Proceedings of 2017 IEEE
International Conference on Mechatronics and Automation
August 6 - 9, Takamatsu, Japan

An Integrated Exploration and Observation Planning for an Efficient Indoor 3D Mapping

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***Abstract*— This paper describes an observation planning for 3D mapping in unknown indoor environments. The task of the robot is to make a 3D description of informative regions in the environment. The robot makes a plan of visiting viewpoints for observing the regions. Since each viewpoint must be reachable, it is also necessary to obtain a free space map, which is usually generated by exploratory movements. For an efficient mapping, we propose a method which integrates exploration and observation planning. We also show through experiments in a simulated environment that the proposed method is more efficient than the one which deals with exploration and observation separately.**

***Index Terms*— 3D mapping, informative region, exploration planning, observation planning, observation viewpoint generation.**

I. Introduction

A 3D map of an indoor environment gives us various useful information such as the shape of the environment and the location of objects. A 3D map is generated by integrating 3D data obtained at many locations. Various SLAM (Simultaneous Localization and Mapping) methods have been proposed for 3D mapping. Endres et al. proposed a SLAM method for RGB-D cameras [1]. Labbé and Michaud [2] developed a system for a large-scale SLAM with visual loop closure detection. Ataer-Cansizoglu et al. [3] proposed Pinpoint SLAM which uses both 2D and 3D point features obtained by an RGB-D camera. Kuramachi et al. [4] proposed a 3D mapping using a LIDAR and a tri-axial inertial sensor. Most of 3D SLAM works focus on obtaining precise maps from a given observation sequence.

For performing 3D mapping in an unknown environments, a robot has to explore the environment autonomously using, for example, a frontier-based method [5]. In 3D exploration, Snarathne and Wang [6] proposed to use surface frontiers. These methods are effective in incrementally obtaining free spaces where a robot can move safely.

Obtaining and processing 3D data for mapping and recognizing objects are usually costly. It is, therefore, desirable to choose a set of viewpoints and/or by which a robot can efficiently get necessary 3D data.

One type of observation planning problem is the Watchman Route Problem (WRP). The WRP is the problem of finding shortest routes from which every point in a given space is visible [7]. By travelling in the shortest routes while obtaining the data of the environment, the movement of the robot is expected to be efficient. The zookeeper's problem (e.g., [8]) and the patrol problem (e.g., [9]) are variants of the WRP. Most works about the WRP mainly focus on the algorithm determining the shortest routes (e.g., [10]).

Another problem is the Art Gallery Problem (AGP). The AGP [11] is a problem of covering the entire art gallery room by determining a set of guards who can survey 360^o about their fixed position. However, solving the WRP and the AGP requires an prior information of the environment, such as the 2D map of the environment.

In unknown environments, we need to consider both exploration and observation. Okada and Miura [12] presented an observation planning for 3D mapping. The robot explores first an unknown environment autonomously and constructs a 2D map. Then a sequence of viewpoints is generated which guides the robot to get 3D data of informative regions. In this work, exploration and 3D mapping are separate processes. Masuzawa and Miura [13] developed a method which combines exploration with observation planning for environment information summarization, where exploration and mapping (i.e., finding and recording important objects) are hierarchically organized.

In this paper, we develop an efficient method for generating a 3D map of indoor environment by integrating an exploration and an observation planning. The task of the robot is to make a 3D description of informative regions. As the robot explores an unknown environment, it chooses and visits a set of viewpoints (called *observation viewpoints*) for 3D data acquisition. So the purpose of the planning method is to generate viewpoints for both exploration and observation which make the robot generate a 3D map efficiently. In addition, this planning carried out on-line, that is, the plan is updated as an enough amount of new information is obtained.

We carry out experiments using V-Rep [14], a 3D simulation environment representing real robots and environments. Fig. 1 shows the robot. We used a Pioneer robot as the platform, a Kinect for getting RGB-D images to construct the 3D map, and two 2D LIDARs for exploration and constructing the 2D map of the environment.

The contribution of the paper is to proposed an integrated exploration and observation planning method and to validate it experimentally.

The rest of the paper is organized as follows. Sec. II descibes a process of generating observation viewpoints. Sec. III explains the planning method in detail. Sec. IV shows experimental results of our integrated planner with comparison with our previous, seperated planner. Sec. V concludes the paper and dicusses future work.

