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(54) **METHODS AND SYSTEMS FOR PREDICTING JOINT NETWORKS IN SUBSURFACE LAYERS**

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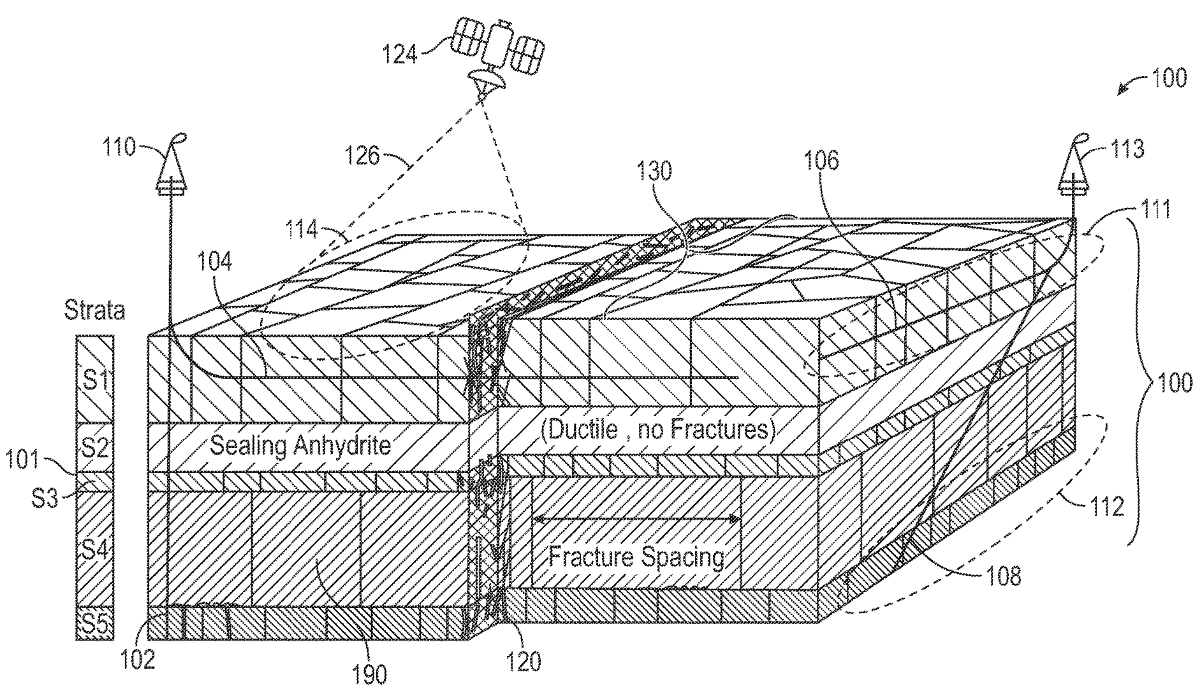
(57) **ABSTRACT**

Methods and systems for synthetic joint network prediction are disclosed. The method may include obtaining a plurality of outcrop pavement images of a plurality of joint networks and determining, using a first machine learning (ML) network, a plurality of detected joint networks using the plurality of outcrop pavement images. The method further includes determining, for each of the plurality of detected joint networks, a set of surface geostatistical properties and creating a database of surface joint properties including the plurality of sets of surface geostatistical properties. The method still further includes generating a synthetic joint network predictor by training a second ML network, using the database of surface joint properties, to produce a synthetic joint network. In addition, the method includes using the synthetic joint network predictor to predict a predicted joint network from a geostatistical description of observed subsurface joints.



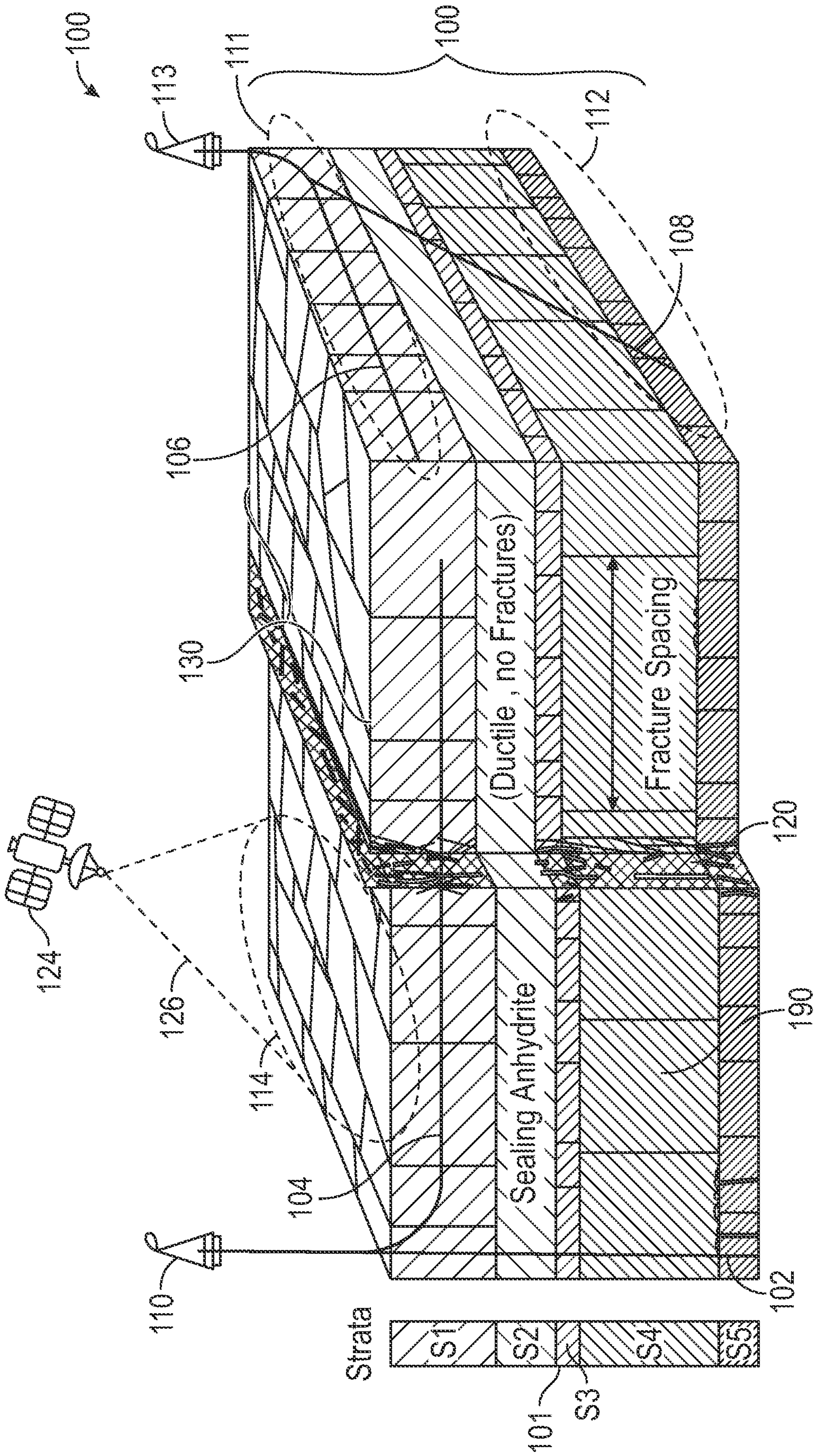

100
113
111
100
112
108
106
130
(Ductile , no Fractures)
Fracture Spacing
124
126
114
104
Sealing Anhydrite
120
190
110
102
Strata
S1
S2
S3
S4
S5
101

FIG. 1

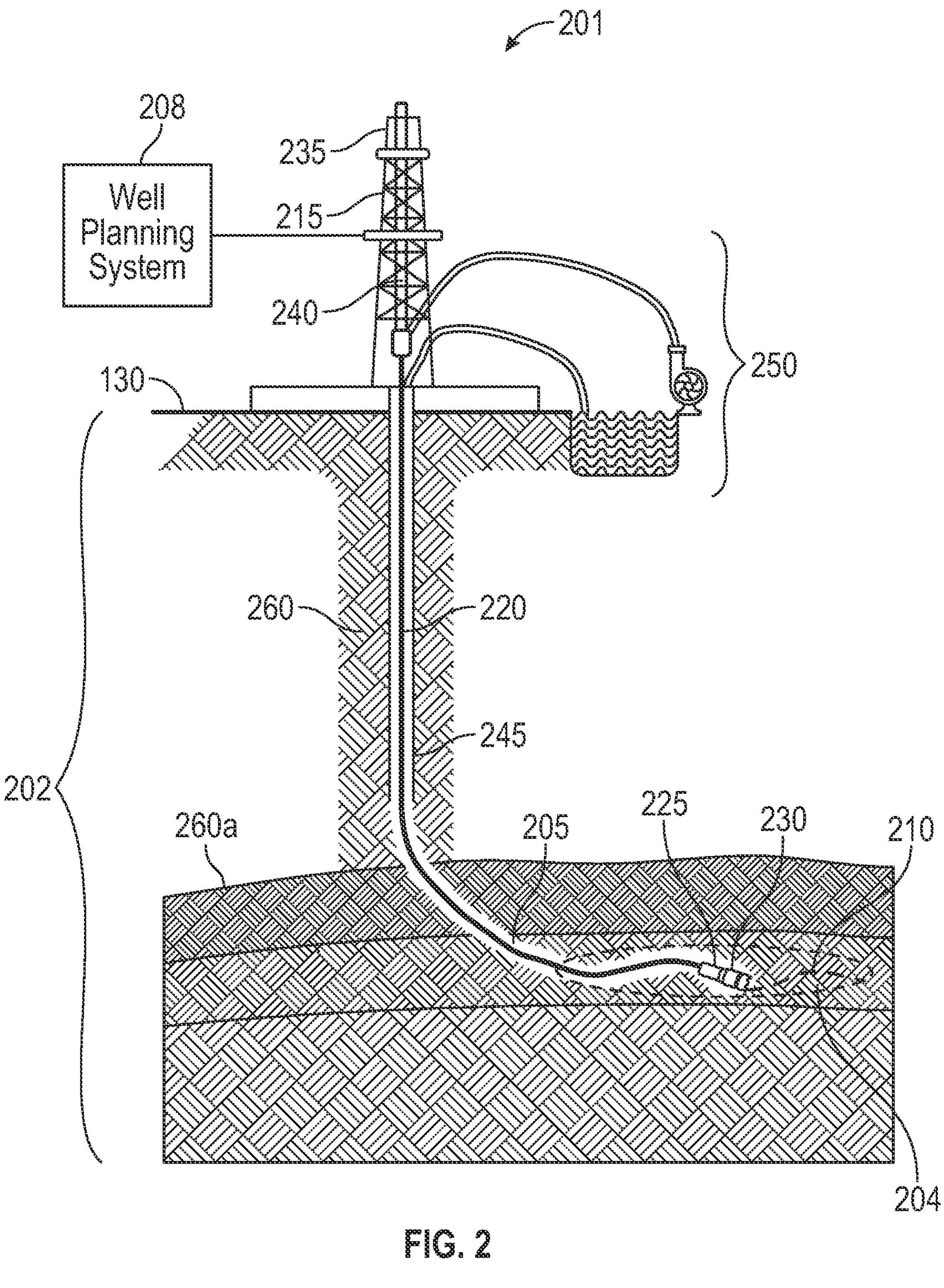

201
208
Well
Planning
System
235
215
240
250
130
260
220
245
202
260a
205
225
230
210
204

FIG. 2

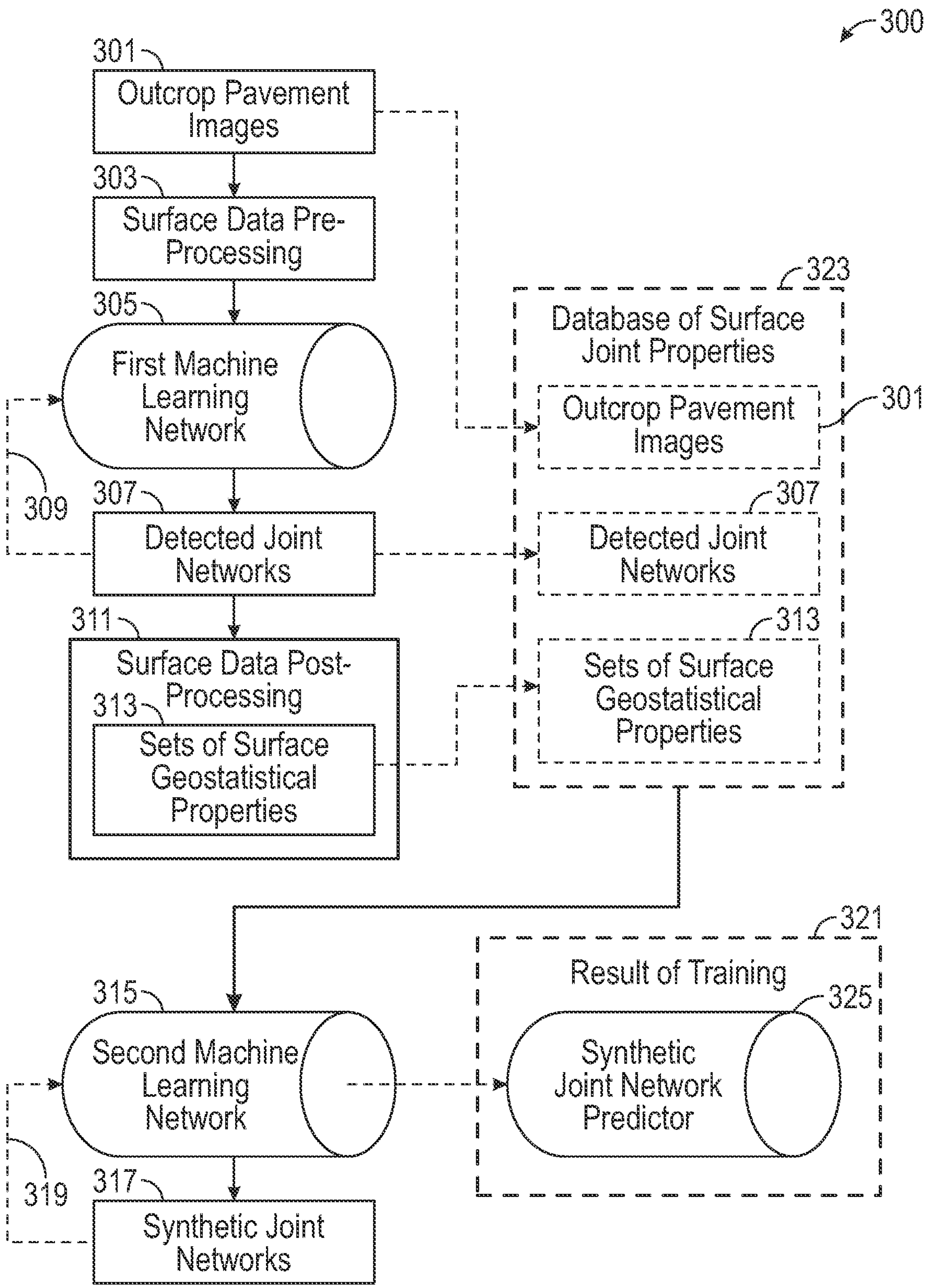

300
301
Outcrop Pavement Images
303
Surface Data Pre-Processing
305
First Machine Learning Network
309
307
Detected Joint Networks
311
Surface Data Post-Processing
313
Sets of Surface Geostatistical Properties
323
Database of Surface Joint Properties
301
Outcrop Pavement Images
307
Detected Joint Networks
313
Sets of Surface Geostatistical Properties
315
Second Machine Learning Network
319
317
Synthetic Joint Networks
321
Result of Training
325
Synthetic Joint Network Predictor

