The Localization of Mindstorms NXT in the Magnetic Unstable Environment Based on Histogram Filtering

Piotr Artiemjew

Department of Mathematics and Computer Sciences, University of Warmia and Mazury, Olsztyn, Poland

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Abstract: During the localization of a robot equipped with a magnetic compass we can encounter the problem of magnetic deviations in the building. It can be caused by electric power sources, working devices or even by the heating system. Magnetic deviations make it difficult to localize the robot in a proper way and could cause the loss of position on the map. In the paper we have tested the method of histogram localization using a map of north directions and emergency north direction. For tests we have designed the robot based on the Mindstorms NXT parts. Our construction consists of NXT brick, four sonars, one compass, one touch sensor and two sensor multiplexers. All software was developed in C++ in the NXT++ library, which is actively supported by the author. Tests were performed in the real environment and the proposed tuned localization method turned out to be resistant to magnetic deviations

1 INTRODUCTION

In this work we have presented the localization filter which works with the magnetic disturbed environment. We have designed a robot based on Mindstorms NXT brick. Using a PD-controller (Bennett, 1993), a simple path planning algorithm (Roy and Thrun, 2002) and modified histogram filtering (Dellaert et al., 1999) we have designed a prototype of a robot which is able to localize itself in the corridors of the building.

1.1 Motivation

The main motivation of this work arises from the practical problem of Mindstorms NXT localization in the building based on the sonar and magnetic compass readings. The problem consists of the magnetic deviations caused by power sources, working devices and the heating system in the building. Ignoring such problems localization is really hindered or even rendered impossible, because after a few steps the robot can lose its position on the map. The solution is to consider a map of magnetic deviations and emergency north direction in the case of permanent loss of position.

1.2 Related Works

There are a few related works in the topic, the more interesting are (Gozick et al., 2011) and (Navarro and Benet, 2009), in which authors propose the building of magnetic maps for indoor navigation purpose. Another interesting solution for localization in corridor environment is (Suksakulchai et al., 2000).

The paper is organized as follows. Section 2 provides basic algorithms, section 3 provides a description of real life experimentation, section 4 provides the summary of results and finally section 5 contains the conclusion and future work.

2 BASIC ALGORITHMS

In this section we have a brief description of well known algorithms necessary for real life localization in the building. We show the steering algorithm, path planning algorithm and finally the basic histogram filtering. Let us begin with the control algorithm.

2.1 Drive Control

One of the key algorithms of mobile robotics are methods of robot motion control with fixed direction, or servo motor control in order to execute a given

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task. One of the most effective algorithms is called the PID-controller (Proportional-Integral-Derivative Controller), where P - means cross track error, D - is the difference of cross track error between iterations of control, and I takes into account the overall error of movement. In mobile robotics it has been proven that part PD is enough for proper control, so in our experiments we use PD controller.

The history of this controller dates back to the 1890s, and one of the first theoretical studies was conducted in 1922 (Minorsky, 1922). The detail history of applications of PID controllers could be found among others in (Bennett, 1993).

2.2 Path Planning

Another necessity for the implementation of the robotic guide in the building is the path planning algorithm. One of the most popular is A* algorithm (Hart et al., 1968), which enables us to find the optimal path between a given starting point and a specified goal with the assumption that we have as an input a complete known map of the building. If we want to get the optimal path to goal from all points on the map, the A* doesn't seems to be effective. A better choice is to use the dynamic programming algorithm (Roy and Thrun, 2002). Dynamic Programming (DP) provides us with a tool for getting a universal moving policy, the optimal path from all points on the map to the fixed goal. Based on the DP algorithm, we could choose the solution which is closest to the optimal one. The DP programming algorithm consists of the following steps: 1) We propagate the cost of reaching the goal from the goal field to all available fields of the grid; 2) We have fixed the policy of movement with the choice of the best direction with minimal effort for reaching the goal.

In summary, the DP algorithm needs a known map, a fixed cost of motion, a fixed goal position, and the strategy of tie resolution during the search for optimal move direction.

