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(54) SYSTEMS AND METHODS FOR DETECTING MACHINES ENGAGED IN ANOMALOUS ACTIVITY

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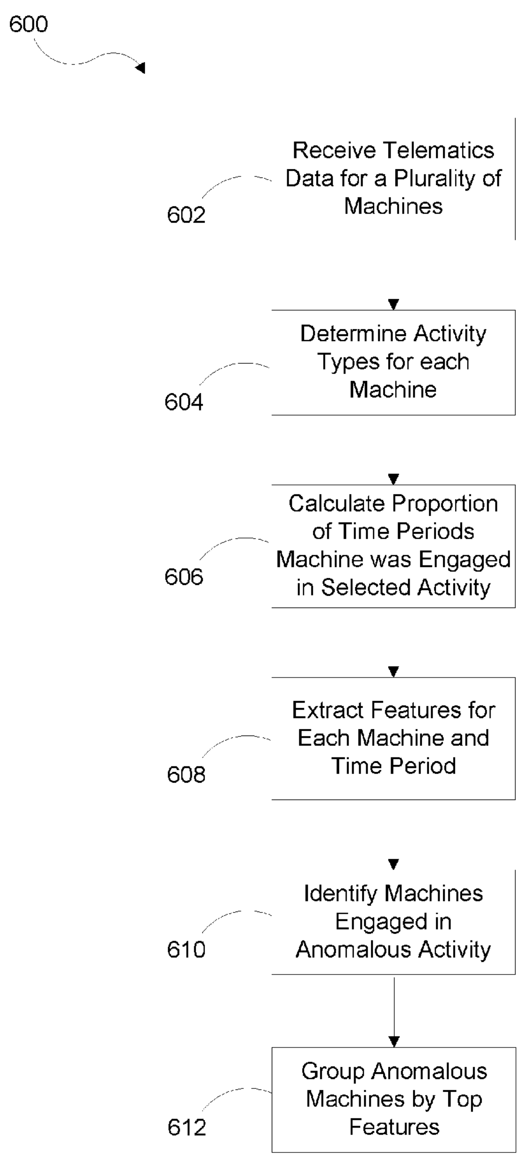
(57) **ABSTRACT**

A method for detecting machines engaged in anomalous activity can include receiving telematics data from a plurality of sensors on each of a plurality of machines and determining one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine. The method can also include calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities. The method further includes extracting one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine. One or more of the plurality of machines engaged in anomalous activity can be identified based on at least the proportion and the one or more extracted features for the machines.



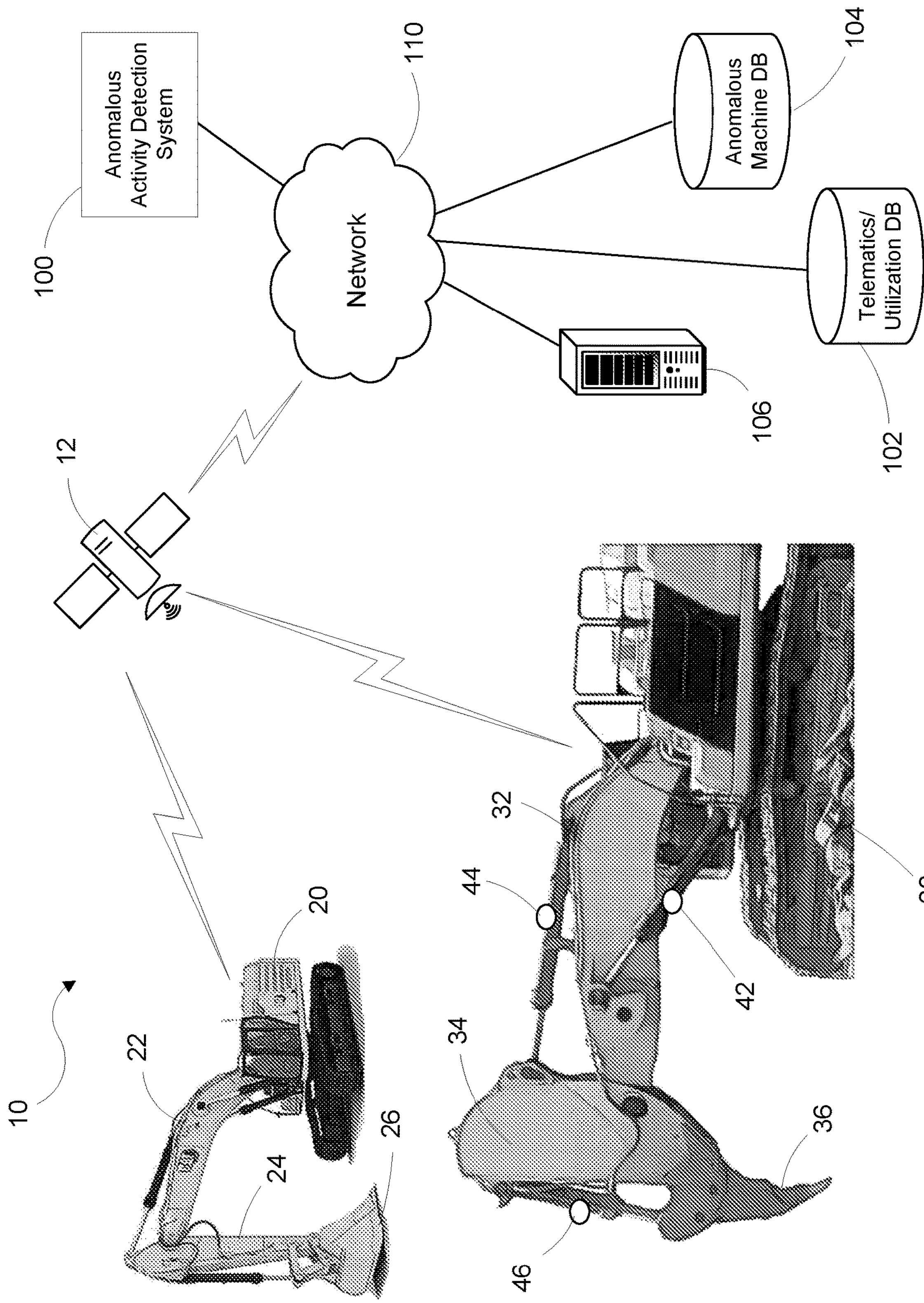

Anomalous Activity Detection System
100
110
Network
Anomalous Machine DB
104
Telematics/ Utilization DB
102
106
12
10
20
22
24
26
30
32
34
36
42
44
46

FIG. 1

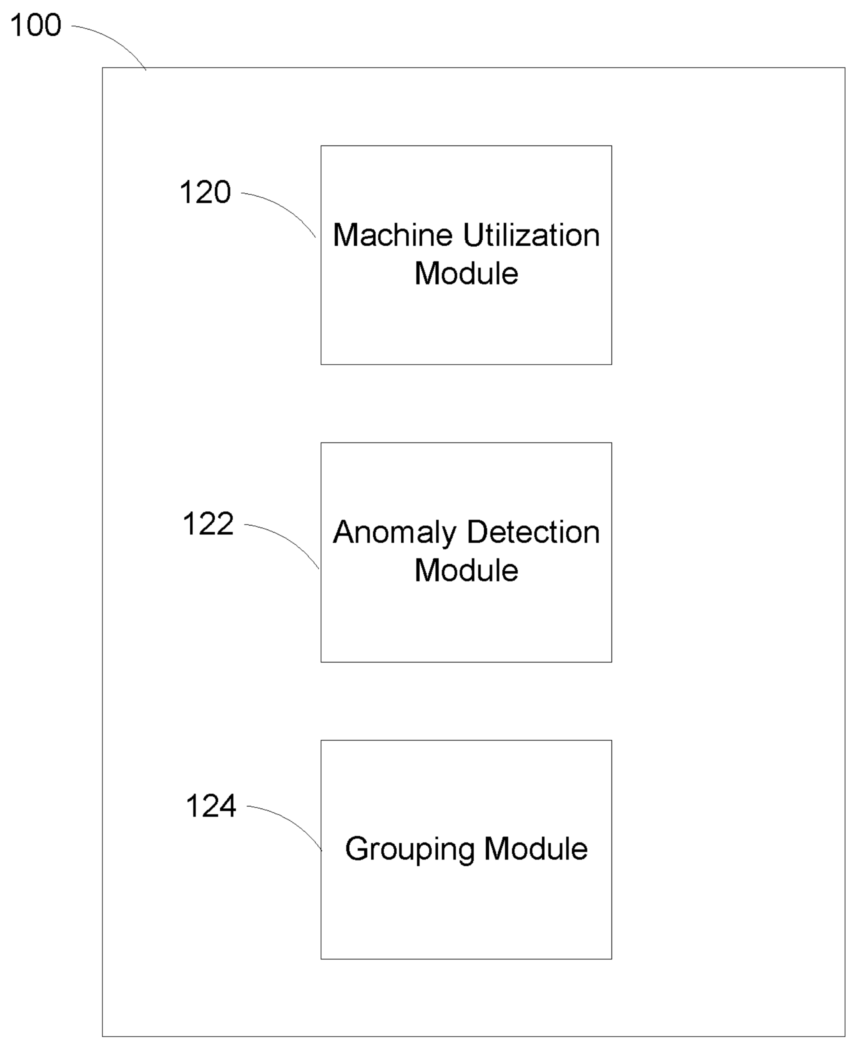

100
120
Machine Utilization Module
122
Anomaly Detection Module
124
Grouping Module

