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The Exploration of Autonomous Mobile Robot Movement Characteristics in Difficult Off-road Conditions of a Coastal Zone

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ABSTRACT

In this paper, we present the results of the study of autonomous mobile robot movement characteristics in a laboratory environment using small-scale ground vehicles. We consider methods of localization, obstacles detection and path planning for the research robot travelling along a coast. In our approach, we provide techniques for simulation of outdoor conditions in the laboratory using special indoor track with various types of road surfaces (sand, stones, grass). The results of the experiment on autonomous movement in off-road conditions are considered and travelling paths of the robot during a computer simulation and movement in a real environment are compared. Position error is estimated for different types of road surfaces and further solutions are proposed.

Keywords: Autonomous ground vehicle, road surfaces, position error estimation, research robot, virtual LIDAR, indoor GPS simulation

Mathematics Subject Classification: 68T40, 68U35

Computing Classification System: I.2.9, I.5.4, I.4.8

1. INTRODUCTION

The use of robotic systems in projects aimed at the continuous measurement of various environmental parameters during topographic and oceanographic fundamental and applied research has shown its high efficiency (Incoul et al., 2014; Wood et al., 2006). While carrying out in-situ measurements it is necessary to perform the installation and movement of the equipment (including power source) between measurement locations. It is also necessary to determine and record coordinates of the setting point each time.

Limitations of time and financial costs also limit the duration and number of experiments. One of the modern approaches to gain experimental data collection is an application of mobile autonomous robots. Such robots usually contain a set of measuring equipment used in a short series of measurements to be taken at various reference points with automatically linking the resulting data sets to a geographic location (Wübbold et al., 2012).

Another important aspect of the use of mobile robots and mobile robot groups is a monitoring of environmental parameters in dangerous and complicated conditions (Zalud et al., 2011; Zakaria et al., 2017). These cases can be related with human-made and natural disasters (e.g. zone of flooding after tsunamis, accidents at nuclear power plants, etc.). Such conditions are related to a number of obstacles and require special chassis and algorithms to control the robot movement with consideration of slipping and rolling effects.

We have developed (Kurkin et al., 2017) and successfully tested (Zaytsev et al., 2017) the mobile robotic system that allows monitoring of atmospheric parameters and sea waves characteristics (water surface displacement) in coastal zones using remote sensing methods and modular chassis with replaceable movers (Figure 1-3).

Figure 1. The mobile robotic system for coastal zone monitoring: wheels movers.

Figure 2. The mobile robotic system for coastal zone monitoring: track movers.

Figure 3. The mobile robotic system for coastal zone monitoring: rotary-screw movers.

This robot includes a remote-control system which allow an operator to drive it via a radio channel. There is a very basic autonomous mode with ability to run on a straight line and stop before obstacles detected through LIDAR system. In comparison to the previous study (Kurkin et al., 2017; Zaytsev et al., 2017), here we consider extended autonomous movement algorithms with ability to follow by a set of reference points and make preplanning and re-planning of a route to avoid obstacles automatically.

2. PROBLEM FORMULATION

The modern state-of-the-art in engineering implies that self-driving cars have become a reality. But driving on a public road is still a difficult task in terms of autonomy level. There are 5 levels of autonomy where 1-2 are mostly ADAS systems, which help a driver to drive more safely by warnings. Level 3 includes taking the control by autopilot with ability to request back manual drive any time, level 4 is almost autonomous system, while level 5 is fully autonomous system. At current time, only 1-3 levels of autonomy are available on the market.

While self-driving cars allow people to travel safely and more comfortable, autonomous research robots can provide much more data during long continuous measurements operating automatically on a set of reference positions at longer distances than manually controlled robots, which require operator support and radio channel. Autonomous robots are very effective in tasks like collecting landscape data, since they provide more accurate trajectories than trajectories obtained with manual control.

In off-road conditions, like coastal zone of certain water bodies, high autonomy level can be achieved even nowadays. Taking in consideration an assumption that our research places are far from populated areas and there is no any traffic in such zones, we can create a fully autonomous vehicle for deep exploration of the desired area.