II. Observation Viewpoint Generation

A. 2D Map of the Environment

We test our observation planning strategy in two environments shown in Figs. 2 (a) and (b). Occupancy grid map [15] is used to represent the 2D map of the environment. SLAM and localization routines from MRPT (Mobile Robot Programming Toolkit) [16] are used for mapping. We classified the occupancy of 2D map into three regions: free space, occupied, and unknown region, based on the probability of each cell. The 2D map is used for exploration and observation planning. Fig. 3 shows the 2D maps of the both of the environments.

B. Informative Region

We are interested in observing only a certain region of the environment which has useful information for further tasks. Okada and Miura [12] heuristically choose such a region as an informative region. Some useful and important small objects, such as books and mobile phones, are usually located on the desks or the shelves. Since determining the outlines of the shelves and the desk is sometimes hard, they assumed that those objects will be in within a certain distance from the room boundary. Our work adopts their assumption to obtain an informative region of the environment. Fig. 4 shows the informative regions based on the 2D map of the environment A and B.

C. Observation Viewpoint Generation

1) Observation Viewpoint Candidates: We adopted a visibility-based viewpoint planning [17] for observation viewpoint generation. The observation viewpoint candidates are obtained by exploiting a topological property of the environment. A skeletonization technique is applied to obtain

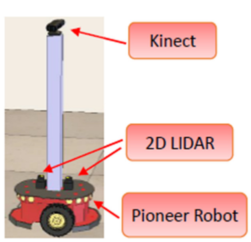
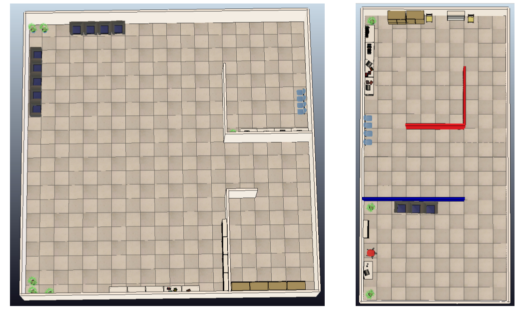
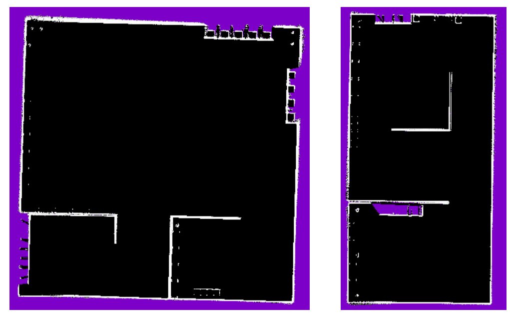


Fig. 1. The robot for the observation.



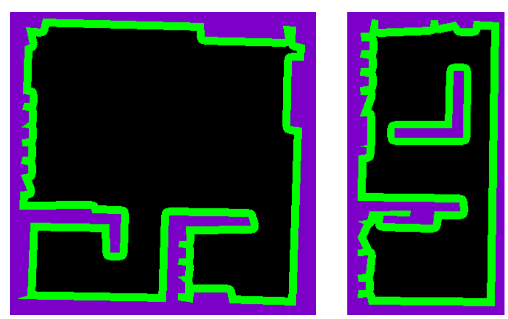
(a) (b)

Fig. 2. The environments for the simulation. The size of environment A (a) is 20 m × 20 m and the size of environment B (b) is 10 m × 20 m.



(a) (b)

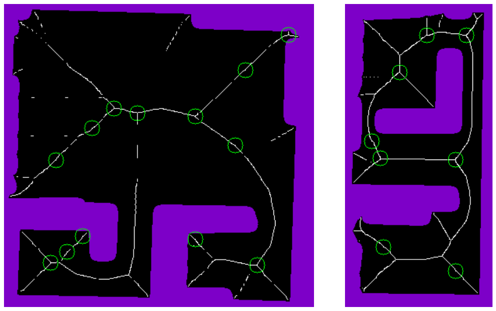
Fig. 3. The 2D map of the environment A (a) and environment B (b). Black region is the free space region, white region is the occupied region, and purple region is the unknown region.