FIG. 3

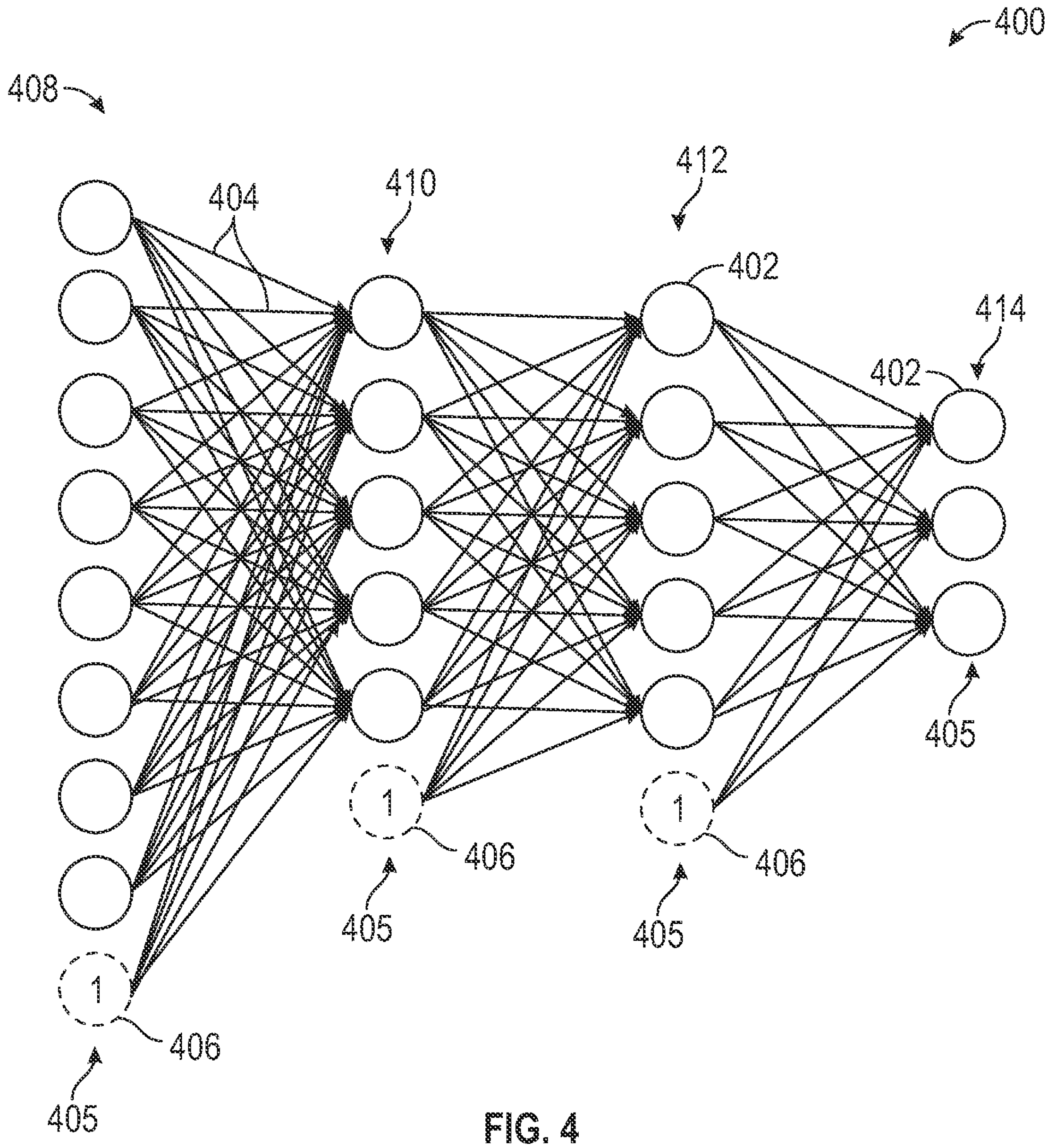


FIG. 4

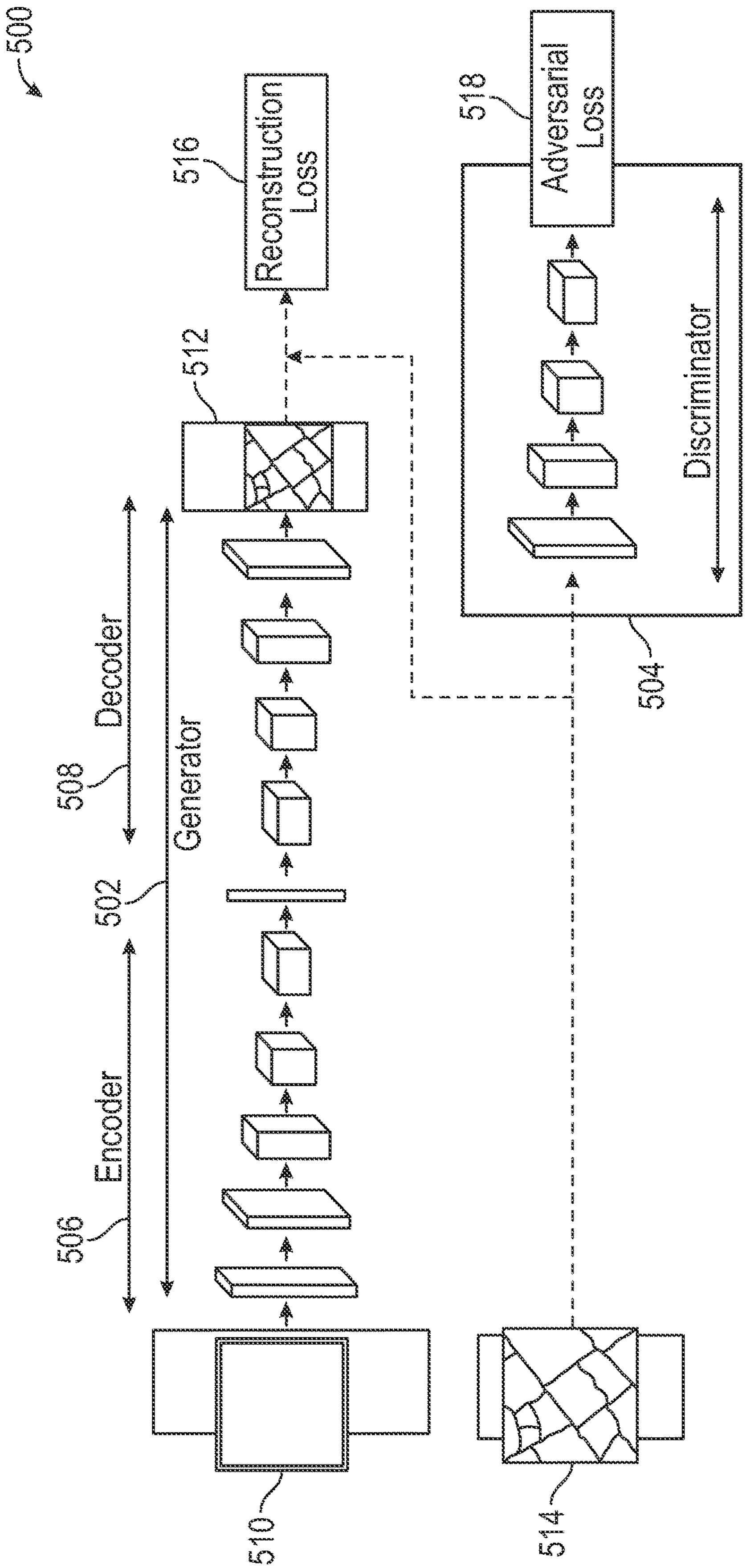

500
Reconstruction Loss
516
Adversarial Loss
518
512
Decoder
508
Generator
502
Encoder
506
Discriminator
504
510
514

FIG. 5

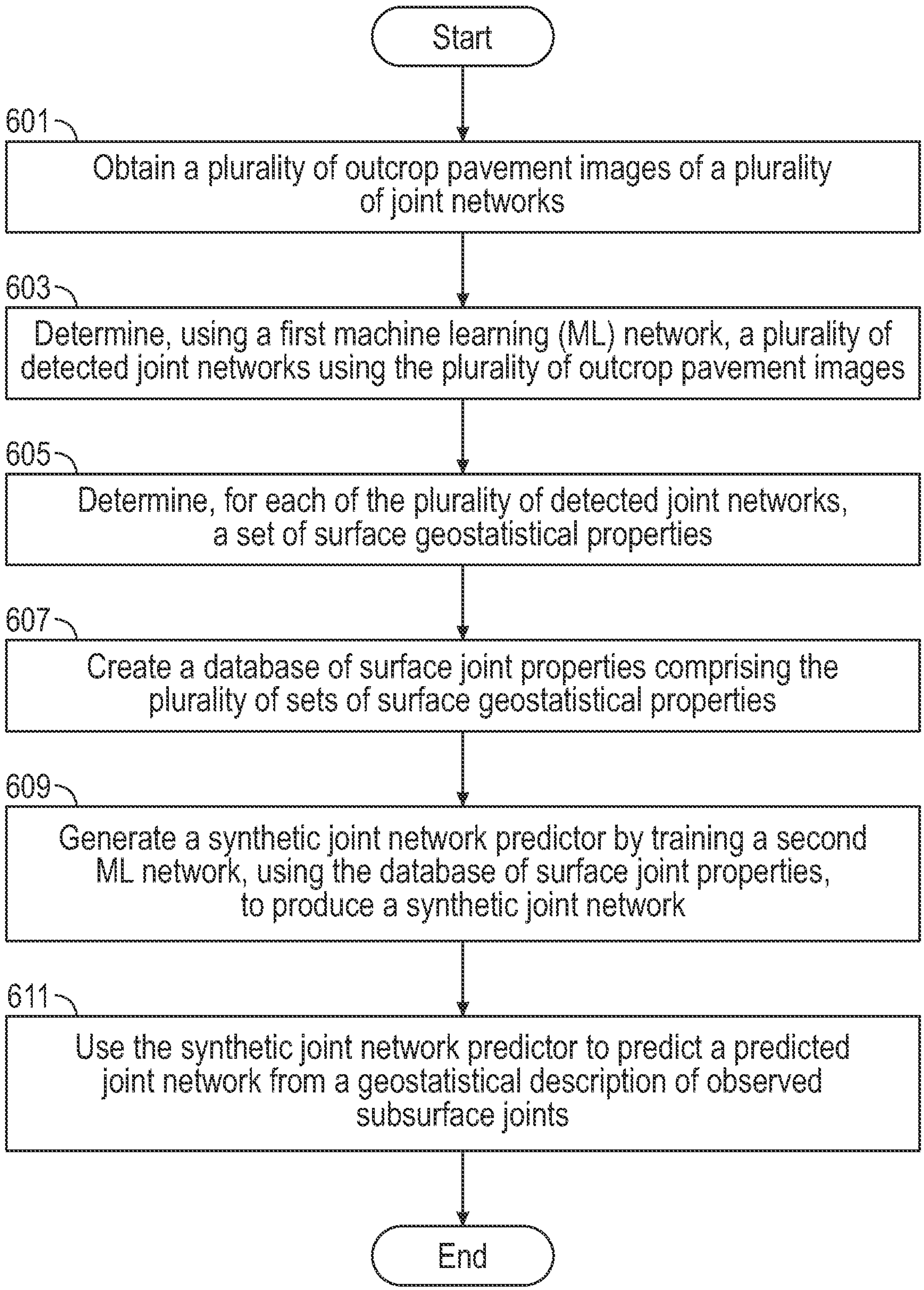

Start
601
Obtain a plurality of outcrop pavement images of a plurality of joint networks
603
Determine, using a first machine learning (ML) network, a plurality of detected joint networks using the plurality of outcrop pavement images
605
Determine, for each of the plurality of detected joint networks, a set of surface geostatistical properties
607
Create a database of surface joint properties comprising the plurality of sets of surface geostatistical properties
609
Generate a synthetic joint network predictor by training a second ML network, using the database of surface joint properties, to produce a synthetic joint network
611
Use the synthetic joint network predictor to predict a predicted joint network from a geostatistical description of observed subsurface joints
End

FIG. 6

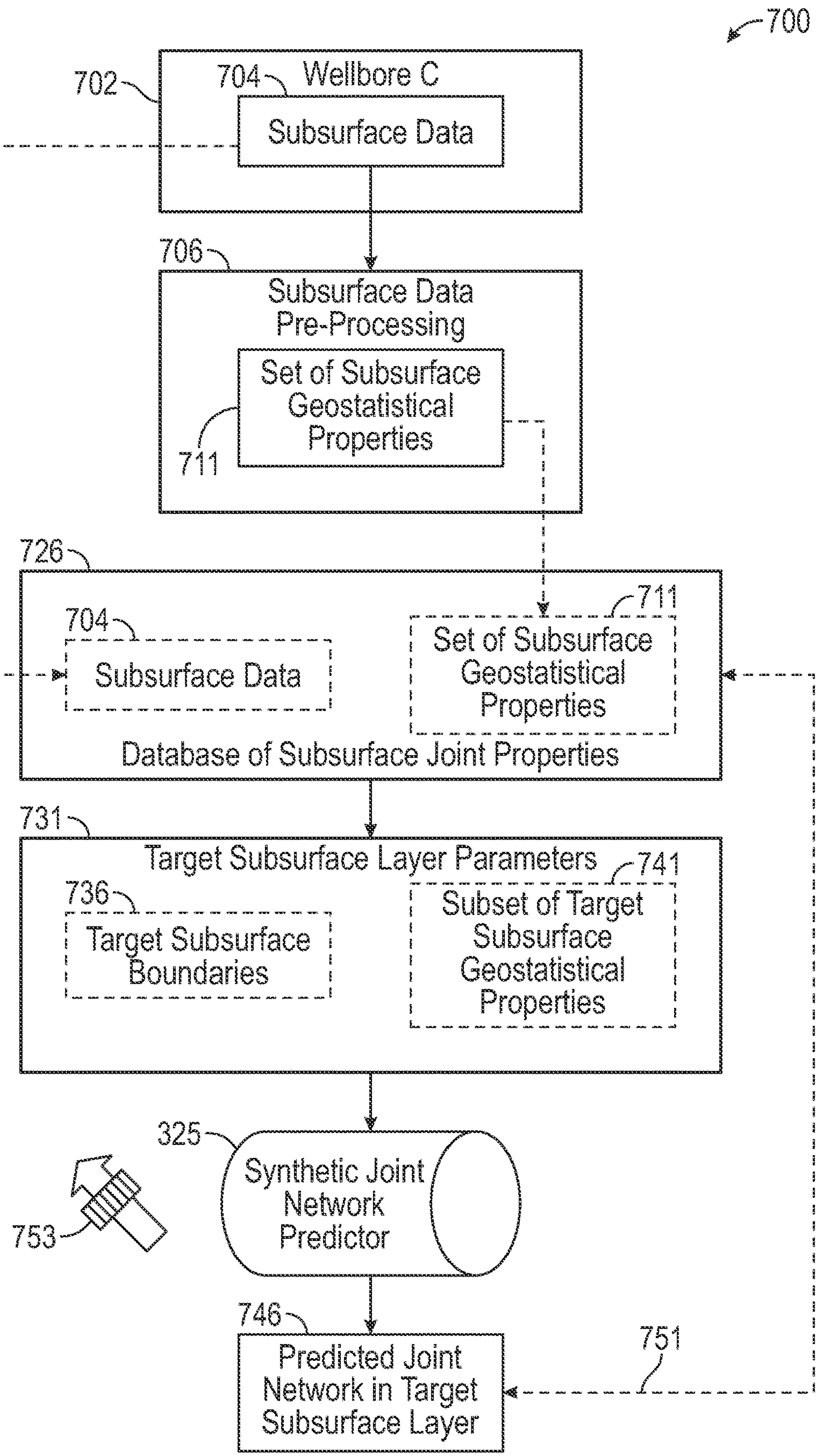

700
702
704
Wellbore C
Subsurface Data
706
Subsurface Data Pre-Processing
Set of Subsurface Geostatistical Properties
711
726
704
Subsurface Data
711
Set of Subsurface Geostatistical Properties
Database of Subsurface Joint Properties
731
Target Subsurface Layer Parameters
736
Target Subsurface Boundaries
741
Subset of Target Subsurface Geostatistical Properties
325
Synthetic Joint Network Predictor
753
746
Predicted Joint Network in Target Subsurface Layer
751

FIG. 7

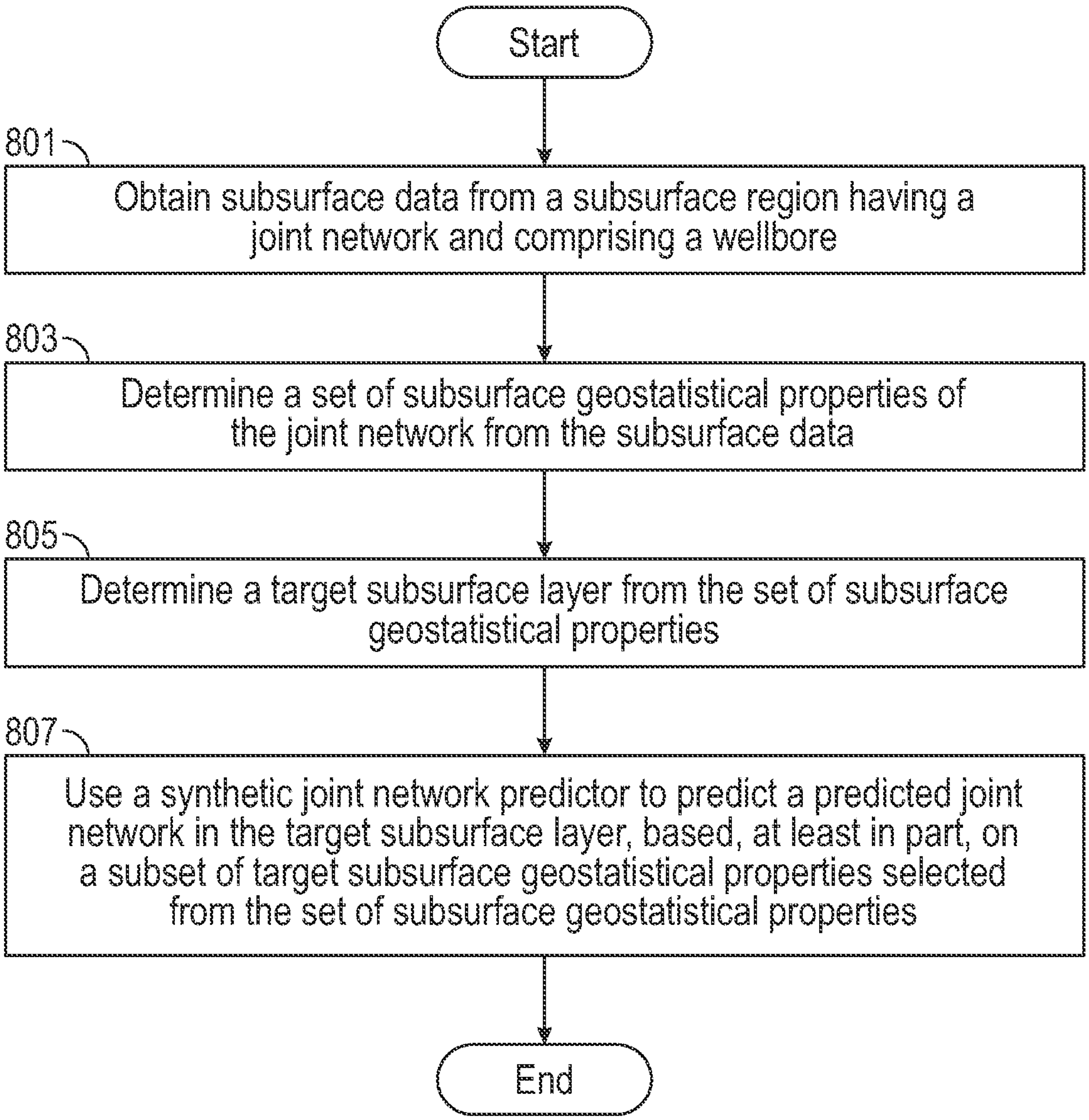

Start
801
Obtain subsurface data from a subsurface region having a joint network and comprising a wellbore
803
Determine a set of subsurface geostatistical properties of the joint network from the subsurface data
805
Determine a target subsurface layer from the set of subsurface geostatistical properties
807
Use a synthetic joint network predictor to predict a predicted joint network in the target subsurface layer, based, at least in part, on a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties
End

FIG. 8

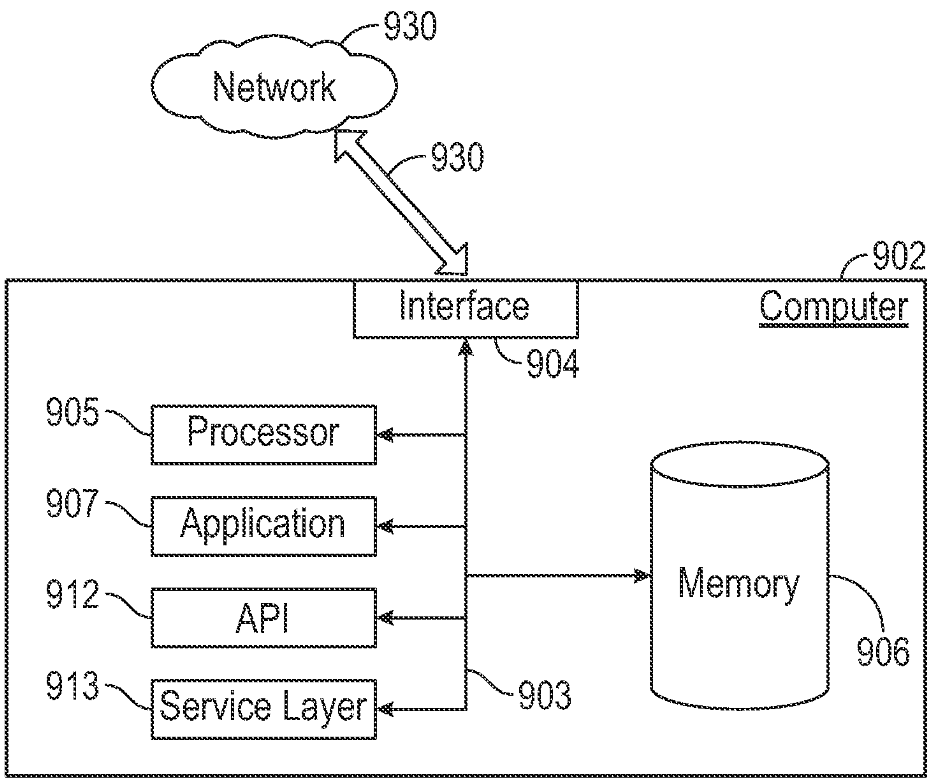

930
Network
930
902
Interface
Computer
904
905
Processor
907
Application
Memory
912
API
906
913
Service Layer
903

FIG. 9

METHODS AND SYSTEMS FOR PREDICTING JOINT NETWORKS IN SUBSURFACE LAYERS

BACKGROUND

[0001] Rock jointing is the predominant type of fracturing in some layered sedimentary rocks, such as limestone and sandstone. Rock jointing in natural fracture systems often takes the form of a network of individual joints. Joint networks are sometimes visible from above the surface in outcrop rock pavements but determining the characteristics of joint networks below the surface, in the subsurface, is difficult. The abundance of joints and their characteristics are important in petroleum engineering and mining operations as joint networks form passageways for flowing oil, gas, and water in the subsurface, and may influence the geomechanical response of rock to drilling. Accordingly, there exists a need to reliably determine the properties of joint networks in the subsurface.

