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DETERMINING DOWNHOLE OPERATION TRANSITIONS FROM WELLBORE MEASUREMENT DATA USING MACHINE LEARNING

Abstract

This application relates to a downhole system that uses a transition detection system to determine transitions between downhole activities or operations for a wellbore based on wellbore measurement data. In various implementations, the transition detection system uses a transition identification machine learning model to generate downhole transition types between downhole operations from wellbore measurement data. Additionally, the transition detection system identifies errors and inaccuracies with activity transitions reported in a downhole operation report based on comparing the downhole operation report to the determined transition times generated by the transition identification machine learning model.

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Background/Summary

BACKGROUND

[0001] In oil and gas operations, a wellbore may be drilled to access fluids, such as liquid and gaseous hydrocarbons, stored in subterranean formations and to extract the fluids from the formations. Wellbores are created using earth-boring tools for drilling wellbores and enlarging the diameters of wellbores. In connection with creating and using wellbores, drilling operation systems collect measurement data and reports associated with the wellbores.

[0002] To elaborate, operation reports are generated to document the various activities performed as part of a drilling operation, such as drilling, cementing, tripping, or circulating drilling fluid, among other activities. These activities are recorded in the operation report, including a time signature for each activity, and may generally be reported manually. Drilling operations may typically involve a significant number of activities (and transitions therebetween), and in some instances, operations reports are not created or completed until many activities have been initiated and/or completed. Thus, in some cases, the time signatures recorded in the report do not accurately reflect the timing of the associated activity. This may result in any number of issues such as inaccurate analyses of the drilling operation, mismanagement of resources, contractual disputes, compliance issues, etc.

[0003] Conventionally, time signature discrepancies are corrected by drilling personnel manually reviewing wellbore measurement data from the downhole operation, for example, in order to identify the correct timing of the activities and manually correct the times in the operation reports. This manual process is not only inefficient, costly, and labor intensive, but is also prone to inaccuracies such as due to human error and fatigue. Thus, improved techniques for identifying errors in operation report time signatures may be advantageous.

Description

BRIEF DESCRIPTION OF THE DRAWINGS

[0004] The following detailed description provides specific and detailed implementations accompanied by drawings. Additionally, each of the figures listed below corresponds to one or more implementations discussed in this disclosure in which:

[0005] FIG. **1** is an example of a downhole system, according to at least one embodiment of the present disclosure;

[0006] FIG. **2**A illustrates an example environment in which a transition detection system is implemented, according to at least one embodiment of the present disclosure;

[0007] FIG. **2**B illustrates an example implementation of a transition detection system as described herein, according to at least one embodiment of the present disclosure;

[0008] FIG. **3**A illustrates an example block diagram of training a transition identification machine learning model to determine transition types for transitions between downhole activities, according to at least one embodiment of the present disclosure;

[0009] FIG. **3**B illustrates an example block diagram of generating training data from reference data, according to at least one embodiment of the present disclosure;

[0010] FIG. **4**A illustrates an example block diagram of generating input data from sample data for applying to a transition identification machine learning model according to various implementations;

[0011] FIGS. **4**B-**4**C illustrate example block diagrams of using a transition detection system to generate estimated transition times according to some embodiments;

[0012] FIG. **5**A illustrates an example flowchart that includes a series of acts in a computer-implemented method for determining transitions in downhole operations according to some implementations;

[0013] FIG. **5**B illustrates an example flowchart that includes a series of acts in a computer-implemented method for determining transitions in downhole operations according to some implementations; and

[0014] FIG. **6** illustrates certain components that may be included within a computing system to implement the transition detection system.

DETAILED DESCRIPTION

[0015] This disclosure generally relates to using a transition detection system to determine transitions between downhole activities or operations for a wellbore using machine learning models based on wellbore measurement data. In various implementations, the transition detection system uses a transition identification machine learning model to efficiently and accurately generate estimated transition types of downhole transition from wellbore measurement data for the downhole operation(s). Additionally, the transition detection system may identify errors or inaccuracies with activity transitions reported in a downhole operation report based on comparing the downhole operation report to estimated transition times output by the transition identification machine learning model.

[0016] According to various implementations, the transition detection system receives wellbore data for a particular wellbore or operation of interest. The transition detection system delineates or segments the wellbore measurement data (e.g., time-series measurement data) by establishing various time points spanning the duration of the wellbore measurement data. For each time point, the transition detection system generates a time window around the time point, with time window portions both before and after the time point. Based on the underlying wellbore measurement data bounded within the time windows for each time point, the transition detection system generates a set of statistical attributes for the time windows and associates these statistical attributes with the time point.

[0017] In one or more embodiments, the transition detection system implements a transition identification machine learning model to predict when, and what type of, downhole operation transitions occurred during the period for which the wellbore measurement data was taken. Based on the statistical attribute sets, the transition identification machine learning model evaluates each time point to estimate the type of transition occurred around that time point, if any. In one example, the transition identification machine learning model is a tree-based model and may process the statistical attribute sets through one or more decision trees to classify transition types. In this way, the transition detection system may identify when a downhole operation transition occurs and the transition type between downhole operations.

[0018] In some implementations, the transition detection system may compare these results to a series of activity transitions and associated time signatures documented in a downhole operation report. The transition detection system may identify one or more instances where the downhole operation reports does not match the estimated transition types. In some implementations, the transition detection system may automatically update the downhole operation report with corrected activity transitions and/or time signatures, or the transition detection system may flag or indicate discrepancies to a drilling engineer.

[0019] As will be discussed in further detail below, the present disclosure includes a number of practical applications having features described herein that provide benefits and/or solve problems associated with identifying downhole operation transitions. Some example benefits are discussed herein in connection with various features and functionalities provided by a transition detection system implemented on one or more computing devices. It will be appreciated that benefits explicitly discussed in connection with one or more embodiments described herein are provided by way of example and are not intended to be an exhaustive list of all possible benefits of the transition detection system.

[0020] For example, the transition detection system described herein improves the accuracy of reported downhole operation transitions, including downhole operation transition types and downhole operation transition times. For instance, downhole operation reports often include errors with respect to downhole operation transitions, which often is the result of incorrect inputs. By determining downhole activity transitions based on measured data from associated downhole operations, the transition detection system accurately determines transition types and times between downhole activities.

[0021] As mentioned earlier, the transition detection system implements a transition identification machine learning model to determine transition types between downhole operations based on wellbore measurement data. To improve accuracy and efficiency, the transition identification machine learning model generates one or more statistical attribute sets from the wellbore measurement data, which is provided as input to the transition identification machine learning model (rather than providing the raw, underlying time-series measurement data). Because the statistical attribute sets characterize statistical features, calculations, or other attributes for segmented sections of the measurement data, the transition identification machine learning model more efficiently classifies transition types as well as generates more accurate operation type classifications. Indeed, using statistical attribute sets enables the transition identification machine learning model to operate in a more streamlined and computationally efficient process to predict the transition types based on the measurement data.

[0022] Further, the transition detection system may be implemented to identify instances where the downhole operation reports identify activity transitions and/or time signatures that differ from what the transition identification machine learning model determined. The transition detection system may automatically correct, flag, or otherwise indicate these instances for review. For example, the transition detection system may generate updated downhole operation reports with one or more activity transitions and/or time signatures corrected.

[0023] Furthermore, the transition detection system may quickly and automatically identify or correct errors in the downhole operation reports that may otherwise require significant time and resources to remedy. This enables scaling operations that were previously bottlenecked with manual user-review. For example, wellbore measurement data has typically been reviewed manually to ensure that the reports agree with the measurements observed in the wellbore. Flagging inconsistencies for review, or in some cases automatically correcting discrepancies, provides significant resource savings, as well as improved accuracy.

