POINT CLOUD REGISTRATION METHOD AND APPARATUS, ELECTRONIC DEVICE, AND COMPUTER STORAGE MEDIUM

TECHNICAL FIELD

[0001] Embodiments of the disclosure relate, but are not limited, to the technical field of machine learning, and particularly to a point cloud registration method and apparatus, an electronic device, and a computer storage medium.

BACKGROUND

[0002] A laser radar or a depth camera may be deployed in various types of scenes such as a monitoring scene and a Three-Dimensional (3D) reconstruction scene to collect point cloud data. Point cloud data, as supplementary data of an image, may be used to acquire more real scene information.

[0003] However, point cloud data collected through a laser radar or a depth camera is usually sparse and incomplete. For example, under the condition that an object is occluded by a certain occlusion, point cloud data of an occluded region of the object cannot be collected. For determining the point cloud data of the occluded region of the object, the object is usually required to be collected and scanned from different angles/positions to obtain different incomplete point cloud data. For completing the incomplete point cloud data of the object, how to implement registration between different incomplete point cloud data is a problem urgent to be solved by technicians.

SUMMARY

[0004] The embodiments of the application provide technical solutions to point cloud registration.

[0005] A first aspect provides a point cloud registration method, which may include that: two frames of point cloud data with partially overlapping data points are acquired; for each of the two frames of point cloud data, a first scale feature of each data point of the point cloud data is constructed according to an initial feature of each data point of the point cloud data; sampling processing of at least one hierarchy is performed based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, where multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy; a second scale feature of each data point in each hierarchy is determined based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point; and registration between the two frames of point cloud data is implemented based on a multi-scale feature of each data point in the two frames of point cloud data, the multi-scale feature including the first scale feature and the second scale feature in each hierarchy.

[0006] In some embodiments, the operation that sampling processing of the at least one hierarchy is performed based on the initial feature of each data point of the point cloud data to obtain the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point may include that: the data points in the point cloud data are determined as basic points corresponding to a first hierarchy, and for each data point, the initial feature of the data point is determined as a basic point feature of the basic point corresponding to the data point in the first hierarchy; basic points corresponding to each hierarchy are sampled to obtain sample points corresponding to each hierarchy; and local features of the sample points corresponding to each hierarchy are constructed according to basic point features of the sample points corresponding to each hierarchy, sample points corresponding to the first hierarchy being basic points corresponding to a second hierarchy, and local features of the sample points corresponding to the first hierarchy being basic point features of the basic points corresponding to the second hierarchy.

[0007] In the embodiments of the disclosure, features in two adjacent hierarchies are transmitted, so that sample points corresponding to different hierarchies and corresponding

local features may be obtained in a process of performing sampling processing of the at least one hierarchy, and with the increase of the number of hierarchies, second scale features of obtained sample points may include more feature information in the point cloud data.

[0008] In some embodiments, the operation that the local features of the sample points corresponding to each hierarchy are constructed according to the basic point features of the sample points corresponding to each hierarchy may include that: for each sample point, a neighborhood set of the sample point and basic point features of multiple neighborhood points in the neighborhood set are acquired; position features of the multiple neighborhood points corresponding to the sample point are determined based on position information of the sample point and position information of the multiple neighborhood points corresponding to the sample point; association weights between the sample point and corresponding multiple neighborhood points are determined based on the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point; and the local feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points.

[0009] In the embodiments of the disclosure, the determined second scale feature of each sample point is determined not only based on the basic point feature of each sample point but also based on the basic point features of the corresponding multiple neighborhood points, so that feature information of the second scale feature of each sample point is enriched. In addition, the second scale feature of each sample point is determined based on the association weights between each sample point in the point cloud data and the neighborhood points around, so that the obtained second scale feature of each sample point may be as close as possible to a practical feature of each sample point, the multi-scale feature of each data point with rich details may further be constructed based on the second scale feature of each sample point, and furthermore, the point cloud registration accuracy may be improved.

[0010] In some embodiments, the operation that the association weights between the sample point and the corresponding multiple neighborhood points are determined based on

the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point may include that: linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain a first feature of the sample point and a second feature of each neighborhood point corresponding to the sample point; and the association weights between the sample point and the corresponding multiple neighborhood points are determined based on the position feature of each neighborhood point corresponding to the sample point, the first feature of the sample point, and the second feature of each neighborhood point corresponding to the sample point.

[0011] In the embodiments of the disclosure, linear transformation and/or nonlinear transformation may be performed on the basic point feature of each sample point and the basic point feature of each corresponding neighborhood point to obtain the first feature of each sample point and the second feature of each neighborhood point, the first feature may be feature information extracted from the basic point feature and corresponding to a weight used for linear transformation and/or nonlinear transformation, and furthermore, the determined association weights may represent association degrees between each sample point and the corresponding multiple neighborhood points under different types of features, so that the determined second scale feature of each sample point may be consistent with the practical feature of each sample point.

[0012] In some embodiments, the operation that linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain the first feature of the sample point and the second feature of each corresponding neighborhood point may include that: channel compression processing is performed on the basic point feature of the sample point from a feature channel dimension to obtain the first feature of the sample point, a feature channel number of the first feature of the sample point being smaller than a feature channel number of the basic point feature of the sample point; and channel compression processing is performed on the basic point feature of each neighborhood point corresponding to the sample point from the feature channel dimension to obtain the second feature of each neighborhood point corresponding to the sample point,

for a same neighborhood point, a feature channel number of the second feature of the neighborhood point corresponding to the sample point being smaller than a feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the first feature being the same as the feature channel number of the second feature.

[0013] In the embodiments of the disclosure, channel compression processing is performed on the basic point features of each sample point and each neighborhood point from the feature channel dimension, so that the channel numbers of the first feature of each sample point and the second feature of each neighborhood point are reduced, and furthermore, a calculation burden of a point cloud registration apparatus in subsequent calculation based on the first feature of each sample point and the second feature of each neighborhood point may be reduced.

[0014] In some embodiments, the operation that the local feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points may include that: a fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points; and the fourth feature of the sample point is merged with the basic point feature of the sample point to obtain the local feature of the sample point.

[0015] In the embodiments of the disclosure, a third feature of each neighborhood point is aggregated with the association weights between the sample point and the corresponding multiple neighborhood points, so that extracted features may be enhanced, and furthermore, the determined second scale feature of each sample point may be as close as possible to the practical feature of each data point.

[0016] In some embodiments, the operation that the fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points may include that: for each of the multiple neighborhood points corresponding to the sample point, linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the neighborhood point to obtain a third feature of the neighborhood point corresponding to the sample point;

the third feature of the neighborhood point corresponding to the sample point is merged with the position feature of the neighborhood point corresponding to the sample point to obtain a neighborhood fused feature of the neighborhood point corresponding to the sample point; and the fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point.

[0017] In the embodiments of the disclosure, features lost in channel compression processing may be recovered to ensure that the fourth feature includes more feature information, so that more features of each data point may be mined to ensure that obtained feature information of each data point is richer.

[0018] In some embodiments, the operation that linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the neighborhood point to obtain the third feature of the neighborhood point corresponding to the sample point may include that: channel compression processing is performed on the basic point feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the third feature of the neighborhood point corresponding to the sample point, a feature channel number of the third feature of the neighborhood point corresponding to the sample point being smaller than the feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the third feature being larger than the feature channel number of the second feature.

[0019] In some embodiments, the operation that the fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point may include that: the association weights between the sample point and the corresponding multiple neighborhood points are aggregated with the neighborhood fused feature of each neighborhood point corresponding to the sample point to obtain an associated feature of each neighborhood point corresponding to the sample point; and the fourth feature of the sample point is determined based on the associated feature of each neighborhood point corresponding to the sample

point.

[0020] In some embodiments, the operation that the fourth feature of the sample point is determined based on the associated feature of each neighborhood point corresponding to the sample point may include that: for each neighborhood point corresponding to the sample point, channel expansion processing is performed on the associated feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the fourth feature of the neighborhood point corresponding to the sample point, a feature channel number of the fourth feature of the neighborhood point corresponding to the sample point being larger than a feature channel number of the associated feature of the neighborhood point corresponding to the sample point, and the feature channel number of the fourth feature being the same as a feature channel number of the initial feature.

[0021] In the embodiments of the disclosure, since dimension compression processing is performed on features extracted through a perceptron to reduce the calculation burden of the point cloud data registration apparatus, and dimension compression processing may result in feature loss, channel expansion processing may be performed on each associated feature to recover the features lost in dimension compression processing to ensure that the fourth feature includes more features. Therefore, more features of each data point may be mined to ensure that the obtained features of each data point are richer.

[0022] In some embodiments, the operation that the second scale feature of each data point in each hierarchy is determined based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point may include that: for each data point in the point cloud data, at least one fusion point corresponding to the data point in each hierarchy is determined from among the multiple sample points corresponding to each hierarchy; and the second scale feature of the data point in each hierarchy is determined based on the at least one fused point corresponding to the data point in each hierarchy and a corresponding local feature.

[0023] In some embodiments, the operation that the second scale feature of the data point in each hierarchy is determined based on the at least one fused point corresponding to the data point in each hierarchy and the corresponding local feature may include that: an interpolation weight between the data point and each fused point in each hierarchy is

determined based on position information of the data point and position information of each fused point in each hierarchy; and the second scale feature of the data point in each hierarchy is determined according to the interpolation weight between the data point and each fused point in each hierarchy and the local feature of each fused point in each hierarchy.

[0024] In the embodiments of the disclosure, under the condition that the multiple sample points corresponding to each hierarchy and the local feature corresponding to each sample point in a present hierarchy are obtained, at least one sample point corresponding to each basic point and an interpolation weight corresponding to each sample point may be determined based on a distance relationship between each data point in the point cloud data and at least one sample point, and the second scale feature in the sample point may be transmitted reasonably to each data point in the point cloud data based on the interpolation weight of each sample point and the corresponding local feature to obtain the second scale feature of each data point in the present hierarchy.

[0025] In some embodiments, the operation that the second scale feature of each data point in each hierarchy is determined based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point may include that: at least one fused point that corresponds to each basic point corresponding to the first hierarchy is determined from each sample point corresponding to the first hierarchy; and the second scale feature of each data point corresponding to each hierarchy is determined based on a local feature of each fused point that corresponds to each basic point corresponding to the first hierarchy.

[0026] In some embodiments, the operation that the second scale feature of each basic point corresponding to each hierarchy is determined based on the local feature of each fused point that corresponds to each basic point corresponding to each hierarchy may include that: a second scale feature of each basic point corresponding to the second hierarchy is transmitted to the first hierarchy as a local feature of each sample point corresponding to the first hierarchy.

[0027] In some embodiments, the operation that the second scale feature of each basic point corresponding to each hierarchy is determined based on the local feature of each

fused point that corresponds to each basic point corresponding to each hierarchy may include that: a fusion weight between the basic point and each fused point is determined based on position information of the basic point and position information of each fused point corresponding to the basic point; and the second scale feature of the basic point is determined according to the fusion weight between the basic point and each fused point and the local feature of each fused point.

[0028] In the embodiments of the disclosure, under the condition that the multiple sample points corresponding to each hierarchy and the local feature corresponding to each sample point in the present hierarchy are obtained, the at least one fused point corresponding to each basic point and the fusion weight corresponding to each fused point may be determined based on a distance relationship between each basic point and at least one sample point in the present hierarchy, the second scale feature in the sample point may be transmitted reasonably to another basic point in the present hierarchy based on the fusion weight of each fused point and the corresponding local feature to obtain the second scale feature of the other basic point in the present hierarchy, and meanwhile, the second scale features of the multiple basic points obtained in the second hierarchy are transmitted to the multiple sample points in the first hierarchy to further determine the second scale features of the multiple basic points corresponding to the first hierarchy until second scale features of all data points in the point cloud data are obtained, so that the calculation burden may be reduced, and meanwhile, the second scale features of the sample points including the local features are transmitted reasonably to each data point to improve the data extraction efficiency. In a feature information transmission process, the second scale feature of the data point is obtained by weighting based on a distance between two points, so that rotational invariance is ensured, meanwhile, the reasonability of a feature fusion process is also ensured, and furthermore, the robustness of a point cloud data registration process may be improved indirectly.

[0029] In some embodiments, the operation that registration between the two frames of point cloud data is implemented based on the multi-scale feature of each data point of the point cloud data may include that: for each data point of the point cloud data, the first scale feature of the data point is fused with the second scale feature in each hierarchy to obtain the multi-scale feature of the data point; a relative pose parameter between the two frames

of point cloud data is determined based on the multi-scale feature of each data point in the two frames of point cloud data; and registration between the two frames of point cloud data is implemented based on the relative pose parameter between the two frames of point cloud data.

[0030] In some embodiments, the two frames of point cloud data may include first point cloud data and second point cloud data, and the operation that the relative pose parameter between the two frames of point cloud data is determined based on the multi-scale feature of each data point of the point cloud data may include that: for each data point of the first point cloud data, a feature distance between the data point of the first point cloud data and each data point of the second point cloud data is obtained based on a multi-scale feature of the data point of the first point cloud data and a multi-scale feature of each data point of the second point cloud data; an initial mapping matrix is established based on the feature distances obtained for respective data points of the first point cloud data; normalization processing is performed on the initial mapping matrix to obtain multiple mapping point pairs, normalization processing being configured to neglect outliers in the first point cloud data and the second point cloud data, and the mapping point pair including a first mapping point in the first point cloud data and a second mapping point in a matching relationship with the first mapping point; and the relative pose parameter between the first point cloud and the second point cloud data is determined based on the multiple mapping point pairs.

[0031] In some embodiments, the operation that normalization processing is performed on the initial mapping matrix to obtain the multiple mapping point pairs may include that: an outlier matching row and an outlier matching column are added to the initial mapping matrix to obtain an intermediate mapping matrix; normalization processing is performed on the intermediate mapping matrix to obtain a processed intermediate mapping matrix; the outlier matching row and the outlier matching column are removed from the processed intermediate mapping matrix to obtain a target mapping matrix, the target mapping matrix including a matching confidence between each first mapping point in the first point cloud data and each data point in the second point cloud data; and a second mapping point corresponding to each first mapping point is determined based on the matching confidence between each first mapping point and each data point in the second point cloud data.

[0032] In the embodiments of the disclosure, since the target mapping matrix is obtained after the outliers are removed from the first point cloud data and the second point cloud data, the target mapping matrix only includes a mapping relationship between mapping points, and a point cloud feature matching result with relatively high robustness may be obtained based on the target mapping matrix to further obtain an accurate relative pose parameter.