(a) (b)

Fig. 4. The informative region of the environment A (a) and environment B (b), are shown in green.

such a topological property. The skeleton map is built by applying a distance transform and a laplacian filter on the 2D map. The center of the room and the intersection of the corridors are retrieved as junctions by a template matching on the skeleton map, and are considered as the observation viewpoint candidates (V'_{o_can}). However, there may be undetected junctions and false detected junctions because the skeleton of the map could be a complex shape (see Fig. 5) and number of the junction templates is limited. If the current set of detected junctions does not cover the entire informative region, the skeletonization and template matching process are applied on



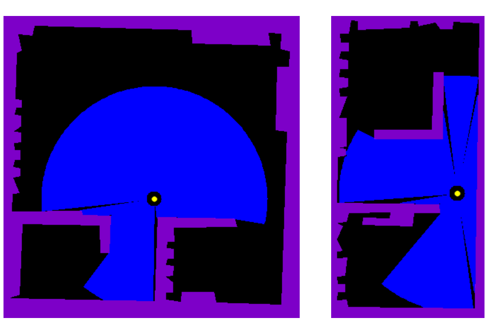
(a) (b)

Fig. 5. The skeleton map of the environment A (a) and environment B (b). The green circles are the detected junctions as the observation viewpoint candidates (V'_{o_can}). However, several false junctions are detected and several junctions are not detected because of the complex shape of the skeleton and the limited number of the junction templates.

the uncovered free space iteratively until the coverage area of the informative region by detected junctions is larger than a threshold th_c. We currently set the threshold th_c = 95%. The method to calculate the coverage is explained below.

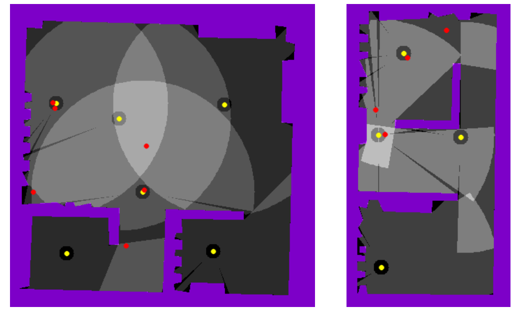
2) Coverage by an Observation Viewpoint: We calculate the coverage area of the informative region by all of the observation viewpoints considering the limitations of the sensor coverage. The depth range limitation of the Kinect is between 0.5 m and 8 m. The robot rotates the Kinect to seven positions for observing the surrounding region because the limitation of the field of view (FoV) of the Kinect (57^o horizontally). We also considered the incident angle limitation which is calculated as the difference between the normal at an observed point and the viewing direction. The incident angle limitation is empirically set to 80^o. Fig. 6 shows the coverage region by an observation viewpoint considering the limitations.

3) Optimal Observation Viewpoint: We adopted Generalized Hybrid Evolutionary Coverage Solver (GHEC-Solver) [18] to get the optimal observation viewpoints. A coverage map is constructed by existing observation viewpoint candidates (V'_{o_can}). In our work, the coverage map considers the limitation of the sensor coverage as shown in Fig. 7.



(a) (b)

Fig. 6. The coverage region by an observation viewpoint (blue region).



(a) (b)

Fig. 7. The viewpoints' coverage map of the environment A (a) and environment B (b) by existing observation viewpoint candidates (V'_{o_can}) (yellow points). The red points are the auxiliary observation viewpoint candidates (V'_{o_aux}).

The brighter region on the coverage map means that region is covered by the more existing observation viewpoints. A sampling of the auxiliary observation viewpoint candidates (V'_{o_aux}) is done based on the distribution function of the coverage region. The brighter region has higher probability to have an auxiliary observation viewpoint candidate. We currently determine the same number of the auxiliary observation viewpoint candidates as that of existing ones, and merge them to obtain a new set (V_{o_can}).

