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Method for deriving surface material properties of surface materials based upon LIDAR data, computing system and non-transitory computer-readable storage medium

Abstract

The disclosure provides a method for deriving a surface absorption property of a surface material from LIDAR data. The method may include receiving cloud points from a LIDAR sensor. The cloud points are characterized by intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates. The method may also include constructing surface segments of the surface material by building triangles from three neighboring cloud points, determining the normal direction for each triangle from each cloud point, and deriving the surface absorption property for the segment of the surface material based upon the average intensity values for the three neighboring cloud points, a known angle of incidence, and the determined normal direction for each of the respective triangle. The method may further include aggregating the derived surface absorption property across a collection of respective triangles to result in the surface absorption property for a type of surface.

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References Cited

U.S. PATENT DOCUMENTS

Patent No.	Issued Date	Patentee Name	U.S. Cl.	CPC
10338223	12/2018	Englard	N/A	G06F 18/217
2019/0179015	12/2018	Raring	N/A	F21K 9/64
2020/0249353	12/2019	Di Cicco	N/A	G01S 7/4808
2021/0033706	12/2020	Funaya	N/A	G06V 20/64
2021/0405200	12/2020	Ding	N/A	G06T 17/05

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Background/Summary

TECHNICAL FIELD
(1) The subject technology pertains to using data or cloud points received from Light Detection and Ranging (LiDAR) sensors to do surface constructions and to derive surface material properties of surface materials.
BACKGROUND
(2) An autonomous vehicle is a motorized vehicle that can navigate without a human driver. An exemplary autonomous vehicle includes a plurality of sensor systems, such as, but not limited to, a camera sensor system, a LIDAR sensor system, a radar sensor system, amongst others, wherein the autonomous vehicle operates based upon sensor signals output by the sensor systems. Specifically, the sensor signals are provided to an internal computing system in communication with the plurality of sensor systems, wherein a processor executes instructions based upon the sensor signals to control a mechanical system of the autonomous vehicle, such as a vehicle propulsion system, a braking system, or a steering system. In some applications, these systems utilize a perception system (or perception stack) that implements various computing vision techniques to reason about the surrounding environment.
SUMMARY
(3) The present technology pertains to deriving a surface absorption property of surface material

from LIDAR data. In one aspect, the technology may include receiving a plurality of cloud points from a LIDAR sensor. The cloud points characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates. The technology may also include constructing a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points. Each of the plurality of triangles is a surface segment. The technology may also include determining the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle. The technology may also include deriving the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangle. The technology may further include aggregating the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface.

(4) Additional aspects, embodiments, and features are set forth in part in the description that follows and will become apparent to those skilled in the art upon examination of the specification or may be learned by the practice of the disclosed subject matter. A further understanding of the nature and advantages of the disclosure may be realized by reference to the remaining portions of the specification and the drawings, which form a part of this disclosure.

Description

BRIEF DESCRIPTION OF THE DRAWINGS
(1) The above-recited and other advantages and features of the present technology will become apparent by reference to specific implementations illustrated in the appended drawings. A person of ordinary skill in the art will understand that these drawings only show some examples of the present technology and would not limit the scope of the present technology to these examples. Furthermore, the skilled artisan will appreciate the principles of the present technology as described and explained with additional specificity and detail through the use of the accompanying drawings in which:
(2) FIG. **1** illustrates an example of a system for managing one or more Autonomous Vehicles (AVs) according to some aspects of the present technology;
(3) FIG. **2**A illustrates a LIDAR sensor scanning a real-world object according to some examples of the present technology;
(4) FIG. **2**B illustrates the reflection from the real-world object of FIG. **2**A detected by a LIDAR sensor according to some examples of the present technology;
(5) FIG. **2**C illustrates cloud points that are collected from the real-world object of FIG. **2**A according to some examples of the present technology;
(6) FIG. **3** is a flowchart of a method for deriving a surface absorption property of surface material from LIDAR data according to some examples of the present technology;
(7) FIG. **4**A is a sketch illustrating a curved surface with triangles having large variations in normal directions according to some examples of the present technology;
(8) FIG. **4**B is a sketch illustrating a relatively flat surface with triangles having small variations in normal directions according to some examples of the present technology; and
(9) FIG. **5** shows an example of a system for implementing certain aspects of the present technology.
DETAILED DESCRIPTION
(10) Various examples of the present technology are discussed in detail below. While specific

implementations are discussed, it should be understood that this is done for illustration purposes only. A person skilled in the relevant art will recognize that other components and configurations may be used without parting from the spirit and scope of the present technology. In some instances, well-known structures and devices are shown in block diagram form to facilitate describing one or more aspects. Further, it is to be understood that functionality that is described as being carried out by certain system components may be performed by more or fewer components than shown.

(11) When an autonomous vehicle (AV) drives on the road, data is captured by LIDAR sensors on the AV. The LIDAR sensors can detect the distances of real-world objects in a scene. The LIDAR sensors output LIDAR data, including intensities of reflected light and angles of incidence from real-world objects. The LIDAR data can be converted to a simulated scene. However, simulated objects or synthetic objects in the simulated scene may not be the same as the real-world objects in the scene on the road. The surface absorption properties of real-world objects may affect the reflections from the objects. The surface absorption property affects surface reflectance, which varies with the type of material of the real-world objects. Therefore, it is important to derive the surface absorption property of the surface material.

(12) The disclosure provides methods that use cloud points received from a LIDAR sensor to do surface constructions and determine surface absorption properties of the surface material.