[0024] As illustrated in the foregoing discussion, this disclosure utilizes a variety of terms to describe the features and advantages of one or more implementations described. To illustrate, this disclosure describes the transition detection system in the context of a drilling operations system.

[0025] As used herein, “wellbore measurement data,” “wellbore data,” “measurement data” and the like may refer to data which each describe an aspect, value, rate, property, state, etc. of a downhole operation. For example, the wellbore data includes time-series measurements of drilling parameters such as a flow rate, temperature, pressure, speed, torque (TOR), rate of penetration (ROP), and weight on bit (WOB). The wellbore measurement data (e.g., time-series measurement data) may include measurements of formation evaluation, wellbore stability, mud properties, survey data, and equipment health and status. Indeed, the measurement data may include any measurement, metric, or value relevant to a downhole operation, and combinations thereof. The wellbore measurement data may include measurements taken from various downhole and/or surface sensors and/or measurements received from one or more computing devices. The data may be time-series data and may be taken periodically (e.g., continuously) throughout a downhole operation such that the measurement data captures a portion or an entirety of the downhole operation. The wellbore measurement data may include information for characterizing and/or describing any aspect of a wellbore operation. In some cases, the wellbore measurement data may include a limited number, predetermined standardized set, or fixed default set of measurement data types for a set of

wellbores.
[0026] As used herein, “downhole operation reports,” “operation reports,” “downhole reports” and the like may refer to data contained or documented within an operation report or log for a downhole operation. For example, the downhole operation reports may document the various activities that are performed during or in pursuit of one or more downhole operations, including transitions between activities or operations. The reports may document relevant time signatures for the downhole operation, such as start and/or end times for various activities or times of transitions between activities. In some cases, the downhole reports may be generated manually, such as by a drilling engineer observing activities at a drilling site. The operation reports may be generated while downhole (e.g., drilling) activities are being conducted, or may be generated after the completion of one or more activities such as part of a review of one or more downhole activities.
[0027] As used herein, “downhole operation,” “downhole activity” and the like may refer to any process, activity, objective, or action that takes place in, around, or with respect to a wellbore. These activities may include drilling, cementing, tripping, mud circulation, logging, completion activities, or any other activity relevant to, or in pursuit of, creating, lengthening, or otherwise operating a wellbore.
[0028] As described herein, various downhole operations and activities may occur within a wellbore, and “downhole transitions,” “downhole operation transitions,” or “transitions” and the like may occur between downhole operations as different stages of the wellbore are reached or carried out. These transitions may manifest through various measurements taken during the downhole operations and transitions.
[0029] The term “machine-learning model” refers to a computer model or computer representation that may be trained (e.g., optimized) based on inputs to approximate unknown functions. For instance, a machine-learning model may include, but is not limited to, a neural network (e.g., a convolutional neural network (CNN), LSTM, graph neural network, or deep learning model), a decision tree (e.g., a gradient-boosted decision tree), a linear regression model, a logistic regression model, Dirichlet allocation (LDA) model, multi-arm bandit model, random forest model, support vector machine (SVM) model, or a combination of these models.
[0030] Additional terms are defined throughout the disclosure in connection with various examples and contexts.
[0031] Additional details will now be provided regarding systems described herein in relation to illustrative figures portraying example implementations. For example, FIG. **1** shows one example of a downhole system **100** for drilling an earth formation **101** to form a wellbore **102**. The downhole system **100** includes a drill rig **103** used to turn a drilling tool assembly **104** which extends downward into the wellbore **102**. The drilling tool assembly **104** may include a drill string **105**, a bottomhole assembly (“BHA”) **106**, and a bit **110**, attached to the downhole end of the drill string **105**.
[0032] The drill string **105** may include several joints of drill pipe **108** connected end-to-end through tool joints **109**. The drill string **105** transmits drilling fluid through a central bore and transmits rotational power from the drill rig **103** to the BHA **106**. In some embodiments, the drill string **105** further includes additional downhole drilling tools and/or components. The drill pipe **108** provides a hydraulic passage through which drilling fluid is pumped from the surface to the bit **110**.
[0033] The BHA **106** may include other downhole drilling tools and components. Examples of additional BHA components include measurement-while-drilling (“MWD”) tools, logging-while-drilling (“LWD”) tools, and measurement sensors.
[0034] To elaborate, while performing downhole (e.g., drilling) activities, wellbore measurement data may be taken, measured, or observed through a variety of (e.g., downhole and/or surface) sensors. In this way, various information may be collected related to the wellbore and/or downhole activity in order to facilitate the techniques described herein. Additionally, in some cases, reports or

logs may be generated for documenting various downhole activities or operations. These reports may indicate an operation type and time signature for various operations or activities (and/or transition between operations or activities) and may be generated manually by drilling personnel.

[0035] The downhole system **100** may include or may be associated with a client device **112** that implements a transition detection system **120** (e.g., implemented on a single client device, a server device,, or across multiple computing devices). The transition detection system **120** may facilitate determining wellbore operation transitions for the wellbore **102**, including identifying and/or correcting one or more incorrect time signatures of an operational report.

[0036] FIG. **2**A illustrates an example environment **200** in which a transition detection system **220** is implemented in accordance with one or more embodiments described herein. As shown in FIG. **2**A, the environment **200** includes a server device **214** representing one or more computing devices (e.g., including processing units, data storage, etc.).

[0037] As shown in FIG. **2**A, the environment **200** includes a downhole operation system **221** implemented on the server device **214**. The downhole operation system **221** may include software and/or hardware for implementing and/or performing one or more of the functions of a downhole system, such as the downhole system **100** of FIG. **1**.

[0038] In some implementations, the downhole operation system **221** on the server device **214** implements a transition detection system **220**. While shown on the server device **214**, the transition detection system **220** may be implemented wholly or in part on the client device **212**, across the server device **214** and the client device **212**, or on or across one or more additional devices, such that different portions or components of the transition detection system **220** are implemented on different computing devices in the environment **200**. Additional details regarding the transition detection system **220** are provided below in connection with FIG. **2**B.

[0039] As shown in FIG. **2**A, the server device **214** may communicate with a client device **212** through a network **216**. The network **216** may include one or multiple networks and may use one or more communication platforms and/or technologies suitable for transmitting data. The network **216** may refer to any data link that enables the transport of electronic data between devices of the environment **200**. The network **216** may refer to a hardwired network, a wireless network, or a combination of a hardwired network and a wireless network. In one or more embodiments, the network **216** includes the internet. The network **216** may be configured to facilitate communication between the various computing devices via well-site information transfer standard markup language (WITSML) or similar protocol, or any other protocol or form of communication.

[0040] The client device **212** may represent one or multiple computing devices, including different types of computing devices. For example, the client device **212** represents a mobile device such as a mobile telephone, a smartphone, a personal digital assistant (PDA), a tablet, a laptop, or any other portable device. Additionally, or alternatively, the client device **212** represents a non-mobile device such as a desktop computer, server device, surface or downhole processor or computer (e.g., associated with a sensor, system, or function of the downhole system), or another non-portable device.

[0041] In one or more implementations, the client device **212** includes a graphical user interface (GUI) thereon (e.g., a screen of a mobile device). In addition, or as an alternative, the client device **212** may be communicatively coupled (e.g., wired or wirelessly) to a display device having a graphical user interface thereon for providing a display of system content. The server device **214** may similarly refer to various types of computing devices. Each of the devices of the environment **200** may include features and/or functionalities described below in connection with FIG. **6**.

[0042] The client device **212** may include a client application **218**. The client application **218** may include an application or interface for interacting with and/or receiving the features of the transition detection system **220** as described herein. In some embodiments, one or more of the functions or features of the transition detection system **220** may be carried out or performed on or by the client application **218**.

