CEAI, Vol.14, No.2, pp. 50-57, 2012 Printed in Romania

Some Applications of Laser Rangefinder in Mobile Robotics

František Duchoň, Martin Dekan, Ladislav Jurišica, Anton Vitko

Institute of Control and Industrial Informatics, Faculty of Electrical Engineering and Information Technology, Slovak University of Technology, Ilkovičova 3, Bratislava, Slovakia (e-mail: frantisek.duchon@stuba.sk, martin.dekan@stuba.sk, ladislav.jurisica@stuba.sk, anton.vitko@stuba.sk)

Abstract: Active ranging sensors are the most popular sensors in mobile robotics. One of them, laser rangefinder, has many advantages over other ranging sensors. Despite its considerably high costs, it is a very accurate, reliable and high-speed sensor. Data from laser rangefinder can be used in many ways. This paper shows some techniques that can be useful in solving tasks such as localization, environmental mapping or navigation. Our approach is based on data pre-processing, using a raw filter as well as a smooth filter. Raw filter allows for reduction of missing and invalid measurements and smooth filter smoothes up the data, so the shape of obstacles can be captured more precisely. In this manner, modified data can be used in further tasks, two of which are presented here: detection of extremes and environmental mapping. Detection of extremes covers corners and discontinuities detection. The result of environmental mapping is a global metric map of the environment. Finally, a short analysis of our future work is presented.

Keywords: laser rangefinder, data preprocessing, raw filter, smooth filter, detection of extremes, environmental mapping

1. INTRODUCTION

The principle of laser rangefinder is well known (Siegwart (2004)). Laser rangefinders can be used in mobile robotics in many different ways. Their properties such as good measurement precision and accuracy make them very effective in range measurement, so they can be used in any tasks that are being solved in mobile robotics. It will be shown, how data from laser scanner can be used in mobile robot localization and navigation, the two most important objectives of mobile robotics. It is important to say, that despite many positive qualities, laser rangefinder has some limitations (Siegwart (2004)). The first limitation is that most laser rangefinders are planar. This means that obstacles or other essential parts of the environment below or above the measurement plane are not detectable (i.e. stairs). The second limitation results from the nature of transmitted energy. Laser rangefinder is not able to detect optically transparent materials. Moreover, the transmitted light reflects from small dust particles, therefore some measurements should be invalid. In addition, measuring against dark and distant objects has lower accuracy. The third limitation is based on modulation of transmitted signal. For single-valued distance measurement the wave-length of transmitted signal is limited, so that it restricts the measuring range of the laser rangefinder. Despite these drawbacks, it is a very efficient and accurate range finding sensor.

Laser rangefinders have multiple applications in mobile robotics. They can be used for object tracking (Sasaki (2009), Brscic (2006)), obstacle avoidance (Negishi (2004)), feature extraction (Premebida (2005), Ueda (2006)), map building or self-localization (Lu (1997), Bahari (2008)). With additional hardware, laser rangefinder can be used for surface scanning or 3D modeling.

The aim of this article is to present a method that uses laser rangefinder for feature extraction and map building. A brief outline of the solution for self-localization is also provided.

The solution we propose does not give better results compared to other solutions, but the computational demands are much lower. Therefore, it is possible to use this method with a cheaper hardware or in tasks that require that results are obtained as quickly as possible. This has been conformed also by Typiak (Typiak (2008)), Bahari (Bahari (2008)) and Brsic (Brscic (2006)). Another positive effect of this fast algorithm is that it allows for the mobile robot to move faster without limiting precision or safety. In our experiments, the results of the proposed algorithms were accurate up to the velocity of 0,5m/s.

These algorithms can also be used as a first step for line extractor methods (Borges (2004), which once again confirms that the use of methods based on simple logic is much more efficient in real time applications, than the use of methods based on highly computationally demanding mathematical solutions.

The results of the proposed algorithms could be refined further, using certain statistical methods, such as incorporating a probabilistic model of laser rangefinder.

2. DATA PREPROCESSING

Due to the limitations of laser rangefinder (Everett (1995)) mentioned above and its mechanical assembly on mobile robot, measured data must be modified. We used laser rangefinder Hokuyo UTM-30LX [Communication Protocol]. Measuring range of this sensor is from 0,1m up to 30m (guaranteed) with angular resolution of 0,25°, detection angle 270° and measuring resolution 1mm. The sensor is mounted on Indoor Mobile Robot as can be seen in Fig 1.

Fig. 1 Laser rangefinder Hokuyo UTM-30LX (detail in left upper corner) mounted on Indoor Mobile Robot.