SUMMARY

[0002] This summary is provided to introduce a selection of concepts that are further described below in the detailed description. This summary is not intended to identify key or essential features of the claimed subject matter, nor is it intended to be used as an aid in limiting the scope of the claimed subject matter.

[0003] Embodiments disclosed herein generally relate to a first method for using a synthetic joint network predictor. The method includes obtaining a plurality of outcrop pavement images of a plurality of joint networks and determining, using a first machine learning (ML) network, a plurality of detected joint networks using the plurality of outcrop pavement images. The method further includes determining, for each of the plurality of detected joint networks, a set of surface geostatistical properties and creating a database of surface joint properties including the plurality of sets of surface geostatistical properties. The method still further includes generating a synthetic joint network predictor by training a second ML network, using the database of surface joint properties, to produce a synthetic joint network. In addition, the method includes using the synthetic joint network predictor to predict a predicted joint network from a geostatistical description of observed subsurface joints.

[0004] Embodiments disclosed herein generally relate to a second method for using a synthetic joint network predictor. The method includes obtaining subsurface data from a subsurface region having a joint network and comprising a wellbore. The method further includes determining a set of subsurface geostatistical properties of the joint network from the subsurface data. The method still further includes determining a target subsurface layer from the set of subsurface geostatistical properties. In addition, the method includes, using a synthetic joint network predictor, predicting a predicted joint network in the target subsurface layer, based, at least in part, on a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties.

[0005] Embodiments disclosed herein generally relate to a system. The system includes a plurality of devices configured to be disposed along a wellbore and configured to obtain subsurface data. The system further includes a computer configured to receive the subsurface data, determine a set of subsurface geostatistical properties of a subsurface joint network from the subsurface data, and determine a target subsurface layer from the set of subsurface geostatistical properties. In addition, the system includes a synthetic joint network predictor configured to predict a predicted joint network in the target subsurface layer based, at least in part, on a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties.

[0006] Other aspects and advantages of the claimed subject matter will be apparent from the following description and the appended claims.

BRIEF DESCRIPTION OF DRAWINGS

[0007] Specific embodiments of the disclosed technology will now be described in detail with reference to the accompanying figures. Like elements in the various figures are denoted by like reference numerals for consistency. The sizes and relative positions of elements in the drawings are not necessarily drawn to scale. For example, the shapes of various elements and angles are not necessarily drawn to scale, and some of these elements may be arbitrarily enlarged and positioned to improve drawing legibility. Further, the particular shapes of the elements as drawn are not necessarily intended to convey any information regarding the actual shape of the particular elements and have been solely selected for ease of recognition in the drawing.

[0008] FIG. **1** depicts a fractured region of rock in accordance with one or more embodiments.

[0009] FIG. **2** depicts a drilling system in accordance with one or more embodiments.

[0010] FIG. **3** depicts a system in accordance with one or more embodiments.

[0011] FIG. **4** depicts a neural network in accordance with one or more embodiments.

[0012] FIG. **5** depicts a generative adversarial network in accordance with one or more embodiments.

[0013] FIG. **6** depicts a flowchart in accordance with one or more embodiments.

[0014] FIG. **7** depicts a system in accordance with one or more embodiments.

[0015] FIG. **8** depicts a flowchart in accordance with one or more embodiments.

[0016] FIG. **9** depicts a system in accordance with one or more embodiments.

DETAILED DESCRIPTION

[0017] In the following detailed description of embodiments of the disclosure, numerous specific details are set forth in order to provide a more thorough understanding of the disclosure. However, it will be apparent to one of ordinary skill in the art that the disclosure may be practiced without these specific details. In other instances, well-known features have not been described in detail to avoid unnecessarily complicating the description.

[0018] Throughout the application, ordinal numbers (e.g., first, second, third, etc.) may be used as an adjective for an element (i.e., any noun in the application). The use of ordinal numbers is not to imply or create any particular ordering of the elements nor to limit any element to being only a single element unless expressly disclosed, such as using the terms “before,” “after,” “single,” and other such terminology. Rather, the use of ordinal numbers is to distinguish between the elements. By way of an example, a first element is distinct from a second element, and the first element may encompass more than one element and succeed (or precede) the second element in an ordering of elements.

[0019] It is to be understood that the singular forms "a," "an," and "the" include plural referents unless the context clearly dictates otherwise. For example, an "oil or gas well," may include any number of "oil or gas wells" without limitation.

[0020] Terms such as "approximately," "substantially," etc., mean that the recited characteristic, parameter, or value need not be achieved exactly, but that deviations or variations, including for example, tolerances, measurement error, measurement accuracy limitations and other factors known to those of skill in the art, may occur in amounts that do not preclude the effect the characteristic was intended to provide.

[0021] It is to be understood that one or more of the steps shown in the flowcharts may be omitted, repeated, and/or performed in a different order than the order shown. Accordingly, the scope disclosed herein should not be considered limited to the specific arrangement of steps shown in the flowcharts.

[0022] Although multiple dependent claims are not introduced, it would be apparent to one of ordinary skill that the subject matter of the dependent claims of one or more embodiments may be combined with other dependent claims.

[0023] In the following description of FIGS. **1-9**, any component described with regard to a figure, in various embodiments disclosed herein, may be equivalent to one or more like-named components described with regard to any other figure. For brevity, descriptions of these components will not be repeated with regard to each figure. Thus, each and every embodiment of the components of each figure is incorporated by reference and assumed to be optionally present within every other figure having one or more like-named components. Additionally, in accordance with various embodiments disclosed herein, any description of the components of a figure is to be interpreted as an optional embodiment which may be implemented in addition to, in conjunction with, or in place of the embodiments described with regard to a corresponding like-named component in any other figure.

[0024] In general, embodiments of the disclosure include systems and methods for predicting joint networks in the subsurface in the vicinity of wellbores drilled in proximity a fractured region of rock. Joint networks are understood to be systems of naturally occurring fractures in rock that are describable through their statistical properties, including, for example, their orientation, size, shape, location, and intensity (or spatial density). A fractured region of rock may refer to an area with natural geological fractures in the earth. A fractured region of rock may be targeted for drilling due to, for example, the presence of a subsurface reservoir of hydrocarbons and one or more wellbores may be drilled, using a drilling system, to penetrate and traverse the fractured region of rock. The wellbore of the well may intersect a joint network in one or more subsurface stratigraphic layers. The systems and methods enable reservoir engineers, simulation engineers, and well completion engineers to quantitatively assess joint network properties in fractured regions of rock. The methods of the disclosure include obtaining information related to natural fracture systems from above the surface, obtaining information related to natural fracture systems from below the surface (i.e., in the subsurface), and configuring a machine learning network to predict the properties of the joint networks in subterranean layers. The predicted joint network may be used to assist wellbore planning, well placement, well completion, and in reservoir flow simulations.

[0025] The geostatistical properties, including the statistical trends relating to joint orientation, spacing, length, and spatial density may be directly measured, at least in part, on the surface of the earth from where the rock layer outcrops, herein referred to as "outcrop pavements." In particular, the geostatistical properties may be determined from outcrop pavements containing joint networks, particularly from outcrops of rock facies similar to those thought to be present in the subsurface region of interest. In one or more embodiments, a first machine learning network is used to detect joint networks from images of outcrop pavements. The geostatistical properties of the detected joint networks may then be determined and characterized and create models of the probability of joint networks exhibiting one or more qualities, for example, the probability a joint network to exhibit a particular spatial density of joints. The surface information regarding joint networks may be organized into a database of surface joint properties. In one or more embodiments, the database of surface joint properties may be used to train a second machine learning network to generate synthetic (i.e., artificial) digital joint networks embodying the properties of real joint networks according to the database of surface joint properties. A synthetic joint network predictor may then be derived from the second machine learning network and used to predict a predicted joint network from a geostatistical description of observed subsurface joints.

[0026] For a given fractured region of rock proximate to a wellbore, information related to subsurface joint networks may be obtained from drill core and near-wellbore images, assuming the wellbore intersects, at least partially, with a present subsurface joint network. Subsurface data may generally refer to subsurface images (e.g., wellbore images) and core samples. The subsurface data may be used to classify structural discontinuities along the path of the wellbore as well as their locations, mineralization (and lack thereof), and modes of displacement. Joints may be identified and selected from the general discontinuities. The identified joints in the subsurface may be processed to determine their geostatistical properties and to create models of the probability of the present joint network(s) exhibiting one or more qualities. In one or more embodiments, a database of subsurface joint properties, including the subsurface geostatistical properties, is created. The database of subsurface joint properties may be used to identify a target subsurface layer, with its own subset of target subsurface geostatistical properties, where further information regarding the joint network, for example, its properties in locations displaced from the wellbore, is sought. In one or more embodiments, a prediction of the joint network is made in the surrounding area extending away from the wellbore, or between wellbores, in the target subsurface layer using the synthetic joint network predictor. Recall that the synthetic joint network predictor is generated by the second machine learning (ML) network trained with a database of surface joint properties. The predicted joint network in the subsurface layer may be used for wellbore planning, well placement, well completion, and in reservoir flow simulations.

[0027] For wellbore planning and placement, the methods of the present disclosure may be used to determine possible outcomes, such as predicted oil and/or gas production, of drilling a wellbore to intersect a subterranean joint network. For example, a wellbore may be planned to intersect with the joint network such that the wellbore is substantially parallel to the direction of joints, thus avoiding forming perpendicular intersections with joints in the network in order to improve communication between the planned wellbore and a target reservoir. Regarding well completion, the methods of the disclosure may inform the placement of mechanical tools or the injection of chemical sealants to control fluid flow within the joint network. For reservoir numerical simulations, the methods of the disclosure yield predicted joint networks in a digital format capable of being incorporated into reservoir flow simulation models. For example, the methods of the disclosure may inform the length of a well to drill according to the predicted flow from the reservoir numerical simulation. In some embodiments, the systems of the disclosure may be used in hydrocarbon reserve estimation, to determine the quantity of oil and gas presently displaced or recovered, and for drainage determination for petroleum field development strategies. Further, the methods may inform the selection of casing and perforation, planning hydraulic fracturing, and the setting of production packers, production tubing and downhole pumps. In one or more embodiments, a well planning system may be used to update a portion of a planned well in a target subsurface layer based, at least in part, on the methods of the present disclosure. Then, a drilling system may be used to drill a well, guided by the planned well.

[0028] FIG. **1** shows a schematic diagram in accordance with one or more embodiments.

[0029] Specifically, FIG. **1** illustrates a fractured region of rock (**100**) embedded in a geological model. The geological model depicts various stratigraphic layers, indicated on the grayscale (**101**), where each layer may exhibit different natural fracture features and structural discontinuities. The surface of the earth (**130**) is indicated as the uppermost portion of the first stratigraphic layer (S**1**). Among the structural discontinuities present may be joints, including regularly spaced joints (**111**) and semi-regularly spaced joints (**112**). Joints are a common geological feature and a type of natural fracture characterized by typically forming systems, or networks, that follow statistical patterns in their spacing and orientation, among other physical attributes. Further, joint networks are typically bounded but fully cross geological layers while exhibiting regular and semi-regular spacing (i.e., spacing that follows a pattern of spacing that is not completely uniform). Joints may often result from extensional tectonic stress may then be altered by chemical processes, such as dissolution and/or recrystallization. Discontinuities in the fractured region of rock (**100**) with regular (**111**) or semi-regular spacing (**112**) may therefore be identified as rock joints. In FIG. **1**, a joint network is depicted in the uppermost stratigraphic layer (**101**) labeled S**1** above the surface of the earth (**130**), while additional joint networks may be present in other subsurface layers, such as the subsurface (S**2**-S**5**). The joint network is readily discernible in the surface of the earth (**130**) as a surface joint network (**114**). Another type of natural fracture, referred to as a fracture cluster (**120**), is present in the center of the geological model representing the fractured region of rock (**100**). A fracture cluster (**120**) is a set of closely spaced fractures in an area of otherwise widely spaced fractures, and fracture clusters do not form networks. A fracture cluster (**120**) can typically be identified as a narrow band of many closely spaced fractures. The presence of a fracture cluster (**120**) reflects a concentration of stresses (notably shear) that cause rock failure within localized regions of rock subject to the concentrated stress.

[0030] Joints, such as those included in the fractured region of rock (**100**) are generally idealized as planes in the rock medium and considered as having their poles in a sphere projected in their surroundings. The pole is a unitary vector orthogonal to the plane with its tail at the origin and its head on the unit sphere. The pole is, in principle, undirected, and may be oriented on either side of the plane and therefore visualized on both upper and lower hemispheres in stereographic projection. It is conventional however for structural geologists to select the lower hemisphere plot, and the pole can be expressed by the plane direction cosines in a Cartesian coordinate system. The dip of a discontinuity (e.g., a joint) is calculated from the angle formed by a plane representing the surface of the earth (**130**) that intersects with the discontinuity plane. The dip is measured between 0 to 90 degrees inclination, where 0 is for horizontal and 90 for vertical. The dip azimuth is measured for the direction of the inclined discontinuity plane. Joint strikes are normal to dip azimuth and may be obtained by adding or subtracting 90 degrees to limit the outcome to a positive integer between 0 and 360.

[0031] The fractured region of rock (**100**) further includes a first well (**110**). The first well (**110**) includes a vertical wellbore (**102**) and a first horizontal wellbore (**104**). The vertical wellbore (**102**) is substantially perpendicular to the rock plane, while the first horizontal wellbore (**104**) is substantially parallel to the rock plane. In FIG. **1**, the vertical wellbore may intersect multiple strata but may not intersect any joints. Wellbore or drill core images from the vertical wellbore (**102**) of the first well (**110**) may therefore be informative of the various stratigraphic layers but lack information related to joint networks present in the subsurface. Meanwhile, the first horizontal wellbore (**104**) intersects many rock joints but traverses only one stratum. Wellbore and drill core images from the first horizontal wellbore (**104**) of the first well (**110**) may therefore be informative of joint networks in the particular stratum (in this case, S1) but lack information related to other strata, particularly deeper strata. The first horizontal wellbore (**104**) further traverses the fracture cluster (**120**), which may be identified via the wellbore and drill core images. In addition to the first well (**110**), the fractured region of rock includes a second well (**113**). The second well (**113**) includes a second horizontal wellbore (**106**) and a sub-horizontal wellbore (**108**). If the plane of the rock is considered to be zero degrees (i.e., perfectly horizontal) then the sub-horizontal wellbore (**108**) may be said to traverse the rock at an angle greater than zero degrees but less than ninety degrees (recall the convention in structural geology to consider the lower hemisphere as positive). A wellbore oriented at zero degrees may, accordingly, be referred to as a horizontal wellbore (e.g., second horizontal wellbore (**106**), and a wellbore oriented at ninety degrees may be considered perpendicular to the rock plane and therefore referred to as a vertical wellbore (e.g., vertical wellbore (**102**)). Like the first horizontal wellbore (**104**), the second horizontal wellbore (**106**) traverses a single stratum but intersects several rock joints.

However, the second horizontal wellbore does not traverse the fracture cluster (**120**). The sub-horizontal wellbore (**108**) may traverse multiple strata and contain information related to joint networks in each strata, subject to the length and orientation of the wellbore. For example, in the illustration of FIG. **1**, S**4** is the only stratum that contains more than one joint intersected by the sub-horizontal wellbore (**108**). Several subsurface regions (e.g., subsurface region (**190**)) may be targeted for a drilling operation. A targeted subsurface region (e.g., subsurface region (**190**)) may be constrained to one stratum or several.

[0032] While FIG. **1** depicts two wells (**110**, **113**), it is to be understood that embodiments of the present disclosure are not limited to fractured region of rocks or other geological settings containing only two wells. In one or more embodiments, only one well may be present. In other embodiments, any number of wells in a substantially localized area may be considered, without limitation. Embodiments of the present disclosure may thus include one, two, or many wells. Further, embodiments of the present disclosure are not limited by the number of wellbores present, and the minimum number of necessary wellbores is one. However, as will be described below, the presence of a plurality of wellbores in the fractured region of rock (**100**) may be useful in accordance with one or more embodiments of the present disclosure.

[0033] The wellbores (**102**, **104**, **106**, **108**) of the wells (**110**, **113**) may facilitate the circulation of drilling fluids during drilling operations, the flow the produced fluid (e.g., hydrocarbons, water, etc.) from the subsurface to the surface during production operations, the injection of substances (e.g., water) into the Earth during injection operations, the placement of monitoring devices (e.g., logging tools) during monitoring operations (e.g., during in situ logging operations). In some embodiments, various control components and sensors are disposed down-hole along the wellbores (**102**, **104**, **106**, **108**). For example, in one or more embodiments, an inflow control valve (ICV) may be disposed along a given wellbore. An ICV is an active component usually installed during well completion. The ICV may partially or completely choke flow into a well. Generally, multiple ICVs may be installed along the reservoir section of a wellbore. Each ICV is separated from the next by a packer. Each ICV can be adjusted and controlled to alter flow within the well and, as the reservoir depletes, prevent unwanted fluids from entering the wellbore. In addition, the control components and sensors may further include a subsurface safety valve (SSSV). The SSSV is designed to close and completely stop flow in the event of an emergency. Generally, an SSSV is designed to close on failure. That is, the SSSV requires a signal to stay open and loss of the signal results in the closing of the valve. In one or more embodiments, a permanent downhole monitoring system (PDHMS) is secured downhole along one or more wellbores (**102**, **104**, **106**, **108**). The PDHMS consists of a plurality of sensors, gauges, and controllers to monitor subsurface flowing and shut-in pressures and temperatures. As such, a PDHMS may indicate, in real-time, the state or operating condition of subsurface equipment and the fluid flow. In one or more embodiments, the PDHMS may further measure and monitor temperature and pressure within the well connected to the wellbore, as well as other properties not listed. The listed valves and sensors may be used individually or collectively for one or more operations, such as for a production or completion operation.

[0034] The wells (**110**, **113**) may each also include a well control system (e.g., a Supervisory Control and Data Acquisition (SCADA) system). The control systems may control or interact with devices, such as the valves and sensors described above, to control various operations of the drilling wells (**110**, **113**). Controlled operations may include well production operations, well completion operations, well maintenance operations, and reservoir monitoring, assessment and development operations. These operations may further be facilitated by communication from the control system to the PDHMS. In some embodiments, the control system includes a computer system that is the same as or similar to that of the computer system depicted in FIG. **9** with its accompanying description. It is emphasized that the plurality of oil and gas field devices described in reference to FIG. **1** are non-exhaustive. Additional devices, such as electrical submersible pumps (ESPs) (not shown) may be present in a fractured region of rock (e.g., fractured region of rock (**100**)) or associated with a well (**110**, **113**) with their associated sensing and control capabilities. For example, an ESP may monitor the temperature and pressure of a fluid local to the ESP and may be controlled through adjustments, issued by the well controller, to ESP speed or frequency.