[0033] In some embodiments, the operation that the second mapping point corresponding to each first mapping point is determined based on the matching confidence between each first mapping point and each data point in the second point cloud data may include that: position information of the second mapping point corresponding to the first mapping point is determined based on the matching confidences between the first mapping point and respective data points in the second point cloud data and position information of respective data points in the second point cloud data.

[0034] In some embodiments, the operation that the relative pose parameter between the first point cloud data and the second point cloud data is determined based on the multiple mapping point pairs may include that: a matrix to be decomposed is established according to the multiple mapping point pairs; and the matrix to be decomposed is decomposed through a Singular Value Decomposition (SVD) algorithm to obtain the relative pose parameter, the relative pose parameter including a translation parameter and a rotation parameter.

[0035] In the embodiments of the disclosure, since the initial mapping matrix is established for the multi-scale feature of each data point in the first point cloud data and the multi-scale feature of each data point in the second point cloud data, in an iterative normalization process of the initial mapping matrix, the mapping point pairs of mutually mapping points in the first point cloud data and the second point cloud data may be determined to further determine the relative pose parameter between the two frames of point cloud data according to the obtained multiple mapping point pairs of the mutually mapping points, and the registration efficiency is improved. In addition, since the outlier matching column and the outlier matching row are added to the initial mapping matrix respectively to obtain the intermediate mapping matrix after the initial mapping matrix is

obtained, multiple mapping point pairs of mutually mapping points in a correct mapping relationship may be obtained in a normalization process of the intermediate mapping matrix by matching the outliers in the two frames of point cloud data to the added outlier matching column and/or outlier matching row and then removing the outlier matching column and the outlier matching row, and the accurate relative pose parameter may be obtained by establishing the target mapping matrix based on the multiple mapping point pairs of the mutually mapping points in the correct mapping relationship, obtained by this method, and parsing the target mapping matrix using the SVD algorithm.

[0036] A second aspect provides a point cloud registration apparatus, which is characterized by including: an acquisition module, configured to acquire two frames of point cloud data with partially overlapping data points; a construction module, configured to construct a first scale feature of each data point of the point cloud data according to an initial feature of each data point of the point cloud data; a sampling module, configured to perform sampling processing of at least one hierarchy based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, where multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy; a determination module, configured to determine a second scale feature of each data point in each hierarchy based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point; and a registration module, configured to implement registration between the two frames of point cloud data based on a multi-scale feature of each data point in the point cloud data, the multi-scale feature including the first scale feature and the second scale feature in each hierarchy.

[0037] A third aspect provides an electronic device, which may include a memory and a processor. The memory may store a computer program capable of running in the processor. The processor may execute the computer program to implement the steps in the method.

[0038] A fourth aspect provides a computer storage medium, which may store one or

more programs. The one or more programs may be executed by one or more processors to implement the steps in the method.

[0039] In the embodiments of the disclosure, in a process of acquiring the features of the data points in each piece of point cloud data, for each data point, not only is the first scale feature with more details constructed, but also sampling processing of the at least one hierarchy is performed on each piece of point cloud data to obtain the sample points capable of representing different sampling scales and the local features corresponding to the sample points and further determine the second scale features of each data point corresponding to different sampling hierarchies. The first scale features and second scale features corresponding to different hierarchies are combined, so that the multi-scale features describing pose information of the point cloud data in the embodiments of the disclosure not only include detailed pose features of the point cloud data but also include pose features of local point clouds of different sampling scales, and using the multi-scale feature, extracted in the embodiments of the disclosure, of each piece of point cloud data may improve the accuracy of the point cloud data registration process.

BRIEF DESCRIPTION OF THE DRAWINGS

[0040] In order to describe the technical solutions of the embodiments of the disclosure more clearly, the drawings required to be used in descriptions about the embodiments or a conventional art will be simply introduced below. It is apparent that the drawings described below are only some embodiments of the disclosure. Other drawings may further be obtained by those of ordinary skill in the art according to these drawings without creative work.

[0041] FIG. 1 is a structure diagram of a monitoring and alerting system according to an embodiment of the disclosure.

[0042] FIG. 2 is an implementation flowchart of a point cloud registration method according to an embodiment of the disclosure.

[0043] FIG. 3 is an implementation flowchart of another point cloud registration

method according to an embodiment of the disclosure.

[0044] FIG. 4 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure.

[0045] FIG. 5 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure.

[0046] FIG. 6 is an implementation flowchart of a point cloud registration method according to another embodiment of the disclosure.

[0047] FIG. 7 is an implementation flowchart of a point cloud registration method according to another embodiment of the disclosure.

[0048] FIG. 8 is an implementation flowchart of a point cloud registration method according to another embodiment of the disclosure.

[0049] FIG. 9 is an implementation flowchart of a point cloud registration method according to another embodiment of the disclosure.

[0050] FIG. 10 is a schematic diagram of a registration effect according to an embodiment of the disclosure.

[0051] FIG. 11 is a schematic diagram of registration effects of different 3D scenes according to an embodiment of the disclosure.

[0052] FIG. 12 is a composition structure diagram of a rotation-invariant point transformer according to an embodiment of the disclosure.

[0053] FIG. 13 is a schematic diagram of hierarchical graphical modeling according to an embodiment of the disclosure.

[0054] FIG. 14 is a composition structure diagram of a Graph Matching Consensus Network (GMCNet) according to an embodiment of the disclosure.

[0055] FIG. 15 is a composition structure diagram of a point cloud registration apparatus according to an embodiment of the disclosure.

[0056] FIG. 16 is a schematic diagram of a hardware entity of an electronic device according to an embodiment of the disclosure.

DETAILED DESCRIPTION

[0057] FIG. 1 is a structure diagram of a monitoring and alerting system according to an embodiment of the disclosure. As shown in FIG. 1, the system 100 may include a point cloud collection component 101, a detection device 102, and a management system 103.

[0058] The point cloud collection component 101 may include one or more laser point cloud scanners. The laser point cloud scanner may be a laser radar or a depth camera.

[0059] The point cloud collection component 101 may be in communication connection with the detection device 102. The detection device 102 may be in communication connection with a server, so that the server may correspondingly control the detection device 102, and the detection device 102 may also use service provided by the server. In some embodiments, the detection device 102 may correspond to only one point cloud collection component 101. In some other implementation modes, the detection device 102 may correspond to multiple point cloud collection components 101. Each point cloud collection component may collect one frame or multiple frames of point cloud data. In some embodiments, the detection device 102 may be arranged in a game place. For example, the detection device 102 may be in communication connection with a server in the game place. In some other implementation modes, the detection device 102 may be arranged at a cloud.

[0060] The detection device 102 may analyze a game table in the game place and a game participant at the game table based on a real-time point cloud collected by the point cloud collection component 101 to determine whether an action of the game participant conforms to a rule or is proper.

[0061] The detection device 102 may be in communication connection with the management system 103. Under the condition that the detection device 102 determines that the action of the game participant is improper, the detection device 102 may send target

alert information to the management system 103 on the game table corresponding to the game participant that does the improper action such that the management system 103 may give an alert corresponding to the target alert information to alert the game participant through the game table.

[0062] In some scenes, the detection device 102 may also be in communication connection with a camera component arranged in the game place to fuse the point cloud and image data for more accurate analysis.

[0063] Point cloud registration is a long-standing problem in computer vision, and is applied to various different tasks, such as tasks of positioning, 3D reconstruction, and six-dimensional pose estimation of objects. In the related art, an iterative closest point method and a variation thereof are usually used for point cloud registration, but registration may be implemented by this method only under limited relative poses. The inventor finds by researches that, if a deep learning method is used, there may be a certain possibility for full-domain point cloud registration. However, a conventional neural network cannot learn rotation-invariant features simply and directly, and completely neglects to learn the rotation-invariant point cloud features. Consequently, the conventional neural network cannot implement full-domain incomplete point cloud registration. The following embodiments will provide a solution to full-domain incomplete point cloud registration based on rotation-invariant features.

[0064] FIG. 2 is an implementation flowchart of a point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 2, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[0065] In S201, two frames of point cloud data with partially overlapping data points are acquired.

[0066] The point cloud registration apparatus may be a calculation module. The calculation module may be an enhanced point cloud feature extraction module. The calculation module may be deployed in a chip, a processor, etc. The chip or the processor may be applied to at least one of the following devices: a mobile phone, a pad, a computer with a wireless transceiver function, a palm computer, a desktop computer, a personal

digital assistant, a portable media phierarchy, an intelligent speaker, a navigation device, a wearable device such as a smart watch, smart glasses and a smart necklace, a pedometer, a digital Television (TV), a Virtual Reality (VR) terminal device, an Augmented Reality (AR) terminal device, a wireless terminal in industrial control, a wireless terminal in self driving, a wireless terminal in remote medical surgery, a wireless terminal in smart grid, a wireless terminal in transportation safety, a wireless terminal in smart city, a wireless terminal in smart home, a vehicle, vehicle-mounted device or vehicle-mounted module in an Internet of vehicles system, etc.

[0067] In some embodiments, each of the two frames of point cloud data may be data collected through a laser radar or a depth camera. In the implementation modes, each piece of point cloud data may be incomplete point cloud data. In some other implementation modes, each piece of point cloud data may be data obtained by transforming the data collected through the laser radar or the depth camera. For example, each piece of point cloud data may be determined based on incomplete point cloud data and rough complete point cloud data obtained by completing the incomplete point cloud data. In the implementation modes, each piece of point cloud data may include the incomplete point cloud data and the rough complete point cloud data.

[0068] The point cloud data may include a large number of data points, and each data point has initial feature information. The point cloud registration apparatus may acquire the initial feature information of each data point and initial feature information of multiple neighboring points of each data point taken as a center point from each piece of point cloud data.

[0069] In an implementation process, the point cloud registration apparatus may acquire at least one batch of point cloud data at one time. Each batch of point cloud data may include multiple data points. Each data point has initial feature information (i.e., multidimensional feature information). A batch of point cloud data may be point cloud data in a 3D image.

[0070] In S202, for each of the two frames of point cloud data, a first scale feature of each data point of the point cloud data is constructed according to an initial feature of each data point of the point cloud data.

[0071] In the embodiment of the disclosure, the initial feature of each frame of point cloud data may include at least one of: 3D coordinate information, an echo count, strength information, a class, Red Green Blue (RGB), a scanning angle, a scanning direction, etc.

[0072] In some embodiments, the initial feature of each data point may be directly determined as the first scale feature of the data point. In some other embodiments, the first scale feature of each data point may be constructed based on the initial feature of each data point and initial features other data points nearby each data point.

[0073] In S203, sampling processing of at least one hierarchy is performed based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, where multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy.

[0074] In some embodiments, at the same time when the first scale feature of each data point is extracted, the local feature corresponding to each data point at a local position of the point cloud data is required to be acquired to describe local distribution conditions of local point clouds of different scales in the point cloud data because the first scale feature is only used to represent a detailed feature for the data point in the point cloud data. Sampling processing of at least one hierarchy may be executed to obtain local features corresponding to at least one sampling scale. Sampling processing of each hierarchy may be configured to sample multiple input data points to obtain multiple sample points corresponding to the present hierarchy, and determine a second scale feature of each sample point based on a feature of each data point in the present hierarchy. Under the condition that the hierarchy number of sampling processing is more than or equal to two, multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are determined as input features for sampling processing of a next hierarchy.

[0075] For example, if input features corresponding to a first hierarchy include totally 50 data points A00, A01, ..., and A49, and an initial feature of each data point, multiple sample points, including totally 10 sample points B00, ..., and B09, and a local feature

corresponding to each sample point may be output. In a process of performing sampling processing of a second hierarchy, the totally 10 sample points B00, ..., and B09 corresponding to the first hierarchy and the local feature corresponding to each sample point may be determined as input features for sampling processing of the second hierarchy.

[0076] In S204, a second scale feature of each data point in each hierarchy is determined based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point.

[0077] In some embodiments, an interpolation weight between each data point and at least one sample point corresponding to each hierarchy is determined based on position information of each data point in the point cloud data and position information of each sample point in the multiple sample points corresponding to each hierarchy. The second scale feature of each data point in each hierarchy is determined according to the interpolation weight between each data point and the at least one sample point corresponding to each hierarchy and the local feature of each sample point in the at least one sample point corresponding to each hierarchy.

[0078] For example, for the multiple sample points corresponding to any hierarchy, after the local feature corresponding to each sample point is determined, for calculating the second scale feature corresponding to each data point, for a target data point in each data point, a distance between the target data point and each sample point is calculated, a difference weight corresponding to each sample point is further calculated based on the distance between the target data point and each sample point, and the second scale feature of the target data point is determined based on a second scale feature of each sample point and the corresponding difference weight.

[0079] In some embodiments, for the target data point in each data point, only difference weights of part of sample points corresponding to a preset number or a preset distance may be acquired based on the position information of the target data point and each sample point, and the second scale feature of the target data point is determined based on second scale features of the part of sample points and the corresponding difference weights.

[0080] In S205, registration between the two frames of point cloud data is implemented based on a multi-scale feature of each data point in the two frames of point cloud data, the multi-scale feature including the first scale feature and the second scale feature in each hierarchy.

[0081] In some embodiments, the first scale feature and second scale feature of each data point in each frame of point cloud data may be fused at first to obtain the multi-scale feature of each data point. Weighted summation may be performed on the first scale feature and at least one second scale feature based on a preset feature weight to obtain the multi-scale feature of each data point. Alternatively, the first scale feature may be stitched with the at least one second scale feature based on a channel dimension to obtain the multi-scale feature. Alternatively, the first scale feature and the at least one second scale feature may be weighted at first based on the preset feature weight, and then the weighted first scale feature and at least one second scale feature are stitched to obtain the multi-scale feature.

[0082] In the embodiment of the disclosure, in a process of acquiring the features of the data points in each piece of point cloud data, for each data point, not only is the first scale feature with more details constructed, but also sampling processing of the at least one hierarchy is performed on each piece of point cloud data to obtain the sample points capable of representing different sampling scales and the local features corresponding to the sample points and further determine the second scale features of each data point corresponding to different sampling hierarchies. The first scale features and second scale features corresponding to different hierarchies are combined, so that the multi-scale features describing pose information of the point cloud data in the embodiment of the disclosure not only include detailed pose features of the point cloud data but also include pose features of local point clouds of different sampling scales, and using the multi-scale feature, extracted in the embodiment of the disclosure, of each piece of point cloud data may improve the accuracy of the point cloud data registration process.