In mobile robot localization and navigation, the coordinate systems of mobile robot and sensor must be identical. The construction of the robot and the detection angle of the laser rangefinder enable simple matching. Each complete scan made by the laser rangefinder contains 1080 entries which represent a 270° angle. It means that some parts of the scan "see" the construction of the robot. In our case this construction represents the front part of the body of the robot that has flat surface. This property can be utilized and that is why a simple function can compute angle difference between the sensor's coordinate system and the robot's coordinate system. Left and right edge of the robot's construction can be located in the scan, i.e. how many entries represent the robot's construction between the left and right edge of the scan. This difference represents angle displacement between the coordinate system of the laser rangefinder and that of a mobile robot:

$$\begin{aligned} rd &= \sum_{i>0,i<180,d_i<300} i-(i-1) \\ ld &= \sum_{i<1080,i>(1080-180),d_i<300} i-(i-1), \\ \delta &= \frac{ld-rd}{2}.0,25 \end{aligned} \tag{1}$$

where rd and ld is number of entries representing robot from right and left edge of the scan, i is index of entry (measurement), d_i is measured distance and δ is angle displacement. Afterwards, each single entry from data array is shifted by this displacement.

After *data shifting*, filtering of data must be applied. We used two types of filters: raw filter and smooth filter (Pásztó (2010)).

Raw filter eliminates missing and invalid measurements. Usually, there are some error messages in the data. They can be considered as missing or invalid measurements. Raw filter eliminates these invalid measurements. At first, values from the interval <min_res;max_res> are set to zero. The values min_res and max_res specify the minimal and maximal valid measurement derived from the guaranteed measurement range. In our case, parameter min_res is equal to 190mm and parameter max_res is equal to 30000mm. If a data sequence of specified length contains a number of invalid measurements lesser than value max_var, then raw filter approximates the missing data in the sequence. The aim of this step is to increase the consistence of the data. The value max_var represents the maximum number of invalid or missing measurements, that will be replaced in the data sequence. For the data replacement, an index of data development ahead of missing data is calculated:

$$dd = \frac{\sum_{i=i_v-n}^{i_v}(d_i-d_{i-1})}{n}, \tag{2}$$

where i is index of data, i_v is index of last valid data ahead of missing data, n is number of valid data used in calculation (i.e. length of data sequence) and d_i is data itself (i.e. measured distances). The index of data development is an integer number. The specification of n depends on environment's characteristics. If the environment is dynamically changing or contains a great number of objects, n must be a small number, as the index of data must represent only a small section of the surroundings of the missing data. On the contrary, if the environment is static or contains few objects, n can be bigger. In this case, the index of data must represent a bigger section of the surroundings of the missing data, so it can represent parts of objects in the environment.

Each entry of the missing data is then replaced as the sum of the last valid measurement and the corresponding multiple of the index of data development d_i:

$$d_m = d_v + \sum_{i=1}^{k} dd, \tag{3}$$

where d_v corresponds to last valid data, k is relative position of d_m and dd is the index of data development.

The principle of data approximation can be explained on a simple example. Let the data sequence contains:

$$d = [800,803,805,0,0,0,815,819,823]$$

It is clear, that zeros in the data sequence represent invalid measurements. In our example, the index of data development is calculated as follows:

$$dd = \left(\frac{(805-803)+(803-800)}{2}\right) = \left(\frac{5}{2}\right) \cong 3$$

Missing data are then derived from the last valid measurement and the index of data development. In our example, modified data:

$$d' = [800,803,805,808,811,814,815,819,823]$$

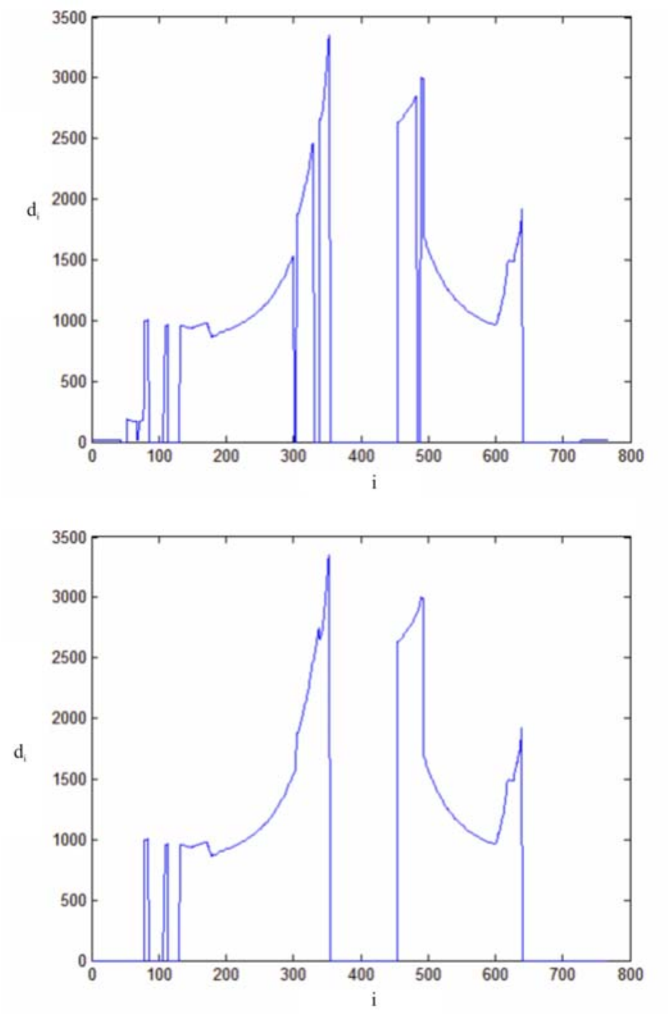


Fig. 2. Example of raw data and data filtered by raw filter.

Smooth filter performs small corrections in two steps.

First step divides data into appropriate segments (Fig. 3). A segment is defined as smooth sequence of data differing from zero that is logically connected. In ideal case, every segment in a scan represents one object. Usually, one segment represents one logical part of the environment. Heuristic parameter segmentDistance defines maximum distance of two consequent measurements in a segment. Value of this parameter depends on the shapes of objects in environment. If there are many sharp-edged objects, segmentDistance should be bigger than in an environment with smooth-edged objects. In our experiments, segmentDistance equal to 100mm was used.

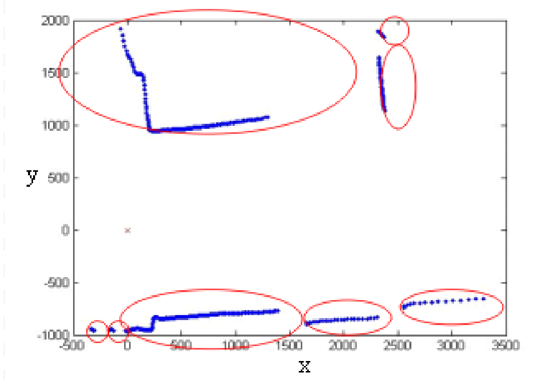
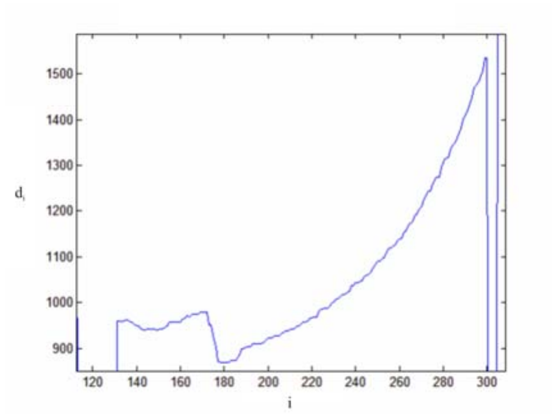


Fig. 3. Data segmentation.

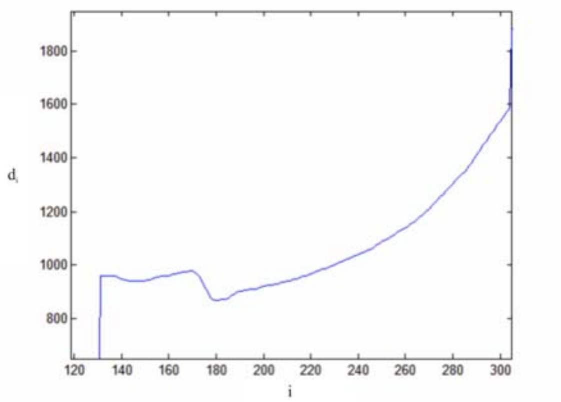
Second step consists of data smoothing by applying a simple moving average technique on each segment (Fig. 4). The simple moving average technique is defined as the calculation of average value in specific number of period - n:

$$SMA = \frac{d_1 + \ldots + d_n}{n}, \tag{4}$$

where $P^1,\ldots,P^n$ stands for measured values (i.e. measured distances) and n is number of periods.



a)



b)

Fig 4. Example of data: a) filtered by raw filter b) filtered by raw and smooth filter