$$V_{o\_can} = V'_{o\_aux} \cup V'_{o\_can}$$

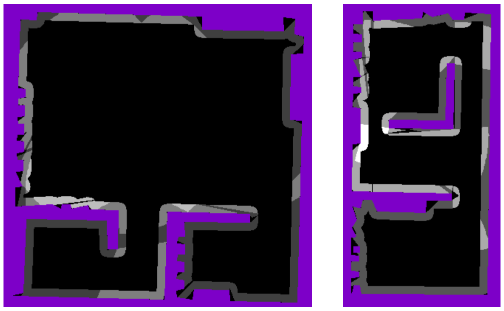
An optimization algorithm is applied on the observation viewpoint candidates (V_{o_can}) by solving the Set Coverage Problem [19] to obtain current optimal observation viewpoints (V'_o). Then, a new coverage map is constructed by current optimal observation viewpoints (V'_o). GHEC-Solver iteratively generates a new set of auxiliary observation viewpoint candidates (V_{o_aux}) based on the new coverage map, and applies the optimization algorithm on the integration of the auxiliary observation viewpoint candidates (V_{o_aux}) and current optimal observation viewpoints (V'_o) to obtain optimal observation viewpoints (V_o). A Hausdorff metric [20] is used to calculate the convergence of the optimal observation viewpoints (V_o), and ascertain the stopping condition of the iterative optimization process.

Since we are interested in observing only informative regions, we consider not the coverage of the entire free space but that of informative regions. We construct an informative region coverage map as shown in Fig. 8, instead of the coverage map in Fig. 7. In addition, we use a greedy algorithm [20] to solve the Set Coverage Problem for quickly obtaining the set of observation viewpoints.

III. Observation Planning

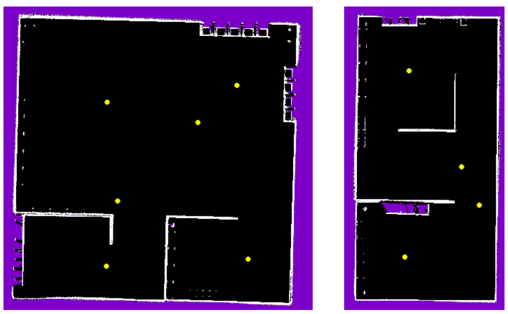
A. Exploration Planning

Since the 2D mapping of the unknown environment is done autonomously by an exploration planning, an exploration viewpoint is needed as the target position. We adopt



(a) (b)

Fig. 8. The informative region coverage map of the environment A (a) and environment B (b).



(a) (b)

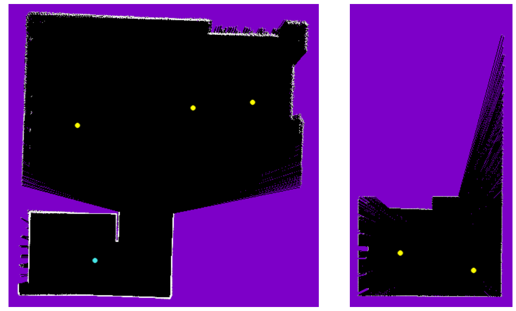
Fig. 9. The yellow points are the optimal observation viewpoints (V_o) of the environment A (a) and environment B (b).

the frontier-based method [5] to determine the exploration viewpoint based on the 2D map of the environment.

A frontier point is a point which is in the free space region and adjacent to the unknown region. All of the frontier points are partitioned into clusters with a distance threshold th_d. We calculate the centroid of each cluster whose number of frontier points is larger than a threshold th_n, and consider it as an exploration viewpoint candidate. By calculating the distance to each exploration viewpoint candidates from the robot position, we determine the exploration viewpoint (V_e) using the closest-frontier strategy [5]. We currently set the threshold th_d = 0.25 m and th_n = 13.

B. Integration of Observation Planning and Exploration Planning

Since we are interested in an efficient observation of the unknown environment, the observation planning is integrated with the exploration planning. The robot calculates the free space area while exploring the environment. If the increment of the free space region area is larger than a threshold th_f, or the entire environment has been already known, the robot generates a new set of observation viewpoints (V_o). Since the robot may have visited several observation viewpoints, and some informative regions have already been observed, the observation viewpoint generation only considers the unobserved informative regions. Fig. 10 shows the observation



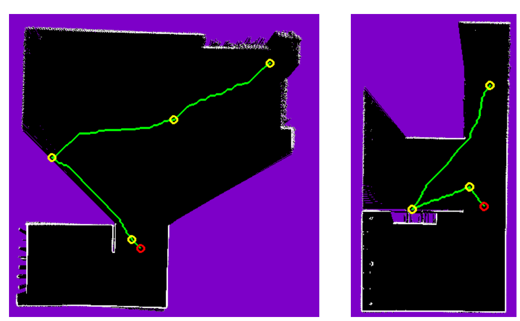
(a) (b)

