Generating a Consistent Global Map under Intermittent Mapping Conditions for Large-scale Vision-based Navigation

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Abstract: Localization is the process to compute sensor poses based on vision technologies such as visual Simultaneous Localization And Mapping (vSLAM). It can generally be applied to navigation systems . To achieve this, a global map is essential such that the relocalization process requires a single consistent map represented with an unified coordinate system. However, a large-scale global map cannot be created at once due to insufficient visual features at some moments. This paper presents an interactive method to generate a consistent global map from intermittent maps created by vSLAM independently via global reference points. First, vSLAM is applied to individual image sequences to create maps independently. At the same time, multiple reference points with known latitude and longitude are interactively recorded in each map. Then, the coordinate system of each individual map is converted into the one that has metric scale and unified axes with the reference points. Finally, the individual maps are merged into a single map based on the relative position of each origin. In the evaluation, we show the result of map merging and relocalization with our dataset to confirm the effectiveness of our method for navigation tasks. In addition, the report on participating in the navigation competition in a practical environment is also discussed.

1 INTRODUCTION

The technology essential to the development of navigation systems and autonomous robots is localization. Localization is the process of estimating the location of a sensor in a specific coordinate system. Particularly, global localization is the estimation of the longitude and latitude of a location in the World Geodetic System (WGS) within the field of navigation. Global navigation satellite system (GNSS) is widely used in outdoor navigation systems because it only needs an antenna to receive signals (Hofmann-Wellenhof et al., 2007). To increase the frequency of the localization outputs, inertial measurement units (IMU) with high frame rates are incorporated in such systems, referred to as an inertial navigation system (INS) (Farrell, 2008). For instance, an image sequence and its their global positions from the INS were recorded while driving to generate Google Street View (Anguelov et al., 2010). Generally, the localization techniques used in existing navigation systems for pedestrians and vehicles focus on estimating 2D coordinates on a map to provide, for instance, a route to a destination. To estimate the height and heading, a barometer and a magnetic sensor can be coupled with such systems (Parviainen et al., 2008).

Vision-based approaches have been proposed to increase the degrees of freedom (DoF) for sensor poses because they can compute both 3 DoF for position and 3 DoF for orientation to represent any rigid motion in 3D space. Such approaches are based on online 3D reconstruction and camera pose estimation using visual SLAM (vSLAM) (Taketomi et al., 2017). With 6 DoF of navigation, the range of applications can be enhanced such that a precise viewing direction in 3D space can be provided as a guidance. For instance, the software libraries for developing AR systems such as the ARKit by Apple or ARCore by Google are used to develop a navigation system for small indoor spaces (Corotan and

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Irgen-Gioro, 2019). Compared with GNSS-based approaches, camera-based ones require pre-processing to generate a map database containing images associated with their poses (Williams et al., 2011; Kendall et al., 2015). For the localization process, an input image is first matched to the images in the database by using an image retrieval technique (Gálvez-López and Tardos, 2012), then the pose of a matched image is used as the estimated pose of the input image. This process is specifically referred to as relocalization within the field of computer vision.

To achieve relocalization, the most important task is to generate a consistent map database containing all the image poses that are represented by the same coordinate system. However, in various practical situations, it is difficult to map all parts of a target environment at once because mapping cannot be performed with insufficient visual features. In other words, the mapping process can be intermittent in a large-scale environment such that each map is individually generated with its own coordinate system. This happens especially in indoor environments due to texture-less human-made objects in corridors or near stairs. Merging multiple discontinuous maps is a crucial problem practically, and is not well-investigated in the literature.

To solve the aforementioned issue, this paper presents a method for generating a consistent global map under intermittent mapping conditions with sparse reference points which longitude and latitude are known. The main idea was originally designed for participation in the competition for large-scale seamless indoor and outdoor localization tasks held at IPIN2019[1]. In the competition, which was based on the EvAAL framework (Potortì et al., 2017), the primary task was to answer the longitude and latitude of given locations in the both indoor and outdoor environments. As a preparation, sparsely-distributed reference points were provided or were able to be measured in the environment by ourselves to calibrate the system. Investigating longitude and latitude on a map is easily achieved by using standard Geographic Information System (GIS) software. If all the reference points are represented in the WGS, individual maps can be merged via the reference points. In this paper, we propose a step-by-step procedure to first generate individual maps and then merge them in the unified coordinate system for global navigation from a practical development point-of-view. This is equivalent to developing GIS-supported vision-based navigation systems. Also, we provide the report on the navigation competition where we participated in by developing a vision-based navigation system.

[1]http://ipin2019.isti.cnr.it/

2 RELATED WORK

Generally, standard vSLAM systems can support a continuously-generated map for relocalization (Mur-Artal et al., 2015). However, merging multiple maps is a practical and crucial problem for large-scale vision-based navigation. In the literature, the approaches can be summarized into two categories.