(13) The disclosed method uses the data captured by the LIDAR sensor when an AV drives on the road to determine actual LIDAR beam intensities and to identify surface materials for use in simulations. The beam intensities captured are used to determine the surface material based on the derived normal vectors at surfaces constructed from cloud points.

(14) FIG. **1** illustrates an example of an AV management system **100**. One of the ordinary skills in the art will understand that, for the AV management system **100** and any system discussed in the present disclosure, there can be additional or fewer components in similar or alternative configurations. The illustrations and examples provided in the present disclosure are for conciseness and clarity. Other embodiments may include different numbers and/or types of elements, but one of the ordinary skills in the art will appreciate that such variations do not depart from the scope of the present disclosure.

(15) In this example, the AV management system **100** includes an AV **102**, a data center **150**, and a client computing device **170**. The AV **102**, the data center **150**, and the client computing device **170** can communicate with one another over one or more networks (not shown), such as a public network (e.g., the Internet, Infrastructure as a Service (IaaS) network, a Platform as a Service (PaaS) network, a Software as a Service (SaaS) network, other Cloud Service Provider (CSP) network, etc.), a private network (e.g., a Local Area Network (LAN), a private cloud, a Virtual Private Network (VPN), etc.), and/or a hybrid network (e.g., a multi-cloud or hybrid cloud network, etc.).

(16) The AV **102** can navigate roadways without a human driver based on sensor signals generated by multiple sensor systems **104**, **106**, and **108**. The sensor systems **104-108** can include different types of sensors and can be arranged about the AV **102**. For instance, the sensor systems **104-108** can comprise Inertial Measurement Units (IMUs), cameras (e.g., still image cameras, video cameras, etc.), light sensors (e.g., LIDAR systems, ambient light sensors, infrared sensors, etc.), RADAR systems, GPS receivers, audio sensors (e.g., microphones, Sound Navigation and Ranging (SONAR) systems, ultrasonic sensors, etc.), engine sensors, speedometers, tachometers, odometers, altimeters, tilt sensors, impact sensors, airbag sensors, seat occupancy sensors, open/closed door sensors, tire pressure sensors, rain sensors, and so forth. For example, the sensor system **104** can be a camera system, the sensor system **106** can be a LIDAR system, and the sensor system **108** can be a RADAR system. Other embodiments may include any other number and type of sensors.

(17) The AV **102** can also include several mechanical systems that can be used to maneuver or operate the AV **102**. For instance, the mechanical systems can include a vehicle propulsion system **130**, a braking system **132**, a steering system **134**, a safety system **136**, and a cabin system **138**,

among other systems. The vehicle propulsion system **130** can include an electric motor, an internal combustion engine, or both. The braking system **132** can include an engine brake, brake pads, actuators, and/or any other suitable componentry configured to assist in decelerating the AV **102**. The steering system **134** can include suitable componentry configured to control the direction of movement of the AV **102** during navigation. The safety system **136** can include lights and signal indicators, a parking brake, airbags, and so forth. The cabin system **138** can include cabin temperature control systems, in-cabin entertainment systems, and so forth. In some embodiments, the AV **102** might not include human driver actuators (e.g., steering wheel, handbrake, foot brake pedal, foot accelerator pedal, turn signal lever, window wipers, etc.) for controlling the AV **102**. Instead, the cabin system **138** can include one or more client interfaces (e.g., Graphical User Interfaces (GUIs), Voice User Interfaces (VUIs), etc.) for controlling certain aspects of the mechanical systems **130-138**.

(18) The AV **102** can additionally include a local computing device **110** that is in communication with the sensor systems **104-108**, the mechanical systems **130-138**, the data center **150**, and the client computing device **170**, among other systems. The local computing device **110** can include one or more processors and memory, including instructions that can be executed by the one or more processors. The instructions can make up one or more software stacks or components responsible for controlling the AV **102**; communicating with the data center **150**, the client computing device **170**, and other systems; receiving inputs from riders, passengers, and other entities within the AV's environment; logging metrics collected by the sensor systems **104-108**; and so forth. In this example, the local computing device **110** includes a perception stack **112**, a mapping and localization stack **114**, a prediction stack **116**, a planning stack **118**, a communications stack **120**, a control stack **122**, an AV operational database **124**, and an HD geospatial database **126**, among other stacks and systems.

(19) The perception stack **112** can enable the AV **102** to "see" (e.g., via cameras, LIDAR sensors, infrared sensors, etc.), "hear" (e.g., via microphones, ultrasonic sensors, RADAR, etc.), and "feel" (e.g., pressure sensors, force sensors, impact sensors, etc.) its environment using information from the sensor systems **104-108**, the mapping and localization stack **114**, the HD geospatial database **126**, other components of the AV, and other data sources (e.g., the data center **150**, the client computing device **170**, third party data sources, etc.). The perception stack **112** can detect and classify objects and determine their current locations, speeds, directions, and the like. In addition, the perception stack **112** can determine the free space around the AV **102** (e.g., to maintain a safe distance from other objects, change lanes, park the AV, etc.). The perception stack **112** can also identify environmental uncertainties, such as where to look for moving objects, flag areas that may be obscured or blocked from view, and so forth. In some embodiments, an output of the prediction stack can be a bounding area around a perceived object that can be associated with a semantic label that identifies the type of object that is within the bounding area, the kinematic of the object (information about its movement), a tracked path of the object, and a description of the pose of the object (its orientation or heading, etc.).

