

IDENTIFICATION OF ZONES AND SNAPSHOTS THROUGH SEQUENCE ANALYSIS

TECHNICAL FIELD

[0001] Various aspects of this disclosure generally relate to autonomous mobile robotics, and more particularly, to place awareness.

BACKGROUND

[0002] Place awareness is a critical component of safe decision-making in autonomous mobile robotics. The significance of place awareness is more appreciable in large-scale outdoor environment in which, safety measures, mission planning, and responsive intelligent behaviour depend on individual circumstances of each specific place. It is necessary for high-level mission planning and autonomous decision-making module to be aware of current place in order to invoke place-specific task objectives in a large-scale mission for long-term autonomy. In this regard, detection of transition between places (e.g. indoor to outdoor transition), or detection of specific scenarios (e.g. travelled from room to road via the main corridor), seriously assists the autonomous mission planning in complex environment.

[0003] The importance of place awareness in self-localization and mapping, as a fundamental requirement of autonomous mobile robots, inspired the development of a group of place detection techniques (i.e., a first approach) from this perspective. Recognition of a revisited place is the crucial requirement for cancelation of accumulated mapping drifts. Besides, identification of similar places contributes to selection of proper frame for merging the maps generated by multiple mobile robots. Moreover, map segmentation to meaningful places provides a more semantically informative model of the environment. In a second approach, given an image of a place and a pool of unordered images from different places, image retrieval techniques identify best matching images from the pool to the image of interest, or alternatively, some more advanced methodologies classify unordered images into groups of related places. This approach for place recognition branches from the general image recognition and image classification research, which is dedicated to recognition of

landmarks and invariant image features under changing environmental situation and viewpoint changes. There is also a third approach to place recognition that relies on external equipment, such as GPS, or relies on processing the available place-specific signals, such as Wi-Fi access point signal, which has demonstrated acceptable performance under the assumption of perfect coverage. In this disclosure, place detection using on-board equipment is studied and the external equipment are used only as supplementary facilities. Thus, the third approach stays out of the attention of this disclosure.

[0004] Through the first approach, researchers face major challenges to maintain metrically accurate map of the environment in large-scale outdoor environment. On the other hand, second approach confronts environmental changes, such as illumination, which highly affect feature selection and feature matching. Moreover, in the first approach, place recognition, which is supposed to assist the mapping module, depends itself on the mapping and localization module. Therefore, once mapping and localization loses accuracy for any reason, place recognition risks total failure. Second approach, which is free from metrical accuracy debate, confronts memory storage demand in long run, since these techniques need to store the feature models of different scenes, in form of a multi-dimensional vector structure, in a codebook for succeeding matching purpose. Moreover, the second approach corresponds a place to one snapshot, which should necessarily capture enough landmark features. It is important to note that, in general, a place might or might not contain a specific landmark, and therefore, it might or might not be representable through a single snapshot. Therefore, it is desirable to look for an alternative solution, which does not rely on metrical accuracy of environment model, and is not sensitive to feature-related concerns.

SUMMARY

[0005] The following presents a simplified summary in order to provide a basic understanding of various aspects of the disclosed invention. This summary is not an extensive overview of all contemplated aspects, and is intended to neither identify key or critical elements of all aspects nor delineate the scope of any or all aspects. The sole purpose is to present some concepts of one or more aspects in a simplified form as a prelude to the more detailed description that is presented later.

[0006] A new methodology for place detection is provided. The methodology identifies places as meaningful subsets of three-dimensional environments, in which, every observation made at different locations of the place is consistently described by similar place descriptors. To compare one place to another, unlike the common approach of comparing two respective descriptor structures, two matrices consisted of descriptor similarities between different observations made from each place are compared. This comparison approach enhances the detection confidence. The descriptor used for place characterization may be the list of eigenvalues of Laplace-Beltrami operator applied to the polygonised surface meshes. These meshes are generated from the three dimensional point cloud data captured by the sensory system. The descriptor is non-feature-based, and may be applied to the entire captured input. The descriptor is applied for characterization of places.

[0007] The advantages of the provided methodology include independence from metrical accuracy, elimination of feature selection and feature association challenges, storage efficiency, and applicability for large-scale outdoor scenarios in addition to insensitivity to environment changes. In GPS denied environment, these properties make the proposed methodology preferable for meaningful environment segmentation, identification of revisited places, and recognition of revisited scenarios, which form the fundamental requirements for identification of loop-closure frames in self-localization and mapping, identification of proper frames for merging multiple maps generated by multiple robots, autonomous start-up location estimation, and autonomous place-specific task assignment. Moreover, whenever GPS data is available, automatic labelling of visited places becomes possible. If the observations are time-stamped, it becomes possible for the detection system to deliver the accurate timing for recognition of revisited places. This facilitates the analysis of other sensory inputs captured at the identified time for any further possible mission-specific analysis.

[0008] The provided solution is not only limited to detection and recognition of places in the environment. The procedure may detect similar snapshots and sequences from the analysis of partial three-dimensional data, captured from any volume, along which a scenario is studied by sporadic sampling during a continuous motion. Identification of revisited or similar snapshots in a long-term study is performed through analysis of meaningful sequences of zones. Zones are meaningful subsets of

the studied volume. These subsets may be identified through the study of similarity among the sequence of recent observations during a continuous motion along the studied volume.