FIG. 2

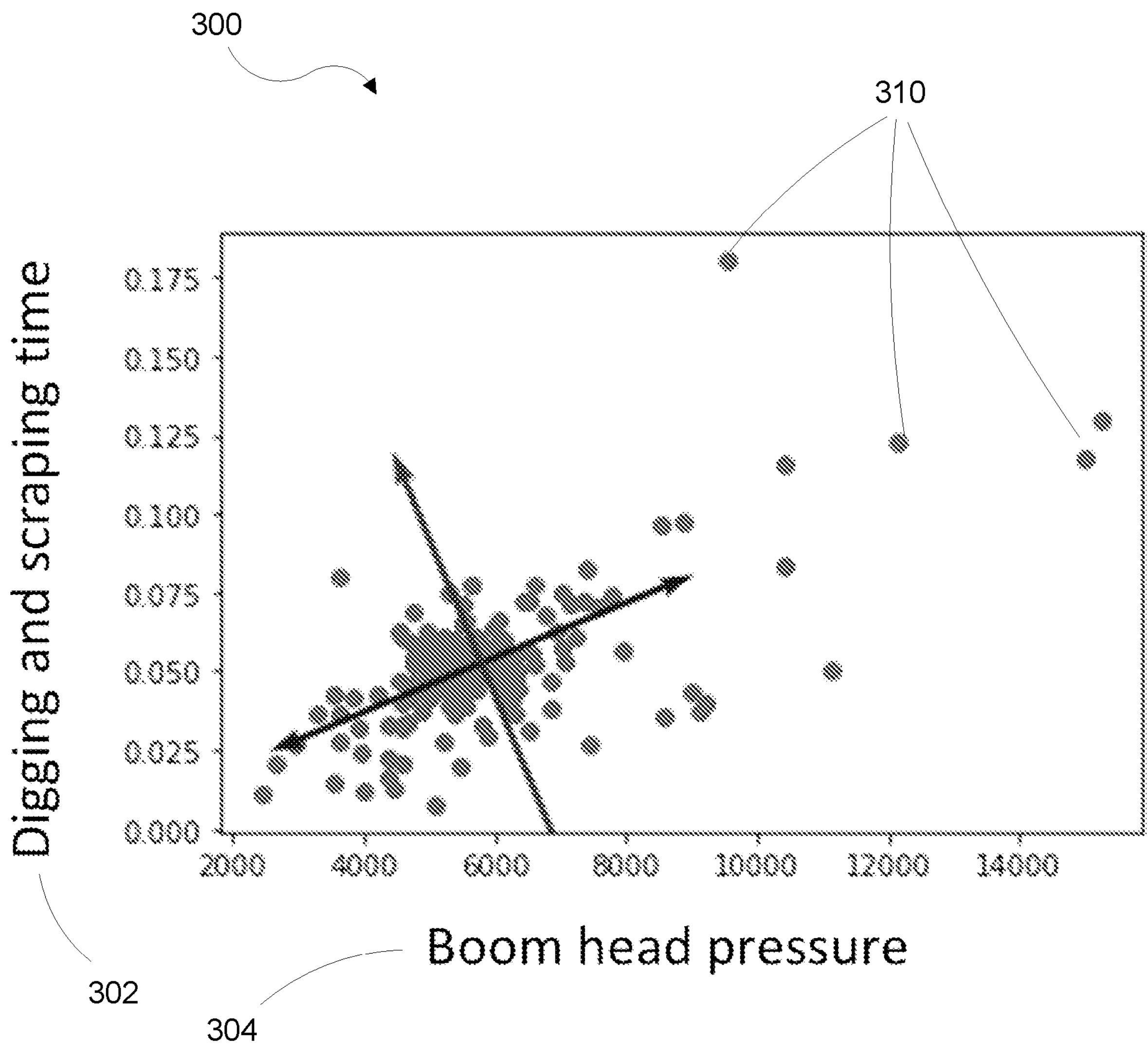

300
310
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
2000
4000
6000
8000
10000
12000
14000
Digging and scraping time
Boom head pressure
302
304

FIG. 3

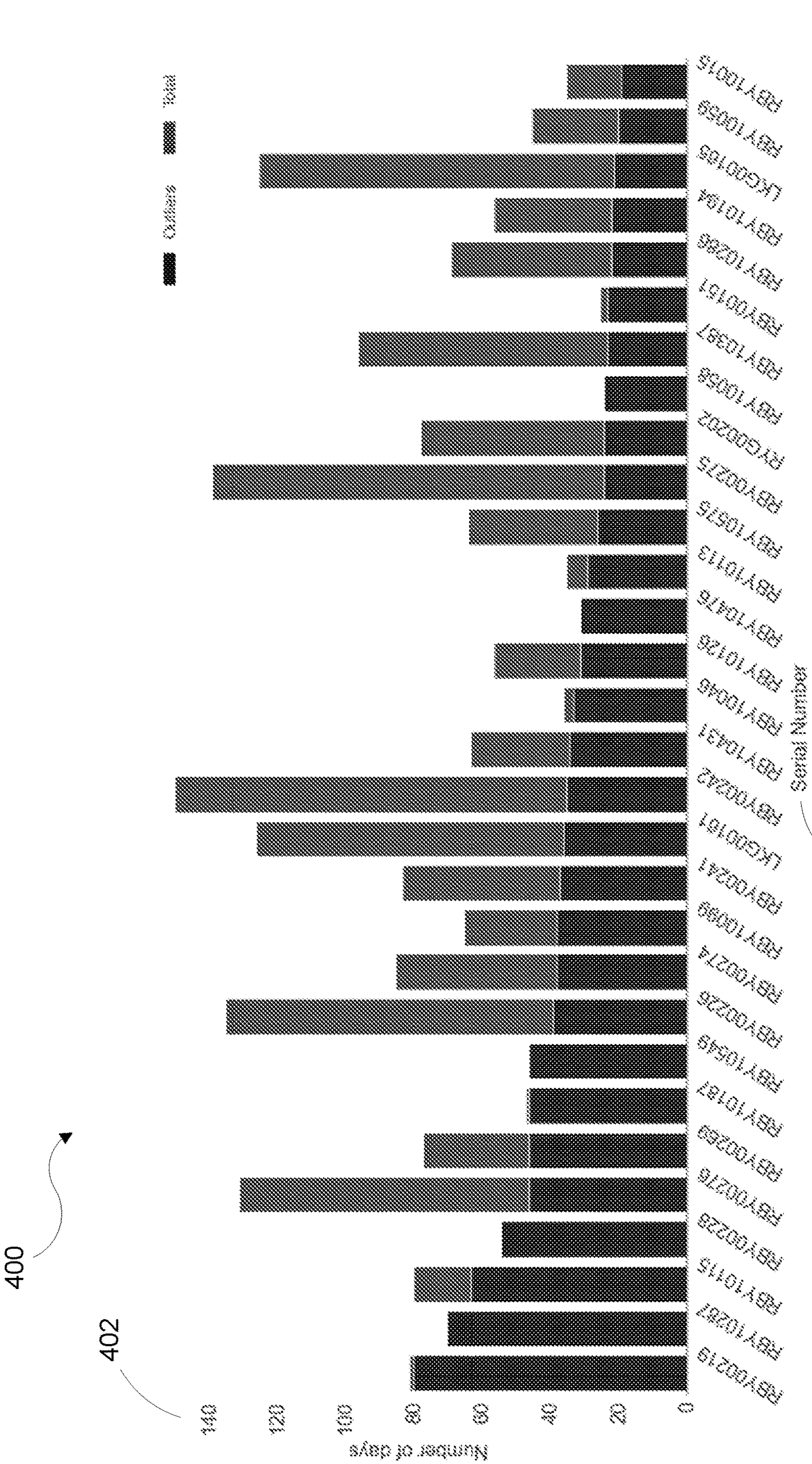

400
402
404
Outliers
Total
Number of days
0
20
40
60
80
100
120
140
Serial Number
RBY00219
RBY10287
RBY10115
RBY00228
RBY00276
RBY00269
RBY10187
RBY10549
RBY00226
RBY00274
RBY10099
RBY00241
LKG00161
RBY00242
RBY10431
RBY10045
RBY10126
RBY10476
RBY10113
RBY10575
RBY00275
RYG00202
RBY10058
RBY10387
RBY00151
RBY10286
RBY10194
LKG00165
RBY10059
RBY10015

