Autonomous robot navigation based on OpenStreetMap geodata

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Abstract—**This paper introduces the appliance of standardized, free to use and globally available geodata for autonomous robot navigation. For this, data from the famous collaborative OpenStreetMap (OSM) mapping project are used. These geodata are public domain and include rich information about streets, tracks, railways, waterways, points of interest, land use, building information and much more. Beyond the spatial information, the geodata contain detailed information about the name, type and width of the streets as well as public speed limits. As a contribution of this paper, the OSM data are integrated for the first time into the robot tasks of localization, path planning and autonomous vehicle control. Following the description of the approach, experimental results in outdoor environments demonstrate the effectiveness of this approach.**

I. Introduction

For any mobile robot, the ability to navigate in its environment is one of the most important capabilities. In general, the navigation task can be defined as the combination of three basic competences: localization, path planning and vehicle control. Localization denotes the robot's ability to determine its own position and orientation (pose) within a global reference frame. Path planning defines the computation of an adequate sequence of motion commands to reach the desired destination from the current robot position. Due to its planning component, path planning is typically done before motion. The planned path is followed by the robot using feedback control. This controller includes reactive obstacle avoidance as well as global path replanning.

In order to solve the navigation task, a representation of the environment is required. For this, some research groups focus their work on building the environmental representation from scratch by SLAM approaches [9] [11]. Typically, these approaches regard mainly the obstacle configuration in the environment. Drivable streets or regions of interest are not considered by these approaches. Other research groups use a predefined environmental representation to solve the navigation task. For example, in [4] a cadastral map with the footprint of buildings is used for robot localization in urban environment. In [3] an environmental map of predefined routes is used for path planning of an autonomous fork lift truck. In the DARPA Grand Challenge competitions, a detailed predefined map of the path [12] and the route network [13] was given to all teams. These data included lane and traffic sign information thus forming the background for autonomous navigation. In these approaches, the environmental representation is typically created by experts for a specific scenario at a certain location. A generalized environmental representation is still missing or is only commercially available in a poorly documented data format.

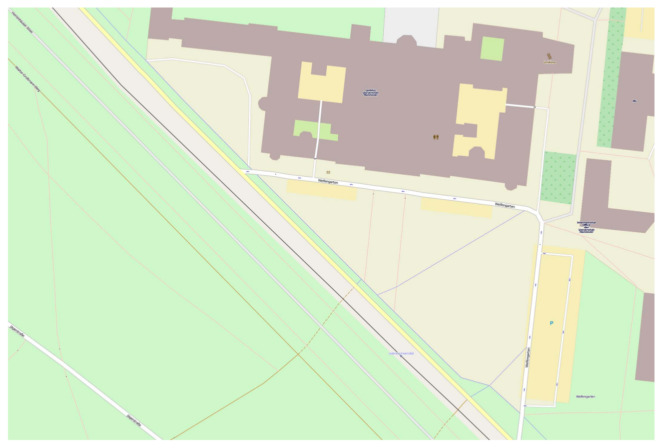

Fig. 1. Exemplary geodata from OpenStreetMap including points of interest, building information as well as way information.

This paper proposes the appliance of standardized geodata from the famous OpenStreetMap project as an environmental representation for autonomous robot navigation. Founded in July 2004, OpenStreetMap (OSM) is a collaborative project which aims to create a free to use and editable map of the world [1]. Different from commercial map distributors like Google, Navteq and Teleatlas, the OSM map is public domain and created by volunteers performing systematic ground surveys with a handheld GPS receiver. More recently, aerial photography and other data from commercial and governmental sources greatly increased the speed of the work and allowed land-use data to be collected more accurately. At the end of 2009, more than 200,000 registered users were contributing to the mapping project [6].

The OSM geodata include rich information about streets, tracks, railways, waterways, points of interest, land use as well as building information. Next to the spatial information, the geodata contain detailed information about the name, type of streets (e.g. highway or footpath), street widths, speed limits, addresses of buildings as well as subway stations and bus stops. Figure 1 illustrates an exemplary map from OpenStreetMap. As this is a collaborative project by volunteers, the accuracy of the geospatial data is undefined

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and depending on the individual quality of surveying. At least in the major cities, the OSM data are more detailed than those of commercial geodata distributors.