(20) The mapping and localization stack **114** can determine the AV's position and orientation (pose) using different methods from multiple systems (e.g., GPS, IMUs, cameras, LIDAR, RADAR, ultrasonic sensors, the HD geospatial database **126**, etc.). For example, in some embodiments, the AV **102** can compare sensor data captured in real-time by the sensor systems **104-108** to data in the HD geospatial database **126** to determine its precise (e.g., accurate to the order of a few centimeters or less) position and orientation. The AV **102** can focus its search based on sensor data from one or more first sensor systems (e.g., GPS) by matching sensor data from one or more second sensor systems (e.g., LIDAR). If the mapping and localization information from one system is unavailable, the AV **102** can use mapping and localization information from a redundant system and/or from remote data sources.

(21) The prediction stack **116** can receive information from the localization stack **114** and objects

identified by the perception stack **112** and predict a future path for the objects. In some embodiments, the prediction stack **116** can output several likely paths that an object is predicted to take along with a probability associated with each path. For each predicted path, the prediction stack **116** can also output a range of points along with the path corresponding to a predicted location of the object along the path at future time intervals along with an expected error value for each of the points that indicates a probabilistic deviation from that point.

(22) The planning stack **118** can determine how to maneuver or operate the AV **102** safely and efficiently in its environment. For example, the planning stack **118** can receive the location, speed, and direction of the AV **102**, geospatial data, data regarding objects sharing the road with the AV **102** (e.g., pedestrians, bicycles, vehicles, ambulances, buses, cable cars, trains, traffic lights, lanes, road markings, etc.) or certain events occurring during a trip (e.g., emergency vehicle blaring a siren, intersections, occluded areas, street closures for construction or street repairs, double-parked cars, etc.), traffic rules and other safety standards or practices for the road, user input, and other relevant data for directing the AV **102** from one point to another and outputs from the perception stack **112**, localization stack **114**, and prediction stack **116**. The planning stack **118** can determine multiple sets of one or more mechanical operations that the AV **102** can perform (e.g., go straight at a specified rate of acceleration, including maintaining the same speed or decelerating; turn on the left blinker, decelerate if the AV is above a threshold range for turning, and turn left; turn on the right blinker, accelerate if the AV is stopped or below the threshold range for turning, and turn right; decelerate until completely stopped and reverse; etc.), and select the best one to meet changing road conditions and events. If something unexpected happens, the planning stack **118** can select from multiple backup plans to carry out. For example, while preparing to change lanes to turn right at an intersection, another vehicle may aggressively cut into the destination lane, making the lane change unsafe. The planning stack **118** could have already determined an alternative plan for such an event. Upon its occurrence, it could help direct the AV **102** to go around the block instead of blocking a current lane while waiting for an opening to change lanes.

(23) The control stack **122** can manage the operation of the vehicle propulsion system **130**, the braking system **132**, the steering system **134**, the safety system **136**, and the cabin system **138**. The control stack **122** can receive sensor signals from the sensor systems **104**-**108** as well as communicate with other stacks or components of the local computing device **110** or a remote system (e.g., the data center **150**) to effectuate operation of the AV **102**. For example, the control stack **122** can implement the final path or actions from the multiple paths or actions provided by the planning stack **118**. This can involve turning the routes and decisions from the planning stack **118** into commands for the actuators that control the AV's steering, throttle, brake, and drive unit.

(24) The communications stack **120** can transmit and receive signals between the various stacks and other components of the AV **102** and between the AV **102**, the data center **150**, the client computing device **170**, and other remote systems. The communications stack **120** can enable the local computing device **110** to exchange information remotely over a network, such as through an antenna array or interface that can provide a metropolitan WIFI network connection, a mobile or cellular network connection (e.g., Third Generation (3G), Fourth Generation (4G), Long-Term Evolution (LTE), 5th Generation (5G), etc.), and/or other wireless network connection (e.g., License Assisted Access (LAA), Citizens Broadband Radio Service (CBRS), MULTEFIRE, etc.). The communications stack **120** can also facilitate the local exchange of information, such as through a wired connection (e.g., a user's mobile computing device docked in an in-car docking station or connected via Universal Serial Bus (USB), etc.) or a local wireless connection (e.g., Wireless Local Area Network (WLAN), Bluetooth®, infrared, etc.).

(25) The HD geospatial database **126** can store HD maps and related data of the streets upon which the AV **102** travels. In some embodiments, the HD maps and related data can comprise multiple layers, such as an areas layer, a lanes and boundaries layer, an intersections layer, a traffic controls layer, and so forth. The areas layer can include geospatial information indicating geographic areas

that are drivable (e.g., roads, parking areas, shoulders, etc.) or not drivable (e.g., medians, sidewalks, buildings, etc.), drivable areas that constitute links or connections (e.g., drivable areas that form the same road) versus intersections (e.g., drivable areas where two or more roads intersect), and so on. The lanes and boundaries layer can include geospatial information of road lanes (e.g., lane centerline, lane boundaries, type of lane boundaries, etc.) and related attributes (e.g., the direction of travel, speed limit, lane type, etc.). The lanes and boundaries layer can also include 3D attributes related to lanes (e.g., slope, elevation, curvature, etc.). The intersections layer can include geospatial information of intersections (e.g., crosswalks, stop lines, turning lane centerlines and/or boundaries, etc.) and related attributes (e.g., permissive, protected/permissive, or protected only left-turn lanes; legal or illegal u-turn lanes; permissive or protected only right turn lanes; etc.). The traffic controls lane can include geospatial information of traffic signal lights, traffic signs, and other road objects and related attributes.