[0009] The provided solution introduces new approach, procedure and methodology to identify previously experienced situations and similar observations. Not only can this technique identify the similarity between observations, but also it can even identify reoccurrences of scenarios and sequences of observations during exploration of a large-scale volume in a long-term travel. This solution may be independent from the output of metrically accurate localization and mapping module. The identification mechanism may be free from network training.

[0010] In one aspect of the disclosure, a method, a computer-readable medium, and an apparatus for the identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations are provided. For each observation, the apparatus may calculate a descriptor that characterizes the observation. The apparatus may determine a similarity value between any two descriptors to form a similarity matrix. The apparatus may identify a plurality of first-type square sub-matrices along the main diagonal of the similarity matrix. The apparatus may identify a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix. Each of the plurality of second-type square sub-matrices may contain multiple first-type square sub-matrices of the plurality of first-type square sub-matrices. The apparatus may identify at least one third-type sub-matrix. Each of the at least one third-type sub-matrix may be an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix. The apparatus may identify the largest elements along the main diagonal of the at least one third-type sub-matrix as candidates for re-observed snapshots.

[0011] To the accomplishment of the foregoing and related ends, the aspects disclosed include the features hereinafter fully described and particularly pointed out in the claims. The following description and the annexed drawings set forth in detail illustrate certain

features of the aspects of the disclosure. These features are indicative, however, of but a few of the various ways in which the principles of various aspects may be employed, and this description is intended to include all such aspects and their equivalents.

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] FIG. 1 is a flowchart of a method of identification of similar observations and sequences.

[0013] FIG. 2 is a diagram showing an example of a place.

[0014] FIG. 3 is a diagram illustrating four different observations from the place shown in FIG. 2.

[0015] FIG. 4 shows an example of a similarity table that is generated from four scans from a volume.

[0016] FIG. 5 is a diagram illustrating an example of identified zones in a similarity matrix by marking major diagonal sub matrices.

[0017] FIG. 6 is a diagram illustrating an example of template matching in a similarity matrix.

[0018] FIG. 7 is a diagram illustrating an example of large diagonal values in the cross-similarity sub matrix indicating similar observations.

[0019] FIG. 8 is a flowchart of a method of identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations.

[0020] FIG. 9 is a conceptual data flow diagram illustrating the data flow between different means/components in an exemplary apparatus.

[0021] FIG. 10 is a diagram illustrating an example of a hardware implementation for an apparatus employing a processing system.

DETAILED DESCRIPTION

[0022] The detailed description set forth below in connection with the appended drawings is intended as a description of various possible configurations and is not intended to represent the only configurations in which the concepts described herein may be practiced. The detailed description includes specific details for the purpose of providing a

thorough understanding of various concepts. However, it will be apparent to those skilled in the art that these concepts may be practiced without these specific details. In some instances, well-known structures and components are shown in block diagram form in order to avoid obscuring such concepts.

[0023] Several aspects of providing place awareness will now be presented with reference to various apparatus and methods. The apparatus and methods will be described in the following detailed description and illustrated in the accompanying drawings by various blocks, components, circuits, processes, algorithms, etc. (collectively referred to as “elements”). These elements may be implemented using electronic hardware, computer software, or any combination thereof. Whether such elements are implemented as hardware or software depends upon the particular application and design constraints imposed on the overall system.

[0024] By way of example, an element, or any portion of an element, or any combination of elements may be implemented as a “processing system” that includes one or more processors. Examples of processors include microprocessors, microcontrollers, graphics processing units (GPUs), central processing units (CPUs), application processors, digital signal processors (DSPs), reduced instruction set computing (RISC) processors, systems on a chip (SoC), baseband processors, field programmable gate arrays (FPGAs), programmable logic devices (PLDs), state machines, gated logic, discrete hardware circuits, and other suitable hardware configured to perform the various functionality described throughout this disclosure. One or more processors in the processing system may execute software. Software shall be construed broadly to mean instructions, instruction sets, code, code segments, program code, programs, subprograms, software components, applications, software applications, software packages, routines, subroutines, objects, executables, threads of execution, procedures, functions, etc., whether referred to as software, firmware, middleware, microcode, hardware description language, or otherwise.

[0025] Accordingly, in one or more example embodiments, the functions described may be implemented in hardware, software, or any combination thereof. If implemented in software, the functions may be stored on or encoded as one or more instructions or code on a computer-readable medium. Computer-readable media includes computer storage media. Storage media may be any available media that can be accessed by a computer. By way of example, and not limitation, such computer-readable media may include a random-access

memory (RAM), a read-only memory (ROM), an electrically erasable programmable ROM (EEPROM), optical disk storage, magnetic disk storage, other magnetic storage devices, combinations of the aforementioned types of computer-readable media, or any other medium that can be used to store computer executable code in the form of instructions or data structures that can be accessed by a computer.

[0026] The present disclosure relates to a methodology of identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations. In one aspect of the disclosure, a methodology is provided for identification of revisited observations and previously experienced scenarios and sequences from identified zones through analysis of patterns in the similarity map. The similarity map may be also referred to as a similarity table or a similarity matrix. In one aspect of the disclosure, a procedure is provided for identification of “zones” as meaningful subsets of the studied volume through analysis of similarity map. These subsets are distinctive compared to the surrounding.