3. DETECTION OF EXTREMES

For detection of extremes in the environment, data divided into segments are used, just as in data smoothing. Segments of short total length (i.e. counted as a number of measured distances) are neglected. Our data analysis proves that a significant environment mark (i.e. extreme) can be detected as local minimum or local maximum in a segment. For this purpose function Extr (Balda (2006)) was used. This function returns the placement of local extremes in a data sequence. The output of the function Extr divides segments into smaller sub-segments. Data in these sub-segments are either increasing or decreasing. If data in the sub-segment are increasing, then each measured distance in this sub-segment is equal to or bigger than the preceding one. Vice versa, if data in the sub-segment are decreasing, then each measured distance in this sub-segment is equal to or smaller than the preceding one:

$$s_{in} : \forall d_i \in s_{in}, d_i \geq d_{i-1}$$
$$s_{de} : \forall d_i \in s_{de}, d_i \leq d_{i-1}, \tag{5}$$

where s_{in} is increasing sub-segment, s_{de} is decreasing sub-segment and d_i are measured distances. Local extremes are located on places of sub-segment type alternation. In this way, two sets of extremes are obtained (Fig. 5). First set defines places of local minimums and second set defines places of local maximums.

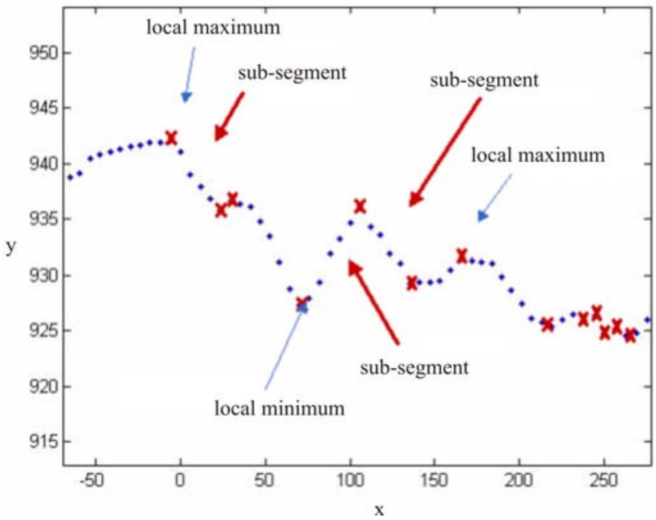


Fig. 5. Examples of sub-segments, local maximum and local minimum in measured data.

For usage in mobile robotics, only significant extremes (e.g. corners or gaps) in the environment are important. Therefore, the function ExtremeProcessing is introduced. This function removes non-significant extremes from the set of extremes. Local extremes divide particular segments into a large number of sub-segments. The vector of each sub-segment is defined by its length and angle in global coordinate system:

$$l = \sqrt{(y_E - y_B)^2 + (x_E - x_B)^2}$$
$$\alpha = a\tan\left(\frac{y_E - y_B}{x_E - x_B}\right), \tag{6}$$

where (x_B, y_B) are coordinates of the starting point of the vector, and (x_E, y_E) are coordinates of the ending point of the sub-segment.

The absolute value of the relative angle of two consequent vectors defines the significance of the extreme and can be calculated:

$$\gamma = |\alpha_1 - \alpha_2|. \tag{7}$$

If this angle is bigger than minAngle and smaller than maxAngle, the extreme is significant (Fig. 7). In our case, minAngle is equal to 40° and maxAngle is equal to 140°. It is clear, that we focused on searching corners.

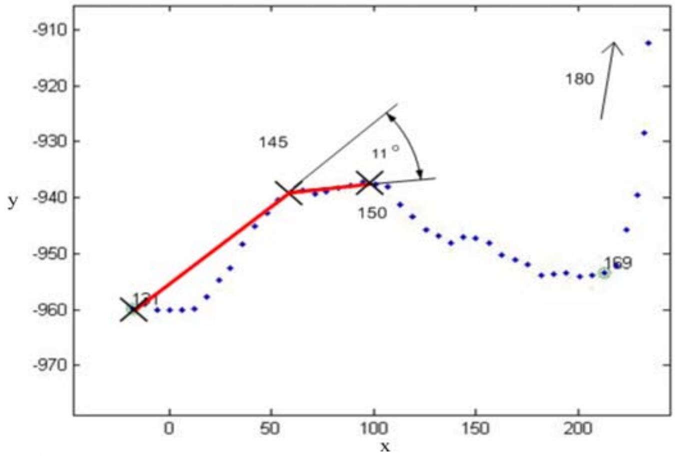


Fig. 6. Non-significant extreme (note: scaling factor of x and y axis is different)

