Paper:

A Quantitative Navigability Measure of Rough Maps

Jooseop Yun and Jun Miura

Department of Information and Computer Sciences, Toyohashi University of Technology
1-1 Hibarigaoka, Tenpaku, Toyohashi, Aichi 441-8580, Japan
Email: jsyun@aisl.ics.tut.ac.jp

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This paper discusses a sketch interface that can be used to guide a mobile robot along a specified path in its unfamiliar place. With the sketch interface, the user draws a rough map to give navigation tasks to robots. Because sketched maps often suffer from various inaccuracies and large errors in landmarks, we discuss what kinds of uncertainties in the rough maps would mainly have effects on navigating a robot. The effects of such inaccuracies on robot navigation are analyzed in simulated environments. A quantitative navigability measure of rough maps is then developed based on the analysis. Experimental results are also presented for validating the navigability measure.

Keywords: mobile robot, rough map, sketch-based navigation, navigability measure.

1. Introduction

Being able to communicate with robots in the same way we interact with people has long been a goal of AI and robotics. The underlying goal of this work is the creation of a robot interface that allows a novice user to guide a robot to perform some navigation tasks. As one strategy for addressing this goal, we have been investigating the use of rough maps. The user sketches an approximate map of the robot's environment and then draws the desired robot trajectory on the map with respect to that environment.

A Rough map has been investigated previously in our work [1]. In the work, we have developed a localization method using a rough map which alleviates considerable efforts for creating and maintaining the map. We have been able to gain some insights into what deserves to be cardinal uncertainties of the map from the characteristics of the rough map used for the robot navigation: lack of information, inexact geometric details, and nonuniform uncertainty model. In this paper, hence, we take existence, dimension, position, and shape uncertainties of landmarks as key uncertainties in rough maps. They were also demonstrated as three strong criteria for a good map in [2]: A good map must, first of all, help users position themselves in an environment (dimension and position uncertainties); next, it must contain an adequate amount of information (existence uncertainty); and finally, the structures drawn on the map should be recognizable (shape uncertainty).

Robot navigation in this work is modeled as a procedural task (i.e., a sequence of steps) to mimic human navigation process. Since navigation failures cause a robot to stray from its intended route, a robot reaching a desired destination by following a specified path is a good indication of the navigation success using the rough maps. We carry out experiments to evaluate rough maps with the key uncertainties using our previous localization method for robot navigation in large-scale outdoor space. In the experiments, we judge the navigation succeeded if the robot arrives at the destination along the predefined trajectory. We define "navigability" as success rate that the robot can reach the destination. From the experimental results, we derive a quantitative navigability measure for evaluating a rough map from its degree of key uncertainties.

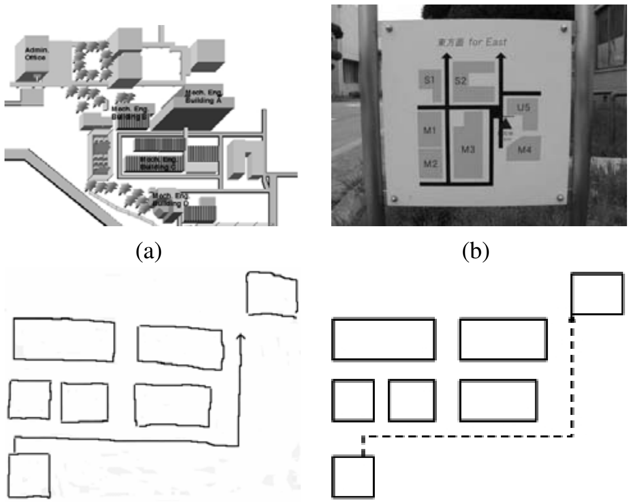
We are also interested in the applicability of the navigability measure to rough maps, since we are investigating the use of such maps for robot navigation. Rough maps are generally incomplete, distorted and schematic, and they tend to mix metrics. As a result, scoring for the purpose of assessment on rough maps is a challenge. We therefore conduct a survey that collects a set of sketched maps and assesses the navigability measure by comparing the measure directly applied to the maps with their subjective evaluation. Furthermore, we validate the navigability measure by comparing computed values of the measure with navigability outputs both from simultaneous simulations of the four key uncertainties.

In the remaining sections of the paper, we first describe related works on human navigation and the use of sketched maps. We also review briefly our previous work of multi-hypothesis localization method using a rough map. We determine a navigability measure of rough maps based on extensive experiments. We then present and discuss experimental results for validating the navigability measure. The conclusion includes a brief discussion on the current status and future directions.

2. Related Work

2.1. Human Navigation

Earlier works indicated the importance of environment landmarks and their spatial relationships in human navi-



(a) (b) (c) (d)

Fig. 1. Manifold types of maps (a) a view of our campus map, (b) a guide map of the campus, (c) a map sketched on paper, (d) an adjusted map fitted into the sketch map.

gation [3, 4]. The works suggested that spatial relationships of landmarks with respect to the desired path may be useful not only for robot navigation but also as an interface between a robot and its user.