In this paper, the building information from OpenStreetMap are applied for robot localization in urban environment. Furthermore, the street data from OSM are used for path planning, to calculate the route (shortest or fastest) from a given starting pose to a certain destination. The planned path is followed by the robot fully autonomously. In addition, the OSM data are used to control the headlights and the turn signals of the robot according to the traffic regulations. For the presented approach, the OSM data are used as available without any preparation or post processing. As far as the authors are aware of, this is the first time OpenStreetMap geodata is integrated into the autonomous robot navigation.

The paper is structured as follows: Section II introduces the data model of the OpenStreetMap geodata in general. Section III presents the appliance of OpenStreetMap data to the robot navigation. Finally, real-world experimental results are presented in Section IV, followed by the conclusion and discussion for future work in Section V.

II. OpenStreetMap Data Model

For regional sections of the planet, an XML file containing the latest revision of the OSM map can be downloaded via the web interface of the project [7]. In addition, regularly updated maps of the entire planet or specific regions are available at that website.

According to the OpenStreetMap specifications [8] [10], the OSM data model consists of three basic geometric elements called *nodes*, *ways* and *relations*. For a detailed description, annotations named *tags* may be added to the elements. The elements are introduced in the following subsections. Please note, that only elements which are related to the geodata are described.

A. Nodes

Nodes are point-shaped geometric elements which are used to represent points of interests (POI) like traffic signs, gas stations and restaurants. In addition, nodes may be interconnected by ways where they are used as basepoints to represent the geometry of the way. Throughout this paper, a single node is defined as follows:

$$n = \left(id_n, lat_n, lon_n, T_n\right) \tag{1}$$

For each node, id_n denotes a globally unique identification number. The latitude of the node is defined by lat_n and the longitude is given by lon_n. In the OSM data model, both latitude and longitude are specified in degrees with seven decimal places, resulting in a worst case uncertainty of $\pm$1cm. To specify the semantics of each node, a subset T_n of m_{Tn} tags is related to the node. These tags are defined as follows:

$$T_n = \left\{t_i\right\}_{i=1\ldots m_{T_n}} \tag{2}$$

where t denotes a single tag. Each tag consists of two elements, a key k and the corresponding value v:

$$t = \left(k, v\right) \tag{3}$$

According to the OSM specification, tags are not typified but given as a plaintext with UTF-8 encoding (see TABLE I for an overview of OSM tags used in this paper).

Finally, each OSM map consists of m_n nodes. They are denoted by the set N as follows:

$$N = \left\{n_i\right\}_{i=1\ldots m_n} \tag{4}$$

B. Ways

Ways are used to model line-shaped geometric objects like roads, railways, rivers, etc. Throughout this paper, a single way is defined as follows:

$$w = \left(id_w, l_w, N_w, T_w\right) \text{ with } N_w \subseteq N \tag{5}$$

Analogue to the nodes, id_w denotes a globally unique identification number of the way. In addition, a layer l_w is associated to the way. This is used to model different levels of heights, like bridges, tunnels or subways. The m_{Nw} nodes representing the geometry of the way w are given by the set N_w as follows:

$$N_w = \left\{n_i\right\}_{i=1\ldots m_{N_w}} \tag{6}$$

To specify the semantics of each way, a subset T_W of m_{Tw} tags is related to the way. These way tags are defined by:

$$T_W = \left\{t_i\right\}_{i=1\ldots m_{T_w}} \tag{7}$$

The way nodes N_w define a line approximating the center of the road. In general, ways are defined without a specific driving direction. The direction may be restricted with the way tag *oneway*. In cases, where the ids of the first node and the last node of the way are identical, ways are interpreted as areas. These areal ways can be used to model the outline of forests, lakes as well as the footprint of buildings.

Finally, each OSM map consists of m_w ways. They are denoted by the set W as follows:

$$W = \left\{w_i\right\}_{i=1\ldots m_w} \tag{8}$$

Fig. 2. Environmental map for localization. Blue indicates the building footprints from a cadastral map. Dark gray regions label building information from OSM.

C. Relations

The element relation is used to model the relationship of geoobjects. Members of a relation can be nodes as well as ways. Relations can be used e.g. to model a tram line. As the element relation is not applied in this paper, this element is not described here. Fore more information, see [10].

D. OSM Tags

For the autonomous navigation based on OpenStreetMap geodata a total of 29 tags are used from the currently 626 possible enumerated tags. An overview of the tags used in this paper with its description, tag name and possible tag values is listed in the following Table I.