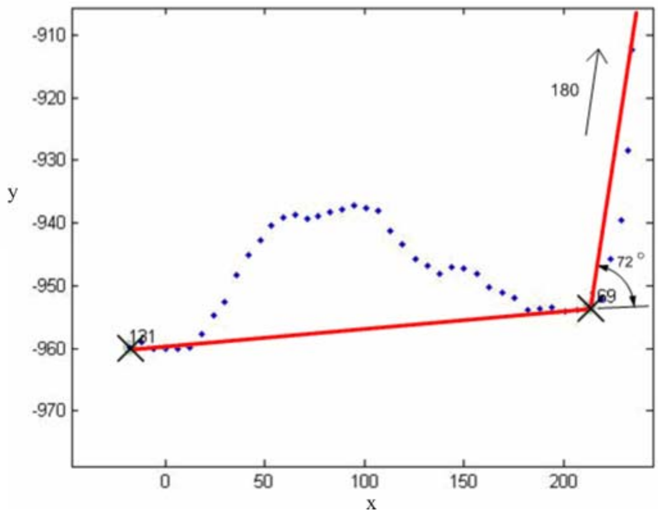


Fig. 7. Significat extreme (note: scaling factor of x and y axis is different).

Finally, significant extremes are classified into real extremes and auxiliary extremes (Fig. 8). Auxiliary extremes are defined as a boundary in measured distances which are bigger than the heuristically defined parameter segmentDistance:

$$he : he \in SE, \left|d_{he} - d_{he-1}\right| > \text{segmentDistance} \vee \left|d_{he} - d_{he+1}\right| > \text{segmentDistance} \quad (8)$$

where he is auxiliary extreme, SE is set of extremes and d_{he} is the distance measured at position of auxiliary extreme. We proposed SegmentDistance equal to 100mm. The auxiliary extreme indicates that the obstacle at a given location probably continues. That is why it can be stated that the detected adjacent extreme is real (e.g. corner). Auxiliary extremes can be utilized as places of interest that must be explored by a robot.

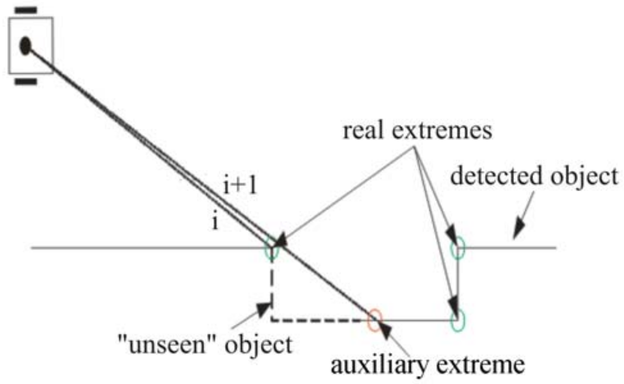


Fig. 8. Classification of extremes.

4. ENVIRONMENTAL MAPPING WITH LASER SCANNER

There are four assumptions defined in our laser rangefinder environmental mapping:

1. Robot starts its activity at coordinates $(0,0,0)$ and the coordinate system of the robot is defined as right-handed. This means, that x and y coordinate of the robot is equal to zero and the robot is oriented in positive x-direction.
2. The map of environment must be orthogonal, like maps used by humans.
3. Environment map is a global metric map.
4. Laser rangefinder measurements are performed at stationary positions, because these measurements do not include compensation for the robot's movement.

With regard to these assumptions, environment map can be created as integration of many local metric maps. In other words, global metric map is created by simply matching the scans from laser rangefinder. Naturally, values in a scan are defined by angle and distance. However, a map is global and metric, i.e. defined in global coordinate system xy. Thus values from a scan must be interpreted into the global map as:

$$\begin{aligned} x_i &= x_{cl} + d_i.\cos(\alpha_i) \\ y_i &= y_{cl} + d_i.\sin(\alpha_i) \end{aligned}, \quad (9)$$

where (x_{cl}, y_{cl}) define the central point of local metric map in global coordinate system, d_i is measured distance and α_i is the corresponding angle of measuring. The coordinates of the central point of local metric map in global coordinate system are defined:

$$\begin{aligned} x_{cl} &= x_{cg} + x_{p,j} \\ y_{cl} &= y_{cg} + y_{p,j} \end{aligned}, \quad (10)$$

where (x_{cg}, y_{cg}) are coordinates of central point of global coordinate system and $(x_{p,j}, y_{p,j})$ are robot coordinates in global coordinate system in step j.