Fig. 10. The observation viewpoints (yellow points) for the current 2D map of the environment A (a) and the environment B (b). The blue point is the visited observation viewpoint.

viewpoints for the current 2D map. The robot will travel to the observation viewpoints for getting RGB-D image of the surrounding region. The exploration viewpoint (V_e) and the observation viewpoints (V_o) are merged as a new sequence of viewpoints (V).

$$V = V_e \cup V_o$$

The robot target is obtained by solving the viewpoints (V) as a Travelling Salesman Problem using 2-opt method. The TSP [21] is the problem of a salesman to determine a shortest route which is required to visit each of the n given cites once and only once. The 2-opt method [22] takes two pairs of the consecutive viewpoints, and switches them if the route becomes shorter. A* algorithm [23] is applied to calculate the distance between the viewpoints. Figs. 11 (a) and (b) show the route for travelling the viewpoints for two 2D maps. The new route is generated if the new sequence of the observation viewpoint is generated, or the distance of the current to previous exploration viewpoint is larger than a threshold th_t. The exploration viewpoint always moves because the free space region is getting larger when robot explores the environment. We currently set the threshold th_f = 100 m^2 and th_t = 5 m.



(a) (b)

Fig. 11. The viewpoint planning for the current 2D map of the environment A (a) and the environment B (b). The yellow circles are the viewpoints, the red circle is the robot position, and the green line is the robot route.

C. 3D Map Generation

Since the limitation of the Kinect FoV, the robot takes 7 RBG-D images of the surrounding region at each of observation viewpoints. The 3D map is genereted based on those images and robot pose by using PointCloud Library [24].

IV. Experimental Result and Discussion

We tested our observation planning algorithm in the two environments (see Fig. 2). We calculated the travelled distance, the total time, and the number of the observation viewpoints which are needed to observe the entire informative region of the environment. We compared two strategies for doing the 3D mapping. Strategy 1 is based on our observation planning which integrates the exploration and the observation viewpoint planning. Strategy 2 is similar with our previous work [12] which separates the exploration and the observation viewpoint planning. In Strategy 2, the robot first explores the entire environment to construct the 2D map. The observation viewpoints are generated based on the 2D map, and the robot observes the environment by using them.

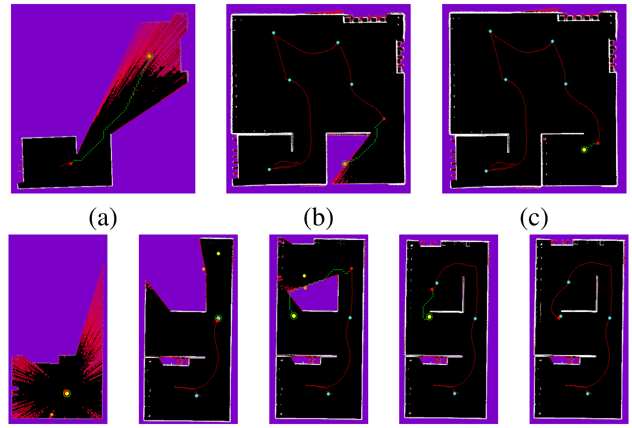
Strategy 1 basically generates locally optimal observation viewpoints for the currently known informative region. Since the observation viewpoints in Strategy 2 are generated after the entire 2D map of the environment is constructed, the number of the observation viewpoints should be globally optimal. Fig. 12 shows the observation process of Strategy 1, and Fig. 13 shows the observation process of Strategy 2 for both of the environments.

Table I shows the comparison of the number of the observation viewpoint, the total time, and the travelled distance. The total time is the time which is needed by the robot to explore, to construct the 2D map, and to observe the environment. Although our strategy generates locally optimal observation viewpoints, the number of visited observation viewpoints of Strategy 1 is equal to that of Strategy 2. In addition, our proposed observation planning is more efficient in terms of the total time and the travelled distance.

The 3D mapping process is done after the exploration and observation are finished for both of the strategy. Fig. 14 shows the 3D map of the informative region for both of the environments.