Humans navigate in the world using dead reckoning, memories of learned landmarks and their spatial relations. Particularly, the usage of landmarks is vitally important in human navigation. The studies based on the vision for action and perception paradigm show that humans use landmarks with two purposes: positioning and servoing [5].

Michon and Denis [6] provide insights into how landmarks are used for human navigation and what are considered to be key points on the route. In studying the route points, they found that the landmarks were used more frequently at four types of critical points: (1) the starting position, (2) the destination position, (3) the turning points, and (4) the major intersections. People thus use the relative positions of landmarks as cues to keep on track and to determine when to turn left or right. To incorporate knowledge of human navigation and the qualitative nature of the spatial information, we expect the rough map to produce what people would consider as important.

2.2. Sketched Map

A sketched map is drawn to help people navigate along a path for the purpose of reaching a destination. A guide map for visitors to our university campus can be considered as a kind of rough map (see **Fig. 1(b)**). An example is shown in **Fig. 1(c)** sketched from the actual environment of our campus in **Fig. 1(a)**. **Fig. 1(d)** shows the same map after it has been arranged so as to be parallel or orthogonal. Although rough maps do not generally contain complete information about a region, they do provide some relevant information for the navigation task.

People sketch rough maps to include landmarks at key points along the path and use spatial relationships to help depict the trajectory. Tversky and Lee [3] found that sketched maps often simplify, even distort, structural information of the environment. This shows that sketches in many domains are not presentations of reality, but representations of reality [4].

A few works which use sketches to direct robot movement have been done. In the work of Kawamura et al., the user specifies a robot path by selecting via points on a sketch of the environment [7]. Artificial landmarks are, however, placed in the scene and on the sketch for navigation. In [8], Stuck presented a system for detecting navigational mistakes made by mobile robots in open environments. It placed more emphasis on visual mistakes like misrecognition. The focus of his work was only to detect and diagnose global mistakes which lead the robot down incorrect paths.

The work similar to ours is that of Skubic et al., in which they describe the use of sketched maps for directing mobile robot navigations [9, 10]. A route is extracted from the sketched path in the form of a sequence of landmark states with corresponding actions, where each landmark state is a qualitative condition based on the spatial relationship of landmarks relative to the robot. Their work was adequate for simple map configurations but not robust in more complex environments. And they did not discuss how the uncertainties in the sketched map affect the navigability of a simulated robot using the map.

3. Rough Map-Based Navigation

This section briefly reviews our multi-hypothesis localization method using a rough map. Refer to our previous paper [11] for more details.

3.1. Rough Map

We investigated the problem of navigation in an outdoor environment about which the robot has some a priori information available, namely in the form of a rough map. The rough map serves as a global map of the environment. This map may not be an accurate representation of the environment but nevertheless it makes the process of exploration, particularly of large-scale space, simpler for the robot. The rough map we use is 2-dimensional and consists of line segments representing paths and buildings in the environment.

We approximate the buildings present in an environment to polygonal objects on the map. We assume that the buildings in the rough map have planar walls and that these planes have both horizontal and vertical edges. This is often the case for buildings as they have windows and doors. We also assume a flat polygon on the top of a building as a roof since roof details on a tall building cannot be seen from the ground level. The characteristics of rough map can be thus summarized as follows; the exact model of map uncertainty is unknown; the uncertainty may be not uniform across the map; the geometric details such as exact outlines, exact dimensions and exact poses of buildings are not available; the map also lacks information about exact models of the building structures.

Relative poses between landmarks in a rough map are allowed to be uncertain. The uncertainty of rough map might cause the robot pose to be inconsistent if it is represented in the global coordinate system of reference. To address this problem, we represent the robot pose in a local coordinate system attached to a landmark which the robot has recognized recently. When the robot finds a new landmark, the robot changes the local coordinate system from the old landmark to the new one with coordinate transformation of its pose based on the relative pose between the old and new landmarks. We refer to the landmark as a local origin. As the robot moves, it changes the local origin. More specifically, we define the robot pose as a pair of a local origin and the pose in a local coordinate system attached to the local origin. Landmarks in the building with the local origin would have smaller positional uncertainty in the local coordinate system than in the global one thereby becoming easier to recognize.

3.2. Multi-Hypothesis Localization

The Kalman filter acts as a pose tracker in this paper. But, a false matching of the observed features to the model features can lead to an irrecoverable lost situation if only a single distribution is maintained. Although the most credible estimation at one time turns out to be totally wrong, a Multiple Hypothesis Localization (MHL) allows alternative pose estimates to be maintained instead of tracking only single best hypothesis. The MHL method has been widely used to solve global localization problems, in which a robot has no knowledge of its initial pose. Instead of starting with an empty hypothesis, in our work, we start with a highly reliable hypothesis of robot pose. A starting robot pose around the true pose and its uncertainty of random size must be supplied by a user.

Our localization method explicitly tracks multiple pose hypotheses, via multiple Kalman filters using the ordered data associations of multiple visual features. The multiple visual features are extracted from observed buildings by using stereo vision: nonvertical borders for the vanishing points to calculate the wall directions of buildings, vertical borders corresponding to the corners of buildings and disparity regions for matching with the walls of buildings. We keep only feasible hypotheses by eliminating infeasible associations of observations and targets using several heuristics.