FIG. 4A

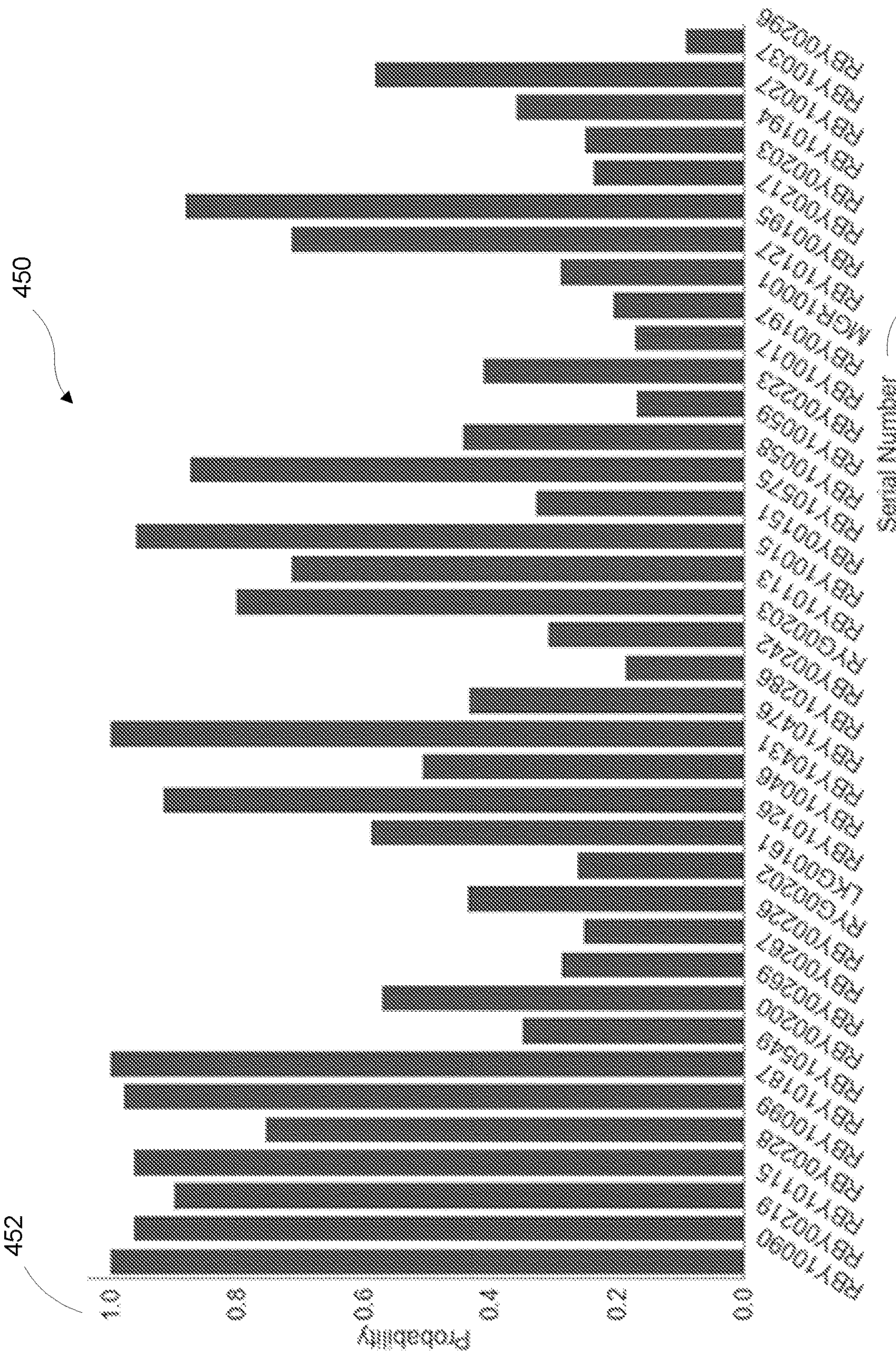

450
452
454
Probability
1.0
0.8
0.6
0.4
0.2
0.0
Serial Number
RBY10090
RBY00219
RBY10115
RBY00228
RBY10099
RBY10187
RBY10549
RBY00200
RBY00269
RBY00287
RBY00226
RYG00202
LKG00161
RBY10126
RBY10046
RBY10431
RBY10476
RBY10286
RBY00242
RYG00203
RBY10113
RBY10015
RBY00151
RBY10575
RBY10058
RBY10059
RBY00223
RBY10017
RBY00197
MCR10001
RBY10127
RBY00195
RBY00217
RBY00203
RBY10194
RBY10027
RBY10037
RBY00296

FIG. 4B

500

502 504 506 508

	serial_number	top_feature_1	top_feature_2	cluster	probability	min_date	max_date	num_days
0	RBY10090	max_bucket_re_press	None	0	1.000000	2020-04-15	2020-07-16	93
1	RBY00219	max_boom_re_press	max_bucket_he_press	1	0.962963	2020-04-07	2020-07-14	81
2	RBY10115	max_boom_re_press	scrapping_digging_fraction	2	0.900000	2020-04-23	2020-07-16	80
3	RBY00228	max_boom_re_press	scrapping_digging_fraction	2	0.962963	2020-04-03	2020-07-16	54
4	RBY10099	max_boom_re_press	max_stick_he_press	3	0.753846	2020-05-08	2020-07-16	65
5	RBY10187	max_bucket_he_press	max_boom_re_press	1	0.978723	2020-04-08	2020-07-16	47
6	RBY10549	scrapping_digging_fraction	max_boom_re_press	2	1.000000	2020-05-19	2020-07-15	48
7	RBY10046	scrapping_digging_fraction	max_boom_re_press	2	0.916667	2020-02-26	2020-04-02	36
8	RBY10476	scrapping_digging_fraction	max_boom_re_press	2	1.000000	2020-06-14	2020-07-16	31
9	RBY10113	scrapping_digging_fraction	max_boom_re_press	2	0.900000	2020-06-12	2020-07-18	35
10	RBY10015	max_boom_re_press	None	4	0.714286	2020-02-28	2020-04-02	35
11	RBY10058	max_bucket_he_press	max_boom_re_press	1	0.875000	2020-01-15	2020-03-09	24
12	RBY00195	max_bucket_he_press	None	5	0.714286	2020-01-01	2020-02-02	21
13	RBY00217	max_boom_re_press	max_stick_he_press	3	0.882353	2020-01-01	2020-02-10	17
14	RBY00216	max_boom_re_press	max_bucket_he_press	1	1.000000	2020-01-10	2020-02-24	9
15	RBY00231	scrapping_digging_fraction	max_boom_re_press	2	0.888889	2020-01-09	2020-02-17	9
16	RBY10050	max_boom_re_press	None	4	1.000000	2020-01-17	2020-01-21	5
17	RBY00154	max_stick_he_press	max_bucket_re_press	6	1.000000	2020-03-02	2020-03-02	1