[0083] FIG. 3 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 3, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[0084] In S301, the data points in the point cloud data are determined as basic points corresponding to a first hierarchy, and for each data point, the initial feature of the data point is determined as a basic point feature of the basic point corresponding to the data point in the first hierarchy.

[0085] In some embodiments, for any frame of point cloud data, in a process of performing first sampling processing, all the data points in the point cloud data are required to be determined as multiple basic points corresponding to the first hierarchy, and the initial feature corresponding to each data point is determined as a basic point feature of the corresponding basic point.

[0086] In S302, basic points corresponding to each hierarchy are sampled to obtain sample points corresponding to each hierarchy.

[0087] In some embodiments, for each hierarchy, multiple basic points corresponding to the hierarchy are required to be sampled, namely multiple sample points corresponding to the hierarchy are determined from multiple data points corresponding to the hierarchy. For any hierarchy, the multiple sample points corresponding to the hierarchy may be configured to represent an overall distribution feature of the multiple basic points corresponding to the hierarchy. It is to be noted that, in a process of performing sampling processing of the at least one hierarchy, with the increase of the number of hierarchies, a larger hierarchy number may correspond to fewer basic points. In general, basic points corresponding to a relatively low hierarchy may be configured to represent detailed distribution information of the point cloud data, and basic points corresponding to a relatively high hierarchy may be configured to represent global distribution information of the point cloud data.

[0088] In some embodiments, the multiple basic points may be sampled to obtain the multiple sample points using Farthest Point Sampling (FPS). For example, it is assumed that there are totally n basic points, and the n basic points form a point set $Q=(f_1, f_2, ..., f_n)$. At first, a basic point f_i is randomly selected as a starting point, and is written in a starting point set $B=(f_i)$. Then, distances between the left n-1 basic points and the point f_i are calculated respectively, and the farthest point fj is selected and written in the starting point set $B=(f_i, f_j)$. Distances between the left n-2 basic points and each point in the point set B

are calculated. Based on the distances, corresponding to a single basic point, with fi and fj, the minimum distance is determined as a distance between the basic point and the point set. As such, n-2 distances to the point set are obtained. The basic point corresponding to the maximum distance (i.e., the basic point farthest from the point set) is written in the starting point $B=(f_i, f_j, f_k)$

[0089] In S303, local features of the sample points corresponding to each hierarchy are constructed according to basic point features of the sample points corresponding to each hierarchy, sample points corresponding to the first hierarchy being basic points corresponding to a second hierarchy, and local features of the sample points corresponding to the first hierarchy being basic point features of the basic points corresponding to the second hierarchy.

[0090] In some embodiments, in the process of performing sampling processing of each hierarchy, the multiple basic points in the hierarchy are sampled to obtain the multiple sample points at first (the number of the sample points is smaller than the number of the basic points), and then the local feature of each sample point in the multiple sample points is obtained based on the basic point feature of each basic point in the multiple basic points. After a local feature of each sample point in multiple sample points corresponding to the first hierarchy is obtained, if sampling processing of a next hierarchy is required to be performed, for the next hierarchy of the first hierarchy, i.e., the second hierarchy, multiple basic points corresponding to the second hierarchy are the multiple sample points obtained in the first hierarchy, and correspondingly, a basic point of each basic point in the second hierarchy is the local feature of the sample point corresponding to the basic point in the first hierarchy. By analogy, a processing of performing sampling processing of a third hierarchy based on the second hierarchy may refer to the process of performing sampling processing of the second hierarchy based on the first hierarchy, and will not be elaborated herein.

[0091] In the embodiment of the disclosure, features in two adjacent hierarchies are transmitted, so that sample points corresponding to different hierarchies and corresponding local features may be obtained in a process of performing sampling processing of the at least one hierarchy, and with the increase of the number of the hierarchies, local features

of obtained sample points may include more pose feature information in the point cloud data.

[0092] FIG. 4 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 4, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[0093] In S401, for each sample point, a neighborhood set of the sample point and basic point features of multiple neighborhood points in the neighborhood set are acquired.

[0094] In some embodiments, for each frame of point cloud data, in the process of performing sampling processing of any hierarchy, the following operation is required to be executed on each sample point in the multiple sample points corresponding to the hierarchy: a neighborhood set corresponding to each sample point is determined based on a K Nearest Neighboring (KNN) algorithm, each neighborhood set including K neighborhood points of the corresponding sample point. It is to be noted that, in a process of executing the KNN algorithm to acquire the neighborhood set of each sample point, for a single sample point, K basic points are required to be selected from the multiple basic points corresponding to the present hierarchy as the K neighborhood points of the sample point. Each sample point may correspond to the same number of neighborhood points. The number of the neighborhood points corresponding to each sample point may be at least two. For example, the number of the neighborhood points corresponding to each sample point may be 2, 3, 5, 10, etc.

[0095] In S402, position features of the multiple neighborhood points corresponding to the sample point are determined based on position information of the sample point and position information of the multiple neighborhood points corresponding to the sample point.

[0096] In some embodiments, for any sample point, the position information of the multiple neighborhood points corresponding to the sample point is acquired, and the position features of the multiple neighborhood points corresponding to the sample point are generated based on a positional relationship between the sample point and each

neighborhood point corresponding to the sample point. For example, the position feature is related to a position distance between the sample point and each neighborhood point. The position distance is used as the position feature, which, compared with using a position vector, has the advantage that an influence of the position vector on a distribution feature of a point cloud when a pose of the point cloud changes may be eliminated. That is, the position feature provided in the embodiment of the disclosure may ensure rotation invariance of the obtained point cloud feature.

[0097] In S403, association weights between the sample point and corresponding multiple neighborhood points are determined based on the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point.

[0098] It is to be noted that the corresponding multiple neighborhood points in the embodiment of the disclosure may refer to the multiple neighborhood points corresponding to the sample point, unless otherwise stated. In an implementation process, for a single sample point, if the sample point corresponds to K neighborhood points, the association weight may include K association weights, and each association weight in the K association weights may represent an association degree between the sample point and each neighborhood point. Each association weight may be represented by a feature vector. A dimension of each association weight may be the same as or different from a dimension of the basic point feature of the sample point.

[0099] In S404, the local feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points.

[00100] In some embodiments, the point cloud registration apparatus may determine the local feature of each sample point based on the basic point feature and association weight of each neighborhood point in the corresponding multiple neighborhood points (corresponding to each sample point). In some other implementation modes, the point cloud registration apparatus may determine the local feature of each sample point based on the basic point feature and association weight of each sample point. In some other implementation modes, the point cloud registration apparatus may determine the local

feature of each sample point based on the basic point feature of each sample point and the basic point feature and association weight of each neighborhood point in the corresponding multiple neighborhood points.

[00101] In the embodiment of the disclosure, the determined local feature of each sample point is determined not only based on the basic point feature of each sample point but also based on the basic point features of the corresponding multiple neighborhood points, so that feature information of the local feature of each sample point is enriched. In addition, the local feature of each sample point is determined based on the association weights between each sample point in the point cloud data and the neighborhood points around, so that the obtained local feature of each sample point may be as close as possible to a practical feature of each sample point, the multi-scale feature of each data point with rich details may further be constructed based on the local feature of each sample point, and furthermore, the point cloud registration accuracy may be improved.

[00102] FIG. 5 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 5, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[00103] In S501, linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain a first feature of the sample point and a second feature of each neighborhood point corresponding to the sample point.

[00104] In the embodiment of the disclosure, performing linear transformation and/or nonlinear transformation on any basic point feature may refer to performing linear transformation on the basic point feature, or performing nonlinear transformation on the basic point feature, or performing linear transformation and then nonlinear transformation on the basic point feature, or performing nonlinear transformation and then linear transformation on the basic point feature, etc.

[00105] In some embodiments, S501 may be implemented in the following manner: for each sample point, the basic point feature of the sample point is input to a first perceptron

to obtain the first feature of the sample point; and for each neighborhood point, the basic point feature of the neighborhood point is input to a second perceptron to obtain the second feature of the neighborhood point. In the embodiment of the disclosure, a dimension of the first feature of the sample point is the same as a dimension of the second feature of the neighborhood point corresponding to the sample point.

[00106] In some other embodiments, S501 may be implemented in the following manner: for each sample point, channel compression processing is performed on the basic point feature of the sample point to obtain the first feature of the sample point; and for each neighborhood point, channel compression processing is performed on the basic point feature of the neighborhood point to obtain the second feature of the neighborhood point.

[00107] In some other implementation modes, S501 may be implemented through following S5011 to S5012.

[00108] In S5011, channel compression processing is performed on the basic point feature of the sample point from a feature channel dimension to obtain the first feature of the sample point, a feature channel number of the first feature of the sample point being smaller than a feature channel number of the basic point feature of the sample point.

[00109] In S5012, channel compression processing is performed on the basic point feature of each neighborhood point corresponding to the sample point from the feature channel dimension to obtain the second feature of each neighborhood point corresponding to the sample point, for a same neighborhood point, a feature channel number of the second feature of the neighborhood point corresponding to the sample point being smaller than a feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the first feature being the same as the feature channel number of the second feature.

[00110] In some embodiments, the operation that channel compression processing is performed on the basic point feature of the sample point may include that: the basic point feature of the sample point is input to the first perceptron, and channel compression processing is performed on the basic point feature of the sample point through a weight in the first perceptron to obtain the first feature. The operation that channel compression

processing is performed on a basic point feature of a first neighborhood point may include that: the basic point feature of the first neighborhood point is input to the second perceptron, and channel compression processing is performed on the basic point feature of the first neighborhood point through a weight in the second perceptron to obtain a second feature.

[00111] In the embodiment of the disclosure, any perceptron (including the first perceptron, the second perceptron, a third perceptron, a fourth perceptron, etc.) may be a Multilayer Perceptron (MLP). The MLP may be a shared MLP. The MLP is a feedforward artificial neural network, and maps a group of input vectors to a group of output vectors.

[00112] Channel compression processing over any basic point feature may be one of linear transformations over the basic point feature. For example, in some feasible implementation modes, channel compression processing may be performed on any basic point feature through a 1×1 convolutional layer.

[00113] In some embodiments, the dimension of the basic point feature may be C, and under the actions of the first perceptron and the second perceptron, the dimension of the obtained second feature may be C/r1. C/r1 may be smaller than C. In some embodiments, r1 may be an integer more than or equal to 2. For example, a value of r1 may be 2, 3, 5, 8, etc.

[00114] In the abovementioned manner, channel compression processing is performed on the basic point features of each sample point and each neighborhood point from the feature channel dimension, so that the channel numbers of the first feature of each sample point and the second feature of each neighborhood point are reduced, and furthermore, a calculation burden of a point cloud registration apparatus in subsequent calculation based on the first feature of each sample point and the second feature of each neighborhood point may be reduced.

[00115] In S502, the association weights between the sample point and the corresponding multiple neighborhood points are determined based on the position feature of each neighborhood point corresponding to the sample point, the first feature of the sample point, and the second feature of each neighborhood point corresponding to the sample point.

[00116] In some embodiments, the point cloud registration apparatus may perform an interactive operation (for example, a concatenation operation and/or a point multiplication operation) on the first feature of each sample point and the second feature of each neighborhood point to determine an association degree between each sample point and each neighborhood point in a neighborhood data point distribution dimension. Meanwhile, the position feature of each neighborhood point corresponding to the sample point is combined to determine an association degree between each sample point and each neighborhood point is determined in a dimension of the distance between the neighborhood data point and the sample point. Finally, the association degree in the neighborhood data point distribution dimension and the association degree in the dimension of the distance of the neighborhood data point are combined to obtain the association weight. The association weight may represent an association degree between each sample point and each neighborhood point.

[00117] Based on a P-dimensional first feature of a sample point and a P-dimensional second feature of each neighborhood point, the point cloud registration apparatus may determine a P-dimensional association degree between the sample point and each neighborhood point in the neighborhood data point distribution dimension, thereby obtaining association weights between the sample point and corresponding multiple neighborhood points. In the same implementation manner, association weights between each sample point in the multiple sample points and corresponding multiple neighborhood points may be obtained. It is to be noted that any implementation mode of determining an association degree between two feature vectors through the two feature vectors shall fall within the scope of protection of the disclosure.

[00118] In the embodiment of the disclosure, linear transformation and/or nonlinear transformation may be performed on the basic point feature of the sample point and the basic point feature of each corresponding neighborhood point to obtain the first feature of the sample point and the second feature of each neighborhood point, the first feature may be feature information extracted from the basic point feature and corresponding to a weight used for linear transformation and/or nonlinear transformation, and furthermore, the determined association weights may represent association degrees between the sample point and the corresponding multiple neighborhood points under different types of features,

so that the determined second scale feature of the sample point may be consistent with the practical feature of the sample point. In the same implementation manner, it may be ensured that the obtained second scale feature of each sample point in the multiple sample points may be consistent with the practical feature of the sample point.

[00119] FIG. 6 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 6, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[00120] In S601, a fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points.

[00121] In some embodiments, S601 may be implemented through S6011 to S6013.

[00122] In S6011, for each of the multiple neighborhood points corresponding to the sample point, linear transformation and/or nonlinear transformation are/is performed on the basic point feature of the neighborhood point to obtain a third feature of the neighborhood point corresponding to the sample point.

[00123] Channel compression processing is performed on the basic point feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the third feature of the neighborhood point corresponding to the sample point. A feature channel number of the third feature of the neighborhood point corresponding to the sample point is smaller than the feature channel number of the basic point feature of the neighborhood point corresponding to the sample point. The feature channel number of the third feature is larger than the feature channel number of the second feature.

[00124] In some embodiments, the operation that channel compression processing is performed on the basic point feature of each first neighborhood point may include that: the basic point feature of each first neighborhood point is input to the third perceptron, and channel compression processing is performed on the basic point feature of each first neighborhood point through a weight in the third perceptron.

[00125] In some embodiments, the dimension of the basic point feature of each neighborhood point may be C, and under the action of the third perceptron, a dimension of the obtained third feature may be C/r2. C/r2 may be smaller than C. In some embodiments, r2 may be an integer more than or equal to 2. For example, a value of r2 may be 2, 3, 5, 8, etc.

[00126] In some embodiments, r1 and r2 are in a multiple relationship. Furthermore, in some embodiments, the feature channel number of the third feature is larger than the feature channel number of the second feature, namely C/r2 is larger than C/r1. In some embodiments, the feature channel number of the second feature is larger than the feature channel number of the third feature, namely C/r1 is larger than C/r2.