4. Definition of a Navigability Measure Through Simulated Navigations

We carried out experiments to measure the navigability of a mobile robot in more than one hundred simulated environments according to the key uncertainties mentioned before. This section proposes a quantitative navigability measure from the experimental results.

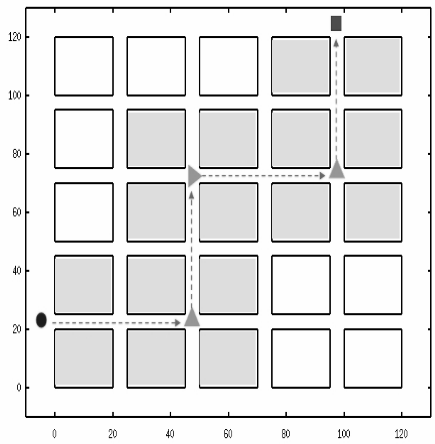


Fig. 2. An environmental map (rectangles: landmarks of buildings; solid rectangles: landmarks along the path; a solid circle: a starting position; a solid square: a destination position; solid triangles: crossroads at subgoals; dashed arrows: a robot path).

4.1. Simulation Implementation

We use our multi-hypothesis localization method using a rough map for analyzing the robot behavior in simulated environments [1]. The simulation system includes a representation of the environment, a vision simulator, and a motion simulator. These components are analogous to real robot's sensing and basic navigation capabilities.

The environmental map is an internal representation of the simulated environments where a simulated robot moves. It consists of two types of objects: paths and buildings. In the simulations, a rough map defined in our previous work is used as the environmental map. **Fig. 2** shows a simulated environment used in one of the simulations, where there are several subgoals at turning points, a starting position, and a destination.

The vision simulator simulates a stereo vision consisting of two conventional cameras with larger field-of-view than used in our previous work. It uses the environmental map to extract observed visual features from the simulated robot's point of view.

The motion simulator simulates the execution of motion commands. The simulated robot move away from the starting position, turns at the subgoals and stops at the destination position in the figure. Since we are using our previous method of multi-hypothesis localization [11], the detailed strategy of the simulated motion is as follows: When the robot recognized a subgoal or a destination, its pose hypothesis would be reserved. When the robot failed to recognize a goal, it travels over more distances searching for the goal. When the robot has missed or ended up failing to locate a goal, its pose hypothesis would be eliminated. The survived hypotheses would be merged if allowable. The robot goes back to one of the merged pose hypotheses and moves on to the target position from its current position without further observations. When the robot finally has misrecognized or not recognized any goal, this leads it to turn at the wrong corner or to the wrong direction causing a navigation failure on the simulated robot. In the paper, we focus mainly on how the uncertainties embedded in rough maps affect the navigability of a simulated robot. Hence, the simulations described below assume no motion uncertainty of the robot for the moment.

4.2. Simulation Results and a Navigability Measure

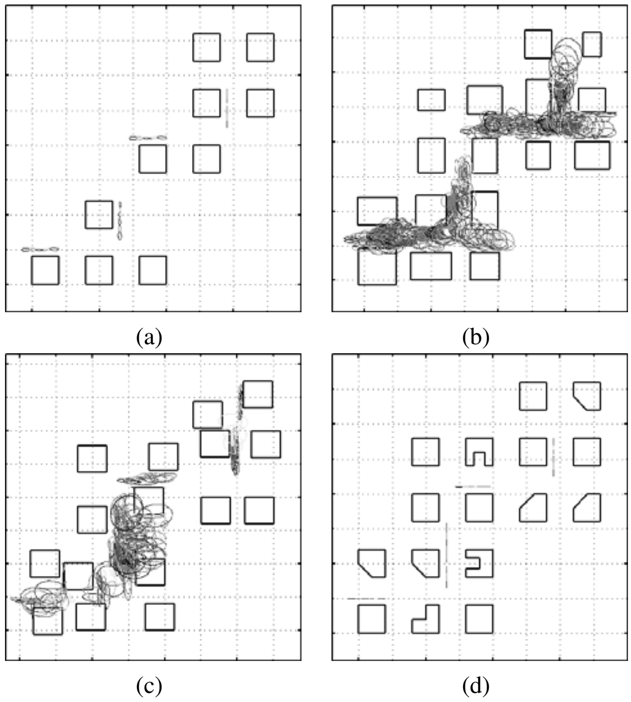
The simulated rough maps model the sketch inaccuracies by the key uncertainties such as existence, scaling or shaping of objects with respect to the real environment. In our experiment, each of the four key uncertainties has 11 possible values from 0 to 100% with 10% interval. Six different paths are also ready for the experiment. Accordingly, there will be $4 \times 11 \times 6$ combinations in each building of the simulated environments by the values of individual key uncertainty and the paths. For each of the combinations, we have executed the experiments in more than one hundred simulated environments. All the key uncertainties are related to only the landmarks along the basic path as shown in **Fig. 2**.