FIG. 5

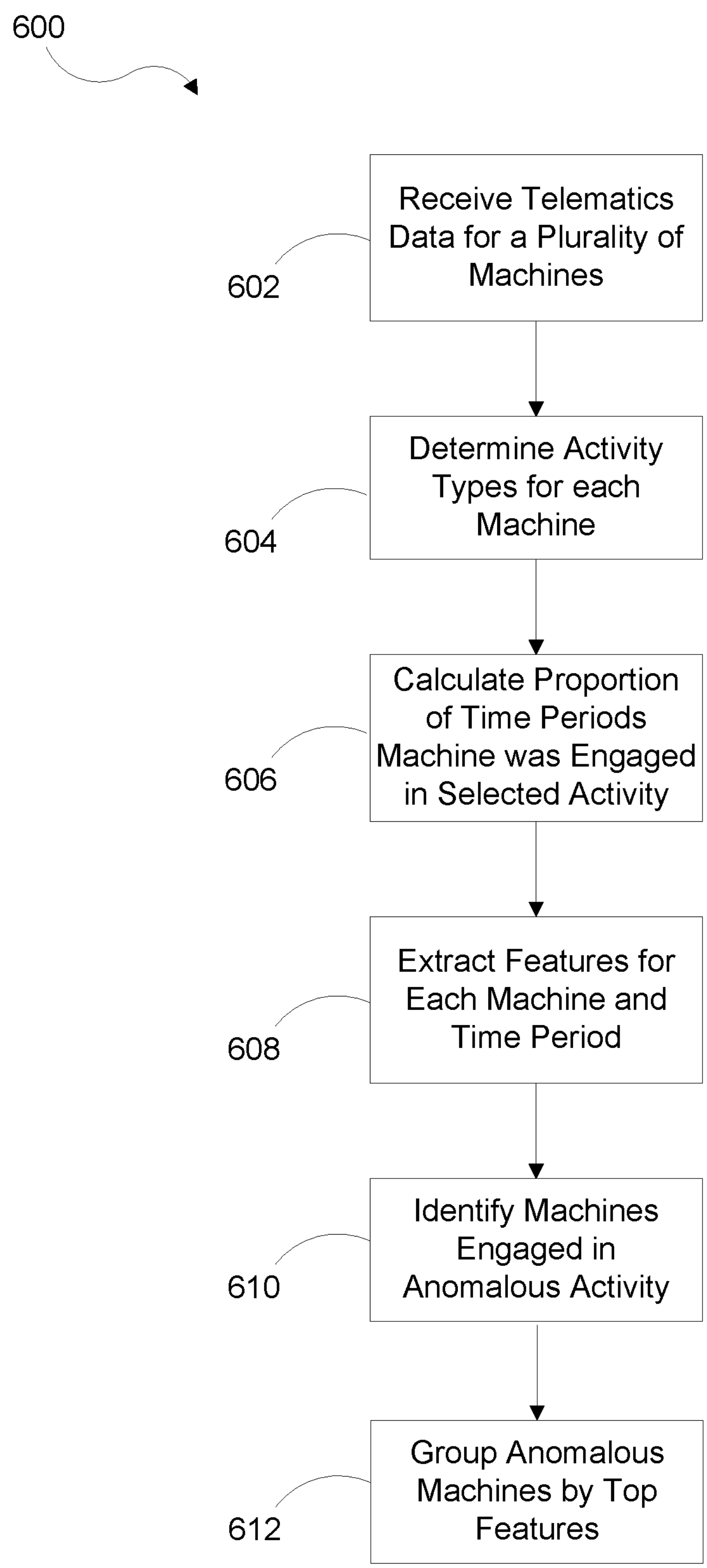

600
602
Receive Telematics Data for a Plurality of Machines
604
Determine Activity Types for each Machine
606
Calculate Proportion of Time Periods Machine was Engaged in Selected Activity
608
Extract Features for Each Machine and Time Period
610
Identify Machines Engaged in Anomalous Activity
612
Group Anomalous Machines by Top Features

FIG. 6

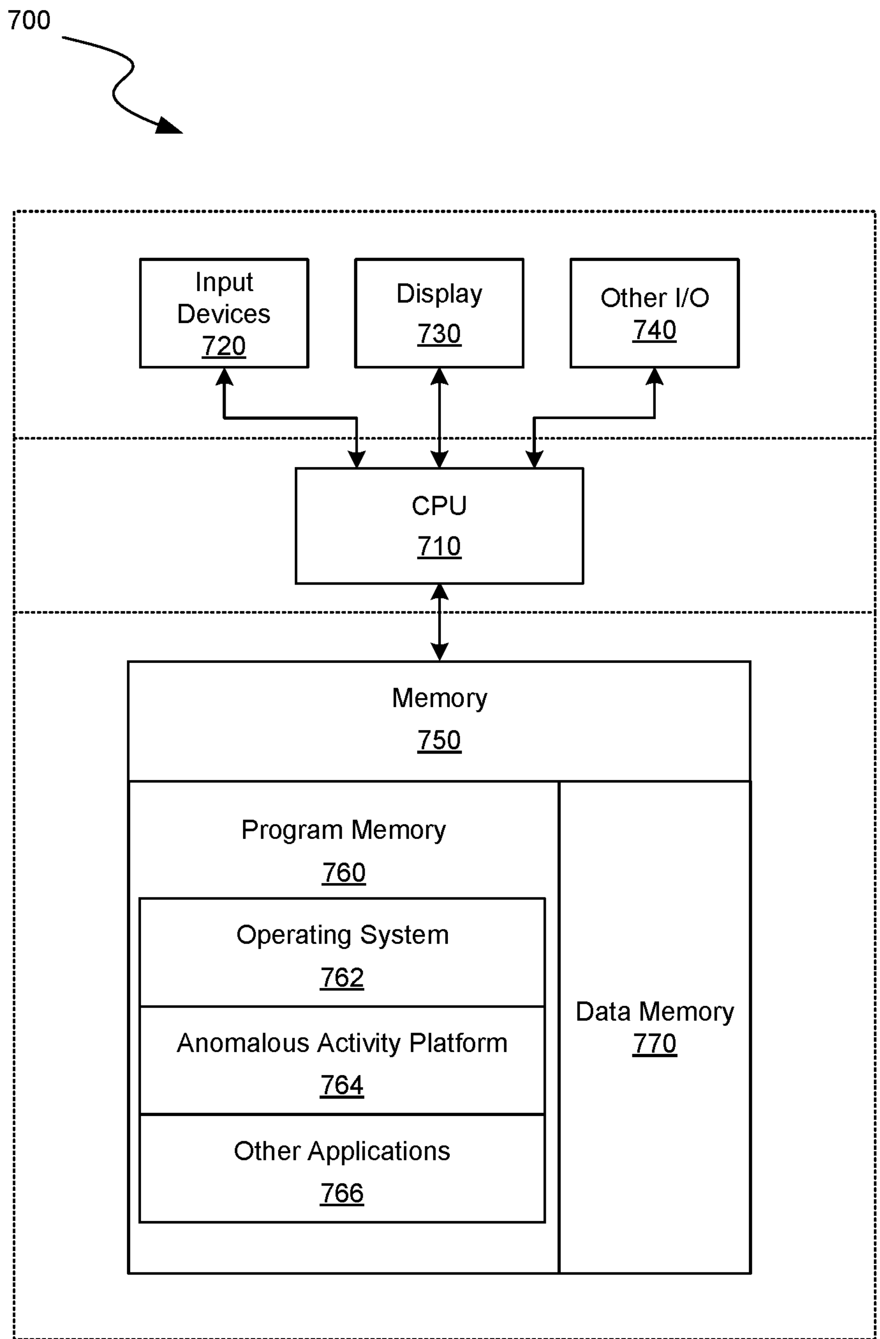

700
Input Devices 720
Display 730
Other I/O 740
CPU 710
Memory 750
Program Memory 760
Operating System 762
Anomalous Activity Platform 764
Other Applications 766
Data Memory 770