[0027] Some embodiments include a detection system that are independent from the metrically accurate self-localization and mapping module. In some embodiments, three-dimensional analysis of large-scale volume may be performed by storing extremely small amount of information. In some embodiments, skipping feature-selection and feature-association phases facilitates the methodology to perform with equal performance in various environmental conditions. In some embodiments, no training of neural network is needed. Training a neural network for identification usually requires a large number of test and training datasets. Introducing new type of data may impose necessity for retrain or even change of the structure of the neural network. Identification mechanism of some embodiments does not involve a training phase. In some embodiments, revisited observations may be detected through detection of scenarios and sequences. This approach increases the cases of “True Positive” detections and increases the detection confidence. In some embodiments, prior knowledge may be fed to the detection system in case the volume-to-be-explored would be accessible before the main mission.

[0028] The procedure of some embodiments does not require image segmentation and feature selection steps. Image segmentation, feature selection, and feature association are the main challenges in traditional place detection techniques. These challenges are the sources of sensitivity to view point changes and sensitivity to environmental changes. Since

the method of some embodiments is non-feature-based, there is no need to store and update the structure conversion database, which may require a huge amount of storage space.

[0029] In some embodiments, the environment being explored is a continuous 3D volume. However, it is possible to divide the environment to meaningful subsets called places. Places are distinctive compared to the surrounding. Instead of corresponding a place to a single descriptor structure, the methodology of some embodiments corresponds places to a matrix of similarity values. This matrix contains the similarity analysis of all the descriptors of different observations made from each place.

[0030] FIG. 1 is a flowchart 100 of a method of identification of similar observations and sequences. In some embodiments, the method may be performed by an apparatus (e.g., the apparatus 902/902' shown in FIG. 9 or FIG. 10).

[0031] At 102, the apparatus may input three-dimensional (3D) scans. In some embodiments, each 3D scan may represent an observation. In some embodiments, the 3D scans may be acquired by any type of sensor or acquisition system. In some embodiments, each 3D scan may result in a 3D point cloud. In some embodiments, the 3D point cloud may be captured by the LiDAR-based sensory system. In some embodiments, the sensory system may facilitate the capture of distance data from the entire surrounding of the robot. In such embodiments, the entire usable distance data from the environment may be captured with high accuracy and high resolution.

[0032] In some embodiments, point clusters with less than 100 point may be removed. In some embodiments, down sampling or voxelization may be performed on the points. In some embodiments, point cloud may be converted to triangulated mesh using greedy method of PCL library. In some embodiments, triangulated mesh may be converted to quadrangles. In some embodiments, surfaces with small number of polygons may be removed. In some embodiments, polygon normal vectors may be verified to direct towards the center. In some embodiments, overlapping polygon nodes may be merged into one node.

[0033] In some embodiments, each 3D scan may result in an observation. FIG. 2 is a diagram 200 showing an example of a place. In the example, a robot carrying the sensory system travelled along the pavement next to a building. The Robot scanned the environment every few meters. FIG. 3 is a diagram 300 illustrating four different observations 302, 304, 306, 308 from the place shown in FIG. 2.

[0034] Referring back to FIG. 1, at 104, the apparatus may generate descriptors based on the input data. In some embodiments, descriptors may be generated through analysis of the input data. The descriptors may be able to uniquely describe each scan. A descriptor may be highly invariant against viewpoint changes. A descriptor may smoothly change when the studied subject smoothly changes.

[0035] In computer vision, a descriptor is a numeric structure from the set of key-features of the studied image. A place descriptor is a numeric model encapsulating intrinsic information for unique identification of a place.

[0036] This disclosure introduces an environment descriptor that can be used for place detection. The descriptor of some embodiments is based on the list of eigenvalues of Laplace-Beltrami operator. In such embodiments, a descriptor may characterize a place. This is achieved through analysis of entire point cloud as a whole (not object by object). The studied point cloud can include visible faces of many objects. These faces and their visible borders and even the attachment of sub-parts are changing when the viewpoint changes. Moreover, the point cloud changes due to noise and occlusion caused by visiting a place from different viewpoints.

[0037] In some embodiments, a descriptor to characterize environments represented by the scanned data similar to the ones depicted in FIG. 3 is provided. The descriptor is introduced hereafter.

[0038] Laplace Beltrami operator over a manifold f is defined as the divergence of the gradient

$$\Delta f = \text{div}(\nabla(f)) = \frac{1}{\sqrt{g}} \partial_i (\sqrt{g} g^{ij} \partial_j), \quad (1)$$

where

$$G = \{g_{ij}\} \quad (2)$$

is the first fundamental form of f and

$$g \triangleq \det(g_{ij}), \quad (3)$$

$$g^{ij} \triangleq (g^{-1})_{ij}. \quad (4)$$

[0039] Laplace Beltrami operator is closely related to the first and second fundamental forms on a surface and therefore, it is related to the mean curvature of the surface through

$$\Delta f = -2Hn. \quad (5)$$

[0040] In equation (5), H denotes the mean curvature and n is the surface normal vector. Laplace Beltrami operator encapsulates the information about the curvature of the surface.