The existence uncertainty is the percentage of removed landmarks excluding subgoals at turning points. The shape uncertainty is the percentage of reshaped landmarks including the subgoals. The percentages of dimension and position uncertainties were generated relative to the dimensions of each landmark including the subgoals. In the simulations of 50% key uncertainties, for example, 50% of landmarks in the cases of existence and shape uncertainties are randomly altered. In the cases of dimension and position uncertainties, 0 to 50% of landmarks are modified at random because these uncertainties tend to mix metrics in the sketched maps.

Figure 3 presents some navigation results of test runs using the simulated rough maps with the key uncertainty of 50%. Notice that the test runs in the figure arrive at the same destination (the landmark on top right) and take into consideration only the landmarks on the path (solid rectangles in **Fig. 2**). The figure shows that the system may handle inaccuracies incident to sketching. The ellipses in the figure denote the unmagnified 3σ error levels of the robot positions on the global or real (for shape uncertainty) map using the MHL method remarked before.

In **Fig. 3(a)**, we removed several objects to show that the simulated rough map does not have to correspond exactly to the real environment. It is evident that the sketch does not have to include every piece of information about the environment, but just the information necessary for the robot to stay on track.

We have also resized and moved objects along the vertical and the horizontal axes, and reshaped objects in the environment as shown in **Fig. 3(b), (c)** and **(d)**, respectively. The robot travels longer distances, but still achieves its destination that was sketched. All tests from most of the simulations yielded similar results of navigation success. However, some of the simulated environments were so inaccurate that it was impossible for the robot to find the correct its path and arrive at the destination (causing navigation failures.)



(a) (b) (c) (d)

Fig. 3. Some navigational results of a simulated robot using a rough map with the 50% uncertainty of (a) existence, (b) dimension, (c) position and (d) shape in the landmarks of buildings along the path shown in **Fig. 2**.

Figure 4 presents the averaged values with standard deviation and the functions fitted to navigability data of the robot using the rough maps with the key uncertainties. The navigability is computed as the likelihood that the robot can reach the assigned destination. The probability of navigational success, p_s, is defined as:

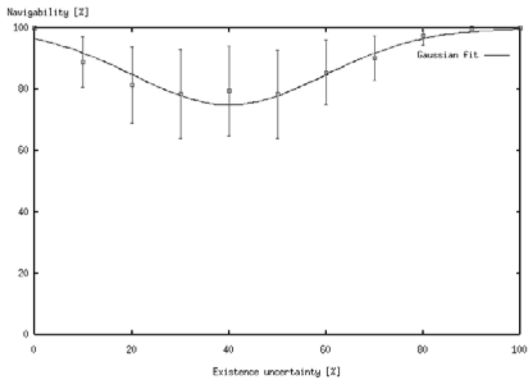
$$p_s = \frac{\text{\# of navigations succeeded}}{\text{\# of navigational runs}}. \quad \cdots\cdots \quad (1)$$

We have fitted the following sigmoid function, $S(x)$:

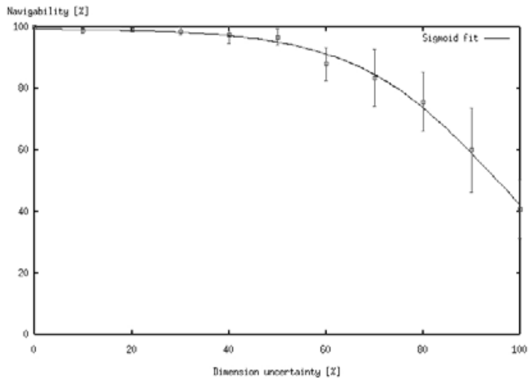
$$S(x) = \frac{a}{1+e^{-\frac{(x-b)}{c}}} \quad \cdots\cdots\cdots\cdots \quad (2)$$

into the result of navigability calculations by the key uncertainties of dimension, position and shape, respectively, because the change of navigability data shows an s-shaped curve. More precisely, it has two horizontal asymptotes in our case to 0% and 100% of navigability, and the curve makes a smooth transition from one to the other with one inflection point.

Surprisingly, the existence uncertainty in rough maps had a different effect on the navigability from the other ones (see **Fig. 4**). As mentioned above, the existence uncertainty is the percentage of removed landmarks excluding subgoals. Assuming no motion uncertainty of the robot for now, we think the robot is likely to recognize the subgoals when there exist all landmarks or no landmarks between them. The robot is, however, liable to misrecognize the subgoals when there exist adjacent landmarks on the same side of them. We have fitted the following



(a)



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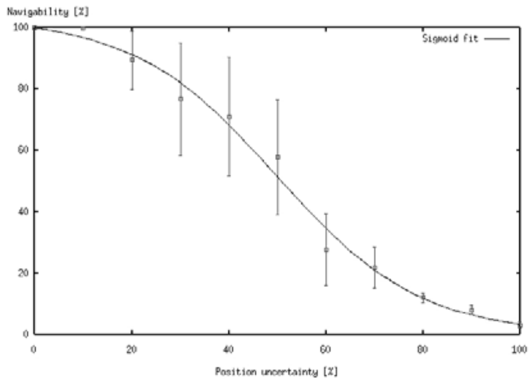