To merge multiple maps into the same coordinate system, one approach is based on the fact that each map contains the same region in the environment (Zou and Tan, 2012; McDonald et al., 2013). In this case, the maps can be easily merged by using the shared feature points of the region. If the shared points exist, the 3D transformation matrix to merge two maps is computed by using the 3D coordinates represented in each map coordinate system. This idea was generally used for mapping the environment with collaborative robots or drones.

As the second approach, a technique of map merging was investigated for developing augmented reality applications (Castle et al., 2008). Basically, the annotations are required to be associated with each map independently such that the associated annotation is visualized only when the map is visible. In other words, it is not necessary to represent all the maps in the same coordinate system even though all of the maps were incorporated into one system in some way. Therefore, AR systems do not always need the absolute positions for placing and visualizing AR annotations because the annotations can be placed relatively with each map.

Compared to the existing approaches, we focus on representing multiple discontinuous maps into one in the unified coordinate system when each map does not share the same regions. As aforementioned, this problem occurs in various situations such as buildings or large-scale environments. To solve this problem, we propose to utilize sparse global reference points for each map, given by GIS, as a prior to merge multiple maps into the same coordinate system.

3 PROPOSED METHOD

Reconstructing a large scale environment based visual information cannot be always performed at once due to the lack of the visual features. In particular, indoor environments, such as a narrow textureless corridor, often contain conditions that make the tracking process in vSLAM fail. In addition, it is inevitable that the camera moves with large rotation while turning corners and climbing stairs in indoor navigation systems, as discussed in Section 6. This also makes vSLAM fail even with visual-inertial approaches. Therefore, maps needs to be intermittently generated in practice. To combat this issue, we propose a method for the creation of multiple small maps and their merger via global reference points.

3.1 Prerequisite

Our basic idea to merge multiple maps into one map is to represent each map in the WGS directly. In other words, some global reference points are required to be acquired when generating each map. This process is designed based on the following reason.

Generally, GNSS signals are not accurately received in indoor environments due to obstacles that make the signals attenuate. Outdoor environments also causes similar results, especially in urban regions with buildings. Therefore, the assumption that global positioning signals are available is not always valid.

Instead, we aim mainly at the situation that we can utilize sets of sparse global positions that can be pre-calibrated as some reference points. For instance, such points are placed in the indoor layout map used when building them. Also, some landmarks can have global coordinate in outdoor environments In this paper, we use GIS to generate such landmarks from satellite images. Even though this may not be a generalized situation and our solution is straightforward, this can be practically achieved in several situations, as organized in the competition for navigation. Therefore, we utilize this prerequisite as a prior for map merging.

3.2 Overview

We first summarize the flow of our proposed framework, as illustrated in Figure 1. The procedure for generating a consistent global map from small submaps can be divided into the following three steps:

1. Map creation with reference point selection
2. Map conversion with reference points
3. Map merging

As mentioned above, the longitude and latitude at some positions in the environment are given in our prior condition, as referred to as global reference points.

In the 1st step, the map is reconstructed by using vSLAM. This operation is performed in several small areas in the environment, each of which does not have to be continuous. In addition, the location of the global reference points, which are presented in the WGS, is required to be recorded in parallel to vSLAM.

In the 2nd step, the coordinate system of each map generated in the 1st step is aligned in terms of scale and orientation. This is because each map is represented in an unknown individual vSLAM coordinate system. This process is necessary to simplify the latter process of merging maps.

In the 3rd step, the individual maps are merged by shifting the origin of each individual coordinate system into the WGS. Finally, all the individual maps are represented in the same coordinate system.

Through these steps, we can obtain an actual scaled global map. Once the map is obtained, it can be applied to any navigation system by performing the relocalization process in vSLAM. The overview of our global navigation system is introduced in Figure 2. Two individual maps that do not share the same region are merged by our proposed method. Then, relocalization is used to estimate the location of an user for a navigation task.