When coordinate functions $f(x, y, z)$ are to be analyzed, Laplace Beltrami operator simplifies to the Laplacian

$$\Delta f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} + \frac{\partial^2 f}{\partial z^2}. \quad (6)$$

[0041] Laplace Beltrami operator has a discrete set of eigenvalues and eigenfunctions. The Laplace eigenvalue problem is described as

$$-\Delta u = \lambda u. \quad (7)$$

[0042] In equation (7), u denotes the eigenfunction associated to the eigenvalue λ . The eigenvalues are real numbers. List of eigenvalues for each scan is a set of numbers increasing from zero to infinity.

[0043] Since Laplace Beltrami operator encapsulates the intrinsic information about the surface such as curvature, it is expected that the eigen spectrum of Laplace Beltrami operator carry intrinsic information about the surface. Hence, the eigenvalue list can serve as surface descriptor.

[0044] The closed-form solution for eigenvalues and eigenfunctions of Laplace Beltrami operator may be derived analytically for rectangles, circles, spheres and other simple primitive shapes. For complicated surfaces, numeric methods may be used to derive the approximated values.

[0045] The first property of the descriptor of some embodiments is that Eigenvalues of an environment are only the union of the eigenvalues of its sub-parts. Each and every eigenvalue of sub-parts of a point cloud are exactly reflected in the list of eigenvalues of the environment as well. Accordingly, if one sub-part is not visible from a certain viewpoint, only the eigenvalues of that sub-part will be removed from the union list and the rest of eigenvalues that are inherited from other sub-parts remain unchanged. This also means that if from one viewpoint, extra objects are in the field of view, some eigenvalues join the union list, but the rest of eigenvalues remain unchanged.

[0046] The second property of the descriptor of some embodiments is that the list of eigenvalues of the noisy version of an object is only deviated from the list of eigenvalues of original object and the amount of deviation is directly related to the amount of noise. So far that the intensity of noise is not to the extent that the structure of object is changed, the structure of the list of eigenvalues remains unchanged. That means, no new eigenvalue is added to the list and no eigenvalue is missed due to non-destructive noise. In another words, for each and every eigenvalue in the list of

eigenvalues of noisy shape, there is a respective pair in the list of eigenvalues of the original shape. Therefore, the eigenvalues change smoothly when there are smooth changes in shape.

[0047] The third property of the descriptor of some embodiments is that union list of eigenvalues of an environment deviates when attachments between sub-parts change. This property is similar to the second property. This means the extent of change in attachment among the sub-parts directly reflects in the amount of deviation of eigenvalues. This can be seen as the effect of occlusion or the effect of changed viewpoint in real situation. The three properties explained above are the most important properties that qualify the union list of eigenvalues to be an informative place descriptor.

[0048] A real environment, such as the one depicted in FIG. 2, is consisted of major objects that might be attached or detached from each other. According to the first property described above, list of eigenvalues of a scan is nothing but the union of the list of eigenvalues of the major objects in the environment. No matter what those objects are, so far that most of eigenvalues of a new observation match a known list (known environment), a match between the characters can be inferred. The second property described above guarantees that non-destructive noise only smoothly affects the list of eigenvalues. The third property described above insures that occlusions and change of viewpoint, which are the reasons for split and merge in visible regions of sub-parts, only result to deviation of the union list of eigenvalues. In most environments, boundaries of the sub-parts are not the real boundaries of an object. In place detection application, borders of sub-parts change due to occlusion caused by the change in viewpoint. The third property insures that the changes of boundaries do not fundamentally change the descriptor. Therefore, list of eigenvalues of Laplace-Beltrami operator is expected to perfectly characterize a point cloud mesh generated out of the input data.

[0049] It should be noted that in real experiments, because of existence of noise, exact matches of eigenvalues cannot be expected from any two scans, even if they are very much the same. A distance function may be defined to compare place descriptors.

[0050] Referring back to FIG. 1, at 106, the apparatus may create a table of similarities. In some embodiments, comparison of similarities among the descriptors

results to the similarity table. FIG. 4 shows an example of a similarity table 400 that is generated from four scans from a volume. Each value in the similarity table 400 represents a similarity value between two corresponding scans. For example, the similarity value between scans 1 and 2 is 83.8, and the similarity value between scans 2 and 4 is 86.6. In some embodiments, the similarity table (e.g., the similarity table 400) may form a similarity matrix.

[0051] When a place contains one rectangle, descriptor of rectangle is included in the descriptor of the place. In some embodiments, counting the number of matching eigenvalues may conclude to the similarity measure. Uniqueness of descriptor implies that descriptor of non-identical surfaces are different. However, it is expected that similarity between surfaces could be inferred from comparison of their descriptors.

[0052] In some cases, counting the exact matches does not help. Instead, matching eigenvalues of inflated descriptors may be counted. However, inflation intensity is not fixed for all the eigenvalues. Inflated descriptor may be generated by assignment of tolerance to eigenvalues of the original descriptor. Perturbed version of a shape has perturbed version of its descriptor. Perturbed version of descriptor may be simulated by assignment of some tolerance to its eigenvalues. If for each eigenvalue λ a tolerance of $\varepsilon\%$ of λ is assumed, inflated version of descriptor is generated.

[0053] The pseudocode below shows an example of the comparison procedure through assignment of inflation value to eigenvalues.