[0035] Drilling operations, including well placement and completion, the placement of manufactured tools or chemicals to enhance, reduce, segregate, or otherwise affect reservoir fluid, the illustrated wells (**110**, **113**) may be referred to herein to the operation of devices collectively referred to as "drilling tools." Drilling tools may be associated with drilling systems located at already drilled wells (e.g., first well (**110**)) and located at areas not yet associated with the wells in order to plan and create new wells. In other words, the first well (**110**) may have a drilling system with its associated drilling tools, or there may be a drilling system located elsewhere on the surface of the earth (**130**). The following includes descriptions of a drilling system and drilling tools used in drilling operations.

[0036] FIG. **2** illustrates a drilling system (**201**) in accordance with one or more embodiments. As shown in FIG. **2**, the drilling system (**201**) may be equipped with a hoisting system, such as a derrick (**215**), which can raise or lower the drillstring (**220**) and other tools required to drill the wellbore (**205**). The drillstring (**220**) may include one or more drill pipes connected to form conduit and a bottom hole assembly (**225**) (BHA) disposed at the distal end of the drillstring (**220**). The BHA (**225**) may include a drill bit (**230**) to cut into rock (**260**), including cap rock (**260***a*). The BHA (**225**) may further include measurement tools, such as a measurement-while-drilling (MWD) tool and logging-while-drilling (LWD) tool. MWD tools may include sensors and hardware to measure downhole drilling parameters, such as the azimuth and inclination of the drill bit (**230**), the weight-on-bit, and the torque. The LWD measurements may include sensors, such as resistivity, gamma ray, and neutron density sensors, to characterize the rock (**260**) surrounding the wellbore (**205**). Both MWD and LWD measurements may be transmitted to the surface of the earth (**130**) using any suitable telemetry system known in the art, such as a mud-pulse or by wired-drill pipe.

[0037] To start drilling, or "spudding in," the wellbore (**205**), the hoisting system lowers the drillstring (**220** suspended from the derrick (**215** towards the planned surface location of the wellbore (**205**). An engine, such as a diesel engine, may be used to supply power to the top drive (**235**) to rotate the drillstring (**220** via the drive shaft (**240**). The weight of the drillstring (**220** combined with the rotational motion enables the drill bit (**230**) to bore the wellbore (**205**).

[0038] The near-surface of the subterranean region of interest (**202**) is typically made up of loose or soft sediment or rock (**260**), so large diameter casing (**245**) (e.g., "base pipe" or "conductor casing") is often put in place while drilling to stabilize and isolate the wellbore (**205**). At the top of the base pipe is the wellhead, which serves to provide pressure control through a series of spools, valves, or adapters (not shown). Once near-surface drilling has begun, water or drill fluid may be used to force the base pipe into place using a pumping system until the wellhead is situated just above the surface of the earth (**130**).

[0039] Drilling may continue without any casing (**245**) once deeper or more compact rock (**260**) is reached. While drilling, a drilling mud system (**250**) may pump drilling mud from a mud tank on the surface of the earth (**130**) through the drill pipe. Drilling mud serves various purposes, including pressure equalization, removal of rock cuttings, and drill bit cooling and lubrication.

[0040] At planned depth intervals, drilling may be paused and the drillstring (**220**) withdrawn from the wellbore (**205**). Sections of casing (**245**) may be connected and inserted and cemented into the wellbore (**205**). Casing string may be cemented in place by pumping cement and mud, separated by a "cementing plug," from the surface of the earth (**130**) through the drill pipe. The cementing plug and drilling mud force the cement through the drill pipe and into the annular space between the casing (**245**) and the wall of the wellbore (**205**). Once the cement cures, drilling may recommence. The drilling process is often performed in several stages. Therefore, the drilling and casing cycle may be repeated more than once, depending on the depth of the wellbore (**205**) and the pressure on the walls of the wellbore (**205**) from surrounding rock (**260**).

[0041] Due to the high pressures experienced by deep wellbores (**205**), a blowout preventer (BOP) may be installed at the wellhead to protect the rig and environment from unplanned oil or gas releases. As the wellbore (**205**) becomes deeper, both successively smaller drill bits (**230**) and casing (**245**) may be used. Drilling deviated or horizontal wellbores (**205**) may require specialized drill bits (**230**) or drill assemblies.

[0042] The drilling system (**201**) may be disposed at and communicate with other systems in the wellbore environment. The drilling system (**201**) may control at least a portion of a drilling operation by providing controls to various components of the drilling operation. In one or more embodiments, the system may receive data from one or more sensors arranged to measure controllable parameters of the drilling operation. As a non-limiting example, sensors may be arranged to measure weight-on-bit, drill rotational speed (RPM), flow rate of the mud pumps (GPM), and rate of penetration of the drilling operation (ROP). Each sensor may be positioned or configured to measure a desired physical stimulus. Drilling may be considered complete when a drilling target with the hydrocarbon reservoir (**204**) is reached or the presence of hydrocarbons is established.

[0043] The drilling system (**201**) may be configured for radial drilling. Radial drilling refers to a method of drilling small generally radially extending tunnels (typically a few inches in diameter) extending from a main well into the formation strata (typically to a maximum of about 300-400 feet). Radial drilling is commonly used to access trapped oil or gas in the near-well formation and stimulate production. Radial drilling tools are often deployed through the main well using coiled tubing, although slickline has also been used. Unlike drillstring (**220**), which is made of multiple rigid sections of pipe that are threaded together in an end-to-end fashion, coiled tubing is a long, continuous length of pipe that is wound on a spool to be stored or transported and then straightened to be pushed into a well. Radial drilling tools may vary depending on the radial drilling technique being used and may include, for example, a downhole mud motor, a jetting nozzle and hose, a milling bit, and others.

[0044] Drilling systems, such as the drilling system (**201**) depicted in FIG. **2**, may also include chemicals and chemical storage systems used to enhance, reduce, segregate, or otherwise affect reservoir fluid and production. A chemical storage system may be installed along a wellbore (**205**) and include a compartment (not shown) in which chemicals may be stored and dispensed. For example, a chemical storage system may include a chemical storage compartment (e.g., a container) containing chemicals and a dispensing mechanism (e.g., a pump) in fluid communication with the chemical storage compartment, where the dispensing mechanism may be used to dispense chemicals from the compartment. In some embodiments, one or more additional chemical storage compartments may be in fluid communication with a dispensing mechanism, such that a single dispensing mechanism may dispense chemicals from multiple chemical storage compartments. In some embodiments, a chemical storage compartment may be a pill capsule containing the chemicals, where the pill capsule may be dissolved under certain downhole environmental conditions to dispense the chemicals. Various configurations of a chemical storage compartment and dispensing mechanism working in conjunction to store and dispense chemicals may be used to form chemical storage systems integrated within drilling systems (e.g., drilling system (**201**)). Chemicals that may be used to enhance, reduce, segregate, or otherwise affect reservoir production and operation include, but are not limited to, H2S scavenging chemicals such as methylene bis-oxazolidine (MBO), ethylenedioxy dimethanol (EDDM), 2-ethyl zinc salt, glyoxal, hemiacetal and monoethanolamine (MEA) triazine. Further chemicals may include H2S adsorption chemicals and scale inhibitors such as inorganic phosphate, organophosphorous and organic polymer backbones such as PBTC (phosphonobutane-1,2,4-tricarboxylic acid), ATMP (amino-trimethylene phosphonic acid) and HEDP (1-hydroxyethylidene-1,1-diphosphonic acid), polyacrylic acid (PAA), phosphinopolyacrylates (such as phosphino polycarboxylic acid (PPCA)), polymaleic acids (e.g., para-methoxyamphetamine (PMA)), maleic acid terpolymers (MAT), sulfonic acid copolymers, such as SPOCA (sulfonated phosphonocarboxylic acid), polyvinyl sulfonates, poly-phosphono carboxylic acid (PPCA) and diethylenetriamine-penta (methylene phosphonic acid) DTPMP. An additional type of possible chemicals include corrosion inhibitors like quaternary amines, amides, imidazolines, and phosphate esters. Further chemicals beyond those listed here are not beyond the scope of the present disclosure.

[0045] To the extent that they may be used for drilling operations, including well placement and completion, the placement of manufactured tools or chemicals to enhance, reduce, segregate or otherwise affect reservoir fluid, some of the devices previously listed, such as ICVs dictating the flow of fluid into a wellbore and ESPs used for adjusting fluid flow within a wellbore (or to propagate one or more chemicals), may be considered drilling tools according to the definition herein.

[0046] The plurality of devices associated with wells (e.g., first well (**110**)) or drilling systems (e.g., drilling system (**201**)) described above may be distributed, local to the sub-processes and associated components, global, connected, etc. The devices may be of various control types, such as a programmable logic controller (PLC) or a remote terminal unit (RTU). For example, a programmable logic controller (PLC) may control valve states, pipe pressures, warning alarms, and/or pressure releases throughout the oil and gas field. In particular, a programmable logic controller (PLC) may be a ruggedized computer system with functionality to withstand vibrations, extreme temperatures, wet conditions, and/or dusty conditions, for example, around a well (e.g., first well (**110**)). With respect to an RTU, an RTU may include hardware and/or software, such as a microprocessor, that connects sensors and/or actuators using network connections to perform various processes in the automation system. As such, a distributed control system may include various autonomous controllers (such as remote terminal units) positioned at different locations throughout the oil and gas field to manage operations and monitor sub-processes. Likewise, a distributed control system may include no single centralized computer for managing control loops and other operations. In accordance with one or more embodiments, the well control system can be a supervisory control and data acquisition (SCADA) system. A SCADA system is a control system that includes functionality for device monitoring, data collection, and issuing of device commands. The SCADA system enables local control among drilling wells and remote control from a control room or operations center.

[0047] Returning to FIG. **1**, the wells (**110**, **113**) may each be drilled with tools to obtain wellbore images and drill core images in addition to logging devices controlled by one or more of the control systems described above. Wellbore imaging devices include, but are not limited to, downhole optical cameras, and acoustic or ultrasonic imaging devices such as borehole televiewers, electrical imaging devices such as microresistivity imaging devices. These may be operated in conjunction with other well logging tools and those used in seismic analysis. Drill core images may be obtained using one or more of the types of imaging devices described using drilled cores obtained from the wellbore.

[0048] Wellbore and drilled core images may be used to determine the structural properties of a subsurface joint network where the wellbore intersects with a subsurface joint network. However, the inherent spacing of joints that may vary across strata, and sometimes within a stratum, can create challenges in inferring the structures of joint networks in the subsurface when considering wellbore and drilled core images. For example, the joint spacing of the first stratum (S**1**), as encountered by the second horizontal wellbore (**106**) intersects regularly spaced joints (**111**). However, a hypothetical wellbore traversing the fifth stratum (S**5**) may encounter semi-regularly spaced joints (**112**), or joints where the spacing is not completely uniform. Further, the distance traversed by a given wellbore as well as its location and orientation can cause difficulties in discerning the spacing, orientation, and spatial density of joints in a joint network that is intersected by the wellbore. For example, measurements of joint spacing obtained from a sub-horizontal wellbore (e.g., sub-horizontal wellbore (**108**)) may initially suggest non-regular joint spacing due to its passage through multiple stratigraphic layers.

[0049] When viewed from above the surface, a surface joint network (**114**) may be discerned as a network of joints with azimuthal orientations that vary on small scales (of order a few degrees) organized into one or more roughly parallel sets. Accordingly, information related to the geostatistical properties of joint networks may be obtained from outcrop pavement images of outcrops containing surface joint networks (e.g., surface joint network (**114**)). Such outcrop pavement images may be obtained from imaging operations (**126**) carried out by aerial vehicles (e.g., aerial vehicle (**124**)). Aerial vehicles may include unmanned aerial vehicles (UAVs) such as drones operated remotely and satellites in low Earth orbit (LEO). Aerial vehicles may also include piloted aircraft such as helicopters and airplanes. The aerial vehicle (**124**) includes imaging equipment, such as a digital camera, and may be used to conduct imaging (**126**) of outcrop pavements containing surface joint networks (**114**). The aerial vehicle (**124**) may explore geological environments that are geographically independent from those associated with wells (**110**, **113**) and accordingly obtain information from a variety of joint networks in diverse geological facies. Embodiments of the present disclosure are not limited to the number or type of aerial vehicles considered, and the minimum number of aerial vehicles required is one, in order to obtain outcrop pavement images containing surface joint networks (e.g., surface joint network (**114**)) from above the surface.

[0050] In general, determining the properties of a joint network in the subsurface is a challenge due to the inaccessibility of the joint network. The problem is further exacerbated by the difficulties posed by the naturally varying structure of joint networks as well as the positions, lengths, and orientations of wellbores that may intersect the joint networks. While joint networks may generally be visible in outcrop pavements, it is difficult to relate the information obtained from the surface to environments in the subsurface. However, determining the properties and structure of joint networks in the subsurface is useful for drilling operations, including well placement and completion, the placement of manufactured tools or chemicals to enhance, reduce, segregate, or otherwise affect reservoir fluid.

[0051] In one aspect, embodiments disclosed herein relate to systems and methods for generating a synthetic joint network predictor using a machine learning framework, and using the synthetic joint network predictor to predict a subsurface joint network from a geostatistical description of observed subsurface joints. Generating a synthetic joint network predictor may include several steps and relies on accurate characterization of joint networks as viewed from above the surface. The geostatistical properties of joints, including the statistical trends relating to joint orientation, spacing, length, and spatial density may be directly determined, at least in part, on the surface of the earth from outcrop pavements containing joint networks. In one or more embodiments, a plurality of joint networks may be detected from outcrop pavement images using a first machine learning network. At least some of the outcrop pavement images may be labeled according to the geological information and specifically, the presence and location of identified joints. Enhanced performance may also be obtained by labeling natural fracture features that are not joints, such as fracture clusters. The outcrop pavement images may come from a variety of diverse geological facies and contain information specific to different geological lithologies and environments. As previously described, joint networks may be described by statistical patterns in their structure. As such, after detection, the geostatistical properties of the detected joint networks may be determined and characterized to create models of the probability of the joint networks the exhibiting one or more qualities. For example, the probability model for the joint network may describe the probability the joint network to exhibit a particular spatial density of joints. The information obtained from joint networks as determined from the surface, including the outcrop images, the detected joint networks, and the determined geostatistical properties may be organized into a database of surface joint properties. In one or more embodiments, the database of surface joint properties may be used to train second machine learning network to generate synthetic (i.e., artificial) digital joint networks embodying the properties of real joint networks according to the database of surface joint properties. In other words, the second machine learning network may be trained generate any number of synthetic joint networks sharing one or more qualities with real joint networks, where the qualities of real joint networks are recorded in the database of surface joint properties. A synthetic joint network predictor may then be derived from the second machine learning network. The synthetic joint network predictor is capable of predicting a predicted joint network according to a geostatistical description of observed subsurface joints. For example, the synthetic joint network predictor may predict a predicted joint network with a specified joint spacing, or according to a probability distribution function relating the probability of a particular joint spacing being present.

[0052] In accordance with one or more embodiments, outcrop pavement images from the surface are processed with a first machine learning network to detect joint networks on the Earth's surface. A second machine model is then used to generate synthetic (that is, artificial) joint networks based on, at least partially, the detected joint networks from the outcrop pavement images. Machine learning, broadly defined, is the extraction of patterns and insights from data. The phrases "artificial intelligence", "machine learning", "deep learning", and "pattern recognition" are often convoluted, interchanged, and used synonymously throughout the literature. This ambiguity arises because the field of "extracting patterns and insights from data" was developed simultaneously and disjointedly among a number of classical arts like mathematics, statistics, and computer science. For consistency, the term machine learning (ML), will be adopted herein, however, one skilled in the art will recognize that the concepts and methods detailed hereafter are not limited by this choice of nomenclature.

[0053] Machine learning (ML) model types may include, but are not limited to, neural networks, random forests, generalized linear models, and Bayesian regression. Further, as defined herein, ML may include algorithmic search methods and optimization methods such as a line search or the genetic algorithm. ML model types are usually associated with additional "hyperparameters" which further describe the model. For example, hyperparameters providing further detail about a neural network may include, but are not limited to, the number of layers in the neural network, choice of activation functions, inclusion of batch normalization layers, and regularization strength. The selection of hyperparameters surrounding a model is referred to as selecting the model "architecture." Generally, multiple model types and associated hyperparameters are tested and the model type and hyperparameters that yield the greatest predictive performance on a hold-out set of data is selected.

[0054] As noted, the objective of the first machine learning network is to detect and extract surface joint networks from outcrop pavement images, and the objective of the second ML network is to generate synthetic joint networks. In accordance with one or more embodiments, FIG. **3** depicts the interactions between the outcrop pavement images and the first and second machine learning network in addition to a plurality of pre-processing operators.

[0055] FIG. **3** depicts a schematic diagram of one possible embodiment of a training setting (**300**). The training setting (**300**) includes the elements and operators involved in obtaining a synthetic joint network predictor (**325**), in accordance with one or more embodiments. In one aspect, obtaining a synthetic joint network predictor (**325**) may include creating a database of surface joint properties (**323**).

[0056] Creating the database of subsurface joint properties may begin with obtaining a plurality of outcrop pavement images (**301**), where each of the plurality of outcrop pavement images (**301**) contains at least one joint network visible on the surface of the earth. However, in one or more embodiments, one or more outcrop pavement images (**301**) may not contain a joint network that is visible on the surface of the earth for reasons described below. The outcrop pavement images may be obtained from an aerial vehicle (not shown). The aerial vehicle may be similar to or the same as the aerial vehicle (**124**) described in relation to FIG. **1**. The aerial vehicle may be a satellite in low Earth orbit (LEO) or in another orbital configuration, an unmanned aerial vehicle (UAV) such as a remote-controlled drone, or a piloted vehicle such as an airplane or helicopter. The aerial vehicle may include a digital camera or another similar device capable of obtaining images of the surface of the Earth from above, in accordance with one or more embodiments. The outcrop pavement images (**301**) may originate from a variety of diverse geological environments and represent a variety of geological facies, containing information specific to different geological lithologies and sedimentation. For example, the outcrop pavement images may include limestone outcrop pavements and sandstone outcrop pavements, in addition to others not listed. The outcrop pavement images may be included in the database of surface joint properties (**323**), as indicated by the dashed lines in FIG. **3**, in accordance with one or more embodiments.

[0057] The outcrop pavement images (**301**) may be processed by a first machine learning network (**305**) to determine a plurality of detected joint networks (**307**). In one or more embodiments, the outcrop pavement images may first undergo pre-processing (e.g., surface data pre-processing (**303**)). Pre-processing may include activities such as numericalization, digitization, filtering and/or smoothing of the data, scaling (e.g., normalization) of the data, feature selection, outlier removal (e.g., z-outlier filtering) and feature engineering. As described above, the objective of the first machine learning network (**305**) is to detect and extract joint networks from outcrop pavement images (**301**). Feature selection includes identifying and selecting a subset of outcrop pavement images (**301**) with the greatest discriminative power with respect to detecting joint networks. For example, in one embodiment, discriminative power may be quantified by calculating the strength of correlation between particular elements of the outcrop pavement images (**301**) and the detected joint networks (**307**). Consequently, in some embodiments, not all of the outcrop pavement images need be passed to the first machine learning network (**305**) and portions of outcrop pavement images may be used instead. Feature engineering encompasses combining, or processing, various outcrop pavement images (**301**) to create derived quantities. The derived quantities can be processed by the first machine learning network (**305**) in addition to, alongside, and instead of the outcrop pavement images (**301**). The outcrop pavement images (**301**) may be processed by one or more "basis" functions such as a polynomial basis function or a radial basis function. In some embodiments, the outcrop pavement images (**301**) are passed to the first machine learning network (**305**) without pre-processing. Many additional pre-processing techniques exist such that one with ordinary skill in the art would not interpret those listed here as a limitation on the present disclosure.