TABLE I
USED OSM TAGS

description	tag key (k)	possible tag values (v)
localization		
general tag for buildings	*building*	*yes*
path-planning and control		
major divided highway with 2 or more lanes	*highway*	*motorway*
link road leading to/from a motorway	*highway*	*motorway_link*
major road that is no motorway	*highway*	*trunk*
link road leading to/from a trunk road	*highway*	*trunk_link*
country road linking larger towns	*highway*	*primary*
link road leading to/from primary roads	*highway*	*primary_link*
country road linking smaller towns	*highway*	*secondary*
link road leading to/from a secondary road	*highway*	*secondary_link*
country road wider than 4 m	*highway*	*tertiary*
no administrative classification	*highway*	*unclassified*
road of unknown classification	*highway*	*road*
road accessing residential areas	*highway*	*residential*
street where pedestrians have priority	*highway*	*living_street*
access to buildings	*highway*	*service*
road mainly for pedestrians	*highway*	*pedestrian*
non-specific or shared-use path	*highway*	*path*
designated cycle way	*highway*	*cycleway*
designated footpath	*highway*	*footway*
actual physical separation	*layer*	*-5 to 5*
street is used as one-way road	*oneway*	*yes/no/-1*
width of the street in meter	*width*	*number*
total number of physical lanes of the way	*lanes*	*number*
road speed limit in km/h	*maxspeed*	*number*
road height limit in m	*maxheight*	*number*
road width limit in m	*maxwidth*	*number*
road proceeds over a bridge	*bridge*	*yes/aqueduct/...*
road proceeds in a tunnel	*tunnel*	*yes*
general access permission	*access*	*yes/private/.../no*

III. ROBOT NAVIGATION WITH OPENSTREETMAP GEODATA

A. Localization

For a precise localization in urban as well as in non-urban environment, a combination of GPS and laser based localization is used in this paper. Presented for the first time in [4], this approach consists of two steps. In the first step, each received GPS position fix is Kalman filtered with wheel odometry and inertial measurement data. In the second step, the Kalman filtered GPS pose is integrated into a Monte Carlo Localization. The Monte Carlo Localization (MCL) or particle filtering is a recursive Bayes filter that estimates the posteriori belief distribution of a robot's pose based on sensor data of motion and perception and a given map of the environment. The belief $Bel(s)$ is represented by a set of n weighted samples (or particles) distributed according to:

$$Bel(s) \approx \{s^{(i)}, w^{(i)}\}_{i=1\ldots n} \tag{9}$$

where each $s^{(i)}$ is a sample of the random variable s, the hypothesized position and orientation of the robot. The importance (or weight) of each sample is determined by the importance factor $w^{(i)}$ which represents the probability of being at the location. The Kalman filtered GPS pose is integrated into the MCL by adding a (small) number of n_{gps} samples drawn from a Gaussian distribution centered at the Kaman filtered GPS position. The standard deviation of the distribution is the equivalent to the estimated uncertainty of the filtered GPS measurement. Additionally, the importance factors of the belief are adjusted according to the quality of the GPS measurement.

The sensory input data are based on 3D laser scans. Using the method of *Virtual 2D Scans* [14], landmark information like vertical planes are extracted from the 3D point cloud.

Within this paper, the OSM map is used for the environmental representation of static landmarks. For this, a subset W_{land} of m_{land} ways describing the outline of buildings is utilized. These ways include the tag $(building, yes)$ and are defined as follows:

$$W_{land} = \{w_l \mid w_l \in W \wedge (building, yes) \in T_{w,l}\} \tag{10}$$

To increase the robustness of the GPS and laser based localization against the influence of GPS outliers and large OSM mapping errors, the importance factor of the GPS samples is adjusted. For this, the weight of each particle included in the footprint of a building is set to zero,

$$w^{(i)} = \begin{cases} 0 & \text{if } w_l \text{ contains } s^{(i)} \\ w^{(i)} & \text{else} \end{cases} \tag{11}$$

Consequently, this particle has no influence on the position result, reducing oscillation between multiple pose hypotheses.

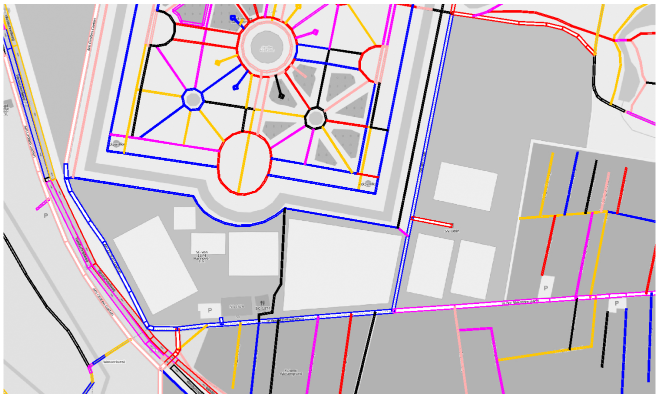

Fig. 3. Street information from OSM. The different colors indicate different ways.

