing patterns in an embodiment of the present invention.

FIG. **13** depicts an exemplary auditory spectrogram in an embodiment of the present invention.

FIG. **14** depicts an exemplary feature space in an embodiment of the present invention.

In the drawings, like reference numbers generally indicate identical or similar elements. Additionally, generally, the left-most digit(s) of a reference number identifies the drawing in which the reference number first appears.

DETAILED DESCRIPTION

Digital Stethoscope and Base Station

FIG. **1** shows an exemplary digital stethoscope **110** and base station **118** of a system **100** for detecting a respiratory abnormality in an embodiment of the present invention. The respiratory abnormality refers to irregularities in the respiration patterns of a patient. The respiratory abnormality can indicate the onset of a respiratory condition in a patient, for example a respiratory disease such as asthma, chronic obstructive pulmonary disease (COPD), bronchitis, emphysema, pneumonia, or a combination thereof. The respiratory abnormality can be indicated by the occurrence of a respiratory event, such as a large number of coughs within a period of time by a patient, a wheeze, a crackle, or a cough that has a sound frequency outside an audible frequency expected from a patient, or a combination thereof. The system **100** can use the digital stethoscope **110** and the base station **118** to detect the respiratory abnormality, or predict a respiratory event or respiratory condition in the future.

The digital stethoscope **110** is an acoustic device for detecting and analyzing noises from a patient's body. The patient can be, for example, a human or an animal. The noises, from the patient's body can be for example a cough, a wheeze, a crackle, a breathing pattern, a heartbeat, a chest motion representing a patient's respiratory cycle, or a combination thereof.

The digital stethoscope **110** can further generate information based on the detection, amplification, and analysis of the noises. For example, in one embodiment, the digital stethoscope **110** can generate a value representing or classifying the noises detected.

In one embodiment, the classification can include classifications such as "normal" or "abnormal." "Normal" refers to the classification of sounds falling within an expected frequency range to be heard from the patient. "Abnormal" refers to the classification of sounds falling outside an expected frequency range to be heard from the patient. Classification can be done by analyzing the noises, by for example, filtering, comparing, processing, or a combination thereof, the noises, against threshold values, stored values, acoustic models, machine learned trained data, machine learning processes, or a combination thereof, and putting the noises into categories, for example "normal" or "abnormal" based on the noises being within a range of frequencies expected to be heard from the patient. The collection, filtering, comparison, and classification of the noises by the digital stethoscope **110** will be discussed further below.

The digital stethoscope **110** can include one or more components. For example, in one embodiment, the digital stethoscope **110** can include a display unit **102**, one or more microphones **106**, and a first housing **108**. The display unit **102** can be any graphical user interface such as a display, a projector, a video screen, a touch screen, or any combination thereof that can present information detected or generated by the digital stethoscope **110** for visualization by a user of the

system **100**. The display unit **102** can enable the visual presentation of information detected or generated by the digital stethoscope **110**.

For example, in one embodiment, the display unit **102** can enable the visual presentation of the noises detected, by for example, displaying a plot of the sound frequencies detected over time, displaying a decibel level of the sounds detected, or displaying a value or visual indicator representing the classification of the noises generated, for example "normal" or "abnormal." In one embodiment, if the digital stethoscope **110** classifies a noise as being "abnormal," the display unit **102** can display an indicator, such as a red colored light, or a message indicating that the noise is "abnormal." Alternatively, if the digital stethoscope **110** classifies the noise as being "normal," the display unit **102** can display an indicator, such as a green colored light, or a message indicating that the noise is "normal."

The display unit **102** can further present other information generated by the digital stethoscope **110**, such as a power level indicator indicating how much power the digital stethoscope has, a volume indicator indicating the volume level of output noises being output by the digital stethoscope **110**, or a network connectivity indicator indicating whether the digital stethoscope **110** is connected to a device or computer network such as a wireless communication network or wired communication network. The aforementioned information are merely exemplary of the types of information that the display unit **102** can display, and are not meant to be limiting.

In one embodiment, the display unit **102** can further include one or more buttons **126** that can be used by the user of the system **100** to enable interaction with the digital stethoscope **110**. For example, the buttons **126** can provide functionality such as powering the digital stethoscope **110** on or off or enable the digital stethoscope **110** to start or stop recording the noises.

In one embodiment, the digital stethoscope **110** can further include one or more microphones **106**A and B. The microphones **106**A and B enable the digital stethoscope **110** to detect and convert the noises into electrical signals for processing by the digital stethoscope **110**, or a further device such as the base station **118**. Microphone **106**A is mounted on a perimeter side of stethoscope **110** to detect noises external to the patient's body. The noises originating from external to the patient's body can be for example background noise, white noise, or a combination thereof. Microphone **106**B may be mounted on a side reverse of display **102** and may detect noises originating from the patient's body.

The microphones **106**A and B can be standalone devices or can be arranged in an array configuration, where the microphones **106** operate in tandem to detect the noises. In one embodiment, each microphone in the array configuration **104** can serve a different purpose. For example, each microphone in the array configuration **104** can be configured to detect and convert into electrical signals the noises at different frequencies or within different frequency ranges such that each of the microphones **106** can be configured to detect specific noises. The noises detected by the microphones **106** can be used to generate the values for classifying the noises as "normal" or "abnormal," and can be further used to predict the respiratory event or respiratory condition in the future.

The digital stethoscope **110** can further have a first housing **108** enclosing the components of the digital stethoscope **110**. The first housing **108** can separate components of the digital stethoscope **110** contained within from other components external to the first housing **108**. For example, the first housing **108** can be a case, a chassis, a box, or a console. In one embodiment, for example, the components of the digital stethoscope **110** can be contained within the first housing **108**. In another embodiment, some components of the digital stethoscope **110** can be contained within the first housing **108** while other components, such as the display **102**, the microphones **106**, the buttons **126**, or a combination thereof, can be accessible external to the first housing **108**. The aforementioned are merely examples of components that can be contained in or on the first housing **108** and are not meant to be limiting. Further discussion of other components of the digital stethoscope **110** will be discussed below.

The system **100** can further include a base station **118**. The base station **118** is a special purpose computing device that enables computation and analysis of the noises obtained by the digital stethoscope **110** in order to detect the respiratory abnormality, or to predict the respiratory event or respiratory condition in the future. The base station **118** can provide additional or higher performance processing power compared to the digital stethoscope **110**. In one embodiment, the base station **118** can work in conjunction with the digital stethoscope **110** to detect, amplify, adjust, and analyze noises from a patient's body by, for example, providing further processing, storage, or communication capabilities to the digital stethoscope **110**. In another embodiment, the base station **118** can work as a standalone device to detect, amplify, adjust, and analyze noises to detect the respiratory abnormality, or to predict the respiratory event or respiratory condition in the future.

The base station **118** can analyze of the noises captured by stethoscope **110**. For example, in one embodiment, the base station **118** can generate values classifying the noises detected as "normal" or "abnormal." The collection, filtering, comparison, and classification of the noises by the base station **118** will be discussed further below.

The base station **118** can include one or more components. For example, in one embodiment, the base station **118** can include a charging pad **114**, one or more air quality sensors **116**, a contact sensor **120**, and a second housing **112**. The charging pad **114** can enable the electric charging of the digital stethoscope **110**, through inductive charging where an electromagnetic field is used to transfer energy between the charging pad **114** and a further device, such as the digital stethoscope **110**, using electromagnetic induction.

In one embodiment, the charging pad **114** can enable electric charging of the digital stethoscope **110** upon detecting contact or coupling, via the contact sensor **120**, between the digital stethoscope **110** and the charging pad **114**. For example, in one embodiment, if the digital stethoscope **110** is coupled to the charging pad **114** by physical placement of the digital stethoscope **110** on the charging pad **114**, the contact sensor **120** can detect a weight or an electromagnetic signal produced by the digital stethoscope **110** on the charging pad **114**, and upon sensing the weight or the electromagnetic signal enable the induction process to transfer energy between the charging pad **114** and the digital stethoscope **110**.

In another embodiment, if the digital stethoscope **110** is coupled to the charging pad **114** by placing the digital stethoscope **110** in proximity of the charging pad **114** without physically placing the digital stethoscope **110** on the charging pad **114**, the contact sensor **120** can detect an electric current or a magnetic field from one or more components of the digital stethoscope **110** and enable the

induction process to transfer energy between the charging pad **114** and the digital stethoscope **110**.

The contact sensor **120** is a device that senses mechanical or electromagnetic contact and gives out signals when it does so. The contact sensor **120** can be, for example, a pressure sensor, a force sensor, strain gauges, piezoresistive/piezoelectric sensors, capacitive sensors, elastoresistive sensors, torque sensors, linear force sensors, an inductor, other tactile sensors, or a combination thereof configured to measure a characteristic associated with contact or coupling between the digital stethoscope **110** and the charging pad **114**. Accordingly, the contact sensor **120** can output a contact measure **122** that represents a quantified measure, for example, a measured force, a pressure, an electromagnetic force, or a combination thereof corresponding to the coupling between the digital stethoscope **110** and the charging pad **114**. For example, the contact measure **122** can detect one or more force or pressure readings associated with forces applied by the digital stethoscope **110** on the charging pad **114**. The contact measure **122** can further detect one or more electric current or magnetic field readings associated with placing the digital stethoscope **110** in proximity of the charging pad **114**.

In one embodiment, the base station **118** can further include one or more air quality sensors **116**. The air quality sensors **116** are devices that detect and monitor the presence of air pollution in a surrounding area. Air pollution refers to the presence of or introduction into the air of a substance which has harmful or poisonous effects on the patient's body. For example, the air quality sensors **116** can detect the presence of particulate matter or gases such as ozone, carbon monoxide, sulfur dioxide, nitrous oxide, or a combination thereof that can be poisonous to the patient's body, and in particular poisonous to the patient's respiratory system.

In one embodiment, based on the air quality sensors **116** detecting the presence of air pollution, the base station **118** can determine whether the amount of air pollution poses a health risk to the patient by, for example, comparing the levels of air pollution to a pollution threshold **124** to determine whether the levels of air pollution in the surrounding area of the base station **118** pose a health risk to the patient. The pollution threshold **124** refers to a pre-determined level for particulate matter or gases measured in micrograms per cubic meter (m/m3), parts per million (ppm), or parts per billion (ppb), that if exceeded poses a health risk to the patient

For example, in one embodiment, if the air quality sensors **116** detect the presence of sulfur dioxide above 75 ppb in the air surrounding the base station **118**, the base station **118** can determine that the air pollution in the surrounding area poses a health risk to the patient. The detection of air pollution can further be used for detecting the respiratory abnormality or to predict the respiratory event or respiratory condition in the future in the patient by allowing the system **100** to determine what factors are contributing to the "normal" or "abnormal" classification of the noises, or what factors are contributing to the data detected and generated by the system **100** which can be used to predict a respiratory event or respiratory condition in the future.

The base station **118** can further have a second housing **112** enclosing the components of the base station **118**. The second housing **112** can separate components of the base station **118** contained within, from other components external to the second housing **112**. For example, the second housing **112** can be a case, a chassis, a box, or a console. In one embodiment, for example, the components of the base station **118** can be contained within the second housing **112**. In another embodiment, some components of the base station **118** can be contained within the second housing **112** while other components, such as the charging pad **114** or the air quality sensors **116** can be accessible external to the second housing **112**. The aforementioned are merely examples of components that can be contained in or on the second housing **112** and are not meant to be limiting. Further discussion of other components of the base station **118** will be discussed below.