[0058] In one or more embodiments, surface data pre-processing (**303**) may include labeling a subset of outcrop pavement images (**301**) to identify joint networks that may be visible in the images as well as labeling features in the images to identify other natural fractures may be mistaken for joint networks, such as shear fractures and veins. Other features that are not joints may also be labeled, such as barren rock containing no natural fractures. Labeling may also include identifying one or more geological attributes in the outcrop pavement images (**301**), such as lithology indicating the presence of limestone, dolomite, or sandstone (or another lithology not listed), the thickness of the imaged layer, and the general structural shape of the imaged region containing the outcrop pavement, for example, indicating an anticline or dome. Labeling a subset of data is a common practice among machine learning applications and enables supervised learning of machine learning models as well as performance verification, and those of ordinary skill in the art will recognize that additional labels may be considered beyond those listed here without limitation to the present disclosure. That is, the listed labels are not to be considered exhaustive or limiting, and additional labels may be easily incorporated without departing from the scope of the disclosure. The database of surface joint properties (**323**) may include the pre-processed outcrop pavement images (**301**) in accordance with one or more embodiments.

[0059] In one or more embodiments, the first machine learning network (**305**) is used to determine a plurality of detected joint networks (**307**) using the plurality of outcrop pavement images (**301**). The first machine learning network (**305**) may be of any ML network type known in the art. In some embodiments, multiple ML network types and/or architectures may be used. Generally, the ML network type and architecture with the greatest performance on a set of hold-out data is selected, where the set of hold-out data has been labeled in accordance with the objective of the ML network. Greater detail surrounding the training procedure for an ML network will be provided below in the context of a neural network. However, generally, training an ML network involves processing data to develop a functional relationship between elements of the data. The result of the training procedure is a trained ML network. The trained ML network may be described as a function relating the inputs and the outputs. In the case of the first machine learning network (**305**), the inputs may be the pre-processed, unprocessed, or both the pre-processed and unprocessed outcrop pavement images (**301**), while the output may be the detected joint networks (**307**). That is, the first machine learning network may be mathematically and abstractly represented as outputs=f(inputs), such that given an input (e.g., outcrop pavement images (**301**)) the first machine learning network may produce an output (e.g., detected joint networks (**307**)).

[0060] In accordance with one or more embodiments, the first machine learning network (**305**) may be a convolutional neural network ("CNN"). A CNN may be more readily understood as a specialized artificial neural network (NN). Thus, a cursory introduction to a NN and a CNN are provided herein. However, it is noted that many variations of NNs and CNNs exist. Therefore, one with ordinary skill in the art will recognize that any variation of the NN or CNN (or any other machine-learned model) may be employed without departing from the scope of this disclosure. Further, it is emphasized that the following discussions of a NN and a CNN are basic summaries and should not be considered limiting.

[0061] A diagram of a neural network is shown in FIG. **4**. At a high level, a neural network (**400**) may be graphically depicted as being composed of nodes (**402**), where here any circle represents a node, and edges (**404**), shown here as directed lines. The nodes (**402**) may be grouped to form layers (**405**). FIG. **4** displays four layers (**408**, **410**, **412**, **414**) of nodes (**402**) where the nodes (**402**) are grouped into columns, however, the grouping need not be as shown in FIG. **4**. The edges (**404**) connect the nodes (**402**). Edges (**404**) may connect, or not connect, to any node(s) (**402**) regardless of which layer (**405**) the node(s) (**402**) is in. That is, the nodes (**402**) may be sparsely and residually connected. A neural network (**400**) will have at least two layers (**405**), where the first layer (**408**) is considered the "input layer" and the last layer (**414**) is the "output layer." Any intermediate layer (**410**, **412**) is usually described as a "hidden layer". A neural network (**400**) may have zero or more hidden layers (**410**, **412**) and a neural network (**400**) with at least one hidden layer (**410**, **412**) may be described as a "deep" neural network or as a "deep learning method." In general, a neural network (**400**) may have more than one node (**402**) in the output layer (**414**). In this case the neural network (**400**) may be referred to as a "multi-target" or "multi-output" network.

[0062] Nodes (**402**) and edges (**404**) carry additional associations. Namely, every edge is associated with a numerical value. The edge numerical values, or even the edges (**404**) themselves, are often referred to as "weights" or "parameters." While training a neural network (**400**), numerical values are assigned to each edge (**404**). Additionally, every node (**402**) is associated with a numerical variable and an activation function. Activation functions are not limited to any functional class, but traditionally follow the form:

$$A = f\left(\sum_{i \in (incoming)} [(\text{node value})_i (\text{edge value})_i]\right), \tag{3}$$

where i is an index that spans the set of "incoming" nodes (**402**) and edges (**404**) and f is a user-defined function. Incoming nodes (**402**) are those that, when viewed as a graph (as in FIG. **4**), have directed arrows that point to the node (**402**) where the numerical value is being computed. Some functions for f may include the linear function $f(x)=x$, sigmoid function

$$f(x) = \frac{1}{1+e^{-x}},$$

and rectified linear unit function $f(x)=\max(0, x)$, however, many additional functions are commonly employed. Every node (**402**) in a neural network (**400**) may have a different associated activation function. Often, as a shorthand, activation functions are described by the function f by which it is composed. That is, an activation function composed of a linear function f may simply be referred to as a linear activation function without undue ambiguity.

[0063] When the neural network (**400**) receives an input, the input is propagated through the network according to the activation functions and incoming node (**402**) values and edge (**404**) values to compute a value for each node (**402**). That is, the numerical value for each node (**402**) may change for each received input. Occasionally, nodes (**402**) are assigned fixed numerical values, such as the value of 1, that are not affected by the input or altered according to edge (**404**) values and activation functions. Fixed nodes (**402**) are often referred to as "biases" or "bias nodes" (**406**), displayed in FIG. **4** with a dashed circle.

[0064] In some implementations, the neural network (**400**) may contain specialized layers (**405**), such as a normalization layer, or additional connection procedures, like concatenation. One skilled in the art will appreciate that these alterations do not exceed the scope of this disclosure.

[0065] As noted, the training procedure for the neural network (**400**) includes assigning values to the edges (**404**). To begin training, the edges (**404**) are assigned initial values. These values may be assigned randomly, assigned according to a prescribed distribution, assigned manually, or by some other assignment mechanism. Once edge (**404**) values have been initialized, the neural network (**400**) may act as a function, such that it may receive inputs and produce an output. As such, at least one input is propagated through the neural network (**400**) to produce an output. Recall, that a given data set will be composed of inputs and associated target(s), where the target(s) represent the "ground truth," or the otherwise desired output. Returning briefly to FIG. **3**, in accordance with one or more embodiments, the input of the neural network is the outcrop pavement images (**301**) and the target is the detected joint networks (**307**). In the context of training, evaluating the performance of the neural network may require having labeled at least a subset of the outcrop pavement images, where labeling may be included in the data pre-processing (e.g., surface data pre-processing (**303**)). Given the objective to detect joint networks based on the outcrop pavement images (**301**), avoiding false positive detections is also important. Therefore, labeling natural fracture features in outcrop pavement images (**301**) that are not joint networks is important, and even including one or more outcrop pavement images (**301**) that do not contain natural fracture features with appropriate labels (e.g., identifying a barren rock face) may be useful.

[0066] Turning back to FIG. **4**, the neural network (**400**) output is compared to the associated input data target(s). The comparison of the neural network (**400**) output to the target(s) is typically performed by a so-called "loss function;" although other names for this comparison function such as "error function," "misfit function," and "cost function" are commonly employed. Many types of loss functions are available, such as the mean-squared-error function, however, the general characteristic of a loss function is that the loss function provides a numerical evaluation of the similarity between the neural network (**400**) output and the associated target(s). The loss function may also be constructed to impose additional constraints on the values assumed by the edges (**404**), for example, by adding a penalty term, which may be physics-based, or a regularization term. Generally, the goal of a training procedure is to alter the edge (**404**) values to promote similarity between the neural network (**400**) output and associated target(s) over the data set. Thus, the loss function is used to guide changes made to the edge (**404**) values, typically through a process called "backpropagation."

[0067] While a full review of the backpropagation process exceeds the scope of this disclosure, a brief summary is provided. Backpropagation consists of computing the gradient of the loss function over the edge (**404**) values. The gradient indicates the direction of change in the edge (**404**) values that results in the greatest change to the loss function. Because the gradient is local to the current edge (**404**) values, the edge (**404**) values are typically updated by a "step" in the direction indicated by the gradient. The step size is often referred to as the "learning rate" and need not remain fixed during the training process. Additionally, the step size and direction may be informed by previously seen edge (**404**) values or previously computed gradients. Such methods for determining the step direction are usually referred to as "momentum" based methods.

[0068] Once the edge (**404**) values have been updated, or altered from their initial values, through a backpropagation step, the neural network (**400**) will likely produce different outputs. Thus, the procedure of propagating at least one input through the neural network (**400**), comparing the neural network (**400**) output with the associated target(s) with a loss function, computing the gradient of the loss function with respect to the edge (**404**) values, and updating the edge (**404**) values with a step guided by the gradient, is repeated until a termination criterion is reached. Common termination criteria are: reaching a fixed number of edge (**404**) updates, otherwise known as an iteration counter; a diminishing learning rate; noting no appreciable change in the loss function between iterations; reaching a specified performance metric as evaluated on the data or a separate hold-out data set. Once the termination criterion is satisfied, and the edge (**404**) values are no longer intended to be altered, the neural network (**400**) is said to be "trained".

[0069] A CNN is similar to a neural network (**400**) in that it can technically be graphically represented by a series of edges (**404**) and nodes (**402**) grouped to form layers. However, it is more informative to view a CNN as structural groupings of weights; where here the term "structural" indicates that the weights within a group have a relationship.

CNNs are widely applied when the data inputs also have a structural relationship, for example, a spatial relationship where one input is always considered "to the left" of another input. Outcrop pavement images have such a structural relationship because each data element, or pixel, in an outcrop pavement image has a spatial location. Consequently, a CNN is an intuitive choice for processing outcrop pavement images.

[0070] A structural grouping, or group, of weights is herein referred to as a "filter." The number of weights in a filter is typically much less than the number of inputs, where here the number of inputs refers to the number of pixels in an image. In a CNN, the filters can be thought as "sliding" over, or convolving with, the inputs to form an intermediate output or intermediate representation of the inputs which still possesses a structural relationship. Like unto the neural network (**400**), the intermediate outputs are often further processed with an activation function. Many filters may be applied to the inputs to form many intermediate representations. Additional filters may be formed to operate on the intermediate representations creating more intermediate representations. This process may be repeated as prescribed by a user. There is a "final" group of intermediate representations, wherein no more filters act on these intermediate representations. In some instances, the structural relationship of the final intermediate representations is ablated; a process known as "flattening". The flattened representation may be passed to a neural network (**400**) to produce a final output. Note, that in this context, the neural network (**400**) is still considered part of the CNN. In a similar manner to a neural network (**400**), a CNN is trained, after initialization of the filter weights, and the edge (**404**) values of the internal neural network (**400**), if present, with the backpropagation process in accordance with a loss function.

[0071] Returning to FIG. **3**, the first machine learning network (**305**) may undergo a first training loop (**309**) including one or more of the steps described in relation to the neural network illustrated in FIG. **4** and in relation to a CNN described above. To summarize, the first training loop (**309**) may include iteratively determining, using the first machine learning network (**305**), a plurality of detected joint networks (**307**) based on the outcrop pavement images (**301**), comparing the detected joint networks (**307**) with the outcrop pavement images that have been labeled to identify natural fracture features as joint networks (and to identify features that are not joint networks), and applying a modification to the first machine learning network (**305**) to affect the determination of the detected joint networks (**307**). In one or more embodiments, the first machine learning network (**305**) may be considered pre-trained, meaning that the first machine learning network (**305**) is capable of determining a plurality of detected joint networks (**307**) without executing the first training loop (**309**). Whether or not the first training loop (**309**) is executed, the first machine learning network (**305**) determines a plurality of detected joint networks (**307**) using the outcrop pavement images (**301**) in accordance with one or more embodiments, and the detected joint networks (**307**) may be included in the database of surface joint properties (**323**).

[0072] To obtain further information from the detected joint networks (**307**) and to prepare the detected joint networks (**307**) to be processed (alongside other data provided by the database of surface joint properties (**323**)), the detected joint networks (**307**) may undergo post-processing (e.g., surface data post-processing (**311**)), in accordance with one or more embodiments. Surface data post-processing (**311**) may include many of the steps described in relation to surface data pre-processing (**303**) including numericalizing the data, digitizing the data, scaling the data, selecting features from the data, and engineering features from the data. However, as previously noted, many additional pre- and post-processing techniques are commonly used, and those of ordinary skill in the art will recognize that additional pre- and post-processing techniques may be applied without departing from the scope of the present disclosure.

[0073] In one or more embodiments, surface data post-processing (**311**) includes determining, for each of the plurality of detected joint networks (**307**), a set of surface geostatistical properties related to the detected joint network. The result of surface data post-processing (**311**), in this case, may be a plurality of sets of surface geostatistical properties (**313**), one for each of the detected joint networks (**307**). Measuring a set of geostatistical properties (i.e., one of the plurality of sets of surface geostatistical properties (**313**)) of a detected joint network (i.e., one of the plurality of detected joint networks (**307**)) may include measuring the joint intensity along one or more scanlines, where a scanline refers to an interval measured across a surface pavement with a predetermined length. The joint intensity of a joint network is given by $I=N/L$, where I is the joint intensity, N is the number of joints detected across the scanline, and L is the length of the scanline. Another geostatistical property that may be measured of the detected joint network may be the joint spacing, which is given by the inverse of joint intensity, or $S=1/I=L/N$, where S is the joint spacing. While joint intensity is a useful metric, a related property referred to as the joint persistence may further be considered among the geostatistical properties. Joint persistence refers to the probability for a joint network to continue (i.e., be present with the same geostatistical qualities) over a given area. Joint persistence may be informed by the joint density, which is defined as the number of joint fractures per unit area, summing over scanlines.

[0074] In addition to determining sets of surface geostatistical properties (**313**) that include information related to the spacing of joints in the detected joint networks (**307**), surface data post-processing (**311**) may further include measuring sets of surface geostatistical properties (**313**) that include information related to the orientations of joints in the detected joint networks (**307**). Of particular interest may be the joint strike angles, where the strike angle is the azimuthal angle measured along an axis perpendicular to the horizontal plane of the rock surface. Joint strikes can be visualized using stereonets, rose diagrams, and X-Y plots, where each will be familiar to those skilled in the art. Briefly, a stereonet is a method to represent the orientation of geological features using stereographic projection, a rose diagram is a histogram in polar or circular form, and an X-Y plot is simply typical Cartesian representation of data along two perpendicular axes. Given the semi-linear nature of joint networks, joint strikes may be usefully averaged along paths to characterize the overall orientation of a given joint network on network-wide scales. Joints are also characterized by their dip angle, which is calculated as the angle between the plane of the joint and a horizontal plane along the surface of the earth. However, as viewed from above, the joint dips may be difficult to measure directly due to the effect of projection from a three-dimensional surface (i.e., the outcrop pavements) to a two-dimensional plane (i.e., the images of outcrop pavements).

[0075] As part of the surface data post-processing (**311**), or otherwise during the creation of the database of surface joint properties (**323**), the sets of surface geostatistical properties (**313**) may be corrected for one or more biases present in the detected joint networks (**307**), in accordance with one or more embodiments. A number of biases may be present in the measured sets of surface geostatistical properties (**313**) collectively referred to as joint property bias. For example, joint property bias may include bias introduced due to the type of aerial vehicle used to obtain the outcrop pavement images (**301**) from which the plurality of detected joint networks (**307**) is determined. The joint networks detected from, for example, satellite imaging, may systematically differ from joint networks detected from UAV or drone imaging impacting the measured surface geostatistical properties. One possible method to correct for joint property bias introduced due to the type of aerial vehicle used to obtain the outcrop pavement images (**301**) may be to identify a particular region for which outcrop pavement images (**301**) from multiple types of aerial vehicles are available and comparing the resulting measured sets of surface geostatistical properties (**313**) from the respective detected joint networks (**307**). Repeating this process over multiple areas for which outcrop pavement images (**301**) are available from multiple types of aerial vehicles may reveal systematic trends which may be manually or automatically removed. As another example, joint property bias may include bias introduced due to the geological environment of the joint network within one or more outcrop pavement images (**301**). Features in the geological environment that may be present with enough frequency to introduce bias could be lithology with poor contrast with respect to natural fractures, and lithology with variable bedding planes dips. Correcting for joint property bias introduced by features in the geological environment may be difficult in these cases and may include removing or flagging outcrop pavement images (**301**), detected joint networks (**307**), and the sets of surface geostatistical properties that have these features.

[0076] Each set of the plurality of sets of surface geostatistical properties (**313**) may include a probability model constructed according to one of more of the individual measured geostatistical properties. A probability model relates the probability of a given joint network to exhibit one or more geostatistical properties, for example, the probability of a joint network to exhibit a given joint spacing or range of joint spacings. In the case of a single set of geostatistical properties for one detected joint network, a variety of joint spaces may be determined, and the probability model may relate the probability of each particular joint spacing based on, for example, their relative frequency. Further, the probability model may relate the probability of a joint network to exhibit one or more geostatistical properties in view of the presence or probability of one or more other geostatistical properties. For example, the probability model may relate the probability of a joint network to exhibit a given joint spacing (or range of joint spacings) in view of a particular joint orientation (or range of joint orientations). In this sense, the probability models for each set of the plurality of sets of surface geostatistical properties (**313**) may be considered a multivariable probability model. The plurality of sets of surface geostatistical properties (**313**), corrected or uncorrected for bias, and including one or more probability models, is included in the database of surface joint properties (**323**) in accordance with one or more embodiments.

[0077] After the plurality of sets of surface geostatistical properties (**313**) has been added to the database of surface joint properties (**323**), the database of surface joint properties may be said to be created. To summarize, the database of surface joint properties (**323**) may include a variety of quantities, including outcrop pavement images (**301**), a plurality of detected joint networks (**307**), and a plurality of sets of surface geostatistical properties (**313**). These data elements may be organized to make clear the association between a given outcrop pavement image, its detected joint network, and the measured set of geostatistical properties associated with the joint network. For example, this association may be cleared by storing each of these data elements in one file, directory, or location on a computer, such as the computer of FIG. **9** and its accompanying description. Alternatively, the association between related data elements in the database of surface joint properties (**323**) may be achieved by assigning each data element with a name following a pre-assigned convention. Many techniques are known in the art for organizing related data elements in a database, and those listed above are not exhaustive and should not be considered limiting with regard to the present disclosure. In one or more embodiments, creating the database of surface joint properties (**323**) includes correcting for structural discontinuities that are not joints and correcting for joint property bias, including bias due to the type of aerial vehicle used to obtain the outcrop pavement images.