FIG. 7

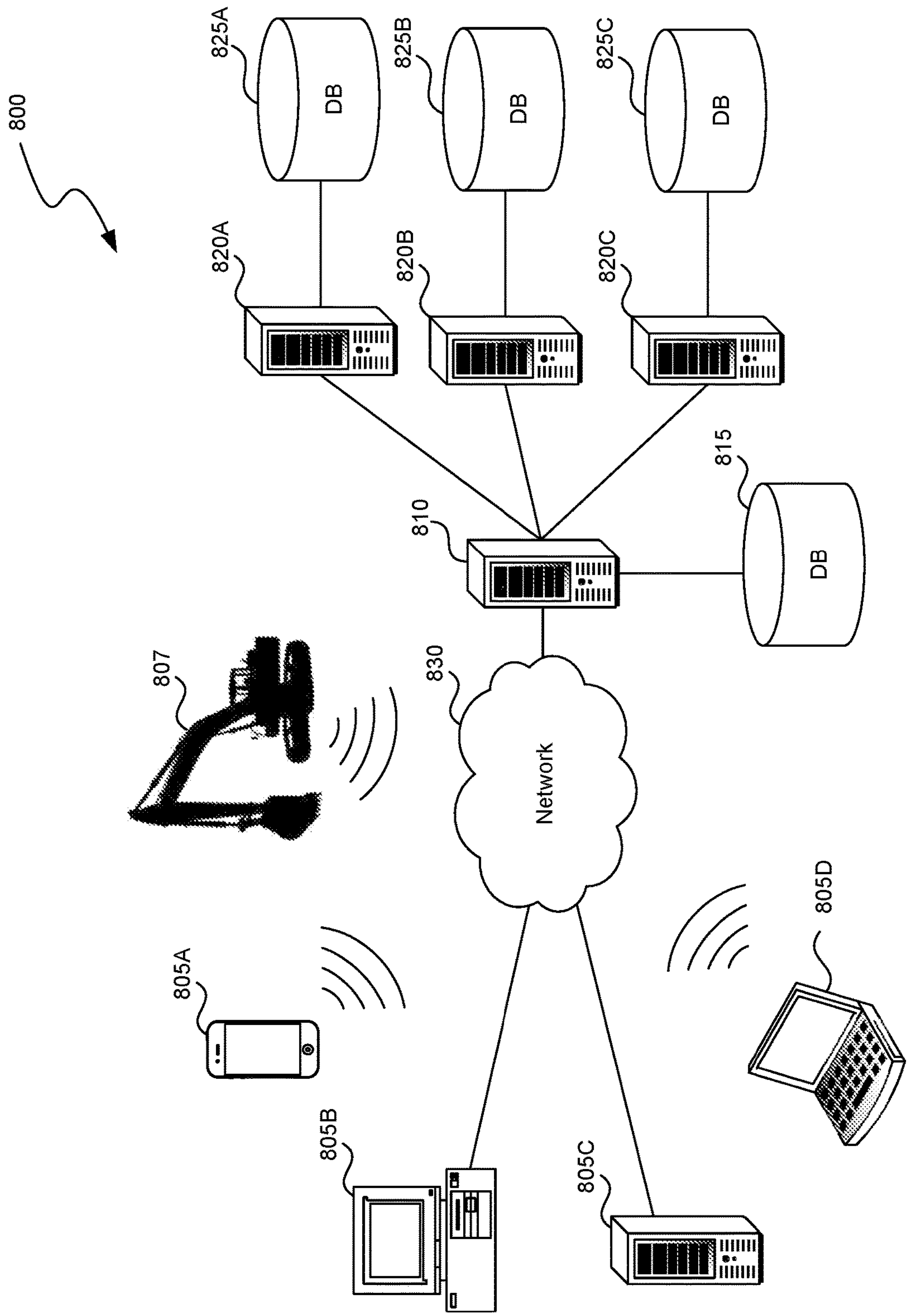

800
825A
DB
825B
DB
825C
DB
820A
820B
820C
810
815
DB
807
830
Network
805A
805B
805C
805D

FIG. 8

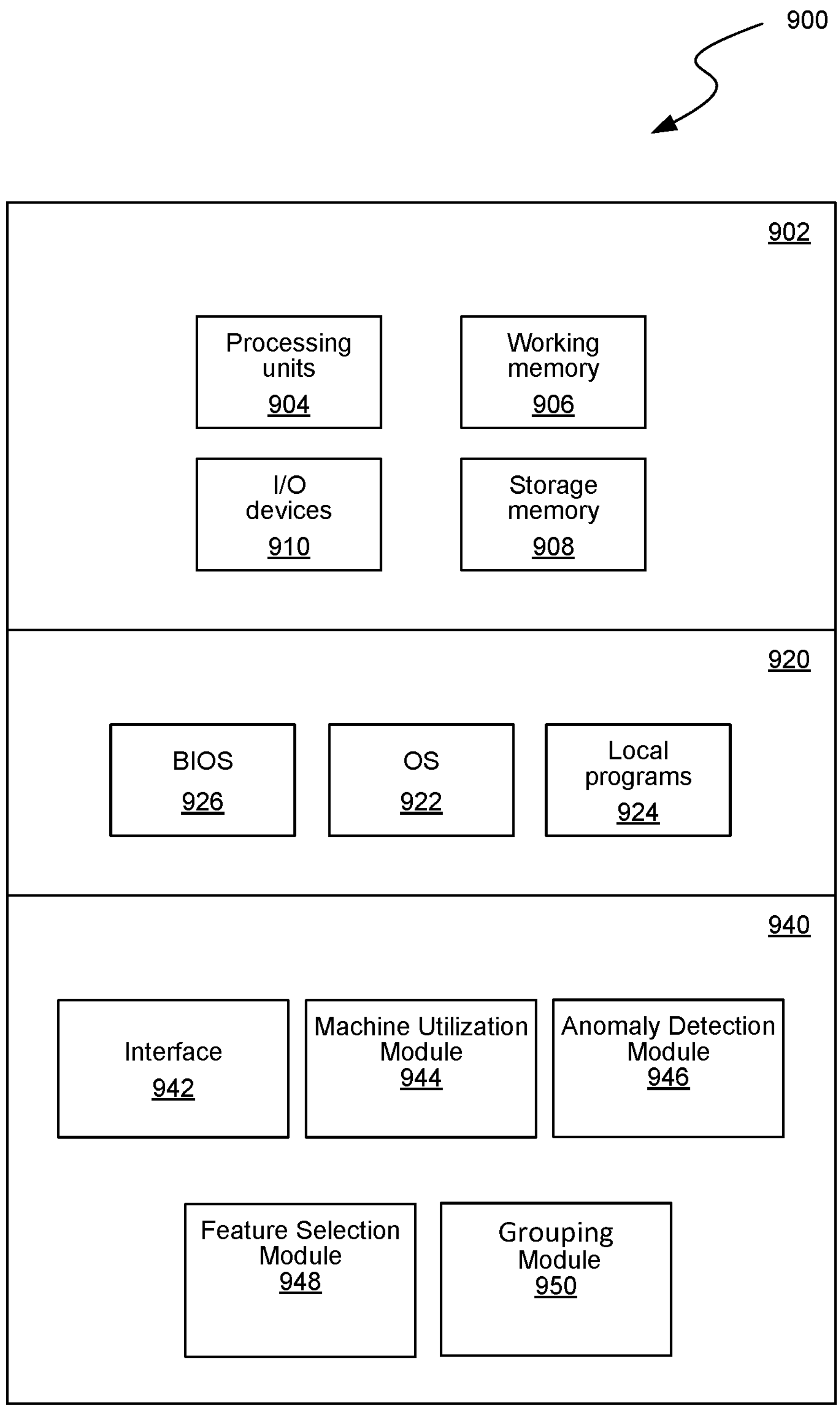

900
902
Processing units
904
Working memory
906
I/O devices
910
Storage memory
908
920
BIOS
926
OS
922
Local programs
924
940
Interface
942
Machine Utilization Module
944
Anomaly Detection Module
946
Feature Selection Module
948
Grouping Module
950

FIG. 9

SYSTEMS AND METHODS FOR DETECTING MACHINES ENGAGED IN ANOMALOUS ACTIVITY

TECHNICAL FIELD

[0001] This patent application is directed to analyzing and identifying machine activity, and more specifically, to detecting machines engaged in anomalous activity.

BACKGROUND

[0002] It is not unusual for equipment, such as an excavator, to be used for activities that the machine was not necessarily designed to perform. In some cases, the activity can be very hard on the excavator and cause premature wear or breakage of various components depending on the activity. This premature wear and breakage can have implications for warranty claims and customer satisfaction. For example, if a user has found a way to use an excavator to perform a task, albeit not within the design parameters of the machine, and the excavator experiences breakdowns the user may become frustrated.

[0003] U.S. Patent Application Publication No. 2012/0041575 to Maeda et al., (hereinafter "Maeda") is directed to anomaly detection for early detection of an anomaly of a plant or a facility. While Maeda discloses improved methods for identifying anomalies in time-series signals (e.g., sensors) using compact learning data, Maeda is not directed to identifying unseen or anomalous machine usage. Thus, there is still a need to identify when machines are being used for activities that the machines were not designed to perform. The systems and methods described herein are directed to overcoming one or more of the deficiencies described above and/or other problems with the prior art.

SUMMARY

[0004] In some embodiments, a method for detecting machines engaged in anomalous activity can include receiving telematics data from a plurality of sensors on each of a plurality of machines and determining one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine. The method can also include calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities. The method further includes extracting one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine. One or more of the plurality of machines engaged in anomalous activity can be identified based on at least the proportion and the one or more extracted features for the machines.