[0043] The environment **200** also includes measurement devices **217**. The measurement devices **217** may include sensor devices, such as downhole and/or surface sensors, or other downhole measurement devices for taking and providing measurements to the transition detection system **220**. For example, the wellbore measurement data (e.g., time-series measurement data) and/or the downhole operation reports may be received and made accessible to the computing devices of the environment **200** via the measurement devices **217**.

[0044] FIG. **2**B illustrates an example implementation of the transition detection system **220** according to at least one embodiment of the present disclosure. As illustrated, the transition detection system **220** includes various components and elements that are implemented in hardware and/or software. For example, the transition detection system **220** includes a data manager **222**, a time window manager **224**, a statistical attribute manager **226**, and a machine learning manager **228**, which may implement a transition identification machine learning model **229**. The transition detection system **220** may also include a data storage **230** having wellbore measurement data **232**, downhole operation reports **234**, and statistical attribute sets **256**.

[0045] The data manager **222** of the transition detection system **120** may receive, collect, or otherwise access a variety of types of data. For example, the data manager **222** may collect, compile, store, and/or manage the various data of the data storage **230**. In some embodiments, the data manager **222** may receive and/or initiate requests of the transition detection system **220** to identify downhole operation transitions within a set of wellbore measurement data as described herein.

[0046] In various embodiments, the time window manager **224** may facilitate generating time windows or time intervals for the wellbore measurement data **232**. The time window manager **224** may generate time windows for specific time points within the wellbore measurement data **232**. Based on the time windows, the statistical attribute manager **226** may determine a set of statistical attributes for each of the time windows. In this way, the statistical attribute set for the various time windows may be provided to the transition identification machine learning model **229** for training and/or executing the model.

[0047] The machine learning manager **228** may facilitate training the transition identification machine learning model **229** based on the statistical attribute sets generated from the wellbore measurement data **232** along with associated transition times indicated in the downhole operation reports **234**. FIGS. **3**A and **3**B illustrate the training of the transition identification machine learning model **229**, including the generation of training data.

[0048] The machine learning manager **228** may execute the trained version of the transition identification machine learning model **229** based on wellbore measurement data **232** for a wellbore (or operation) of interest to identify transitions (and associated times) between activities in the wellbore measurement data **232**. In this way, the transition detection system **220** may facilitate updating the downhole operation reports **234** to provide a more accurate overview of the various activities of a downhole operation. FIGS. **4**A, **4**B, and **4**C illustrate the transition detection system **220** implementing the transition identification machine learning model **229** to determine or predict transition types.

[0049] While one or more embodiments described herein describe features and functionalities performed by specific components **222-228** of the transition detection system **220**, specific features described in connection with one component of the transition detection system **220** may be performed by one or more of the other components of the transition detection system **220**.

[0050] By way of example, one or more of the data receiving, gathering, or storing features of the data manager **222** may be delegated to other components of the transition detection system **220**. As another example, while wellbore data time windows be generated by the time window manager **224**, in some instances, some or all of these features may be performed by the statistical attribute manager **226** (or other component of the transition detection system **220**). Indeed, it will be appreciated that some or all of the specific components may be combined into other components and specific functions may be performed by one or across multiple components **222-228** of the transition detection system **220**.

[0051] Each of the components of the transition detection system **220** may be implemented in software, hardware, or both. For example, the components of the transition detection system **220** include instructions stored on a computer-readable storage medium and executable by at least one processor of one or more computing devices. When executed by the processor, the computer-executable instructions of the transition detection system **220** cause a computing device to perform the methods (e.g., computer-implemented methods) described herein. As another example, the components of the transition detection system include hardware, such as a special-purpose processing device to perform a certain function or group of functions. In some instances, the components of the transition detection system include a combination of computer-executable instructions and hardware.

[0052] Furthermore, the components of the transition detection system may be implemented as one or more operating systems, stand-alone applications, modules of an application, plug-ins, library functions, functions called by other applications, and/or cloud-computing models. Additionally, the components of the transition detection system may be implemented as one or more web-based applications hosted on a remote server and/or implemented within a suite of mobile device applications or "apps."

[0053] As mentioned above, the transition detection system **220** uses a transition identification machine learning model **229** to determine transition types. These transition types may indicate a change between two downhole operations or activities represented in wellbore measurement data. Accordingly, FIG. **3**A illustrates an example block diagram of training a transition identification machine learning model to determine transition types for transitions between downhole activities.

[0054] As shown, FIG. **3**A includes training data **360**, the transition detection system **220** with a transition identification machine learning model **229**, and a loss model **362**. The training data **360** includes statistical attribute sets **356** and ground-truth transition types **358**. In one or more implementations, the statistical attribute sets **356** are generated from wellbore measurement data **342**. Additional details regarding generating the training data **360** are provided next in connection with FIG. **3**B before returning to describe the operations shown in FIG. **3**A

[0055] FIG. **3**B illustrates a block diagram example of generating training data from reference data, according to some implementations. The reference data **348** may include the wellbore measurement data **342** (e.g., time-series measurement data) and downhole operation reports **344**. In some implementations, the reference data **348** may be associated or correlated with one or more reference wellbores, which may be offset wellbores or other wellbores for which the wellbore measurement data **342** and downhole operation reports **344** have already been collected. For example, the reference data **348** may be accessible through a wellbore database or library including information for many wellbores.

[0056] As shown, the transition detection system **220** includes a time window model **350** and a statistical attribute generation model **354**. The transition detection system **220** may receive the reference data **348** and provide it to a time window model **350** to generate time window data **352**. To explain, the time window model **350** may identify activity transitions **338** for an associated reference wellbore from downhole operation reports **344** along with time signatures **340** corresponding to the activity transitions **338**. For each of the activity transitions **338** in the downhole operation reports **344**, the time window model **350** may identify a corresponding time signature that establishes a time point **341**. The time point **341** signals a transition time between downhole operations that occur at a wellbore (i.e., an activity transition).

[0057] The time point **341** may apply to multiple measurements and measurement data types included in the wellbore measurement data **342** for a wellbore. For example, a time point identified from the downhole operation reports **344** may indicate that an activity transition **338** occurred at a time signature of 11:15 AM. The time window model **350** may accordingly generate a time point

341 corresponding to 11:15 AM for each instance of the wellbore measurement data **342** (e.g., a flowrate, temperature, speed, tool status, etc.) to generate the time window data **352**. In this way, the time point **341** may facilitate identifying and synchronizing a different types of measurements of a reference wellbore for the time window data **352**.

[0058] In some implementations, the time window model **350** generates time windows **343** (e.g., window portions) to represent the time window data **352**. The time windows **343** may correspond to the time point **341**. For example, the time windows **343** may include a first time window before the time point **341** and a second time window after the time point **341**. The time windows **343** may capture measurement data from the one or more measurement types that have measurement data occurring within one of the time windows **343**. Additionally, for each time point, the transition detection system **220** may create an associated pair of time windows **343** (e.g., or a single time window having first and second portions).

[0059] The time windows **343** may be windows or intervals of time having a predefined length. For example, the time windows **343** may be intervals of 15 minutes, 30 minutes, 1 hour, 2 hours, 3 hours, 5 hours, or more. The time windows **343** may be of equal length or may be different lengths of time. In this way, the time window data **352** may include the wellbore measurement data **342** defined by the time point **341** and the time windows **343**, while excluding other portions of the wellbore measurement data **342** not falling within the time windows **343**.