[0078] In one or more embodiments, a second machine learning network (**315**) is used to process the information contained by the database of surface joint properties (**323**) to determine a plurality of synthetic joint networks (**317**). A synthetic joint network may be considered an artificial joint network, or a joint network that does not necessarily exist in nature. However, the synthetic joint networks (**317**) determined by the second machine learning network (**315**) are determined in such a way that they are realistic and embody one or more qualities of real joint networks in nature. The realism of the plurality of synthetic joint networks (**317**) is ensured by the configuration of the second machine learning network (**315**) described as follows. The second machine learning network (**315**) may be of any ML network type known in the art, such as an artificial neural network, a decision tree (or ensemble of decision trees such as a random forest or gradient boosted trees), a support vector machine, or another algorithm using Gaussian processing techniques or evolutionary computation, among others not listed.

[0079] In one or more embodiments, the second machine learning network (**315**) is a generative adversarial network (GAN). Again, like the CNN, a detailed description of a GAN exceeds the scope of this disclosure. However, in summary, a GAN is generally composed of two machine-learned models that interact cyclically and are configured to perform opposing tasks. The two-component machine-learned models of a GAN are typically called a generator and a discriminator. In general, the task of the generator is to produce a data object (e.g., an image) such that the generated object is indiscernible from a "real," or non-generated data object. The task of the discriminator is to determine if a given data object is real or if the given data object was produced by the generator. Thus, these tasks may be said to be in opposition (i.e., adverse, or adversarial) because the generator is tasked to produce a data object that cannot be distinguished from a real data object by the discriminator while the discriminator is specifically tasked to identify data objects generated by the generator. As with the machine learning models previously described, the generator and discriminator of a GAN (each a machine-learned model in itself) are parameterized by a set of weights (or edge values) that must be learned during training.

[0080] The training process of a GAN possesses unique characteristics. Training a GAN consists of determining the weights that minimize a given loss function, however, the loss function is typically split into two parts, namely, a reconstruction loss and an adversarial loss. Reconstruction loss quantifies the differences between real and generated data that is meant to embody the characteristics present in the real data without reference to the discriminator. Adversarial loss quantifies the ability of the discriminator to determine how closely the probability distributions of one or more properties present in the proposed image resemble the probability distribution of the same one or more properties in real data. During training, the generator receives input-target pairs and seeks to minimize the reconstruction loss and the adversarial loss. Typically, the generator is trained for a fixed number of iterations (e.g., fixed number of data examples, fixed number of data batches, fixed number of epochs, etc.) or until reaching a stopping criterion. Subsequently, the discriminator is given an assortment of real data objects and some data objects generated with the generator. It is noted that the label, or target, of the data objects processed by the discriminator during training is known. The adversarial loss is used to guide and update the weights of both the discriminator and the generator. In other words, guided by the adversarial loss, the weights of the generator are updated to produce a data object that cannot be distinguished from a real (or original) data object by the discriminator. Again, use of the adversarial loss to update the discriminator and the generator may be applied for a fixed number of iterations (e.g., fixed number of data examples, fixed number of data batches, fixed number of epochs, etc.) or until reaching a stopping criterion. In some instances, the process of training the generator and the generator and discriminator as guided by the reconstruction loss and the adversarial loss, respectively, is repeated cyclically until the discriminator can no longer distinguish between real and fake data objects due to the realism of the data objects produced by the generator. Typically, once trained, the discriminator of a GAN is discarded and the generator is used to generate data objects with sufficient realism. This provides the general framework for obtaining a synthetic joint network predictor (**325**) based on the second machine learning network (**315**), in accordance with one or more embodiments. That is, the result of training (**321**) the second machine learning network may be said to be the synthetic joint network predictor (**325**) that is obtained.

[0081] The second machine learning network (**315**) may be a generative adversarial network (GAN) and make use of CNNs. For example, a GAN which uses deep convolutional neural networks (i.e., a CNN with more than one hidden layer), may be referred to as a DCGAN. FIG. **5** depicts, in accordance with one or more embodiments, the general architecture of GAN (**500**). The GAN (**500**) includes two primary components: a generator (**502**) and a discriminator (**504**), in accordance with the description above of a GAN. Both the generator (**502**) and the discriminator (**504**) may be composed of blocks, represented in FIG. **5** as graphical blocks. The blocks represent layers in a neural network that perform one or more convolutions and other operations applied to the data, such as normalization, dropout, processing by an activation function, and others not listed.

[0082] The generator (**502**) may be considered the combination of two individual operators: an encoder (**506**) and a decoder (**508**). In the case of the second machine learning network (**315**) used to determine a plurality of synthetic joint networks (**317**), the generator (**502**) may begin with an initial image (**510**) containing no joint network, or an image of a joint network with random or otherwise predetermined properties. Through the processes of encoding by the encoder (**506**) and decoding by the decoder (**508**), the generator processes the initial image (**510**) and outputs a generated image (**512**) that may be different than the initial image (**510**). In one or more embodiments, the generator begins with an initial image (**510**) of a joint network that has properties randomly sampled from the plurality of sets of geostatistical properties (**313**). Generally, the encoder (**506**) may be composed of convolutional blocks that act to compress elements of the initial image (**510**). The role of the decoder (**508**) is to decompress the encoded input to form the generated image (**512**).

[0083] The discriminator (**504**) represents the second half of a GAN working in tandem, or as will be described, adversely, with the first half represented by the generator (**502**). In one or more embodiments, the discriminator (**504**) is also composed of convolutional blocks. The role of the discriminator is to compare a proposed image (**514**) with one or more "real" images to determine the probability that the proposed image (**514**) is not real or exhibits properties that differ significantly from the real images. Considering the application of the second machine learning network (**315**) that is used to determine a plurality of synthetic joint networks (**317**), the role of the generator (**502**) is to begin with an initial image (**510**) and apply processes of encoding and decoding, and obtain a generated image (**512**) containing a synthetic joint network, where the processing is guided by the database of surface joint properties (**323**) as further described below and to ensure the generated image (**512**) containing the synthetic joint network is realistic. The second machine learning network (**315**) may then use the discriminator (**504**) to evaluate the proposed image (**514**), which may be similar to or the same as the generated image (**512**) just described. However, the discriminator (**504**) may also consider proposed images (**514**) that are real in order to further evaluate its ability to discriminate between real and fake (or generated) joint networks. The evaluation may make further use of the database of surface joint properties (**323**), which contains the necessary information related to real joint networks.

[0084] In one or more embodiments, the discriminator (**504**) may include a plurality of discriminators acting on different scales of the image. For example, the discriminator (**504**) may include a "micro" discriminator acting on small scales a fraction of the size of the image and a "macro" discriminator operating on large scales similar to the size of the image. In the case of the second machine learning network (**315**) that is used to determine a plurality of synthetic joint networks (**317**), the micro discriminator may be used to determine the likelihood of one particular joint property being present, for example, the likelihood of a joint network present in the proposed image (**514**) having a particular joint spacing. Meanwhile, the macro discriminator may be used to determine the likelihood of each and every joint property of the joint network of the proposed joint network being present, in view of the joint properties with respect to each other. Recall that the probability models, that may be included among the sets of surface geostatistical properties (**313**), may readily contain this information for real joint networks, and the role of the macro discriminator in this example may be to calculate a similar probability model for the synthetic joint network and compare it to those that are stored in the sets of surface geostatistical properties (**313**). In practice, one with ordinary skill in the art will appreciate that many adaptions and alterations can be made to the general GAN (**500**) architecture of FIG. **5** without departing from the scope of this disclosure.

[0085] As with the machine learning models previously described both the generator (**502**) of the GAN (**500**) and the discriminator (**504**) of the GAN (**500**) may be parameterized by a set of weights (or edge values). Training the GAN (**500**) includes determining the weights that minimize a given loss function. GANs (**500**) commonly include two classes of loss functions, namely, reconstruction loss (**516**) and adversarial loss (**518**). Reconstruction loss (**516**) refers to a measure of difference calculated directly between generated images (**512**) and real images, while adversarial loss is a measure between the predicted or generated probability distributions of one or more properties present in the generated image (**512**) compared to real probability distributions of the same one or more properties. The following includes a brief description of how these loss functions may be applied in a training loop, referred to as second training loop (**319**) in FIG. **3**, used to train the second machine learning network (**315**) which is a GAN, in accordance with one or more embodiments.

[0086] During training, both the generator (**502**) and discriminator (**504**) of the GAN (**500**) interact with the database of surface joint properties (**323**). The input, or starting point and initial image (**510**), is an image with no joint network present. The properties of the image may be random or predetermined in another way. The objective of the GAN (**500**) may be to generate a synthetic joint network according to one or more pre-specified joint network properties. Note that the following example is only for illustrative purposes and is not to be considered limiting. As an illustration, the objective of the GAN (**500**) may be to generate a synthetic joint network with a given joint spacing of Y meters. In this example, the target may include an outcrop pavement image with a joint spacing of Y meters, a detected joint network with a joint spacing of Y meters, and a set of surface geostatistical properties including a probability model for joint networks with a joint spacing of Y meters, where each of these elements are stored in the database of surface joint properties (**323**). After applying the processes of the encoder (**506**) and the decoder (**508**), a generated image (**512**) including a synthetic joint network is obtained. The reconstruction loss may be calculated where the proposed image (**514**) is the same as the generated image (**512**), and in this case, quantifies the differences between the either the outcrop pavement image with a joint spacing of Y meters or the detected joint network with a joint spacing of Y meters, and the generated synthetic joint network. To minimize the reconstruction loss, the generator (**502**) is encouraged to produce generated images (**512**) with synthetic joint networks that are similar to the original outcrop pavement image with a joint spacing of Y meters or detected joint network with a joint spacing of Y meters. During training, the discriminator (**504**) may be given a training dataset including the targets listed above (e.g., an outcrop pavement image with a joint spacing of Y meters, a detected joint network with a joint spacing of Y meters, and a set of surface geostatistical properties including a probability model for joint networks with a joint spacing of Y meters), and generated images (**512**) that have been processed by the generator (**502**). That is, the discriminator (**504**) receives proposed images (**514**) that include both "real" images and "fake" images generated by the generator (**502**). The adversarial loss (**518**) may be calculated for each proposed image (**514**) and in this case, quantifies how closely the probability distributions of one or more properties present in the proposed image resemble the probability distribution of the same one or more properties in real data. Following the same example from above, the adversarial loss quantifies how closely the probability of properties in the synthetic joint network generated under the objective of generating a joint network with a joint spacing of Y meters compares to the probability models of real joint networks that have a joint spacing of Y meters. Again, it is emphasized that the preceding example is only to be considered as an illustration of how a GAN (**500**) might be trained and should not be considered limiting. Many alterations to the training procedure described above are known to those skilled in the art. In practice, the objective of the GAN (**500**) may be to produce a joint network with many other pre-specified joint network properties, or with combinations of pre-specified joint network properties.

[0087] Both the reconstruction loss (**516**) and the adversarial loss (**518**) are used to guide and update the weights of both the discriminator (**504**) and the generator (**502**). In other words, guided by both the reconstruction loss (**516**) and the adversarial loss (**518**), the weights of the generator (**502**) are updated to produce a generated image (**512**) containing a synthetic joint network, which cannot be distinguished from an original (or real) image of an outcrop pavement image or detected joint network by the discriminator (**504**).

[0088] One with ordinary skill in the art will recognize that the architectures of the generator (**502**) and the discriminator (**504**) of the GAN (**500**) of FIG. **5** are represented to generally. In practice, these architectures may be altered to include additional components and functionality such as residual connections, normalization, and various convolutions taken at different length scales. As such, the second machine-learning network is not limited by the GAN (**500**) depicted in FIG. **5**. Once trained, the discriminator (**504**) of the GAN (**500**) may be discarded and the generator (**502**) may be used to generate one or more synthetic joint networks or images of synthetic joint networks that resemble real joint networks in nature.

[0089] Returning to FIG. **3**, the synthetic joint network predictor (**325**) may be obtained by discarding the discriminator of the second machine learning network (**315**), in accordance with one or more embodiments. Put differently, in one or more embodiments, the synthetic joint network predictor may be said to be derived from the generator of the second machine learning network (**315**). The synthetic joint network predictor (**325**) is capable of determining a predicted joint network according to one or more pre-specified joint network properties. As the only requisite input to the synthetic joint network predictor (**325**) is a specification of a desired joint network property to be manifested by a generated synthetic joint network, the synthetic joint network predictor (**325**) is also capable of determining a subsurface joint network from a geostatistical description of observed subsurface joints. The predicted subsurface joint network, in this case, will resemble the properties of real joint networks according to the database of surface joint properties used in training the second machine learning network (**315**) and therefore the synthetic joint network predictor (**325**).

[0090] The operation of processing outcrop pavement images to obtain a synthetic joint network predictor is summarized in the flow chart of FIG. **6**. In Block **601**, a plurality of outcrop pavement images of a plurality of joint networks is obtained. Many of the outcrop pavement images may each contain a joint network, and thus it may be said that there is a plurality of joint networks without undue ambiguity. However, not all outcrop pavement images obtained necessarily contain a joint network. The plurality of outcrop pavement images may be obtained from an aerial vehicle. The aerial vehicle may be a satellite in low Earth orbit (LEO) or in another orbital configuration, an unmanned aerial vehicle (UAV) such as a remote-controlled drone, or a piloted vehicle such as an airplane or helicopter. The aerial vehicle may include a digital camera or another similar device capable of obtaining images of the Earth's surface from above, in accordance with one or more embodiments. The plurality of outcrop pavement images may originate from a variety of diverse geological environments and represent a variety of geological facies, containing information specific to different geological lithologies and sedimentation.

[0091] In Block **603**, a first machine learning network may be used to determine a plurality of detected joint networks from the plurality of outcrop pavement images. In one or more embodiments, the outcrop pavement images may first undergo pre-processing. Pre-processing may include activities such as numericalization, digitization, filtering and/or smoothing of the data, scaling (e.g., normalization) of the data, feature selection, outlier removal (e.g., z-outlier filtering) and feature engineering. In one or more embodiments, pre-processing may also include labeling the outcrop pavement images to identify certain features as natural fractures that are joints, natural fractures that are not joints, and other features that may be present. Determining the plurality of detected joint networks may also include training the first machine learning network using a subset of the labeled outcrop pavement images. However, in one or more embodiments, the first machine learning network may be used pre-trained, that is, without the need of performing the described training, to determine the plurality of detected joint networks. Various embodiments of the first machine learning network have been described in relation to FIGS. **3** and **4**. For example, in one or more embodiments, the first machine learning network is a convolutional neural network (CNN).

[0092] In Block **605**, a set of surface geostatistical properties may be determined for each of the detected joint networks. As each detected joint network may have an associated set of geostatistical properties, it may be said that there is a plurality of sets of surface geostatistical properties without undue ambiguity. The determination of the plurality of sets of surface geostatistical properties may be included as part of a post-processing step of the detected joint networks, which may include other operations similar to those listed in reference to data pre-processing in addition to other operations not listed. Each of the sets of surface geostatistical properties may include information related to both joint spacing and joint orientation or one of the two. Joint spacing, in addition to relating the average spacing between joints along a scanline, may also refer to measures of joint intensity, joint density, joint length, and joint persistence within the joint network. Joint orientation may include both joint dips and joint strikes measured within the detected joint network. Each set of the plurality of sets of surface geostatistical properties may include a probability model constructed according to one of more of the individual measured geostatistical properties. The probability models relate the probability of a given joint network to exhibit one or more surface geostatistical properties, for example, the probability of a joint network to exhibit a given joint spacing, range of joint spacings, or joint spacing and orientation, among other possible probabilities. In this sense, the probability models for each set of the plurality of sets of surface geostatistical properties may be considered a multivariable probability model.

[0093] In Block **607**, a database of surface joint properties may be created including the plurality of sets of surface geostatistical properties. The database of surface joint properties may also include the plurality of outcrop pavement images, and the plurality of detected joint networks. The database of surface joint properties may be stored on a computer that is similar or the same as the computer depicted in FIG. **9** and its accompanying description. In one or more embodiments, creating the database of surface joint properties may further include correcting for joint property bias among the various data elements of the database of surface joint properties. Joint property bias may include bias introduced due to the type of aerial vehicle used to obtain the outcrop pavement images is determined. As another example, joint property bias may include bias introduced due to the geological environment of the joint network within one or more outcrop pavement images.

[0094] In Block **609**, a synthetic joint network predictor is generated by training a second machine learning network, using the database of surface joint properties, to produce a synthetic joint network. Various embodiments of the second machine learning network have been described in relation to FIGS. **3-5**. For example, in one or more embodiments, the second machine learning network is a generative adversarial network (GAN). The GAN may make use of CNNs. In accordance with one or more embodiments, the GAN includes a generator, which attempts to generate synthetic or artificial joint networks that appear realistic, and a discriminator, which attempts to classify proposed images or joint networks as either real or fake. Training a GAN include iteratively updating the weights that parameterize both the generator and the discriminator according to a loss function, where the loss function may include both adversarial loss and reconstruction loss, until the discriminator cannot reliably distinguish the joint networks created by the generator from real joint networks. Recall that the database of surface joint properties includes at least, the plurality of sets of surface geostatistical properties, and may further include the plurality outcrop pavement images and the plurality of detected joint networks. In one or more embodiments, training the second machine learning network involves interacting with the database of surface joint properties, where one or more data elements of the database of surface joint properties is used in the calculation of a loss function.

[0095] In Block **611**, a synthetic joint network predictor may be used to predict a subsurface joint network from a geostatistical description of observed subsurface joints. In one or more embodiments, the synthetic joint network predictor is obtained by discarding the discriminator of the second machine learning network and derived from the generator of the second machine learning network. The synthetic joint network predictor may predict a joint network according to one or more pre-specified joint network properties that was used during the training process of the second machine learning network. As the only requisite input to the synthetic joint network predictor is a specification of a desired joint network property to be manifested by a generated synthetic joint network, the synthetic joint network predictor is capable of predicting a subsurface joint network from a geostatistical description of observed subsurface joints. The predicted subsurface joint network, in this case, will resemble the properties of real joint networks according to the database of surface joint properties used in training the second machine learning network and therefore the synthetic joint network predictor.

[0096] In one aspect, embodiments disclosed herein relate to systems and methods for predicting joint networks in the subsurface in the vicinity of drilling systems or in a fractured region of rock. For a given fractured region of rock, information related to subterranean joint networks may be obtained from drill core and wellbore images obtained proximately to a drilled wellbore, assuming the wellbore intersects, at least partially, with a present subterranean joint network. Either drill core images or wellbore images may be used, or both, and together these may be referred to as subsurface data. The subsurface data may be used to classify structural discontinuities along with path of the wellbore as well as their locations, mineralization (and lack thereof), and modes of displacement. Joints may be identified from the general discontinuities based on their dips, or orientation relative to bedding planes, the presence of aperture (or lack of cementation), as well as their frequency. Further measurements of the identified joints may be obtained to characterize the subsurface geostatistical properties of the subsurface joint network including the statistical trends of joint orientation, spacing, length, and spatial density in the vicinity of the wellbore. For accurate statistical description, the subsurface measurements may be cleaned to remove discontinuities that are not joints, including shear fractures, veins, and stylolite, and to correct for missing or otherwise biased measurements (e.g., based on the orientation or location of the wellbore). In one or more embodiments, a database of subsurface joint properties is created including the subsurface data, the subsurface measurements, and the geostatistical properties of the subsurface joint network. The database of subsurface joint properties may be used to identify a target subsurface layer, with its own subset of target subsurface geostatistical properties, where further information regarding the joint network is sought. In one or more embodiments, a prediction of the joint network, or a prediction of the properties of the joint network, is made in the surrounding area extending away from the wellbore in the target subsurface layer using the synthetic joint network. Recall that the synthetic joint network predictor is generated by the second machine learning (ML) network trained with a database of surface joint properties, described above in reference to FIGS. **3-5**. In one or more embodiments, the prediction involves correlating and matching the geostatistical properties from the target subsurface layer to the surface geostatistical properties described above. The predicted joint network in the subsurface layer may be used for wellbore planning, well placement, well completion, and in reservoir flow simulations. In one or more embodiments, the synthetic joint network predictor may be configured to update, using a well planning system, a portion of a planned well in the target subsurface layer based, at least in part, on the predicted joint network. The synthetic joint network predictor may further be configured to transmit a signal to a computer or user device associated with a drilling system to drill a well guided by the planned well.