[0005] In some aspects, the one or more selected activities includes digging and scrapping. In further aspects, the one or more features includes a maximum hydraulic pressure for one or more cylinders on the machine. In some aspects of the technology, identifying the one or more of the plurality of machines engaged in anomalous activity includes analyzing the proportion and the one or more extracted features using principal component analysis to identify outlier activity time periods for each machine. In still further aspects, identifying one or more of the plurality of machines engaged in anomalous activity includes identifying machines that have a percentage of outlier days exceeding a selected threshold. In some aspects, the method can further comprise for each machine identified as engaged in anomalous activity, calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines, selecting the two top features with the highest relative difference, and grouping the machines with the same two top features. In some aspects, each of the series of activity time periods is a day.

[0006] In some embodiments, a system for detecting machines engaged in anomalous activity can include one or more processors and one or more memory devices having instructions stored thereon. When executed, the instructions cause the processors to receive telematics data from a plurality of sensors on each of a plurality of machines and determine one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine. The processors can also calculate a proportion of the activity time periods in which each machine was engaged in one or more selected activities. The processors also extract one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine. One or more of the plurality of machines engaged in anomalous activity can be identified based on at least the proportion and the one or more extracted features for the machines.

[0007] In some embodiments, one or more non-transitory computer-readable media can store computer-executable instructions that, when executed by one or more processors, cause the one or more processors to perform operations. The operations can include receiving telematics data from a plurality of sensors on each of a plurality of machines and determining one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine. The operations also include calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities. The operations can further include extracting one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine. One or more of the plurality of machines engaged in anomalous activity can be identified based on at least the proportion and the one or more extracted features for the machines.

BRIEF DESCRIPTION OF THE DRAWINGS

[0008] The systems and methods described herein may be better understood by referring to the following Detailed Description in conjunction with the accompanying drawings, in which like reference numerals indicate identical or functionally similar elements:

[0009] FIG. **1** is a diagram illustrating an overview of an environment in which some implementations can operate according to embodiments of the disclosed technology;

[0010] FIG. **2** is a block diagram illustrating an overview of an anomalous activity detection system according to some embodiments of the disclosed technology;

[0011] FIG. **3** is a diagram depicting using principal component analysis to identify outlier activity according to embodiments of the disclosed technology;

[0012] FIG. **4**A is a chart illustrating the proportion of outlier days for various machines according to some embodiments of the disclosed technology;

[0013] FIG. **4**B is a chart illustrating the probability of anomalous activity of various machines according to some embodiments of the disclosed technology;

[0014] FIG. **5** is a table illustrating the grouping of anomalous machines having the same features according to some embodiments of the disclosed technology;

[0015] FIG. **6** is a flow diagram showing a method for detecting machines engaged in anomalous activity according to some embodiments of the disclosed technology;

[0016] FIG. **7** is a block diagram illustrating an overview of devices on which some implementations can operate;

[0017] FIG. **8** is a block diagram illustrating an overview of an environment in which some implementations can operate; and

[0018] FIG. **9** is a block diagram illustrating components which, in some implementations, can be used in a system employing the disclosed technology.

[0019] The headings provided herein are for convenience only and do not necessarily affect the scope of the embodiments. Further, the drawings have not necessarily been drawn to scale. For example, the dimensions of some of the elements in the figures may be expanded or reduced to help improve the understanding of the embodiments. Moreover, while the disclosed technology is amenable to various modifications and alternative forms, specific embodiments have been shown by way of example in the drawings and are described in detail below. The intention, however, is not to unnecessarily limit the embodiments described. On the contrary, the embodiments are intended to cover all suitable modifications, combinations, equivalents, and alternatives falling within the scope of this disclosure.

DETAILED DESCRIPTION

[0020] Various examples of the systems and methods introduced above will now be described in further detail. The following description provides specific details for a thorough understanding and enabling description of these examples. One skilled in the relevant art will understand, however, that the techniques and technology discussed herein may be practiced without many of these details. Likewise, one skilled in the relevant art will also understand that the technology can include many other features not described in detail herein. Additionally, some well-known structures or functions may not be shown or described in detail below so as to avoid unnecessarily obscuring the relevant description.

[0021] The terminology used below is to be interpreted in its broadest reasonable manner, even though it is being used in conjunction with a detailed description of some specific examples of the embodiments. Indeed, some terms may even be emphasized below; however, any terminology intended to be interpreted in any restricted manner will be overtly and specifically defined as such in this section.

[0022] Disclosed are methods and systems for detecting machines engaged in anomalous activity e.g., equipment, such as an excavator, being used for activities that the machine was not necessarily designed to perform. In some cases, the anomalous activities can be very hard on a machine and cause premature wear or breakage of various components depending on the activity. This premature wear and breakage can have implications for warranty claims and customer satisfaction. In addition, identifying anomalous activities can identify opportunities to enhance a machine's design and/or develop new attachments that may be better suited to the activity.

[0023] FIG. **1** illustrates an environment **10** in which some implementations of the anomalous activity detection system **100** can operate according to embodiments of the disclosed technology. As noted above, it is not unusual for equipment to be used for activities that a machine was not necessarily designed to perform. For example, customers have been known to replace an excavator bucket with a ripper attachment. A conventional excavator, such as excavator **20**, includes a boom **22**, a stick **24**, and a bucket **26**. Excavator **30** has been modified by replacing not only the bucket, but the boom and stick as well. The bucket has been replaced with a ripper attachment **36** and the boom has been replaced with a shortened boom **32**. The stick has been replaced with a much shorter arm **34** and the relative pivot points for each component have changed. It should be noted that excavator **30** has been significantly modified for ripping material, yet the conventional sensor inputs, e.g., boom cylinder pressure **42**, stick cylinder pressure **44**, and bucket cylinder pressure **46**, are maintained. Thus, an anomalous activity may not be detected simply by noting that one or more of the sensor inputs is missing. Furthermore, excavator **30** is only an example of a machine being used for anomalous activities. There are other anomalous activities where a machine is not necessarily modified, but used in an unconventional manner that can stress components in ways they were not necessarily designed to withstand.

[0024] The system environment **10** can include multiple machines, such as excavator **20** and modified excavator **30**, a satellite **12**, telematics/utilization database **102**, an anomalous machine database **104**, a telematics processing system **106**, and a network **110**. The anomalous activity detection system **100** can be connected to the telematics/utilization database **102**, the anomalous machine database **104**, and the telematics processing system **106** via network **110**. The telematics/utilization database **102** and the telematics processing system **106** can receive telematics data from the excavators **20** and **30** via satellite **12**. Cell radio, wifi, Bluetooth®, etc. are additional examples of suitable data transmission modes. The telematics data can include events, diagnostics, and sensor data from the excavators, such as from the boom cylinder pressure sensor **42**, stick cylinder pressure sensor **44**, and bucket cylinder pressure sensor **46**, to name a few.

[0025] In some embodiments, the telematics processing system **106** determines a machine utilization pattern for the machines based on the telematics data. For example, a machine learning model (such as a neural network) can be applied to estimate each machine's utilization pattern based on telematics data (i.e., telemetry data). As an example, an excavator can have a use pattern of activities including 50% mass excavation, 20% grading, and 30% tracking (i.e., traveling from place to place).

[0026] In some embodiments, a utilization model can use mathematical models that classify equipment activity or application frequencies, which can include regression, support vector machines, and neural nets, depending on the level of detail and complexity required. These models may differentiate between, for example, mass excavation, dirt moving, trenching, scraping, digging, grading, loading, tracking, or idle time. Models may supplement standard telematics data with additional sensors to measure the intensity of use. In some embodiments, the resulting machine utilization patterns, or activity data, can be provided to the anomalous activity detection system **100**.

[0027] As shown in FIG. **2**, the anomalous activity detection system **100** can comprise a Machine Utilization module

120, an Anomaly Detection module 122, and a Grouping module 124. In some embodiments, the Machine Utilization module 120 receives data from the Telematics/Utilization database 102 and/or telematics data from the sensors on the excavators, such as from the boom cylinder pressure sensor 42, stick cylinder pressure sensor 44, and bucket cylinder pressure sensor 46. In some embodiments, the Machine Utilization module 120 can apply a machine learning model to estimate each machine's utilization pattern based on the telematics data. Module 120 can also calculate a proportion of the activity time periods (e.g., days) in which each machine was engaged in one or more selected activities, such as digging and scraping. It should be noted that while the Machine Utilization module 120 can determine how a machine is being used for known applications, anomalous activity may not be differentiated from other known activities with a similar severity. For example, machines using a ripper attachment may be assigned a utilization pattern suggesting digging and scraping activities as the closest match.

