RISK VDBMAPPING – ENRICHED VOLUMETRIC INFORMATION FOR RISK-AWARE MISSIONS

Lennart Puck, Samuel Mauch, Marvin Grosse Besselmann, Tristan Schnell, Timothée Buettner, Arne Roennau, and Rüdiger Dillmann

FZI Forschungszentrum Informatik, 76137 Karlsruhe, Germany, puck@fzi.de

ABSTRACT

Exploration missions require a quick and thorough mapping of the environment. The Risk extension of the VDBMapping framework allows the assets to have an occupancy map, additional information about the surroundings, and a risk map. The map is capable of storing information in the occupied and free space. Thereby allowing the robot to assess and navigate in a risk-aware fashion. The framework furthermore allows incorporating information from different sources such as drone or satellite imagery. In the context of the intelliRISK2 project, the risk-aware mapping framework was tested in the Tabernas desert in an analog mission.

Key words: LaTeX; Planetary Exploration, Walking Robots, Mapping, Analog Mission.

1. INTRODUCTION

While exploring different planets, rovers and other assets might encounter a multitude of different hazards. Since the delay between mission control and asset increases with the distance of the mission targets, the robots need to understand their surroundings to act risk-aware. One step towards increasing the robot's autonomy is generating a detailed environmental map enriched with additional information. Therefore, we introduce Risk VDBMapping, an extension of the VDBMapping Framework by Grosse Besselmann et al. [1], which builds on top of OpenVDB [2]. VDBMapping is a volumetric 3D Mapping Framework with efficient processing of long-range data into high-resolution grids.

Our proposed extension allows us to store additional information in each voxel efficiently. To minimize the impact of the memory footprint, each voxel only contains data of known information. This leads to a layered approach of additional data, where each layer must not be filled in each voxel. In our approach, the additional layers are used to store data of the physical properties of the environment that, in turn, can then be processed to determine the hazards that originate from each voxel.

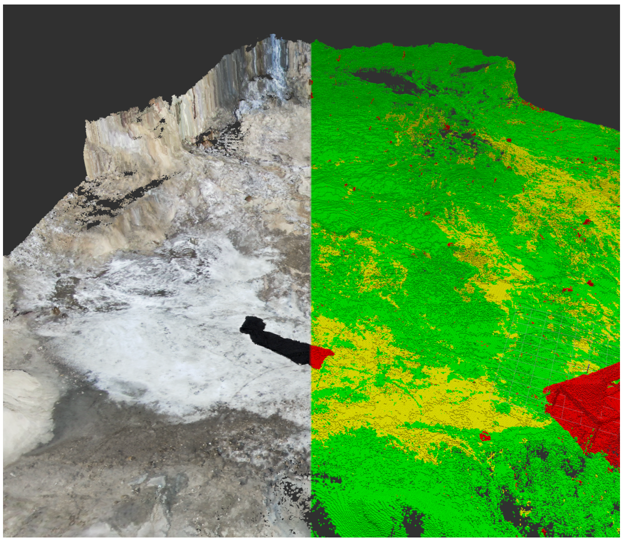

Figure 1. Overlay of risk map and RGB map of the terrain of the analog mission in the Tabernas desert. The analog mission was part of the intelliRISK2 project [3], in which both external and internal risks are analyzed.

In contrast to previous approaches, our approach can store additional information in the occupied and the free space. This allows us to integrate data such as temperature, signal strength, or radiation into the map. Structural information, such as surface normals, can also be calculated and included. These are especially helpful in utilizing the data structure for risk-aware path planning. The paths can not only account for the physical properties of the ground the robot is walking on but, for example, could additionally utilize signal strength to avoid areas where connection losses could happen. The data can be integrated during the runtime of the robot and accounts for moving obstacles such as other assets.

Additional features of the proposed mapping framework include incorporating RGB information from additional sources, such as satellite or drone images. The asset can include this information in mission-planning steps by incorporating this information into the map before the robot has completely explored the area.

Each layer of the map can be stored and loaded from PCD format, thereby making the data usable for other approaches. Together with visualizing the different layers, the enriched volumetric 3D maps could aid both the robot as well as the operators. Through the information, the robot collects the operators have additional information they can take into account for mission operations.