[0097] FIG. **7** depicts a schematic diagram of one possible embodiment of a production setting (**700**). The production setting (**700**) includes the elements and operators involved in using a synthetic joint network predictor (**325**) to predict a joint network in a target subsurface layer (**746**), in accordance with one or more embodiments.

[0098] The production setting (**700**) may include a wellbore labeled here as wellbore C (**702**). Wellbore C (**702**) may be similar to the wellbores depicted in FIG. **1** and the accompanying description. Wellbore C (**702**) may be located in a fractured region of rock, such as the fractured region of rock depicted in FIG. **1** and the accompanying description. The wellbore C (**702**) traverses, at least partially, a subsurface joint network and intersects a plurality of joints. Wellbore C (**702**) may be located as part of a drilled well or a planned well that has not yet been fully drilled, and wellbore C (**702**) may further be associated with a drilling system and a well-planning system. The drilling system and the well-planning system may be similar or the same as the drilling system and the well-planning system described in reference to FIG. **2**. The wellbore C (**702**) may be located in the fractured region of rock with a known position, a known length, and orientation (both azimuthally and with respect to the bedding plane). The wellbore C (**702**) is equipped with the necessary tools and devices to obtain subsurface data. The subsurface data may include wellbore images and drill core images in addition to other standard logging measurements. Wellbore imaging devices include, but are not limited to, downhole optical cameras, and acoustic or ultrasonic imaging devices such as borehole televiewers, electrical imaging devices such as microresistivity imaging devices. These may be operated in conjunction with other well logging tools and those used in seismic analysis. Drill core images may be obtained using one or more of the types of imaging devices described using drilled cores obtained from the wellbore. Although only one wellbore (e.g., wellbore C (**702**)) is depicted in FIG. **7**, one or more additional wellbores may be considered in the context of the present disclosure without limitation. However, the minimum requirement is a single wellbore that traverses, at least partially, a subsurface joint network and intersects a plurality of joints.

[0099] The subsurface data (**704**), including wellbore imaging or drill core images (or both), is used to obtain subsurface measurements of a joint network that is at least partially traversed by the wellbore C (**702**) and that has a plurality of joints intersected by the wellbore C (**702**). The subsurface measurements may be obtained and interpreted automatically or by a trained geologist. The subsurface measurements may include, in addition to a label of the data type from which it originated (i.e., wellbore imaging or drill core), classifications of discontinuity type encountered by the wellbore (e.g., fracture, vein, fault, conductive fracture, joint, layer-bound fracture, stylolite, etc.), location of the discontinuity, mineralization (and lack thereof), mode of displacement, and orientation of the discontinuity. The list of subsurface measurements provided is not exhaustive, and additional subsurface measurements may be considered without departing from the scope of the present disclosure. The subsurface data (**704**) may include a sequence of all recorded joints (and other discontinuities) along the wellbore C (**702**). The joint intersection to the wellbore C (**702**) may be recorded as measured depth (MD) or with some other coordinate system. The depth from non-vertical wellbores is routinely converted to the true vertical subsea (TVDSS) to locate joints within host rock layers. The subsurface measurements may be integrated in a data storage system and linked to a georeferenced subterranean region in the form of a three dimensional numerical-geological model, stratigraphic column of the subsurface rock formation, or sedimentary basin.

[0100] In accordance with one or more embodiments, the subsurface data (**704**) and the subsurface measurements may undergo subsurface data pre-processing (**706**) which may assist in identifying joints in the subsurface measurements and otherwise alter or modify the subsurface data (**704**). Subsurface data pre-processing (**706**) may include partitioning or filtering the subsurface measurements according to one or more properties. For example, rock joints may be identified and selected from the database using their dips measured with respect to bedding planes, the presence of aperture (or lack of cementation), as well as their frequency. Barren fractures, by contrast, are typically oriented less than 70 degrees with respect to bedding planes, and their orientation may separate such discontinuities from rock joints. Joints are typically oriented perpendicular to bedding planes, however, some tolerance (of about 30 degrees) may be applied to account for natural deviations in either joint dips, wellbore survey measurements errors, or data interpretation errors caused by the automated processing or by the trained geologist. Further, other discontinuities may also be separated from joints from the subsurface measurements. For example, shear fractures are typically oriented with 45-60-degree inclination and stylolite typically exhibit less than 10-degree dip with serrated plane and mineral fills. Fracture clusters may be identified through their small spacing. As in all applications involving identifying previously unknown features from data, there is a tradeoff between purity (e.g., the rate at which natural fractures are correctly classified), and completeness (e.g., the total fraction of joints detected compared to the total number of rock joints that may be present). However, as will be described below, additional methods may be applied to account for missing joints, and in this sense, it may be advantageous to consider purity as more significant than completeness, that is, considering correctly identifying rock joints more important than identifying all rock joints. Subsurface data pre-processing (**706**) may also include other common data pre-processing techniques such as digitization, smoothing of the data, scaling (e.g., normalization) of the data, feature selection, outlier removal (e.g., z-outlier filtering) and feature engineering. In one or more embodiments, joints are identified through the filtering process described above (or through another other process not listed).

[0101] Subsurface data pre-processing (**706**) may include determining a set of subsurface geostatistical properties (**711**) of the joint network using joints identified from the subsurface measurements, in accordance with one or more embodiments. The set of subsurface geostatistical properties (**711**) may include many similar or the same types of geostatistical measurements included by the plurality of sets of surface geostatistical properties described in relation to FIG. **3**. For example, the set of subsurface geostatistical properties may include measures of joint intensity, joint spacing, joint density, and joint persistence. Further, the set of subsurface geostatistical properties may include measures of joint orientation, including both joint dip and joint strike. Note that in contrast to the plurality of sets of surface geostatistical properties that describe joint networks as viewed from the surface, the set of subsurface geostatistical properties describe a joint network as viewed from the subsurface (i.e., according to the subsurface measurements). Further, note that the plurality of sets of surface geostatistical properties may refer to (several) geographically independent joint networks and need not refer to the same joint network from which the set of subsurface geostatistical properties is measured.

[0102] The set of subsurface geostatistical properties (**711**) may include a probability model constructed according to one of more of the individual measured geostatistical properties. The probability model relates the probability of a given joint network to exhibit one or more geostatistical properties, for example, the probability of a joint network to exhibit a given joint spacing or range of joint spacings. In the case of a set of subsurface geostatistical properties for one joint network, a variety of joint spaces may be determined, and the probability model may relate the probability of each particular joint spacing based on, for example, their relative frequency. Further, the probability model may relate the probability of a joint network to exhibit one or more geostatistical properties in view of the presence or probability of one or more other geostatistical properties. For example, the probability model may relate the probability of a joint network to exhibit a given joint spacing (or range of joint spacings) in view of a particular joint orientation (or range of joint orientations). In this sense, the probability model for the set of subsurface geostatistical properties (**711**) may be considered a multivariable probability model.

[0103] The set of subsurface geostatistical properties (**711**) may be used to create a database of subsurface joint properties (**726**). In one or more embodiments, the subsurface data (**704**) may also be stored in the database of subsurface joint properties (**726**). The database of subsurface joint properties (**726**) may be stored on a computer that is similar to or the same as the computer of FIG. **9** and its accompanying description. These data elements may be organized to make clear the association between a given subsurface measurement and its joint(s) or other feature, if the subsurface measurement does not refer to a joint, and the appropriate subsurface geostatistical properties (and/or probability model). For example, this association may be made clear by storing each of these data elements in one file, directory, or location on a computer, such as the computer of FIG. **9** and its accompanying description. Alternatively, the association between related data elements in the database of subsurface joint properties (**726**) may be achieved by assigning each data element with a name following a pre-assigned convention. Many techniques are known in the art for organizing related data elements in a database, and those listed above are not exhaustive and should not be considered limiting with regard to the present disclosure.

[0104] As part of the creation of the database of subsurface joint properties (**726**) the set of subsurface geostatistical properties (**711**) may be corrected for one or more biases present in the detected joint networks (**307**), in accordance with one or more embodiments. A number of biases may be present in the measured set of subsurface geostatistical properties (**711**) collectively referred to as joint property bias. For example, joint dips may need to be corrected due to the tilting of bedding planes. Bedding planes are naturally deposited flat in sedimentary basins, and they remain flat unless folded or faulted. This correction is not required for low dips (between 1 to 10 degrees) already covered by the tolerance of joints (approximately 30 degrees within vertical). Bedding planes in highly faulted and folded regions must be rectified by applying a correction to inclined bedding planes such that they are horizontal and adding the same inclination degrees to the discontinuity dips. Another example of joint property bias that may be present is due to the orientation, length traversed, and location of the wellbore C (**702**) which may lead to certain joints, depending on their orientation, being missed altogether. The wellbore C (**702**) data may have different geometry such as vertical and horizontal, and any inclination degree in between. To estimate a bias based on the orientation of the wellbore C (**702**), joint strikes can be plotted against azimuth degrees of the wellbores at the intersections on a Cartesian coordinate grid. This visualization may assist in determining the collective bias of borehole orientations on sampling the joint network in the subsurface.

[0105] The Terzaghi correction, and its modified versions, can also be used to correct for intensity of parallel joint sets. In principle, wellbores miss parallel joints and show greater spacing than is true for oblique joints thus affecting estimates of certain fracture trends. Wellbores, such as wellbore C (**702**), only give the correct spacing for those joint systems perpendicular to well path. The spacing of a joint set is corrected based on the angle (φ) between the mean pole of the joints of the set and the wellbore azimuth, $S_s=S_j \cos \varphi$. Many additional techniques to measure and correct for joint property bias due to the orientation of the wellbore (e.g., wellbore C (**702**)) are known in the art and may be applied without departing from the scope of this disclosure. For example, a basic statistical test such as the Komolgorov-Smirnov test may be conducted to compare the measured orientation of joints from subsurface measurements with those of known orientation to determine the amount of bias present in the subsurface measurements. Applying corrections to the joint spacing and orientations, according to one or more methods described above, may influence the resulting probability models of joint network properties associated with the set of subsurface geostatistical properties (**711**), in accordance with one or more embodiments.

[0106] The database of subsurface joint properties (**726**), including the set of subsurface geostatistical properties (**711**) may be used to select and determine target subsurface layer parameters (**731**) that define the extent and measured joint properties in a particular subsurface layer. For example, the target subsurface layer parameters (**731**) may include the target subsurface boundaries (**736**) that define its three-dimensional shape. Further, the target subsurface boundaries (**736**) may include the target subsurface layer thickness, orientation, and extent, or only one of these parameters individually. In one or more embodiments, only two-dimensional information of the target subsurface layer boundaries (**736**) may be considered. The target subsurface layer parameters (**731**) may also include the subset of target subsurface geostatistical properties (**741**), where the subset of target subsurface geostatistical properties (**741**) are a subset of the set of subsurface geostatistical properties (**711**) specific to the target subsurface layer.

[0107] The target subsurface layer parameters (**731**) may be used as an input to the synthetic joint network predictor (**325**) in order to determine a predicted joint network in the target subsurface layer (**746**). Recall that the synthetic joint network predictor (**325**) may be generated from the second machine learning network (**315**) as depicted in FIG. **3** and described in the accompanying description. The synthetic joint network predictor (**325**) is trained predict a subsurface joint network according to a geostatistical description. Thus, the synthetic joint network predictor (**325**) may be used to determine a predicted joint network in the target subsurface layer (**746**) with the properties specified by, at least, the subset of target subsurface geostatistical properties (**741**). In accordance with one or more embodiments, the target subsurface boundaries (**736**) are also used alongside the subset of target subsurface geostatistical properties (**741**) to specify an input to the synthetic joint network predictor. The target subsurface boundaries (**736**) may influence the shape and orientation of the predicted joint network in the target subsurface layer (**746**) and more specifically, the shape and orientation of the produced image. In other words, the predicted joint network may be scaled and rotated according to the specifications of the target subsurface boundaries. Recall that the second machine learning network (**315**) that is used, at least in part, to generate the synthetic joint network predictor (**325**), is trained to produce synthetic joint networks that share the properties of real joint networks in nature. As such, the predicted joint network in the target subsurface layer (**746**) will be a synthetic joint network that resembles real joint networks in nature that exhibit the subset of target subsurface geostatistical properties (**741**). Consequently, the relative joint lengths, branching structure, number of joint sets, and joint orientations will be physically realistic and therefore reliable for wellbore planning, well placement, well completion, and usage in reservoir flow simulations.

[0108] In one or more embodiments, the synthetic joint network predictor (**325**) may include the database of surface joint properties (**323**) or be in communication with the database of surface joint properties (**323**). In one or more embodiments, predicting the predicted joint network in the target subsurface layer (**746**) with the synthetic joint network predictor (**325**) may include correlating the set of subset of target subsurface geostatistical properties (**741**) and the set of surface geostatistical properties to specify an input for the synthetic joint network predictor. Recall that the synthetic joint network predictor (**325**) is capable of predicting a joint network from a geostatistical description of observed subsurface joints (e.g., subset of target subsurface geostatistical properties (**741**)). However, the input to the synthetic joint network predictor (**325**) may be modified according prior information obtained concerning joint networks, for example, the information obtained from joint networks as viewed from above the surface. For example, consider a joint network with subset of target subsurface geostatistical properties of joint spacing with Y meters and P degrees joint strike. In the database of surface joint properties, there may also be one or more joint networks with properties of joint spacing with Y meters joint and P degrees joint strike. As has been discussed, the subsurface geostatistical properties of a joint network may be biased for one reason or another (e.g., due to the orientation of a borehole). However, surface joint networks are not expected to be biased in the same ways. Further, subsurface data (**704**) are obtained proximate to the wellbore, by necessity, and the degree to which joint properties may change away from the wellbore may be difficult to ascertain from the subsurface data alone. By contrast, the change of joint properties as a function of position is easily measured on surface joint networks. As such, rather than directly inputting the observed subset of target subsurface geostatistical properties (**741**) to the synthetic joint network predictor (**325**), the subset of target subsurface geostatistical properties (**741**) may be correlated and modified according to the set of surface geostatistical properties of joint networks prior to being processed by the synthetic joint network predictor. In this way, a further degree of realism may be achieved for the predicted joint network in the target subsurface layer (**746**).

[0109] Once the synthetic joint network predictor (**325**) predicts the predicted joint network in the target subsurface layer (**746**), reference analogue determination (**751**) may be done, in accordance with one or more embodiments. Reference analogue determination (**751**) includes adding additional labels to either the database of subsurface joint properties (**726**) or the database of surface joint properties (**323**) or both. The labels added to the database of subsurface joint properties (**726**) and/or the database of surface joint properties (**323**) may identify certain outcrop pavements as analogous to certain subsurface region models or indicate that a model of a particular subsurface region is similar to another subsurface region or layer with a different environment. This process may be done automatically by determining correlations between the properties of the predicted joint network in the target subsurface layer (**746**) with one or more data elements in the database of surface joint properties (**323**) and/or the database of subsurface joint properties (**726**). Alternatively, the process may be carried out by a trained geologist or geophysicist.

[0110] The predicted joint network in the target subsurface layer (**746**) may be used for wellbore planning, well placement, well completion, and in reservoir flow simulations. In one or more embodiments, the synthetic joint network predictor is configured to update, using a well planning system, a portion of a planned well in the target subsurface layer based, at least in part, on the predicted joint network.

[0111] A well plan may be generated using a well planning system (e.g., the well planning system (**208**) of FIG. **2**). The well plan may include a starting surface location of the wellbore (e.g., the wellbore C (**702**) of FIG. **7**), or a subsurface location within an existing wellbore, from which the wellbore may be drilled. Further, the well plan may include a terminal location that may intersect with a drilling target, for example, a targeted hydrocarbon-bearing formation, a planned wellbore path from the starting location to the terminal location, and the location of the target subsurface layer.

[0112] The well planning system (e.g., well planning system (**208**)) may include a computer system such as the one described in reference to FIG. **9**. The computer system may include one or more computer processors in communication with computer memory containing geophysical and geomechanical models, subsurface and surface data sets, information relating to drilling hazards, and constraints imposed by the limitations of an associated drillstring of a well drilling system (e.g., drilling system (**201**)). The well planning system may further include dedicated software to determine the well plan and associated drilling parameters, such as the planned wellbore diameter, the location of planned changes of the wellbore diameter, the planned depths at which casing will be inserted to support the wellbore and to prevent formation fluids entering the wellbore, and the drilling mud weights and types that may be used during drilling the wellbore. If casing is used, the well plan may include casing type or casing depths. Furthermore, the well plan may consider other engineering constraints such as the maximum wellbore curvature ("dog-leg") that the drillstring of the drilling system (e.g., drilling system (**201**)) may tolerate and the maximum torque and drag values that the drilling system (e.g., drilling system (**201**)) may provide. The well plan may further define associated drilling parameters, such as the planned depths at which drilling may be paused and casing will be inserted to support the wellbore to prevent formation fluids entering the wellbore and the drilling mud weights (densities) and types that may be used during drilling of the wellbore. The well plan may also define the drilling parameters associated with the placement of manufactured tools or chemicals to enhance, reduce, segregate, or otherwise affect reservoir fluid. For example, the well plan may include defining the operation of a chemical storage system installed along the wellbore. Various configurations of a chemical storage compartment and dispensing mechanism working in conjunction to store and dispense chemicals may be used to form chemical storage systems integrated within drilling wells.

[0113] The synthetic joint network predictor (**325**) may further be configured to transmit a signal to a computer or user device associated with a drilling system (e.g., drilling system (**201**)) to drill a well guided by the planned well. The signal transmitted to the drilling system (e.g., drilling system (**201**)) is represented by the arrow labeled command X (**753**). The computer or user device may be similar to or the same as the computer described in FIG. **9** and the accompanying description. The signal or command X (**753**) may be transmitted remotely over a distributed network (e.g., Wi-Fi) or through a physical mechanism for data transfer such as fiber optic cables.

[0114] It is emphasized that many modifications may be made to the production setting (**700**) and the application of the synthetic joint network predictor (**325**) used to predict a predicted joint network in a target subsurface layer (**746**) without departing from the scope of this present disclosure. For example, the wellbore (e.g., wellbore C (**702**)) may include a construction or configuration not included in the description above, and the same may be said regarding the well-planning system (e.g., well planning system (**208**)) and the drilling system (e.g., drilling system (**201**)).