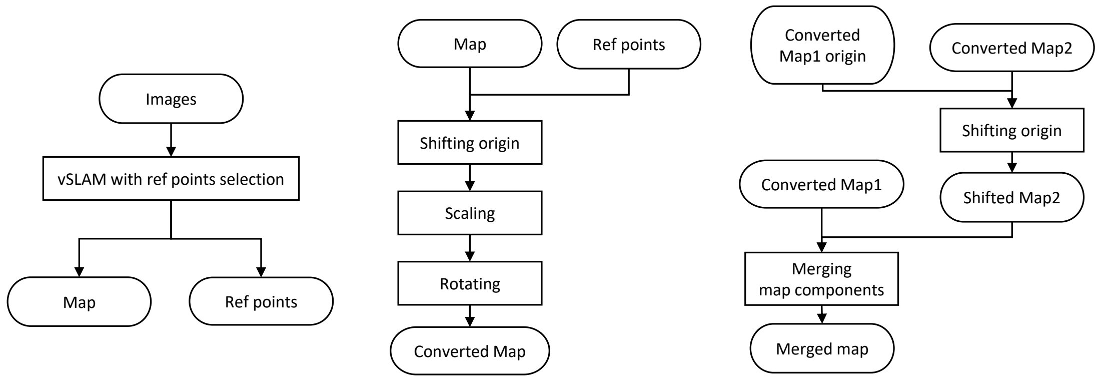
3.3 Map Creation

This process is generally based on vSLAM to generate feature points and images associated with their pose in each vSLAM coordinate system. Here, we describe how to interactively record the reference points with known latitude and longitude, in parallel to vSLAM, as illustrated in Figure 1(a). The detail of our vSLAM architecture for our global navigation system is explained in Section 4.

Each time users reach the location of a reference point during mapping, the pose at the reference point in the vSLAM coordinate system and the feature points observed in the image are saved in association with the latitude and longitude. If the height at the reference point is available, for instance, at multifloor buildings, height is also saved. In our implementation, each reference point has identification data (ID) such that a list of reference points is prepared in advance, as illustrated in Figure 3. At the reference point, it is necessary for users to assign the ID of each reference point with an image.

Generally, we assume that the reference points are provided as some landmarks beforehand, as described in Section 3.1. If necessary, this procedure can be easily performed by using a standard GIS software[2], which is typically used in navigation systems. This interactive process is independent of the vSLAM so that any GIS software and vSLAM methods can be used. It should be noted that at least 3 reference points must be saved for each map.

[2]https://www.qgis.org



(a) Map creation (b) Map conversion (c) Map merging

Figure 1: Flow of each step in our proposed method. (a) shows the flow of map creation. By using vSLAM, the map is generated. In addition, the reference points are recorded interactively. (b) shows the flow of map conversion. Based on the reference points, the coordinate system of each map is converted through three steps: shifting origin, scaling, and rotating. (c) shows the flow of map merging. Based on the relative positions between the origins of the converted maps, all of the maps are merged by shifting them to the WGS.

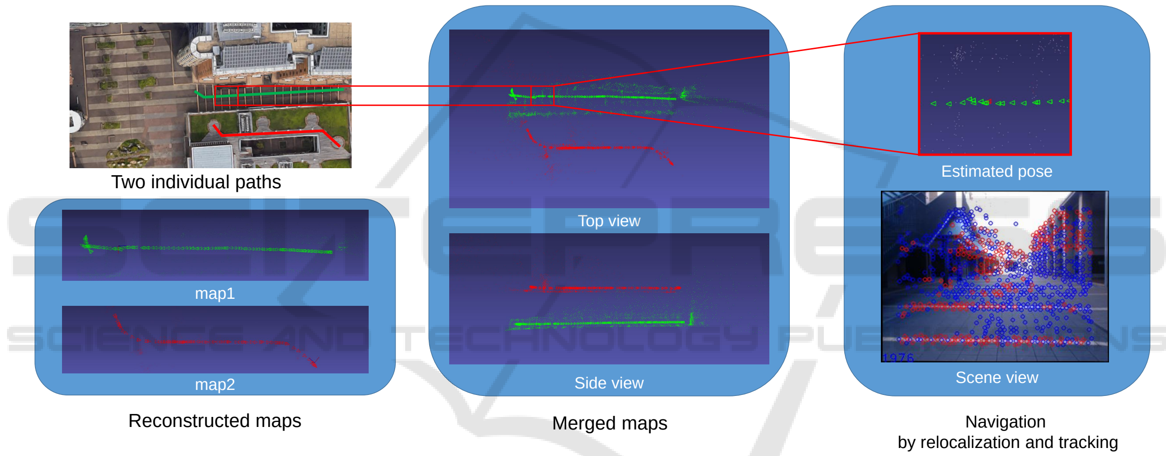


Figure 2: Overview of our global navigation system. First, the maps are reconstructed independently. Then, these maps are merged into one by our proposed method. After that, relocalization is performed on the merged map for navigation. Red dots represent the feature points in the map database, and blue ones are not in the database in the scene view.

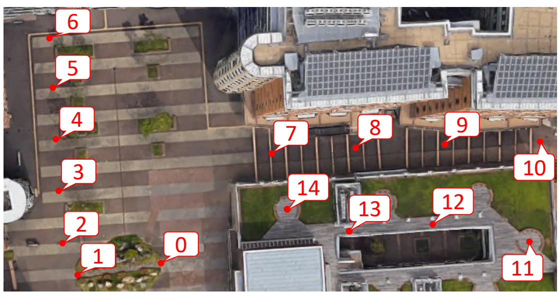


Figure 3: Reference points. Reference points and their ID are illustrated. Using a standard GIS software, the latitude and longitude at any point on the map can be created easily.