The proposed framework was tested together with the intelliRISK2 project [3] in the Tabernas desert in Spain. The area of the field test was next to the area of the 2018 ExoFiT mission location [4]. The ExoFiT Mission was conducted in a more even area with a larger sand area with only minor outcrops. In comparison, the intelliRISK2 field test had a more unstructured ground with different ground types. The proposed mapping framework could efficiently generate maps of the trial area, which were then fused with drone footage to create high-resolution 3D maps of the area. An enriched map was generated through different learning approaches, such as haptic ground assessment and visual ground classification. This map included the different ground types found in the area and could, in turn, be utilized for risk-aware path planning.

Our proposed enriched framework is a step towards risk-ware missions. Operators and assets can better understand the surroundings and conduct safer missions through detailed information in both the occupied and free space.

The paper is structured as follows: First, in Section 2, we will investigate current mapping methods with risk awareness. Afterward, our proposed framework of RISK VDBMapping is detailed in Section 3. Section 4 briefly overviews the created simulation environment. In Section 5, the results of the field test in the Tabernas desert are highlighted. Section 6 summarizes and discusses the next steps for risk-aware mapping and navigation.

2. RELATED WORK

Most mapping approaches focus on occupancy mapping. However, some approaches allow incorporating additional information into a map, which can be utilized for navigation.

In a 2D scenario, it is often sufficient to project the environment into a discrete 2D such as an Occupancy Grid [5]. Each grid cell could then be adjusted to take values for the surroundings' risk, which could be integrated into a 2D risk planner.

However, as soon as the environment becomes more complex, especially in the context of planetary exploration, it is not sufficient to project everything into 2D. The elevation maps proposed by Herbert et al. [6] often can be used. They can incorporate uncertainties, elevation, and unknown areas. Fankhauser et al. [7] propose a robot-centric approach for elevation mapping.

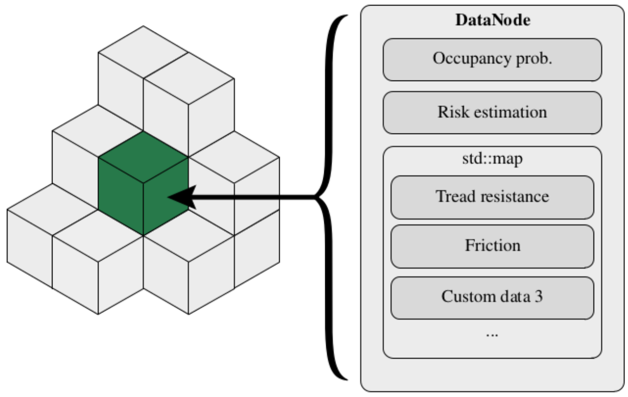

Figure 2. Custom DataNode for Risk Assessment. Each voxel contains just the data on properties of the surroundings, where it has information. On each handling of the voxel, the risk estimation is updated.

Elevation maps give a 2.5D projection of the environment. For a complete 3D mapping, different data structures have to be used. Hornung et al. [8] use Octrees to create an efficient mapping framework. OpenVDB [2] is a real-time capable data structure. Both Grosse Besselmann et al. [1] and Macenski et al. [9] utilize OpenVDB for 3D mapping frameworks.

However, all these approaches are limited to occupancy maps, additional information is not integrated into the data structure. An approach based on 2.5D maps with multiple layers and additional information, such as surface normals or traversability, was proposed by Fankhauser et al. in [10]. Ono et al. [11] combine a digital elevation map and visually classified terrain types in a weighted sum approach to calculate risk-aware paths. The different inputs account for both occupancy and traversability due to ground types. Puck et al. [12] proposed extending the OctoMap [8] by additional terrain properties. In this approach, terrain types and properties can be stored in individual layers and fused for each robot to calculate the associated risk. Ashour et al. [13] provide a different approach for risk maps based on the OctoMap [8]. In their approach, they add semantic information about risks into the voxels of the map. Through a visualization, they can highlight the risk type and severity.

All the approaches are limited to storing the risk values alongside the occupancy of the environment. Only the risks of obstacles and ground can be assessed for path planning. A free space assessment for risks next to the occupancy is missing.