(26) The AV operational database **124** can store raw AV data generated by the sensor systems **104**-**108**, stacks **112**-**122**, and other components of the AV **102** and/or data received by the AV **102** from remote systems (e.g., the data center **150**, the client computing device **170**, etc.). In some embodiments, the raw AV data can include HD LIDAR point cloud data, image data, RADAR data, GPS data, and other sensor data that the data center **150** can use for creating or updating AV geospatial data or for creating simulations of situations encountered by AV **102** for future testing or training of various machine-learning algorithms that are incorporated in the local computing device **110**.

(27) The data center **150** can be a private cloud (e.g., an enterprise network, a co-location provider network, etc.), a public cloud (e.g., an Infrastructure as a Service (IaaS) network, a Platform as a Service (PaaS) network, a Software as a Service (SaaS) network, or other Cloud Service Provider (CSP) network), a hybrid cloud, a multi-cloud, and so forth. The data center **150** can include one or more computing devices remote to the local computing device **110** for managing a fleet of AVs and AV-related services. For example, in addition to managing the AV **102**, the data center **150** may also support a ridesharing service, a delivery service, a remote/roadside assistance service, street services (e.g., street mapping, street patrol, street cleaning, street metering, parking reservation, etc.), and the like.

(28) The data center **150** can send and receive various signals to and from the AV **102** and the client computing device **170**. These signals can include sensor data captured by the sensor systems **104**-**108**, roadside assistance requests, software updates, ridesharing pick-up and drop-off instructions, and so forth. In this example, the data center **150** includes a data management platform **152**, an Artificial Intelligence/Machine-learning (AI/ML) platform **154**, a simulation platform **156**, a remote assistance platform **158**, a ridesharing platform **160**, and a LIDAR data analysis platform **162**, among other systems.

(29) The data management platform **152** can be a "big data" system capable of receiving and transmitting data at high velocities (e.g., near real-time or real-time), processing a large variety of data and storing large volumes of data (e.g., terabytes, petabytes, or more of data). The varieties of data can include data having differently structured (e.g., structured, semi-structured, unstructured, etc.), data of different types (e.g., sensor data, mechanical system data, ridesharing service, map data, audio, video, etc.), data associated with different types of data stores (e.g., relational databases, key-value stores, document databases, graph databases, column-family databases, data analytic stores, search engine databases, time-series databases, object stores, file systems, etc.), data originating from different sources (e.g., AVs, enterprise systems, social networks, etc.), data having different rates of change (e.g., batch, streaming, etc.), or data having other heterogeneous characteristics. The various platforms and systems of the data center **150** can access data stored by the data management platform **152** to provide their respective services.

(30) The AI/ML platform **154** can provide the infrastructure for training and evaluating machine-learning algorithms for operating the AV **102**, the simulation platform **156**, the remote assistance

platform **158**, the ridesharing platform **160**, and other platforms and systems. Using the AI/ML platform **154**, data scientists can prepare data sets from the data management platform **152**; select, design, and train machine-learning models; evaluate, refine, and deploy the models; maintain, monitor, and retrain the models; and so on.

(31) The simulation platform **156** can enable testing and validation of the algorithms, machine-learning models, neural networks, and other development efforts for the AV **102**, the remote assistance platform **158**, the ridesharing platform **160**, and other platforms and systems. The simulation platform **156** can replicate a variety of driving environments and/or reproduce real-world scenarios from data captured by the AV **102**, including rendering geospatial information and road infrastructure (e.g., streets, lanes, crosswalks, traffic lights, stop signs, etc.) obtained from a cartography platform; modeling the behavior of other vehicles, bicycles, pedestrians, and other dynamic elements; simulating inclement weather conditions, different traffic scenarios; and so on.

(32) The remote assistance platform **158** can generate and transmit instructions regarding the operation of the AV **102**. For example, in response to an output of the AI/ML platform **154** or other system of the data center **150**, the remote assistance platform **158** can prepare instructions for one or more stacks or other components of the AV **102**.

(33) The ridesharing platform **160** can interact with a customer of a ridesharing service via a ridesharing application **172** executing on the client computing device **170**. The client computing device **170** can be any type of computing system, including a server, desktop computer, laptop, tablet, smartphone, smart wearable device (e.g., smartwatch, smart eyeglasses or other Head-Mounted Display (HMD), smart ear pods, or other smart in-ear, on-ear, or over-ear device, etc.), gaming system, or other general purpose computing device for accessing the ridesharing application **172**. The client computing device **170** can be a customer's mobile computing device or a computing device integrated with the AV **102** (e.g., the local computing device **110**). The ridesharing platform **160** can receive requests to pick up or drop off from the ridesharing application **172** and dispatch the AV **102** for the trip.

(34) The LIDAR data analysis platform **162** may derive a surface absorption property of surface material from LIDAR data. The LIDAR data analysis platform **162** may construct a surface structure by building a plurality of triangles from the cloud points from a LIDAR sensor. The cloud points are characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates. The LIDAR data analysis platform **162** may also determine the normal direction for each of the plurality of triangles. The LIDAR data analysis platform **162** may also derive the surface absorption property of the surface material based upon the intensities, incidence angles, and the normal direction for each of the plurality of triangles.