3.4 Map Conversion

In this section, we explain how to compute the transformation from each vSLAM coordinate system to the aligned one, as illustrated in Figure 1(b). The overview of the computation process is illustrated in Figure 4. This operation is performed for each small map obtained by vSLAM, as explained in Section 3.3.

3.4.1 Shifting Origin

The origin of the map is automatically determined when vSLAM is initialized such that the initial camera coordinate system is used as the vSLAM coordinate system (Mur-Artal et al., 2015). It is helpful if the latitude and longitude of the origin of the vS-

LAM coordinate system are known to simplify later processes. Therefore, we first set the origin of the vSLAM coordinate system at one of the reference points. More concretely, the inverse pose at a reference point is multiplied with other poses and feature points so that the origin can be set to the reference point.

3.4.2 Scaling

With monocular vSLAM, the scale is unknown, and is determined such that the distance between two initial positions is one. Even with IMU, the scale factor may not be accurately computed or be drifted due to noise. Therefore, we propose to scale the map with global reference points, as an alternative approach.

If we know the metric distance between 2 reference points, we can perform the scaling. The distance, in meters, can be calculated from the latitude and longitude between two reference points with GIS software. At two reference points, the scale is calculated as the ratio between the distance in meters and that in the vSLAM coordinate system. Furthermore, the scaling parameter is calculated by taking the average of multiple ratios as follows.

$$\begin{aligned} d_i &= ||{p_0}^{ref} - {p_{i+1}}^{ref}|| \\ D_i &= ||{P_0}^{ref} - {P_{i+1}}^{ref}|| (i \in [0, N-1]) \end{aligned} \tag{1}$$

$$s = \sum_{i=0}^{N-1} \frac{D_i}{d_i} \tag{2}$$

where N is the number of reference points, ${p_i}^{ref}$ and ${P_i}^{ref}$ are the position of i-th reference points in the vSLAM coordinate system and in the WGC, respectively. Also, d_i and D_i are the distances from the origin of the i-th reference points in the vSLAM coordinate system and in the WGC, and s is a scaling parameter.

3.4.3 Rotating

The orientation of each scaled vSLAM coordinate system is aligned by this process. In this process, the unified coordinate system for all the maps is defined as follows: the direction of each x-axis is set to that along the meridian, and that of z-axis faces the equator direction.

Let $R_x(\alpha)$, $R_y(\beta)$ and $R_z(\gamma)$ be rotation matrices against each axis and α, β, and γ be their angles, respectively. Assuming that the rotated result of the vSLAM coordinate system with the rotation matrices corresponds to the unified coordinate system, the movement on the x-axis of the vSLAM coordinate system can be converted into the movement on the meridian direction, and the z-axis is on the equator direction. Then, the latitude and longitude can be calculated from the x and z components of the reference point in the scaled and rotated vSLAM coordinate system.

The rotation matrix can be obtained by the following optimization. First, rotation angles α, β, and γ is given to initialize a rotation matrix. Next, the x and z components of the reference points in the coordinate system transformed by the rotation matrix are converted into latitude and longitude by using meters to degrees translation. Then, by comparing the error between the estimated one and the actual one given at the reference point, and the residuals can be defined for the optimization. Since these residues depends on α, β, and γ angles, we can solve this by the non-linear least squares problem with the following equations.

$$\begin{aligned} Res_{lat}(\alpha,\beta,\gamma) &= Lat_{actual} - Lat_{estimated}(\alpha,\beta,\gamma) \\ Res_{lon}(\alpha,\beta,\gamma) &= Lon_{actual} - Lon_{estimated}(\alpha,\beta,\gamma) \end{aligned} \tag{3}$$

$$\min_{\substack{\alpha,\gamma\in[-180^\circ,180^\circ] \\ \beta\in[-90^\circ,90^\circ]}} \frac{1}{2}\sum_{i=0}^{N-1} ||{Res_{lat}}^2 + {Res_{lon}}^2||^2 \tag{4}$$

where N is the number of reference points. Due to the range of the parameters, the initial angles may need to be set appropriately such that the camera view direction is initially parallel to the ground. In our system, the optimization was implemented using the Ceres solver[3].

3.5 Map Merging

In this section, the maps created individually are merged into one map. Owing to the two former processes, we were able to obtain multiple independent maps with the same scale and the same axis orientation. Therefore, it is possible to merge the maps with only focusing on shifting the positional relationship of the origin of each coordinate system, as illustrated in Figure 1(c).

3.5.1 Shifting Origin

The origin of each map corresponds to a reference point used for the shifting, as explained in Section 3.4.1. The base map is first selected from one of the individual maps. Then, by shifting the entire map based on the relative position between the base origin and the other map origins, the coordinate system of the other map is converted to that of the base map.