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• INPUT DNA1, DNA2 as array of floating point numbers
• MATCHED_CASES = 0
• TOLERANCE = 0.01
• FOR i = 1 to LENGTH_OF (DNA1)
  ○ FOR j = 1 to LENGTH_OF (DNA2)
    ▪ m = j @ ARGMIN (ABS (DNA1 (i) -DNA2 (j)))
  ○ LOOP j
  ○ FOR k = 1 to LENGTH_OF (DNA1)
    ▪ n = k @ ARGMIN (ABS (DNA1 (k) -DNA2 (m)))
  ○ LOOP k
  ○ IF (n=i) THEN
    ▪ IF (ABS (DNA1 (i) -DNA2 (m)) <
      TOLERANCE * ((DNA1 (i) +DNA2 (m)) / 2) THEN
      • MATCHED_CASES ++;
    ▪ ENDIF
    ▪ REMOVE (DNA1 @ i)
    ▪ REMOVE (DNA2 @ m)
    ▪ i = 0
  ○ ELSE

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        ▪   i = n
        ▪   CONTINUE
    ○   ENDIF
•   LOOP i
•   OUTPUT MATCHED_CASES

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[0054] In the procedure described above, first step is to identify the closest pairs of eigenvalues between the compared descriptors. For all the eigenvalues of one descriptor, the closest eigenvalue from the other descriptor is found. Then the median μ of each pair is calculated. If the eigenvalues of the pair are within the distance of “ $\epsilon\%$ of μ ” from μ , the pair denotes a matched case. In this disclosure, ϵ equals 1 for all real situation case studies. “Matched cases” variable, counted according to the pseudocode above, is taken as the similarity measure. This value indicates the similarity between any arbitrary two descriptors (e.g., DNA1 and DNA2). It is possible to normalize the resultant number by total number of eigenvalues in descriptors. This way, the similarity value can be represented in percentage and so the anticipated similarity may be used as the threshold for detection of two similar descriptors.

[0055] Referring back to FIG. 1, at 108, the apparatus may identify distinctive zones in the similarity matrix. In a continuous motion, zones are identified as a group with higher similarities. These groups may be identified as square sub matrices along the main diagonal of the similarity matrix, the square sub matrices containing similarity values higher than the adjacent matrix elements.

[0056] FIG. 5 is a diagram illustrating an example of identified zones in a similarity matrix 500 by marking major diagonal sub matrices. In some embodiments, the similarity matrix 500 is formed by comparing the descriptors of 29 scans/observations. In the example, zones 502, 504, and 506 are identified along the main diagonal of the similarity matrix 500. Each of the zones 502, 504, and 506 contains similarity values that are higher than the adjacent matrix elements.

[0057] Referring back to FIG. 1, at 110, the apparatus may identify similar sequences of zones. In some embodiments, similar sequences of zones may be identified through template matching in the similarity matrix. Template is a sequence that starts from starting element of one zone and ends to the last element of a subsequent zone. Reoccurrence of a sequence may be identified if a matched matrix is found along the main diagonal of the similarity matrix, or along the same horizontal (or vertical) sub-

matrix that contains the template. The cross section is another sub matrix that may be referred to as a cross-similarity sub matrix. The cross-similarity sub matrix represents the similarity between two sequences of observations.

[0058] FIG. 6 is a diagram illustrating an example of template matching in a similarity matrix 600. In the example, sequences of zones are identified in the similarity matrix 600. For example, sequence 602 starts from the starting element of zone 604 and ends to the last element of zone 608. In another example, sequence 610 starts from the starting element of zone 612 and ends to the last element of zone 614. The sequences 602 and 610 may be found to be similar as a result of template matching. The cross-similarity sub matrix 620 may represent the similarity between the sequences 602 and 610. As shown, the cross-similarity sub matrix 620 has the same rows as the sequence 602 in the similarity matrix 600, and the same columns as the sequence 610 in the similarity matrix 600.

[0059] Referring back to FIG. 1, at 112, the apparatus may detect similar observations from cross-similarity sub matrix. In some embodiments, similar observations may be identified by checking the diagonal elements of the cross-similarity sub matrix. The highest similarity values among the diagonal elements of the cross similarity sub-matrix shows which scan (e.g., the scan corresponding to the row of an element) is similar to which (e.g., the scan corresponding to the column of the element).

[0060] FIG. 7 is a diagram 700 illustrating an example of large diagonal values in the cross-similarity sub matrix 702 indicating similar observations. In the example, first matching pairs of snapshots (represented by element 704) show about 93% of descriptor similarity (1858 out of 2000 pairs of eigenvalues), and the second matching pair (represented by element 706) show about 95% descriptor similarity (1898 out of 2000 pairs of eigenvalues). Therefore, the scan corresponding to the row of the element 704 may be similar to the scan corresponding to the column of the element 704. Similarly, the scan corresponding to the row of the element 706 may be similar to the scan corresponding to the column of the element 706.

[0061] The methodology of some embodiments may incorporate onboard sensory system for analysis. However, in an arbitrary application, one may use other complimentary sensors, such as GPS, or any combination of mapping and semantic

labeling techniques to provide meaningful tags to identified zones. It should be re-emphasized that after the formation of the table of similarities, possibly assisted by companion labeling techniques, the methodology is capable of identification without any further reliance on any other sensory system or localization technique.

[0062] Some embodiments may be used extensively for place detection in mobile robotics. A few applications in mobile robotics are presented below but it should be noted that the applications of the methodology might be far beyond place detection and mobile-robotics-related applications.