Referring now to FIG. **1**A, therein is shown an exemplary architecture of the digital stethoscope **110** in an embodiment. In various embodiments, the digital stethoscope **110** can include, alternatively or additionally:

- a grip ring **140** located around a first upper portion **142** of the first housing **108** which provides a gripping surface for a user of the system **100** to hold the digital stethoscope **110**;
- a glass lens **144** of the display unit **102**, which protects the display components, such as for example liquid crystal displays (LCD) of the display unit **102**. The glass lens **144** can sit on top of a housing gasket **146**, which stabilizes and holds the glass lens **144**;
- a display housing unit **148**, on which the housing gasket **146** sits and which contains the components of the display unit **102**, such as for example the LCDs;
- a flex backing **150** which on which the display housing **148** sits and which provides stability for the display housing **148**;
- a flex assembly **152**, on which the flex backing **150** sits and which provides stability for the flex backing **150**;
- a retainer clip **154** which holds the flex assembly **152** in place;
- a battery housing **156**, to which a battery board **158** can couple, and which can hold battery components of the digital stethoscope **110**;
- a first printed circuit board assembly **164**, which can hold the circuitry, including any processors, memory components, active and passive components, or a combination thereof, of the digital stethoscope **110**;
- one or more first screws **162** that couples the first printed circuit board assembly **164** to the other components of the digital stethoscope **110**;
- an audio jack **168** to allow output of noise signals detected by the digital stethoscope **110**;
- a microphone assembly **170**, on which the microphones **106** can be housed;
- components such as an O-ring **172** and one or more coils **166** that couple the microphone assembly **170** to the first printed circuit board assembly **164**.
- a first bottom portion **174** of the first housing **108** on which the microphone assembly **170** sits;
- a diaphragm membrane **182** which forms the bottom surface of the digital stethoscope **110**, and which is coupled to the first bottom portion **174** of the first housing **108** with one or more second screws **176** and one or more washers **178**; and
- a diaphragm ring **180** coupled to the diaphragm membrane **182**, which provides a gripping surface for the first bottom portion **174** of the digital stethoscope **110**, such that the digital stethoscope **110** does not slip when placed on a surface.

The aforementioned components are merely exemplary and represent one embodiment of the digital stethoscope **110**.

Referring now to FIG. **1**B, that figure illustrates an exemplary architecture of the base station **118** in an embodi-

ment of the present invention. In various embodiments, the base station **118** can include, alternatively or additionally:

- a second upper portion **134** of the second housing **112**;
- a second printed circuit board assembly **130** which can hold the circuitry, including any processors, memory components, active and passive components, or a combination thereof, of the base station **118**;
- one or more third screws **132** that couples the second printed circuit board assembly **130** to the second upper portion **134** of the second housing **112** via one or more second connectors **126**;
- one or more coils **128**, coupled to the second printed circuit board assembly **130**, which can detect the weight or the electromagnetic signal produced by the digital stethoscope **110** on the base station **118**;
- a second bottom portion **136** of the second housing **112**, which forms the bottom surface of the base station **118**; and
- one or more bumpers **138** to cover and protect the third screws **132**.

The aforementioned components are merely exemplary and represent one embodiment of the base station **118**.

Referring now to FIG. **2**A, that figure shows a network diagram of the system **100** for detecting the respiratory abnormality including further components of the digital stethoscope **110** and base station **118** in an embodiment of the present invention. FIG. **2**A shows an embodiment where the digital stethoscope **110** is connected to the base station **118** through a device or computer network, such as a wireless or wired network, via a communication path **246**. FIG. **2**A further shows an embodiment where a remote server **242** is connected to the digital stethoscope **110** and the base station **118** via the communication path **246**.

The remote server **242** can provide additional or higher performance processing power compared to the digital stethoscope **110** and the base station **118**. In one embodiment, the remote server **242** can work in conjunction with the digital stethoscope **110**, the base station **118**, or a combination thereof to analyze the detected noises. For example, in one embodiment, the remote server **242** can provide some or all of the processing power of the system **100** to process the information detected or generated by the digital stethoscope **110**, the base station **118**, or a combination thereof.

In one embodiment, the remote server **242** can further provide additional storage capabilities to the digital stethoscope **110**, the base station **118**, or a combination thereof by enabling the storage of information detected or generated by the digital stethoscope **110**, the base station **118**, or a combination thereof, and provide access to the digital stethoscope **110**, the base station **118**, or a combination thereof of the information for later use. For example, in one embodiment, the remote server **242** can store the noises detected by the digital stethoscope **110**, the base station **118**, or a combination thereof for later retrieval by the digital stethoscope **110**, the base station **118**, or a combination thereof.

In one embodiment, the remote server **242** can further provide information, such as the pre-determined threshold values, stored values, acoustic models, machine learned trained data, machine learning processes, configuration data, or a combination thereof to the digital stethoscope **110**, the base station **118**, or a combination thereof to allow the digital stethoscope **110**, the base station **118**, or a combination thereof to perform some or all of their functions. For example, the remote server **242** can store and provide access to the pollution threshold **124** to the base station **118** to allow the base station **118** to perform the computations and comparisons needed to detect and monitor the presence of air pollution in the surrounding area.

In one embodiment, the remote server **242** can further provide configuration data, such as software updates, including updated acoustic models, machine learned trained data, machine learning processes, or a combination thereof to the digital stethoscope **110**, the base station **118**, or a combination thereof to allow the digital stethoscope **110**, the base station **118**, or a combination thereof to perform computations and analysis in order to determine the classifications of the noises and to detect the respiratory abnormality or to predict the respiratory event or respiratory condition in the future.

The remote server **242** can be any of a variety of centralized or decentralized computing devices. For example, the remote server **242** can be a laptop computer, a desktop computer, grid-computing resources, a virtualized computing resource, cloud computing resources, routers, switches, peer-to-peer distributed computing devices, a server, or a combination thereof. The remote server **242** can be centralized in a single room, distributed across different rooms, distributed across different geographical locations, or embedded within a telecommunications network. The remote server **242** can couple with the communication path **246** to communicate with the digital stethoscope **110**, the base station **118**, or a combination thereof.

The communication path **246** can span and represent a variety of networks and network topologies. For example, the communication path **246** can include wireless communication, wired communication, optical communication, ultrasonic communication, or a combination thereof. For example, satellite communication, cellular communication, Bluetooth, Infrared Data Association standard (IrDA), wireless fidelity (WiFi), and worldwide interoperability for microwave access (WiMAX) are examples of wireless communication that can be included in the communication path **246**. Cable, Ethernet, digital subscriber line (DSL), fiber optic lines, fiber to the home (FTTH), and plain old telephone service (POTS) are examples of wired communication that can be included in the communication path **246**. Further, the communication path **246** can traverse a number of network topologies and distances. For example, the communication path **246** can include direct connection, personal area network (PAN), local area network (LAN), metropolitan area network (MAN), wide area network (WAN), or a combination thereof.

Also for illustrative purposes, the system **100** is shown with the digital stethoscope **110**, the base station **118**, and the remote server **242** as end points of the communication path **246**, although it is understood that the system **100** can have a different partition between the digital stethoscope **110**, the base station **118**, the remote server **242**, and the communication path **246**. For example, the digital stethoscope **110**, the base station **118**, and the remote server **242**, or a combination thereof can also function as part of the communication path **246**.

In one embodiment, the digital stethoscope **110** can include further components including a first control unit **210**, a first storage unit **218**, a first communication unit **204**, the first display unit **102**, the microphone array **104**, a first location unit **256**, and a battery **288**. The first control unit **210** can include a first control interface **212**. The first control unit **210** can execute a first software **224** to provide the intelligence of the system **100**. The first control unit **210** can be implemented in a number of different ways. For example, the first control unit **210** can be a first processor **214**, a first

field programmable gate array (FPGA) **216**, an application specific integrated circuit (ASIC), an embedded processor, a microprocessor, a hardware control logic, a hardware finite state machine (FSM), a digital signal processor (DSP), or a combination thereof.

The first control interface **212** can be used for communication between the first control unit **210** and other components of the digital stethoscope **110**. The first control interface **212** can also be used for communication that is external to the digital stethoscope **110**. The first control interface **212** can receive information from the other components of the digital stethoscope **110** or from external sources, or can transmit information to the other components of the digital stethoscope **110** or to external destinations. The external sources and the external destinations refer to sources and destinations external to the digital stethoscope **110**. The first control interface **212** can be implemented in different ways and can include different implementations depending on which components or external units are being interfaced with the first control interface **212**. For example, the first control interface **212** can be implemented with a pressure sensor, an inertial sensor, a microelectromechanical system (MEMS), optical circuitry, waveguides, wireless circuitry, wireline circuitry such as a bus interface, an application programming interface (API), or a combination thereof.

The first storage unit **218** can store the first software **224** to provide the intelligence of the system **100**. For illustrative purposes, the first storage unit **218** is shown as a single element, although it is understood that the first storage unit **218** can be a distribution of storage elements. Also for illustrative purposes, the system **100** is shown with the first storage unit **218** as a single hierarchy storage system, although it is understood that the system **100** can have the first storage unit **218** in a different configuration. For example, the first storage unit **218** can be formed with different storage technologies forming a memory hierarchal system including different levels of caching, main memory, rotating media, or off-line storage. The first storage unit **218** can be a volatile memory, a nonvolatile memory, an internal memory, an external memory, or a combination thereof. For example, the first storage unit **218** can be a nonvolatile storage such as non-volatile random access memory (NVRAM), Flash memory, disk storage, or a volatile storage such as static random access memory (SRAM) or a first dynamic random access memory (DRAM) **254**.

The first storage unit **218** can include a first storage interface **220**. The first storage interface **220** can be used for communication between the first storage unit **218** and other components of the digital stethoscope **110**. The first storage interface **220** can also be used for communication that is external to the digital stethoscope **110**. The first storage interface **220** can receive information from the other components of the digital stethoscope **110** or from external sources, or can transmit information to the other components or to external destinations. The first storage interface **220** can include different implementations depending on which components or external units are being interfaced with the first storage unit **218**. The first storage interface **220** can be implemented with technologies and techniques similar to the implementation of the first control interface **212**.

The first communication unit **204** can enable external communication to and from the digital stethoscope **110**. For example, the first communication unit **204** can permit the digital stethoscope **110** to communicate with the remote server **242**, the base station **118**, an attachment, such as a peripheral device, and the communication path **246**. The first communication unit **204** can also function as a communication hub allowing the digital stethoscope **110** to function as part of the communication path **246** and not be limited to be an end point or terminal unit to the communication path **246**. The first communication unit **204** can include active and passive components, such as microelectronics or an antenna, for interaction with the communication path **246**. The first communication unit **204** can further have circuitry, such as a first Bluetooth circuit **206**, a wireless fidelity (WiFi) circuit, a Near Field Communication (NFC) circuit, or a combination thereof for interaction with the communication path **246**.

The first communication unit **204** can include a first communication interface **208**. The first communication interface **208** can be used for communication between the first communication unit **204** and other components of the digital stethoscope **110**. The first communication interface **208** can receive information from the other components of the digital stethoscope **110** or from external sources, or can transmit information to the other components or to external destinations. The first communication interface **208** can include different implementations depending on which components are being interfaced with the first communication unit **204**. The first communication interface **208** can be implemented with technologies and techniques similar to the implementation of the first control interface **212**. The first communication unit **204** can couple with the communication path **246** to send information to the remote server **242**, the base station **118**, or a combination thereof.

The first location unit **256** can generate location information, current heading, and current speed and acceleration of the digital stethoscope **110**, as examples. The first location unit **256** can be implemented in many ways. For example, the first location unit **256** can include components, such as a GPS receiver, an inertial navigation system, a cellular-tower location system, a pressure location system, an accelerometer **226**, a gyroscope, or any combination thereof. The components can be used in conjunction with other components of the digital stethoscope **110** to detect movements or the location of the patient. For example, in one embodiment, the accelerometer **226** can be used to detect whether the patient or a portion of the patient's body is moving, for example to detect a chest motion representing a patient's respiratory cycle. For example, if the digital stethoscope **110** is placed on the patient's chest, the accelerometer **226** can detect the up and down movement of the patient's chest to determine the frequency and speed at which the patient's chest is moving. In one embodiment, the location unit **256** can further be used to detect the physical location of the digital stethoscope **110**, such as the geographic location. For example, the location unit **256** can detect the location of the digital stethoscope **110** by using the accelerometer **226** in conjunction with the other components, and determine that a patient may be physically moving from one geographic location to another.

In one embodiment, the detection of the movement can generate information and data regarding the noises detected by the digital stethoscope **110**. For example, if rapid movement of the digital stethoscope **110** is detected and the digital stethoscope **110** detects high frequency noises at the same time, the digital stethoscope **110** can determine that there is high likelihood that the patient may be moving excessively and can further determine that some of the noise generated by the movement should be removed or filtered because it constitutes unwanted background noise. The information detected as a result of the movement can further be used by the digital stethoscope **110** to adjust and analyze the noises, by for example using the information to amplify certain

frequencies of the noises that are desired or necessary for the detection of the respiratory abnormality or to reduce or suppress certain frequencies of the noises that are unwanted and not necessary for the detection of the respiratory abnormality. As a result, the digital stethoscope **110** can reduce noise and amplify the noises to further improve the accuracy when detecting the respiratory abnormality, or to predict a respiratory event or respiratory condition at a future time.