(35) FIG. **2**A illustrates a LIDAR sensor scanning a real-world object according to some examples of the present technology. As illustrated in FIG. **2**A, incoming light rays **206** from a LIDAR sensor **202** are reflected off a real-world object (e.g., vehicle) **204** at light hitting locations **208** represented by 3D coordinates X, Y, and Z. Outgoing light rays **210** bounced from the vehicle **204** are directed in various directions.

(36) FIG. **2**B illustrates the reflection from the real-world object of FIG. **2**A detected by a LIDAR sensor according to some examples of the present technology. As illustrated, an angle of incidence Φ is the angle between the incoming light ray **206** from the LIDAR sensor **202** and the outgoing light ray **210** reflected off a surface **212** associated with a type of material, e.g., car paint, glass. The intensities reflected off the real-world object received by the LIDAR sensor **202** may vary with the angle of incidence and the surface material of the real-world object. A normal direction **211** is perpendicular to the surface **212** and splits the angle of incidence Φ into half to have an angle θ.

(37) In some variations, Cos θ may vary from 0 to 1 when θ varies from 90° to 0°.

(38) FIG. **2**C illustrates cloud points that are collected from the real-world object of FIG. **2**A according to some examples of the present technology. As an example, the real-world object is selected as a vehicle. Cloud points **214** are the data collected from the LIDAR sensor **202** and can

collectively form a point cloud. The point cloud may be reviewed and a human or an algorithm may label a vehicle as being represented in the point cloud. It can be hard to see that the point cloud includes a vehicle, but a vehicle can be perceived and is illustrated by solid lines **216**.

(39) In some embodiments, a surface of a portion of the vehicle can be reconstructed. The reconstruction may be done by building triangles **218** from three closest cloud points **214**. For example, the cloud points A, B, and C are connected to form triangle **218**. Each triangle **218** has the normal direction **211**, which is perpendicular to triangle **218**. The normal direction **211** is derived from the vectors AB and AC and is a cross-product of vectors AB and AC.

(40) While it can be difficult to visually perceive a vehicle included in a point cloud, the identification of a vehicle within the point cloud can be improved using an understanding of the reflectance properties of the vehicle and more helpfully an understanding of reflection properties of different surfaces of the vehicle. The derived reflectance or surface absorption property from various materials helps reconstruct the vehicle because it may facilitate additional identification of headlights or taillights of vehicle, windows of the vehicle, or vehicle tires or wheels.

(41) It should be noted that while the present technology is described with respect to identifying surface properties of vehicles, that the present technology applies equally to identifying surface properties of any surface in a point cloud.

(42) FIG. **3** illustrates an example method **300** for deriving a surface absorption property of surface material from LIDAR data. Although example method **300** depicts a particular sequence of operations, the sequence may be altered without departing from the scope of the present disclosure. For example, some of the operations depicted may be performed in parallel or in a different sequence that does not materially affect the function of method **300**. In other examples, different components of an example device or system that implements the method **300** may perform functions at substantially the same time or in a specific sequence.

(43) According to some examples, method **300** may include receiving a plurality of cloud points from a LIDAR sensor at block **305**. For example, the data management platform **152** illustrated in FIG. **1** may receive a plurality of cloud points from a LIDAR sensor. The cloud points are characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates. The LIDAR data can originate for data collected by LIDAR sensors on AV **102**.

(44) In some variations, the LIDAR sensor uses infrared light for sensing a scene. The advantage of using infrared light is that the reflection does not change with the color of the objects, regardless of black, white, red, or blue body.

(45) According to some examples, method **300** may include constructing a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points at block **310**. For example, the LIDAR data analysis platform **162** of the data center **150** illustrated in FIG. **1** may construct a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points. Each of the plurality of triangles is a surface segment.

(46) To construct surface segments or triangles, one of the plurality of cloud points may be selected as a starting point cloud. For example, a center coordinate in the point cloud may be considered a starting point, based upon x, y, z coordinates. A triangle can be built by connecting these cloud points based upon the starting cloud point and two nearest neighboring cloud points to the starting cloud point. A normal vector can then be identified from the triangle formed from the cloud points and used to determine the surface absorption property.

(47) In some variations, method **300** may include selecting one of the three neighboring cloud points as a starting point cloud. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may select one of the three neighboring cloud points as a starting point cloud.

(48) In some variations, method **300** may include searching for the closest first and second cloud

points from the starting point cloud within a threshold distance. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may search for the closest first and second cloud points within a threshold distance from the starting cloud point. The threshold distance limits the search of the closest point within a range. If the search fails within the threshold distance, the search may start with a different cloud point.

(49) In some variations, method **300** may include forming the first triangle from the closest first and second cloud points and the starting point. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may form a first triangle from the closest first and second cloud points and the starting point. More triangles can be formed or created this way by connecting the closest cloud points.

(50) According to some examples, method **300** may include determining the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle at block **315**. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may determine the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle. The normal direction affects the intensity reflected from the real-world object back to the LIDAR sensor. For example, if the normal direction is aligned with the incident light signals from the LIDAR sensor, the reflection is higher than any other angle. If the normal direction is close to the surface, the reflection is nearly zero.

(51) In some variation, method **300** may include determining a difference between the normal directions of neighboring triangles. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may determine a difference between the normal directions of neighboring triangles. The difference between the normal directions of neighboring triangles may suggest a curved surface or a flat surface depending upon a large difference or a small difference.

(52) According to some examples, method **300** may include deriving the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangles at block **320**. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may derive the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangle.

(53) In some variations, the deriving the surface absorption property for the respective segment is a product of the average intensity values for the three neighboring cloud points making up the respective triangle and cosine of the angle of incidence to the normal direction for the respective triangle.