B. Path Planning

For path planning, an optimal path from the current robot pose s to the given destination d is searched. Using the OpenStreetMap geodata for path planning, a subset W_{path} of all OSM ways W is considered. The ways in this subset contain the tag key *highway* and **any** available tag value (represented by "-" in Eq. 12) and are therefore designated as drivable streets, cycle ways, paths and footways.

$$W_{path} = \{w_p \mid w_p \in W \wedge (highway,-) \in T_{w,p}\} \tag{12}$$

With the representation of all admissible ways W_{path}, path planning is performed with the well-known A* search algorithm [5]. This algorithm computes a least-cost path from the starting node to the given destination minimizing the following cost function:

$$f(n_i) = g(n_i) + h(n_i) \tag{13}$$

where $g(n_i)$ represents the path costs, the costs from the starting node to the current node n_i. The heuristic estimate of the remaining costs to the destination is denoted by $h(n_i)$. For path planning, the resultant path is computed **either** as the **shortest** or the **fastest** route. Computing the shortest path, the cost calculation is based on the length of the way segments and the straight-line distance for the heuristic estimate $h(n_i)$. For the fastest path, the travel times for $g(n_i)$ are computed from the length of the way segments divided by the particular speed limits using the OSM tag *maxspeed*. The heuristic estimate $h(n_i)$ is based on the travel time from the straight-line distance divided by the maximum robot velocity. In addition, the OSM tags *access*, *oneway*, *maxheight* and *maxwidth* are considered for path cost calculation. In case a way segment is not approvable for navigation, the path costs $g(n_i) = \infty$ are set to infinite, excluding the way segment from path planning.

The result path of the planning algorithm is a set P of m waypoints p:

$$P = \{p_i\}_{i=1\ldots m} \tag{14}$$

Defining the base trajectory of the resultant path, each waypoint contains data about its global coordinates x and y, the maximum velocity v for approaching that waypoint and the lateral corridor width d of the path:

$$p = (x, y, v, d) \tag{15}$$

The maximum waypoint velocity v is computed as the minimum of the desired robot velocity and the maximum allowed speed limit on the particular path segment using the OSM tag *maxspeed*. The lateral boundary of the path corridor is based on the OSM street width using the tag *width*. In case this tag is not available, the width is approximated by predefined values using the *highway* tag value and/or the number of way lanes given by the OSM tag *lanes*.

C. Path Following

Following the preplanned path is achieved by a hybrid feedback controller introduced in [2]. This controller enables precise path tracking as well as obstacle avoidance. The obstacle avoidance consists of two parts, reactive obstacle avoidance based on 3D sensory data and global path replanning.

Reactive obstacle avoidance is achieved by adjusting the lateral offset of the robot with respect to the base trajectory of the path. For each path segment, the lateral displacement is upper bounded by the lateral boundary of the path corridor d_i. Next to obstacle avoidance, the vehicle speed is reduced in the presence of perceived obstacles.

In addition, global path replanning is performed to circumvent obstacles which cannot be avoided reactively. For this, an alternative path to the destination is computed.

D. Lightning control

Based on the planned path P, the ways W_{path}, the turn signals and the headlights of the robot are controlled autonomously.

For the control of the turn signals, the region s_{turn} in front and behind the current robot position is considered. Within this region, the change of heading of the planned path is computed for each path waypoint p. Next, the number of ways connected to each path waypoint is determined. The turn signals are activated if the change of heading exceeds 45 degrees and more than two ways are connected to the path waypoint. The direction of the turn signals (left or right) is based on the sign of the path change angle.

For headlight control, the region s_{light} in front and behind the current robot position is considered. The headlights are activated if at least one path waypoint within this region corresponds to a way containing the tag *tunnel*. In addition, the lights are activated if any way segment within this area passes under a bridge. For this, the tags *bridge* and the tag *layer* for the spatial level of the ways are checked.

Fig. 4. Autonomous mobile robot RTS-HANNA.

Fig. 5. Localization results of a test run starting at S and ending at the point labeled with E. The blue line indicates the results with the cadastral map and the red line the results with the OSM building information.