[00127] In S6012, the third feature of the neighborhood point corresponding to the sample point is merged with the position feature of the neighborhood point corresponding to the sample point to obtain a neighborhood fused feature of the neighborhood point corresponding to the sample point.

[00128] In some embodiments, the third feature of each neighborhood point may be merged with the position feature of each neighborhood point by element-wise summation to obtain the neighborhood fused feature of each neighborhood point.

[00129] In S6013, the fourth feature of the sample point is determined based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point.

[00130] In some embodiments, S6013 may be implemented in the following manner: the association weights between the sample point and the corresponding multiple neighborhood points are aggregated with the neighborhood fused feature of each neighborhood point corresponding to the sample point to obtain an associated feature of each neighborhood point corresponding to the sample point; and the fourth feature of the sample point is determined based on the associated feature of each neighborhood point corresponding to the sample point.

[00131] In some implementation modes, for each neighborhood point, under the

condition that a dimension of the neighborhood fused feature of the neighborhood point is N times a dimension of the association weight, the associated feature of the neighborhood point is determined based on the neighborhood fused feature of the neighborhood point and N association weights, N being an integer more than or equal to 1.

[00132] For example, under the condition that the dimension of the neighborhood fused feature of each neighborhood point is C/r2, the dimension of the association weight between each data point and each neighborhood point is C/r1, and C/r2 is N times C/r1, the C/r1-dimensional association weight may be duplicated for N times to obtain a C/r2-dimensional association weight. Then, each element in the C/r2-dimensional neighborhood fused feature is correspondingly multiplied by each element in the C/r2-dimensional association weight to obtain a C/r2-dimensional associated feature of each neighborhood point.

[00133] In some other implementation modes, under the condition that the dimension of the association weight is M times the dimension of the neighborhood fused feature, the associated feature of each neighborhood point is determined based on the association weight and M neighborhood fused features of each neighborhood point, M being an integer more than or equal to 1.

[00134] For example, under the condition that the dimension of the neighborhood fused feature of each neighborhood point is C/r2, the dimension of the association weight between each data point and each neighborhood point is C/r1, and C/r1 is M times C/r2, the C/r2-dimensional neighborhood fused feature of each neighborhood point may be duplicated for M times to obtain a C/r1-dimensional neighborhood fused feature of each neighborhood point. Then, each element in the C/r1-dimensional neighborhood fused feature of each neighborhood point is correspondingly multiplied by each element in the C/r1-dimensional association weight to obtain a C/r1-dimensional associated feature.

[00135] For each neighborhood point corresponding to the sample point, channel expansion processing is performed on the associated feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the fourth feature of the neighborhood point corresponding to the sample point. A feature channel number of the fourth feature of the neighborhood point corresponding to the sample point

is larger than a feature channel number of the associated feature of the neighborhood point corresponding to the sample point. The feature channel number of the fourth feature is the same as a feature channel number of the initial feature.

[00136] In some embodiments, the operation that channel expansion processing is performed on the associated feature of each neighborhood point corresponding to the sample point from the feature channel dimension may include that: the associated feature of each neighborhood point is input to the fourth perceptron, and channel expansion processing is performed on the associated feature of each neighborhood point through a weight in the fourth perceptron.

[00137] For example, under the condition that the dimension of the obtained associated feature of each neighborhood point is C/r2, channel expansion processing may be performed by r2 times to obtain a C-dimensional fourth feature. Under the condition that the dimension of the obtained associated feature of each neighborhood point is C/r1, channel expansion processing may be performed by r1 times to obtain a C-dimensional fourth feature. That is, channel expansion processing is configured to obtain the fourth feature of which the feature channel number is the same as that of the initial feature.

[00138] Through the method, features lost in channel compression processing may be recovered to ensure that the fourth feature includes more feature information, so that more features of each data point may be mined to ensure that obtained feature information of each data point is richer.

[00139] In S602, the fourth feature of the sample point is merged with the basic point feature of the sample point to obtain the local feature of the sample point.

[00140] In some implementation modes, merging the fourth feature of the sample point and the basic point feature of the sample point may refer to performing element-wise summation on the fourth feature of each sample point and the basic point feature of each sample point.

[00141] In this manner, since dimension compression processing is performed on features extracted through a perceptron to reduce the calculation burden of the point cloud data registration apparatus, and dimension compression processing may result in feature

loss, channel expansion processing may be performed on each associated feature to recover the features lost in dimension compression processing to ensure that the fourth feature includes more features. Therefore, more features of each data point may be mined to ensure that the obtained features of each data point are richer.

[00142] In the embodiment of the disclosure, a third feature of each neighborhood point is aggregated with the association weights between the sample point and the corresponding multiple neighborhood points, so that extracted features may be enhanced, and furthermore, the determined local feature of each sample point may be as close as possible to the practical feature of each data point.

[00143] FIG. 7 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 7, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[00144] In S701, for each data point in the point cloud data, at least one fused point corresponding to the data point in each hierarchy is determined from among the multiple sample points corresponding to each hierarchy.

[00145] For each data point, K sample points in the multiple sample points corresponding to each hierarchy may be determined as the at least one fused point corresponding to the data point using the KNN algorithm. It is to be noted that a local feature of the fused point is the same as the local feature of the corresponding sample point.

[00146] In S702, the second scale feature of the data point in each hierarchy is determined based on the at least one fused point corresponding to the data point in each hierarchy and the corresponding local feature.

[00147] S702 may be implemented through S7021 to S7022.

[00148] In S7021, an interpolation weight between the data point and each fused point in each hierarchy is determined based on position information of the data point and position information of each fused point in each hierarchy.

[00149] In S7022, the second scale feature of the data point in each hierarchy is determined according to the interpolation weight between the data point and each fused point in each hierarchy and the local feature of each fused point in each hierarchy.

[00150] For example, for the multiple sample points corresponding to any hierarchy, after the local feature corresponding to each sample point is determined, for calculating the second scale feature corresponding to each data point, for a target data point in each data point, a distance between the target data point and each sample point is calculated, a difference weight corresponding to each sample point is further calculated based on the distance between the target data point and each sample point, and the local feature of the target data point is determined based on a second scale feature of each sample point and the corresponding difference weight.

[00151] In some embodiments, for the target data point in each data point, only difference weights of part of sample points corresponding to a preset number or a preset distance may be acquired based on the position information of the target data point and each sample point, and the second scale feature of the target data point is determined based on local features of the part of sample points and the corresponding difference weights.

[00152] In the embodiment of the disclosure, under the condition that the multiple sample points corresponding to each hierarchy and the local feature corresponding to each sample point in a present hierarchy are obtained, at least one sample point corresponding to each basic point and an interpolation weight corresponding to each sample point may be determined based on a distance relationship between each data point in the point cloud data and at least one sample point, and the second scale feature in the sample point may be transmitted reasonably to each data point in the point cloud data based on the interpolation weight of each sample point and the corresponding local feature to obtain the second scale feature of each data point in the present hierarchy.

[00153] FIG. 8 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 8, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[00154] In some embodiments, for any frame of point cloud data, after the sample points corresponding to each hierarchy and the local feature corresponding to each sample point are obtained, since the at least one sample point corresponding to each hierarchy may be partial point cloud data in the point cloud data, for obtaining features of all data points corresponding to each hierarchy, the features of all the data points corresponding to each hierarchy are required to be obtained based on the local feature of each sample point in each hierarchy.

[00155] In some embodiments, since the multiple sample points corresponding to each hierarchy are obtained from multiple basic points corresponding to the hierarchy, for the basic points corresponding to the sample points in each hierarchy, the local features corresponding to the sample points may be directly determined as second scale features of the basic points. Therefore, only second scale features of the other basic points that are not sample points in the multiple basic points are required to be determined.

[00156] In some other embodiments, the second scale feature of each basic point in each hierarchy is required to be redetermined.

[00157] The second scale feature of each basic point may be determined through S801 to S802.

[00158] In S801, at least one fused point that corresponds to each basic point corresponding to the first hierarchy is determined from each sample point corresponding to the first hierarchy.

[00159] In some embodiments, after the multiple sample points corresponding to the first hierarchy and the local feature corresponding to each sample point are obtained, the at least one fused point corresponding to each basic point may be determined from the multiple sample points corresponding to the first hierarchy based on the position information of each sample point and the position information of each basic point corresponding to the first hierarchy. At least one sample point corresponding to any basic point is determined from the multiple sample points as at least one fused point corresponding to the basic point using the KNN algorithm.

[00160] For example, if the first hierarchy corresponds to totally 50 basic points A00,

A01, ..., and A49 and totally 10 sample points B00, ..., and B09. In sampling processing process, one sample point corresponds to multiple basic points. That is, one sample point is determined based on multiple basic points. For example, sample point B01 may be determined based on totally 8 basic points A00 to A06. In S801, multiple sample points corresponding to each basic point are required to be determined from the multiple sample points based on the position information of each sample point and each basic point. For example, for basic point A00, at least one sample point nearby the basic point is required to be determined as at least one fused point corresponding to A00. Under the condition that totally three sample points B00 to B02 around A00 are acquired based on a preset acquisition method, B00 to B02 are determined as fused points that correspond to A00.

[00161] It is to be noted that, under the condition that the position information of the basic point is the same as the position information of the sample point, the local feature of the sample point may be directly determined as the local feature of the basic point, and at least one fused point of the sample point is not required to be determined.

[00162] The multiple basic points corresponding to the hierarchy are the multiple sample points corresponding to a previous hierarchy, and so on. When sampling processing is performed, all the data points in the point cloud data are determined as basic points, and all the data points are sampled to obtain the multiple sample points corresponding to the first hierarchy. Therefore, the sample points corresponding to each hierarchy are a point cloud.

[00163] In S802, the second scale feature of each data point corresponding to each hierarchy is determined based on a local feature of each fused point that corresponds to each basic point corresponding to the first hierarchy.

[00164] In some embodiments, for any basic point, weighted summation may be directly performed on the local feature of each fused point corresponding to the basic point to obtain the second scale feature corresponding to the basic point.

[00165] In some embodiments, the second scale feature of each basic point corresponding to the second hierarchy is transmitted to the first hierarchy as the local feature of each sample point corresponding to the first hierarchy.

[00166] In some embodiments, S802 may further be implemented through S8021 to S8022.

[00167] In S8021, a fusion weight between the basic point and each fused point is determined based on position information of the basic point and position information of each fused point corresponding to the basic point.

[00168] The fusion weight between the basic point and each fused point is inversely proportional to a distance between the basic point and the fused point. That is, if a basic point corresponds to multiple fused points, including a first fused point and a second fusion, a distance between the first fused point and the basic point being longer than a distance between the second fused point and the basic point, a fusion weight between the first fused point and the basic point is less than a fusion weight between the second fused point and the basic point. In the abovementioned manner, the second scale feature of the basic point may be affected less by the fused point farer away from the basic point, and the second scale feature of the basic point may be affected more by the fused point closer to the basic point.

[00169] In S8022, the second scale feature of the basic point is determined according to the fusion weight between the basic point and each fused point and the local feature of each fused point.

[00170] In the embodiment of the disclosure, under the condition that the multiple sample points corresponding to each hierarchy and the local feature corresponding to each sample point in the present hierarchy are obtained, the at least one fused point corresponding to each basic point and the fusion weight corresponding to each fused point may be determined based on a distance relationship between each basic point and at least one sample point in the present hierarchy, the second scale feature in the sample point may be transmitted reasonably to another basic point in the present hierarchy based on the fusion weight of each fused point and the corresponding local feature to obtain the second scale feature of the other basic point in the present hierarchy, and meanwhile, the second scale features of the multiple basic points obtained in the second hierarchy are transmitted to the multiple sample points in the first hierarchy to further determine the second scale features of the multiple basic points corresponding to the first hierarchy until second scale

features of all data points in the point cloud data are obtained, so that the calculation burden may be reduced, and meanwhile, the second scale features of the sample points including the local features are transmitted reasonably to each data point to improve the data extraction efficiency. In a feature information transmission process, the second scale feature of the data point is obtained by weighting based on a distance between two points, so that rotational invariance is ensured, meanwhile, the reasonability of a feature fusion process is also ensured, and furthermore, the robustness of a point cloud data registration process may be improved indirectly.

[00171] FIG. 9 is an implementation flowchart of another point cloud registration method according to an embodiment of the disclosure. As shown in FIG. 9, the method is applied to a point cloud registration apparatus. The method includes the following operations.

[00172] In S901, for each data point of the point cloud data, the first scale feature of the data point is fused with the second scale feature in each hierarchy to obtain the multi-scale feature of the data point.

[00173] In some embodiments, the two frames of point cloud data include first point cloud data and second point cloud data. For multiple data points in the first point cloud data, a first scale feature and second scale feature of each data point may be merged to obtain a multi-scale feature of each data point in the first point cloud data. Since the first scale feature and each second scale feature represent point cloud distributions corresponding to the data point in different sampling hierarchies, the feature fusion operation may be completed in a feature stitching manner to retain point cloud distribution features of the point cloud data in multiple sampling hierarchies.

[00174] For example, if a first scale feature of a target data point is a feature vector with N1 channels, and a second scale feature of the target data point in at least one hierarchy includes a feature vector with N2 channels and a feature vector with N3 channels, after the first scale feature of the target data point is fused with the second scale feature corresponding to each hierarchy, a multi-scale feature with (N1+N2+N3) channels may be obtained.

[00175] In S902, a relative pose parameter between the two frames of point cloud data is determined based on the multi-scale feature of each data point in the two frames of point cloud data.

[00176] A matrix may be established for a feature similarity between the multi-scale feature of each data point in the first point cloud data and a multi-scale feature of each data point in the second point cloud data, and the matrix is iteratively decomposed to obtain a relative pose parameter between the first point cloud data and the second point cloud data. It is to be noted that the feature similarity may be determined by a feature distance between the two multi-scale features.

[00177] In some embodiments, the feature distance between the two multi-scale features may be determined by a feature distance between first scale features in the two multi-scale features and a feature distance between second scale features corresponding to each sampling hierarchy. Furthermore, the feature distance between the two multi-scale features may be obtained by setting different distance weights for the feature distance between the first scale features and the feature distance between the second scale features corresponding to each sampling hierarchy, and performing weighted summation.

[00178] In some embodiments, S902 may be implemented through S9021 to S9024.