[0028] In some embodiments, the Anomaly Detection module 122 is configured to extract one or more features, e.g., maximum cylinder pressure, for each machine for each of the series of activity time periods from the associated telematics data. Machines engaged in anomalous activity can be identified based on at least the proportion of days in which each machine was engaged in e.g., digging and scraping and the one or more extracted features for the machines. In some embodiments, the Anomaly Detection module 122 identifies the machines engaged in anomalous activity by analyzing the proportion and the one or more extracted features using principal component analysis to identify outlier days for each machine and identifying machines that have a percentage of outlier days exceeding a selected threshold (e.g., 60 percent).

[0029] In some embodiments, the Grouping module 124 can be configured to calculate a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines. The two top features with the highest relative difference are selected and machines having the same top two features are grouped together. This grouping can facilitate an analysis of anomalous machines that might be in the same geographic region or owned by the same operator, for example.

[0030] FIG. 3 is a graph 300 illustrating a representative principal component analysis of the proportion of digging and scraping time 302 versus a feature, e.g., boom head pressure 304, for multiple machines in order to identify outlier days 310. Each point represents a machine on a given day.

[0031] FIG. 4A is a chart 400 illustrating the proportion of outlier days identified from graph 300 against total days 402 for various machines by serial number 404. FIG. 4B is a chart 450 illustrating the probability 452 of anomalous activity of various machines by serial number 454. In some embodiments, the probability 452 can be calculated as the percent of total days that are identified as outlier days as shown in chart 400, for example. In some embodiments, machines are identified as being engaged in anomalous activity when the probability 452 exceeds a selected threshold (e.g., 60 percent).

[0032] FIG. 5 is a table 500 illustrating grouping the anomalous machines 502 into groups or clusters 508. As disclosed above a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines is calculated for each anomalous machine. The two top features 504 and 506 with the highest relative difference are selected and machines having the same top two features are grouped together. For example, all of the machines having top features of max_boom_re_press and scrapping_digging_fraction are grouped in the number 2 cluster 508.

[0033] FIG. 6 is a flow diagram showing a method 600 for detecting machines engaged in anomalous activity according to some embodiments of the disclosed technology. The method 600 can include receiving telematics data from a plurality of sensors on each of a plurality of machines at step 602. At step 604, one or more activity types can be determined for each machine over a series of activity time periods (e.g., days) based on the associated telematics data for each machine. The method can also include calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities, such as digging and scrapping, at step 606. At step 608, one or more features are extracted for each machine for each of the series of activity time periods from the associated telematics data for each machine. In some embodiments, the one or more features includes a maximum hydraulic pressure for one or more cylinders on the machine. The method also includes identifying, at step 610, one or more of the plurality of machines engaged in anomalous activity based on at least the proportion and the one or more extracted features for the machines. In some embodiments, the method can include grouping anomalous machines by top features at step 612. Grouping the machines can include for each machine identified as engaged in anomalous activity, calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines, selecting the two top features with the highest relative difference, and grouping the machines with the same two top features.

Suitable System

[0034] The techniques disclosed here can be embodied as special-purpose hardware (e.g., circuitry), as programmable circuitry appropriately programmed with software and/or firmware, or as a combination of special-purpose and programmable circuitry. Hence, embodiments may include a machine-readable medium having stored thereon instructions which may be used to cause a computer, a microprocessor, processor, and/or microcontroller (or other electronic devices) to perform a process. The machine-readable medium may include, but is not limited to, optical disks, compact disc read-only memories (CD-ROMs), magneto-optical disks, ROMs, random access memories (RAMs), erasable programmable read-only memories (EPROMs), electrically erasable programmable read-only memories (EEPROMs), magnetic or optical cards, flash memory, or other type of media/machine-readable medium suitable for storing electronic instructions.

[0035] Several implementations are discussed below in more detail in reference to the figures. FIG. 7 is a block diagram illustrating an overview of devices on which some implementations of the disclosed technology can operate. The devices can comprise hardware components of a device 700 that detects machines engaged in anomalous activity, for example. Device 700 can include one or more input devices 720 that provide input to the CPU (processor) 710, notifying it of actions. The actions are typically mediated by a hardware controller that interprets the signals received from the input device and communicates the information to the CPU **710** using a communication protocol. Input devices **720** include, for example, sensors, a mouse, a keyboard, a touchscreen, an infrared sensor, a touchpad, a wearable input device, a camera- or image-based input device, a microphone, or other user input devices.

[0036] CPU **710** can be a single processing unit or multiple processing units in a device or distributed across multiple devices. CPU **710** can be coupled to other hardware devices, for example, with the use of a bus, such as a PCI bus or SCSI bus. The CPU **710** can communicate with a hardware controller for devices, such as for a display **730**. Display **730** can be used to display text and graphics. In some examples, display **730** provides graphical and textual visual feedback to a user. In some implementations, display **730** includes the input device as part of the display, such as when the input device is a touchscreen or is equipped with an eye direction monitoring system. In some implementations, the display is separate from the input device. Examples of display devices are: an LCD display screen; an LED display screen; a projected, holographic, or augmented reality display (such as a heads-up display device or a head-mounted device); and so on. Other I/O devices **740** can also be coupled to the processor, such as a network card, video card, audio card, USB, FireWire or other external device, sensor, camera, printer, speakers, CD-ROM drive, DVD drive, disk drive, or Blu-Ray device.

[0037] In some implementations, the device **700** also includes a communication device capable of communicating wirelessly or wire-based with a network node. The communication device can communicate with another device or a server through a network using, for example, TCP/IP protocols. Device **700** can utilize the communication device to distribute operations across multiple network devices.

[0038] The CPU **710** can have access to a memory **750**. A memory includes one or more of various hardware devices for volatile and non-volatile storage, and can include both read-only and writable memory. For example, a memory can comprise random access memory (RAM), CPU registers, read-only memory (ROM), and writable non-volatile memory, such as flash memory, hard drives, floppy disks, CDs, DVDs, magnetic storage devices, tape drives, device buffers, and so forth. A memory is not a propagating signal divorced from underlying hardware; a memory is thus non-transitory. Memory **750** can include program memory **760** that stores programs and software, such as an operating system **762**, Anomalous Activity Detection Platform **764**, and other application programs **766**. Memory **750** can also include data memory **770** that can include database information, etc., which can be provided to the program memory **760** or any element of the device **700**.

[0039] Some implementations can be operational with numerous other general purpose or special purpose computing system environments or configurations. Examples of well-known computing systems, environments, and/or configurations that may be suitable for use with the technology include, but are not limited to, personal computers, server computers, handheld or laptop devices, cellular telephones, mobile phones, wearable electronics, gaming consoles, tablet devices, multiprocessor systems, microprocessor-based systems, programmable consumer electronics, network PCs, minicomputers, mainframe computers, IoT devices, on-board microcontrollers, edge computing devices, distributed computing environments and/or cloud platforms that include any of the above systems or devices, or the like.

[0040] FIG. **8** is a block diagram illustrating an overview of an environment **800** in which some implementations of the disclosed technology can operate. Environment **800** can include one or more client computing devices **805**A-D, examples of which can include device **700**. Environment **800** can also include one or more machines **807**. Client computing devices **805** and machines **807** can operate in a networked environment using logical connections through network **830** to one or more remote computers, such as a server computing device **810**.

[0041] In some implementations, server computing device **810** can be an edge server that receives client requests and coordinates fulfillment of those requests through other servers, such as servers **820**A-C. Server computing devices **810** and **820** can comprise computing systems, such as device **700**. Though each server computing device **810** and **820** is displayed logically as a single server, server computing devices can each be a distributed computing environment encompassing multiple computing devices located at the same or at geographically disparate physical locations. In some implementations, each server computing device **820** corresponds to a group of servers.

[0042] Client computing devices **805** and server computing devices **810** and **820** can each act as a server or client to other server/client devices. Server **810** can connect to a database **815**. Servers **820**A-C can each connect to a corresponding database **825**A-C. As discussed above, each server **820** can correspond to a group of servers, and each of these servers can share a database or can have their own database. Databases **815** and **825** can warehouse (e.g., store) information. Though databases **815** and **825** are displayed logically as single units, databases **815** and **825** can each be a distributed computing environment encompassing multiple computing devices, can be located within their corresponding server, or can be located at the same or at geographically disparate physical locations.