2.3 Robot Localization

In this section we present one of the most popular method of robot localization (Dellaert et al., 1999) - the histogram filtering. First of all we make the assumption that we have a fully known map, and we have a robot supported by the required sensors. The general idea is refreshing the probability of robot location after movement and senses from the sonars. Location can be achieved by subsequent refreshing of probability by multiple movement and sense individually. With the assumption that moving is a little imprecise, the robot loses information regarding position after movement and gains information after sense. In refreshing of the location after sense, the histogram filtering use Bayes Rule, $P(x_i|Sense) = \frac{P(Sense|x_i)*P(x_i)}{P(Sense)}$, where $P(Sense|x_i)$ is the probability of sense (precision of sense), $P(x_i)$ is the probability of location before update, P(Sense) is the sum of probabilities from all fields of the map, the value by which we normalize all values of the map. The next step of filtration consists of an update after movement (convolution of probability) - it depends on precision of movement. In the real world the motion is uncertain. Update after movement consists of computing total probability, $P(x_i) = \sum_i P(x_j) * P(x_i|x_j)$ This is the probability of location in the field x_i after movement from the fields x_j with fixed precision of motion.

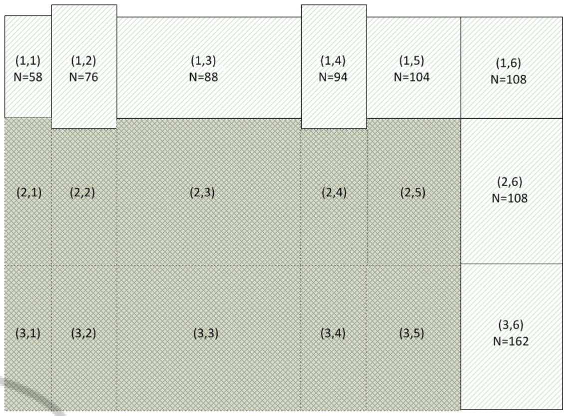


Figure 1: Real map coordinates and grid north direction values.

3 REAL LIFE SOLUTION

For experimental reason we have chosen the corridor of a real building and described it in the following way. The corridor was split into eight distinctive available areas - see Fig. 1. Because of magnetic disturbance we consider the map of north direction readings - see Fig. 1. The basic map consists of readings in four directions (north, south, east and west) from sonar from central points of all the selected areas, see Fig. 2 and Tab. 1. Additionally we use the map of field boundaries which is useful in the convolution of histogram filtering, which is shown in Fig. 3 and Tab. 2.

3.1 The Disturbance of Sonar Readings Caused by Magnetic Deviation

In the localization on the real map we encounter the

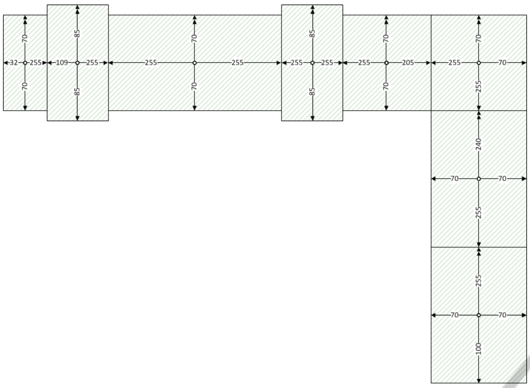


Figure 2: Readings from the sonar on the four map directions from central points of the map fields - useful for localization; The north direction is marked as a double arrow.

Table 1: Readings from the sonar with a magnetic stable environment. The north direction is the same for all fields of the map - see also Fig. 2.

map coord.	*North*	*South*	*East*	*West*
(1,1)	70	70	255	32
(1,2)	85	85	255	110
(1,3)	70	70	255	255
(1,4)	85	85	255	255
(1,5)	70	70	205	255
(1,6)	70	255	70	255
(2,6)	240	255	70	70
(3,6)	255	100	70	70

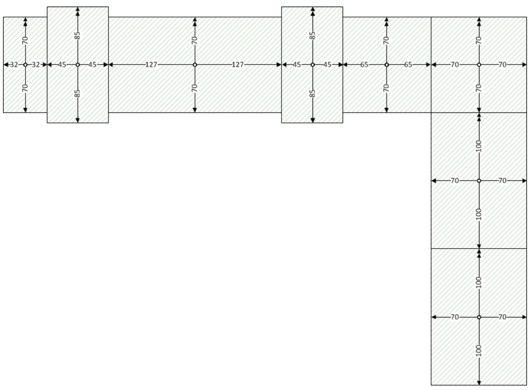


Figure 3: Map boundaries - useful in the convolution of histogram filtration; The North direction is marked as double arrow.