The first location unit **256** can include a first location interface **258**. The first location interface **258** can be used for communication between the first location unit **256** and other components of the digital stethoscope **110**. The first location interface **258** can also be used for communication that is external to the digital stethoscope **110**. The first location interface **258** can be implemented with technologies and techniques similar to the implementation of the first control interface **212**.

The battery **288** is the power source for the digital stethoscope **110**. In one embodiment, the battery **288** can include one or more electrochemical cells with external connections provided to power the digital stethoscope **110**. The electrochemical cells can include primary or non-rechargeable cells, secondary or rechargeable cells, or a combination thereof. For example, in one embodiment, the electrochemical cells can include secondary cells that can be charged wirelessly using electromagnetic induction. In one embodiment, electrochemical cells can include primary cells such as alkaline batteries, lithium batteries, or a combination thereof.

In one embodiment, the base station **118** can include further components including a second control unit **236**, a second storage unit **248**, a second communication unit **228**, and sensor unit **202**. The second control unit **236** can include a second control interface **238**. The second control unit **236** can execute a second software **252** to provide the intelligence of the system **100**. The second software **252** can operate independently or in conjunction with the first software **224**. The second control unit **236** can provide additional performance compared to the first control unit **210**. The second control unit **236** can be a second processor **240**, a second field programmable gate array (FPGA) **244**, an application specific integrated circuit (ASIC), an embedded processor, a microprocessor, a hardware control logic, a hardware finite state machine (FSM), a digital signal processor (DSP), or a combination thereof.

The second control unit **236** can include a second control interface **238**. The second control interface **238** can be used for communication between the second control unit **236** and other components of the base station **118**. The second control interface **238** can also be used for communication that is external to the base station **118**. The second control interface **238** can receive information from the other components of the base station **118** or from external sources, or can transmit information to the other components of the base station **118** or to external destinations. The external sources and the external destinations refer to sources and destinations external to the base station **118**. The second control interface **238** can be implemented in different ways and can include different implementations depending on which components or external units are being interfaced with the second control interface **238**. For example, the second control interface **238** can be implemented with a pressure sensor, an inertial sensor, a microelectromechanical system (MEMS), optical circuitry, waveguides, wireless circuitry, wireline circuitry such as a bus interface, an application programming interface (API), or a combination thereof.

The second storage unit **248** can be sized to provide additional storage capacity to supplement the first storage unit **218**. For illustrative purposes, the second storage unit **248** is shown as a single element, although it is understood that the second storage unit **248** can be a distribution of storage elements. Also for illustrative purposes, the system **100** is shown with the second storage unit **248** as a single hierarchy storage system, although it is understood that the system **100** can have the second storage unit **248** in a different configuration. For example, the second storage unit **248** can be formed with different storage technologies forming a memory hierarchal system including different levels of caching, main memory, rotating media, or off-line storage. The second storage unit **248** can be a volatile memory, a nonvolatile memory, an internal memory, an external memory, or a combination thereof. For example, the second storage unit **248** can be a nonvolatile storage such as non-volatile random access memory (NVRAM), Flash memory, disk storage, or a volatile storage such as static random access memory (SRAM) or a second dynamic random access memory (DRAM) **222**.

The second storage unit **248** can include a second storage interface **250**. The second storage interface **250** can be used for communication between the second storage unit **248** and other components of the base station **118**. The second storage interface **250** can also be used for communication that is external to the base station **118**. The second storage interface **250** can receive information from the other components of the base station **118** or from external sources, or can transmit information to the other components or to external destinations. The second storage interface **250** can include different implementations depending on which components or external units are being interfaced with the second storage unit **248**. The second storage interface **250** can be implemented with technologies and techniques similar to the implementation of the second control interface **238**.

The second communication unit **228** can enable external communication to and from the base station **118**. For example, the second communication unit **228** can permit the base station **118** to communicate with the digital stethoscope **110**, the remote server **242**, an attachment, such as a peripheral device, and the communication path **246**. The second communication unit **228** can also function as a communication hub allowing the base station **118** to function as part of the communication path **246** and not be limited to be an end point or terminal unit to the communication path **246**. The second communication unit **228** can include active and passive components, such as microelectronics or an antenna, for interaction with the communication path **246**. The second communication unit **228** can further have circuitry, such as a second Bluetooth circuit **230**, a wireless fidelity (WiFi) circuit, a Near Field Communication (NFC) circuit, an internet-of-things (IoT) modem **232**, or a combination thereof for interaction with the communication path **246**.

The second communication unit **228** can include a second communication interface **234**. The second communication interface **234** can be used for communication between the second communication unit **228** and other components of the base station **118**. The second communication interface **234** can receive information from the other components of the base station **118** or from external sources, or can transmit information to the other components or to external destinations. The second communication interface **234** can include different implementations depending on which components are being interfaced with the second communication unit **228**. The second communication interface **234** can be imple-

mented with technologies and techniques similar to the implementation of the second control interface **238**.

The sensor unit **202** can enable the base station **118** to obtain one or more sensed readings **286** used to perform one or more of the base station's **118** functions. The sensed readings **286** can include information or data obtained by the sensor unit **202**, the purpose of which is to detect events or changes in the environment of the base station **118** and to send the information to components of the base station **118**, the digital stethoscope **110**, the remote server **242**, external devices such as a peripheral device, or a combination thereof to facilitate the functionality of the system **100**. The sensed readings **286** can include the contact measure **122** or the amount of air pollution in the surrounding area. In one embodiment, the sensor unit **202** can include the air quality sensors **116**, the contact sensor **120**, or a combination thereof.

The sensor unit **202** can include a sensor unit interface **260**. The sensor unit interface **260** can be used for communication between the sensor unit **202** and other components of the base station **118**. The sensor unit interface **260** can also be used for communication that is external to the base station **118**. The sensor unit interface **260** can receive information from the other components of the base station **118** or from external sources, or can transmit information to the other components of the base station **118** or to external destinations. The sensor unit interface **260** can include different implementations depending on which components of the base station **118** or external units are being interfaced with the sensor unit **202**. The sensor unit interface **260** can be implemented with technologies and techniques similar to the implementation of the second control interface **238**.

Referring now to FIG. **2**B, that figure shows an exemplary control flow **200** of the system **100** for detecting the respiratory abnormality in an embodiment. In one embodiment, one or more auditory signals **262** can be detected by the digital stethoscope **110** using the microphones **106**. The auditory signals **262** can include the noises from the patient's body or from external to the patient's body. By way of example, FIG. **2**B depicts two auditory signals **262**, where "C1" represents a cough, crackle, or wheeze originating from the patient's body and "N1" represents a noise signal resulting from noises generated external to the patient's body, for example background noise from a patient's environment. In one embodiment, the auditory signals **262** can be saved in a sound file **290**, such as a .wav file generated by the digital stethoscope **110**. In one embodiment, once the auditory signals **262** are detected and saved in the sound file **290**, the digital stethoscope **110** can amplify, adjust, and analyze the auditory signals **262** in the sound file **290**, by for example, subtracting, suppressing, or filtering N1 to leave only C1. In one embodiment, the sound file **290** can be stored on the first storage unit **218**, the second storage unit **248**, or the remote server **242**.

In one embodiment, the digital stethoscope **110**, the base station **118**, or a combination thereof can further generate a configuration file **264** and store the information from detecting, amplifying, adjusting, and analyzing the auditory signals **262** in the configuration file **264**. The configuration file **264** is a computer file, such as a text file, that contains the information from detecting, amplifying, adjusting, and analyzing the auditory signals **262**. In one embodiment, the configuration file **264** can be stored in and accessed from the first storage unit **218**, the second storage unit **248**, or the remote server **242**. In one embodiment, the configuration file **264** can include information such as a classification value **266** indicating whether the auditory signals **262** indicate a respiratory sound, noise, or auditory tone that is classified as "normal" or "abnormal." The configuration file **264** can further include a timestamp **268** indicating when the auditory signals **262** were detected, an accelerometer data **272** obtained from the accelerometer **226** indicating movement of the patient, a cough count **274** indicating the number of coughs detected by the digital stethoscope **110** over a period of time, or a combination thereof.

In one embodiment, the configuration file **264** can further include information about devices of the system **100**, such as a serial number **270** of the digital stethoscope **110** to indicate what device detected the auditory signals **262**. The aforementioned are merely exemplary and other information detected and generated by the digital stethoscope **110** can be stored in the configuration file **264**.

In one embodiment, the configuration file **264** can be sent to one or more devices of the system **100**. For example, the configuration file **264** can be sent to the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof to be used in performing adjustments or analysis of the auditory signals **262**, or to detect a respiratory abnormality or to predict a respiratory event or respiratory condition in the future. For example, in one embodiment where the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof are performing some or all of the processing of the auditory signals **262**, the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof can receive the auditory signals **262** via the sound file **290**, and further information via the configuration file **264**, parse the two files, extract information from the two files, and perform processing based on the information contained in the two files.

Referring now to FIG. **2**C, therein is shown a further exemplary architecture of the digital stethoscope **110** in an embodiment of the present invention. FIG. **2**C shows an embodiment where the digital stethoscope **110** includes the first control unit **210** and the first storage unit **218**. The first control unit **210** can include the first processor **214** and the first FPGA **216**. The first storage unit **218** can include the first DRAM **254**. The first processor **214** and the first FPGA **216** can be coupled using the first control interface **212**. The first storage unit **218** can be coupled to the first control unit **210** using the first storage interface **220**. For example, in one embodiment, the first DRAM **254** can be coupled, via the first storage interface **220** to the first processor **214**.

In one embodiment, the first processor **214**, the first FPGA **216**, and the first DRAM **254** can work in conjunction to process the auditory signals **262** detected by the microphones **106** or the array configuration **104**. In one embodiment, the first processor **214** can act as a controller and control the coordination, communications, scheduling, and transfers of data between the first FPGA **216**, the first DRAM **254**, or other components of the digital stethoscope **110**. For example, in one embodiment, the first processor **214** can receive the auditory signals **262** from the microphones **106**, and transfer the auditory signals **262** to the first FPGA **216** for further processing. In one embodiment, once the first FPGA **216** has completed its operations, the first FPGA **216** can transfer the output or data generated as a result of its operations back to the first processor **214**, which can further transfer the output or data to the first DRAM **254** for storage. In one embodiment, the first processor **214** can further enable the generation of the configuration file **264**. In one embodiment, the first processor **214** can further enable the generation of the sound file **290**.

In one embodiment, the first FPGA **216** can perform the processing of the auditory signals **262**. The first FPGA **216**

can include one or more logic blocks, including one or more reconfigurable logic gates, that can be pre-programmed or configured to perform calculations or computations on the auditory signals **262**, and to generate output or data to detect the respiratory abnormality, or to predict a respiratory event or respiratory condition in the future. The first FPGA **216** can, for example, have its logic blocks preconfigured with threshold values, stored values, acoustic models, machine learned trained data, machine learning processes, configuration data, or a combination thereof that can be used to perform the processing on the auditory signals **262**, the result of which is to detect the respiratory abnormality, or to predict the respiratory event or respiratory condition in the future.

For example, in one embodiment the first FPGA **216** can be preconfigured with a machine learning process, for example a convolutional neural network model, which can have one or more weights **276** associated therewith. The weights **276** refer to values, parameters, thresholds, or a combination thereof that act as filters in the machine learning process and represent particular features of the sounds, noises, and acoustic tones of a respiratory abnormality, respiratory event, respiratory condition, or a combination thereof. The weights **276** can be iteratively adjusted based on machine learned trained data.

Continuing with the example, the first FPGA **216** can, in one embodiment, use the machine learning process, including the weights **276** to detect whether the auditory signals **262** contain a sound, noise, or acoustic tone indicative of a respiratory abnormality, or whether the auditory signals **262** are indicative of a respiratory event or respiratory condition in the future. Further discussion of the processing done by the first FPGA **216** will be discussed below.