[0060] In some embodiments, the transition detection system **220** generates statistical attribute sets **356** based on the reference data **348**. For example, a statistical attribute generation model **354** may receive the time window data **352** and may determine or calculate various statistical calculations based on the time window data **352**. The statistical attribute generation model **354** may determine a set of statistical attributes for each of the time windows **343** corresponding to each time point. In some implementations, for each time point, the statistical attribute generation model **354** may generate a first statistical attribute subset for the first time window and a second statistical attribute subset for the second time window. The statistical attribute sets **356** may include statistical attributes for any (or all) of the different measurement types of the wellbore measurement data **342** bounded by the time windows **343**.

[0061] The statistical attribute sets **356** may include one or more statistical calculations or features of the underlying data bounded by the time windows **343**. For example, the statistical attribute generation model **354** may determine an average, mean, median, mode, minimum, maximum, standard deviation, variance, quartile, peak, valley, or other statistical calculation of the wellbore measurement data. The statistical attribute sets **356** may include any attribute, value, feature, or calculation, and combinations thereof. In various implementations, the statistical attribute sets **356** includes 100, 200, or more distinct attributes or features that are identifiable in the wellbore measurement data **342**, bounded by the time windows **343**. In this way, the wellbore measurement data **342** is represented by statistical attributes that occur within a predetermined time of a known activity transition type.

[0062] The transition detection system **220** may generate the training data **360** based on the statistical attribute sets **356**. For example, for each statistical attribute set (e.g., corresponding to a given time point and associated time windows), the transition detection system **220** may identify the corresponding activity transition from the downhole operation reports **344** and may associate or correlate the activity transition with the statistical attribute set as a ground-truth transition type. As shown, the training data **360** may include the statistical attribute sets **356** which may characterize a behavior, performance, or aspect of the wellbore at or around a given time point and ground-truth transition types **358** that identify the type of transition took place within the wellbore at the time point **341**.

[0063] Returning back to FIG. **3**A, the transition detection system **220** may train the transition identification machine learning model **229** using the training data **360**. The transition identification machine learning model **229** may be trained to determine an estimated transition type **361** for a transition between downhole operations based on the statistical characterizations included in the training data **360**. The transition identification machine learning model **229** is often trained offline but may be trained on the fly.

[0064] In various implementations, such as the one shown, the transition identification machine learning model **229** includes a tree-based architecture having one or more hierarchical, tree-like structures. In various instances, the transition identification machine learning model **229** is a decision tree model, a random forest or ensemble of decision trees, or a gradient boosting model.

[0065] To elaborate, in some instances, the transition identification machine learning model **229** is a tree-based model that includes a hierarchical structure of decision nodes, branches, and leaf nodes. Each node represents a decision based on a specific feature and each leaf represents a candidate transition type for which the transition identification machine learning model **229** may classify the statistical attribute sets **356**. The tree-based structure is built through the recursive splitting of the decision nodes into further decision nodes through training of the transition identification machine learning model **229** as described below.

[0066] In some instances, the transition detection system **220** utilizes a leaf-based model for the transition identification machine learning model **229**. A leaf-based model allows the transition detection system **220** to use unbalanced growth and/or splitting among nodes to minimize losses of nodes. In various implementations, the transition detection system **220** implements a light gradient boosting machine architecture (LGBM or LightGBM) along with the leaf-based model. For example, the transition detection system **220** uses an LGBM classifier to identify transition types between downhole operations.

[0067] In various implementations, the transition detection system **220** processes each input statistical attribute set and generates an input feature vector or a dimensional array containing numerical values each representing one of the various attributes of a statistical attribute set. The transition identification machine learning model **229** then processes the feature vector through a sequence of decision nodes, where the transition identification machine learning model **229** evaluates a specific feature of the input vector and makes a decision based on the feature's value. In this way, the transition identification machine learning model **229** recursively navigates through the tree structure making decisions at each node based on different features until a leaf node is reached, providing the final output prediction of an estimated transition type **361**.

[0068] In some embodiments, the transition identification machine learning model **229** includes an ensemble architecture that utilizes multiple decision trees. For example, the transition identification machine learning model **229** may process the input vector through separate decision trees independently. The outputs are then combined, such as through voting or averaging, to generate a final ensemble prediction of the estimated transition type **361**.

[0069] In some embodiments, the transition identification machine learning model **229** may determine a probability or confidence of the estimated transition type **361**. For example, the probability may be determined based on the voting of the various trees, based on a logistic function such as a LGBM classifier, through calibration techniques such as Platt scaling or isotonic regression, or any other suitable technique for determining multi-classification probabilities.

[0070] In implementations where the transition identification machine learning model **229** determines several of the candidate transition types as possible outputs, the transition identification machine learning model **229** may determine a confidence or probability of each of these possibilities (or all of the candidate transition types). The estimated transition type **361** may be determined by the transition identification machine learning model **229** based on having a highest probability among the candidate transition types.

[0071] As mentioned, the transition identification machine learning model **229** may not converge to a single candidate transition type but may return several candidate transition types as possible outputs for a given time point of the training data **360**. In some implementations, the transition identification machine learning model **229** may combine the several candidate transition type predictions, such as through voting or averaging, to generate a final ensemble prediction of the estimated transition type **361** to determine an estimated transition type.

[0072] In some embodiments, the transition identification machine learning model **229** may output a null transition type indicating that no downhole operation transition took place at an associated time point of the training data **360**. For example, the transition identification machine learning model **229** may be trained to output the null transition type based on each of the candidate transition types having a probability below a transition threshold value.

[0073] In some implementations, the transition identification machine learning model **229** is implemented as another type of machine learning model, such as a neural network architecture. For example, the transition identification machine learning model **229** may be a Monte Carlo Dropout prediction model, a U-Net neural network, or a U-Net++ neural network.

[0074] As mentioned above, the transition detection system **220** may train the transition identification machine learning model **229** based on the training data **360**. For example, the transition detection system **220** may provide the statistical attribute sets **356** for a given time point to the transition identification machine learning model **229**, and the transition identification machine learning model **229** may predict or determine an estimated transition type for the given time point. The estimated transition type along with the ground-truth transition type for the time point may be provided to the loss model **362** to evaluate the performance of the transition identification machine learning model **229** during the training process.

[0075] In various implementations, the loss model **362** implements or more loss functions or techniques such as cross-entropy loss, Gini impurity, deviance, etc. to determine and estimated transition type error amount. In various implementations, the transition detection system **220** provides the error or loss amount back to the transition identification machine learning model **229** as label feedback **364** to train and fine-tune the transition identification machine learning model.

[0076] Additionally, in one or more implementations, the transition detection system **220** uses the label feedback **364** to train, optimize, and/or fine-tune the decision tree(s) of the transition identification machine learning model **229** through techniques such as recursive partitioning and/or boosting. For example, the transition detection system **220** uses the loss model **362** to facilitate selecting a feature and corresponding threshold for separating the statistical attribute sets **356** into homogeneous subsets and generating or splitting corresponding decision nodes to generate one or more decision trees.

[0077] As another example, the transition detection system **220** uses the loss model **362** to facilitate generating trees sequentially, with each tree correcting the errors of the previous tree. The transition detection system **220** may iteratively train the transition identification machine learning model **229** in this way with respect to many time points of the training data **360** to further fine-tune the transition identification machine learning model **229** for a set number of iterations, until it converges, until the training data is exhausted, or until a satisfactory level of accuracy is otherwise achieved.

[0078] As described earlier, in some embodiments, the transition detection system **220** generates training data **360** that includes statistical attribute sets **356** generated by the transition detection system **220** for various time points **341** and time windows **343** in relation to the wellbore measurement data **342**. In one or more implementations, the transition detection system **220** does not generate or does not use the statistical attribute sets with the transition identification machine learning model. In these implementations, the transition detection system **220** trains the transition identification machine learning model **229** directly based on the wellbore measurement data **348** (e.g., raw or processed time-series data). For example, the transition detection system **220** provides the wellbore measurement data **348** from one or more data sources directly to the transition identification machine learning model **229** rather than pre-processing the measurement data into a statistical attribute set.