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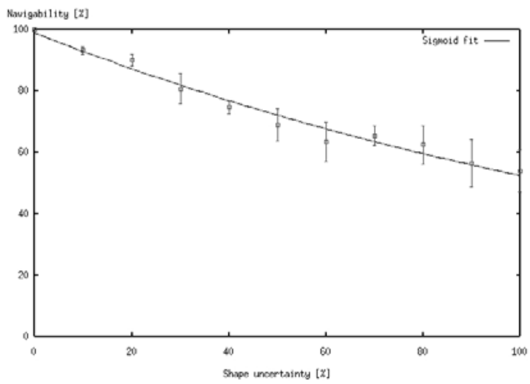


(d)

Fig. 4. Mean navigability data [%] with standard deviation and the fitted curve using the simulated rough maps with respect to the key uncertainty [%] of (a) existence, (b) dimension, (c) position, and (d) shape in landmarks.

Table 1. Parameter values of fitted navigability functions.

Uncertainty	*a*	*b*	*c*
Existence	0.250	0.400	0.200
Dimension	0.996	0.954	-0.147
Position	1.033	0.499	-0.148
Shape	2423	-12.31	-1.578

Gaussian-based function, $G(x)$:

$$G(x) = 1 - ae^{-\frac{(x-b)^2}{2c^2}} \quad \text{. . . . .} \quad (3)$$

into the result of navigability calculations by this key uncertainty. **Table 1** describes the parameter values of one Gaussian-based function and three sigmoid functions that fitted for the navigability data under the key uncertainties.

From the analysis of preliminary simulations by combining the key uncertainties, we have found there were weak correlations among the effects of key uncertainties on the navigability. Consequently, we performed the simulations independently according to individual key uncertainties and determined the navigability measure $N(e, d, p, s)$ of a rough map by a product of fitted navigability functions:

$$N(e,d,p,s) = G(e) \cdot S(d) \cdot S(p) \cdot S(s) \quad \text{. . . .} \quad (4)$$

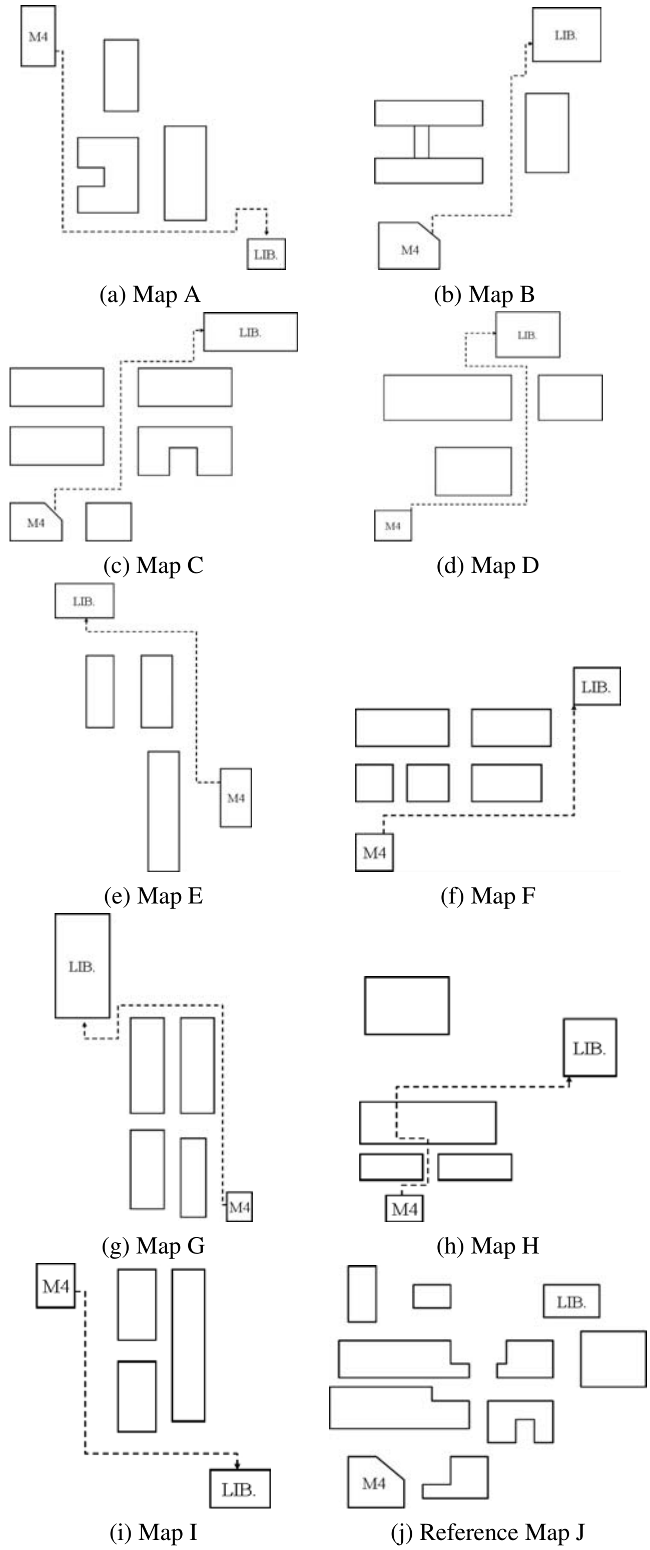
where e, d, p, and s represent the uncertainty of existence, dimension, position, and shape in the map, respectively. The reason of the product is because the navigability might be aggravated if at least one value of the navigability functions is quite low.