[00179] In S9021, for each data point of the first point cloud data, a feature distance between the data point of the first point cloud data and each data point of the second point cloud data is obtained based on a multi-scale feature of the data point of the first point cloud data and a multi-scale feature of each data point of the second point cloud data.

[00180] In S9022, an initial mapping matrix is established based on the feature distances obtained for respective data points of the first point cloud data.

[00181] Under the condition that a data point number of the first point cloud data is N, and a data point number of the second point cloud data is M, a size of the obtained initial mapping matrix is N×M. Each matrix value m_{ij} in the initial mapping matrix is generated based on a multi-scale feature of an ith data point in the first data point and a multi-scale feature of a jth data point in the second point cloud data.

[00182] In some embodiments, the matrix value m_{ij} in the initial mapping matrix may be determined through formula (1-1):

[00183] $m_{ij} = e^{\alpha - \|x_i - x_j\|_2^2 / \sqrt{|\mathbf{C}|}}$, $\forall\, i \in N$, $\forall\, j \in M$, Formula (1-1).

[00184] Here, $|\mathbf{C}|$ is a feature channel size of the multi-scale feature, and α is a predefined parameter, to ensure the numerical stability.

[00185] In S9023, normalization processing is performed on the initial mapping matrix to obtain multiple mapping point pairs, normalization processing being configured to neglect outliers in the first point cloud data and the second point cloud data, and the mapping point pair including a first mapping point in the first point cloud data and a second mapping point in a matching relationship with the first mapping point.

[00186] In some embodiments, the initial mapping matrix is iteratively normalized using an optimal transport theory (Sinkhorn normalization) to eliminate the outliers from the first point cloud data and the second point cloud data to obtain a target mapping matrix. In a normalization processing process, a mapping point pair in a mapping relationship between the first point cloud data and the second point cloud data point may be retained. The mapping point pair includes a first mapping point in the first point cloud data and a corresponding second mapping point in the second point cloud data. The outliers are other data points that do not belong to any mapping point pair in the first point cloud data and the second point cloud data.

[00187] In some embodiments, S9022 may be implemented in the following manner: an outlier matching row and an outlier matching column are added to the initial mapping matrix to obtain an intermediate mapping matrix; normalization processing is performed on the intermediate mapping matrix to obtain a processed intermediate mapping matrix; the outlier matching row and the outlier matching column are removed from the processed intermediate mapping matrix to obtain a target mapping matrix, the target mapping matrix including a matching confidence between each first mapping point in the first point cloud data and each data point in the second point cloud data; and a second mapping point corresponding to each first mapping point is determined based on the matching confidence between each first mapping point and each data point in the second point cloud data.

[00188] For the N×M initial mapping matrix, an outlier matching row and outlier matching column of which numerical values are 1 are required to be added to obtain an (N+1)×(M+1) intermediate mapping matrix. Adding the outlier matching row and the outlier matching column are equivalent to adding a virtual data point to each of the first point cloud data and the second point cloud data, the virtual data point being configured to establish a mapping relationship with the outlier. In a process of performing normalization processing on the intermediate mapping matrix based on the optimal transport theory, for any data point in each real data point and virtual data point in the first point cloud data, a matching confidence of existence of a mapping relationship between the data point (including the real data point and the virtual data point) and a data point in the second point cloud data may be obtained. The data point in the second point cloud data may include a real data point and the virtual data point.

[00189] The outlier in the first point cloud data is matched with no data point in the second point cloud data, and meanwhile, the outlier in the second point cloud data is also matched with no data point in the first point cloud data. In an iterative normalization process, a matched mapping point may be determined from first M columns for a mapping point in the first point cloud data, a matching confidence with the matched mapping point being 1. Alternatively, there are at least two mapping points having a relatively high matching confidence in the first M columns, no matched data point may be determined from the first M columns for the outlier in the first point cloud data, and only an added (M+1)th column may be determined as a matched data point, namely a matching confidence between the outlier in the first point cloud data and the virtual data point in the second point cloud data is relatively high. Similarly, a matched mapping point may be determined from first N rows for a mapping point in the second point cloud data, no matched data point may be determined from the first N rows for the outlier in the second point cloud data, and only an added (N+1)th row may be determined as a matched data point. Therefore, after the added outlier matching row and outlier matching column are removed from the processed intermediate mapping matrix, the outliers may be deleted indirectly from the first point cloud data and the second point cloud data. Based on the above example, in the present step, the added (N+1)th row and (M+1)th column are required to be removed to obtain multiple mapping point pairs in a correct mapping

relationship only and obtain the target mapping matrix based on the obtained multiple mapping point pairs.

[00190] Position information of the second mapping point corresponding to the first mapping point may be determined based on the matching confidences between the first mapping point and respective data points in the second point cloud data and position information of respective data points in the second point cloud data.

[00191] In some embodiments, under the condition that there is a data point of which a matching confidence with a first mapping point in the first point cloud data is 1 in M data points in the second point cloud data, the data point in the second point cloud data is determined as a second mapping point corresponding to the first mapping point, and the first mapping point and the second mapping point are determined as a mapping point pair.

[00192] In some other embodiments, under the condition that there is no data point of which a matching confidence with a first mapping point in the first point cloud data is 1 in the M data points in the second point cloud data, a matching confidence between the first mapping point and each data point in the M data points in the second point cloud data is acquired, position information of each data point in the M data points in the second point cloud data is acquired, and weighted summation may be performed on the position information of each data point based on the matching confidence with each data point to construct a second mapping point that forms a mapping relationship with the first mapping point. The second mapping point may not be in the second point cloud data. The second mapping point is constructed based on the second point cloud data.

[00193] A method for determining the second mapping point corresponding to the first mapping point may be implemented through formula (1-2):

[00194] $[m^*(x_i)] = \frac{1}{\sum_j m_{ij}^*} \sum_j^M y_i \cdot m_{ij}^*$ formula (1-2).

[00195] In formula (1-2), $m^*(x_i)$ represents the first mapping point in the first cloud point data in the target mapping matrix, $y[m^*(x_i)]$ is the second mapping point, and m_{ij}^* represents the matching confidence between the ith first point cloud data point and jth second point cloud data point in the target mapping matrix.

[00196] In the abovementioned manner, since the target mapping matrix is obtained after the outliers are removed from the first point cloud data and the second point cloud data, the target mapping matrix only includes a mapping relationship between mapping points, and a point cloud feature matching result with relatively high robustness may be obtained based on the target mapping matrix to further obtain an accurate relative pose parameter.

[00197] In S9024, the relative pose parameter between the first point cloud and the second point cloud data is determined based on the multiple mapping point pairs.

[00198] In some embodiments, S9023 may be implemented in the following manner: a matrix to be decomposed is established according to the multiple mapping point pairs; and the matrix to be decomposed is decomposed through an SVD algorithm to obtain the relative pose parameter, the relative pose parameter including a translation parameter and a rotation parameter.

[00199] The multiple mapping point pairs between the first point cloud data and the second point cloud data may be determined based on the target mapping matrix to establish the matrix to be decomposed. The multiple mapping point pairs may be represented as a set v. Furthermore, the matrix H to be decomposed shown as formula (1-3) may be established.

[00200] $\boldsymbol{H} = \sum_{x_i \in \mathcal{X}_v} (x_i - \bar{x}) \cdot (\mathcal{y}_{m(x_i)} - \bar{\mathcal{y}})^T$ formula (1-3).

[00201] In formula (1-3), $\bar{x} = \frac{1}{|\mathcal{X}_v|} \sum_{x_i \in \mathcal{X}_v} x_i$, $\bar{\mathcal{y}} = \frac{1}{|\mathcal{y}_v|} \sum_{\mathcal{y}_i \in \mathcal{y}_v} \mathcal{y}_i$, $\mathcal{X}_v$ is any data point that belongs to the set v in the first point cloud data, and $\mathcal{Y}_v$ is any data point that belongs to the set v and corresponds to $\mathcal{X}_v$ in the second point cloud data.

[00202] The matrix H may be parsed through the SVD algorithm to obtain optimal $\mathbf{R}_{\mathcal{X}\mathcal{y}} = \boldsymbol{V}\boldsymbol{U}^T$ and $\mathbf{t}_{\mathcal{X}\mathcal{y}} = -\mathbf{R}_{\mathcal{X}\mathcal{y}} \cdot \bar{x} + \bar{\mathcal{y}}$, $\boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^T = \mathcal{F}_{\mathrm{SVD}}(\boldsymbol{H})$. $\mathbf{R}_{\mathcal{X}\mathcal{y}}$ is a rotation parameter, and $\mathbf{t}_{\mathcal{X}\mathcal{y}}$ is a translation parameter.

[00203] In S903, registration between the two frames of point cloud data is implemented based on the relative pose parameter between the two frames of point cloud data.

[00204] In the embodiment of the disclosure, since the initial mapping matrix is

established for the multi-scale feature of each data point in the first point cloud data and the multi-scale feature of each data point in the second point cloud data, in an iterative normalization process of the initial mapping matrix, the mapping point pairs of mutually mapping points in the first point cloud data and the second point cloud data may be determined to further determine the relative pose parameter between the two frames of point cloud data according to the obtained multiple mapping point pairs of the mutually mapping points, and the registration efficiency is improved. In addition, since the outlier matching column and the outlier matching row are added to the initial mapping matrix respectively to obtain the intermediate mapping matrix after the initial mapping matrix is obtained, multiple mapping point pairs of mutually mapping points in a correct mapping relationship may be obtained in a normalization process of the intermediate mapping matrix by matching the outliers in the two frames of point cloud data to the added outlier matching column and/or outlier matching row and then removing the outlier matching column and the outlier matching row, and the accurate relative pose parameter may be obtained by establishing the target mapping matrix based on the multiple mapping point pairs of the mutually mapping points in the correct mapping relationship, obtained by this method, and parsing the target mapping matrix using the SVD algorithm.

[00205] An exemplary application of the embodiment of the application in a practical application scene will be described below. Descriptions will be made taking adaptively selecting calculation kernels under different scales through a point cloud selection core module to achieve rotation invariance in point cloud learning as an example.

[00206] In some embodiments, a point cloud is usually defined as a set of data points, each data point may include coordinates X, Y and Z, and these data points may be configured to represent a 3D shape or scene. Considering that a 3D grid consists of vertices, edges, and faces, a frame of point cloud may be used as a discrete sample set of a continuous smooth 3D curved surface observed from a complete 3D model (grid). Therefore, Partial-to-Partial (P2P) point cloud registration practically refers to aligning two sample point sets to align two incomplete 3D shapes. On the other hand, a 3D shape may be described through the following two types local features: (1) a pose-equivariant feature (such as a space coordinate and a surface direction) that describes a pose and position of the 3D shape, and a pose-equivariant feature (such as a surface curvature) that describes a

local feature pattern and structure of the 3D shape. Based on the above finding, in the application, a pose-invariant feature of a coded incomplete point cloud is tried to be matched to further optimize pose-equivariant features alignments for P2P point cloud registration. It is to be noted that the edge describing the three-dimensional grid corresponds to pose/distance information between each data point/sample data and the corresponding neighborhood point in the abovementioned embodiments.

[00207] In some embodiments, for partial point clouds under unrestricted rotations, the rotation invariance of point features is deeply analyzed in the application. Moreover, a GMCNet is provided based on the analysis. The GMCNet constructs hierarchical graphs based on multi-scale rotation-invariant neighboring point relations to code robust rotation-invariant point features. By constructing the hierarchical graphs, structural corresponding relationships of maximum common subgraphs may be estimated to solve P2P registration problems. Furthermore, in the application, a new rotation-invariant point transformer module is designed to adaptively use local point feature relations. In the application, two data sets are redesigned to evaluate P2P point cloud registration under free rotations: (1) a 3D object shape synthesized from ModelNet40, and (2) a real 3D scene in 3DMatch. Clearly, registration solutions of the GMCNet for the synthesized 3D object and the real 3D scene are superior to conventional learning-based methods. Referring to FIG. 10, a schematic diagram of registration effects achieved by different registration methods for two partial point clouds of a 3D object shape under any rotation angle is shown. It can be seen from FIG. 10 that the registration effect achieved by the GMCNet provided in the application is closest to a real registration result, and is best and better than the other registration methods (such as Deep Closest Point (DCP), Deep Gaussian Mixture Registration (DeepGMR), and Iterative Distance-Aware Similarity matrix convolution (IDAM)). For registration of partial point clouds corresponding to the real 3D scene, a registration process may be completed only through the method of the application. Referring to FIG. 11, a schematic diagram of a registration effect of the GMCNet for two partial point clouds of a real 3D scene under any rotation angle is shown. Specifically, the GMCNet implements unsupervised learning of rotation-invariant features.

[00208] Under the condition that a source point cloud and a target point cloud are provided, the source point cloud may be represented as $= \{x_1, \ldots, x_N\} \subset \mathbb{R}^3$, and the target

point cloud may be represented as $\mathcal{Y} = \{y_1, \ldots, y_N\} \subset \mathbb{R}^3$. A purpose of the application is to register the source point cloud to the target point cloud, namely to find a rigid transformation parameter $\mathbf{T}_{\mathcal{X}\mathcal{Y}} = [\mathbf{R}_{\mathcal{X}\mathcal{Y}}, \mathbf{t}_{\mathcal{X}\mathcal{Y}}]$ including a translation parameter $\mathbf{t}_{\mathcal{X}\mathcal{Y}} \in \mathbb{R}^3$ and a rotation parameter $\mathbf{R}_{\mathcal{X}\mathcal{Y}} \in \mathrm{SO}(3)$ to map each x_i to corresponding $y_{m(x_i)}$. For P2P registration, $\mathcal{X}$ and $\mathcal{Y}$ are two frames of different point clouds with an overlapping region. A target function may be defined as formula (2-1):

[00209] $$E(\mathbf{R}_{\mathcal{X}\mathcal{Y}},\ \mathbf{t}_{\mathcal{X}\mathcal{Y}},\ m) = \frac{1}{N}\sum_{i=1}^{N}\left\|\mathbf{R}_{\mathcal{X}\mathcal{Y}} \cdot x_i + \mathbf{t}_{\mathcal{X}\mathcal{Y}} - y_{m(x_i)}\right\|^2$$ formula (2-1).