Table 2: Map of field boundaries useful in the convolution of histogram filtration - see also Fig. 3.

map coord.	*North*	*South*	*East*	*West*
(1,1)	70	70	32	32
(1,2)	85	85	45	45
(1,3)	70	70	127	127
(1,4)	85	85	45	45
(1,5)	70	70	65	65
(1,6)	70	70	70	70
(2,6)	100	100	70	70
(3,6)	100	100	70	70

problem of magnetic disturbance mentioned in the Introduction. Considering the only one north direction

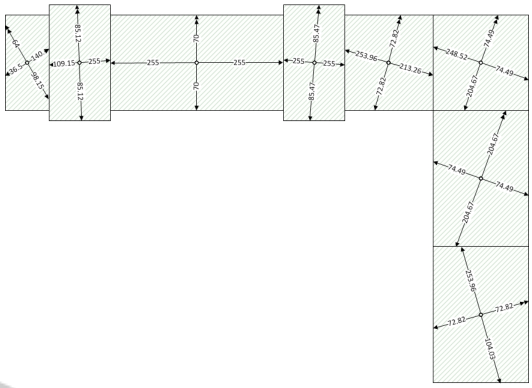


Figure 4: Readings from the sonar on the four map directions from central points of the map fields with magnetic disturbance of north direction; The north direction is marked as a double arrow; There is assumption that the real value of north on the map is $N = 88$ and the robot measure this value in the $(1,3)$ coordinates.

Table 3: Readings from sonar with magnetic unstable environment with the assumption that the real value of north on the map is $N = 88$ - see also Fig. 4. The map of magnetic deviations is shown in Fig 1 and visualization in Fig. 4.

map coord.	*North*	*South*	*East*	*West*
(1,1)	64	98.15	140.87	36.95
(1,2)	85.12	85.12	255	109.15
(1,3)	70	70	255	255
(1,4)	85.47	85.47	255	255
(1,5)	72.82	72.82	213.26	253.96
(1,6)	74.49	204.67	74.49	248.52
(2,6)	204.67	204.67	74.49	74.49
(3,6)	72.82	72.82	104.03	253.96

of the map $N = 88$, from the field $(1,3)$, in case of magnetic disturbance shown in Fig. 1 and Fig. 4 we get the reading on the map shown in Fig 4 and Tab. 3. As we can see the ability of localization is lowering and with high deviation the robot can even lose his position.

In Tab. 4 we have data from sense part of histogram filtering, particularly the probability of robot localization computed with use of similarity measure from the equation 2. The real measure for all grid boxes are stored in the Fig. 2 and Tab. 1.

Table 4: Localization ability for all fields after perfect measure - the north direction is the same for the whole map; Data from the histogram filter after a single north-south-east-west(NSEW) sense - in the magnetic stable environment; for distance measure from equation 2; In the columns we have ability of location for particular coordinates.

	(1,1) *pos*	(1,2) *pos*	(1,3) *pos*	(1,4) *pos*	(1,5) *pos*	(1,6) *pos*	(2,6) *pos*	(3,6) *pos*
(1,1)	**0.157**	0.137	0.137	0.128	0.139	0.124	0.108	0.112
(1,2)	0.140	**0.153**	0.138	0.144	0.140	0.131	0.105	0.110
(1,3)	0.135	0.133	**0.159**	0.150	0.153	0.111	0.086	0.091
(1,4)	0.127	0.141	0.152	**0.158**	0.145	0.118	0.093	0.099
(1,5)	0.139	0.137	0.155	0.146	**0.157**	0.115	0.090	0.095
(1,6)	0.121	0.125	0.110	0.115	0.112	**0.161**	0.138	0.143
(2,6)	0.086	0.082	0.069	0.074	0.071	0.113	**0.198**	0.168
(3,6)	0.096	0.092	0.079	0.085	0.081	0.126	0.181	**0.183**

We make the assumption that $N_{(i,j)}$, $S_{(i,j)}$, $E_{(i,j)}$, $W_{(i,j)}$ is the basic distance to obstacles in the field with (i,j) coordinates, and N', S', E', W' is the distance to obstacles after the single sense of the four directional radar - see Fig. 5. The distance between the original values and the sensed values has been defined based on two basic metrics defined as those on equation 1 and 2.

$$x_{(i,j)} = field\_distance_{(i,j)},\ y = actual\_sense$$

$$d_1(x_{(i,j)}, y) = \frac{A_1 + B_1}{4} \tag{1}$$

$$A_1 = \left(1 - \frac{|N_{(i,j)} - N'|}{N_{(i,j)} + N'}\right) + \left(1 - \frac{|S_{(i,j)} - S'|}{S_{(i,j)} + S'}\right)$$

$$B_1 = \left(1 - \frac{|E_{(i,j)} - E'|}{E_{(i,j)} + E'}\right) + \left(1 - \frac{|W_{(i,j)} - W'|}{W_{(i,j)} + W'}\right)$$

$$d_2(x_{(i,j)}, y) = \frac{A_2 + B_2}{2} \tag{2}$$

$$A_2 = \left(1 - \frac{|(N_{(i,j)} + S_{(i,j)}) - (N' + S')|}{N_{(i,j)} + S_{(i,j)} + N' + S'}\right)$$

$$B_2 = \left(1 - \frac{|(E_{(i,j)} + W_{(i,j)}) - (E' + W')|}{E_{(i,j)} + W_{(i,j)} + E' + W'}\right)$$