5. Experiments for the Validation of Navigability Measure

This section describes the validation experiments for the assessment of our navigability measure in two distinct ways. First, we compare the ordering of maps on the measure directly applied to a set of sketched maps with their subjective evaluation by experimental survey. Second, we also compare navigability values computed by the measure with those produced by the simultaneous simulations, where the four key uncertainties are simultaneously considered.

5.1. Comparison of Map Orderings by the Survey and the Measure

The first experiment of survey for validation has two stages. In the first stage, the students in our building (M4 in **Fig. 5**) were asked to sketch a map showing the environment and the route to the library on paper. Route sketches are composed of the sequence of a starting position, progressions, turnings and a destination position. We did not ask that the sketches be drawn to an accurate scale and did not expect that they would be. The 9 sketched



(a) Map A (b) Map B
(c) Map C (d) Map D
(e) Map E (f) Map F
(g) Map G (h) Map H
(i) Map I (j) Reference Map J

Fig. 5. Adjusted maps from sketches surveyed by students with a reference map for their subjective evaluation, also describing a route through our university campus (from M4 building to Library).

maps after adjusted for analysis are shown in **Fig. 5(a)** to **(i)**. The sketched routes did not always follow the same path with respect to the landmarks.

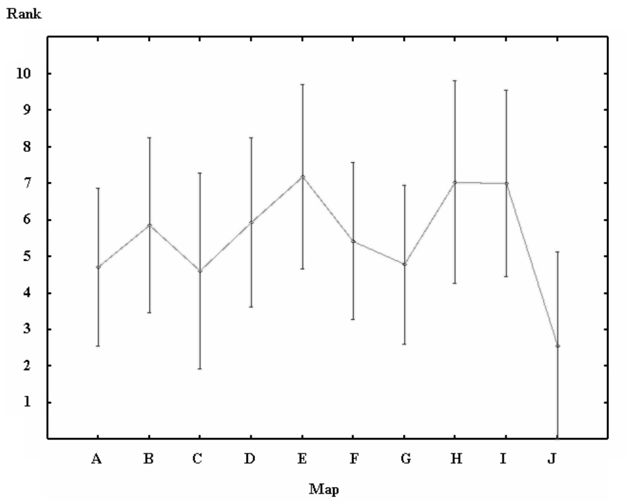


Fig. 6. Mean ranks of student's rating from maps A to J, with standard error bars. The rating of 1 indicates the best map, while 10 is the worst map.

Table 2. Rank values with standard deviation of maps.

Map	*Mean rank*	*Standard deviation*	*Min. rank*	*Max. rank*
A	4.71	2.158	1	9
B	5.86	2.384	2	9
C	4.61	2.671	1	10
D	5.93	2.308	2	10
E	7.18	2.525	2	10
F	5.43	2.150	2	9
G	4.79	2.166	2	8
H	7.04	2.769	2	10
I	7.00	2.539	2	10
J	2.57	2.559	1	9

In the second stage, we showed the 9 maps processed in the first stage and a reference map in **Fig. 5(j)** to 40 students in our building including the sketchers. The subjects were then asked to rate the maps and to fill in a questionnaire about the reasons for the rating. The main three reasons they commented were (1) the same cardinal orientation of a sketch with respect to an actual environment, (2) sufficient information of landmarks, and (3) a plain path with apparent turning points.

Figure 6 shows the evaluation result of the 10 maps from A to J rated by surveying students. The result depicts averaged ratings of each map on a rank of 1 to 10 (1 being best and 10 being worst) with a standard deviation. **Table 2** summarizes the survey result graphed in **Fig. 6** across 40 subjects' ratings. The mean rank with its standard deviation, minimum and maximum ranks of each map are shown in the table. Not surprisingly, the reference map J was rated to the highest mean rank.

To further examine the rough maps, we analyzed the spatial relationships among landmarks in terms of existence, dimension, position and shape uncertainties of the

Table 3. Percent levels of key uncertainties in the maps.

Map	*Existence*	*Dimension*	*Position*	*Shape*
A	84	59	28	30
B	84	80	43	30
C	50	60	27	40
D	84	250	134	30
E	72	93	83	40
F	58	69	31	40
G	67	110	44	50
H	84	154	113	20
I	72	89	40	40
J	0	0	0	0

Table 4. Navigability indices of the sketched maps.