Referring now to FIG. **2**D, therein is shown a further exemplary architecture of the base station **118** in an embodiment of the present invention. FIG. **2**D shows an embodiment where the base station **118** includes the second control unit **236**, the sensor unit **202**, the second communication unit **228**, and a wireless charging unit **278**. The second control unit **236** can include the second processor **240** and the second FPGA **244**. The sensor unit **202** can include the contact sensor **120** and the air quality sensors **116**. The second communication unit **228** can include the IoT modem **232** and the second Bluetooth circuit **230**. The second Bluetooth circuit **230** can further include a real time audio circuit **280** and a data transfer circuit **282**. The real time audio circuit **280** and the data transfer circuit **282** can enable the base station **118** to connect to multiple devices simultaneously over a Bluetooth connection. For example, in one embodiment, the real time audio circuit **280** can enable a Bluetooth connection to the digital stethoscope **110** to send or receive the auditory signals **262** or the sound file **290** containing the auditory signals **262**, and the data transfer circuit **282** can enable simultaneous Bluetooth connection to a further device, such as a mobile phone **284** to communicate outputs or data generated by the base station **118** as a result of processing the auditory signals **262**. In one embodiment, the IoT modem **232** can further be used to communicate outputs or data generated by the base station **118** to a further device, for example the remote server **242**. In one embodiment, the IoT modem **232** can further be used to receive configuration data, such as software updates, including updated acoustic models, machine learned trained data, machine learning processes, firmware, or a combination thereof from the remote server **242**. In one embodiment, the base station **118** can further communicate the software updates to the digital stethoscope **110** using the second Bluetooth circuit **230**.

The second processor **240** and the second FPGA **244** can be coupled using the second control interface **238**. The second communication unit **228** can couple to the second control unit **236** using the second communication interface **234**. The sensor unit **202** can couple to the second control unit **236** using the sensor unit interface **260**. The sensor unit **202** can couple to the wireless charging unit **278** using the sensor unit interface **260**.

In one embodiment, the second processor **240** can act as a controller and control the coordination, communications, scheduling, and transfers of data between the second FPGA **244** and other components of the base station **118**. For example, in one embodiment, the second processor **240** can receive the auditory signals **262** from the digital stethoscope **110** via the second communication unit **228**, and transfer the auditory signals **262** to the second FPGA **244** for further processing. In one embodiment, once the second FPGA **244** has completed its operations, the second FPGA **244** can transfer the output or data generated as a result of its operations back to the second processor **240**, which can further transfer the output or data to other components of the base station **118**. For example, the second processor **240** can further transfer the output or data to the second communication unit **228** for transfer to the remote server **242**, the mobile device **284**, the digital stethoscope **110**, or a combination thereof. The mobile device **284** can be a device associated with a user of the system **100** that the base station **118** can use to communicate the output or data generated by the base station **118**, the digital stethoscope **110**, the remote server **242**, or a combination thereof to a user of the system **100**. The mobile device **284** can be, for example, a mobile phone, a smart phone, a tablet, a laptop, or a combination thereof.

In one embodiment, the second processor **240** can further generate the configuration file **264** and store values, variables, configuration data, time stamps, or data detected or generated therein. In one embodiment, the second processor **240** can further generate the sound file **290** for storing the auditory signals **262**.

In one embodiment, the second FPGA **244** can perform the processing of the auditory signals **262**. The second FPGA **244** can include one or more logic blocks, including one or more reconfigurable logic gates, that can be pre-programmed or configured to perform calculations or computations on the auditory signals **262**, and to generate output or data generated to detect the respiratory abnormality, or to predict a respiratory event or respiratory condition in the future. The second FPGA **244** can, for example, have its logic blocks preconfigured with threshold values, stored values, acoustic models, machine learned trained data, machine learning processes, configuration data, or a combination thereof that can be used to perform the processing on the auditory signals **262**, the result of which is to detect the respiratory abnormality, or to predict the respiratory event or respiratory condition in the future.

For example, in one embodiment the second FPGA **244** can be preconfigured with a machine learning process, for example a convolutional neural network model, which can have one or more weights **276** as shown in FIG. **2**C, associated therewith. In another embodiment, the second FPGA **244** can be preconfigured with a machine learning process, for example a long short term memory (LSTM) network model, which can have one or more weights **276** associated therewith. In one embodiment, the second FPGA

244 can be work with the remote server 242 to implement the machine learning process, for example the convolutional neural network model, or the LSTM network model, wherein the second FPGA 244 and the remote server 242 can divide the processing needed to perform the computations done by the machine learning process.

Continuing with the example, the second FPGA 244 can, in one embodiment, use the machine learning process to detect whether the auditory signals 262 contain a sound, noise, or acoustic tone indicative of a respiratory abnormality. In another embodiment, the second FPGA 244 can use the machine learning process to predict a respiratory event or respiratory condition in the future using the auditory signals 262. Further discussion of the processing done by the second FPGA 244 will be discussed below.

The wireless charging unit 278 can enable the electric charging of the digital stethoscope 110, through inductive charging by, for example, generating the electromagnetic field used to transfer energy between the charging pad 114 of FIG. 1, and a further device, such as the digital stethoscope 110 using electromagnetic induction. The wireless charging unit 278 can include the processors, active and passive components, circuitry, control logic, or a combination thereof to enable the inductive charging. In one embodiment, the wireless charging unit 278 can couple to the contact sensor 120 to enable the inductive charging. For example, in one embodiment, if the contact sensor 120 detects contact or coupling between the digital stethoscope 110 and the charging pad 114, the contact sensor 120 can generate the contact measure 122 of FIG. 1, which can be sent to the wireless charging unit 278. The wireless charging unit 278 upon receiving the contact measure 122 can determine that a coupling between the digital stethoscope 110 and the charging pad 114 has occurred and can activate the base station's 118 processors, active and passive components, circuitry, control logic, or a combination thereof to generate the electromagnetic field and begin transferring energy between the charging pad 114 and the digital stethoscope 110. In one embodiment, the wireless charging unit 278 can further power off the base station 118 during the time period in which it is charging the digital stethoscope 110 by, for example, generating a signal to the second processor 240 that charging is taking place and that the components of the base station 118 should be in an off or idle mode during the time period.

In one embodiment, the wireless charging unit 278 can further enable the activation of the base station 118 based on determining a termination of the coupling between the digital stethoscope 110 and the charging pad 114. For example, in one embodiment, the wireless charging unit 278 can detect a termination of the coupling between the digital stethoscope 110 and the charging pad 114 based on a change in the contact measure 122. For example, in one embodiment, if the digital stethoscope 110 is removed from the charging pad 114, the contact sensor 120 can generate a contact measure 122 indicating the removal, and can send the contact measure 122 to the wireless charging unit 278. The wireless charging unit 278 upon receiving the contact measure 122 can determine that the coupling between the digital stethoscope 110 and the charging pad 114 is no longer present and can send a signal to the second processor 240 to activate or power up the components of the base station 118, so that the base station 118 can perform computations and processing on auditory signals 262, or communicate with further devices such as the digital stethoscope 110, the mobile device 284, the remote server 242, or a combination thereof.

Convolutional Neural Network to Detect Abnormality

Referring now to FIG. 3, therein is shown an exemplary second control flow 300 for detection of the respiratory abnormality in an embodiment of the present invention. For brevity of description, in this embodiment, the second control flow 300 will be described as being performed using the digital stethoscope 110. This description is merely exemplary and not meant to be limiting. In other embodiments, the second control flow 300 can be performed using the base station 118, the remote server 242, or a combination thereof.

In one embodiment, the second control flow 300 can be implemented with modules and sub-modules, the components of the digital stethoscope 110, or a combination thereof. In one embodiment, the second control flow 300 can include a receiver module 304, a subtraction module 306, a filter module 308, and a convolution neural network module 310. In one embodiment, the receiver module 304 can couple to the subtraction module 306. The subtraction module 306 can couple to the filter module 308. The filter module 308 can couple to the convolution neural network module 310.

The receiver module 304 can enable receiving of one or more signals or data by the digital stethoscope 110. In one embodiment, the signals or data can be, for example, the auditory signals 262, the accelerometer data 272, or a combination thereof, and can be received via the microphones 106 of FIG. 1, the accelerometer of FIG. 2A, the configuration file 264, the sound file 290, or a combination thereof. By way of example, FIG. 3 depicts two auditory signals 262, where "C1" represents a cough, crackle, or wheeze originating from the patient's body and "N1" represents a noise signal resulting from noises generated external to the patient's body, for example background noise from a patient's environment. FIG. 3 further depicts the accelerometer data 272, where "A1" represents the accelerometer data 272. In one embodiment, C1, N1, and A1, represent time series signals and data, in which the signals are measured over a period of time and can be represented mathematically by one or more time functions 302, in which the value of the time functions 302 vary based on time.

In one embodiment, the receiver module 304 can further enable the conversion of the time functions 302 into one or more frequency domain functions 330, in which the time functions 302 can be represented with respect to a frequency component of the signals or data. The frequency domain functions 330 can be used by the digital stethoscope 118 to perform further calculations or processing of the auditory signals 262, the accelerometer data 272, or a combination thereof to detect the respiratory abnormality. For example, in one embodiment, C1 and N1 can be represented as a combined time function 302 x(t), where x(t) can be represented by equation (1) below:

$$x(t)=y(t)+N(t) \quad (1)$$

In equation (1), y(t) represents the time function 302 of C1 and N(t) represents the time function 302 of N1. The receiver module 304 can convert x(t) into a frequency domain function 330 by, for example, performing a Fourier transformation or Fast Fourier transformation on x(t) such that the frequency domain function 330 is obtained, where x'(w) in FIG. 3 represents the frequency domain function 330 of x(t). In one embodiment, the digital stethoscope 110 can then use x'(w) to perform its calculations and computations. Similarly, in one embodiment, the receiver module 304 can convert the acceleration data 272 from a time function 302 to a frequency domain function 330 using similar techniques.

In one embodiment, once the receiver module **304** receives the auditory signals **262**, the accelerometer data **272**, or a combination thereof and converts the signals from a time function **302** to frequency domain functions **330**, the receiver module **304** can pass control and the frequency domain functions **330** to the subtraction module **306**. The subtraction module **306** can enable the adjusting the auditory signals **262** received from the receiver module **304** by removing or filtering of unwanted auditory signals **262**, for example a background noise created by the movement of the patient and picked up by the accelerometer **226**, or other noise signals originating external to the patient's body, to obtain a noise free or nearly noise free auditory signals **262**. The subtraction module **306** can enable the removal or filtering of unwanted auditory signals **262** by implementing a filter to remove unwanted sound frequencies. In one embodiment, the filter can be implemented using hardware, software, or a combination thereof. For example, the filter can be implemented to perform the functions of, or be, a low pass filter, a high pass filter, a bandpass filter, a Butterworth filter, a Chebyshev filter, a Bessel filter, a Elliptic filter, or a combination thereof.

In one embodiment, the subtraction module **306** can implement the filter such that the filter performs removal or filtering based on equation (2) below:

$$x(w)=y(w)-(\alpha\beta\Delta N(w)) \quad (2)$$

In equation (2), x(w) represents the filtered frequency domain function **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof obtained from the receiver module **304**, y(w) represents the frequency domain function **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof obtained from the receiver module **304** that should be kept by the digital stethoscope **110**, N(w) represents the frequency domain function **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof obtained from the receiver module **304** that should not be kept by the digital stethoscope **110**, and α, β, and Δ are variables that can be integers or whole numbers used to determine how much of N(w) should be subtracted from y(w) such that a low noise or noise free signal remains. In one embodiment, α, β, and Δ can be varied or adjusted over time based on the noise conditions in which the digital stethoscope **110** is used. For example, in one embodiment, α, β, and Δ can be varied or adjusted every 20, 50, or 100 milliseconds. In one embodiment, α, β, and Δ can be varied or adjusted wherein α, β, and Δ are large values in a high noise environment, such as a noisy office environment, or small values in a low noise environment, such as a quiet office environment. In one embodiment, α, β, and Δ can be a set of pre-determined values. In another embodiment, α, β, and Δ can change dynamically based on changes in the noise levels detected by the digital stethoscope **110**. In one embodiment, α, β, and Δ can be pre-configured values in the first FPGA **216** or can be obtained from the base station **118**, the remote server **242**, or a combination thereof.

In one embodiment, once the subtraction module **306** performs its adjustment and filtering of the auditory signals **262**, the accelerometer data **272**, or a combination thereof, the subtraction module **306** can pass control and the filtered frequency domain functions **330** of the auditory signals **262** to the filter module **308**. The filter module **308** enables the generation of an auditory spectrogram **312** by further separating or filtering the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof into one or more frequency bands **336** representing the different audible frequencies of the filtered frequency domain functions **330** of the auditory signals **262**, the accelerometer data **272**, or a combination thereof.

