Occupancy Grid Map Generation from OSM Indoor Data for Indoor Positioning Applications

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Abstract: In recent years, there is a growing interest in indoor positioning due to the increasing amount of applications that employ position data. Current approaches determining the location of objects in indoor environments are facing problems with the accuracy of the sensor data used for positioning. A solution to compensate inaccurate and unreliable sensor data is to include further information about the objects to be positioned and about the environment into the positioning algorithm. For this purpose, occupancy grid maps (OGMs) can be used to correct such noisy data by modelling the occupancy probability of objects being at a certain location in a specific environment. In that way, improbable sensor measurements can be corrected. Previous approaches, however, have focussed only on OGM generation for outdoor environments or require manual steps. There remains need for research examining the automatic generation of OGMs from detailed indoor map data. Therefore, our study proposes an algorithm for automated OGM generation using crowd-sourced OpenStreetMap indoor data. Our experiments with nine different building map datasets demonstrate that the proposed method provides reliable OGM outputs. The proposed algorithm now enables the integration of environmental information into positioning algorithms to finally increase the accuracy of indoor positioning applications.

1 INTRODUCTION

Indoor positioning has received much attention in recent years due to the vast amount of applications that employ position data. Indoor positioning is the process of determining the location of objects in indoor environments. Positioning systems are applied to localise and track assets in production buildings, to navigate persons through indoor environments or to analyse a person's trajectory in elderly care applications, for example. Such systems use different types of technologies, such as inertial sensors, visual markers, cameras, time of flight (ToF) sensors, or Wi-Fi-based technologies. All these localisation techniques have different disadvantages in indoor environments, which lead to inaccurate localisation results. Wi-Fi signals, for instance, can be interfered by metallic objects, ToF-based approaches require a line of sight and inertial sensor data is prone to error accumulation. Even technologies such as ultra-wideband systems with a theoretically achievable accuracy of 10 cm can be influenced by the environment, so that the positioning error reaches values of up to 3 m. As a consequence, the acquired sensor data can be inaccurate and unreliable, which results in invalid localisations, such as persons detected within a wall.

In order to compensate localisation errors, it is necessary to include further information about the object to be positioned and about the environment into the positioning algorithm. One possibility to improve the localisation accuracy is the integration of indoor map data: the given structure of buildings with its specific spacial dimensions, such as corridors, stairways and doors, allows an elimination of invalid positions. Moreover, by considering the structure of indoor environments, both probable and improbable object occurrences can be defined. A person walking through a building will probably not walk directly near the wall and will definitely not pass through a wall. An incorrectly acquired position within a wall could then be adjusted to a valid position next to the wall. Methods that are implementing such position corrections are described in Section 2. The described example is visualised in Figure 1.

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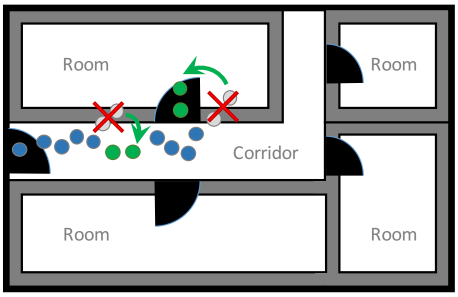


Figure 1: Localisation Example: Correction of Incorrect Sensor Data by including Information about Indoor Environment. The Blue and Grey Dots Indicate Sensor Measurements Whereas Grey Dots Correspond to Invalid Positions, E. G. within a Wall, That Can Be Adjusted to a Correct Position Indicated by Green.

The occurrence probability of a specific object within a building can be modelled by means of so-called occupancy grid maps (OGMs), which represent the occupancy probability of an object on the floor plan of a building. The OGM is modelled by a cell matrix whereas each cell is a square area of the indoor environment holding the probability of being occupied. Hence, generating OGMs requires floor plans and consequently indoor data of buildings. Since indoor data about building had either been generally not available or is only provided in form of Computer Aided Design (CAD) formats, an alternative data source was created by the OpenStreetMap (OSM) community: indoor map data has been collected by volunteers and now provides detailed crowd-sourced information about the structure of buildings. These mapping activities have been being increased in recent years and have led to a wider availability of indoor data. An overview of mapped data is listed in the OSM Wiki (OSM-Community, 2020).