[3]http://ceres-solver.org

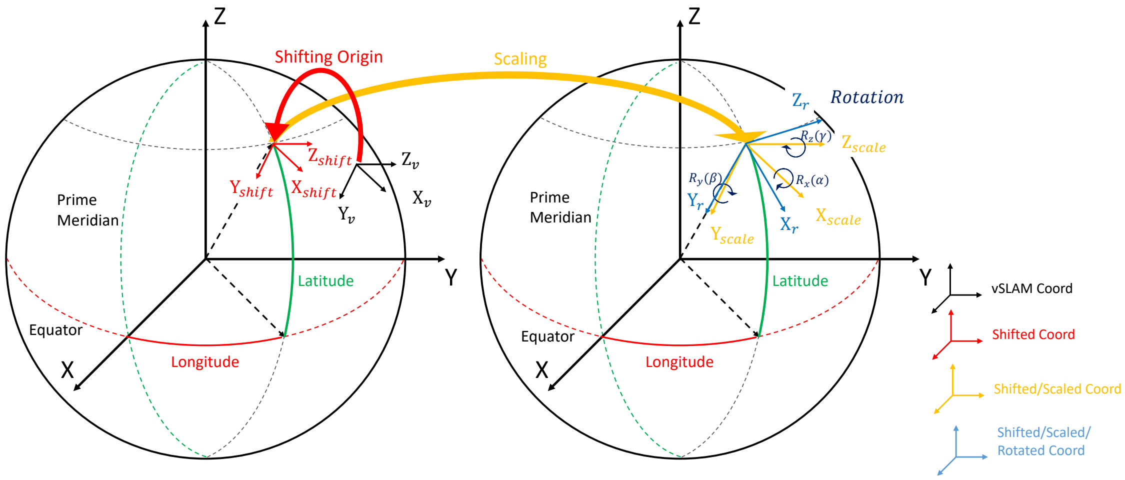


Figure 4: Map conversion. First, the vSLAM coordinate system in black is convert into the red one by shifting origin. Next, the red one is converted into yellow one by scaling. Finally, the yellow one is converted into blue one by rotating.

3.5.2 Merging Map Component

With the above operation, the map representation has been converted to the same coordinate and origin. Therefore, merging individual maps created independently is completed by combining the map components together.

4 IMPLEMENTATION DETAILS OF VSLAM

In this section, we describe the details of the vSLAM implementation used to create the map for our navigation system.

4.1 Feature Choice

The first thing to do when performing feature point-based vSLAM is feature choice. In ORB-SLAM(Mur-Artal et al., 2015), which is one of the state-of-the-art approaches of vSLAM, ORB is selected because of the speed of detection. In fact, ORB detection is extremely fast compared to other features and is suitable for real-time operation. However, the repeatability or stability is sometimes not enough for stable vSLAM.

We compared the ORB and AKAZE features (Alcantarilla and Solutions, 2011) in terms of feature detection stability. As a result, in outdoor environments, where there are enough textures, there was no significant difference. However, in indoor environments where there are less textures, ORB occasionally cannot detect the stable features between two consecutive images in practice. It is an indispensable requirement to detect the same feature stably to maintain the tracking function. Therefore, we selected AKAZE as the feature used in our system. To guarantee real-time operation, we have reduced the resolution of the input image. This is the trade-off between the computational cost and stability. Even though we used the lower resolution, the accuracy was not drastically degraded for the navigation tasks.

4.2 Map Components

In terms of vSLAM architecture, our system mostly refers to ORB-SLAM and the map is represented by keyframes and 3D map points. The main difference is the data for global reference points. We used two main structures, which were divided into a map structure and frame structure, for our map merging. The elements of frame structure are as follows:

- 3D-pose in vSLAM coordinate system
- Observed feature point descriptor, its coordinates on the image plane, and whether the point has been reconstructed or not
- Bag of visual words (BoVW) feature vector of the frame
- Latitude, longitude and height in metric world scale at reference points
- A list of keyframes that observe feature points common for other frames. This defines the scope of local Bundle Adjustment (BA).

The elements of map structure are as follows:

- A list of frame structures reconstructed as keyframes

- A list of reconstructed 3D points, its coordinates in the vSLAM coordinate system, and keyframes observing each of them
- Latitude, longitude, and height at map origin in the metric world scale

4.3 Matching Method

As similar to other vSLAM methods based on PTAM (Klein and Murray, 2007), our system has three functions: tracking, mapping and bundle adjustment. As mentioned earlier, most of our system follows ORB-SLAM(Mur-Artal et al., 2015). Specifically, some changes have been made to the method of feature point matching in the tracking and mapping for further stability in both indoor and outdoor environments.