The auditory spectrogram **312** refers to a two dimensional visual representation of the spectrum of frequencies of the filtered frequency domain functions **330** of the auditory signals **262**, the accelerometer data **272**, or a combination thereof. The auditory spectrogram **312** can be represented as a chart, image, matrix, heat map, or other visual depiction showing a plot of the frequencies and the magnitudes associated with the frequencies of the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof. The auditory spectrogram **312** can enable the sharpening or amplification of the frequency components filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof to better depict what sounds, noises, or acoustic tones are present in the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof. The auditory spectrogram **312** can be used in the processing of the filtered frequency domain functions **312** of the auditory signals **262**, accelerometer data **272**, or a combination thereof to detect the respiratory abnormality, and result in more accurately determining the respiratory abnormality due to the ability of the auditory spectrogram **312** to sharpen and amplify the frequency components of the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof.

In one embodiment, the filter module **308** can generate the auditory spectrogram **312** by implementing one or more cochlear filters **332** which the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof can be passed through, and wherein the cochlear filters **332** are based on a cochlear model **314**. The cochlear model **314** refers to the mathematical model or representation of the mechanics of a mammalian cochlea. In one embodiment, the cochlear model **314** can be implemented using hardware, software, or a combination thereof. For example, the cochlear filters **332** can include processors, active and passive components, circuitry, control logic, or a combination thereof implementing the cochlear model **314**. In one embodiment, the cochlear filters **332** can separate different audible frequencies into one or more frequency ranges that a mammalian cochlea can hear.

For example, in one embodiment, the filter module **308** can implement one hundred and twenty-eight (128) cochlear filters **332** representing the one hundred and twenty eight different frequency ranges that can be heard by the mammalian cochlea. As such, the filter module **308** can mimic the human ear. In one embodiment, the output of the filter module **308** based on further filtering using the cochlear filters **332**, the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof is the auditory spectrogram **312**. The auditory spectrogram **312** can visually represent the frequency ranges obtained from further filtering the filtered frequency domain functions **330** of the auditory signals **262**, accelerometer data **272**, or a combination thereof.

In one embodiment, once the filter module **308** generates the auditory spectrogram **312**, the filter module **308** can pass control and the auditory spectrogram **312** to the convolution neural network module **310**. The convolution neural network module **310** can enable the detection of the respiratory abnormality by performing a convolution procedure **316** on the auditory spectrogram **312** and further passing the results

to a neural network **326** for classification as "normal" or "abnormal." The designation of "normal" or "abnormal" indicates whether the auditory signals **262**, accelerometer data **272**, or a combination thereof detected by the digital stethoscope **110** indicates a respiratory abnormality.

The convolution procedure **316** refers to a mathematical operation on two functions to produce a third function that expresses how the shape of one of the functions is modified by the other function. In one embodiment, the convolution procedure **316** can be implemented based on equation (3) below:

$$f[x, y] * g[x, y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1, n_2] \cdot g[x - n_1, y - n_2] \quad (3)$$

$$f[x, y] * g[x, y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[x - n_1, y - n_2] \cdot g[n_1, n_2]$$

In equation (3), f*g represents the third function, "f" and "g" represent the two functions that the convolution procedure **316** is being performed on, x and y represent variables that the functions "f" and "g" depend on, and "n1" and "n2" represent an amount of shift. In one embodiment, the convolution neural network module **310** can implement the convolution procedure **316** using hardware, software, or a combination thereof. For example, the convolution neural network module **310** can include processors, active and passive components, circuitry, control logic, or a combination thereof implementing the convolution procedure **316**.

In one embodiment, the auditory spectrogram **312** can represent one of the functions in equation (3), for example "f" In one embodiment, the convolution neural network module **310** can perform the convolution procedure **316** on the auditory spectrogram **312** by convoluting the auditory spectrogram **312** with a further function, for example one or more convolution functions **318**, which can represent "g" in equation (3). In one embodiment, the convolution functions **318** can be one or more matrices of size N×N, where N represents an integer. For example, the convolution functions **318** can be a 3×3 matrix, 5×5 matrix, 10×10 matrix, or any other sized matrix. In one embodiment, the convolution functions **318** can further have one or more values represented by integers or whole numbers for their N×N elements. The one or more values can be the same or different for each N×N element. The one or more values can further be the same or different for each of the convolution functions **318**.

In one embodiment, the one or more values of the convolution functions **318** can be obtained through a training process in which the one or more values are obtained through back propagation of machine learned trained data. The machine learned trained data can be, for example previous auditory spectrograms **312** representing known respiratory abnormalities, for example sounds, noises, auditory tones, or a combination thereof caused by a cough, a crackle, a wheeze, an asthma attack or other respiratory event or respiratory condition. The back propagation can generate the one or more values of the convolution functions **318** by calculating and attempting to reconstruct a known output, such as previously analyzed auditory spectrograms **312** representing known respiratory abnormalities, and determining what values the convolution functions **318** must have to reconstruct the previously analyzed auditory spectrograms **312** representing known respiratory abnormalities. As such, the one or more values of the convolution functions **318** can be obtained and can be optimized to extract one or more features, such as curves, peaks, valleys, shapes, lines, or colors represented in the previously analyzed auditory spectrogram **312** which can be used to reconstruct the previously analyzed auditory spectrograms **312**. Once determined, the one or more values of the convolution functions **318** can further be used to subsequently recognize the same features in further auditory spectrograms **312**, such that the convolution functions **318** can be used to recognize respiratory abnormalities from auditory signals **262**, accelerometer data **272**, or a combination thereof detected by the digital stethoscope **110**.

Continuing with the example, once the convolution functions **318** and their values are generated, the convolution neural network module **310** can perform the convolution procedure **316** on the auditory spectrogram **312** using the convolution functions **318** by performing the convolution procedure **316** over N×N frames of the auditory spectrogram **312** and multiplying the values of the N×N frame of the auditory spectrogram **312** with the values of the convolution functions **318**. As a result, a further matrix is generated with one or more convolution values **320** representing the extracted features of the auditory spectrogram **312** for that N×N frame. The convolution values **320** can be integers or whole numbers that give quantified values to the features of the auditory spectrogram **312** for a particular N×N frame. By way of example, in areas where the auditory spectrogram **312** has a value greater than 0, the convolution values **320** generated can be positive integers assuming the one or more values of the convolution functions **318** are also non-zero. However, in areas where the auditory spectrogram **312** has a zero value, the convolution values **320** generated can be zero.

In one embodiment, the convolution procedure **316** can be performed repeatedly to successively compress the auditory spectrogram **312** into one or more convolution matrices **322**, each having less rows and columns than the previous convolution matrices **322** generated as a result of the convolution procedure **316**. In one embodiment, the generation of the subsequent convolution matrices **322** can depend on the values of the previous convolution matrices **322**. For example, in one embodiment, if two convolution matrices **322** are generated as a result of the convolution procedure **316**, the first can have the size M×M and the second can have the size T×T, wherein the second can have its convolution values **320** depend on the first, and where M>T. In one embodiment, the convolution matrices **322** can be stored in the first DRAM, wherein the convolution matrices **322** can be used in successive calculation of further convolution matrices **322**.

In one embodiment, as a result of performing the convolution procedure **316** successively, a convolution vector **324** can be generated containing convolution values **320**. For example, in one embodiment, the convolution vector **324** can be an M×1 vector, where M is an integer, such as a 20×1 vector, containing convolution values **320**. In one embodiment, the convolution vector **324** can be used as the input to a machine learning process, for example the neural network **326**, which can be used to determine whether the convolution vector **324** representing a compressed version of the auditory spectrogram **312**, accelerometer data **272**, or a combination thereof indicates a respiratory abnormality. The neural network **326** refers to an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation.

The neural network **326** can use the weights **276** of FIG. **2**C and one or more biases **334** for each of its nodes or neurons which can be used to determine whether the auditory signals **262** represent a respiratory abnormality. Biases **334** refer to values, variables, parameters, or a combination thereof which enables the neural network **326** to better fit the data to assist the neural network **326** to learn patterns. In one embodiment, the weights **276** and biases **334** can be integers or whole numbers. The weights **276** and biases **334** can connect nodes or neurons of the neural network **326**, and can determine the strength of each connection between each node or neuron such that the higher the value for the weights **276** and biases **334** for a given connection, the more the connection will affect the overall computations and outcomes of the neural network **326**. In one embodiment, the weights **276** and biases **334** can be determined and obtained in a similar process of back propagation of training data similar to what was described above with respect to the one or more values of the convolution functions **318**. For the purposes of discussion, it is assumed that the weights **276** and biases **334** are already known and optimized for detecting the respiratory abnormality.

Continuing with the example, in one embodiment, the neural network **326** can further have a confidence level **328** associated with its output. The confidence level **328** can be a value, variable, parameter, or a combination thereof which, if the output of the neural network **326** exceeds, the neural network **326** can determine that the output can be classified as either "normal" or "abnormal." By way of example, if the confidence level **328** is set to for example "90%," any output of the neural network **326** indicating that the neural network **326** believes the auditory signals **262**, accelerometer data **272**, or a combination thereof detected is greater than or equal to 90% "normal" or "abnormal" will be accepted as a valid result and classified accordingly by the neural network **326**. In one embodiment, if the confidence level **328** is met or exceeded as a result of the processing by the neural network **326**, the digital stethoscope **110** can generate the classification value **266** indicating a "normal" or "abnormal" classification, and display an indicator based on the classification value **266**, such as a red or green colored light, or a message indicating that the auditory signals **262** are "abnormal" or "normal."

It has been discovered that the use of the convolutional neural network module **310** described above allows the digital stethoscope **110** to generate the classification value **266** and display the indicator in real time when used in conjunction with the architecture of the digital stethoscope **110** because it uses less computing resources, such as processing power and memory as opposed to conventional methods of detecting a respiratory abnormality. Real time refers to the instance where the classification value **266** and the indicator can be displayed almost instantly or within milliseconds of receipt of the auditory signals **262**, the accelerometer data **272**, or a combination thereof by the digital stethoscope **110**.

It has been further discovered that the ability to generate the classification value **266** and display the indicator in real time significantly improves the current state of the art by allowing patients or users of the system **100** to be notified of a respiratory abnormality instantaneously and seek treatment immediately. It has been further discovered that the ability of patients or users of the system **100** to be notified of the respiratory abnormality in real time can result in the ability to potentially save more patient lives by allowing patients to know that they need to seek medical treatment rapidly if a respiratory abnormality is detected.

Referring now to FIG. **4**A, therein is shown an exemplary depiction of the functioning of the receiver module **304** and the subtraction module **306** in an embodiment of the present invention. In the embodiment shown in FIG. **4**A, once the auditory signals **262** are received, by the receiver module **304**, the auditory signals **262** can be converted from time functions **302** to frequency domain functions **330** as discussed previously with respect to FIG. **3**. By way of example, FIG. **4**A shows two frequency domain functions y(w) and N(w). In the embodiment shown in FIG. **4**, y(w) can represent the frequency domain function **330** of auditory signals **262** obtained by the receiver module **304** that should be kept by the digital stethoscope **110** while N(w) can represent the frequency domain function **330** of auditory signals **262** obtained by the receiver module **304** that should not be kept by the digital stethoscope **110**. Further, y(w) and N(w) are shown as containing one or more frequencies as depicted by a first frequency band set **402** and a second frequency band set **404**. The first frequency band set **402** and the second frequency band set **404** represent the different frequencies contained within y(w) and N(w) and can be obtained by converting the time functions **302** to the frequency domain functions **330**. For example, in one embodiment, boxes labeled as "1" of the first frequency band set **402** or the second frequency band set **404** can represent an audible portion of y(w) or N(w) that has a high frequency, while boxes labeled as "4" of the first frequency band set **402** or the second frequency band set **404** can represent an audible portion of y(w) or N(w) that has a low frequency. In one embodiment, y(w) and N(w) can be passed to the subtraction module **306** so that the subtraction module **306** can filter out any unwanted noise portions, for example all or some of N(w) according to equation (2) above for each of the first frequency band set **402** and the second frequency band set **404**.