[00210] A registration process may be implemented alternately through the following two blocks. (1) Mapping m between $\mathcal{X}$ and $\mathcal{Y}$ is predicted. (2) Present optimal rotation $\mathbf{R}_{\mathcal{X}\mathcal{Y}}$ and translation $\mathbf{t}_{\mathcal{X}\mathcal{Y}}$ are estimated using mapping points $\mathcal{X}_v \subset \mathcal{X}$ and $\mathcal{Y}_v \subset \mathcal{Y}$. On the premise that predicted mapping m is given, optimal $\mathbf{R}_{\mathcal{X}\mathcal{Y}} = \boldsymbol{V}\boldsymbol{U}^T$ and $\mathbf{t}_{\mathcal{X}\mathcal{Y}} = -\mathbf{R}_{\mathcal{X}\mathcal{Y}} \cdot \bar{x} + \bar{y}$, $\boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^T = \mathcal{F}_{\mathrm{SVD}}(\boldsymbol{H})$ may be obtained by SVD.

[00211] $$\boldsymbol{H} = \sum_{x_i \in \mathcal{X}_v}(x_i - \bar{x}) \cdot (y_{m(x_i)} - \bar{y})^T$$ formula (2-2).

[00212] In formula (2-2), $\bar{x} = \frac{1}{|\mathcal{X}_v|}\sum_{x_i \in \mathcal{X}_v} x_i$, and $\bar{y} = \frac{1}{|\mathcal{Y}_v|}\sum_{y_i \in \mathcal{Y}_v} y_i$.

[00213] For estimating mapping m, a coded deep feature thereof is matched by a learning-based method through formula (2-3):

[00214] $$m(x_i, \mathcal{Y}) = \mathcal{F}_{\mathrm{map}}\left[\mathrm{softmax}\left(\Phi_{\mathcal{Y}} \cdot \Phi_{x_i}^{\mathrm{T}}\right)\right]$$ formula (2-3).

[00215] Here, $\mathcal{F}_{\mathrm{map}}[\cdot]$ represents a mapping function that may be learned, and $\Phi_{\mathcal{X}} \in \mathbb{R}^{N \times C}$ and $\Phi_{\mathcal{Y}} \in \mathbb{R}^{M \times C}$ are embed dense point features of each point in $\mathcal{X}$ and $\mathcal{Y}$ respectively.

[00216] With respect to rotation-invariant mapping, for estimating an accurate corresponding relationship between $\mathcal{X}$ and $\mathcal{Y}$, it is very important to code $\Phi_{\mathcal{X}}$ and $\Phi_{\mathcal{Y}}$, invariant to $\mathbf{t} \in \mathbb{R}^3$ and $\in \mathrm{SO}(3)$ (3D rotation groups of the Lie group). Convolutional networks may keep translation invariance, but it is also important to keep rotation invariance, referring to formula (2-4):

[00217] $\mathcal{F}[\Phi(\mathcal{X})] = \mathcal{F}[\Phi(\mathbf{R} \cdot \mathcal{X})]$ formula (2-4).

[00218] In a process of encoding a rotation-invariant point feature (corresponding to the multi-scale feature in the abovementioned embodiment), an input initial feature is required to be rotation-invariant, and a network structure of a encoding network for the multi-scale feature is also required to ensure that an output feature is rotation-invariant. Considering that a relative neighborhood relationship of a local point is rotation-invariant, in the application, a significant rotation-invariant point feature is constructed to estimate robust point feature mapping between $\mathcal{X}$ and $\mathcal{Y}$, the rotation-invariant point feature considering node similarities, pairwise edge similarities, and high-order smoothness terms. Therefore, in the application, a frame of point cloud is represented by a neighborhood graph $\{\mathcal{G}\}$, each $\mathcal{G} = (\mathcal{V},\ \mathcal{E},\ \mathbf{X})$ consisting of a node set $\mathcal{V}$, an edge set $\mathcal{E}$, and a node feature set X. In this sense, $\mathcal{X}$ and $\mathcal{Y}$ are represented as neighborhood graphs $\{\mathcal{G}_s = (\mathcal{V}_s,\ \mathcal{E}_s,\ \mathbf{X})\}$ and $\{\mathcal{G}_t = (\mathcal{V}_t,\ \mathcal{E}_t,\ \mathbf{Y})\}$ respectively. A purpose of the application is to estimate mapping m between pose-equivariant $\mathcal{V}_s$ and $\mathcal{V}_t$ based on pose-invariant X and Y.

[00219] In some embodiments, the application provides a rotation-invariant point transformer module, i.e., a PT module. As shown in FIG. 12, the module includes an input module 1201, KNN 1202, a shared MLP 1203, a shared MLP 1204, a position encoding module 1209, a shared MLP 1205, an aggregation module 1206, a shared MLP 1207, and an output module 1208.

[00220] The input module 1201 is configured to receive an initial feature and position information of a data point.

[00221] The KNN 1202 is configured to acquire initial features and position information of K neighborhood points of the data point.

[00222] The shared MLP 1203 is configured to convert the initial feature of the data point into a first feature corresponding to the data point in the abovementioned embodiments.

[00223] The shared MLP 1204 is configured to convert the initial features of the K neighborhood points corresponding to the data point into a second feature corresponding to each neighborhood point in the abovementioned embodiments.

[00224] The position encoding module 1209 is configured to generate position features in the abovementioned embodiments based on the position information of the data point and the position information of the K neighborhood points.

[00225] The shared MLP 1205 is configured to convert the initial features of the K neighborhood points corresponding to the data point into a third feature corresponding to each neighborhood point in the abovementioned embodiments.

[00226] The aggregation module 1206 is configured to fuse the merged third features and position features, and an association weight to obtain associated features in the abovementioned embodiments.

[00227] The shared MLP 1207 is configured to convert the associated features into a fourth feature.

[00228] The output module 1208 is configured to merge the fourth feature and a basic point feature to obtain a feature corresponding to each hierarchy/scale (corresponding to the first scale feature and second scale feature in the abovementioned embodiments).

[00229] In some embodiments, in a feature extraction process in FIG. 12, neighborhood graphs such as formulas (2-5) to (2-7) including point features and spatial positions thereof may be constructed to code local point feature relations:

[00230] $\mathbf{x}_i^{out} = \sum_{j \in \mathcal{N}(i)} \alpha(\mathbf{x}_{\mathcal{N}(i)}, \rho_{\mathcal{N}(i)})_j \odot \left(\beta(\mathbf{x}_j) + \rho_i(x_j)\right)$ formula (2-5);

[00231] $\alpha(\mathbf{x}_{\mathcal{N}(i)}, \rho_{\mathcal{N}(i)})_j = \gamma\left(\delta(\mathbf{x}_{\mathcal{N}(i)}, \rho_{\mathcal{N}(i)})\right)_j$ formula (2-6); and

[00232] $\delta(\mathbf{x}_{\mathcal{N}(i)}, \rho_{\mathcal{N}(i)}) = \left[\left[\sigma(\mathbf{x}_i) - \xi(\mathbf{x}_j) + \rho_i(x_j)\right]_{\forall j \in \mathcal{N}(i)}\right]$ formula (2-7).

[00233] Here, $\rho_i(x_j) = \eta\left(\|x_i - x_j\|_2\right)$, β, γ, σ, ξ, η are all shared MLP layers, $\mathcal{N}(i)$ is a KNN graph of a center point x_i, $\odot$ is a Hadamard product (obtained by multiplying corresponding positions of the matrix), and a relation function δ combines all feature vectors $\mathbf{x}_j \in \mathbf{x}_{\mathcal{N}(i)}$ and position vectors (embedding) $(x_i, x_j) \in \rho_{\mathcal{N}(i)}$ by concatenation operations. The PT module uses a distance $\|x_i - x_j\|_2$ of each point pair

rather than a scaling direction vector $(x_i - x_j)$, so that rotation invariance in the operations is ensured. The rotation invariance of the PT module in the application may be proved by following formulas (2-8) to (2-9):

[00234] $\mathcal{F}[\Phi(\mathcal{X})] = \mathcal{F}[\Phi(\mathbf{R} \cdot \mathcal{X})]$ formula (2-8); and

[00235] $\mathcal{F}[\Phi(\mathbf{R} \cdot \mathcal{X})] = \sum_{\mathcal{N}(i) \subset \{\mathbf{R} \cdot \mathcal{X}\}} f[\{\mathbf{x}, \rho\} \circ \{\mathbf{R} \cdot \mathcal{X}\}]$

[00236] $= \sum_{\mathcal{N}(i) \subset \{\mathcal{X}\}} f[\{\mathbf{x}, \rho\} \circ \{\mathcal{X}\}] = \mathcal{F}[\Phi(\mathcal{X})]$ formula (2-9).

[00237] Here, $f[\cdot]$ represents all linear operations, and $\mathbf{x}[\cdot]$, $\rho[\cdot]$, and $\mathcal{N}(i)$ are all rotation-invariant functions.

[00238] In some embodiments, the application also provides a hierarchical graphical modeling method. Since a local surface curvature changes relatively smoothly, neighborhood graphs for point clouds are further constructed to further calculate high-order smoothness terms in the application. As shown in FIG. 13, for point cloud data of a first hierarchy, iterative sampling may be performed at least once to obtain point cloud data of a second hierarchy and point cloud data of a third hierarchy. In the application, centroid points are sampled using an iterative FPS algorithm, and local points are grouped using a KNN graph. It is to be noted that always selecting a first point of a point set in an implemented FPS operation is permutation-variant. Therefore, in the embodiments of the application, features of the sampled centroid points are not used directly, and instead, spatial positions of the centroid points are interpolated to recover the centroid points to original point resolutions. Use of this hierarchical structure has the following two major advantages. 1) Smooth local point features may be generated under different scales. 2) The sampling process is favorable for removing outliers. In addition, a permutation variation process of FPS may be considered as data augmentation in a training process. It is to be noted that the second hierarchy and third hierarchy herein correspond to the at least one hierarchy in the abovementioned embodiments.

[00239] The GMCNet shown in FIG. 14 may be constructed through the PT module and the hierarchical structure. The GMCNet may concatenate learned features of all hierarchies to code rotation-invariant features. In some embodiments, the rotation-invariant feature

may be represented as formula (2-10):

[00240] $\mathbf{X}_i = \left[\mathbf{x}_i,\ \phi\left(\mathbf{x}^1_{\mathcal{N}(i)}\right),\ \psi\left(\mathbf{x}^2_{\mathcal{N}(i)}\right)\right]$ formula (2-10).

[00241] Here, $\mathbf{x}_i$ is a node feature obtained by convolutional encoding of a graph of the first hierarchy 1401, and $\phi\left(\mathbf{x}^1_{\mathcal{N}(i)}\right)$ and $\psi\left(\mathbf{x}^2_{\mathcal{N}(i)}\right)$ are coded by adjacent features of the second hierarchy 1402 and the third hierarchy 1403 respectively. Finally, multi-scale features (rotation-invariant features) 1404 corresponding to the source point cloud and the target point cloud respectively may be obtained.

[00242] In some embodiments, a feature matching penalty of $\mathbf{X}_i$ and $\mathbf{Y}_j$ may be defined as formula (2-11):

[00243] $$\mathrm{E}\left(\mathrm{X_i}, \mathrm{Y_j}\right) = \lambda_1 \mathrm{E_u}\left(\mathrm{x_i}, \mathrm{y_j}\right) + \lambda_2 \mathrm{E_h^1}\left(\phi\left(\mathrm{x}^1_{\mathcal{N}(\mathrm{i})}\right), \phi\left(\mathrm{y}^1_{\mathcal{N}(\mathrm{j})}\right)\right)$$

$$+\lambda_3 \mathrm{E_h^2}\left(\psi\left(\mathrm{x}^2_{\mathcal{N}(\mathrm{i})}\right), \psi\left(\mathrm{y}^2_{\mathcal{N}(\mathrm{j})}\right)\right) \text{ formula (2-11).}$$

[00244] Here, $E(\cdot)$ represents a similarity between $\mathbf{X}_i$ and $\mathbf{Y}_j$, the similarity including a unitary term $E_u(\cdot)$ and two high-order smoothness terms $E_h^1(\cdot)$ and $E_h^2(\cdot)$, and λ_1, λ_2, and λ_3 are weighted parameters designed for setting channel sizes of coded features of each hierarchy. It is to be noted that, during training, $\mathbf{X}_i$ and $\mathbf{Y}_j$ are coded without any supervision loss function.

[00245] In some embodiments, a corresponding initial matching matrix may be established through the matching penalty in formula (2-11). Each matrix value in the initial matching matrix is determined by features of a data point in source point cloud data and a data point in target point cloud data.

[00246] In some embodiments, the application also provides a robustness transformation estimation method. An element feature distance between $\mathbf{X}_i$ and $\mathbf{Y}_j$ is directly calculated to estimate initial m_{ij}, as shown in formula (2-12):

[00247] $m_{ij} = e^{\alpha - \left\|x_i - x_j\right\|_2^2 / \sqrt{|\mathrm{C}|}}, \forall\, i \in N, \forall\, j \in M$ Formula (2-12).

[00248] Here, $|\mathbf{C}|$ is a feature channel size, and α is a predefined parameter to ensure numerical stability.

[00249] Afterwards, the initial mapping matrix is established between the multi-scale features 1404 corresponding to the source point cloud and the target point cloud respectively, and the initial mapping matrix is iteratively updated through a matrix updating module 1405. In some embodiments of the application, outliers are rejected through an optimal transport theory hierarchy (Sinkhorn normalization layers), and a row and column starting with 1 are added to the mapping matrix m. After a plurality of iterations, the previously added row and column are neglected. That is, first *M* columns and first *N* rows are determined as a final matching matrix m^*. In the matching matrix, $\sum_i^N m_{ij}^* \leq 1$, and $\sum_j^M m_{ij}^* \leq 1$. Furthermore, formula (2-13) may be obtained:

[00250] $\boldsymbol{H} = \sum_{i=1}^{N_y} c_i\,(x_i - \bar{x}) \cdot (\mathcal{y}[m^*(x_i)] - \bar{\mathcal{y}})^T$ formula (2-13).

[00251] Here, $\bar{x} = \sum_{i=1}^{N} c_i \cdot x_i$, $\bar{\mathcal{y}} = \sum_{i=1}^{N} c_i \cdot \mathcal{y}[m^*(x_i)]$, $[m^*(x_i)] = \frac{1}{\sum_j m_{ij}^*} \sum_j^M \mathcal{y}_i \cdot m_{ij}^*$, and $c_i = \sum_j^M m_{ij}^*$. c_i represents a confidence of the point x_i, and m_{ij} represents a matching confidence between x_i and $\mathcal{y}_i$. $\mathbf{R}_{\mathcal{X}\mathcal{y}}$ and $\mathbf{t}_{\mathcal{X}\mathcal{y}}$ may be obtained by SVD through a decomposition module 1406.