[0079] To elaborate, in various implementations, the transition identification machine learning model is trained to determine an estimated transition type **361** for a transition between downhole operations based on the identifying patterns, relationships, statistical characterizations, and other attributes directly from the wellbore measurement data **342**. In some cases, the transition detection system **220** may generate an input feature vector representing these various features identified from the wellbore measurement data **342** and may process the input feature vector through the series of nodes of the transition identification machine learning model to determine transition types and/or transition times.

[0080] In these implementations, the transition identification machine learning model may recursively process the wellbore measurement data as input through the tree and leaf architecture to provide a final output prediction of an estimated transition type **361**. Then, the transition detection system **220** may use the loss model **362** to fine-tune the predictions of the transition identification machine learning model. In this way, the transition identification machine learning model **229** may be trained to predict transition types for an operation of a wellbore based on measurement data from the wellbore.

[0081] Once trained, in various implementations, the transition detection system **220** uses the transition identification machine learning model **229** to automatically generate transition types for an operation of a wellbore of interest for which downhole transition types and/or time signatures may not be known or verified. To illustrate, FIG. **4**A shows an example block diagram of generating input data from sample data for applying to the transition identification machine learning model according to various implementations. FIGS. **4**B-**4**C illustrate example block diagrams of using a transition detection system **220** to generate estimated transition times according to some embodiments.

[0082] As shown in FIG. **4**A, the transition detection system **220** executes the transition identification machine learning model **229** to generate statistical attribute sets **456**. As illustrated, the transition detection system **220** generates the statistical attribute sets **456** based on wellbore measurement data **442**, which is part of a wellbore data **462** for a subject wellbore. In some implementations, the wellbore data **462** is associated or correlated with one or more operations within a subject wellbore, or a wellbore of interest. In another example, the wellbore data **462** may be associated with a specific downhole operation (e.g., a collection of downhole activities) of interest of a wellbore.

[0083] In some cases, the wellbore data **462** may be associated with corresponding operation reports for the subject wellbore including, for example, activity transitions and time signatures similar to corresponding elements described above in connection with FIG. **3**B. In some instances, one or more activity transitions and/or associated time signatures of these downhole operation reports may not be known, may be incorrect, or may otherwise need verifying. In these instances, the transition detection system **220** may generate the statistical attribute sets **456** based on the wellbore measurement data **442** to serve as an input for the transition identification machine learning model **229**, which determines one or more wellbore operation transition types and transition times (described below), where the transition detection system **220** uses the determined transition types and transition times to verify (or add) entries the downhole operation reports.

[0084] As shown, the transition detection system **220** includes a time window model **450** and a statistical attribute generation model **454**. In some implementations, the time window model **450** generates time window data **452** based on the wellbore measurement data **442**. For example, the time window model **450** may determine one or more (e.g., often several) time points **441**. The time window model **450** may generate the time points **441** according to a rolling time interval throughout the wellbore measurement data **442**. For example, the time window model **450** may generate a time point for every 5 minutes, 10 minutes, 15 minutes, 30 minutes, 1 hour, or other rolling time interval of the wellbore measurement data **442**. Thus, the time window model **450** may generate time points that may span some or all of the wellbore measurement data **442**. As shown in FIG. **4**A, the time window model **450** generates three different instances of the time points **441**

within the time window data **452** labeled as “A,” “B,” and “C.”
[0085] The rolling interval nature of the time points **441** differs from the time point **341** described above with FIG. **3**B that is used to generate the training data **360**. As described above in FIG. **3**B, the time point **341** is determined based on an associated time signature indicated in the downhole operation reports **344**. However, the time window model **450** may not have reliable time signatures available. Accordingly, the time window model **450** employs a series of time points at designated intervals to detect when transitions occur at the subject wellbore based on the wellbore measurement data **442**.
[0086] In some implementations, the time window model **450** generates time windows **443** in the time window data **452**. The time windows **443** may correspond to the time points **441**. For example, for each time point, the time window model **450** may determine a first time window before the time point and a second time window after the time point. In some cases, for the same time point, the time window model **450** may generate separate instances of the time windows **343** for different measurement types. In other cases, the time window model **450** combines the different measurement types in the same time window In any case, each of the time points **441** may include an associated pair of time windows **443**. In some implementations, the time window model **450** generates a single time window that includes the first and second portions described above.
[0087] The time windows **443** may be windows or intervals of time having any predefined length, such as that discussed above in connection with the training data. In an example, both of the time windows **443** may be 1 hour in length each such that the time windows **443** span from 1 hour before a time point to 1 hour after the time point. In some examples, the time windows **443** may be different lengths, including different lengths for each of the time windows **443** in a pair of time windows **443** corresponding to a given time point.
[0088] As shown, the transition detection system **220** determines the statistical attribute sets **456** based on the wellbore measurement data **442** for a wellbore. As described above, the statistical attribute sets **456** may include any of a variety of statistical calculations or features. The statistical attribute generation model **454** may generate a set of statistical attributes for each time point indicated in the time window data **452**. In particular, the statistical attribute generation model **454** generates a statistical attribute set for each segmented section of the wellbore measurement data **442** represented in the time window data **452** by the time points **441**. For example, for each time point, the statistical attribute generation model **454** may determine a first statistical attribute subset (“Set A”) for the first time window of a first time point (“Time Point A”). The statistical attribute generation model **454** may similarly generate a second statistical attribute subset (“Set B”) for a the second time window of a second time point (“Time Point B”).
[0089] As noted above, the statistical attribute sets **456** may include statistical characterizations for various type of measurement data included in the wellbore measurement data **442** for a given time point. For example, for a given time point, a statistical attribute set may include features such as a mean, minimum, maximum, standard deviation, etc. for a fluid flow rate (e.g., for both the before and after time windows), and may also indicate a mean, minimum, maximum, standard deviation, etc. for a temperature, pressure, speed, torque, or any other measurement at the associated time point. In this way, the statistical attribute sets **456** provides a robust statistical and temporal characterization of each timepoint through for one or more measurement types (or a combination of measurement types) that describe many different properties of a downhole operation, which the transition detection system **220** uses to determine when downhole operation transitions occur.
[0090] As shown in FIGS. **4**B-**4**C, the transition detection system **220** includes the transition identification machine learning model **229**. In these figures, the transition identification machine learning model **229** represents a trained decision tree model with tuned weights and parameters and other trained components. The transition identification machine learning model **229** generates a transition type **461** from a statistical attribute set **457** (or a set of statistical attribute sets). **470**
[0091] In particular, in FIG. **4**B, the transition detection system **220** uses the transition

identification machine learning model **229** to generate a transition type **461** from a statistical attribute set **457**. The transition types **461** in this way may facilitate characterizing, based on measurement data from a wellbore of interest, the various downhole activity types, and transitions therebetween, for a downhole operation of the wellbore of interest. Additionally, the transition detection system **220** may provide each of the statistical attribute sets **456** (FIG. **4**A) for the time points **441** to the transition identification machine learning model **229** to determine whether (and what type) of downhole operation transition occurred at each of the time points **441**.

[0092] As mentioned above, the transition detection system **220** may train the transition identification machine learning model **229** based solely on wellbore measurement data (e.g., raw or processed time-series data). Accordingly, in some embodiments, the transition detection system **220** uses the transition identification machine learning model **229** to determine the transition type **461** using wellbore measurement data as an input. In some cases, determining transition types based on wellbore measurement data, instead of statistical attribute sets for example, may simplify and streamline the transition type prediction process by eliminating the need to pre-process the wellbore measurement data and generate the statistical attribute sets.