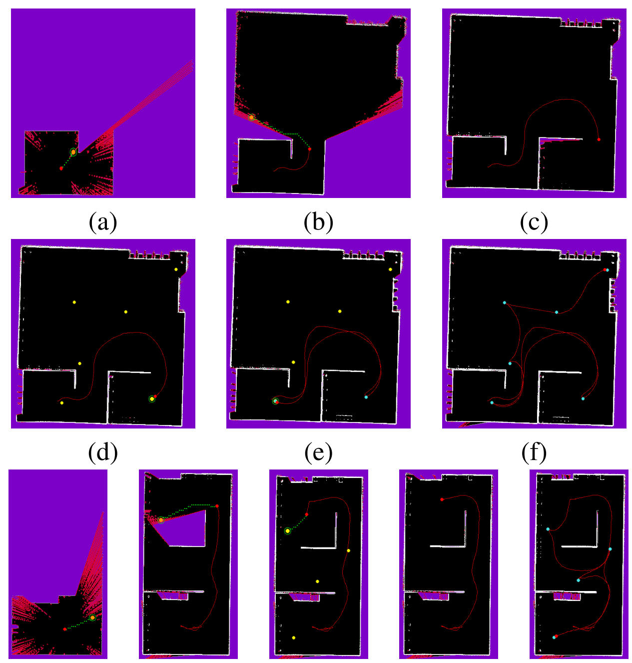
TABLE I
EXPERIMENTAL RESULT

	Environment A		Environment B	
	Strategy 1	Strategy 2	Strategy 1	Strategy 2
Number of the visited observation viewpoints	6	6	4	4
Total time	654.1 s	885.91 s	323.98 s	510.39 s
Travelled distance	44.54 m	78.66 m	32.97 m	60.99 m



(a) (b) (c)
(d) (e) (f) (g) (h)

Fig. 12. The observation process of the environment A (a)-(c) and the environment B (d)-(h) for Strategy 1. The viewpoint as robot target is indicated by green circle.

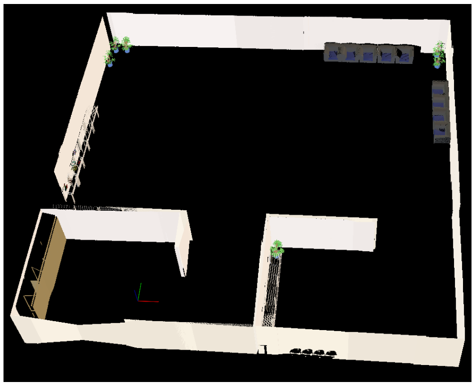


(a) (b) (c)
(d) (e) (f)
(g) (h) (i) (j) (k)

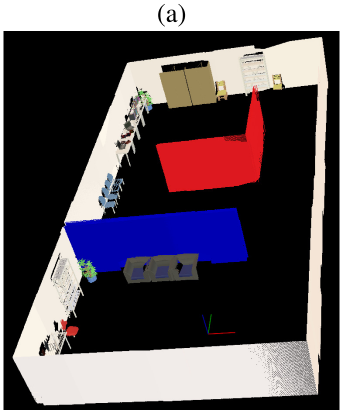
Fig. 13. The exploration process (a)-(c) and the observation process of the environment A (d)-(f) for Strategy 2. The exploration process (g) (h) and the observation process of the environment B (i)-(k) for Strategy 2. The viewpoint as robot target is indicated by green circle.

V. Conclusion

We have presented an efficient observation planning for unknown environments by integrating exploration and observation viewpoint planning. Since generating the optimal sequence of observation viewpoints is hard without any prior information of the environment, we repeatedly generate a locally-optimal viewpoint sequence based on the information of the explored regions. We compared our method with the



(a)



(b)

Fig. 14. The 3D map of the environment A (a) and the environment B (b). Since we set a threshold for the coverage of the informative region, some regions may not be observed.

one which handles exploration and observation separately, and showed that our planner has the same number of visited observation viewpoints but with a shorter time and traveled distance.

The proposed method has succeeded in 3D map generation but only in simulated environments. One future work is to evaluate the method using a real robot. Adding an object recognition capability is also future work. This could require further integration of a viewpoint planning for object recognition (e.g., [13]) into the current framework.

ACKNOWLEDGMENT

This work is in part supported by JSPS KAKENHI Grant Number 17H01799.

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