[0063] Some embodiments may be used in detection of novel places. Novel places refer to any newly visited place that is different from the previously detected place in a continuous motion.

[0064] Some embodiments may be used in transition detection or sequence detection. Such embodiments may match a new sequence of two observed places with previous observations of the current mission or the sequences fed to the system as prior knowledge. Examples are “transition from corridor to indoor” or “transition from indoor to outdoor.”

[0065] Some embodiments may be used in scenario detection. Such embodiments may detect transition from one place to another via other link places. Example could be “transition from indoor to road via garden.”

[0066] Some embodiments may be used in detection of loop closure clues (for simultaneous localization and mapping (SLAM) algorithms). Such embodiments may pinpoint the best time stamps to search for loop closure data frame candidates.

[0067] Some embodiments may be used in startup location estimation. If prior knowledge about the environment-to-be-explored exists, such embodiments may enable the intelligent vehicle to guess its initial position.

[0068] Some embodiments may be used in detection of map merging frame candidates. Such embodiments may pinpoint the best time stamps to search for map merging data frame candidates in a distributed multi-vehicle exploration mission.

[0069] Some embodiments may be used in fault detection or malicious intrusion detection. In such embodiments, localization module may estimate the location of the robot based on the fusion of multiple sensors. Any malfunction (e.g., unchanging camera frame, frozen LiDAR (light detection and ranging), disconnection of wheel

encoders, etc.) or falsified signal (e.g., falsified GPS generated signal) fed into any of the sensors or fusion system could cause severe safety and security issues for the autonomous vehicle. Such embodiments may be used as a counter check to identify malicious intrusions and cyber-attacks or as a counter check for fault detection in localization module.

[0070] FIG. 8 is a flowchart 800 of a method of identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations. In some embodiments, the method may be performed by an apparatus (e.g., the apparatus 902/902' shown in FIG. 9 or FIG. 10). In some embodiments, operations performed by the method may correspond to operations described above with reference to FIG. 1.

[0071] At 802, for each observation, the apparatus may calculate a descriptor that characterizes the observation. In some embodiments, the descriptor may smoothly change with smooth changes of the observation. In some embodiments, the descriptor may change in proportion to the changes of the observation. In some embodiments, the descriptor may be a list of eigenvalues of Laplace-Beltrami operator over a surface mesh generated from 3-dimensional point cloud data. In some embodiments, the 3-dimensional point cloud data may be obtained by scanning visible subset of the volume.

[0072] At 804, the apparatus may determine a similarity value between any two descriptors to form a similarity matrix. In some embodiments, a similarity value may be determined by comparing descriptors of two observations.

[0073] At 806, the apparatus may identify a plurality of first-type square sub-matrices along the main diagonal of the similarity matrix. In some embodiments, each similarity value within each of the plurality of first-type square sub-matrices may be greater than a threshold value.

[0074] At 808, the apparatus may identify a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix. Each of the plurality of second-type square sub-matrices may contain multiple first-type square sub-matrices. In some embodiments, each of the plurality of second-type square sub-matrices may start from the beginning of a first first-type square sub-matrix and end at the end of a subsequent first-type square sub-matrix.

[0075] At 810, the apparatus may identify at least one third-type sub-matrix. Each of the at least one third-type sub-matrix may be an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix. In some embodiment, to identify the at least one third-type sub-matrix, the apparatus may identify similar second-type square sub-matrices by comparing patterns of the plurality of second-type square sub-matrices.

[0076] At 812, the apparatus may identify the largest elements along the main diagonal of the at least one third-type sub-matrix as candidates for re-observed snapshots.

[0077] FIG. 9 is a conceptual data flow diagram 900 illustrating the data flow between different means/components in an exemplary apparatus 902. The apparatus 902 may be a computing device or a system including multiple computing devices.

[0078] The apparatus 902 may include a descriptor generation component 904 that generates descriptors for 3D scans. In one embodiment, the descriptor generation component 904 may perform the operations described above with reference to 104 in FIG. 1 or 802 in FIG. 8.

[0079] The apparatus 902 may include a similarity matrix component 906 that creates a similarity matrix based on the descriptors provided by the descriptor generation component 904. In one embodiment, the similarity matrix component 906 may perform the operations described above with reference to 106 in FIG. 1 or 804 in FIG. 8.

[0080] The apparatus 902 may include a re-observation identification component 908 that identifies candidates for re-observed snapshots using the similarity matrix provided by the similarity matrix component 906. In one embodiment, the re-observation identification component 908 may perform the operations described above with reference to 108, 110, or 112 in FIG. 1, or 806, 808, 810, or 812 in FIG. 8.

[0081] The apparatus 902 may include additional components that perform each of the blocks of the algorithm in the aforementioned flowcharts of FIGS. 1 and 8. As such, each block in the aforementioned flowcharts of FIGS. 1 and 8 may be performed by a component and the apparatus may include one or more of those components. The components may be one or more hardware components specifically configured to carry out the stated

processes/algorithm, implemented by a processor configured to perform the stated processes/algorithm, stored within a computer-readable medium for implementation by a processor, or some combination thereof.