[00252] A conventional neural network does not use rotation-invariant point cloud features, and thus may implement registration of incomplete point clouds under restricted rotations only. The embodiments of the applications start with learning rotation-invariant point cloud features, and outlier removal operations are combined to implement point cloud feature point matching with relatively high robustness.

[00253] The core thought of the application is inputting noisy rotation-invariant point cloud features and then using a deep learning network to improve the robustness and stability of learned point cloud features, while features obtained by encoding of a conventional deep learning network are still relatively sensitive to rotations. Rotations may not affect distances of point pairs in point clouds, and further may not affect constructed KNN graphs, the feature extraction network of the application mainly includes KNN graphs and multiple network hierarchies. Rotation-invariant features obtained by encoding

of the multiple network hierarchies respectively may be merged into a feature of a relatively high dimension as a rotation-invariant feature finally for matching to ensure that the rotation-invariant feature may include detail information of multiple scales. In addition, after matched point cloud pairs are obtained, paired outliers are removed by Sinkhorn normalization, and then a relative pose between two incomplete point clouds is optimized by weighted SVD to implement registration of the incomplete point clouds.

[00254] In the disclosure, a better incomplete point cloud registration result is obtained by verification on multiple data sets.

[00255] Based on the abovementioned embodiments, the embodiments of the disclosure provide a point cloud registration apparatus. Each unit of the apparatus and each module of each unit may be implemented through a processor in an electronic device.

[00256] FIG. 15 is a composition structure diagram of a point cloud registration apparatus according to an embodiment of the disclosure. As shown in FIG. 15, the point cloud registration apparatus 1500 includes an acquisition module 1501, a construction module 1502, a sampling module 1503, a determination module 1504, and a registration module 1505.

[00257] The acquisition module 1501 is configured to acquire two frames of point cloud data with partially overlapping data points.

[00258] The construction module 1502 is configured to, for each of the two frames of point cloud data, construct a first scale feature of each data point of the point cloud data according to an initial feature of each data point of the point cloud data.

[00259] The sampling module 1503 is configured to perform sampling processing of at least one hierarchy based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, where multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy.

[00260] The determination module 1504 is configured to determine a second scale

feature of each data point in each hierarchy based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point.

[00261] The registration module 1505 is configured to implement registration between the two frames of point cloud data based on a multi-scale feature of each data point in the two frames of point cloud data, the multi-scale feature including the first scale feature and the second scale feature in each hierarchy.

[00262] In some embodiments, the sampling module 1503 is further configured to: determine the data points in the point cloud data as basic points corresponding to a first hierarchy, and for each data point, determine the initial feature of the data point as a basic point feature of the basic point corresponding to the data point in the first hierarchy; sample basic points corresponding to each hierarchy to obtain sample points corresponding to each hierarchy; and construct local features of the sample points corresponding to each hierarchy according to basic point features of the sample points corresponding to each hierarchy, sample points corresponding to the first hierarchy being basic points corresponding to a second hierarchy, and local features of the sample points corresponding to the first hierarchy being basic point features of the basic points corresponding to the second hierarchy.

[00263] In some embodiments, the sampling module 1503 is further configured to, for each sample point, acquire a neighborhood set of the sample point and basic point features of multiple neighborhood points in the neighborhood set, determine position features of the multiple neighborhood points corresponding to the sample point based on position information of the sample point and position information of the multiple neighborhood points corresponding to the sample point, determine association weights between the sample point and corresponding multiple neighborhood points based on the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point, and determine the local feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points.

[00264] In some embodiments, the sampling module 1503 is further configured to

perform linear transformation and/or nonlinear transformation on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain a first feature of the sample point and a second feature of each neighborhood point corresponding to the sample point, and determine the association weights between the sample point and the corresponding multiple neighborhood points based on the position feature of each neighborhood point corresponding to the sample point, the first feature of the sample point, and the second feature of each neighborhood point corresponding to the sample point.

[00265] In some embodiments, the sampling module 1503 is further configured to perform channel compression processing on the basic point feature of the sample point from a feature channel dimension to obtain the first feature of the sample point, a feature channel number of the first feature of the sample point being smaller than a feature channel number of the basic point feature of the sample point, and perform channel compression processing on the basic point feature of each neighborhood point corresponding to the sample point from the feature channel dimension to obtain the second feature of each neighborhood point corresponding to the sample point, for a same neighborhood point, a feature channel number of the second feature of the neighborhood point corresponding to the sample point being smaller than a feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the first feature being the same as the feature channel number of the second feature.

[00266] In some embodiments, the sampling module 1503 is further configured to determine a fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points, and merge the fourth feature of the sample point and the basic point feature of the sample point to obtain the local feature of the sample point.

[00267] In some embodiments, the sampling module 1503 is further configured to, for each of the multiple neighborhood points corresponding to the sample point, perform linear transformation and/or nonlinear transformation on the basic point feature of the neighborhood point to obtain a third feature of the neighborhood point corresponding to the sample point, merge the third feature of the neighborhood point corresponding to the

sample point and the position feature of the neighborhood point corresponding to the sample point to obtain a neighborhood fused feature of the neighborhood point corresponding to the sample point, and determine the fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point.

[00268] In some embodiments, the sampling module 1503 is further configured to perform channel compression processing on the basic point feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the third feature of the neighborhood point corresponding to the sample point, a feature channel number of the third feature of the neighborhood point corresponding to the sample point being smaller than the feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the third feature being larger than the feature channel number of the second feature.

[00269] In some embodiments, the sampling module 1503 is further configured to aggregate the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point to obtain an associated feature of each neighborhood point corresponding to the sample point, and determine the fourth feature of the sample point based on the associated feature of each neighborhood point corresponding to the sample point.

[00270] In some embodiments, the sampling module 1503 is further configured to, for each neighborhood point corresponding to the sample point, perform channel expansion processing on the associated feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the fourth feature of the neighborhood point corresponding to the sample point, a feature channel number of the fourth feature of the neighborhood point corresponding to the sample point being larger than a feature channel number of the associated feature of the neighborhood point corresponding to the sample point, and the feature channel number of the fourth feature being the same as a feature channel number of the initial feature.

[00271] In some embodiments, the determination module 1504 is further configured to, for each data point in the point cloud data, determine at least one fused point corresponding to the data point in each hierarchy from among the multiple sample points corresponding to each hierarchy, and determine the second scale feature of the data point in each hierarchy based on the at least one fused point corresponding to the data point in each hierarchy and a corresponding local feature.

[00272] In some embodiments, the determination module 1504 is further configured to determine an interpolation weight between the data point and each fused point in each hierarchy based on position information of the data point and position information of each fused point in each hierarchy, and determine the second scale feature of the data point in each hierarchy according to the interpolation weight between the data point and each fused point in each hierarchy and the local feature of each fused point in each hierarchy.

[00273] In some embodiments, the determination module 1504 is further configured to determine at least one fused point that corresponds to each basic point corresponding to the first hierarchy from each sample point corresponding to the first hierarchy, and determine the second scale feature of each data point corresponding to each hierarchy based on a local feature of each fused point that corresponds to each basic point corresponding to the first hierarchy.

[00274] In some embodiments, the determination module 1504 is further configured to transmit a second scale feature of each basic point corresponding to the second hierarchy to the first hierarchy as a local feature of each sample point corresponding to the first hierarchy.

[00275] In some embodiments, the determination module 1504 is further configured to determine a fusion weight between the basic point and each fused point based on position information of the basic point and position information of each fused point corresponding to the basic point, and determine the second scale feature of the basic point according to the fusion weight between the basic point and each fused point and the local feature of each fused point.

[00276] In some embodiments, the registration module 1505 is further configured to, for

each data point of the point cloud data, fuse the first scale feature of the data point and the second scale feature in each hierarchy to obtain the multi-scale feature of the data point, determine a relative pose parameter between the two frames of point cloud data based on the multi-scale feature of each data point in the two frames of point cloud data, and implement registration between the two frames of point cloud data based on the relative pose parameter between the two frames of point cloud data.

[00277] In some embodiments, the registration module 1505 is further configured to, for each data point of first point cloud data, obtain a feature distance between the data point of the first point cloud data and each data point of second point cloud data based on a multi-scale feature of the data point of the first point cloud data and a multi-scale feature of each data point of the second point cloud data, establish an initial mapping matrix based on the feature distances obtained for respective data points of the first point cloud data, perform normalization processing on the initial mapping matrix to obtain multiple mapping point pairs, normalization processing being configured to neglect outliers in the first point cloud data and the second point cloud data, and the mapping point pair including a first mapping point in the first point cloud data and a second mapping point in a matching relationship with the first mapping point, and determine the relative pose parameter between the first point cloud and the second point cloud data based on the multiple mapping point pairs.

[00278] In some embodiments, the registration module 1505 is further configured to add an outlier matching row and an outlier matching column to the initial mapping matrix to obtain an intermediate mapping matrix, perform normalization processing on the intermediate mapping matrix to obtain a processed intermediate mapping matrix, remove the outlier matching row and the outlier matching column from the processed intermediate mapping matrix to obtain a target mapping matrix, the target mapping matrix including a matching confidence between each first mapping point in the first point cloud data and each data point in the second point cloud data, and determine a second mapping point corresponding to each first mapping point based on the matching confidence between each first mapping point and each data point in the second point cloud data.

[00279] In some embodiments, the registration module 1505 is further configured to determine position information of the second mapping point corresponding to the first

mapping point based on the matching confidences between the first mapping point and respective data points in the second point cloud data and position information of respective data points in the second point cloud data.

[00280] In some embodiments, the registration module 1505 is further configured to establish a matrix to be decomposed according to the multiple mapping point pairs, and decompose the matrix to be decomposed through an SVD algorithm to obtain the relative pose parameter, the relative pose parameter including a translation parameter and a rotation parameter.

[00281] The point cloud registration apparatus 1100 is the point cloud registration apparatus in any abovementioned method.

[00282] The above descriptions about the apparatus embodiments are similar to descriptions about the method embodiments and beneficial effects similar to those of the method embodiments are achieved. Technical details undisclosed in the apparatus embodiments of the disclosure may be understood with reference to the descriptions about the method embodiments of the disclosure.

[00283] It is to be noted that, in the embodiments of the disclosure, when implemented in form of a software function module and sold or used as an independent product, the point cloud registration method may also be stored in a computer storage medium. Based on such an understanding, the technical solutions of the embodiments of the disclosure substantially or parts making contributions to the related art may be embodied in form of a software product. The computer software product is stored in a storage medium, including a plurality of instructions configured to enable an electronic device to execute all or part of the method in each embodiment of the disclosure. The storage medium includes various media capable of storing program codes such as a U disk, a mobile hard disk, a Read Only Memory (ROM), a magnetic disk, or an optical disk. Therefore, the embodiments of the disclosure are not limited to any specific hardware and software combination.

[00284] FIG. 16 is a schematic diagram of a hardware entity of an electronic device according to an embodiment of the disclosure. As shown in FIG. 16, the hardware entity

of the electronic device 1600 includes a processor 1601 and a memory 1602. The memory 1602 stores a computer program capable of running in the processor 1601. The processor 1601 executes the program to implement the steps in the method of any abovementioned embodiment. The electronic device 1600 may be any device applied to a chip or processor listed above.

[00285] The memory 1602 stores the computer program capable of running in the processor 1601. The memory 1602 is configured to store an instruction and application executable for the processor 1601, may also cache data (for example, image data, audio data, voice communication data and video communication data) to be processed or having been processed by the processor 1201 and each module in the electronic device 1600 and may be implemented through a flash or a Random Access Memory (RAM).

[00286] The processor 1601 executes the program to implement the steps of any abovementioned point cloud registration method. The processor 1601 usually controls overall operations of the electronic device 1600.

[00287] The embodiments of the disclosure provide a computer storage medium, which stores one or more programs. The one or more programs may be executed by one or more processors to implement the steps of the point cloud registration method in any abovementioned embodiment.

[00288] It is to be pointed out here that the above descriptions about the storage medium and device embodiments are similar to the descriptions about the method embodiment, and beneficial effects similar to those of the method embodiment are achieved. Technical details undisclosed in the storage medium and device embodiments of the disclosure are understood with reference to the descriptions about the method embodiment of the disclosure.

[00289] The processor or point cloud registration apparatus in the embodiments of the disclosure may be an integrated circuit chip and has a signal processing capability. In an implementation process, each step of the method embodiments may be completed by an integrated logical circuit of hardware in the processor or an instruction in a software form. The processor may be at least one of an Application Specific Integrated Circuit (ASIC), a

Digital Signal Processor (DSP), a Digital Signal Processing Device (DSPD), a Programmable Logic Device (PLD), a Field Programmable Gate Array (FPGA), a Central Processing unit (CPU), a Graphics Processing Unit (GPU), a Neural-network Processing Unit (NPU), a controller, a microcontroller, or a microprocessor. The processor or the point cloud registration apparatus may implement or execute each method, step and logical block diagram disclosed in the embodiments of the disclosure. The universal processor may be a microprocessor or the processor may also be any conventional processor, etc. The steps of the method disclosed in combination with the embodiment of the disclosure may be directly embodied to be executed and completed by a hardware decoding processor or executed and completed by a combination of hardware and software modules in the decoding processor. The software module may be located in a mature storage medium in this field such as a RAM, a flash memory, a ROM, a Programmable ROM (PROM), or Electrically Erasable PROM (EEPROM), and a register. The storage medium is located in a memory, and the processor reads information in the memory and completes the steps of the method in combination with hardware.

[00290] It can be understood that the memory or computer storage medium in the embodiments of the disclosure may be a volatile memory or a nonvolatile memory, or may include both the volatile and nonvolatile memories. The nonvolatile memory may be a ROM, a PROM, an Erasable PROM (EPROM), an EEPROM or a flash memory. The volatile memory may be a RAM, and is used as an external high-speed cache. It is exemplarily but unlimitedly described that RAMs in various forms may be adopted, such as a Static RAM (SRAM), a Dynamic RAM (DRAM), a Synchronous DRAM (SDRAM), a Double Data Rate SDRAM (DDR SDRAM), an Enhanced SDRAM (ESDRAM), a Synchlink DRAM (SLDRAM), and a Direct Rambus RAM (DR RAM). It is to be noted that the memory of a system and method described in the disclosure is intended to include, but not limited to, memories of these and any other proper types.