Referring now to FIG. **4**B, therein is shown an exemplary depiction of the functioning of the filter module **308** and the generation of the auditory spectrogram **312** in an embodiment of the present invention. In the embodiment shown in FIG. **4**B, the filtered frequency domain functions **330** of the auditory signals **262** is shown as being passed to the filter module **308**. The filter module **308** is further shown with the cochlear filters **332**. In one embodiment, the filtered frequency domain functions **330** of the auditory signals **262** can pass through the cochlear filters **332**. As a result of passing the filtered frequency domain functions **330** of the auditory signals **262** through the cochlear filters **332**, the auditory spectrogram **312** is generated. The auditory spectrogram **312** can be generated by, for example plotting the frequencies filtered by the cochlear filters **332** on a plot showing time versus frequency. In one embodiment, the auditory spectrogram **312** can further indicate the frequency bands **336** of the auditory signals **262**.

Referring now to FIG. **4**C, therein is shown an exemplary depiction of the functioning of the convolution neural network module **310** in an embodiment of the present invention. In the embodiment shown in FIG. **4**C, the auditory spectrogram **312** is shown. Further, the convolution functions **318** are shown as being represented by the one or more boxes representing matrices of size N×N. The convolution neural network module **310** can perform the convolution procedure **316** by convoluting the auditory spectrogram **312** with the convolution functions **318** by shifting the convolution functions **318** over the auditory spectrogram **312** and multiplying the values for N×N frames of the auditory spectrogram **312** with the values of the convolution functions **318**. As a result, the convolution matrices **322** are

generated with convolution values **320**. FIG. **4**C further depicts the generation of the subsequent convolution matrices **322**. In one embodiment, the subsequent convolution matrices **322** can be generated by for example a pooling process **406**, in which subsequent convolution matrices **322** are generated by reducing the dimensions of the previous convolution matrices **322** generated.

By way of example, a first convolution matrix **408** can be generated as a result of the convolution procedure **316**. In one embodiment, a second convolution matrix **410** can subsequently be generated based on the first convolution matrix **408** by the pooling process **406**, by for example, taking groups of sub-elements of the first convolution matrix **408** and generating the second convolution matrix **410** based on the sub-elements. For example, if the first convolution matrix **408** is an M×M sized matrix, the first convolution matrix **408** can be broken down into sub-matrices, for example R×R sized sub-matrices, and a value chosen from the R×R sub-matrix can be taken as one of the convolution values **320** of the second convolution matrix **410**. The pooling process **406** can be done in a variety of ways, including max pooling in which the maximum value for the R×R sub-matrix is taken as one of the convolution values **320** of the second convolution matrix **410**. In another embodiment, the pooling process **406** can be done by average pooling in which the values of the R×R sub-matrix are averaged and the average is taken as one of the convolution values **320** of the second convolution matrix **410**.

In one embodiment, the pooling process **406** can be done repeatedly to successively compress the auditory spectrogram **312** and generate the convolution vector **324**. The convolution vector **324** can then be input to the neural network **326** which can use the weights **276** and biases **334** to determine whether the convolution vector **324** represents a respiratory abnormality by classifying the convolution values **320** associated with the convolution vector **324** as being "normal" or "abnormal."

In one embodiment, the second control flow **300** described above can further be used to make other classifications based on the auditory signals **262** detected by the digital stethoscope **110**. For example, in addition to detecting a respiratory abnormality and making a classification of "normal" or "abnormal," the digital stethoscope **110** can classify the auditory signals **262** as a particular type of sound, noise, acoustic tone, or a combination thereof using the same processes described above with respect to the control flow **300**. For example, in one embodiment, the digital stethoscope **110** using the second control flow **300**, can classify the auditory signals **262** as a wheeze, a crackle, or a cough based on the convolutional neural network module **310** having its convolution functions **318** and neural network **326** trained to recognize a wheeze, a crackle, or a cough based on training with machine learned trained data representing known sounds, noises, auditory tones, or a combination thereof caused by a cough, a crackle, a wheeze, or a combination thereof. As such, the classifications such as "cough" or "no cough," "crackle" or "no crackle," or "wheeze" or "no wheeze" can be generated.

In one embodiment, the coughs, crackles, or wheezes detected can be saved in the configuration file **264** as the cough count **274** and can be used to predict a future respiratory event or respiratory condition. For example, if the cough count **274** is known and exceeds a certain threshold, for example, is greater than the average number of coughs for the patient within a certain time period, and the digital stethoscope **110** further detects that the coughs indicate a respiratory abnormality, the digital stethoscope **110** can, for example, further generate a parameter, value, or variable indicating that a respiratory event or respiratory condition is likely in the future and save the information in the configuration file **264**, which can further be shared with the base station **118**, the remote server **242**, or a combination thereof to alert the patient or a user of the system **100** of the likelihood of the respiratory event or respiratory condition. In one embodiment, the prediction of the respiratory event or respiratory condition can further be aided by the use of machine learning processes, for example a long short term memory (LSTM) network model. The LSTM network model will be discussed further below.

Forecasting Using an LSTM

Referring now to FIG. **5**A, therein is shown an exemplary feature map **500** used to predict a respiratory event or respiratory condition in the future in an embodiment of the present invention. The feature map **500** is a chart, image, matrix, plot, or other visual depiction showing one or more map features **512** versus time. In one embodiment, the feature map **500** can be generated by the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof. The map features **512** refer to parameters, variables, or a combination thereof that are used to predict a respiratory event or respiratory condition in the future. The map features **512** describe one or more conditions at a particular time or over a period of time that can affect the onset of a respiratory event or respiratory condition.

For example, in one embodiment, the map features **512** can include, environmental data, data regarding the patient, or a combination thereof, indicating an environmental condition at a particular time or over a period of time affecting the onset of a respiratory event or respiratory condition, or patient data, including data regarding coughs, crackles, wheezes, or a combination thereof, indicating the onset of a respiratory event or respiratory condition. For example, the map features **512** can include environmental data indicating how much pollution is in the air at a particular time, how much pollen is in the air at a particular time, the air quality at a particular time, or can include data regarding the patient, such as data regarding whether the patient is coughing or wheezing at a certain time, the severity of the patient's cough, crackle, or wheeze at a certain time, how many times a patient is coughing or wheezing over a period of time, or a combination thereof. As such, the map features **512** can include a pollution level data **502**, a weather data **504**, a severity score **506** indicating how severe a patient's cough, crackle, wheeze, respiratory event, or respiratory condition is at a given time, the cough count **274**, a pollen data **510**, or a combination thereof.

In one embodiment the severity score **506** can be categorized indicating the level of severity of the patient's cough, crackle, wheeze, respiratory event, or respiratory condition at a given time. In one embodiment, the categorization can be, for example on a scale of 1-6 where, 1 indicates no or non-present severity, 2 indicates intermittent severity, 3 indicates mild severity, 4 indicates moderate severity, 5 indicates severe or high severity, and 6 indicates acute severity in which the patient should get immediate medical attention. In one embodiment, the severity score **506** can be determined by the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof by analyzing the auditory signals **262** received from the digital stethoscope **110**, and analyzing the auditory signals **262** pursuant to the second control flow **300** or equivalent control flow to determine the category of the severity score **506**,

wherein the neural network **326** or a further neural network can be used to determine the category of the severity score **506**.

Continuing with the example, in one embodiment, the map features **512** can be obtained from the digital stethoscope **110**, the base station **118**, or a combination thereof, and the components thereof including for example the microphones **106**, the air quality sensors **116**, or a combination thereof. In one embodiment, the map features **512**, the feature map **500**, or a combination thereof can be used as an input to a machine learning process that can be used to predict a respiratory event or respiratory condition in the future. For example, the map features **512**, the feature map **500**, or a combination thereof can be the input to an LSTM process **514** to predict the respiratory event or respiratory condition in the future. In one embodiment, more than one feature map **500** can be the input to the LSTM process **514** to predict the respiratory event or respiratory condition in the future. The LSTM process **514** refers to artificial recurrent neural network (RNN) architecture which uses feedback to make predictions about future events.

Referring now to FIG. **5**B, therein is shown an exemplary depiction of the LSTM process **514** used to predict a third respiratory event **520** occurring for the patient at a future time in an embodiment of the present invention. The LSTM process **514** of FIG. **5**B can work in the following manner. In the embodiment of FIG. **5**B, one or more time buckets **518** are shown as represented by "n−1," "n," and "n+1," wherein the time buckets **518** contain information regarding the map features **512** at a particular instance of time or over a period of time. In one embodiment, the time buckets **518** can be implemented as data structures, variables, parameters, or a combination thereof as nodes in the LSTM process **514**. In one embodiment, each instance of the time buckets **518** can be predicted by implementing a look back feature **516**, which references the map features **512** of previous time buckets **518** and performs a probability calculation to determine the likelihood that future time buckets **518** will have map features **512** exhibiting certain characteristics or having certain values. For example, "n" can be predicted by referencing the map features **512** of "n−1," and "n+1" can further be predicted by referencing the map features **512** of "n−1," "n," and so forth.

In one embodiment, the prediction is done by comparing the map features **512** of past time buckets **518** to one another and finding one or more patterns or correlations between the map features **512**. The patterns or correlations can be, for example, map features **512** indicating a high probability of exhibiting a certain characteristic or having a certain value based on one or more previous map features **512** exhibiting certain characteristics or having certain values. By way of example, if it is determined that when pollution is high and a patient has a certain number of coughs during the period when the pollution is high, there is a high probability that the severity scores **506** of a patient's coughs, crackles, or wheezes will be "5"-severe or "6"-acute, the LSTM process **514** can look for that pattern or correlation when comparing the map features **512** of past time buckets **518**, and if that pattern or correlation is detected, can predict that in instances where a pollution level is getting to a high level and the patient has a certain number of coughs building up to a certain threshold, the severity score **506** of those coughs is likely to be "5"-severe or "6"-acute in the near future. The example is merely exemplary and not meant to be limiting.

In one embodiment, the LSTM process **514** can contain weights **276** associated with the look back feature **516**, similar to the weights **276** described with respect to FIG. **2**C. The weights **276** can be used to determine the strength of each connection between the time buckets **518** such that the higher the value for the weights **276** for a given look back feature **516**, the more the map features **512** of the particular time buckets **518** associated with the look back feature **516** will affect the overall computations and predictions of the LSTM process **514**. In one embodiment, the weights **276** can be determined and obtained in a similar process of back propagation of training data similar to what was described above with respect to the one or more values of the convolution functions **318**. For the purposes of discussion, it is assumed that the weights **276** are already known and optimized for predicting map features **512** for future time buckets **518** based on a history of known map features **512** associated with known respiratory events and respiratory conditions.

In one embodiment, the predictions made by the LSTM process **514** can further be output to the digital stethoscope **110**, the base station **118**, the remote server **242**, or a combination thereof. For example, if the LSTM process **514** predicts that a patient will have a severe or acute respiratory event or respiratory condition in the near future, an output can be generated indicating the likelihood of the respiratory event or respiratory condition to, for example, the display unit **102** of the digital stethoscope **110** indicating the prediction.

It has been discovered that the use of the LSTM process **514** described above allows the digital stethoscope **110**, the base station **118**, or the remote server **242** to generate accurate predictions for the likelihood of occurrence of respiratory events or respiratory conditions. It has been further discovered that the ability to generate predictions regarding respiratory events or respiratory conditions significantly improves the current state of the art by allowing patients or users of the system **100** to be notified of respiratory events or respiratory conditions before they occur and allow patients or users of the system **100** to seek treatment in advance of a medical emergency. It has been further discovered that the ability of patients or users of the system **100** to be notified of the respiratory events or respiratory conditions can result in the ability to potentially save more patient lives by allowing patients to know that they need to seek medical treatment rapidly if a respiratory event or respiratory condition is predicted.

Convolutional Auto-Encoder to Predict Future Respiratory Noises

Referring now to FIG. **6**, therein is shown an exemplary third control flow **600** for forecasting characteristics of a future respiratory event or respiratory condition in an embodiment of the present invention. For brevity of description, in this embodiment, the third control flow **600** will be described as being performed using the base station **118**. This description is merely exemplary and not meant to be limiting. In other embodiments, the third control flow **600** can be performed using the digital stethoscope **110**, the remote server **242**, or a combination thereof.