[0115] The operation of processing subsurface measurements and applying a synthetic joint network predictor to predict a subsurface joint network is summarized in the flow chart of FIG. **8** according to one or more embodiments. In

Block **801**, subsurface data may be obtained from a subsurface region having a joint network and comprising a wellbore. The subsurface data include wellbore images and drill core images in addition to other standard logging measurements. Subsurface measurements may be determined and interpreted automatically or by a trained geologist. The subsurface measurements may include, in addition to a label of the data type from which it originated (i.e., wellbore imaging or drill core), classifications of discontinuity type encountered by the wellbore (e.g., fracture, vein, fault, conductive fracture, joint, layer-bound fracture, stylolite, etc.), location of the discontinuity, mineralization (and lack thereof), mode of displacement, and orientation of the discontinuity. The list of subsurface measurements provided is not exhaustive, and additional subsurface measurements may be considered without departing from the scope of the present disclosure.

[0116] The subsurface measurements and the subsurface data may undergo subsurface data pre-processing which may assist in identifying joints in the subsurface measurements and otherwise alter or modify the subsurface measurements. Subsurface data pre-processing may include partitioning or filtering the subsurface measurements according to one or more properties, numericalization, digitization, smoothing of the data, scaling (e.g., normalization) of the data, feature selection, outlier removal (e.g., z-outlier filtering) and feature engineering.

[0117] In Block **803**, a set of subsurface geostatistical properties of the joint network is determined from the subsurface data, which may include the subsurface measurements. Joints may be identified according to one or more subsurface measurements or features in the subsurface data, for example, the spacings of the discontinuities encountered by the wellbore. The set of subsurface geostatistical properties is then determined using the identified joints. The set of subsurface geostatistical properties may include many similar or the same types of geostatistical measurements included by the plurality of sets of surface geostatistical properties described in relation to FIGS. **3** and **7**. For example, the set of subsurface geostatistical properties may include measures of joint intensity, joint spacing, joint density, and joint persistence. Further, the set of subsurface geostatistical properties may include measures of joint orientation, including both joint dip and joint strike. The set of subsurface geostatistical properties may include a probability model constructed according to one of more of the individual measured geostatistical properties. The probability model relates the probability of a given joint network to exhibit one or more geostatistical properties, for example, the probability of a joint network to exhibit a given joint spacing or range of joint spacings. Further, the probability model may relate the probability of a joint network to exhibit one or more geostatistical properties in view of the presence or probability of one or more other geostatistical properties in the form a multivariable probability model.

[0118] In one or more embodiments, a database of subsurface joint properties is created including the set of subsurface geostatistical properties of the joint network. In one or more embodiments, the subsurface measurements and subsurface data may also be stored in the database of subsurface joint properties. As part of the creation of the database of subsurface joint properties the set of subsurface geostatistical properties may be corrected for one or more biases present in the identified joint networks, in accordance with one or more embodiments. A number of biases may be present in the measured set of subsurface geostatistical properties collectively referred to as joint property bias. For example, joint property bias may include bias due to the tilting of bedding planes and bias due to the configuration of the wellbore, including its orientation, length traversed, and location.

[0119] In Block **805**, a target subsurface layer is determined from set of subsurface geostatistical properties. The parameters that define the target subsurface layer may be selected from the database of subsurface joint properties. For example, the target subsurface layer parameters may include the target subsurface boundaries that define its two or three-dimensional shape and may include the target subsurface layer thickness, orientation, and extent. The target subsurface layer parameters may also include the subset of target subsurface geostatistical properties, where the subset of target subsurface geostatistical properties are a subset of the set of subsurface geostatistical properties specific to the target subsurface layer.

[0120] In Block **807** a synthetic joint network predictor is used to predict a predicted joint network in the target subsurface layer, based, at least in part, on a set of subset of target subsurface geostatistical properties of the target subsurface layer selected from the database of subsurface joint properties. The synthetic joint network predictor is trained to predict a subsurface joint network from a geostatistical description of observed subsurface joints. Thus, the synthetic joint network predictor may be used to determine a predicted joint network in the target subsurface layer with the properties specified by, at least, the subset of target subsurface geostatistical properties. In accordance with one or more embodiments, the target subsurface boundaries are also used alongside the subset of target subsurface geostatistical properties to specify an input to the synthetic joint network predictor. The target subsurface boundaries may influence the shape and orientation of the predicted joint network in the target subsurface layer and more specifically, the shape and orientation of the produced image.

[0121] In one or more embodiments, the joint network may include the database of surface joint properties described earlier or be in digital communication with the database of surface joint properties. Accordingly, in one or more embodiments, predicting the predicted joint network in the target subsurface layer with the synthetic joint network predictor may include correlating the subset of target subsurface geostatistical properties and the set of surface geostatistical properties to specify an input for the synthetic joint network predictor. Rather than directly inputting the observed subset of target subsurface geostatistical properties to the synthetic joint network predictor, the subset of target subsurface geostatistical properties may be correlated and modified according to the set of surface geostatistical properties of a joint network as viewed from above the surface prior to being processed by the synthetic joint network predictor.

[0122] In accordance with one or more embodiments reference analogues may be determined between the predicted joint network in the target subsurface layer and one or more related surface pavements. Reference analogue determination includes adding additional labels to either the database of subsurface joint properties or the database of surface joint properties or both. The labels added to the database of subsurface joint properties and/or the database of surface joint properties may identify certain outcrop pavements as analogous to certain subsurface region models or indicate that a model of a particular subsurface region is similar to another subsurface region or layer with a different environment.

[0123] In one or more embodiments, a well-planning system is used to update a portion of a planned well in the target subsurface layer, based, at least in part, on the predicted joint network. The well-planning system may include a computer system such as the one described in reference to FIG. **9**. The computer system may include one or more computer processors in communication with computer memory containing geophysical and geomechanical models, subsurface and surface data sets, information relating to drilling hazards, and constraints imposed by the limitations of an associated drillstring of a well drilling system. The well planning system may further include dedicated software to determine the well plan and associated drilling parameters, such as the planned wellbore diameter, the location of planned changes of the wellbore diameter, the planned depths at which casing will be inserted to support the wellbore and to prevent formation fluids entering the wellbore, and the drilling mud weights and types that may be used during drilling the wellbore. The well plan may also define the drilling parameters associated with the placement of manufactured tools or chemicals to enhance, reduce, segregate, or otherwise affect reservoir fluid. For example, the well plan may include defining the operation of a chemical storage system installed along the wellbore.

[0124] In one or more embodiments, a drilling system is used to drill a well guided by the planned well. The drilling system may include a drill bit attached by a drillstring to a drill rig located on the surface of the earth. The drill rig may include framework, such as a derrick to hold drilling machinery. A top drive sits at the top of the derrick and provides torque, typically a clockwise torque, via the drive shaft to the drillstring in order to drill. The drilling system further includes the necessary tools to execute the various procedures and operations that may be included in the well-plan, described above and in reference to FIG. **7**, that guides the drilling of a well using the drilling system.

[0125] Embodiments of the present disclosure may be implemented on a computer system. FIG. **9** is a block diagram of a computer system (**902**) used to provide computational functionalities associated with described algorithms, methods, functions, processes, flows, and procedures as described in the instant disclosure, according to one or more embodiments. The illustrated computer (**902**) is intended to encompass any computing device such as a server, desktop computer, laptop/notebook computer, wireless data port, smart phone, personal data assistant (PDA), tablet computing device, one or more processors within these devices, or any other suitable processing device such as an edge computing device, including both physical or virtual instances (or both) of the computing device. An edge computing device is a dedicated computing device that is, typically, physically adjacent to the process or control with which it interacts.

[0126] Additionally, the computer (**902**) may include a computer that includes an input device, such as a keypad, keyboard, touch screen, or other device that can accept user information, and an output device that conveys information associated with the operation of the computer (**902**), including digital data, visual, or audio information (or a combination of information), or a GUI.

[0127] The computer (**902**) can serve in a role as a client, network component, a server, a database or other persistency, or any other component (or a combination of roles) of a computer system for performing the subject matter described in the instant disclosure. In some implementations, one or more components of the computer (**902**) may be configured to operate within environments, including cloud-computing-based, local, global, or other environment (or a combination of environments).

[0128] At a high level, the computer (**902**) is an electronic computing device operable to receive, transmit, process, store, or manage data and information associated with the described subject matter. According to some implementations, the computer (**902**) may also include or be communicably coupled with an application server, e-mail server, web server, caching server, streaming data server, business intelligence (BI) server, or other server (or a combination of servers).

[0129] The computer (**902**) can receive requests over network (**930**) from a client application (for example, executing on another computer (**902**) and responding to the received requests by processing the said requests in an appropriate software application. In addition, requests may also be sent to the computer (**902**) from internal users (for example, from a command console or by other appropriate access method), external or third-parties, other automated applications, as well as any other appropriate entities, individuals, systems, or computers.

[0130] Each of the components of the computer (**902**) can communicate using a system bus (**903**). In some implementations, any or all of the components of the computer (**902**), both hardware or software (or a combination of hardware and software), may interface with each other or the interface (**904**) (or a combination of both) over the system bus (**903**) using an application programming interface (API) (**912**) or a service layer (**913**) (or a combination of the API (**912**) and service layer (**913**). The API (**912**) may include specifications for routines, data structures, and object classes. The API (**912**) may be either computer-language independent or dependent and refer to a complete interface, a single function, or even a set of APIs. The service layer (**913**) provides software services to the computer (**902**) or other components (whether or not illustrated) that are communicably coupled to the computer (**902**). The functionality of the computer (**902**) may be accessible for all service consumers using this service layer. Software services, such as those provided by the service layer (**913**), provide reusable, defined business functionalities through a defined interface. For example, the interface may be software written in JAVA, C++, or other suitable language providing data in extensible markup language (XML) format or another suitable format. While illustrated as an integrated component of the computer (**902**), alternative implementations may illustrate the API (**912**) or the service layer (**913**) as stand-alone components in relation to other components of the computer (**902**) or other components (whether or not illustrated) that are communicably coupled to the computer (**902**). Moreover, any or all parts of the API (**912**) or the service layer (**913**) may be implemented as child or sub-modules of another software module, enterprise application, or hardware module without departing from the scope of this disclosure.

[0131] The computer (**902**) includes an interface (**904**). Although illustrated as a single interface (**904**) in FIG. **9**, two or more interfaces (**904**) may be used according to particular needs, desires, or particular implementations of the computer (**902**). The interface (**904**) is used by the computer (**902**) for communicating with other systems in a distributed environment that are connected to the network (**930**). Generally, the interface (**904**) includes logic encoded in software or hardware (or a combination of software and hardware) and operable to communicate with the network (**930**). More specifically, the interface (**904**) may include software supporting one or more communication protocols associated with communications such that the network (**930**) or interface's hardware is operable to communicate physical signals within and outside of the illustrated computer (**902**).

[0132] The computer (**902**) includes at least one computer processor (**905**). Although illustrated as a single computer processor (**905**) in FIG. **9**, two or more processors may be used according to particular needs, desires, or particular implementations of the computer (**902**). Generally, the computer processor (**905**) executes instructions and manipulates data to perform the operations of the computer (**902**) and any algorithms, methods, functions, processes, flows, and procedures as described in the instant disclosure.

[0133] The computer (**902**) also includes a memory (**906**) that holds data for the computer (**902**) or other components (or a combination of both) that can be connected to the network (**930**). The memory may be a non-transitory computer readable medium. For example, memory (**906**) can be a database storing data consistent with this disclosure. Although illustrated as a single memory (**906**) in FIG. **9**, two or more memories may be used according to particular needs, desires, or particular implementations of the computer (**902**) and the described functionality. While memory (**906**) is illustrated as an integral component of the computer (**902**), in alternative implementations, memory (**906**) can be external to the computer (**902**).

[0134] The application (**907**) is an algorithmic software engine providing functionality according to particular needs, desires, or particular implementations of the computer (**902**), particularly with respect to functionality described in this disclosure. For example, application (**907**) can serve as one or more components, modules, applications, etc. Further, although illustrated as a single application (**907**), the application (**907**) may be implemented as multiple applications (**907**) on the computer (**902**). In addition, although illustrated as integral to the computer (**902**), in alternative implementations, the application (**907**) can be external to the computer (**902**).

[0135] There may be any number of computers (**902**) associated with, or external to, a computer system containing computer (**902**), wherein each computer (**902**) communicates over network (**930**). Further, the term "client," "user," and other appropriate terminology may be used interchangeably as appropriate without departing from the scope of this disclosure. Moreover, this disclosure contemplates that many users may use one computer (**902**), or that one user may use multiple computers (**902**).

[0136] Embodiments of the present disclosure may provide at least one of the following advantages. The abundance of joints and their characteristics are important in petroleum engineering and mining operations as joint networks form passageways for flowing oil, gas, and water in the subsurface. Accordingly, there exists a need to reliably determine the properties of joint networks in the subsurface. However, determining the presence, and more specifically, the structure of a subsurface joint network is difficult given the inaccessibility of the joint network. Further, most non-invasive methods for determining features of natural fracture networks in the subsurface, such as seismic data, cannot be used to detect and characterize joints in the subsurface. Standard well logs which may measure porosity and permeability also cannot be used to identify and accurately characterize joints in the subsurface. Nonetheless, measurements of joints in the subsurface may be readily available in the vicinity of drilled wellbores, and these subsurface measurements may be obtained using tools already present at most drill sites. The present disclosure provides a method for using readily obtainable subsurface measurements to accurately predict the properties of joint networks in the subsurface by integrating subsurface measurements of joint network properties with surface measurements of joint networks in a machine learning framework.

[0137] The usage of surface information in predicting joint networks in the subsurface yields a greater degree of reliability compared to methods of predicting subsurface joint network properties using only subsurface measurements. First, a plurality of biases may be present in subsurface measurements, for example, due to borehole orientation or location and large-scale structure in bedding planes. Such biases are not present in surface data, like outcrop pavement images. Further, subsurface measurements are always made proximate to the wellbore, by necessity, and the degree to which joint properties in the subsurface may change away from the wellbore may be difficult to ascertain. By contrast, the change of joint properties as a function of position is easily measured on surface joint networks. In addition, a variety of aerial vehicles are capable of obtaining a plurality of outcrop pavement images containing joint networks, especially remote-controlled drones. Accordingly, obtaining the necessary surface information is cost effective.

[0138] The methods for developing a synthetic joint network predictor are both flexible and highly generalizable, making little or no assumptions about geological properties of joint networks, except that joints, as natural fracture systems, typically exist in networks and may be characterized according to basic geostatistical properties. For example, the synthetic joint network predictor, in principle, could be tailored to generate joint networks for a wide variety of geological facies, assuming sufficient training data (e.g., outcrop pavement images) is obtained with the necessary labeling. Further, the predicted joint networks are able to be scaled and rotated to fit into a variety of target subsurface layers. However, despite the flexibility and generalizability provided by the machine learning framework, the present disclosure retains strong interpretability through the usage of well-understood geostatistics. That is, the machine learning models are trained using basic and well-understood measurements commonly employed in geology and geophysics.

[0139] Although only a few example embodiments have been described in detail above, those skilled in the art will readily appreciate that many modifications are possible in the example embodiments without materially departing from this invention. Accordingly, all such modifications are intended to be included within the scope of this disclosure as defined in the following claims.

What is claimed is:

1. A method, comprising:
obtaining a plurality of outcrop pavement images of a plurality of joint networks;
determining, using a first machine learning (ML) network, a plurality of detected joint networks using the plurality of outcrop pavement images;
determining, for each of the plurality of detected joint networks, a set of surface geostatistical properties;
creating a database of surface joint properties comprising the plurality of sets of surface geostatistical properties;
generating a synthetic joint network predictor by training a second ML network, using the database of surface joint properties, to produce a synthetic joint network; and
using the synthetic joint network predictor to predict a predicted joint network from a geostatistical description of observed subsurface joints.

2. The method of claim 1, further comprising:
obtaining subsurface data from a subsurface region having a joint network and comprising a wellbore;
determining a set of subsurface geostatistical properties of the joint network from the subsurface data;
determining a target subsurface layer from the set of subsurface geostatistical properties;
wherein using the synthetic joint network, the predicted joint network is predicted in the target subsurface layer according to a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties.

3. The method of claim 1, wherein the plurality of outcrop pavement images comprises outcrop pavement images from a plurality of different geological facies.

4. The method of claim 1, wherein the set of surface geostatistical properties comprises joint orientation.

5. The method of claim 1, wherein creating the database of surface joint properties comprises correcting for structural discontinuities that are not joints.

6. The method of claim 1:
wherein the second ML network is a generative adversarial network comprising a generator and a discriminator;
wherein the synthetic joint network predictor is derived from the generator.

7. A method, comprising:
obtaining subsurface data from a subsurface region having a joint network and comprising a wellbore;
determining a set of subsurface geostatistical properties of the joint network from the subsurface data;
determining a target subsurface layer from the set of subsurface geostatistical properties; and
using a synthetic joint network predictor, predicting a predicted joint network in the target subsurface layer, based, at least in part, on a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties.

8. The method of claim 7, wherein the synthetic joint network predictor is generated by a second machine learning (ML) network trained with a database of surface joint properties.

9. The method of claim 8, further comprising:
obtaining a plurality of outcrop pavement images of a plurality of joint networks;
determining, using a first ML network, a plurality of detected joint networks using the plurality of outcrop pavement images;
determining, for each of the plurality of detected joint networks, a set of surface geostatistical properties; and
creating the database of surface joint properties comprising the plurality of sets of surface geostatistical properties.

10. The method of claim 7, further comprising:
updating, using a well planning system, a portion of a planned well in the target subsurface layer based, at least in part, on the predicted joint network; and
drilling, using a drilling system, a well guided by the planned well.

11. The method of claim 7, wherein determining the target subsurface layer further comprises determining, at least, two-dimensional boundaries of the target subsurface layer.

12. The method of claim 7, wherein predicting a predicted joint network in the target subsurface layer further comprises correlating the set of target subsurface geostatistical properties and a set of surface geostatistical properties to specify an input for the joint network predictor.

13. The method of claim 7, further comprising determining reference analogues between the predicted joint network in the target subsurface layer and one or more related surface pavements.

14. A system, comprising:
a plurality of devices configured to be disposed along a wellbore and configured to obtain subsurface data;
a computer configured to:
receive the subsurface data,
determine a set of subsurface geostatistical properties of a subsurface joint network from the subsurface data, and
determine a target subsurface layer from the set of subsurface geostatistical properties; and
a synthetic joint network predictor configured to predict a predicted joint network in the target subsurface layer based, at least in part, on a subset of target subsurface geostatistical properties selected from the set of subsurface geostatistical properties.

15. The system of claim 14 wherein the synthetic joint network predictor is generated by a second machine learning (ML) network trained with a database of surface joint properties.

16. The system of claim 15, further comprising:
a first ML network configured to:
receive a plurality of outcrop pavement images comprising a plurality of joint networks, and
determine a plurality of detected joint networks using the plurality of outcrop pavement images,
wherein the computer is further configured to:
determine, for each of the plurality of detected joint networks, a set of surface geostatistical properties, and
create the database of surface joint properties comprising the plurality of sets of surface geostatistical properties.

17. The system of claim 14, further comprising a well planning system configured to update a portion of a planned well in the target subsurface layer based, at least in part, on the predicted joint network.

18. The system of claim 17, further comprising a drilling system configured to drill a well guided by the planned well.

19. The system of claim **14**, wherein the joint network predictor is configured to determine reference analogues between the predicted joint network in the target subsurface layer and one or more related surface pavements.

20. The system of claim **14**, wherein the subsurface data comprises wellbore images.

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