(54) If the reflection is a direct reflection from the real-world object, while the intensity is low. This may suggest that the surface material has low reflectance, such as a tire of a vehicle. If the reflection is a direct reflection from the real-world object, while the intensity is high, this may suggest that the surface material has high reflectance, such as a taillight or a headlight.

(55) According to some examples, method **300** may include aggregating the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface at block **325**. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may aggregate the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface.

(56) The surface absorption property may be surface reflectance. Some materials may have high reflectance for light signals, while other materials may have low reflectance for the light signals.

For example, the surface reflectance from different portions of the AV may vary, such as vehicle body, taillights or headlights, windows, or tires, among others.

(57) According to some examples, method **300** may include utilizing the surface absorption property for the type of surface to improve a representation of the type of surface in a simulated environment, whereby intensity values recorded by a simulated LIDAR in the simulated environment are more accurate at block **330**. For example, the simulation platform **156** illustrated in FIG. **1** may utilize the surface absorption property for the type of surface to improve a representation of the type of surface in a simulated environment. The intensity values recorded by a simulated LIDAR in the simulated environment are more accurate due to the consideration of the surface absorption properties or surface reflectance of the surface material.

(58) A human may label the cloud points initially as a vehicle, a pedestrian, or a light pole by a human. The simulation platform further analyzes these cloud points to produce a more realistic representation of the type of surface by adding a surface reflectance modifier.

(59) The surface reflectance modifier may be introduced in simulations. The surface reflectance modifier may vary from 0 to 255. For example, light signals may have very low reflections from tires. The surface reflectance modifier may be assumed as 5 on a scale from 0 to 255. Light signals may have low reflections from car paint and vehicle window and rims. The surface reflectance modifier may be assumed as 50, 80, and 100 for the car paint, window or glass, and rims, respectively, on a scale from 0 to 255. Light signals may have high reflections from headlights or taillights that are retro-reflectors. The surface reflectance modifier may be assumed as 150-200 for the headlights and taillights, on a scale from 0 to 255.

(60) According to some examples, method **300** may include training a machine-learning algorithm to recognize objects using LIDAR cloud points recorded in the simulated environment, whereby the machine-learning algorithm learns to recognize objects in part based on intensity values associated with surface materials making up the objects at block **335**. For example, the AI/ML platform **154** illustrated in FIG. **1** may train a machine-learning algorithm to recognize objects using LIDAR cloud points recorded in the simulated environment. The machine-learning algorithm learns to recognize objects in part based on intensity values associated with surface materials making up the objects.

(61) In some variations, the machine-learning algorithm is trained using a labeled dataset. The labeled dataset includes cloud points with intensity values that are within a labeled bounding box that provides a semantic label identifying the type of object.

(62) For example, the machine-learning algorithm may look at the intensity of the cloud points and determine that the point cloud looks like a bush without the derived material type. However, the machine-learning algorithm may look at both the intensity of the cloud points and the derived material type to determine that the cloud points may be a windshield or a wheel for a vehicle. The derived material type helps identify the object along with the light intensity using the machine-learning algorithm.

(63) Method **300** may also include determining surface curvature based upon the pattern of the normal directions. For example, when a plurality of closest cloud points to a small angle range (e.g., less than 20 degrees angle), the surface is likely flat. When a plurality of closest cloud points to a large angle range (e.g., greater than 20 degrees angle), the surface is likely curved.

(64) In some variations, method **300** may include deriving the surface material based upon the intensity variations with incident angles and the derived attenuation. For example, if the intensity pattern changes steeply with angles, and the derived attenuation is low, it may suggest that the surface material has high reflectance, such as taillight or headlight. If the intensity pattern does not change much with angles, and the derived attenuation is high, it may suggest that the surface material has low reflectance, such as the vehicle body.

(65) FIG. **4**A is a sketch illustrating a curved surface with triangles having large variations in normal directions according to some examples of the present technology. As illustrated in FIG. **4**A,

surface pattern **400**A is constructed from triangles **406**A, which are built from cloud points **404**A. Each triangle **406**A has a normal direction **402**A perpendicular to the triangle. The normal directions **402**A are pointed in various directions, suggesting that surface **400**A is a curved surface.

(66) FIG. **4B** is a sketch illustrating a relatively flat surface with triangles having small variations in normal directions according to some examples of the present technology. As illustrated in FIG. **4B**, surface pattern **400**B is constructed from triangles **406**B, which are built from cloud points **404**B. Each triangle **406**B has a normal direction **402**B perpendicular to the triangle. The normal directions **402**B are pointed down within a narrow range of angles, suggesting that the surface **400**A is relatively flat.

(67) In some variations, method **300** may include concluding that the surface material represented by the neighboring triangles is curved when the difference between the normal directions of the neighboring triangles is greater than 20-degrees. For example, the LIDAR data analysis platform **162** illustrated in FIG. **1** may conclude that the surface material represented by the neighboring triangles is curved when the difference between the normal directions of the neighboring triangles is greater than 20-degrees.

(68) FIG. **5** shows an example of computing system **500**, which can be, for example any computing device making up the local computing system **110**, the client computing device **170**, the computing component in data center **150**, or the components thereof in which the components of the system are in communication with each other using connection **505**. Connection **505** can be a physical connection via a bus, or a direct connection into processor **510**, such as in a chipset architecture. Connection **505** can also be a virtual connection, networked connection, or logical connection.