IV. Experimental Results

To demonstrate the appliance of OpenStreetMap geodata for autonomous robot navigation, two experiments have been performed for this paper. The first experiment focuses on the localization in urban environment using the outline of buildings from OSM. The second experiment applies the OSM street data for robot path planning and navigation. Both experiments have been conducted with our robot RTS-HANNA in real-world environment.

The robot is based on an off-the shelf *Kawasaki Mule 3010 Diesel 4x4* side-by-side vehicle. Fully street licensed, this vehicle is equipped with a drive-by-wire retrofit kit from PARAVAN GmbH. This system enables manual as well as fully computer control of the vehicle. In addition, headlights, turn signals, horn and wipers are controllable by computer. The environmental perception is based on a pair of continuously rotating 3D laserscanner *RTS-ScanDriveDuo* with an update rate of 0.8 Hz each. Additionally, an *Ibeo Lux* 3D laserscanner is used for fast obstacle detection in the main driving direction. GPS data as well as inertial and wheel-odometry data are available for navigation. Data acquisition and processing are performed on three embedded PCs with Linux/Xenomai real-time operating system.

A. Localization

The localization experiment was conducted at the campus site of the Leibniz Universität Hannover. This urban area comprises of open space and 19 buildings including an office building with a maximum height of 50 m. In this environment, the robot RTS-HANNA was driven manually on a path of 860 m length. The path starts from S and ends at the point labeled with E (see Fig. 5). On this path, the robot was driven centered in the streets with a maximum speed of 2.5 m/s and an average speed of 1.6m/s. For environmental perception, landmark information were extracted from the 3D laser data using the *Virtual 2D Scan* [14] approach. The Virtual 2D Scan was used as sensory input for the GPS and laser-based Monte Carlo localization method.

For this experiment, the same localization method was used with commercial cadastral data as well as with OSM building data. For the cadastral data, the ground truth accuracy is specified with 0.5 m. The particle filter in both localization approach uses 200 samples and a generous estimate of the sensor variance of 1 m. Ten percent of the samples are distributed according to the Kalman filtered GPS measurement. For the localization, all required algorithms as well as data acquisition are computed in real-time onboard the robot. For evaluation purposes, all processed data are logged as well.

Figure 5 illustrates the results of the different approaches. The blue line denotes the localization result using the cadastral environmental map. The red line indicates the results based on the OpenStreetMap building representation. According to Fig. 5, both localization results are principally similar in shape, but not congruent. On that run, the mean position difference between both localizations is 4.9 m with a maximum of 14.95 m. The mean angular difference is 1.3 deg with a maximum difference of 9.4 deg.

As the localization algorithm, the parameters as well as the sensory input data were identical, the main reason for this difference of the localization results is the erroneous building information from OSM. Compared to the cadastral map (see Fig. 2), the footprint of buildings in the OSM map is basically correct in shape and global orientation, but the absolute position of most of the buildings is incorrect. The position computed from the cadastral map can be assumed as “correct” in its global coordinates. However, using the localization for robot motion the localization results with OSM show that it is consistent with the street information from OpenStreetMap.

B. Path Planning and Control

In the second experiment, the OpenStreetMap data were used for path planning and control. This experiment was hold nearby the Royal Gardens of Herrenhausen, Hannover. For robot localization, again the GPS and laser-based Monte Carlo localization with OSM data were used.

Fig. 6. Path planning result of a test run starting at S and ending at the point labeled with E. The blue line indicates the planned path with OpenStreetMap data and red line the driven path of the robot.

As in the previous experiment, all required algorithms for the localization, path planning and control as well as data acquisition are computed in real-time onboard the robot. For evaluation purposes, all processed data are logged as well.

For this experiment, a desired destination was given to the robot. In Fig. 6, this is denoted with the point labeled *E*. Starting from the current robot location *S*, the path planning approaches required 20 ms to compute the optimal shortest path to the destination. For this, 51 out of 10294 nodes and 15 out of 1256 ways were considered (see also Fig. 3). The resultant path consists of 26 nodes and has a length of 1200 m. It includes a passage under a bridge, two left turns as well as two right turns. The planned path was followed by the robot fully autonomously with a maximum speed of 4 m/s. Because of obstacle interference on the path, the robot followed the planned path autonomously with an average speed of 2.9 m/s. The planned path is illustrated in Fig. 6 in blue and the resultant position on the path by the red line.