To date, little attention has been paid to the involvement of OSM indoor data in OGM generation. This paper therefore examines OSM indoor map data as a data source for the generation of OGMs and introduces a procedure to create such OGMs as an input for indoor positioning algorithms.

The paper is structured as follows: Section 2 presents state-of-the-art methods for OGM generation and outlines the research gap. Thereupon, Section 3 introduces the proposed procedure to generate OGMs from OSM indoor data by illustrating the system concept overview and subsequently describing the realisation of the single system modules. The obtained results are presented and discussed in Section 4. Finally, Section 5 concludes the paper and gives an outlook on future work.

2 RELATED WORK

Occupancy grid mapping was initially introduced by Moravec and Elfes in 1985 (Moravec and Elfes, 1985). Originally, this mapping procedure was developed for noisy sonars and called “mapping with known poses”. In literature, especially in the field of **probabilistic robotics**, occupancy grid mapping is often referred to as the process of generating maps from noisy and uncertain sensor data while the position of the robot with the attached sensors such as cameras, laser range scanners and LIDAR is known (Matthies and Elfes, 1988), (Konolige, 1997), (Thrun, 2001). In this mapping problem, the aim is to build an occupancy map of the environment, in which the occurrence of obstacles is stored.

For **positioning/localisation**, the opposite problem has to be solved: Based on an existing map, the position of objects shall be derived, also in the presence of noisy sensor data. In our case, the existing map is an OSM indoor map that has to be transformed in an occupancy grid map first. In this context, OGM generation is the transform of a floor plan into independent discrete cells. Each cell stores a variable estimating the grade of its occupancy. The variable can either be binary or continuous, stating whether the cell is occupied or not or indicating the grade of occupancy, i. e. the occupancy probability of the object to be localised.

Extant literature gives insight on how OSM maps are transferred to OGMs and thereafter used for localisation purposes.

In their publications, Kurdej et al. present a localisation system for intelligent vehicles that uses **OSM outdoor map data** as a-priori information (Kurdej, 2015), (Kurdej et al., 2012). This systems generates OGMs based on OSM road and building information and matches sensor data from optical sensors against these OGMs.

Herrera et al. are the first to generate OGMs from **OSM indoor maps** (Herrera et al., 2013), (Herrera et al., 2014). Their algorithm derives the OGMs from a manually defined graph network that overlays the indoor map data. This graph consists of nodes, which were defined by empirical studies and denote probable indoor positions. However, these nodes have to be **manually added** to the graph.

Naik et al. proposed OSM-based indoor data for robot navigation and generated a primitive OGM for that purpose (Naik et al., 2019). This generation methodology involves only a **limited set of objects**, namely information about rooms and corridors. Moreover, the OGM distinguishes between **only two occupancy states**.

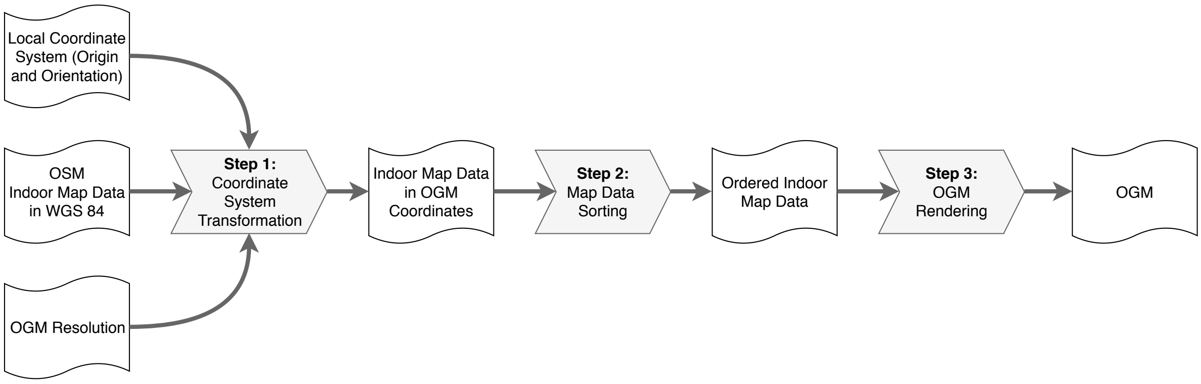


Figure 2: Concept Overview: The Algorithm for OGM Generation Is Divided into Three Main Steps.