The error of robot position estimation is the main limitation of this principle. This error is also translated into map. Thus, the techniques reducing error of robot position estimation must be used (e.g. Kalman filtering, statistical methods of odometry error estimation etc.) (Balogh (2007), Miková (2008), Rodina (2010), Teslić (2010)). However these techniques require not only information about the robot's position from odometry, but also position estimation from other sensors. That is why we propose the algorithm for environment extremes detection. Using a simple triangulation and trilateration, detected extremes can be simply used for estimation of relative changes in a robot's position. For more information about this technique, see (Jurišica 2009)).

5. EXPERIMENTS

A simple room, as shown in Fig. 12, was used for the verification of the proposed approach. Raw measured data can be seen in Fig. 9. As outlined in Section 2, preprocessing of raw data was applied. First, it is necessary to shift the data to achieve unification of the laser's and robot's coordinate system. Such data shifting as can be seen in Fig. 10, is usually a small number. Data filtering results in more consistent and realistic data. This can be seen from the comparison of Fig. 9 and Fig. 10. Let us consider euther of the walls. In Fig. 10 the walls are much smoother, which corresponds more closely to the character of the real environment.

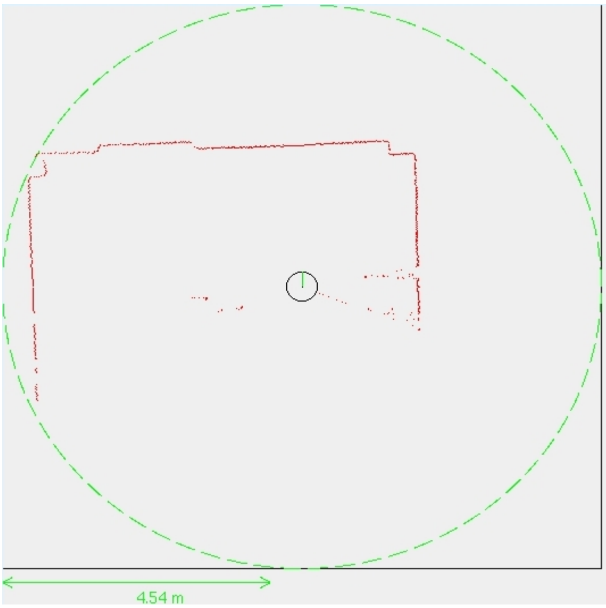


Fig. 9. Laser rangefinder data without shifting and filtering. Red dots are measured data in local coordinate system of the robot. Green dash line stands for maximum measuring range of the laser rangefinder. Example of data details can be found in Fig. 2. and Fig. 4.

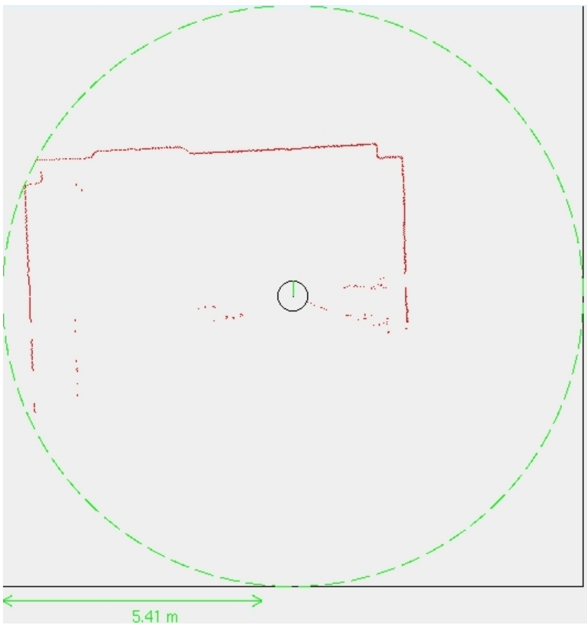


Fig. 10. Laser rangefinder data with correction 0,5° and data filtering. Example of data details can be found in Fig. 2 and Fig. 4.

According to the procedures in Section 3, algorithms were applied on preprocessed data in order to search for extremes in the environment. The algorithm successfully found all the environment extremes as defined in Section 3.

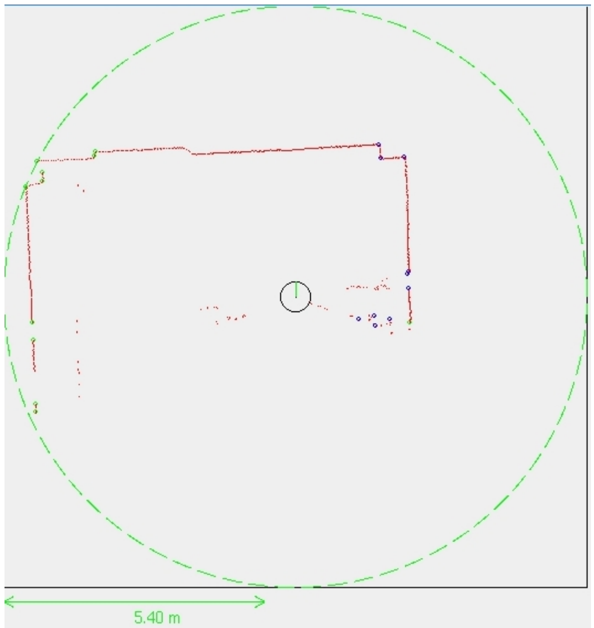


Fig. 11. Data with detected extremes (blue dots - real extremes, green dots - auxiliary extremes).

