A Hybrid Map Representation for Simultaneous Localization and Mapping of the Internal Ruins Environment *

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Abstract—According to morphological characteristics in the interior of ruins after an earthquake disaster, a map representation technique for ruins environment is presented, and a corresponding simultaneous localization and mapping algorithm on the basis of hybrid map is proposed. Based on the topological metric hybrid map, the algorithm describes ruins environment at different levels. At global level, the topological map organizes the overall structure and also ensures the computing capability and ambient adaptability. Then, through building a local metric map at each topological node region, irregular obstacles formed by random seismic damage are described. Finally, experiments in an artificial ruins environment show that the algorithm can realize localization and mapping at the complicated environment.

Keywords—ruins environment; simultaneous localization and mapping; topological map; hybrid map representation

I. INTRODUCTION

Simultaneous localization and mapping (SLAM) is to simultaneously estimate positions of surrounding landmarks and positions of the mobile robot itself while mapping. Therein, the localization of the robot and the map of the environment are both unknown and the estimate process is lack of an absolute reference. The localization and mapping are interdepending, iterative and highly relevant. Throughout the last decade this topic has been widely studied, and successfully extended the SLAM from theory to application.

Interior surface of the seismic disaster belongs to unknown and complicated environments. Robot localization and environmental perception directly affect viability and adaptability of the rescue robot system and the execution efficiency of rescue tasks. One of the challenges of SLAM problem in ruins environment is how to choose a map to describe the unknown environment, and the map can updated along with the robot position simultaneously. In addition, how to reduce computational complexity of algorithms for the complex environment is particularly important.

In recent years, many researchers introduced the concept of hybrid map to reduce the complexity at view of the map building. DenseSLAM in [1] presented a hybrid metric map representation (HYMM) that combines feature maps with other metric dense information. The global feature map is partitioned into a series of connected local triangular regions (LTRs) in which a local density map is built. [2] proposed a unified Bayesian approach to hybrid metric-topological SLAM to ensure the robustness and accuracy in large-scale environment. These maps however cannot be applied to represent the interior surface of ruins environments directly. The SLAM facing ruins environments then gradually become a hot topic. For a narrow ditch leading to the wide space in collapsed buildings, Keiji Nagatani used a three-dimensional map representation called S-DEM for three-dimensional spatial location and environment modeling [3]. Based on the data exchange and association via RFID, Alexander Kleiner and Dali Sun presented DSLAM method which does not require any radio communication. This method is on basis of the non-selfish sharing of information for pedestrians without direct communication [4]. In [5], Behdad Soleimani presented a disaster invariant feature (DIF) which utilizes for the localization of unmanned aerial vehicles. Algorithm uses street detection from aerial images to detect the DIF. However, these SLAM methods do not solve the mapping problem for internal ruins environments.

SLAM algorithm for internal ruins environments not only requires an appropriate description for environmental behaviors, but also needs to have the accuracy and speed. The above mentioned methods can not meet these requirements simultaneously. According to morphological characteristics of the interior surface of the seismic disasters, this paper proposes a hybrid map representation method with a map building mechanism for representation of ruins environments. The proposed SLAM algorithm improves the ability to describe ruins environments and reduces the computing complexity for rescue needs.

The rest of this paper is organized as follows. Section II presents the building mechanism of the map representation in ruins environment. Section III describes the architecture of the SLAM based on the topological metric hybrid map. The

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implementation of SLAM system based on the hybrid map is presented in section IV. Section V presents system experiments and analysis. Finally, some conclusions are summarized.

II. MAP BUILDING MECHANISM FOR RUINS ENVIRONMENTS

The decision of map representation for SLAM in ruins environments depends on the environmental characteristics and the task requirement. The building mechanism of the map representation is proposed to identify a suitable representation for ruins.

A. Morphological Characteristics of the Interior Surface of the Seismic Disasters

Ruins refer to the destructive pattern of the seismic disasters. The internal environment is composed of severely damaged or completely collapsed structures and connecting pipes [6].

![Fig. 1. General destructive patterns and corresponding contours of the interior surface of the seismic disasters](image)

The interior surface of ruins environments mainly includes the damage morphology of slab-column structures after the earthquake. A large number of the broken building components (including fracture slabs, columns, beams, etc.) randomly stack in ruins space, as shown in Fig. 1. General destructive patterns, such as fracture or slit of walls and columns, appear complex boundaries in the two-dimensional plane. Moreover, the global structure of environment has no or little change after a disaster. The distribution of obstacles is stochastically, and environments are lack of appropriate unified characteristics.