To summarise, the presented related work either focusses on OSM outdoor data or is lacking a full automation of the OGM generation and is only covering a small part of building features. Therefore, we propose a methodology for a highly automated generation of OGMs based on OSM indoor maps that is involving as much as possible information about the interior of a building.

3 METHODOLOGY

This section first provides an overview about the algorithm with its single steps and thereafter explains the realisation of every step as well as the input and the output data in detail.

3.1 Concept Overview

Our proposed algorithm for OGM generation is divided into three steps: coordinate transformation, data sorting and OGM rendering, as can be seen in Figure 2.

In the first step, the input OSM map data, which is represented in WGS-84 (World Geodetic System 1984) format has to be **transformed into OGM coordinates**. Therefore, the coordinates of the indoor map data are firstly converted to a metric representation and to a local coordinate system (LCS) that, together with its origin and orientation, has to be defined depending on the specific positioning application that will use the OGMs. This transformation is necessary to represent all objects, i. e. both objects from the OSM map as well as objects to be located, in the same local and metric coordinate system. A transformation of indoor data into local metric format brings the benefit of compatibility to other devices. Other devices might be industrial robots also working with a local metric coordinate system or devices processing a given grid map. Afterwards, a transformation from the metric LCS in OGM coordinates is applied based on a manually defined OGM resolution. Thereby, the OGM coordinates represent the cell indices of the OGM.

During **map data sorting**, all indoor map objects are assigned to a specific priority level that corresponds to a layer in the rendering process, where the OGM is rendered layer by layer in a fixed order. This assignment is based on the OSM tags of each geo object. For the OGM rendering, we defined a certain order in a lookup table to achieve sensible OGM outputs. This is necessary, because geo objects within OSM data sets may be overlapping. For instance, room areas and their walls are described by two separate geo objects, whereas the mapped area of the room may be overlapping with its mapped walls. At this point, the OSM mapping scheme considers walls as a second layer over room areas, so that the mapped wall boundaries define the real-world physical walls above underlying room areas. Now consider an exemplary rendering output of unsorted data: Rendering the walls of a room before rendering its area would lead to a loss of wall position information due to the ”over-rendering” of walls by the room area. This example illustrates the necessity of a sensible data sorting in accordance with OSM mapping schemes. Next to the *chronological order* objects will be rendered, the layer specifies the *occupancy probability* for objects in that level, and the *shape* the object will be rendered with.

Finally, the OGM is built by **rendering** the map objects that were assigned to the specific layers with their according probabilities.

3.2 Realisation

3.2.1 Input Data

The algorithm requires three sets of input information: The OSM indoor map data, the origin of the local coordinate system and the desired grid map resolution. The OSM indoor map data is stored within an XML (Extensible Markup Language) file including indoor geo objects, such as rooms, walls, doors and corridors, characterised by a set of nodes with longitude and latitude coordinates as well as by OSM tags, which are describing the meaning of each object.

The second required information are the position and orientation of the LCS. The position consists of a WGS-84 coordinate (latitude and longitude) and the orientation is defined by the rotation angle between the ordinate of the WGS-84 coordinate system and the ordinate of the LCS. The origin of the LCS as well as the rotation angle can be set by using the JOSM (Java-OpenStreetMap)-Editor (OSM-Community, 2019a) with measurement functionalities provided by plug-ins (OSM-Community, 2019b).

The grid maps resolution is the third input data of this algorithm and it is specified in pixels per meter (px/m). This resolution is used for the conversion of geo object positions to the OGM coordinate system, which is using pixels as units.