The third control flow **600**, can enable forecasting characteristics of a future respiratory event or respiratory condition by using one or more feature spaces **602** generated based on the auditory signals **262**, wherein the feature spaces **602** are a three dimensional map or representation of the auditory signals **262**. In one embodiment, the feature spaces **602** can be generated by the base station **118**, for example, by the second FPGA **244** after receiving the auditory signals **262**. The feature spaces **602** can be a chart, image, matrix, plot, or other visual depiction representing the auditory signals **262** as a three dimensional map. The feature spaces

602 can have one or more variables with values representing characteristics of the auditory signals 262. For example, in one embodiment, the variables can include a frequency associated with the auditory signals 262 at a particular time, a rate representing a map of auditory nerve firing rate indicated by the auditory signals 262 at a particular time, and a severity representing the magnitude of the auditory signal 262 at a particular time. The feature spaces 602 can be generated using the same techniques as generating the auditory spectrogram 312, where the auditory signals 262 can be received, converted into the frequency domain functions 330, and filtered using the cochlear model 314 to obtain the variables of the feature spaces 602. Once the feature spaces 602 are generated, the third control flow 600 can be used to forecast characteristics of a future respiratory event or respiratory condition using the feature spaces 602.

The third control flow 600 can be implemented with modules and sub-modules, the components of the base station 118, or a combination thereof. In one embodiment, the third control flow 600 can include the convolution neural network module 310, a reverse convolution module 604, a validation module 606, and a long short term memory module 610. In one embodiment, the convolution neural network module 310 can couple to the reverse convolution module 604. The convolution neural network module 310 can further couple to the long short term memory module 610 via a storage 608. The reverse convolution module 604 can couple to the validation module 606.

In one embodiment, the convolution neural network module 310, as previously described with respect to FIG. 3, can receive the feature spaces 602 and perform the convolution procedure 316 on the feature spaces 602 to generate a convolution vector 324 for each of the feature spaces 602. In one embodiment, once the convolution vector 324 is generated, the convolution vector 324 can be saved in a storage 608 for later use by the long short term memory module 610. The storage 608 can be the second storage unit 248 or a further storage unit external to the base station 118, such as an external database, hard drive, volatile memory, nonvolatile memory, or a combination thereof.

In one embodiment, once the convolution neural network 310 has completed the convolution procedure 316 for each of the feature spaces 602, each convolution vector 324 and control can further be passed to the reverse convolution module 604. The reverse convolution module 604 enables the reverse process of the convolution neural network module 310, such that the reverse convolution module 604 can decode and reconstruct the feature spaces 602 by, for example, reversing the computations done by the convolution neural network module 310 to generate the feature spaces 602 from the convolution vector 320. In one embodiment, the reversing of the convolution vector 324 can be used to forecast characteristics of a future respiratory event or respiratory condition as will be described below. The reverse convolution module 604 can perform the reverse process of the convolution neural network module 310, by for example performing a reverse of the convolution procedure 316 by undoing all the calculations performed by the convolution procedure 316.

In one embodiment, once the reverse convolution module 604 reconstructs the feature spaces 602, it can pass the reconstructed feature spaces 602 and control to the validation module 606. The validation module 606 enables the validation of the of the computations of the reverse convolution module 604 by for example comparing the reconstructed feature spaces 602 with the feature spaces 602 received by the convolution neural network module 310. For example, in one embodiment, the comparison can include comparing the values of the variables, for example the frequency, rate, and scale of each the reconstructed feature spaces 602 with the same variables for feature spaces 602 received by the convolution neural network module 310 and determining whether they are equal or within an error tolerance, such that the two can be considered equivalent. If the validation module 606 determines that the values are equivalent, the computations of the reverse convolution module 310 can be considered valid such that reverse convolution module 604 can later be used to forecast characteristics of a future respiratory event or respiratory condition.

In one embodiment, once the validation module 606 has validated the computations of the reverse convolution module 604, control can pass to the long short term memory module 610. The long short term memory module 610 can enable and implement the LSTM process 514 as described with respect to FIG. 5B. In one embodiment, the long short term memory module 610 can retrieve each saved convolution vector 324 from the storage 608 and perform the LSTM process 514 using each convolution vector 324 in a similar fashion as was described with the time buckets 518 of FIG. 5B. By way of example, the long short term memory module 610 can replace the time buckets 518 with each convolution vector 324 and predict a future convolution vector 324 using the values of each convolution vector 324.

In one embodiment, the long short term memory module 610 can look for patterns as described with respect to FIG. 5B using a look back feature 516 and weights 276 trained based on a history of respiratory events or respiratory conditions, but with respect to the convolution vectors 324 such that the long short term memory module 610 can forecast characteristics of a future respiratory event or respiratory condition based on each previous convolution vector 324.

By way of example, if the long short term memory module 610 determines that each previous convolution vector 324 indicates a trend towards feature spaces 602 for a known respiratory event or respiratory condition, the long short term memory module 610 can forecast characteristics of future feature spaces 602 such that the long short term memory module 610 can predict or forecast particular feature spaces 602 indicating a particular respiratory event or respiratory condition. In one embodiment, the forecasting can be done by generating a predicted convolution vector 324 with predicted values indicating the predicted or forecasted characteristics of the forecast feature spaces 602. The predicted or forecast feature spaces 602 can further be generated by decoding or reversing the predicted convolution vector 324 via the reverse convolution procedure module 604.

In one embodiment, the predicted or forecast feature spaces 602 can further be output to the digital stethoscope 110, the base station 118, the remote server 242, or a combination thereof. For example, if the long short term memory module 610 forecasts that a patient will have feature spaces 602 indicating a particular respiratory event or respiratory condition in the near future, an output can be generated indicating the forecast or predicted feature spaces 602 to, for example, the display unit 102 of the digital stethoscope 110 and an alert can be sent to the patient or user of the system 100 indicating the forecasting.

It has been discovered that the use of the third control flow 600 described above allows the digital stethoscope 110, the base station 118, or the remote server 242 to generate accurate predictions for the likelihood of occurrence of

respiratory events or respiratory conditions without the need to know about environmental conditions at a particular time or over a period of time affecting the onset of a respiratory event or respiratory condition and can generate forecasts of characteristics of respiratory events or respiratory conditions based on the auditory signals **262**. It has been further discovered that the ability to generate predictions regarding respiratory events or respiratory conditions significantly improves the current state of the art by allowing patients or users of the system **100** to be notified of a respiratory event or respiratory conditions before they occur and allow patients or users of the system **100** to seek treatment in advance of a medical emergency. It has been further discovered that the ability of patients or users of the system **100** to be notified of the respiratory events or respiratory conditions can result in the ability to potentially save more patient lives by allowing patients to know that they need to seek medical treatment rapidly if a respiratory event or respiratory condition is predicted.

Referring now to FIG. **7**, therein is shown an exemplary depiction of the third control flow **600** for forecasting characteristics of a future respiratory event or respiratory condition in an embodiment of the present invention. In the embodiment of FIG. **7**, two feature spaces **602** are shown, as indicated by **602**A and **602**B representing a frequency, rate, and scale of the auditory signals **262** at different times T(1) and T(2). FIG. **7** further shows **602**A and **602**B undergoing the convolution procedure **316**, as indicated by **704**A and **704**B. As a result, one or more convolution matrix spaces **702** are generated, as indicated by **702**A, **702**B, **702**C, and **702**D. **702**A, **702**B, **702**C, and **702**D, similar to the convolution matrices **322**, represent spaces generated from doing the convolution procedure **316** on three dimensional feature spaces **602**, such that they represent three dimensional matrix spaces. FIG. **7** further shows the convolution matrix spaces **702** being compressed from one iteration of the convolution procedure **316** to the next such that the convolution matrix spaces **702** of a subsequent iteration are smaller than the convolution matrix spaces **702** of the previous iteration, similar to what was described with respect to FIGS. **3** and **4**C, until the convolution matrix spaces **702** can be formed into a convolution vector **324** associated with each of the feature spaces **602**. The convolution vector **324** associated with each of the feature spaces **602** are represented as **324**A and **324**B. FIG. **7**, further shows the reversing or decoding of the convolution procedure **316**, as indicated by **708**A and **708**B to generate one or more reverse convolution matrix spaces **704**, as indicated by **704**A and **704**B. The reverse convolution matrix spaces **704** represent three dimensional matrix spaces generated from performing the reverse convolution procedure **316** on **324**A and **324**B. FIG. **7** further shows one or more reconstructed feature spaces **710**, as indicated by **710**A and **710**B, generated based on performing the reversing of the convolution procedure **316** on the reverse convolution matrix spaces **704**.

In the embodiment shown in FIG. **7**, each of **324**A and **324**B can further be used to forecast characteristics of a future respiratory event or respiratory condition based on having the LSTM process **514**, as done by the long short term memory module **610**, performed using **324**A and **324**B as the inputs of the LSTM process **514**. For example, FIG. **7** shows the LSTM process **514** performed, as indicated by **514**A and **514**B, such that a prediction vector **324**N, representing a predicted convolution vector **324** is generated for a future time, indicated by T(N). The prediction vector **324**N can have a reverse convolution procedure **316** performed on it, as indicated by **708**N to generate a predicted feature space **710**N representing the forecasted characteristics of a future respiratory event or respiratory condition.

The system **100** has been described with module functions or order as an example. The system **100** can partition the modules differently or order the modules differently. For example, the first software **224**, the second software **252**, or a combination thereof, can include the modules for the system **100**. As a specific example, the first software **224**, the second software **252**, or a combination thereof can include the receiver module **304**, the subtraction module **306**, the filter module **308**, the convolution neural network module **310**, the reverse convolution module **604**, the validation module **606**, the long short term memory module **610**, and associated sub-modules included therein.

The first control unit **210**, the second control unit **236**, or a combination thereof, can execute the first software **224**, the second software **252**, or a combination thereof, to operate the modules. For example, the first control unit **210**, the second control unit **236**, or a combination thereof, can execute the first software **224**, the second software **252**, or a combination thereof, to implement the receiver module **304**, the subtraction module **306**, the filter module **308**, the convolution neural network module **310**, the reverse convolution module **604**, the validation module **606**, the long short term memory module **610**, and associated sub-modules included therein.

The modules described in this application can be implemented as instructions stored on a non-transitory computer readable medium to be executed by the first control unit **210**, the second control unit **236**, or a combination thereof. The non-transitory computer readable medium can include the first storage unit **218**, the second storage unit **248**, or a combination thereof. The non-transitory computer readable medium can include non-volatile memory, such as a hard disk drive, non-volatile random access memory (NVRAM), solid-state storage device (SSD), compact disk (CD), digital video disk (DVD), or universal serial bus (USB) flash memory devices. The non-transitory computer readable medium can be integrated as a part of the system **100** or installed as a removable portion of the system **100**.

Exemplary Methods

Referring now to FIG. **8**, therein is shown an exemplary method **800** of operating the system **100** in an embodiment of the present invention. The method **800** includes: receiving, from a microphone, an auditory signal as shown in box **802**; generating an auditory spectrogram based on the auditory signal as shown in box **804**; performing a convolution procedure on the auditory spectrogram to generate one or more convolution values, wherein the convolution values represent a compressed version of a portion of the auditory spectrogram, and wherein the convolution procedure is trained to generate one or more features for detecting the respiratory abnormality as shown in box **806**; applying one or more weights to the convolution values, wherein the weights are trained for detection of the respiratory abnormality as shown in box **808**; generating a classification value based on applying the weights to the convolution values, wherein the classification value indicates whether the auditory signal includes the respiratory abnormality as shown in box **810**; and outputting the classification value as shown in box **812**.

Referring now to FIG. **9**, therein is shown a further exemplary method **900** of operating the system **100** in an embodiment of the present invention. The method **900** includes: receiving, over a period of time from a microphone of a digital stethoscope, an auditory signal as shown in box **902**; generating an auditory spectrogram based on the audi-

tory signal as shown in box **904**; analyzing, with a control unit of the digital stethoscope, the auditory spectrogram to determine whether the auditory signal represents a cough as shown in box **906**; tracking, with the control unit of the digital stethoscope, the cough in a cough log as shown in box **908**; and transmitting based on the cough log, with a communication unit of the digital stethoscope to a cloud-based service, a message indicating a number of coughs tracked over the period of time for storage on a remote server as shown in box **910**.