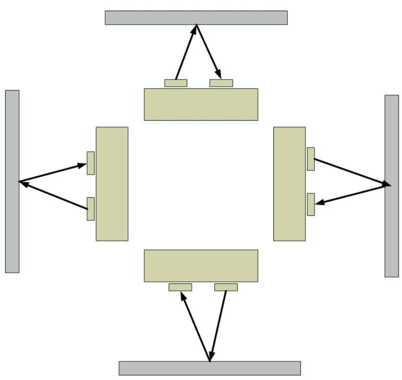


Figure 5: Demonstration of four directional sonar.

The data from the four directional radar in an unstable magnetic environment is shown in Fig. 4 and Tab 3. The data from histogram filtering in such an environment is presented in Tab 5.

The result for the metric from equation 1 and magnetic stable environment is in Tab. 6, and for magnetic unstable grid in Tab. 7.

Table 5: Localization ability for all fields with an unstable magnetic environment; Data from histogram filtering after a single north-south-east-west sense; for distance measure from equation 2.

	(1,1) *pos*	(1,2) *pos*	(1,3) *pos*	(1,4) *pos*	(1,5) *pos*	(1,6) *pos*	(2,6) *pos*	(3,6) *pos*
(1,1)	**0.141**	0.137	0.137	0.128	0.137	0.129	0.112	0.145
(1,2)	0.136	**0.153**	0.138	0.144	0.141	0.136	0.110	0.148
(1,3)	0.120	0.133	**0.159**	0.150	0.152	0.115	0.090	0.140
(1,4)	0.124	0.141	0.152	**0.157**	0.148	0.123	0.098	0.135
(1,5)	0.124	0.137	0.155	0.146	**0.155**	0.119	0.094	0.144
(1,6)	0.114	0.125	0.110	0.116	0.113	**0.154**	0.142	0.122
(2,6)	0.115	0.082	0.069	0.074	0.072	0.106	**0.176**	0.079
(3,6)	0.126	0.092	0.079	0.085	0.082	0.119	0.178	**0.089**

Table 6: Localization ability for all fields with an unstable magnetic environment; Data from a histogram filter after a single north-south-east-west(NSEW) sense; for distance measure from equation 1.

	(1,1) *pos*	(1,2) *pos*	(1,3) *pos*	(1,4) *pos*	(1,5) *pos*	(1,6) *pos*	(2,6) *pos*	(3,6) *pos*
(1,1)	**0.174**	0.131	0.129	0.121	0.125	0.093	0.097	0.108
(1,2)	0.142	**0.161**	0.136	0.143	0.132	0.108	0.111	0.122
(1,3)	0.140	0.137	**0.160**	0.151	0.156	0.127	0.087	0.098
(1,4)	0.132	0.145	0.152	**0.159**	0.148	0.126	0.094	0.106
(1,5)	0.136	0.133	0.155	0.147	**0.160**	0.131	0.091	0.102
(1,6)	0.091	0.098	0.114	0.113	0.118	**0.178**	0.144	0.113
(2,6)	0.085	0.090	0.070	0.075	0.073	0.128	**0.200**	0.164
(3,6)	0.101	0.106	0.084	0.091	0.088	0.108	0.176	**0.186**

3.2 Lowering Ability of Localization Caused by Magnetic Deviations

In this subsection we show the effect of magnetic disturbance on localization ability. In the second and third column of Tab. 8 we have the level of localization before and after magnetic disturbance using the metric from Eq. 2, the data without disturbance is in Tab. 4 and with magnetic disturbance in Tab. 5. A similar result for metric from Eq. 1 is shown in the fourth and fifth column of Tab. 8, data non disturbed are from Tab. 6, and with magnetic disturbance in Tab 7.

As we can see the localization ability is lower because of magnetic disturbance and even in this simple example the robot could lose its position.

In the next subsections we have shown, our exemplary, the north direction estimation methods based on the granules of knowledge in terms of Rough Set Theory (Pawlak, 1992), particularly based on the granules in sense of (Polkowski, 2005) and (Polkowski, 2007) and simple similarity measures.