Fig. 12 Environment used for mapping, robot is at the starting position

In mapping, the assumptions stated in Section 4 were confirmed. The error of robot position estimation was, indeed, transferred into the map. Our robot uses only odometry for the position estimation, which is why bigger error is transferred into the map when the robot turns (Fig. 14). When the robot performs only simple moves, such as straightforward movement, the introduced error is much smaller. The error occurs due the properties of laser rangefinder and odometry. Usually, laser rangefinder stores data in the buffer. That is why the data do not correspond to the position from which they were obtained (see Section 6). Moreover, odometry alone is not suitable for precise positioning of the robot.

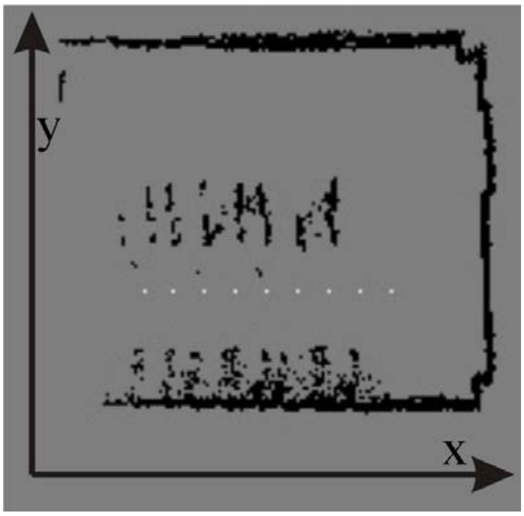


Fig. 13. Environment map created from 9 positions (white dots)

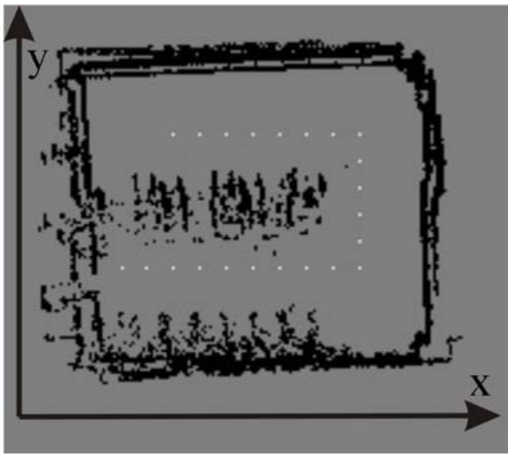


Fig. 14. Environment map created from 22 positions (white dots)

6. CONCLUSIONS AND FUTURE WORK

There are many ways to make use of detected extremes. They can be stored in form of a histogram (Mei (2008)). This histogram can be used as environment representation, which occupies less memory than classic environment representations. Moreover, environmental mapping can be simplified by storing of extremes instead of storing the entire map. Detected extremes can be useful in topological map creation, and finally, they can also be used for solving SLAM or for localization of the robot itself. What is more, defined auxiliary extremes may refer to areas that are not well known. To create a complete map of environment, these areas must be explored by the robot.

The methods presented here have one big advantage over other methods. They are not computationally demanding. This property is very useful in mobile robotics, as a mobile robot solves many tasks in real time. Solution of each task has to be computed in milliseconds. That is why we made an attempt to propose simple methods that are close to human understanding. Of course, there are more robust methods available, however our methods were tested in real environment on real hardware and in real time and we can claim that they are quick and effective.

However, the presented methods have some shortcomings. As mentioned above, errors from sensors are transferred into the data. For instance, errors from position estimation, grid impreciseness, and errors from laser rangefinder buffering and measuring are translated into the environment map. Therefore, our future work will focus on better position estimation. The first step to accomplish this aim is the reduction of odometry errors and elimination of systematic errors of sensors measurement. In the next step, several methods such as the above mentioned odometry and methods based on laser rangefinder and visual systems would be combined into a fusion method of position estimation.

ACKNOWLEDGMENTS

This work was supported by MS SR under contract VMSP-P-0004-09 and VEGA 1/0690/09.