Map	*Navigability* [%]
A	61.902
B	37.458
C	46.627
D	0.008
E	3.816
F	44.190
G	10.831
H	0.022
I	29.553
J	95.068

buildings used as landmarks. For estimating the dimension and position uncertainties, we fixed the starting position and scaled the sketched maps against the reference map. While scaling, we used the least-squares method of the distances among the centers of landmarks in both the maps. Finally, we determined the best scale and estimated the quantities of the uncertainties. The percentage amounts of the key uncertainties embedded in the sketched maps against the reference map are shown in **Table 3**.

Using the uncertainty values in **Table 3**, we calculated the navigability of each map using the navigability measure of Eq. (4). As shown in **Table 4**, the best map excluding a reference map had a navigability index of 61.902%, whereas the worst map had an index of 0.008%.

To discuss the relation between the subjective evaluation and the navigability by proposed measure, we have included the graph of relationship between the mean ranks shown in **Table 2** and the navigability indices shown in **Table 4**. As shown in **Fig. 7**, they seem to be correlated with respect to one another. However, we think their theoretical relation may be not linear (a dotted line in the figure), because the vertical axis is qualitative while the horizontal axis is quantitative in the graph.

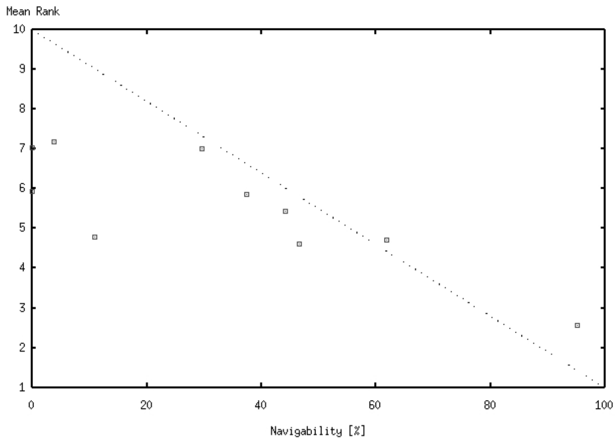


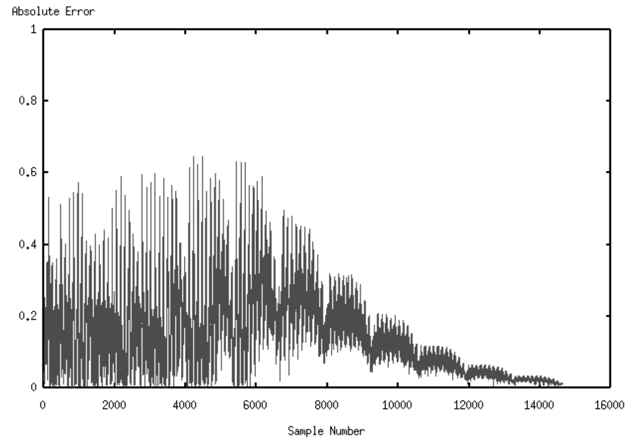
Fig. 7. Relation of the 10 sketched maps between mean ranks by the subjective evaluation and navigability data by the proposed measure.

Table 5. Difference between the orderings in the maps by the survey and the navigability measure.

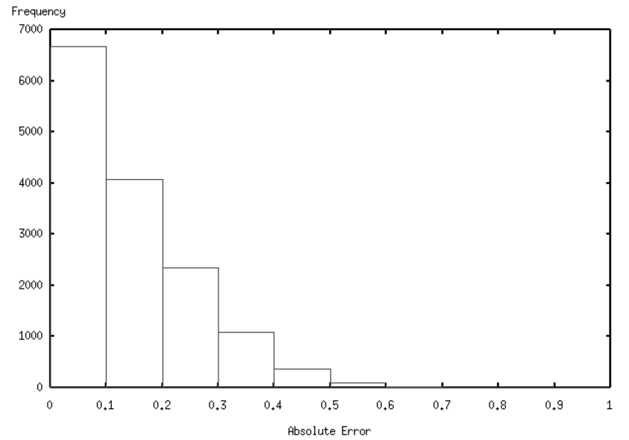
Map	*Survey Order*	*Navigability Order*	*Difference*
A	3	2	1
B	6	5	1
C	2	3	1
D	7	10	3
E	10	8	2
F	5	4	1
G	4	7	3
H	9	9	0
I	8	6	2
J	1	1	0

Then, we ordered the maps by two different ways, using the surveyed rating and using the navigability measure, respectively. This gives thereby the maps two kinds of ranking of 1 to 10 (1 being best and 10 being worst). **Table 5** compares the orderings of the maps. The rough maps represented a broad range of uncertainties and the routes sketched also did not follow the same path with respect to the landmarks. In spite of these variances, the ordering differences of each map did not vary widely, moreover considering the students' approximate surveying. The differences were less than 3 except for maps D and G, which is comparable to the standard deviation of surveyed rating (see **Table 2**).

We can raise the following reasons for the relative significance in the ordering differences of the maps D and G. In the case of map D, even familiar with the campus, the subjects are liable to puzzle over its large simplicity. Moreover, it was rated worst by the navigability measure because of its very large uncertainties in dimension and position. For the case of map G, its deceptive simplicity seems to have a positive effect on the subjects familiar



(a)



(b)

Fig. 8. Comparison between navigability values computed by the measure and experimental results produced by the simultaneous simulations: (a) absolute errors of navigability data (b) histogram of absolute errors.

with our campus. It was, however, also rated low by the navigability measure because of its large uncertainties in dimension and shape.