3.3 An Estimation of North Direction after Sense for 4-sonar Radar

$$Grid = \{obj_{(1,1)}, obj_{(1,2)}, obj_{(1,3)}, obj_{(1,4)}, obj_{(1,5)}, obj_{(1,6)}, obj_{(2,6)}, obj_{(3,6)}\}$$

$$A = \{N, S, E, W, North\_direction\}$$

Table 7: Localization ability for all fields with an unstable magnetic environment; Data from a histogram filter after a single north-south-east-west(NSEW) sense; for distance measure from equation 1.

	(1,1) *pos*	(1,2) *pos*	(1,3) *pos*	(1,4) *pos*	(1,5) *pos*	(1,6) *pos*	(2,6) *pos*	(3,6) *pos*
(1,1)	**0.154**	0.131	0.129	0.120	0.124	0.095	0.101	0.114
(1,2)	0.135	**0.161**	0.136	0.143	0.135	0.114	0.118	0.125
(1,3)	0.123	0.137	**0.160**	0.151	0.155	0.128	0.094	0.146
(1,4)	0.123	0.145	0.152	**0.159**	0.150	0.130	0.101	0.141
(1,5)	0.128	0.133	0.155	0.147	**0.158**	0.132	0.097	0.150
(1,6)	0.109	0.098	0.114	0.113	0.117	**0.168**	0.137	0.133
(2,6)	0.105	0.090	0.070	0.075	0.073	0.122	**0.182**	0.088
(3,6)	0.123	0.106	0.084	0.091	0.089	0.111	0.169	**0.104**

Table 8: The effect of magnetic disturbance of localization ability. In the table we have the difference between the best locating probability and the second one in decreasing order.

	non disturbed $eq2$	*disturbed* $eq2$	*non disturbed* $eq1$	*disturbed* $eq1$
(1,1)	0.017	0.005	0.032	0.019
(1,2)	0.012	0.012	0.016	0.016
(1,3)	0.004	0.004	0.005	0.005
(1,4)	0.008	0.007	0.008	0.008
(1,5)	0.004	0.003	0.004	0.003
(1,6)	0.03	0.018	0.047	0.036
(2,6)	0.017	$-0.002(lost)$	0.024	0.013
(3,6)	0.015	$-0.059(lost)$	0.022	$-0.046(lost)$

3.3.1 Actual North Direction Estimation Based on ε - Granules of Knowledge

Our general variant of north direction estimation is the following,

$$g^{\varepsilon}_{r_{gran}}(o_{sense}) = C_1$$

$$C_1 = \{obj_{(i,j)} \in Grid : \frac{IND^{\varepsilon}(o_{sense}, obj_{(i,j)})}{|A|-1} \geq r_{gran}\}$$

where,

$$\varepsilon = min(\varepsilon' \in \{0.01, 0.02, ..., 1.0\} : card(g^{\varepsilon'}_{r_{gran}}(o_{sense})) \geq 1)$$

$$IND^{\varepsilon}(o_{sense}, obj_{(i,j)}) = C_2$$

$$C_2 = \{a \in \{N,S,E,W\} : \frac{|a(o_{sense}) - a(obj_{(i,j)})|}{a(o_{sense}) + a(obj_{(i,j)})} \leq \varepsilon\}$$

in our case $r_{gran} = 1.0$

$$North\_after\_sense = C_3$$

$$C_3 = \{\frac{\sum(North\_direction(obj_{(i,j)}))}{card(g^{\varepsilon}_{r_{gran}}(o_{sense}))} : obj_{(i,j)} \in g^{\varepsilon}_{r_{gran}}(o_{sense})\}$$

Table 9: Original Senses from the central points of Grid fields with measured north directions; (G,A).

$obj.no.$	N	S	E	W	$North\ direction$
$obj_{(1,1)}$	70	70	255	32	58
$obj_{(1,2)}$	85	85	255	110	76
$obj_{(1,3)}$	70	70	255	255	88
$obj_{(1,4)}$	85	85	255	255	94
$obj_{(1,5)}$	70	70	205	255	104
$obj_{(1,6)}$	70	255	70	255	108
$obj_{(2,6)}$	240	255	70	70	108
$obj_{(3,6)}$	255	100	70	70	162

Table 10: Exemplary sense.