B. Building criterions for simultaneous localization and mapping

Target space $O^c$ is built according to objectives requirements and assessment criteria of the SLAM system, as in (1).

$$O^c = \{C_i | i = 1 : k\}$$

(1)

Building criterions $c_i$ are as follows:

1) Applicability $C_1$ refers to the ability of map representation to describe the target environment and to satisfy the task requirement.

2) Accuracy $C_2$ refers to the precision of environmental description which can be measured by estimate covariance of the robot and features’ positions.

3) Computational property $C_3$ refers to the computation property such as algorithm complexity and memory consumption.

4) Interaction $C_4$ refers to whether outputs of the algorithm are in line with human cognitive habits and applicable for planning and navigation.

C. Comparison of commonly map representations

According to the above building criterions, a comparison of the common map representations is analyzed, that is given in Table 1.

![Table 1. Comparison of common map representations](image)

<table>
<thead>
<tr>
<th>Maps</th>
<th>Applicability(C1)</th>
<th>Accuracy(C2)</th>
<th>Computational(C3)</th>
<th>Interaction(C4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topology (P1)</td>
<td>0.5</td>
<td>0.1</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Grid (P2)</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
<td>0.5</td>
</tr>
<tr>
<td>Feature (P3)</td>
<td>0.1</td>
<td>0.9</td>
<td>0.5</td>
<td>0.1</td>
</tr>
</tbody>
</table>

1) Topological map $P_1$ is a kind of brief map with relative spatial relationships. The map belongs to the approximate description which has low storage space and time requirements. The method is suitable for large-scale indoor environment and is able to organize the advanced features of the environment.

2) Metric map used the unified coordinate to express environment characteristics. It is suitable for low dimensional static space. Grid map $P_2$ can express irregular obstacles and achieve accurate positions, but precision and computation are conflicted. Feature map $P_3$ is compact and has more feature matching opportunities. But feature map is limited to special environments.

D. Decision of the map representation for the interior of ruins environments

A map representation for the SLAM system in ruins environments needs to meet requirements of morphological characteristics of the interior surface and efficiency requirements for emergent search and rescue. Namely, weights of applicability criterion and computational capability criterion are higher priority. The multi-objective decision space $D^P$ can be obtained according to the comparison result of schemes.

$$D^P = \{f(P_j) | j = 1 : k\}$$

(2)

The interior of the ruins environment after the seismic disaster belongs to the large scale semi-structural indoor environment. The semi-collapsed building has invariant structures such as walls and columns. The environment has certain prior knowledge. Typical characteristics of indoor environment before disaster can be used as the basis of the node identification for the global topological map. Moreover, the structure and the connectivity of buildings under ideal conditions can be provided by the global map to meet the computational cost criterion and interaction criterion.

The irregularity and complexity of the interior surface of the seismic disasters cannot be expressed with the appropriate parameters and is difficult to predict types of parameters. Local
metric information is described by grid maps to meet the demand for applicability and accuracy criterions. Considering the unevenness of the ruin terrain, grid map is built as the technical reserves for 2.5-dimensional maps which combine the elevation information.

Based on the odometry information, the dead reckoning is utilized for the kinematics prediction on the localization module. On the basis of the current primary feature extraction results, the module realizes robot localization in real time through iterative prediction and update. At actual rescue missions, the accuracy is not the only target for the quality assessment of the mapping and localization. The demands for the practical applications also need to be considered according to different tasks. Therefore, a composite location method which includes two levels of logical positions and precise positions is proposed to satisfy application demands for the coverage efficiency and accuracy respectively.

Global processing module provides the basis of expression for the topological map building. Firstly, corners and line segments are extracted from the ranging data as primary features. Secondly, the advanced features (such as doors and corridor corners) are identified according to the distribution of primary features. Finally, the effective topological information is extracted to deal with the topological node list including the generation of the new node and the update of existed nodes.

Based on grid maps, the local processing module is responsible for the detailed description of irregular obstacles at each node region. After the pre-treatment of the raw data, a local map is created on the new node region and the grid map is initialized and updated.

3) Environmental representation layer: Based on the topological metric hybrid map, the algorithm represents the coherence of the overall structure and details of the destructive region at different levels. Complex environmental features are organized and the spatial connectivity is identified rapidly through the global topological map. The grid maps at each node provide the metric information for local area, including the precise position and detailed mapping.

IV. BUILDING OF THE SLAM SYSTEM BASED ON THE TOPOLOGICAL METRIC HYBRID MAP

The architecture of the SLAM system is divided by functions for the interior of ruins environments. Destructive patterns of ruins environments have characteristics of complex contour and uneven features density, and semi-collapsed environment exist invariant features such as walls and columns. According to the same raw sensor data, the hierarchical collapsed map gives a set of environment representation for different needs of rescue mission. The ideal distribution of advanced features in the internal building is represented by the global topological map. The precise location and environment information are particular described by the local metric maps. The algorithm realizes the simultaneous localization and mapping for the interior of ruins environment at qualitative and quantitative levels.