[0082] FIG. 10 is a diagram 1000 illustrating an example of a hardware implementation for an apparatus 902' employing a processing system 1014. In some embodiments, the apparatus 902' may be the apparatus 902 described above with reference to FIG. 9. The apparatus 902' may include one or more computing devices. The processing system 1014 may be implemented with a bus architecture, represented generally by the bus 1024. The bus 1024 may include any number of interconnecting buses and bridges depending on the specific application of the processing system 1014 and the overall design constraints. The bus 1024 links together various circuits including one or more processors and/or hardware components, represented by the processor 1004, the components 904, 906, 908, and the computer-readable medium / memory 1006. The bus 1024 may also link various other circuits such as timing sources, peripherals, voltage regulators, and power management circuits, which are well known in the art, and therefore, will not be described any further.

[0083] The processing system 1014 includes a processor 1004 coupled to a computer-readable medium / memory 1006. The processor 1004 is responsible for general processing, including the execution of software stored on the computer-readable medium / memory 1006. The software, when executed by the processor 1004, causes the processing system 1014 to perform the various functions described *supra* for any particular apparatus. The computer-readable medium / memory 1006 may also be used for storing data that is manipulated by the processor 1004 when executing software. The processing system 1014 further includes at least one of the components 904, 906, 908. The components may be software components running in the processor 1004, resident/stored in the computer readable medium / memory 1006, one or more hardware components coupled to the processor 1004, or some combination thereof.

[0084] In the following, various aspects of this disclosure will be illustrated:

[0085] In various embodiments, a method, apparatus, or computer program for identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations are provided. The apparatus may: for each observation, calculate a descriptor that characterizes the observation;

determine a similarity value between any two descriptors to form a similarity matrix; and identify candidates for re-observed snapshots based on the similarity matrix.

[0086] In various embodiments, to identify the candidates for re-observed snapshots, the apparatus may: identify a plurality of first-type square sub-matrices along main diagonal of the similarity matrix; identify a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix, each of the plurality of second-type square sub-matrices containing multiple first-type square sub-matrices of the plurality of first-type square sub-matrices; identifying at least one third-type sub-matrix, each of the at least one third-type sub-matrix being an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix; and identify the largest elements along the main diagonal of the at least one third-type sub-matrix as the candidates for re-observed snapshots.

[0087] In various embodiments, each similarity value within each of the plurality of first-type square sub-matrices may be greater than a threshold value.

[0088] In various embodiments, each of the plurality of second-type square sub-matrices may start from the beginning of a first first-type square sub-matrix and end at the end of a subsequent first-type square sub-matrix.

[0089] In various embodiments, to identify at least one third-type sub-matrix, the apparatus may identify similar second-type square sub-matrices by comparing patterns of the plurality of second-type square sub-matrices.

[0090] In various embodiments, the descriptor may change in proportion to changes of the observation.

[0091] In various embodiments, the descriptor may be a list of eigenvalues of Laplace-Beltrami operator over a surface mesh generated from 3-dimensional point cloud data.

[0092] In various embodiments, the 3-dimensional point cloud data may be obtained by scanning visible subset of the volume.

[0093] In various embodiments, a similarity value may be determined by comparing descriptors of two observations.

[0094] A person skilled in the art will appreciate that the terminology used herein is for the purpose of describing various embodiments only and is not intended to be limiting of the present invention. As used herein, the singular forms "a", "an" and "the" are intended to include the plural forms as well, unless the context clearly indicates otherwise. It will be further understood that the terms "comprises" and/or "comprising," when used in this specification, specify the presence of stated features, integers, steps, operations, elements, and/or components, but do not preclude the presence or addition of one or more other features, integers, steps, operations, elements, components, and/or groups thereof.

[0095] It is understood that the specific order or hierarchy of blocks in the processes / flowcharts disclosed is an illustration of exemplary approaches. Based upon design preferences, it is understood that the specific order or hierarchy of blocks in the processes / flowcharts may be rearranged. Further, some blocks may be combined or omitted. The accompanying method claims present elements of the various blocks in a sample order, and are not meant to be limited to the specific order or hierarchy presented.

[0096] The previous description is provided to enable any person skilled in the art to practice the various aspects described herein. Various modifications to these aspects will be readily apparent to those skilled in the art, and the generic principles defined herein may be applied to other aspects. Thus, the claims are not intended to be limited to the aspects shown herein, but is to be accorded the full scope consistent with the language claims, wherein reference to an element in the singular is not intended to mean "one and only one" unless specifically so stated, but rather "one or more." The word "exemplary" is used herein to mean "serving as an example, instance, or illustration." Any aspect described herein as "exemplary" is not necessarily to be construed as preferred or advantageous over other aspects. Unless specifically stated otherwise, the term "some" refers to one or more. Combinations such as "at least one of A, B, or C," "one or more of A, B, or C," "at least one of A, B, and C," "one or more of A, B, and C," and "A, B, C, or any combination thereof" include any combination of A, B, and/or C, and may include multiples of A, multiples of B, or multiples of C. Specifically, combinations such as "at least one of A, B, or C," "one or more of A, B,

or C,” “at least one of A, B, and C,” “one or more of A, B, and C,” and “A, B, C, or any combination thereof” may be A only, B only, C only, A and B, A and C, B and C, or A and B and C, where any such combinations may contain one or more member or members of A, B, or C. All structural and functional equivalents to the elements of the various aspects described throughout this disclosure that are known or later come to be known to those of ordinary skill in the art are expressly incorporated herein by reference and are intended to be encompassed by the claims. Moreover, nothing disclosed herein is intended to be dedicated to the public regardless of whether such disclosure is explicitly recited in the claims. The words “module,” “mechanism,” “element,” “device,” and the like may not be a substitute for the word “means.” As such, no claim element is to be construed as a means plus function unless the element is expressly recited using the phrase “means for.”