[00291] It is to be understood that "one embodiment" or "an embodiment" or "the embodiment of the disclosure" or "the abovementioned embodiment" or "some implementation modes" or "some embodiments" mentioned in the whole specification means that specific features, structures or characteristics related to the embodiment are included in at least one embodiment of the disclosure. Therefore, "in one embodiment" or

"in an embodiment" or "the embodiment of the disclosure" or "the abovementioned embodiment" or "some implementation modes" or "some embodiments" appearing everywhere in the whole specification does not always refer to the same embodiment. In addition, these specific features, structures or characteristics may be combined in one or more embodiments freely as appropriate. It is to be understood that, in each embodiment of the disclosure, a magnitude of a sequence number of each process does not mean an execution sequence and the execution sequence of each process should be determined by its function and an internal logic and should not form any limit to an implementation process of the embodiments of the disclosure. The sequence numbers of the embodiments of the disclosure are adopted not to represent superiority-inferiority of the embodiments but only for description.

[00292] In some embodiments provided by the disclosure, it is to be understood that the disclosed device and method may be implemented in another manner. The device embodiment described above is only schematic, and for example, division of the units is only logic function division, and other division manners may be adopted during practical implementation. For example, multiple units or components may be combined or integrated into another system, or some characteristics may be neglected or not executed. In addition, coupling or direct coupling or communication connection between each displayed or discussed component may be indirect coupling or communication connection, implemented through some interfaces, of the device or the units, and may be electrical and mechanical or adopt other forms.

[00293] The units described as separate parts may or may not be physically separated, and parts displayed as units may or may not be physical units, and namely may be located in the same place, or may also be distributed to multiple network units. Part of all of the units may be selected according to a practical requirement to achieve the purposes of the solutions of the embodiments.

[00294] In addition, each function unit in each embodiment of the disclosure may be integrated into a processing unit, each unit may also serve as an independent unit and two or more than two units may also be integrated into a unit. The integrated unit may be implemented in a hardware form and may also be implemented in form of hardware and

software function unit.

[00295] The methods disclosed in some method embodiments provided in the disclosure may be freely combined without conflicts to obtain new method embodiments.

[00296] The characteristics disclosed in some product embodiments provided in the disclosure may be freely combined without conflicts to obtain new product embodiments.

[00297] The characteristics disclosed in some method or device embodiments provided in the disclosure may be freely combined without conflicts to obtain new method embodiments or device embodiments.

[00298] Those of ordinary skill in the art should know that all or part of the steps of the method embodiment may be implemented by related hardware instructed through a program, the program may be stored in a computer storage medium, and the program is executed to execute the steps of the method embodiment. The storage medium includes: various media capable of storing program codes such as a mobile storage device, a ROM, a magnetic disk or a compact disc.

[00299] Or, when implemented in form of a software function module and sold or used as an independent product, the integrated unit of the disclosure may also be stored in a computer storage medium. Based on such an understanding, the technical solutions of the embodiments of the disclosure substantially or parts making contributions to the related art may be embodied in form of a software product. The computer software product is stored in a storage medium, including a plurality of instructions configured to enable a computer device (which may be a personal computer, a server, a network device or the like) to execute all or part of the method in each embodiment of the disclosure. The storage medium includes: various media capable of storing program codes such as a mobile hard disk, a ROM, a magnetic disk, or an optical disc.

[00300] In the embodiments of the disclosure, the descriptions about the same steps and the same contents in different embodiments may refer to those in the other embodiments. Singular forms "a/an", "said" and "the" used in the embodiments and appended claims of the disclosure are also intended to include plural forms unless other meanings are clearly expressed in the context.

[00301] It is to be understood that term "and/or" used in the disclosure is only an association relationship describing associated objects and represents that three relationships may exist. For example, A and/or B may represent three conditions: independent existence of A, existence of both A and B and independent existence of B. In addition, character "/" in the disclosure usually represents that previous and next associated objects form an "or" relationship.

[00302] It is to be noted that, in each embodiment involved in the disclosure, all the steps may be executed or part of the steps may be executed if a complete technical solutions may be formed.

[00303] The above is only the implementation mode of the disclosure and not intended to limit the scope of protection of the disclosure. Any variations or replacements apparent to those skilled in the art within the technical scope disclosed by the disclosure shall fall within the scope of protection of the disclosure. Therefore, the scope of protection of the disclosure shall be subject to the scope of protection of the claims.

CLAIMS

1. A point cloud registration method, comprising:

acquiring two frames of point cloud data with partially overlapping data points;

for each of the two frames of point cloud data, constructing a first scale feature of each data point of the point cloud data according to an initial feature of each data point of the point cloud data;

performing sampling processing of at least one hierarchy based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, wherein multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy;

determining a second scale feature of each data point in each hierarchy based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point; and

implementing registration between the two frames of point cloud data based on a multi-scale feature of each data point in the two frames of point cloud data, the multi-scale feature comprising the first scale feature and the second scale feature in each hierarchy.

2. The method of claim 1, wherein performing sampling processing of the at least one hierarchy based on the initial feature of each data point of the point cloud data to obtain the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point comprises:

determining the data points in the point cloud data as basic points corresponding to a first hierarchy, and for each data point, determining the initial feature of the data point as a basic

point feature of the basic point corresponding to the data point in the first hierarchy;

sampling basic points corresponding to each hierarchy to obtain sample points corresponding to each hierarchy; and

constructing local features of the sample points corresponding to each hierarchy according to basic point features of the sample points corresponding to each hierarchy,

wherein sample points corresponding to the first hierarchy are basic points corresponding to a second hierarchy, and local features of the sample points corresponding to the first hierarchy are basic point features of the basic points corresponding to the second hierarchy.

3. The method of claim 2, wherein constructing the local features of the sample points corresponding to each hierarchy according to the basic point features of the sample points corresponding to each hierarchy comprises:

for each sample point, acquiring a neighborhood set of the sample point and basic point features of multiple neighborhood points in the neighborhood set;

determining position features of the multiple neighborhood points corresponding to the sample point based on position information of the sample point and position information of the multiple neighborhood points corresponding to the sample point;

determining association weights between the sample point and corresponding multiple neighborhood points based on the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point; and

determining the local feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points.

4. The method of claim 3, wherein determining the association weights between the sample

point and the corresponding multiple neighborhood points based on the basic point feature of the sample point and the basic point features and position features of the multiple neighborhood points corresponding to the sample point comprises:

performing linear transformation and/or nonlinear transformation on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain a first feature of the sample point and a second feature of each neighborhood point corresponding to the sample point; and

determining the association weights between the sample point and the corresponding multiple neighborhood points based on the position feature of each neighborhood point corresponding to the sample point, the first feature of the sample point, and the second feature of each neighborhood point corresponding to the sample point.

5. The method of claim 4, wherein performing linear transformation and/or nonlinear transformation on the basic point feature of the sample point and the basic point feature of each neighborhood point corresponding to the sample point to obtain the first feature of the sample point and the second feature of each neighborhood point corresponding to the sample point comprises:

performing channel compression processing on the basic point feature of the sample point from a feature channel dimension to obtain the first feature of the sample point, a feature channel number of the first feature of the sample point being smaller than a feature channel number of the basic point feature of the sample point; and

performing channel compression processing on the basic point feature of each neighborhood point corresponding to the sample point from the feature channel dimension to obtain the second feature of each neighborhood point corresponding to the sample point, for a same neighborhood point, a feature channel number of the second feature of the neighborhood point corresponding to the sample point being smaller than a feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the first feature being the same as the feature channel number of the second feature.

6. The method of any one of claims 3 to 5, wherein determining the local feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points comprises:

determining a fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points; and

merging the fourth feature of the sample point and the basic point feature of the sample point to obtain the local feature of the sample point.

7. The method of claim 6, wherein determining the fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points comprises:

for each of the multiple neighborhood points corresponding to the sample point, performing linear transformation and/or nonlinear transformation on the basic point feature of the neighborhood point to obtain a third feature of the neighborhood point corresponding to the sample point;

merging the third feature of the neighborhood point corresponding to the sample point and the position feature of the neighborhood point corresponding to the sample point to obtain a neighborhood fused feature of the neighborhood point corresponding to the sample point; and

determining the fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point.

8. The method of claim 7, wherein performing linear transformation and/or nonlinear transformation on the basic point feature of the neighborhood point to obtain the third feature of the neighborhood point corresponding to the sample point comprises:

performing channel compression processing on the basic point feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the third feature of the neighborhood point corresponding to the sample point, a feature channel number of the third feature of the neighborhood point corresponding to the sample point being smaller than the feature channel number of the basic point feature of the neighborhood point corresponding to the sample point, and the feature channel number of the third feature being larger than the feature channel number of the second feature.

9. The method of claim 7 or 8, wherein determining the fourth feature of the sample point based on the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point comprises:

aggregating the association weights between the sample point and the corresponding multiple neighborhood points and the neighborhood fused feature of each neighborhood point corresponding to the sample point to obtain an associated feature of each neighborhood point corresponding to the sample point; and

determining the fourth feature of the sample point based on the associated feature of each neighborhood point corresponding to the sample point.

10. The method of claim 9, wherein determining the fourth feature of the sample point based on the associated feature of each neighborhood point corresponding to the sample point comprises:

for each neighborhood point corresponding to the sample point, performing channel expansion processing on the associated feature of the neighborhood point corresponding to the sample point from the feature channel dimension to obtain the fourth feature of the neighborhood point corresponding to the sample point, a feature channel number of the fourth feature of the neighborhood point corresponding to the sample point being larger than a feature channel number of the associated feature of the neighborhood point corresponding to the sample

point, and the feature channel number of the fourth feature being the same as a feature channel number of the initial feature.

11. The method of any one of claims 1 to 10, wherein determining the second scale feature of each data point in each hierarchy based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point comprises:

for each data point in the point cloud data, determining at least one fused point corresponding to the data point in each hierarchy from among the multiple sample points corresponding to each hierarchy; and

determining the second scale feature of the data point in each hierarchy based on the at least one fused point corresponding to the data point in each hierarchy and a corresponding local feature of the at least one fused point.

12. The method of claim 11, wherein determining the second scale feature of the data point in each hierarchy based on the at least one fused point corresponding to the data point in each hierarchy and the corresponding local feature comprises:

determining an interpolation weight between the data point and each fused point in each hierarchy based on position information of the data point and position information of each fused point in each hierarchy; and

determining the second scale feature of the data point in each hierarchy according to the interpolation weight between the data point and each fused point in each hierarchy and the local feature of each fused point in each hierarchy.

13. The method of any one of claims 1 to 12, wherein implementing registration between the two frames of point cloud data based on the multi-scale feature of each data point of the point

cloud data comprises:

for each data point of the point cloud data, fusing the first scale feature of the data point and the second scale feature in each hierarchy to obtain the multi-scale feature of the data point;

determining a relative pose parameter between the two frames of point cloud data based on the multi-scale feature of each data point in the two frames of point cloud data; and

implementing registration between the two frames of point cloud data based on the relative pose parameter between the two frames of point cloud data.

14. The method of claim 13, wherein the two frames of point cloud data comprise first point cloud data and second point cloud data, and determining the relative pose parameter between the two frames of point cloud data based on the multi-scale feature of each data point of the point cloud data comprises:

for each data point of the first point cloud data, obtaining a feature distance between the data point of the first point cloud data and each data point of the second point cloud data based on a multi-scale feature of the data point of the first point cloud data and a multi-scale feature of each data point of the second point cloud data;

establishing an initial mapping matrix based on the feature distances obtained for respective data points of the first point cloud data;

performing normalization processing on the initial mapping matrix to obtain multiple mapping point pairs, normalization processing being configured to reject outliers in the first point cloud data and the second point cloud data, and the mapping point pair comprising a first mapping point in the first point cloud data and a second mapping point in a matching relationship with the first mapping point; and

determining the relative pose parameter between the first point cloud and the second point cloud data based on the multiple mapping point pairs.

15. The method of claim 14, wherein performing normalization processing on the initial mapping matrix comprises:

adding an outlier matching row and an outlier matching column to the initial mapping matrix to obtain an intermediate mapping matrix;

performing normalization processing on the intermediate mapping matrix to obtain a processed intermediate mapping matrix;

removing the outlier matching row and the outlier matching column from the processed intermediate mapping matrix to obtain a target mapping matrix, the target mapping matrix comprising a matching confidence between each first mapping point in the first point cloud data and each data point in the second point cloud data; and

determining a second mapping point corresponding to each first mapping point based on the matching confidence between each first mapping point and each data point in the second point cloud data.

16. The method of claim 15, wherein determining the second mapping point corresponding to each first mapping point based on the matching confidence between each first mapping point and each data point in the second point cloud data comprises:

determining position information of the second mapping point corresponding to the first mapping point based on the matching confidences between the first mapping point and respective data points in the second point cloud data and position information of respective data points in the second point cloud data.

17. The method of claim 14 or 15, wherein determining the relative pose parameter between the first point cloud data and the second point cloud data based on the multiple mapping point pairs comprises:

establishing a matrix to be decomposed according to the multiple mapping point pairs;

and

decomposing the matrix to be decomposed through a Singular Value Decomposition (SVD) algorithm to obtain the relative pose parameter, the relative pose parameter comprising a translation parameter and a rotation parameter.

18. A point cloud registration apparatus, comprising:

an acquisition module, configured to acquire two frames of point cloud data with partially overlapping data points;

a construction module, configured to, for each of the two frames of point cloud data, construct a first scale feature of each data point of the point cloud data according to an initial feature of each data point of the point cloud data;

a sampling module, configured to perform sampling processing of at least one hierarchy based on the initial feature of each data point of the point cloud data to obtain multiple sample points of the point cloud data corresponding to each hierarchy and a local feature corresponding to each sample point, wherein multiple sample points obtained by sampling processing of a previous hierarchy and a local feature corresponding to each sample point are input features for sampling processing of a next hierarchy;

a determination module, configured to determine a second scale feature of each data point in each hierarchy based on the multiple sample points of the point cloud data corresponding to each hierarchy and the local feature corresponding to each sample point; and

a registration module, configured to implement registration between the two frames of point cloud data based on a multi-scale feature of each data point in the two frames of point cloud data, the multi-scale feature comprising the first scale feature and the second scale feature in each hierarchy.

19. A point cloud registration device, comprising:

a memory, configured to store executable instructions; and

a processor, configured to execute the executable instructions stored in the memory to implement the method of any one of claims 1 to 17.

20. A computer-readable storage medium, storing executable instructions, configured to be executed by a processor to implement the method of any one of claims 1 to 17.