The described input data is parsed at the initialisation of the algorithm and stored in an internal data structure for further processing in the following computing steps.

3.2.2 Step 1: Coordinate System Transformation

Because indoor positioning systems are comprised of several system components with their own single coordinate systems, it is necessary that all the different components share the same local coordinate system in the overall indoor positioning application. Such components can be different kind of sensors, robots or algorithms that further process positioning data.

For OGM generation, the input data needs to be transformed into OGM coordinates, which then represent the originally metric dimensions of an indoor environment in OGM pixel coordinates, as already outlined in Figure 2. By means of a geographic library (Karney, 2013), (Karney, 2019), the indoor map coordinates will be transferred from WGS-84 format into a metric coordinate system by solving the inverse geodesic problem, which determines the shortest route between two points on the surface of the Earth. Thereby, the results are the metric distance components on the latitude and longitude arc Δx_ω and Δy_ω between the origin of the LCS as well as a node of a geo object at the position (x_{L1}, y_{L1}). Afterwards the rotation angle α of the LCS is applied to finally transform Δx_ω and Δy_ω into local x and y coordinates. Figure 3 visualises this coordinate system transformation.

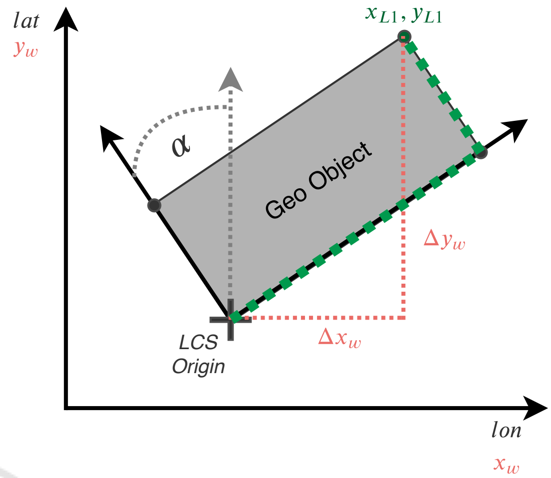


Figure 3: Transformation of a Geo Object at Position (X_{l1}, Y_{l1}) given in WGS-84 Coordinates to a Metric LCS. Δx_ω and Δy_ω Represent the Distance Components on the Latitude and Longitude Arc between the Origin of the LCS and a Geo Object. α Is the Rotation Angle between the WGS-84 Coordinate System and the LCS.

Finally, the map data in LCS coordinates is transformed in OGM coordinates. This is achieved by manually defining the resolution of the OGM in pixels per meter (px/m) and afterwards multiplying each LCS coordinate with this resolution value to obtain rounded OGM coordinates in Pixels (px). The choice of the resolution depends on the accuracy of the positioning system, whose results shall be improved. For instance, an UWB system with an accuracy of 20 cm can use an OGM with a resolution of 5 px/m.

3.2.3 Step 2: Map Data Sorting

As already described in Section 3.1, an ordered map data set is necessary for generating an OGM with a layer-wise rendering methodology that also involves over-rendering. Though, due to the structure of the OSM data definition, the geo objects within the indoor map data are unsorted and might be overlapping. Therefore, a lookup table that assigns relevant tags of the geo objects to a specific rendering layer was created. This lookup table is shown in Figure 4.

The first rendering layer (L1) holds basic indoor geo objects with the lowest limitations for positionable objects, such as rooms, corridors, steps, stairways or elevators. In that sense, lowest limitations refers to the highest probability for a valid indoor po-

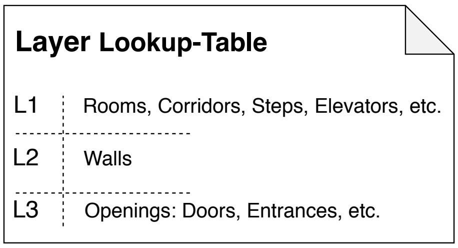


Figure 4: Lookup Table to Assign Geo Objects by Means of Their Application-Relevant Tags to a Specific Rendering Layer.

sition. The second layer (L2) contains all kinds of walls that definitely restrict the freedom of movement of positionable objects. Openings, such as doors and entrances, are considered separately to be placed as a third layer (L3) atop of walls and to enable the overwriting of limitations set by the walls.