5.2. Comparison with the Navigability by Simultaneous Simulations

For further validating the measure for navigability, we compare navigability values computed by the measure with those produced by the simultaneous simulations where the four key uncertainties are simultaneously considered. More specifically, each of the four key uncertainties has 11 possible values from 0 to 100% with 10% interval. Accordingly, there are $11 \times 11 \times 11 \times 11$ (14,641) samples of simultaneous combinations by the four key uncertainties. We have executed the experiments in more than one hundred simulated environments for each sample of the combinations. The navigability outputs are then averaged over several hundreds number of simulations.

As shown in **Fig. 8(a)**, the experimental results were evaluated using absolute errors of the navigability values acquired by both the measure and the simultaneous simulations. **Fig. 8(b)** shows the histogram for the absolute errors, where the frequency has decreased exponentially according to the absolute errors. The absolute errors exhibit the statistics with mean value of 0.141 and standard deviation of 0.013.

The histogram reveals the fact that the navigability measure indeed captures the experimental navigability relatively well. Although some large deviations did occur, the navigability measure was able to generate comparable navigability data for the most part. This is very promising considering the small number of key uncertainties put on the measure.

We have examined two different methods for validating the navigability measure; ordering differences by the survey and absolute errors by the simultaneous simulations. The results of two validation experiments show the potential feasibility of the quantitative navigability measure we proposed. The present study also shows that the map sketches, when carefully analyzed and when evaluated by others for goodness, provide principles for designing the effective rough maps: an adequate amount of information included (corresponding to existence uncertainty); preserving proportions among structures, preserving relative positions of structures, and homogeneity of scale (corresponding to dimension and position uncertainties); ease of locating structures, ease of recognizing structures, and ease of identifying goals (corresponding to shape uncertainty).

6. Conclusion and Future Work

In this paper, we have proposed and evaluated a quantitative measure of navigability on sketched maps for mobile robots navigating through unfamiliar large-scale environments. We have validated our navigability measure with huge simulated maps. We first compared the simulation results with the survey results and then compared navigability values computed by the measure with navigability outputs produced by the simultaneous simulations of the four key uncertainties. The survey study, in which the subjects produced and rated rough maps, provides an evidence for the effects of key uncertainties on the navigability of the maps. While there were some large deviations in the validation study by the simultaneous simulations, the results thus far seem promising even at the early stages of this work. The present research also provides guidelines for constructing the rough maps of high navigability.

While we analyze and define a navigability measure only in terms of the configuration of rough maps, the navigation strategy of the robot may influence heavily its navigability. The results on proposed navigability measure are limited to our navigation strategy and in fact would be changed for a different strategy.

Although our results show the reality of the key uncertainties, it is clearly not a universal or entire set of uncertainties. A future direction of this work will therefore focus on other key uncertainties excluded for the moment. For example, the key uncertainties will include the number of turning points on the path and the uncertainty of road network not right-angled, when considering the motion uncertainty of robot. These are intended for the robustness of the method to create consistent and reliable robot directives based on different sketches of various scenes.

The work on rough maps for robot navigation is not yet complete. The work presented here is a step towards the quantitative navigability evaluation of rough maps. Another future work is to testify the validity of the measure through experiments of rough map-based navigation of a real mobile robot with real sensory data.

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Name:
Jooseop Yun

Affiliation:
Researcher, Department of Information and Computer Sciences, Toyohashi University of Technology

Address:
1-1 Hibarigaoka, Tenpaku, Toyohashi, Aichi 441-8580, Japan

Brief Biographical History:
2001- Department of Computer-Controlled Mechanical Systems, Osaka University
2008- Present Department of Information and Computer Sciences, Toyohashi University of Technology

Main Works:
- Computer vision
- Robot vision
- Vision and motion planning of mobile robots

Membership in Academic Societies:
- The Robotics Society of Japan (RSJ)

Name:
Jun Miura

Affiliation:
Professor, Department of Information and Computer Sciences, Toyohashi University of Technology

Address:
1-1 Hibarigaoka, Tenpaku, Toyohashi, Aichi 441-8580, Japan

Brief Biographical History:
1989- Department of Mechanical Engineering, Osaka University
1994-1995 Visiting Scientist at Computer Science Department, Carnegie Mellon University
2007- Present Department of Information and Computer Sciences, Toyohashi University of Technology

Main Works:
- Vision and motion planning of mobile robots
- Sensing planning
- Robot vision

Membership in Academic Societies:
- The Japanese Society of Mechanical Engineers (JSME)
- The Robotics Society of Japan (RSJ)
- The Japanese Society of Artificial Intelligence (JSAI)
- Information Processing Society of Japan (IPSJ)
- The Institute of Electronics Information Communication Engineers (IEICE)
- The Institute of Electrical and Electronics Engineers (IEEE)
- Association for the Advancement of Artificial Intelligence (AAAI)