The basic idea of matching in ORB-SLAM is to increase the reliability of matching by giving spatial constraints to candidate feature points that are to be matched. In addition to this idea, we used GMS (Bian et al., 2017) as a means to further give the constraint to matching. This reinforces the concept of emphasizing spatial information between feature points.

5 EVALUATION

To investigate the performance of our proposed method, we show the results of map merging and relocalization with our dataset taken at our campus. As a prototype of handheld navigation systems, the pedestrian captured images while having the laptop with a monocular web camera facing to the moving direction.

5.1 Dataset

For the map database, we captured image sequences at three discontinuous paths with different level of floors, as illustrated in Figure 5(a). The reference points were placed, as illustrated in Figure 3.

For the relocalization task, we captured the image sequence on the other day. The path was designed to include both the path in the database and the one in unknown regions, as illustrated in Figure 6(a). The color on the path is coded in the order of time series from red, blue, green, yellow, and white.

5.2 Result of Map Merging

Figure 5 illustrates both the paths used for the map database and the merged map. By comparing Figure 5(a) and (b), the trajectory in the merged map was approximately same as the paths used for the map database. In addition, as illustrated in Figure 5(c), the merged map contains the discontinuous levels of the floors. Therefore, it can qualitatively be confirmed that the intermittently-generated maps have been successfully merged.

5.3 Result of Relocalization

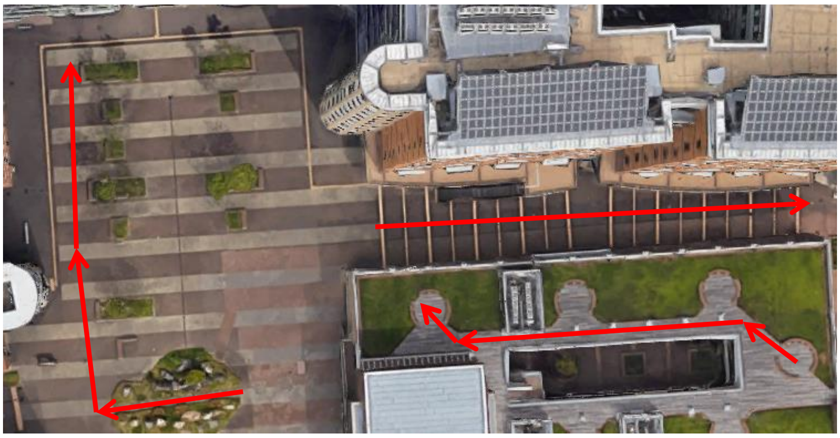
Next, we present the relocalization result with the merged map for navigation tasks. To visualize the estimated longitude and latitude, we used Google Earth[4] that takes the KML file converted from the logs of latitude and longitude.

From Figure 6(b), it can be observed that that red dots are scattered in places far from the actual path. This noisy results occurred during the relocalization. This means that it may have been caused by attempting to relocalize with another scene due to unsuccessful image retrieval. Next, the path shown in blue dots was correctly estimated owing to tracking after relocalization. In the green dots, some inaccurate results were observed at the right side of the image. Similar to the failure in the relocalization process, there was a moment when tracking was lost during rotating the camera. At this moment, the relocalization was performed again, and sometimes failed due to the low accuracy of image retrieval. In addition, the green, yellow, and a part of white dots were captured at unknown paths that have not been mapped. Unless tracking was lost, vSLAM created a new map so that the latitude and longitude were computed. Finally, in the last part of the white dots, the trajectory was accurately recovered. This is because the result of the relocalization with the known map.

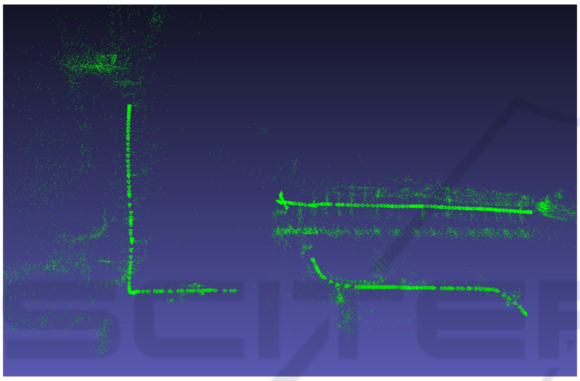
5.4 Limitation

The above results showed that the localization for navigation tasks can be estimated by relocalization and vSLAM. However, the scale drift was observed in the yellow dots although the estimated paths were approximately same as the actual ones. These dots represent the path that were not included in the map database. This is basically a fundamental problem of monocular visual odometry. To avoid this problem, the navigation task to be applied needs to have a route determined in advance so that the all of the maps for navigation should be prepared.