3. RISK VDBMAPPING

As most approaches mainly deal with occupancy and neglect further information, we developed the Risk VDBMapping framework. This allows us to utilize the

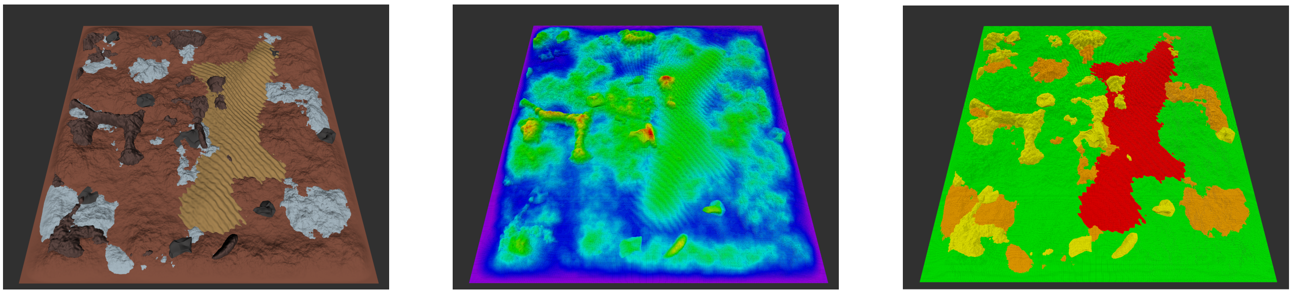

Figure 3. Different visualization of a simulated environment in the extended VDB Map. From left to right: RGB Visualization of different ground types of a simulated Martian environment; the visualization of the occupancy map with color coding depending on the voxel height; the risk classes associated with each voxel, red being more hazardous.

occupancy and additional information simultaneously. There are two significant approaches to incorporating additional information into the original framework: either a new layer with values for each additional data source is filled, or the voxels contain the information of the different data sources.

The first approach allows for better handling of the values and would be more beneficial for free space risks. However, since a new map has to be generated for each layer, it is not as memory efficient. To this end, we opted for the second approach, with one single map with a custom data node in the voxels.

The extension builds around the idea that we only want to store the needed date in each voxel. However, more information must be stored since we need more than an occupancy value. Therefore, the custom grid types are not sufficient anymore. The adapted data node consists of a float value for the occupancy, a float value for the associated risk of the voxel, and a std::map of the different properties of the surroundings. The resulting structure is visualized in figure 2.

Different risks must be assessed depending on the robot and the missions. A wheeled robot will be in danger from different surroundings properties than a legged one or even a flying robot. Terrain risks can be determined by physical properties utilizing a visual assessment [14] or haptic analysis [15]. Structural risk can be determined using the generated occupancy map by doing a geometric analysis on the map. Therefore, the risk is newly calculated each time new sensor data is integrated into a voxel.

Since different input modalities might be used, the known values for different properties in a voxel might not be known. Lidar data has a more extensive range than camera data. If only a visual assessment from the camera data is performed, not all voxels have associated information at the beginning. To account for this, a flag is set in the voxels if risks are known or could be calculated. This leads to marked voxels, which might be worth exploring in future steps.

A linear model and weighted sum approach account for the different influences of properties on the risk for an individual model. For each robot, the relevant properties can be defined, including the expected scale and direction of optimality. Furthermore, it can be defined how heavy the influence of each parameter on the risk assessment weighs. With this, a robot-specific risk can be analyzed. In future steps, this model could be a learned model for each robot, and the properties and occupancy could be made interchangeable between different maps and, therefore, robots.

4. SIMULATION ENVIRONMENT

A comprehensive pipeline for a simulated environment was set up for ease of integration and evaluation. In a first step, an environment has to be created, this can be achieved by using 3D graphic software such as Blender [16]. This allows the creation of a map with different terrain types, which can be used as a base for different terrain properties. To convert the 3D Models with Blender, a tool was written to create PCL [17] files. This tooling uses voxelization to create a voxel-based representation from a mesh. In this case, a Triangle-Box intersection test is used.

This tool allows the creation of PCL files from any .obj file. A Digital Terrain Models taken by the HiRISE camera on the Mars Reconnaissance Orbiter can also be loaded and transformed into a VDB instance. Figure 3 shows the result of a Blender environment with different terrain properties. The left image shows the VDB map with RGB information, where the different terrains are distinguishable. In the middle, the occupancy map with a color coding depending on the height of the voxel is displayed. The right image shows the risk map generated through the different terrain properties. This tooling allows an easy setup for future tasks, such as path planning with risk awareness.

5. FIELD TEST

The field test, part of the intelliRISK2 project [3], was conducted in the Spanish Tabernas desert (see Figure 4). The chosen location is where the first ExoFiT field tests were held [4]. However, not the exact spot was used since the intelliRISK2 analog mission did target different aspects compared to the ExoFiT trials. The ExoFiT mission focused on conducting a complete mission, maneuvering the asset from the lander towards a prospecting goal. Whereas in the intellIRISK2 analog mission, the focus was on evaluating different components of the autonomous robotic stack. This includes components of the risk-aware sensing of the environment and incorporating them into the risk map and planning with these maps, as well as sensing the internal feeling of the robot. The second leads to better fault detection and reactive behavior if the robot encounters external influences or internal hard and software failures.