[0093] In some embodiments, the transition detection system **220** compares the transition types **461** to corresponding activity transitions for the wellbore as indicated in the downhole operation reports. To elaborate, FIG. **4**C expands upon FIG. **4**B by adding a report comparison model **470** for generating an updated downhole operation report **473** (e.g., automatically report updates without needing user interaction). As shown in FIG. **4**C, the report comparison model **470** may compare an activity transitions **439** and an associated time signatures **437** of a downhole operation report **445** to the transition type **461** predicted by the transition identification machine learning model **229**.

[0094] In some instances, the report comparison model **470** may identify one or more instances (e.g., one or more time points) where activity transitions and/or time signatures of the downhole operation reports differ from that indicated in the determined transition types. For example, the downhole operation reports may indicate that an activity transition of a specific type occurs at a time signature, and the transition types predicted by the transition identification machine learning model **229** indicate a different type of activity transition for the associated time signature. In another example, the downhole operation reports may indicate that an activity transition of a specific type occurs at a time signature and the transition types predicted by the transition identification machine learning model **229** indicate that the activity transition of that specific type occurred at a different time signature.

[0095] In various implementations, based on identifying discrepancies between the downhole operation reports and the estimated transition types, the transition detection system **220** updates a downhole operation report. For example, based on a comparison performed by the report comparison model **470** between the downhole operation report **445** and the transition type **461**, the transition detection system **220** generates an updated downhole operation report **473**, which may include indications of transition discrepancies of the downhole operation report **445** and the statistical attribute set **457**. In some implementations, the report comparison model **470** may provide a flag, alert, or may otherwise indicate the discrepancies to downhole personnel for review.

[0096] In some embodiments, the transition detection system **220** may automatically update the downhole operation report **445**. For example, based on the report comparison model **470**, the transition detection system **220** may update or correct the activity transition **439** and/or the associated time signature**437** in the updated downhole operation reports **473**. In various implementations, the transition detection system **220** automatically updates a downhole operation report of a wellbore to indicate the determined transition of the transition type within the time window and/or time signature.

[0097] In some embodiments, the report comparison model **470** may update one or more of these values based on a probability threshold of an associated transition type. For example, if the transition identification machine learning model **229** determines a transition type **461** with a probability or confidence above the threshold value, the transition detection system **220** automatically corrects the associated value in the updated downhole operation reports if the value differs from what is indicated in the downhole operation report. In another example, the transition detection system **220** may not update or change a value in a downhole operation reports if the associated transition type is at or below a threshold value and may instead flag or alert to the discrepancy.

[0098] As described above, the transition detection system **220** may be implemented to identify times and types of downhole activity transitions for a downhole operation of interest based on measurement data for the downhole operation. By used the transition identification machine learning model, the transition detection system **220** provides a more accurate and reliable characterization of the downhole operation over that of a conventional downhole operation report, which may be flawed, include errors, or otherwise be inaccurate.

[0099] Now turning to FIGS. **5**A-**5**B, each of these figures illustrates an example flowchart that includes a series of acts in a computer-implemented method for determining transitions in downhole operations according to some implementations. In particular, both FIGS. **5**A-**5**B illustrate an example series of acts representing a computer-implemented method for determining a transition type between downhole operations using a transition identification machine learning model.

[0100] While FIGS. **5**A-**5**B each illustrates a series of acts representing a computer-implemented method according to one or more implementations, alternative implementations may omit, add to, reorder, and/or modify any of the acts shown. Furthermore, the acts of FIGS. **5**A-**5**B may be performed as part of a method (e.g., a computer-implemented method). Alternatively, a computer-readable medium may include instructions that, when executed by a processing system with a processor, cause a computing device to perform the acts of FIGS. **5**A-**5**B.

[0101] In some implementations, a system (e.g., a processing system including a processor) may perform the acts of FIGS. **5**A-**5**B. For example, the acts include a system that includes a processing system and computer memory including instructions that, when executed by the processing system, cause the system to perform various actions or steps.

[0102] Turning now to FIG. **5**A, this figure includes a series of act **500**, with an act **510** of determining a time window based on a time point. For instance, in example implementations, the act **510** involves determining a time window based on a time point within wellbore data measured for a wellbore.

[0103] As further shown, the series of acts **500** includes an act **520** of generating a statistical attribute set. For instance, in example implementations, the act **520** involves generating, from the wellbore data, a statistical attribute set for the time window.

[0104] As further shown, the series of acts **500** includes an act **530** of determining a transition type using a transition identification machine learning model. For instance, in example implementations, the act **530** involves determining, for the time window, a transition type for a transition between downhole operations using a transition identification machine learning model based on the statistical attribute set for the time window. In various implementations, the series of acts **500** omits or skips the act **530**.

[0105] As further shown, the series of acts **500** includes an act **540** of providing the transition type for updating a downhole operation report. For instance, in example implementations, the act **540** involves automatically updating a downhole operation report of the wellbore to indicate the transition of the transition type within the time window based on determining the transition type within the time window using the transition identification machine learning model. In some instances, the act **540** includes providing the transition type associated with the time point for the transition between the downhole operations for updating a downhole operation report for the wellbore. In some embodiments, the act **540** includes updating an operation report of the wellbore with the time signature of the transition type. In various implementations, updating the operation report of the wellbore occurs automatically, without user input or interaction with the operation report within the time window.

[0106] In some cases, the series of acts **500** includes generating the statistical attribute set is based on measurement data associated with the downhole operations for the wellbore. In some cases, the series of acts **500** includes generating the statistical attribute set is based on different measurement data types measured for the wellbore. In some cases, the measurement data includes time-series measurement data from one or more downhole sensors or one or more surface sensors.

[0107] In some cases, the series of acts **500** includes identifying the transition type at a time signature within the downhole operation report and updating the time signature for the transition type in the downhole operation report to correspond with the time point. In some cases, the series of acts **500** includes generating the statistical attribute set based on determining one or more of a mean, median, maximum, minimum, and standard deviation based on the time window for the time point. In some cases, the series of acts **500** includes generating the statistical attribute set based on generating a first statistical attribute subset for a first portion of the time window before the time point and a second statistical attribute subset for a second portion of the time window after the time point.

[0108] In some cases, the transition identification machine learning model determines the transition type by classifying the time window for the time point based on a group of candidate transition types, and the transition type is selected based on having the highest probability among the group of candidate transition types. In some cases, the group of candidate transition types includes a null transition type indicating no transition of the downhole operations, and the transition identification machine learning model determines the null transition type when no downhole operation transitions occur within a given window. In some cases, the transition identification machine learning model determines the null transition type for a given time window based on determining that a transition probability for the given time window is below a transition threshold value.

[0109] In some cases, the transition identification machine learning model uses a decision leaf-based architecture to determine the transition type. In some cases, the series of acts **500** includes training the transition identification machine learning model by comparing transition types determined from measured wellbore data for a set of time windows to corresponding reported transition types reported for time signatures within the set of time windows.

[0110] In some cases, the series of acts **500** includes generating training data for the transition identification machine learning model based on receiving downhole operation reports of downhole operations for a set of reference wellbores, based on receiving one or more sets of wellbore measurement data for the set of reference wellbores, based on associating or correlating the downhole operation reports with the one or more sets of wellbore measurement data based on time windows, and based on generating labeled training data by combining correlated transition types with the one or more sets of wellbore measurement data based on time signatures of downhole operation transition times from the downhole operation reports.