CLAIMS

WHAT IS CLAIMED IS:

1. A method of identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations, the method comprising:

for each observation, calculating a descriptor that characterizes the observation;
determining a similarity value between any two descriptors to form a similarity matrix; and
identifying candidates for re-observed snapshots based on the similarity matrix.

2. The method of claim 1, wherein the identifying of the candidates for re-observed snapshots comprises:

identifying a plurality of first-type square sub-matrices along main diagonal of the similarity matrix;

identifying a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix, each of the plurality of second-type square sub-matrices containing multiple first-type square sub-matrices of the plurality of first-type square sub-matrices;

identifying at least one third-type sub-matrix, each of the at least one third-type sub-matrix being an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix; and

identifying largest elements along main diagonal of the at least one third-type sub-matrix as the candidates for re-observed snapshots.

3. The method of claim 2, wherein each similarity value within each of the plurality of first-type square sub-matrices is greater than a threshold value.

4. The method of any one of claims 2-3, wherein each of the plurality of second-type square sub-matrices starts from a beginning of a first first-type square sub-matrix and ends at an end of a subsequent first-type square sub-matrix.
5. The method of any one of claims 2-4, wherein the identifying of the at least one third-type sub-matrix comprises identifying similar second-type square sub-matrices by comparing patterns of the plurality of second-type square sub-matrices.
6. The method of any one of claims 1-5, wherein the descriptor changes in proportion to changes of the observation.
7. The method of any one of claims 1-6, wherein the descriptor is a list of eigenvalues of Laplace-Beltrami operator over a surface mesh generated from 3-dimensional point cloud data.
8. The method of claim 7, wherein the 3-dimensional point cloud data is obtained by scanning visible subset of the volume.
9. The method of any one of claims 1-8, wherein a similarity value is determined by comparing descriptors of two observations.
10. An apparatus for identification of previously observed subsets of a volume being explored through recognition of similar sequences of partial observations, the apparatus comprising:
 - at least one memory; and
 - at least one processor coupled to the at least one memory and configured to:
 - for each observation, calculate a descriptor that characterizes the observation;
 - determine a similarity value between any two descriptors to form a similarity matrix; and
 - identify candidates for re-observed snapshots based on the similarity matrix.

11. The apparatus of claim 10, wherein, to identify the candidates for re-observed snapshots, the at least one processor is configured to:

identify a plurality of first-type square sub-matrices along main diagonal of the similarity matrix;

identify a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix, each of the plurality of second-type square sub-matrices containing multiple first-type square sub-matrices of the plurality of first-type square sub-matrices;

identify at least one third-type sub-matrix, each of the at least one third-type sub-matrix being an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix; and

identify largest elements along main diagonal of the at least one third-type sub-matrix as the candidates for re-observed snapshots.

12. The apparatus of claim 11, wherein each similarity value within each of the plurality of first-type square sub-matrices is greater than a threshold value.

13. The apparatus of any one of claims 11-12, wherein each of the plurality of second-type square sub-matrices starts from a beginning of a first first-type square sub-matrix and ends at an end of a subsequent first-type square sub-matrix.

14. The apparatus of any one of claims 11-13, wherein the identifying of the at least one third-type sub-matrix comprises identifying similar second-type square sub-matrices by comparing patterns of the plurality of second-type square sub-matrices.

15. The apparatus of any one of claims 10-14, wherein the descriptor changes in proportion to changes of the observation.

16. The apparatus of any one of claims 10-15, wherein the descriptor is a list of eigenvalues of Laplace-Beltrami operator over a surface mesh generated from 3-dimensional point cloud data.
17. The apparatus of claim 16, wherein the 3-dimensional point cloud data is obtained by scanning visible subset of the volume.
18. The apparatus of any one of claims 10-17, wherein a similarity value is determined by comparing descriptors of two observations.
19. A non-transitory computer-readable medium storing computer executable code, comprising instructions for:
- for each observation, calculating a descriptor that characterizes the observation;
 - determining a similarity value between any two descriptors to form a similarity matrix; and
 - identifying candidates for re-observed snapshots based on the similarity matrix.
20. The non-transitory computer-readable medium of claim 19, wherein the instructions for identifying of the candidates for re-observed snapshots comprise instructions for:
- identifying a plurality of first-type square sub-matrices along main diagonal of the similarity matrix;
 - identifying a plurality of second-type square sub-matrices along the main diagonal of the similarity matrix, each of the plurality of second-type square sub-matrices containing multiple first-type square sub-matrices of the plurality of first-type square sub-matrices;
 - identifying at least one third-type sub-matrix, each of the at least one third-type sub-matrix being an intersection of two second-type square sub-matrices in such a way that rows of the third-type sub-matrix in the similarity matrix are the same as rows of one of the two second-type square sub-matrices in the similarity matrix and columns of the third-type sub-matrix in the similarity matrix are the same as columns of the other of the two second-type square sub-matrices in the similarity matrix; and
 - identifying largest elements along main diagonal of the at least one third-type sub-matrix as the candidates for re-observed snapshots.