Figure 4. Location of the intelliRISK2 field test. The area consists of diverse terrain with different ground types: salt, sand, rocks, and bedrock. The robots were tasked to traverse the environment and map their surroundings. Left of the area is the location of the ExoFiT missions.

During the field test for the risk map generation, an ANYmal C by ANYbotics [18] was used as the main asset. To distinguish the different ground properties, a semantic segmentation was deployed. The different ground types in the experiments were salt, sand, rocks, bedrock, and man-made structures. The segmentation is based on a mobilenet [19] so that it can run directly on the robot. The segmentation results are then passed to the RISK VDBMap and inserted into the map. Other properties, such as signal strength and robot wellbeing, were recorded during the mission. Each voxel that is accessed is then used in the current risk calculation. Thereby resulting in an overall risk map for the walking robot, which then can be used for risk-aware path planning.

Next to the live recorded maps, there are maps generated in post-processing. In Figure 5, the results of these maps are shown. On the left, the environment's volumetric map was fused with a drone's RGB information. Combining data from two different assets resulted in a rich map, which helps the operator to understand the environment. On the right side, the drone image was passed through the semantic segmentation, and the results were incorporated into the map. From this, the resulting risk map was generated. In green, the safer areas where sand and small rocks are located. In yellow, the patches of salt are highlighted, and in red, the man-made structures and more considerable obstacles.

6. CONCLUSION

In this work, an extension of the VDB Mapping framework was proposed. By incorporating additional data on different properties of the surroundings, a robot's risks can be calculated. The calculation uses a linear model and a weighted sum approach. Each robot has its mapping of relevant properties that influence its risks.

Furthermore, different data sources can be combined into a single map. The occupancy map of one asset can be combined with the image data of another asset. Not only can properties and risks in the occupied space be handled, but free space risks, such as signal strength, can also be included in the risk map. The framework was evaluated in simulation and an analog mission in the Spanish Tabernas desert.

In the future, mapping the properties to robot-specific risks could be a from simulation-learned approach with potential live updates.

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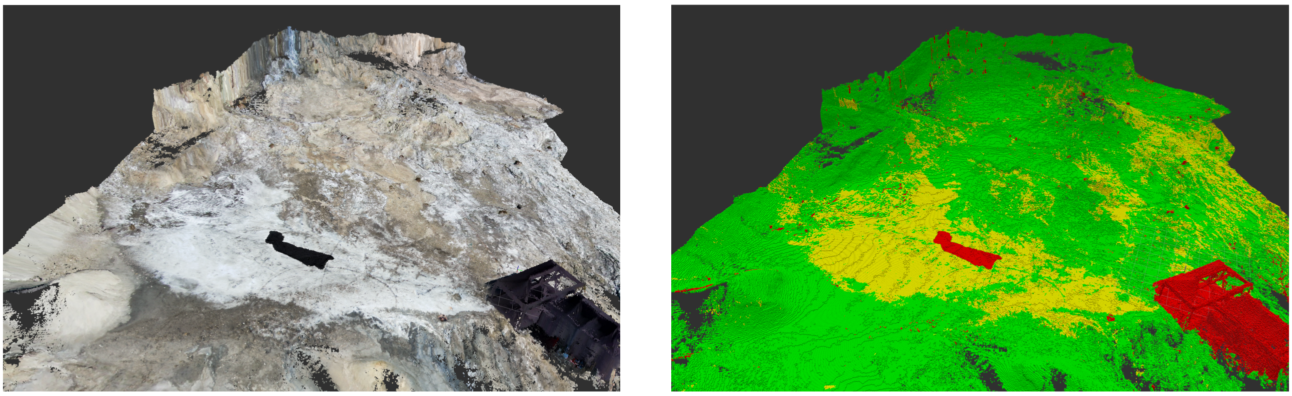

Figure 5. VDB Maps from the field test location in the Tabernas desert. On the left side, an RGB map was generated in postprocessing. The sensor data of the asset was used to generate the voxel map, which was enriched with images from a drone, to get a clean volumetric map. The drone image was analyzed using semantic segmentation, and the different ground classes were identified. According to the classes, the risk was calculated and included in the RISK VDB Map, which can be seen on the right.

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