REFERENCES

Bahari N., Becker M., Firouzi H.(2008). Feature Based Localization in an Indoor Environment for a Mobile Robot Based on Odometry, Laser, and Panoramic Vision Data, *ABCM Symposium Series in Mechatronics*, Vol. 3, pp. 266-275.

Balda, M., extr.m, (2006). Positions of local extremes in a sequence.

Balogh, R. (2007). Practical Kinematics of the Differential Driven Mobile Robot. In: *Acta Mechanica Slovaca*, pp. 11-16, 2-A. ISSN 1335-2393.

Borges G. A., Aldon M. J. (2004). Line Extraction in 2D Range Images for Mobile Robotics, *Journal of Intelligent & Robotic Systems*, Vol. 40, Num. 3, pp. 267-297.

Brscic D., Hashimoto H. (2006). Tracking of Objects in Intelligent Space Using Laser Range Finders, Int. *Conf. on Industrial Technology*, December 15-17, pp. 1723-1728.

Communication Protocol Specification For SCIP2.0 Standard, (10. oct. 2006)., *Hokuyo Automatic* Co., LtD.

Everett, H.R. (1995). Sensors for Mobile Robots, Theory and Application. A K Peters Ltd, ISBN 1-56881-048-2.

http://www.mathworks.com/matlabcentral/fileexchange/10272-quick-search-for-local-extremes.

http://www.scs.ryerson.ca/mfiala/robotics_club/robot_projects/ufkes_laser_pioneer/hokuyoprotocol.pdf

Jurišica L., Duchoň F. (2009). Triangulation of Mobile Robot Position with Detected Ingerent Environment Landmarks, International *Journal of Mechanics and Control*, Vol. 10, No. 2 ISSN 1590-8844, pp. 15-25.

Lu F., Milios E. (1997). Robot Pose Estimation in Unknown Environments by Matching 2D Range Scans, *Journal of*

Intelligent and Robotic Systems, Volume 18 Issue 3, March.

Mei, Y., Androutsos, D. (12/2008). Affine invariant shape descriptors: the ICA-Fourier descriptor and the PCA-Fourier descriptor, Pattern Recognition, *ICPR 2008*. 19th International Conference, pp.1-4.

Miková, Ľ., Kelemen, M., Kelemenová, T. (2008). Four wheels inspection robot with differential wheels control. In: *Acta Mechanica Slovaca*, pp. 548-558, 3-B/2008. ISSN 1335-2393.

Negishi Y., Miura J., Shirai Y. (2004). Mobile Robot Navigation in Unknown Environments Using Omnidirectional Stereo and Laser Range Finder, Int. *Conf. on Intelligent Robots and Systems*, September 28 – October 2, Sendai, pp. 2737-2742.

Pásztó, P., Hubinský, P. (1/2010). Application of a Visual System for Mobile Robot Navigation (OpenCV). In: *AT&P Journal Plus*, pp. 62-65, ISSN 1336-5010.

Premebida, C., Nunes, U. (2005). Segmentation and Geometric Primitives Extraction from 2D Laser Range Data for Mobile Robot Applications. *Robotica 2005*, Actas do Encontrol Cientifico, pp. 17-25.

Rodina, J., Hubinský, P. (2010). Mono Axial Vehicle Platform for Education Purposes. In: *Robotics in Education 2010 : Proceedings of the 1st International Conference*, pp. 139-145. 16.-17. 9. 2010, Slovak University of Technology in Bratislava, ISBN 978-80-227-3353-3.

Sasaki T., Hashimoto H. (2009). Calibration of Laser Range Finders Based on Moving Object Tracking in Intelligent Space, Int. *Conf. on Networking, Sensing and Control*, Okyama, March 26-29, pp. 620-625.

Siegwart, R., Nourbakhsh, I.R. (2004). Introduction to Autonomous Mobile Robots. *Massachusetts Institute of Technology*, ISBN-13 978-0-262-19502-7.

Teslić, L., Škrjanc, I., Klančar, G. (2010). EKF-Based Localization of a Wheeled Mobile Robot in Structured Environments. *Journal of Intelligent & Robotic Systems* doi: 10.1007/s10846-010-9441-8.

Typiak A. (2008). Use of Laser Rangefinder to Detecting in Surroundings of Mobile Robot the Obstacles, *Symposium on Automation and Robotics in Construction*, June 26-29, pp. 246-251.

Ueda, T., Kawata H., Tomizawa T., Ohya A., Yuta S. (2006). Mobile SOKUKI Sensor System: Accurate Range Data Mapping System with Sensor Motion, Int. *Conf. on Autonomous Robots and Agents*, pp. 309-314.