	N	S	E	W	$North\ direction$
o_{sense}	N_{sense}	S_{sense}	E_{sense}	W_{sense}	$N_{estimation}$

3.3.2 Actual North Direction Estimation Based on Similarity Measures

The equivalent method for similarity measures is the following,

$$g^{\varepsilon}(o_{sense}) = \{obj_{(i,j)} \in Grid : \ d(o_{sense}, obj_{(i,j)}) \leq \varepsilon\}$$

$$\varepsilon = max(\varepsilon' \in \{0.01, 0.02, ..., 1.0\} : card(g^{\varepsilon'}(o_{sense})) \geq 1)$$

$$North\_after\_sense = C_4$$

$$C_4 = \{\frac{\sum(North\_direction(obj_{(i,j)}))}{card(g^{\varepsilon}(o_{sense}))} : obj_{(i,j)} \in g^{\varepsilon}(o_{sense})\}$$

where d is the fixed similarity measure, for example those from equations 1 and 2.

3.4 Emergency North - Useful in Case of Mis-localization

The defined emergency north direction consists of $card\{Grid\} - 2$ elements, because the highest and smallest values are removed from consideration - see the Eq. 3. The emergency north direction is useful in case of permanent lose of the position on the map.

$$Emergency\_North = C_8 \tag{3}$$

$$C_8 = \frac{\sum_{obj_{(i,j)} \in Grid'} North\_direction(obj_{(i,j)})}{card\{Grid\} - 2}$$

where,

$$Grid' = \{obj_{(i,j)} : obj_{(i,j)} \in Grid \backslash \{obj'_{(i,j)} : obj'_{(i,j)} \in$$

$$\in \{obj''_{(i,j)} : max(North\_direction(obj''_{(i,j)})), min(North\_direction(obj''_{(i,j)}))\}\}\}$$

3.5 Cost and Policy to Get Goal

In this subsection we have the computed cost of movement with assumption that the goal position is in the coordinates $(2,6)$ - see Fig. 6, and the policy of movement (Roy and Thrun, 2002) see Fig. 7. We made assumption that the cost of a single move is an equal one, and that the robot can move in the direction of south, west, north and east. The minimal cost of reaching the goal is propagated back from the goal to all fields on the map. Based on the minimal cost of reaching the goal, we can generate a universal moving policy, where in the case of more than one possibility of move, we choose the last conflicted value with the use of a fixed searching order, south, west, north and east. We have shown a really simple example, with the assumption that the robot can move precisely in one of four directions. Considering more complex solution, the agent can move in any direction with uncertainty, which requires multiple approximations of this policy ending in the stable point - without changes in policy.

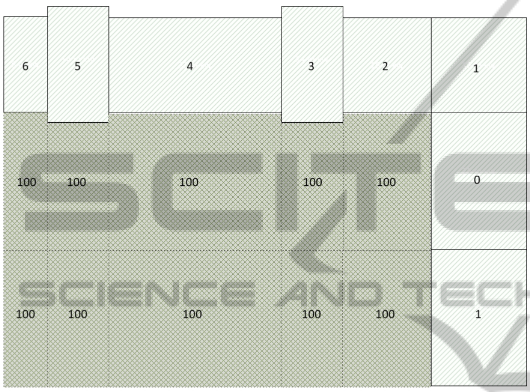


Figure 6: Cost of reaching the goal in coordinates (2,6).

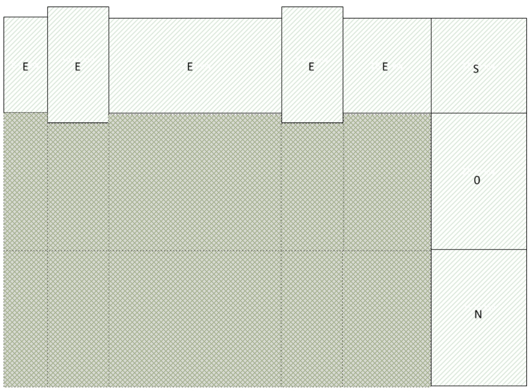
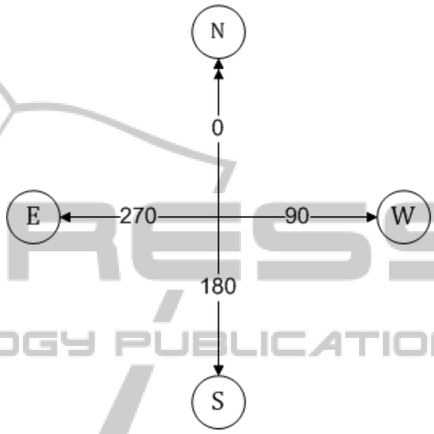


Figure 7: Universal Policy of reaching the goal in (2,6) coordinates.