(69) In some embodiments, computing system **500** is a distributed system in which the functions described in this disclosure can be distributed within a data center, multiple data centers, a peer network, etc. In some embodiments, one or more of the described system components represents many such components each performing some or all of the function for which the component is described. In some embodiments, the components can be physical or virtual devices.

(70) Example system **500** includes at least one processing unit (CPU or processor) **510** and connection **505** that couples various system components including system memory **515**, such as read-only memory (ROM) **520** and random-access memory (RAM) **525** to processor **510**. Computing system **500** can include a cache of high-speed memory **512** connected directly with, in close proximity to, or integrated as part of processor **510**.

(71) Processor **510** can include any general purpose processor and a hardware service or software service, such as services **532**, **534**, and **536** stored in storage device **530**, configured to control processor **510** as well as a special-purpose processor where software instructions are incorporated into the actual processor design. Processor **510** may essentially be a completely self-contained computing system, containing multiple cores or processors, a bus, memory controller, cache, etc. A multi-core processor may be symmetric or asymmetric.

(72) To enable user interaction, computing system **500** includes an input device **545**, which can represent any number of input mechanisms, such as a microphone for speech, a touch-sensitive screen for gesture or graphical input, keyboard, mouse, motion input, speech, etc. Computing system **500** can also include output device **535**, which can be one or more of a number of output mechanisms known to those of skill in the art. In some instances, multimodal systems can enable a user to provide multiple types of input/output to communicate with computing system **500**. Computing system **500** can include communications interface **540**, which can generally govern and manage the user input and system output. There is no restriction on operating on any particular hardware arrangement, and therefore the basic features here may easily be substituted for improved hardware or firmware arrangements as they are developed.

(73) Storage device **530** can be a non-volatile memory device and can be a hard disk or other types of computer-readable media which can store data that are accessible by a computer, such as magnetic cassettes, flash memory cards, solid state memory devices, digital versatile disks,

cartridges, random access memories (RAMs), read-only memory (ROM), and/or some combination of these devices.

(74) The storage device **530** can include software services, servers, services, etc., that when the code that defines such software is executed by the processor **510**, it causes the system to perform a function. In some embodiments, a hardware service that performs a particular function can include the software component stored in a computer-readable medium in connection with the necessary hardware components, such as processor **510**, connection **505**, output device **535**, etc., to carry out the function.

(75) For clarity of explanation, in some instances, the present technology may be presented as including individual functional blocks including functional blocks comprising devices, device components, steps or routines in a method embodied in software, or combinations of hardware and software.

(76) Any of the steps, operations, functions, or processes described herein may be performed or implemented by a combination of hardware and software services or services, alone or in combination with other devices. In some embodiments, a service can be software that resides in memory of a client device and/or one or more servers of a content management system and perform one or more functions when a processor executes the software associated with the service. In some embodiments, a service is a program or a collection of programs that carry out a specific function. In some embodiments, a service can be considered a server. The memory can be a non-transitory computer-readable medium.

(77) In some embodiments, the computer-readable storage devices, mediums, and memories can include a cable or wireless signal containing a bit stream and the like. However, when mentioned, non-transitory computer-readable storage media expressly exclude media such as energy, carrier signals, electromagnetic waves, and signals per se.

(78) Methods according to the above-described examples can be implemented using computer-executable instructions that are stored or otherwise available from computer-readable media. Such instructions can comprise, for example, instructions and data which cause or otherwise configure a general purpose computer, special purpose computer, or special purpose processing device to perform a certain function or group of functions. Portions of computer resources used can be accessible over a network. The executable computer instructions may be, for example, binaries, intermediate format instructions such as assembly language, firmware, or source code. Examples of computer-readable media that may be used to store instructions, information used, and/or information created during methods according to described examples include magnetic or optical disks, solid-state memory devices, flash memory, USB devices provided with non-volatile memory, networked storage devices, and so on.

(79) Devices implementing methods according to these disclosures can comprise hardware, firmware and/or software, and can take any of a variety of form factors. Typical examples of such form factors include servers, laptops, smartphones, small form factor personal computers, personal digital assistants, and so on. The functionality described herein also can be embodied in peripherals or add-in cards. Such functionality can also be implemented on a circuit board among different chips or different processes executing in a single device, by way of further example.

(80) The instructions, media for conveying such instructions, computing resources for executing them, and other structures for supporting such computing resources are means for providing the functions described in these disclosures.

(81) Although a variety of examples and other information was used to explain aspects within the scope of the appended claims, no limitation of the claims should be implied based on particular features or arrangements in such examples, as one of ordinary skill would be able to use these examples to derive a wide variety of implementations. Further and although some subject matter may have been described in language specific to examples of structural features and/or method steps, it is to be understood that the subject matter defined in the appended claims is not necessarily

limited to these described features or acts. For example, such functionality can be distributed differently or performed in components other than those identified herein. Rather, the described features and steps are disclosed as examples of components of systems and methods within the scope of the appended claims.