[0043] Network **830** can be a local area network (LAN) or a wide area network (WAN), but can also be other wired or wireless networks. Network **830** may be the Internet or some other public or private network. Client computing devices **805** can be connected to network **830** through a network interface, such as by wired or wireless communication. While the connections between server **810** and servers **820** are shown as separate connections, these connections can be any kind of local, wide area, wired, or wireless network, including network **830** or a separate public or private network.

[0044] FIG. **9** is a block diagram illustrating components **900** which, in some implementations, can be used in a system employing the disclosed technology. The components **900** include hardware **902**, general software **920**, and specialized components **940**. As discussed above, a system implementing the disclosed technology can use various hardware, including processing units **904** (e.g., CPUs, GPUs, APUs, etc.), working memory **906**, storage memory **908**, and input and output devices **910**. Components **900** can be implemented in a client computing device such as client computing devices **805** or on a server computing device, such as server computing device **810** or **820**.

[0045] General software **920** can include various applications, including an operating system **922**, local programs **924**, and a basic input output system (BIOS) **926**. Specialized components **940** can be subcomponents of a general software application **920**, such as local programs **924**. Specialized components **940** can include a Machine Utilization Module **944**, an Anomaly Detection Module **946**, a Feature Selection Module **948**, a Grouping Module **950**, and components that can be used for transferring data and controlling the specialized components, such as Interface **942**. In some implementations, components **900** can be in a computing system that is distributed across multiple computing devices or can be an interface to a server-based application executing one or more of specialized components **940**.

[0046] Those skilled in the art will appreciate that the components illustrated in FIGS. **7-9** described above, and in each of the flow diagrams discussed above, may be altered in a variety of ways. For example, the order of the logic may be rearranged, sub steps may be performed in parallel, illustrated logic may be omitted, other logic may be included, etc. In some implementations, one or more of the components described above can execute one or more of the processes described herein.

INDUSTRIAL APPLICABILITY

[0047] In some embodiments, an anomalous activity detection system can include a Machine Utilization Module **944**, an Anomaly Detection Module **946**, a Feature Selection Module **948**, and a Grouping Module **950** (FIG. **9**). In operation, the Machine Utilization Module **944** can use telematics data from the sensors on excavators **20** and **30**, such as from the boom cylinder pressure sensor **42**, stick cylinder pressure sensor **44**, and bucket cylinder pressure sensor **46**, to estimate the machines' utilization patterns. The Feature Selection Module **948** can analyze the telematics data to identify features, e.g., boom cylinder pressure, that can be combined with the machine utilization pattern information to identify outlier days for each machine. The Anomaly Detection Module **946** uses principal component analysis to identify days in which the utilization pattern and selected features indicate outliers **310**. Grouping Module **950** can group anomalous machines by top features. The top features are determined by calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines. The machines with the same top two features with the highest relative difference are grouped together to facilitate investigating the cause of the anomalous activity. In some embodiments, machines in the same group or cluster can be mapped to compare their geographic location. For example, anomalous machines confined to a relatively small geographic region could indicate that the machines are being used to perform a task that is not within the design parameters of the machine and/or has been modified such as with a ripper attachment.

Remarks

[0048] The above description and drawings are illustrative and are not to be construed as limiting. Numerous specific details are described to provide a thorough understanding of the disclosure. However, in some instances, well-known details are not described in order to avoid obscuring the description. Further, various modifications may be made without deviating from the scope of the embodiments.

[0049] Reference in this specification to "one embodiment" or "an embodiment" means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment of the disclosure. The appearances of the phrase "in one embodiment" in various places in the specification are not necessarily all referring to the same embodiment, nor are separate or alternative embodiments mutually exclusive of other embodiments. Moreover, various features are described which may be exhibited by some embodiments and not by others. Similarly, various requirements are described which may be requirements for some embodiments but not for other embodiments.

[0050] The terms used in this specification generally have their ordinary meanings in the art, within the context of the disclosure, and in the specific context where each term is used. It will be appreciated that the same thing can be said in more than one way. Consequently, alternative language and synonyms may be used for any one or more of the terms discussed herein, and any special significance is not to be placed upon whether or not a term is elaborated or discussed herein. Synonyms for some terms are provided. A recital of one or more synonyms does not exclude the use of other synonyms. The use of examples anywhere in this specification, including examples of any term discussed herein, is illustrative only and is not intended to further limit the scope and meaning of the disclosure or of any exemplified term. Likewise, the disclosure is not limited to various embodiments given in this specification. Unless otherwise defined, all technical and scientific terms used herein have the same meaning as commonly understood by one of ordinary skill in the art to which this disclosure pertains. In the case of conflict, the present document, including definitions, will control.

What is claimed is:

1. A method for detecting machines engaged in anomalous activity, the method comprising:

receiving telematics data from a plurality of sensors on each of a plurality of machines;

determining one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine;

calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities;

extracting one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine; and

identifying one or more of the plurality of machines engaged in anomalous activity based on at least the proportion and the one or more extracted features for the machines.

2. The method of claim **1**, wherein the one or more selected activities includes digging and scrapping.

3. The method of claim **1**, wherein the one or more features includes a maximum hydraulic pressure for one or more cylinders on the machine.

4. The method of claim **1**, wherein identifying the one or more of the plurality of machines engaged in anomalous activity includes analyzing the proportion and the one or more extracted features using principal component analysis to identify outlier activity time periods for each machine.

5. The method of claim **4**, wherein identifying one or more of the plurality of machines engaged in anomalous activity includes identifying machines that have a percentage of outlier days exceeding a selected threshold.

6. The method of claim **5**, further comprising, for each machine identified as engaged in anomalous activity, calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines, selecting the two top features with the highest relative difference, and grouping the machines with the same two top features.

7. A system for detecting machines engaged in anomalous activity, the system comprising:

one or more processors; and

one or more memory devices having stored thereon instructions that when executed by the one or more processors cause the one or more processors to:

receive telematics data from a plurality of sensors on each of a plurality of machines;

determine one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine;

calculate a proportion of the activity time periods in which each machine was engaged in one or more selected activities;

extract one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine; and

identify one or more of the plurality of machines engaged in anomalous activity based on at least the proportion and the one or more extracted features for the machines.

8. The system of claim **7**, wherein the one or more selected activities includes digging and scrapping.

9. The system of claim **7**, wherein the one or more features includes a maximum hydraulic pressure for one or more cylinders.

10. The system of claim **7**, wherein identifying the one or more of the plurality of machines engaged in anomalous activity includes analyzing the proportion and the one or more extracted features using principal component analysis to identify outlier activity time periods for each machine.

11. The system of claim **10**, wherein identifying one or more of the plurality of machines engaged in anomalous activity includes identifying machines that have a percentage of outlier days exceeding a selected threshold.

12. The system of claim **11**, further comprising, for each machine identified as engaged in anomalous activity, calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines, selecting the two top features with the highest relative difference, and grouping the machines with the same two top features.

13. The system of claim **7**, wherein each of the series of activity time periods is a day.

14. One or more non-transitory computer-readable media storing computer-executable instructions that, when executed by one or more processors, cause the one or more processors to perform operations comprising:

receiving telematics data from a plurality of sensors on each of a plurality of machines;

determining one or more activity types for each machine over a series of activity time periods based on the associated telematics data for each machine;

calculating a proportion of the activity time periods in which each machine was engaged in one or more selected activities;

extracting one or more features for each machine for each of the series of activity time periods from the associated telematics data for each machine; and

identifying one or more of the plurality of machines engaged in anomalous activity based on at least the proportion and the one or more extracted features for the machines.

15. The non-transitory computer-readable media of claim **14**, wherein the one or more selected activities includes digging and scrapping.

16. The non-transitory computer-readable media of claim **14**, wherein the one or more features includes a maximum hydraulic pressure for one or more cylinders.

17. The non-transitory computer-readable media of claim **14**, wherein identifying the one or more of the plurality of machines engaged in anomalous activity includes analyzing the proportion and the one or more extracted features using principal component analysis to identify outlier activity time periods for each machine.

18. The non-transitory computer-readable media of claim **17**, wherein identifying one or more of the plurality of machines engaged in anomalous activity includes identifying machines that have a percentage of outlier days exceeding a selected threshold.

19. The non-transitory computer-readable media of claim **18**, further comprising, for each machine identified as engaged in anomalous activity, calculating a difference between a mean value of each feature and a mean value of that feature for non-anomalous machines, selecting the two top features with the highest relative difference, and grouping the machines with the same two top features.

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