3.2.4 Step 3: OGM Rendering

As a final step of the OGM generation, the rendering is performed.

Thereby, every floor of a building with its specific geometry results in a separate OGM. Consequently, a canvas is created for every floor and the dimensions of these canvases are defined by the lowest and highest OGM coordinates of every floor, which designate the canvas boundaries.

The rendering itself handles 8 bit grey scale values, which encode positioning probabilities in a range from 0 % (0.0) to 100 % (1.0). When rendering indoor areas of Layer L1, i. e. rooms, corridors or steps, these areas are filled with a grey scale value of 0.75 as it is shown in Figure 5b. Using a probability value of 75 % instead of 100 % allows to subsequently add popular paths with even higher probabilities, so the grid map can be optimized in retrospect in case such frequently used paths are known.

This step is followed by rendering a gradient tube adjacent to the inner boundaries of the resulting area of Layer L1, see Fig. 5c. By means of this gradient behaviour, a lower probability of positions at the boundaries of indoor areas is modelled. Hence, the occupancy probability decreases towards the walls in the shape of a smoothed circle in our case, while the grey value the circle is filled with is linearly reduced with increasing radius. Other shapes, such as normal distributions, are sensible as well. The dimensions of the shape are relative to the size of the indoor area.

In the next step, the walls of Layer L2 are rendered atop of the L1 area. Walls are also modelled as areas and are filled with a positioning probability of 0.0, which ensures that this area is inaccessible for positionable objects and persons. This rendering step is visualised in Figure 5d.

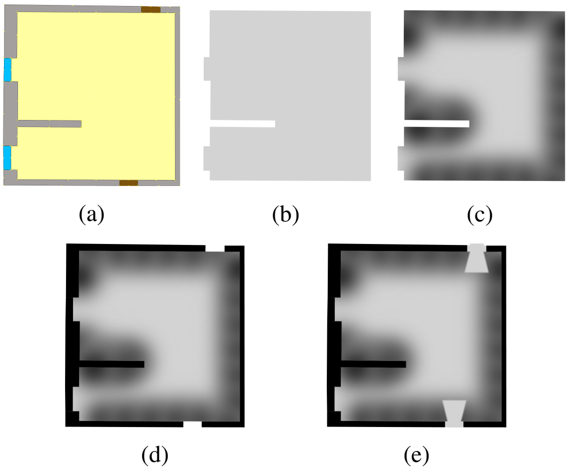


Figure 5: Illustration of the OGM Rendering Process. 5a: Example OSM Indoor Map with Windows (Blue), Walls (Grey), Openings (Red) and the Room Area Itself (Yellow). 5b: Resulting Area of L1.with Basic Indoor Objects. 5c: Boundary Modelling with Gradients. 5d: Rendering of Walls in L2. 5e: Rendering of Openings in L3.

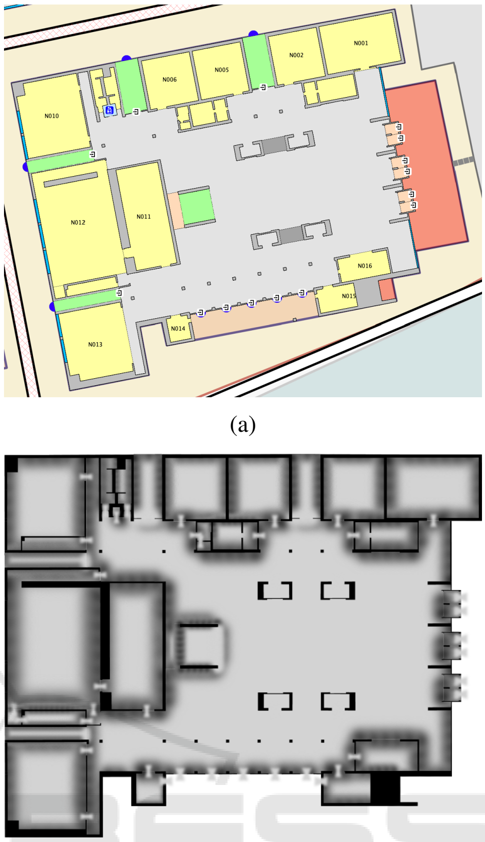
As shown in Figure 5e, Layer L3 includes openings and their probability behaviour of the area around them. The openings are rendered atop of the previous layers and represent a positioning probability of 0.75. Empirical experiences have shown that people enter or leave openings in a shape similar to a funnel. In case of openings that are accessible in both direction, two funnels are used for rendering, so that the resulting shape resembles a hourglass shape. The funnels are rendered perpendicular to the wall surrounding the respective opening.