Referring now to FIG. **10**, therein is shown a further exemplary method **1000** of operating the system **100** in an embodiment of the present invention. The method **1000** includes: receiving, from a microphone of a digital stethoscope, a first noise signal at a first time as shown in box **1002**; analyzing the first noise signal to determine a first severity score indicating how severe a first respiratory event of a patient captured in the first noise signal is as shown in box **1004**; receiving, from the microphone of the digital stethoscope, a second noise signal captured at a second time as shown in box **1006**; analyzing the second noise signal to determine a second severity score indicating how severe a second respiratory event of the patient captured in the second noise signal is as shown in box **1008**; generating a prediction indicating a likelihood of a third respiratory event occurring for the patient at a future time based on applying a first weight to the first severity score and a second weight to the second severity score, wherein the first and second weights are trained based on a history of respiratory events as shown in box **1010**; outputting the prediction as shown in box **1012**.

Referring now to FIG. **11**, therein is shown a further exemplary method **1100** of operating the system **100** in an embodiment of the present invention. The method **1100** includes: receiving, from a microphone of a digital stethoscope, a first noise signal capturing a first respiratory event at a first time as shown in box **1102**; generating a first feature space representing the first noise signal as shown in box **1104**; encoding the first feature space into a first convolution vector using a convolution procedure as shown in box **1106**; receiving, from the microphone of the digital stethoscope, a second noise signal capturing a second respiratory event at a second time as shown in box **1108**; generating a second feature space representing the second noise signal as shown in box **1110**; encoding the second feature space into a second convolution vector using the convolution procedure as shown in box **1112**; determining a predicted convolution vector based on the first and second feature spaces as shown in box **1114**; and decoding the predicted convolution vector into a predicted feature space representing a sound made by the future respiratory event as shown in box **1116**.

Other Examples and Embodiments

Referring now to FIG. **12**, therein is shown exemplary spectrograms **1200** representing breathing patterns in an embodiment of the present invention. The spectrograms **1200** of FIG. **12**, similar to what was described with respect to the auditory spectrogram **312** of FIG. **3**, are two dimensional visual representations of the spectrum of frequencies of known noises, from the patient's body, for example a cough, a crackle, a wheeze, a breathing pattern, or a combination thereof. FIG. **12** shows two spectrograms **1200** representing two different breathing patterns, one for a normal breathing pattern **1202**, indicating no respiratory abnormality, and one for a wheeze breathing pattern **1204**, indicating a respiratory abnormality associated with a wheeze. In one embodiment, the breathing patterns and their representations in the form of the spectrograms **1200** can be used as a part of the back propagation process, as described with respect to FIGS. **3** and **5**, to train the weights **276** and biases **334** of the machine learning processes used by the system **100** which are used by the system **100** to perform the detection of the respiratory abnormality, or to predict a respiratory event or respiratory condition in the future. For example, the spectrograms **1200** can be used to train the weights **276** and biases **334** used in the neural network **326**, the LSTM process **514**, or a combination thereof by for example using the spectrograms **1200** as examples of known breathing patterns which the system **100** can attempt to reconstruct through back propagation, and in the process determine the values of the weights **276** and biases **334** to reconstruct the spectrograms **1200**. The biases **334** and weights **276** can subsequently be used to make future predictions about auditory signals **262** and classify them, by for example, classifying them as "normal" or "abnormal" based on the processes previously described

Referring now to FIG. **13**, therein is shown an exemplary auditory spectrogram **312** in an embodiment of the present invention. FIG. **13** shows a depiction of the auditory spectrogram **312** as described with respect to FIG. **3**. FIG. **13** further shows how the auditory spectrogram **312** amplifies and sharpens the frequency components of an auditory signal **262**. For example, FIG. **13**, shows the frequency components of an auditory signal **262** as white marks. Further, FIG. **13** shows the magnitude of the frequency components by indicating lighter shades of white for frequency components that comprise a larger portion of the auditory signal **262** for a given time.

Referring now to FIG. **14**, therein is shown an exemplary feature space **602** in an embodiment of the present invention. FIG. **14** shows an exemplary frequency, rate, and scale of an auditory signals **262** at different times plotted against one another other. For clarity and ease of description, the frequency, rate, and scale are plotted as two dimensional visual representations where each of the frequency, rate, and scale is plotted against only one of the other variables, despite being described in FIGS. **6** and **7** as a three dimensional map or representation of the auditory signals **262**. The combination of the plots of FIG. **14** represents the feature space **602**. FIG. **14** further shows three plots **1402**, **1404**, and **1406**. Plot **1402** represents a plot of the scale vs. rate. Plot **1404** represents a plot of frequency vs. rate. Plot **1406** represents a plot of scale vs. frequency. As described in FIGS. **6** and **7**, the plots can be constructed and reconstructed to make the predictions regarding respiratory events or respiratory conditions in the future.

The above embodiments are described in sufficient detail to enable those skilled in the art to make and use the invention. It is to be understood that other embodiments would be evident based on the present disclosure, and that system, process, or mechanical changes may be made without departing from the scope of an embodiment of the present invention.

In the above description, numerous specific details are given to provide a thorough understanding of the invention. However, it will be apparent that the invention may be practiced without these specific details. To avoid obscuring an embodiment of the present invention, some well-known circuits, system configurations, and process steps are not disclosed in detail.

The term "module" or "unit" referred to herein can include software, hardware, or a combination thereof in an embodiment of the present invention in accordance with the context in which the term is used. For example, the software can be machine code, firmware, embedded code, or appli-

cation software. Also for example, the hardware can be circuitry, a processor, a microprocessor, a microcontroller, a special purpose computer, an integrated circuit, integrated circuit cores, a pressure sensor, an inertial sensor, a micro-electromechanical system (MEMS), passive devices, or a combination thereof. Further, if a module or unit is written in the system or apparatus claims section below, the module or unit is deemed to include hardware circuitry for the purpose and the scope of the system or apparatus claims.

The modules and units in the following description of the embodiments can be coupled to one another as described or as shown. The coupling can be direct or indirect, without or with intervening items between coupled modules or units. The coupling can be by physical contact or by communication between modules or units.

The above detailed description and embodiments of the disclosed system **100** are not intended to be exhaustive or to limit the disclosed system **100** to the precise form disclosed above. While specific examples for the system **100** are described above for illustrative purposes, various equivalent modifications are possible within the scope of the disclosed system **100**, as those skilled in the relevant art will recognize. For example, while processes and methods are presented in a given order, alternative implementations may perform routines having steps, or employ systems having processes or methods, in a different order, and some processes or methods may be deleted, moved, added, subdivided, combined, or modified to provide alternative or sub-combinations. Each of these processes or methods may be implemented in a variety of different ways. Also, while processes or methods are at times shown as being performed in series, these processes or blocks may instead be performed or implemented in parallel, or may be performed at different times.

The resulting method, process, apparatus, device, product, and system is cost-effective, highly versatile, and accurate, and can be implemented by adapting components for ready, efficient, and economical manufacturing, application, and utilization. Another important aspect of an embodiment of the present invention is that it valuably supports and services the historical trend of reducing costs, simplifying systems, and increasing performance.

These and other valuable aspects of the embodiments of the present invention consequently further the state of the technology to at least the next level. While the invention has been described in conjunction with a specific best mode, it is to be understood that many alternatives, modifications, and variations will be apparent to those skilled in the art in light of the descriptions herein. Accordingly, it is intended to embrace all such alternatives, modifications, and variations that fall within the scope of the included claims. All matters set forth herein or shown in the accompanying drawings are to be interpreted in an illustrative and non-limiting sense.

What is claimed is:

1. A computer-implemented method for forecasting characteristics of a future respiratory event comprising:

receiving, from a microphone of a digital stethoscope, a first noise signal capturing a first respiratory event at a first time;

generating, by one or more computing devices, a first feature space representing the first noise signal;

encoding, by the one or more computing devices, the first feature space into a first convolution vector using a spatial convolution procedure;

receiving, from the microphone of the digital stethoscope, a second noise signal capturing a second respiratory event at a second time;

generating, by the one or more computing devices, a second feature space representing the second noise signal;

encoding, by the one or more computing devices, the second feature space into a second convolution vector using the spatial convolution procedure;

determining, by the one or more computing devices, a predicted convolution vector based on the first and second feature spaces;

decoding, by the one or more computing devices, the predicted convolution vector into a predicted feature space representing a sound made by the future respiratory event; and

transmitting, by the one or more computing devices, the predicted feature space to a display unit for output, wherein the output indicates the likelihood of the future respiratory event.

2. The method of claim **1** wherein the first, second, and predicted feature spaces are three-dimensional spaces with values each signifying a frequency, rate, and severity of the first noise signal, the second noise signal, and the sound made by the future respiratory event.

3. The method of claim **1** wherein the first noise signal, second noise signal, and the sound made by the future respiratory event are coughs.

4. The method of claim **1** wherein the first noise signal, second noise signal, and the sound made by the future respiratory event are wheezes.

5. The method of claim **1** wherein encoding the first and second feature spaces comprises repeatedly performing the spatial convolution procedure on the first and second feature spaces to generate one or more convolution values, wherein the convolution values represent a compressed version of a portion of the first and second feature spaces.

6. The method of claim **5** wherein decoding the predicted convolution vector comprises repeatedly performing an inverse of the spatial convolution procedure to generate the predicted feature space.

7. The method of claim **1** wherein determining the predicted convolution vector based on the first and second feature spaces comprises:

applying a first weight to the first convolutional vector to generate a first intermediate vector; and

calculating a second intermediate vector based on applying a second weight to the second convolutional vector, wherein the first and second weights are values trained based on a history of respiratory events.

8. A non-transitory computer readable medium including instructions for forecasting characteristics of a future respiratory event comprising:

receiving, from a microphone of a digital stethoscope, a first noise signal capturing a first respiratory event at a first time;

generating, by one or more computing devices, a first feature space representing the first noise signal;

encoding, by the one or more computing devices, the first feature space into a first convolution vector using a spatial convolution procedure;

receiving, from the microphone of the digital stethoscope, a second noise signal capturing a second respiratory event at a second time;

generating, by the one or more computing devices, a second feature space representing the second noise signal;

encoding, by the one or more computing devices, the second feature space into a second convolution vector using the spatial convolution procedure;

determining, by the one or more computing devices, a predicted convolution vector based on the first and second feature spaces;

decoding, by the one or more computing devices, the predicted convolution vector into a predicted feature space representing a sound made by the future respiratory event; and

transmitting, by the one or more computing devices, the predicted feature space to a display unit for output, wherein the output indicates the likelihood of the future respiratory event.

9. The non-transitory computer readable medium of claim **8** with instructions wherein the first, second, and predicted feature spaces are three-dimensional spaces with values each signifying a frequency, rate, and severity of the first noise signal, the second noise signal, and the sound made by the future respiratory event.

10. The non-transitory computer readable medium of claim **8** with instructions wherein the first noise signal, second noise signal, and the sound made by the future respiratory event are coughs.

11. The non-transitory computer readable medium of claim **8** with instructions wherein the first noise signal, second noise signal, and the sound made by the future respiratory event are wheezes.

12. The non-transitory computer readable medium of claim **8** with instructions wherein encoding the first and second feature spaces comprises repeatedly performing the spatial convolution procedure on the first and second feature spaces to generate one or more convolution values, wherein the convolution values represent a compressed version of a portion of the first and second feature spaces.

13. The non-transitory computer readable medium of claim **12** with instructions wherein decoding the predicted convolution vector comprises repeatedly performing an inverse of the spatial convolution procedure to generate the predicted feature space.

14. The non-transitory computer readable medium of claim **8** with instructions wherein determining the predicted convolution vector based on the first and second feature spaces comprises:

applying a first weight to the first convolutional vector to generate a first intermediate vector; and

calculating a second intermediate vector based on applying a second weight to the second convolutional vector, wherein the first and second weights are values trained based on a history of respiratory events.

* * * * *

专利名称(译)	预测未来呼吸事件的特征及其应用		
公开(公告)号	US10702239	公开(公告)日	2020-07-07
申请号	US16/659392	申请日	2019-10-21
发明人	MCLANE, IAN MITRA		
IPC分类号	A61B5/08 A61B7/00 G16H50/20 A61B7/04 A61B5/00		
CPC分类号	A61B7/04 G16H50/20 A61B5/7425 A61B5/7267 A61B5/0823 A61B7/003 A61B5/7275		

摘要(译)

本文公开的实施例改进了数字听诊器及其应用和操作。 第一种方法使用卷积检测呼吸异常。 第二种方法是为患者咳嗽。 第三种方法根据检测到的趋势预测呼吸事件。 第四种方法预测未来呼吸事件的特征。 在第五实施例中,提供了一种用于数字听诊器的基站。