3.6 PD-controller

For demonstration purposes we use a robot equipped with two servo motors, for wheels control, HiTechnic compass sensor for control of motion in the intended direction, and a central unit which allows us to control the robot remotely. The PD-controller (Bennett, 1993) for the steering of Mindstorm NXT robot consists of control of two wheels with fixed velocity. By building a PD-controller we convert the readings from the compass in the way shown in Figs. 9 and 10. After conversion, readings from the compass towards to intended direction are shown in Fig. 8. During conversion we have two variants; the first one occurs when the intended direction is $k < 180$ (see Fig. 9), and the second one occurs when the intended direction is $k >= 180$ - see Fig. 10.

We have implemented the controller in C++ with the use of NXT++ library, (see (NXT++, 2014)). In the last step we have tuned the parameters of the controller for optimal control.



Readings from compass in degrees, we make assumption, that value 0 means north, 180 south, 90 east, 270 west.

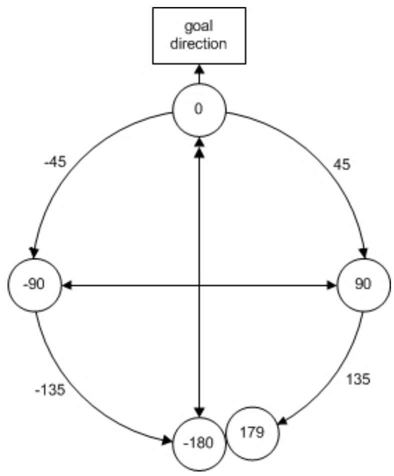


Figure 8: Compass directions after conversion.

4 SUMMARY OF EXPERIMENTS

To attain the objective we have used the modular library NXT++ - on the GPLv2 licence. For laboratory use we have developed additional drivers for the library and released the new version of this li-

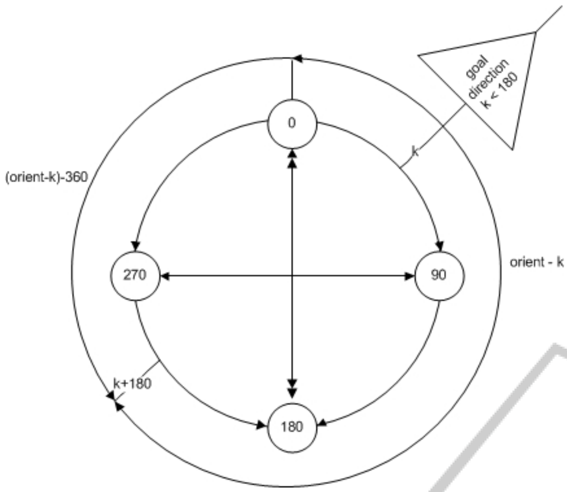


Figure 9: Direction conversion for $k < 180$, parameter *orient* is the original reading from the compass (the value for conversion).

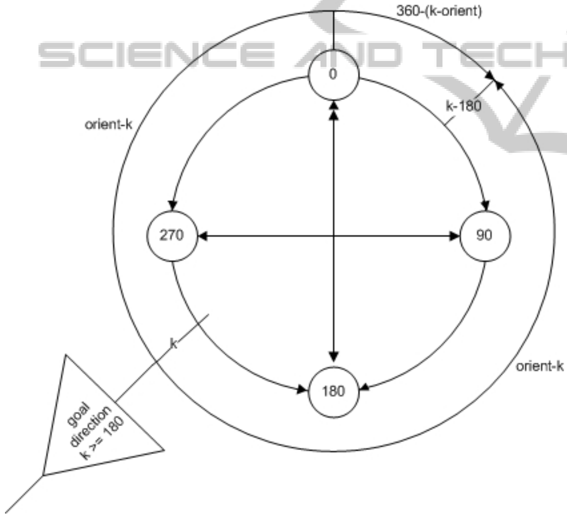


Figure 10: Direction conversion for $k \geq 180$, parameter *orient* is the original reading from the compass (the value for conversion.

brary available in (NXT++, 2014). We have developed drivers for HiTechnic multiplexers and included them in the library. As a computing engine we use a computer connected with the robot via a bluetooth module. The robot which we have used for experimental purposes is shown in Fig. 11. The software which we have developed for localization is hosted on Github - see (RoboGuide.project, 2014). The exemplary movie from our experiments is available at (Video.of.histogram.filtering.for.Mindstorms.NXT, 2014). In our experiments we use four-directional radar from Fig. 5 in move, it is because we want to see the effect of sense part of histogram filtering. And the localization ability was better after multiple sense

Figure 11: The construction of our robot - the robot is based on an aluminium frame (designed by (Artiemjew, 2014)) ; we have used Lego Mindstorms NXT bricks; there are four sonar sensors, a magnetic compass and a touch sensor; there are two HiTechnic sensor multiplexers - the first for digital and the second for analog sensors; there are two servo motors in use.

in move than by single four directional sense. As a metric for sense we use formula from Eq. 2, this metric works best in corridors of building among tested metrics. The north direction is estimated based on the method from Sect. 3.3, and the emergency north in the way from the Sect. 3.4.