Finally, applying the complete algorithm to OSM indoor data of a certain building delivers an OGM for each level of this building, which is the output data of the OGM generation algorithm.

4 RESULTS AND DISCUSSION

We performed experiments with 9 different building map data sets, which have qualitatively shown that the algorithm delivers reasonable OGMs. An example for one of these generated OGMs, which represents a complete floor of a building, is shown in Figure 6. When comparing the input, i. e. the OSM indoor data, with the rendered OGM, it can be seen that the different objects of the three layers are correctly represented in form of probability grey scale values. Our study therefore proved that the proposed automated generation of OGMs from crowd-sourced OSM indoor data provides reliable results, provided that the indoor environment was mapped correctly.

Nevertheless, the algorithm still has three limitations, which should be contemplated in future work: Firstly, the algorithm does not automatically evaluate the quality and correctness of the input OSM data. Because this data is mapped by volunteers without any special training, the data can be very imprecise and even necessary features such as doors may be missing and can therefore negatively affect the resulting OGM. With the current implementation, no automatic validation of the input data is performed, so that a manual plausibility check of the generated OGM had to be performed. Consequently, validating the input data is still an open subject to be solved. Secondly, hourglasses, which are rendered with a fixed pre-defined size at door positions, are not seamlessly connected to the base probability of the indoor area. This is because the width of the probability gradient at the borders of the indoor area depends on the size of this area (as noted in Section 3.2.4). Accordingly, the size of the hourglass should be dynamically adapted to the room size as well. Thirdly, the current placement of the hourglass in narrow corners of a room lead to an unwanted overwriting of wall information.



(a)

(b)

Figure 6: OGM Output Generated from OSM Indoor Data. 6a: Example OSM Indoor Map of a Floor in a Building. 6b: OGM Generated from the given OSM Indoor Map Data.

5 FUTURE WORK

In addition to the limitations, which have been presented in the previous section and which will be handled in future, there are two further developments planned:

As next step, we focus on the integration of the generated OGMs in an UWB positioning systems in order to improve positioning accuracy. Therefore, the OGM shall be used in combination with a particle filter to eliminate invalid samples. By means of practical experiments, the impact of OGMs on the accuracy improvement will be evaluated.

Furthermore, in future versions of this method implementation, points of interest (POIs) and popular paths in buildings will be integrated in the OGM, as already pointed out in Section 3.2.4.

The kind of POIs depends on the use case of the intended positioning system. For instance, an indoor navigation for museum visitors must consider the area around paintings as places with high probabilites for positions. Because paintings are typically mounted at walls, the occupancy value of the OGM in such areas must be increased.

For the definition of popular paths can be applied both, manual as well as automated approaches: A manual solution is to ask several persons to manually draw paths in the map they think probable to be frequently used. More appropriate, however, would be automatised methods. One sensible solution is a learning-based approach where most frequently used paths are derived from the actual positioning output and a kind of heat map is generated. The more detections are registered in a cell of an OGM, the higher is the path probability, i. e. the heat, of this cell. A further method could determine paths by applying skeletonisation algorithms on the indoor map areas whereas the remaining topological skeleton denotes these paths. Finally, another option is to determine direct paths between relevant objects, for example the direct lines of sight from one door to other doors in a room.

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