Claims

1. A method for deriving a surface absorption property of surface material from LIDAR data, the method comprising: receiving a plurality of cloud points from a LIDAR sensor, the cloud points characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates, constructing a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points, wherein each of the plurality of triangles is a surface segment; determining the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle; deriving the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangle; and aggregating the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface.
2. The method of claim 1, wherein the constructing the plurality of surface segments of the surface material by building the plurality of triangles comprises: selecting one of the three neighboring cloud points as a starting point cloud; searching for the closest first and second cloud points from the starting point cloud within a threshold distance; and forming a first triangle from the closest first and second cloud points and the starting point.
3. The method of claim 1, further comprising: determining a difference between the normal directions of neighboring triangles; and concluding that the surface material represented by the neighboring triangles is curved when the difference between the normal directions of the neighboring triangles is greater than 20-degrees.
4. The method of claim 1, wherein the LIDAR sensor uses infrared light for sensing a scene.
5. The method of claim 1, wherein the deriving the surface absorption property for the respective segment is a product of the average intensity values for the three neighboring cloud points making up the respective triangle and cosine of the angle of incidence to the normal direction for the respective triangle.
6. The method of claim 1, further comprising utilizing the surface absorption property for the type of surface to improve a representation of the type of surface in a simulated environment, whereby intensity values recorded by a simulated LIDAR in the simulated environment are more accurate.
7. The method of claim 1, further comprising training a machine-learning algorithm to recognize objects using LIDAR cloud points recorded in the simulated environment, whereby the machine-learning algorithm learns to recognize objects in part based on intensity values associated with surface materials making up the objects.
8. The method of claim 7, wherein the machine-learning algorithm is trained using a labeled dataset, wherein the labeled dataset comprises cloud points with intensity values that are within a labeled bounding box that provides a semantic label identifying the type of object.
9. A computing system comprising: a storage device configured to store instructions; a processor configured to execute the instructions and cause the processor to: receive a plurality of cloud points from a LIDAR sensor, the cloud points characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates,

construct a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points, wherein each of the plurality of triangles is a surface segment, determine the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle, derive the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangle, and aggregate the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface.

10. The computing system of claim 9, wherein the processor is configured to execute the instructions and cause the processor to: select one of the three neighboring cloud points as a starting point cloud; search for the closest first and second cloud points from the starting point cloud within a threshold distance; and form a first triangle from the closest first and second cloud points and the starting point.

11. The computing system of claim 9, wherein the processor is configured to execute the instructions and cause the processor to: determine a difference between the normal directions of neighboring triangles; and conclude that the surface material represented by the neighboring triangles is curved when the difference between the normal directions of the neighboring triangles is greater than 20-degrees.

12. The computing system of claim 9, wherein the deriving the surface absorption property for the respective segment is a product of the average intensity values for the three neighboring cloud points making up the respective triangle and cosine of the angle of incidence to the normal direction for the respective triangle.

13. The computing system of claim 9, wherein the processor is configured to execute the instructions and cause the processor to utilize the surface absorption property for the type of surface to improve a representation of the type of surface in a simulated environment, whereby intensity values recorded by a simulated LIDAR in the simulated environment are more accurate.

14. The computing system of claim 9, wherein the processor is configured to execute the instructions and cause the processor to train a machine-learning algorithm to recognize objects using LIDAR cloud points recorded in the simulated environment, whereby the machine-learning algorithm learns to recognize objects in part based on intensity values associated with surface materials making up the objects.

15. A non-transitory computer-readable storage medium comprising instructions, the instructions, when executed by a computing system, cause the computing system to: receive a plurality of cloud points from a LIDAR sensor, the cloud points characterized by respective intensity values corresponding to reflections off the surface material of a real-world object and respective 3D coordinates; construct a plurality of surface segments of the surface material by building a plurality of triangles from combinations of three neighboring cloud points from among the received plurality of cloud points, wherein each of the plurality of triangles is a surface segment; determine the normal direction for each of the plurality of triangles from the 3D coordinates of each of the cloud points in the combination of three neighboring cloud points making up a respective triangle; derive the surface absorption property for a respective segment of the surface material based upon the average intensity values for the three neighboring cloud points making up a respective triangle, a known angle of incidence received from the LIDAR sensor, and the determined normal direction for each of the respective triangle; and aggregate the derived surface absorption property across a collection of respective triangles making up the surface segments to result in the surface absorption property for a type of surface.

16. The non-transitory computer-readable storage medium of claim 15, wherein the computer-

readable medium further comprises instructions that, when executed by the computing system, cause the computing system to: select one of the three neighboring cloud points as a starting point cloud; search for the closest first and second cloud points from the starting point cloud within a threshold distance; and form a first triangle from the closest first and second cloud points and the starting point.

17. The non-transitory computer-readable storage medium of claim 15, wherein the computer-readable medium further comprises instructions that, when executed by the computing system, cause the computing system to: determine a difference between the normal directions of neighboring triangles; and conclude that the surface material represented by the neighboring triangles is curved when the difference between the normal directions of the neighboring triangles is greater than 20-degrees.

18. The non-transitory computer-readable storage medium of claim 15, the deriving the surface absorption property for the respective segment is a product of the average intensity values for the three neighboring cloud points making up the respective triangle and cosine of the angle of incidence to the normal direction for the respective triangle.

19. The non-transitory computer-readable storage medium of claim 15, wherein the computer-readable medium further comprises instructions that, when executed by the computing system, cause the computing system to utilize the surface absorption property for the type of surface to improve a representation of the type of surface in a simulated environment, whereby intensity values recorded by a simulated LIDAR in the simulated environment are more accurate.

20. The non-transitory computer-readable storage medium of claim 15, wherein the computer-readable medium further comprises instructions that, when executed by the computing system, cause the computing system to train a machine-learning algorithm to recognize objects using LIDAR cloud points recorded in the simulated environment, whereby the machine-learning algorithm learns to recognize objects in part based on intensity values associated with surface materials making up the objects.