[0111] In some cases, the series of acts **500** includes generating a statistical attribute set for each time window in the set of time windows from wellbore measurement data associated with the downhole operations for the wellbore, and providing statistical attribute sets for time windows to the transition identification machine learning model to determine the transition types.

[0112] Turning now to FIG. **5**B, this figure includes a series of acts **550** having the act **560** determining a time window based on a time point. For instance, in example implementations, the act **560** involves determining a time window based on a time point within wellbore data measured for a wellbore.

[0113] As further shown, the series of acts **550** includes an act **570** of determining a transition type using a transition identification machine learning model. For instance, in example implementations, the act **570** involves determining a transition type within the time window for a transition between downhole operations of the wellbore using a transition identification machine learning model based on the wellbore data.

[0114] As further shown, the series of acts **550** includes an act **580** of associating the transition type with the time point. For instance, in example implementations, the act **580** involves associating the transition type with the time point based on determining the transition type within the time window.
[0115] As further shown, the series of acts **550** includes an act **590** of providing the transition type and the time point for updating a downhole operation report. For instance, in example implementations, the act **590** involves providing the transition type and the time point for updating a time signature of the transition type within a downhole operation report of the wellbore.
[0116] In some cases, the transition identification machine learning model determines the transition type based on time-series measurement data of a plurality of different measurement data types measured for the downhole operations for the wellbore. In some cases, the transition identification machine learning model determines the transition type by classifying the time window for the time point based on a group of candidate transition types, and the transition type is selected based on having a highest probability among the group of candidate transition types.
[0117] Turning now to FIG. **6**, this figure illustrates certain components that may be included within a computer system **600**. One or more computer systems may be used to implement the various devices, components, and systems described herein.
[0118] The computer system **600** includes a processor **601**. The processor **601** may be a general-purpose single- or multi-chip microprocessor (e.g., an Advanced RISC (Reduced Instruction Set Computer) Machine (ARM)), a special purpose microprocessor (e.g., a digital signal processor (DSP)), a microcontroller, a programmable gate array, etc. The processor **601** may be referred to as a central processing unit (CPU). Although just a single processor is shown in the computer system **600** of FIG. **6**, in an alternative configuration, a combination of processors (e.g., an ARM and DSP) could be used.
[0119] The computer system **600** also includes memory **603** in electronic communication with the processor **601**. The memory **603** may include computer-readable storage media and may be any available media that may be accessed by a general purpose or special purpose computer system. Computer-readable media that store computer-executable instructions are non-transitory computer-readable media (device). Computer-readable media that carry computer-executable instructions are transmission media. Thus, by way of example and not limitations, embodiment of the present disclosure may include at least two distinctly different kinds of computer-readable media: non-transitory computer-readable media (devices) and transmission media.
[0120] Both non-transitory computer-readable media (devices) and transmission media may be used temporarily to store or carry software instructions in the form of computer readable program code that allows performance of embodiments of the present disclosure. Non-transitory computer-readable media may further be used to persistently or permanently store such software instructions. Examples of non-transitory computer-readable storage media include physical memory (e.g., RAM, ROM, EPROM, EEPROM, etc.), optical disk storage (e.g., CD, DVD, HDDVD, Blu-ray, etc.), storage devices (e.g., magnetic disk storage, tape storage, diskette, etc.), flash or other solid-state storage or memory, or any other non-transmission medium which may be used to store program code in the form of computer-executable instructions or data structures and which may be accessed by a general purpose or special purpose computer, whether such program code is stored or in software, hardware, firmware, or combinations thereof.
[0121] Instructions **605** and data **607** may be stored in the memory **603**. The instructions **605** may be executable by the processor **601** to implement some or all of the functionality disclosed herein. Executing the instructions **605** may involve the use of the data **607** that is stored in the memory **603**. Any of the various examples of modules and components described herein may be implemented, partially or wholly, as instructions **605** stored in memory **603** and executed by the processor **601**. Any of the various examples of data described herein may be among the data **607** that is stored in memory **603** and used during execution of the instructions **605** by the processor **601**.

[0122] A computer system **600** may also include one or more communication interfaces **609** for communicating with other electronic devices. The one or more communication interfaces **609** may be based on wired communication technology, wireless communication technology, or both. Some examples of communication interfaces include a Universal Serial Bus (USB), an Ethernet adapter, a wireless adapter that operates in accordance with an Institute of Electrical and Electronics Engineers (IEEE) 802.11 wireless communication protocol, a Bluetooth® wireless communication adapter, and an infrared (IR) communication port.

[0123] The one or more communication interfaces **609** may connect the computer system **600** to a network. A "network" or "communications network" may generally be defined as one or more data links that enable the transport of electronic data between computer systems and/or modules, engines, or other electronic devices, or combinations thereof. When information is transferred or provided over a communication network or another communications connection (either hardwired, wireless, or a combination of hardwired or wireless) to a computing device, the computing device properly views the connection as a transmission medium. Transmission media may include a communication network and/or data links, carrier waves, wireless signals, and the like, which may be used to carry desired program or template code means or instructions in the form of computer-executable instruction or data structures and which may be accessed by a general purpose or special purpose computer.

[0124] A computer system **600** may also include one or more input devices **611** and one or more output devices **613**. Some examples of input devices include a keyboard, mouse, microphone, remote control device, button, joystick, trackball, touchpad, and lightpen. Some examples of output devices include a speaker and a printer. One specific type of output device that is typically included in a computer system **600** is a display device **615**. Display devices **615** used with embodiments disclosed herein may utilize any suitable image projection technology, such as liquid crystal display (LCD), light-emitting diode (LED), gas plasma, electroluminescence, or the like. A display controller **617** may also be provided, for converting data **607** stored in the memory **603** into one or more of text, graphics, or moving images (as appropriate) shown on the display device **615**.

[0125] The various components of the computer system **600** may be coupled together by one or more buses, which may include one or more of a power bus, a control signal bus, a status signal bus, a data bus, other similar components, or combinations thereof. For the sake of clarity, the various buses are illustrated in FIG. **6** as a bus system **619**.

[0126] The techniques described herein may be implemented in hardware, software, firmware, or any combination thereof, unless specifically described as being implemented in a specific manner. Any features described as modules, components, or the like may also be implemented together in an integrated logic device or separately as discrete but interoperable logic devices. If implemented in software, the techniques may be realized at least in part by a non-transitory processor-readable storage medium including instructions that, when executed by at least one processor, perform one or more of the methods (e.g., computer-implemented methods) described herein. The instructions may be organized into routines, programs, objects, components, data structures, etc., which may perform particular tasks and/or implement particular data types, and which may be combined or distributed as desired in various embodiments.

[0127] Further, upon reaching various computer system components, program code in the form of computer-executable instructions or data structures may be transferred automatically or manually from transmission media to non-transitory computer-readable storage media (or vice versa). For example, computer executable instructions or data structures received over a network or data link may be buffered in memory (e.g., RAM) within a network interface module (NIC), and then eventually transferred to computer system RAM and/or to less volatile non-transitory computer-readable storage media at a computer system. Thus, it should be understood that non-transitory computer-readable storage media may be included in computer system components that also (or even primarily) utilize transmission media.

[0128] The embodiments of the transition detection system have been primarily described with reference to wellbore drilling operations; the transition detection system described herein may be used in applications other than the drilling of a wellbore. In other embodiments, the transition detection system according to the present disclosure may be used outside a wellbore or other downhole environment used for the exploration or production of natural resources. For instance, the transition detection system of the present disclosure may be used in a borehole used for placement of utility lines. Accordingly, the terms “wellbore,” “borehole” and the like should not be interpreted to limit tools, systems, assemblies, or methods of the present disclosure to any particular industry, field, or environment.