5 CONCLUSION

In this work we have designed an algorithm for the proper localization of a robot in an unstable magnetic environment. To achieve our goal we have designed a robot which is based on the Mindstorms NXT parts with additional multiplexers and a compass sensor by HiTechnic. We have developed drivers for multiplexers in the modular library NXT++ and performed laboratory and real environment tests. These tests demonstrate the effectiveness of our approach - the localization is resistant to magnetic deviations. It turn out that for such imprecise stuff like Mindstorms NXT, it is better to use 4 directional radar in move and metric for localization, which consider overall distance between walls of the corridor. In our future work, we plan to optimize the robo guide library (RoboGuide.project, 2014) and use it in the net of corridors. We have also plan to extend our experimental methods to use in the other localization algorithms like particle filtering and Kalman filtering. The future tasks will be partially supported by Scientific Robotic Circle of University of Warmia and Mazury - see (NKR-UWM, 2014).

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REFERENCES

Artiemjew, L. (2014). Designer of robot frame - http://lechart.ovh.org/eng/ and https://www.facebook.com/lech.artiemjew.

Bennett, S. (1993). A history of control engineering. In *IET*, pages 1930–1955.

Dellaert, F., Fox, D., Burgard, W., and Thrun, S. (1999). Monte carlo localization for mobile robots. In *Robotics and Automation, 1999. Proceedings. 1999 IEEE International Conference on*, volume 2, pages 1322–1328 vol.2.

Gozick, B., Subbu, K., Dantu, R., and Maeshiro, T. (2011). Magnetic maps for indoor navigation. *Instrumentation and Measurement, IEEE Transactions on*, 60(12):3883–3891.

Hart, P., Nilsson, N., and Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. *Systems Science and Cybernetics, IEEE Transactions on*, 4(2):100–107.

Minorsky, N. (1922). Directional stability of automatically steered bodies. In *J. Amer. Soc. Naval Eng. 34 (2)*, pages 280–309.

Navarro, D. and Benet, G. (2009). Magnetic map building for mobile robot localization purpose. In *Proceedings of the 14th IEEE International Conference on Emerging Technologies & Factory Automation*, ETFA'09, pages 1742–1745, Piscataway, NJ, USA. IEEE Press.

NKR-UWM (2014). http://www.uwm.edu.pl/nkr/. *Robotic Circle of University of Warmia and Mazury*.

NXT++ (2014). NXT++ library 2014 - a library in C++ for programming Mindstorms NXT. *By Cory Walker, extentended by David Butterworth and Piotr Artiemjew*.

Pawlak, Z. (1992). *Rough Sets: Theoretical Aspects of Reasoning About Data*. Kluwer Academic Publishers, Norwell, MA, USA.

Polkowski, L. (2005). Formal granular calculi based on rough inclusions. In *Granular Computing, 2005 IEEE International Conference on*, volume 1, pages 57–69 Vol. 1.

Polkowski, L. (2007). Granulation of knowledge in decision systems: The approach based on rough inclusions. the method and its applications. In Kryszkiewicz, M., Peters, J., Rybinski, H., and Skowron, A., editors, *Rough Sets and Intelligent Systems Paradigms*, volume 4585 of *Lecture Notes in Computer Science*, pages 69–79. Springer Berlin Heidelberg.

RoboGuide.project (2014). https://github.com/boxero/robo-guide.

Roy, N. and Thrun, S. (2002). Motion planning through policy search. In *Intelligent Robots and Systems, 2002. IEEE/RSJ International Conference on*, volume 3, pages 2419–2424 vol.3.

Suksakulchai, S., Thongchai, S., Wilkes, D., and Kawamura, K. (2000). Mobile robot localization using an electronic compass for corridor environment. In *Systems, Man, and Cybernetics, 2000 IEEE International Conference on*, volume 5, pages 3354–3359 vol.5.

Video.of.histogram.filtering.for.Mindstorms.NXT (2014). NXT histogram filtering: http://youtu.be/Im5IYMRbAp0. *by Piotr Artiemjew*.