A. Building of the global topological map

According to the criteria of the mentioned applicability $C_1$, computational capability $C_3$ and interaction $C_4$, the topological map is the global map at the qualitative level. The ruins almost belong to a typical large-scale indoor environment before the
earthquake. Therefore there is a prior knowledge and invariant features which can be defined as topological nodes.

Building of the topological map mainly refers to the definition and identification of the topological nodes. The difference between each topological modeling method is how to build and classify nodes and how to process the uncertainty [7].

Currently, there is no a uniform definition for topological nodes [8-9]. The node refers to the geometric center of the channel intersection region such as the end of the corridor, the corner of channels and the entrance of rooms. Algorithm uses features of line segments and corners to identify the advanced features such as doors and corners. The map combines of the topological node areas and effective topological information.

A typical large-scale indoor environment usually can be divided into several intersection areas of channels such as doors and ends of the corridor. This intersection of channels is defined as the topological node region.

\[
N = \{ I_i = A_j \cap A_k | i \geq 1, j \geq 1, k > 1, j \neq k \} \tag{3}
\]

Among them, \( I_i \) refers to the intersection region at which the node is located, namely the corridor passage pairwise intersecting areas. The topological node \( N \) is located in the geometric center of the corresponding intersection region.

Corridor \( A \) refers to a channel of the topological map and composes of the walls and several doors on both sides. \( A \) is defined as follows:

\[
A = \{ D_i, W_j | i \geq 0, j \geq 2 \} \tag{4}
\]

The recognition of wall \( W_i \) is achieved by the extraction of the vector line segment from the laser ranging data. Moreover, the algorithm takes into account the measurement uncertainties.

At an unknown environment, there may be no channel intersection region within the sensor observed visual field. In other words, the number of primary nodes is not appropriate. Therefore, the door \( D \) is a secondary node to assist mapping.

\[
D = \{ g_i, g_j | d_{g_i, g_j} \neq 0, i \geq 1, j \geq 1 \} \tag{5}
\]

Among them, the corner feature \( g \) is the basic element of primary features on the global topological map. The corner feature represents points of intersection around the door frame. The vector direction of two adjacent corners is normal each other. There is a certain distance between them.

Building of the global topological map primarily refers to the identification process of the topological node. The workflow is shown in Fig. 4. The robot localization uses the form of the logical location at the topological map level. Only the number and category of the owning node area is identified, the precision coordinates are ignored. The rough positioning in logical localization has similarities with the human intelligence.

Specific building steps include the pre-treatment of the original laser data, the extraction of primary features such as line segments and corners, the identification of advanced features such as corridor corners and doors, and the initialization with update of the global topological map.

1) Extraction of the primary feature: The line segment features are extracted according to each frame sensor data. Then on this basis, the intersection of the adjacent segment is defined as the corner feature. First of all, the adaptive method detects breakpoint based on the density of observation data. Additionally, the iterative end point fit (IEPF) [10] algorithm is used to extract line segment feature \( l \) in the form of polar coordinates and to calculate parameter error. Finally, adjacent segments which satisfy the angle requirement is found. The line intersection formula is used to calculate the location of the corner feature. Then the angle bisector direction is defined as the direction of corner and use the covariance propagating algorithm to calculate the positioning variance based on the observation accuracy. The extraction process for primary feature is expressed as:

\[
S_g^{ij} = \{ g_j | j = 1: n \} \leftarrow \{ l_i | i = 1: m \} \leftarrow (Z^0) \tag{6}
\]

Wherein, \( Z^0 \) is the original observation data. \( S_g^{ij} \) is the set of feature extraction results including the primary straight line segments feature \( l \) and corner feature \( g \).

2) Identification of the advanced features: According to the aforementioned definition of nodes, geometric properties of the advanced features and the distribution of primary features are used to complete the identification. Walls of corridor usually consist of two approximately parallel line segments and an open area of channel characteristics. The ranging data always appears a jump phenomenon. The corridor corner feature is crosswise which includes approximate vertical line segments. The estimate process of the wall feature takes advantage of corner point features. The identification of the door feature uses intersection points which are on both side of the doorframe.

3) Building of the global topological map: The topological nodes are distributed based on the corresponding binding advanced features. The geometry center of the corridor corner is defined as a topological major node. The geometric center of
door is defined as a secondary node. The corridor pathway represents the topological connections. According to current extraction results of the robot work area, the topological node list is updated in real-time and a new node is generated as the initialized trigger condition for a local metric map.