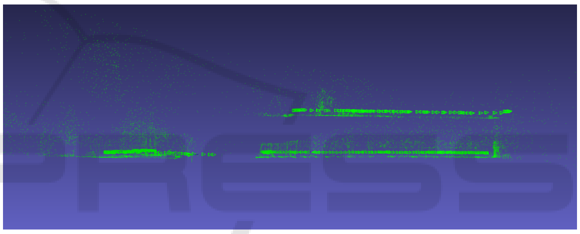
[4]https://www.google.com/earth/



(a) Paths for map database



(b) Top view of reconstructed maps



(c) Side view of reconstructed maps

Figure 5: Result of reconstructed maps in our campus. (a) represents paths when creating the map database. The approximate scale of the image is 120 by 70 square meter. (b) and (c) are top and side views of the merged map. The estimated paths qualitatively matched the actual paths.

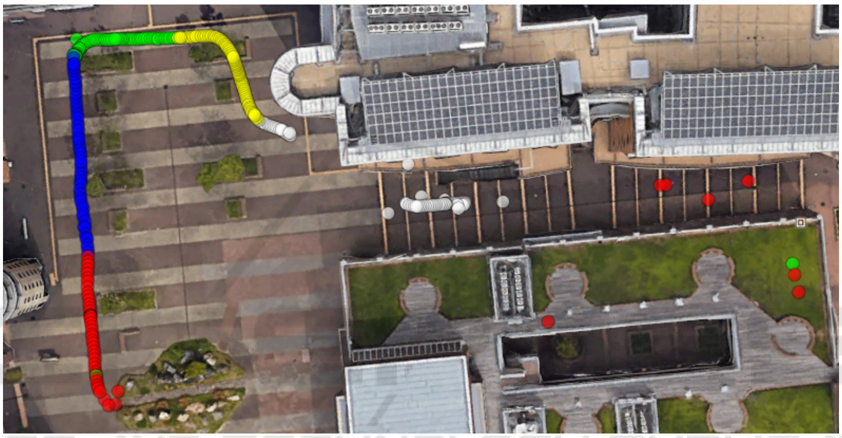
6 PARTICIPATION IN THE NAVIGATION COMPETITION

As an attempt to apply our method to realistic problems, we participated in track 2 of the competition held at IPIN2019. This competition focused on evaluating the accuracy of both indoor and outdoor navigation systems that answered the longitude and latitude of given locations. The user of our system was prepared by the organizers. To participate in the competition, we selected a monocular camera only as a simplest sensor configuration. Our strategy was to build a map of the venue on the survey and setup day that was scheduled one day before the competition, and then to use relocalization and vSLAM on the competition day. Compared with benchmarking datasets for vehicles and drones, this competition focused on handheld indoor and outdoor navigation systems, and clarified some specific problems for this issue as follows:

- **Time Needed for Creating Map Database.** Before the competition, the path for the competition was closed. Only the entire venue that could be passed by the pedestrian was disclosed. Therefore, we needed to reconstruct all of the environment in advance.

  Figure 7 illustrates the aerial photo of the competition venue and the map we reconstructed. The venue was approximately 170 by 200 square meter with three floor levels. With our proposed method, the venue was reconstructed even under intermittent mapping conditions. However, it was quite difficult to reconstruct the entire venue within a few hours only. For instance, it is necessary to capture two image sequences of to-and-from paths at one corridor because the path for the competition is unknown. Also, there was an open space where is hard to be reconstructed. Since most of the paths we reconstructed was not in-

(a) Path for relocalization



(b) Estimated longitude and latitude

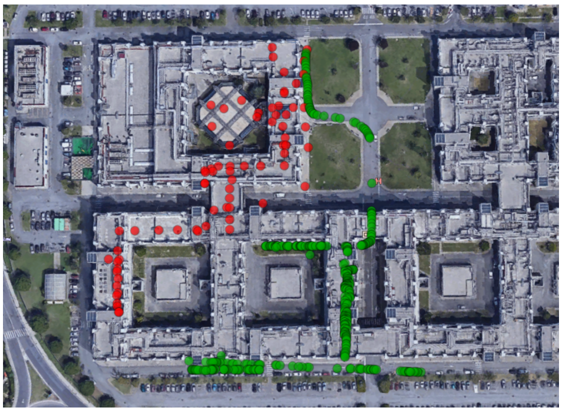
Figure 6: Result of relocalization. (a) is the path for relocalization. This include a part of Figure 5(a). (b) is the estimated latitude and longitude visualized with Google Earth. Coded color represent the order of time-series: red, blue, green, yellow and white. The inaccurate results such as some of red and green dots were generated when relocalization was performed and when tracking was temporarily lost. At the area where the map database did not contain at green and yellow dots, the trajectory was correctly estimated owing to vSLAM after relocalization.

cluded in the path for the navigation tasks, we were not able to answer the most of the locations correctly.