Based on the OSM data, the robot indicates its turning with its turn signals while following the preplanned path. Before passing the bridge, the robot activates its headlights in advance. Figure 7 illustrates the status of the turn signals and headlights in dependence of the position on the path.

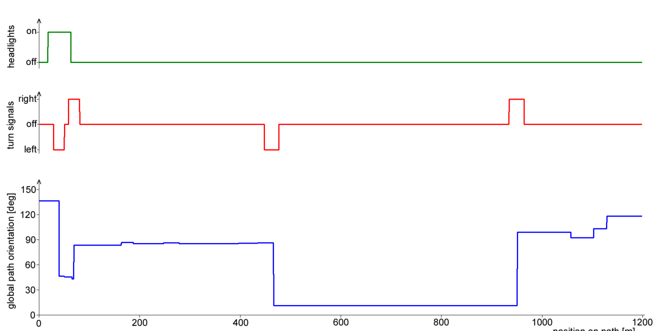

Fig. 7. Status of the headlights (green line) and the turn signals (red line) in dependence of the position on the path. The blue line indicates the global orientation of the planned path.

V. Conclusion And Future Work

This paper proposes the appliance of free available geodata from the OpenStreetMap project for robot navigation for the first time. The OSM data are typically not as precise as commercial data, but include detailed information about streets, tracks, railways, waterways, points of interest, land use as well as building information. Within this paper, the building information are used for robot localization in urban environments. Moreover, the street data are used for path planning and controlling of a single robot to a given destination. While following the planned path, the turn signals as well as the headlights are controlled based on OSM data. Future work is to use more of the rich OSM data for the robot navigation task. This includes the information of traffic signs as well as the right of way checking at road intersections. Finally, it would be a benefit, if the robot could use its extensive sensors to map and explore the environment and contribute to the OpenStreetMap mapping project.

References

[1] M. Haklay and P. Weber. OpenStreetMap: User-Generated Street Maps. *International Journal of Pervasive Computing*, vol. 7, no. 4, pp. 12-18, Oct.-Dec. 2008.

[2] M. Hentschel, O. Wulf and B. Wagner. A Hybrid Feedback Controller for Car-Like Robots – Combining Reactive Obstacle Avoidance and Global Replanning. *International Journal of Integrated Computer Aided Engineerng*, Vol. 14 No 1, 2007.

[3] M. Hentschel, D. Lecking and B. Wagner. Deterministic Path Planning and Navigation for an Autonomous Fork Lift Truck, 6th IFAC Symposium on Intelligent Autonomous Vehicles (IAV), Toulouse, France, 2007.

[4] M. Hentschel, O. Wulf and B. Wagner. A GPS and Laser-based Localization for Urban and Non-Urban Outdoor Environments. IEEE/RSJ 2008 International Conference on Intelligent Robots and Systems (IROS), Nice, France, 2008.

[5] N. J. Nilsson, *Principles of Artificial Intelligence*. Berlin, New York. Springer Publisher, 1982.

[6] OpenStreetMap database statistics: http://wiki.openstreetmap.org/wiki/Stats, 2010.

[7] OpenStreetMap project homepage: http://www.openstreetmap.org, 2010.

[8] OpenStreetMap map features: http://wiki.openstreetmap.org/wiki/Map_Features, 2010.

[9] P. Pfaff, R. Triebel, C. Stachniss, P. Lamon, W. Burgard and R. Siegwart. Towards Mapping of Cities. IEEE International Conference on Robotics and Automation (ICRA '07), Rome, Italy, April 2007.

[10] F. Ramm and J. Topf. *OpenStreetMap: Using and Enhancing the Free Map of the World*. UIT Cambridge Ltd, 2010.

[11] J. Sprickerhof, A. Nüchter, K. Lingemann and J. Hertzberg. An Explicit Loop Closing Technique for 6D SLAM, 4th European Conference on Mobile Robots (ECMR), Mlini/Dubrovnik, Croatia, 2009.

[12] S. Thrun et al.. Stanley, The Robot that Won the DARPA Grand Challenge. *Journal of Field Robotics*, 2006.

[13] C. Urmson et al. . Autonomous Drivin in Urban Environments: Boss and the Urban Challenge. *Journal of Field Robotics Special Issue on the 2007 DARPA Urban Challenge, Part I*, Vol. 25, No. 8, 2008.

[14] O. Wulf, K. O. Arras, H. I. Christensen and B. Wagner. 2D Mapping of Cluttered Indoor Environments my Means of 3D Perception. International Conference on Robotics and Automation (ICRA), 2004.