[0129] One or more specific embodiments of the present disclosure are described herein. These described embodiments are examples of the presently disclosed techniques. Additionally, in an effort to provide a concise description of these embodiments, not all features of an actual embodiment may be described in the specification. It should be appreciated that in the development of any such actual implementation, as in any engineering or design project, numerous embodiment-specific decisions will be made to achieve the developers' specific goals, such as compliance with system-related and business-related constraints, which may vary from one embodiment to another. Moreover, it should be appreciated that such a development effort might be complex and time consuming, but would nevertheless be a routine undertaking of design, fabrication, and manufacture for those of ordinary skill having the benefit of this disclosure.

[0130] Additionally, it should be understood that references to “one embodiment” or “an embodiment” of the present disclosure are not intended to be interpreted as excluding the existence of additional embodiments that also incorporate the recited features. For example, any element described in relation to an embodiment herein may be combinable with any element of any other embodiment described herein. Numbers, percentages, ratios, or other values stated herein are intended to include that value, and also other values that are “about” or “approximately” the stated value, as would be appreciated by one of ordinary skill in the art encompassed by embodiments of the present disclosure. A stated value should therefore be interpreted broadly enough to encompass values that are at least close enough to the stated value to perform a desired function or achieve a desired result. The stated values include at least the variation to be expected in a suitable manufacturing or production process, and may include values that are within 5%, within 1%, within 0.1%, or within 0.01% of a stated value.

[0131] A person having ordinary skill in the art should realize in view of the present disclosure that equivalent constructions do not depart from the spirit and scope of the present disclosure, and that various changes, substitutions, and alterations may be made to embodiments disclosed herein without departing from the spirit and scope of the present disclosure. Equivalent constructions, including functional “means-plus-function” clauses are intended to cover the structures described herein as performing the recited function, including both structural equivalents that operate in the same manner, and equivalent structures that provide the same function. It is the express intention of the applicant not to invoke means-plus-function or other functional claiming for any claim except for those in which the words ‘means for’ appear together with an associated function. Each addition, deletion, and modification to the embodiments that falls within the meaning and scope of the claims is to be embraced by the claims.

[0132] The terms “approximately,” “about,” and “substantially” as used herein represent an amount close to the stated amount that is within standard manufacturing or process tolerances, or which still performs a desired function or achieves a desired result. For example, the terms “approximately,” “about,” and “substantially” may refer to an amount that is within less than 5% of, within less than 1% of, within less than 0.1% of, and within less than 0.01% of a stated amount. Further, it should be understood that any directions or reference frames in the preceding description are merely relative directions or movements. For example, any references to “up” and “down” or “above” or “below” are merely descriptive of the relative position or movement of the related

elements.
[0133] The present disclosure may be embodied in other specific forms without departing from its spirit or characteristics. The described embodiments are to be considered as illustrative and not restrictive. The scope of the disclosure is, therefore, indicated by the appended claims rather than by the foregoing description. Changes that come within the meaning and range of equivalency of the claims are to be embraced within their scope.

Claims

1. A computer-implemented method for determining transitions in downhole operations, comprising: determining a time window based on a time point within wellbore data measured for a wellbore; generating, from the wellbore data, a statistical attribute set for the time window; determining, for the time window, a transition type for a transition between downhole operations using a transition identification machine learning model based on the statistical attribute set for the time window; and providing the transition type associated with the time point for the transition between the downhole operations for updating a downhole operation report for the wellbore.
2. The computer-implemented method of claim 1, wherein generating the statistical attribute set is based on measurement data associated with the downhole operations for the wellbore.
3. The computer-implemented method of claim 2, wherein generating the statistical attribute set is based on different measurement data types measured for the wellbore.
4. The computer-implemented method of claim 2, wherein the measurement data includes time-series measurement data from one or more downhole sensors or one or more surface sensors.
5. The computer-implemented method of claim 1, further comprising: identifying the transition type at a time signature within the downhole operation report; and updating the time signature for the transition type in the downhole operation report to correspond with the time point.
6. The computer-implemented method of claim 1, wherein generating the statistical attribute set includes determining one or more of a mean, median, maximum, minimum, or standard deviation based on the time window for the time point.
7. The computer-implemented method of claim 1, wherein generating the statistical attribute set includes generating a first statistical attribute subset for a first portion of the time window before the time point and a second statistical attribute subset for a second portion of the time window after the time point.
8. The computer-implemented method of claim 1, wherein: the transition identification machine learning model determines the transition type by classifying the time window for the time point based on a group of candidate transition types; and the transition type is selected based on having a highest probability among the group of candidate transition types.
9. The computer-implemented method of claim 8, wherein: the group of candidate transition types includes a null transition type indicating no transition of the downhole operations; and the transition identification machine learning model determines the null transition type when no downhole operation transitions occur within a given window.
10. The computer-implemented method of claim 9, wherein the transition identification machine learning model determines the null transition type for a given time window based on determining that a transition probability for the given time window is below a transition threshold value.
11. The computer-implemented method of claim 1, wherein the transition identification machine learning model uses a decision leaf-based architecture to determine the transition type.
12. The computer-implemented method of claim 1, further comprising training the transition identification machine learning model by comparing transition types determined from measured wellbore data for a set of time windows to corresponding reported transition types reported for time signatures within the set of time windows.
13. The computer-implemented method of claim 12, further comprising generating training data for

the transition identification machine learning model based on: receiving downhole operation reports of downhole operations for a set of reference wellbores; receiving one or more sets of wellbore measurement data for the set of reference wellbores; correlating the downhole operation reports with the one or more sets of wellbore measurement data based on time windows; and generating training data by combining correlated transition types with the one or more sets of wellbore measurement data based on time signatures of downhole operation transition times from the downhole operation reports.

14. The computer-implemented method of claim 12, further comprising: generating a statistical attribute set for each time window in the set of time windows from wellbore measurement data associated with the downhole operations for the wellbore; and providing statistical attribute sets for time windows to the transition identification machine learning model to determine the transition types.

15. A computer-implemented method for determining transitions in downhole operations, comprising: determining a time window based on a time point within wellbore data measured for a wellbore; determining a transition type within the time window for a transition between downhole operations of the wellbore using a transition identification machine learning model based on the wellbore data; and using the transition identification machine learning model, automatically updating a downhole operation report of the wellbore to indicate the transition of the transition type within the time window based on the transition type within the time window.

16. The computer-implemented method of claim 15, wherein the transition identification machine learning model determines the transition type based on a statistical attribute set generated from time-series measurement data measured for the downhole operations for the wellbore.

17. The computer-implemented method of claim 15, wherein: the transition identification machine learning model determines the transition type by classifying the time window for the time point based on a group of candidate transition types; and the transition type is selected based on having a highest probability among the group of candidate transition types.

18. A system, comprising: a processor; memory in electronic communication with the processor; and instructions stored in the memory, the instructions being executable by the processor to: determine a time window based on a time point within wellbore data measured for a wellbore; generate, from the wellbore data, a statistical attribute set for the time window; determine, for the time window, a transition type for a transition between downhole operations using a transition identification machine learning model based on the statistical attribute set for the time window; and provide the transition type associated with the time point for the transition between the downhole operations for updating a downhole operation report for the wellbore.

19. The system of claim 18, wherein: determining the time window includes determining a first portion of the time window before the time point and determining a second portion of the time window after the time point; and generating the statistical attribute set includes generating a first statistical attribute subset for the first portion of the time window and a second statistical attributes subset for the second portion of the time window.

20. The system of claim 18, further comprising: identifying the transition type at a time signature within the downhole operation report; and updating the time signature for the transition type in the downhole operation report to correspond with the time point.