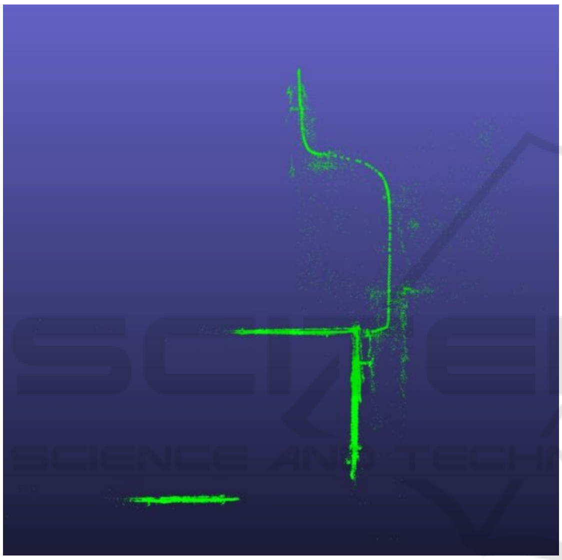
- **Appearance Similarity in Building.**
  In our method, relocalization is based only on visual information. When there are scenes which appearance is similar, it is not easy to correctly relocalize. As illustrated in Figure 8, the appearance at different floors was similar in the building. Additional sensors such as magnetic field could be useful to differentiate them.

- **Scale Drift.**
  In monocular vSLAM, the scale drift was often considered as a major topic. In many cases, the drift has been occurred during rotation. However, even in the case of linear motions, there was a tendency that the drift occurred when feature points were not detected near the camera, and detected at a distant region, illustrated in Figure 9. This specifically occurred in the texture-less narrow corridors.

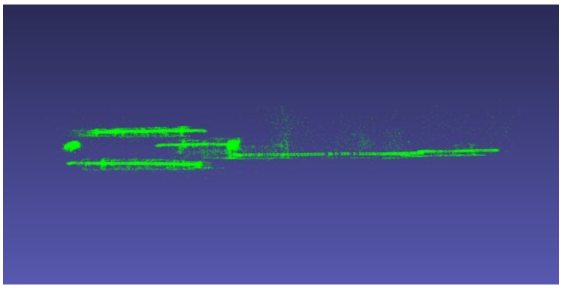
- **Blur by Handheld Motions.**
  The creation of the map is carefully done to not to generate noise. In particular, since blur will often occur, extra caution is required when turning corners and walking at stairs. The importance of caution in creating this map is a well-known fact to us, but it is not so for end users operating it as an application. In fact, when a non-specialist used the system, the blur was so great that tracking became a challenging problem because it was difficult to detect the same features at the time of map creation.



(a) Competition Venue



(b) Top view of our map



(c) Side view of our map

Figure 7: Results of our reconstruction at the competition cite. (a) is an aerial photo of the competition venue. The venue is approximately 170 by 200 square meter. The path illustrated in red is the ground truth of the path used for the competition. The path in green is where we reconstructed in advance. (b) and (c) are top and side views of our reconstructed map.

(a) 1st floor

(b) 2nd floor

Figure 8: Appearance similarity. (a) was captured at 1st floor and (b) was captured at 2nd floor. Since similar features were extracted from these scenes, it was difficult to differentiate them based on image retrieval.

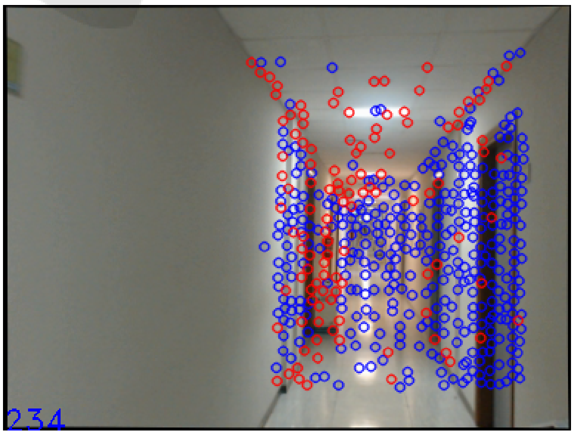


Figure 9: Scale drift. There was a tendency of the scale drift to occur in scenes with poor front view textures and rich distant textures.

The knowledge obtained by participating in the competition mostly depended on not our map merge technique but vSLAM techniques and their constraints. Therefore, it is necessary to improve the method of vSLAM itself in future research.

7 CONCLUSION

We proposed a method for generating a consistent global map from an intermittently created map. As explained in the Section5, it was shown that independent individual maps can be merged by our method, and position estimation is possible by relocalization to the merged maps. On the other hand, participation in IPIN has made us aware of challenges in applying to realistic problems. This issue is independent of the map merge method, and is a common problem that vSLAM has. Therefore, future studies should focus on the vSLAM method itself.

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