B. Building of the local metric map

The interior of ruins environments with damage patterns around walls and columns is mainly generated by the stochastic earthquake. It is impossible to pre-build the robust model because of the absence of prior knowledge. According to the building criterions of applicability $C_1$ and accuracy $C_2$, local grid maps are created at each topological node area to describe details for irregular obstacles. It ensures the accuracy of the localization and mapping at the target area.

The building of the hybrid map is based on the advanced features which are extracted and recognized from the observations. A local grid map is initialized at each node region along with the generation of a new topological node. The grid map is similar to a bitmap representation. The Bayesian method is used to update the grid status in the mapping which is also called grid occupation probability calculation.

The building process of the local map is divided into the initialization and update phases. Grids accuracy is determined according to the expression range. The initial probability is usually set to 0.5 while initializing the grid status. Bayesian estimation used "odds" on the updated phase. The iterative loop update formula is performed by:

$$\log \frac{p(m_{ij} | Z^k, X^k)}{1 - p(m_{ij} | Z^k, X^k)} = \log \frac{p(m_{ij} | z_k, x_k)}{1 - p(m_{ij} | z_k, x_k)} + \log \frac{p(m_{ij} | Z^{k-1}, X^{k-1})}{1 - p(m_{ij} | Z^{k-1}, X^{k-1})}$$

(7)

Among them, $p(m_{ij} | z_k, x_k)$ indicates the sensor reverse observation model [11]. The model describes renewal amplitude of the grid map based on each frame observation whose value is determined by the relationship between the observation $z$ and the detection range $r$.

The building process of the local metric map is shown in Fig. 5. The algorithm iteratively updates grids based on the Bayesian method according to each frame laser sensor data.

V. EXPERIMENTS AND ANALYSIS

In this section, the feasibility and effectiveness of the proposed algorithm is verified in an artificial ruins environment which simulates internal patterns of real ruins environments.

Experimental environment as shown in Fig. 6(a), there are curved walls, prominent columns, corners and other indoor characteristics in the corridor environment. The total experimental area is about 350m$^2$. In order to simulate the scene after earthquakes, typical local destructive patterns which are referenced to the wall cracks, steels reveal and collapsed debris are reproduced at the experimental environment. The wall damage cracks are simulated by the gaps between boxes. The building broken components are randomly stacked on both sides of the corridor to form irregular barriers. The correspondences between specific experimental scenes and typical local destructive patterns of ruins are marked in Fig. 6(a).

As shown in Fig. 6(b), this experiment uses the shape-shifting search and rescue robot AMOEBA-I which is developed by Shenyang institute of automation Chinese academy of sciences. The robot has strong environmental adaptability and high mobility. It can realize the application of the special operations such as rescue. The laser scanning distance sensor URG-04LX is carried by the robot. The detection distance of the sensor is 4 m. The angular resolution is about 0.36 degree.

The experimental results of the SLAM algorithm based on hybrid topological metric map are shown in Fig. 7. Black points are the positions of the topological nodes which are refer to doors at this experimental environment. The localizations of each node are extracted from the geometrical relationship of the corresponding corner features. Topological nodes and relationships between them build the global topological map. The blue lines are environment approximate contours. The dotted line shows the estimation of robot trajectory. The right side of the Fig. 7 shows the result of the whole local metric maps which is obtained by fusing multi vice partial maps. Each grid map corresponds to a topological node. The coordinate system is located at the center of each grid map. For comparison, the contour schematic of the environment
structure in ideal conditions is also shown in the right side of Fig. 7.

![Fig. 7. Algorithm experimental results](image)

To analyze the experimental results at different levels, this hybrid method uses the global topological map and the local grid map to model robot environment. The global environment connectivity is provided by the topological map with strong computational capability. The node is identified based on the feature extraction. The identification is used to get the topological node list and to provide the area for local mapping. The integration of grid maps which are described irregular obstacles at each node area is ensured the premise of computational capability and environmental applicability.

VI. CONCLUSION

According to the morphological characteristics of the interior surface of ruins environment, such as complex contours and uneven density of features, this paper has presented an effective map building mechanism of the selection of map representation methods. Based on the topological metric hybrid map, the architecture of the SLAM system is designed. Using the invariant feature at semi-collapse environment after disasters, the collection of environmental representations is built to meet different requirements of the rescue mission. The distribution of advanced features inside buildings under ideal conditions has been described based on the global topological map. Local metric maps are utilized for accurate localization and particular representation for damaged structures. Simultaneous localization and mapping in ruins environment has been also implemented at qualitative and quantitative levels respectively. The algorithm has strong computing and interaction capabilities which demonstrated in an artificial ruins environment.

REFERENCES