But in the conditions of a coastal zone there are some other factors that can lead to difficulties in operation of an autonomous vehicle. They can include various obstacles like trees, and difficult movement conditions like dry sand, wet sand, stones, grass, etc. As a result, too fast movement on a surface with big stones, broken trees (like in after tsunami zone) may cause a damage of a robot as well as too slow movement on wet sand or snow may result to robot stuck. Path planning and movement control algorithms can have a significant error during the movement in complex off-road conditions. And these factors are difficult to consider, using a completely virtual environment and computer simulation.

Another problem with collecting movement data in different conditions is a limitation due to time and financial costs of the expedition to different natural environments, including a transportation of the robot to a coastal zone. Such expeditions are related with much time and high expenses, thus, it makes sense only at final stages of the robot evaluation.

As a result, developing autonomous algorithms and obtaining how they are affected by inhomogeneous environment is a topical problem of the present study.

3. PROBLEM SOLUTION

3.1. The autonomous movement algorithm

To create and test an autonomous control algorithm and obtain movement characteristics of unmanned ground vehicles controlled by such an algorithm in various difficult conditions we developed small scale robots and an indoor track with different types of coverage at laboratory facilities.

The tasks of the research robot basically consist of the passage of a predetermined route along the coastline, performing recording of environment characteristics and detection of obstacles to avoid collisions.

In such conditions, the use of GPS systems of high accuracy (GNSS) has shown its effectiveness (Jilek, 2015; Zhang, 2014). Therefore, in this study, we have chosen the use of GPS systems of high accuracy as the main data source for navigation.

However, a scale reduction and indoor environment bring a restriction on the equipment used. A GPS receiver cannot receive a satellite signal, and LIDAR has too large size and weight to be installed on a small-scale robot. Increasing the scale of a robot is undesirable, as it leads to the need to increase the size of the room and the elements of the track, which are limited by a laboratory area.

One of the methods of navigating a robot under laboratory conditions is the use of high resolution encoders mounted on wheels (Davidek et al., 2016). But such an approach strongly depends on the structure of the robot and the coverage on which it moves.

Thus, when using multi-axis robots that perform a turn by changing only the speed of rotation of several wheels, as well as when driving under slipping conditions, a significant cumulative error occurs in determining the coordinates by this method.

Another approach for solving indoor navigation problem is the use of video cameras and image recognition algorithms for the robot localization (Chaudhary et al., 2016; Kovács et al., 2016), and, we selected this method for indoor navigation.

To provide autonomous ability to the robot in laboratory facilities we developed a software that consists of image processing blocks, operating on a video stream to filter out background, obstacles detection module to provide obstacles coordinates, virtual GPS module to provide a position and azimuth estimation of the robot, virtual LIDAR module to detect obstacles, occupancy grid module to collect information about detected obstacles as a map, path correction to make route re-planning, path setup to set reference points, pilot module to process movement and vehicle controller to send commands to the robot hardware, see Figure 4.

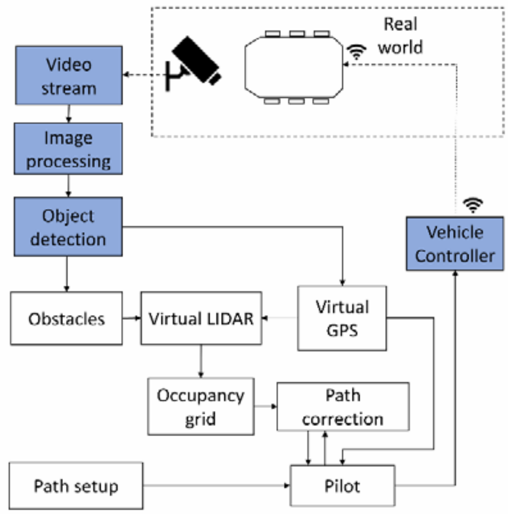


Figure 4. The structure of the software for unmanned movement in the laboratory environment.

Block diagram of the algorithm for autonomous movement, including the detection of obstacles, collision avoidance and path planning based on modified A* algorithm (Duchon et al., 2014), is shown in Figure 5. For the operation of the algorithm, a set of points specifying the route is required.

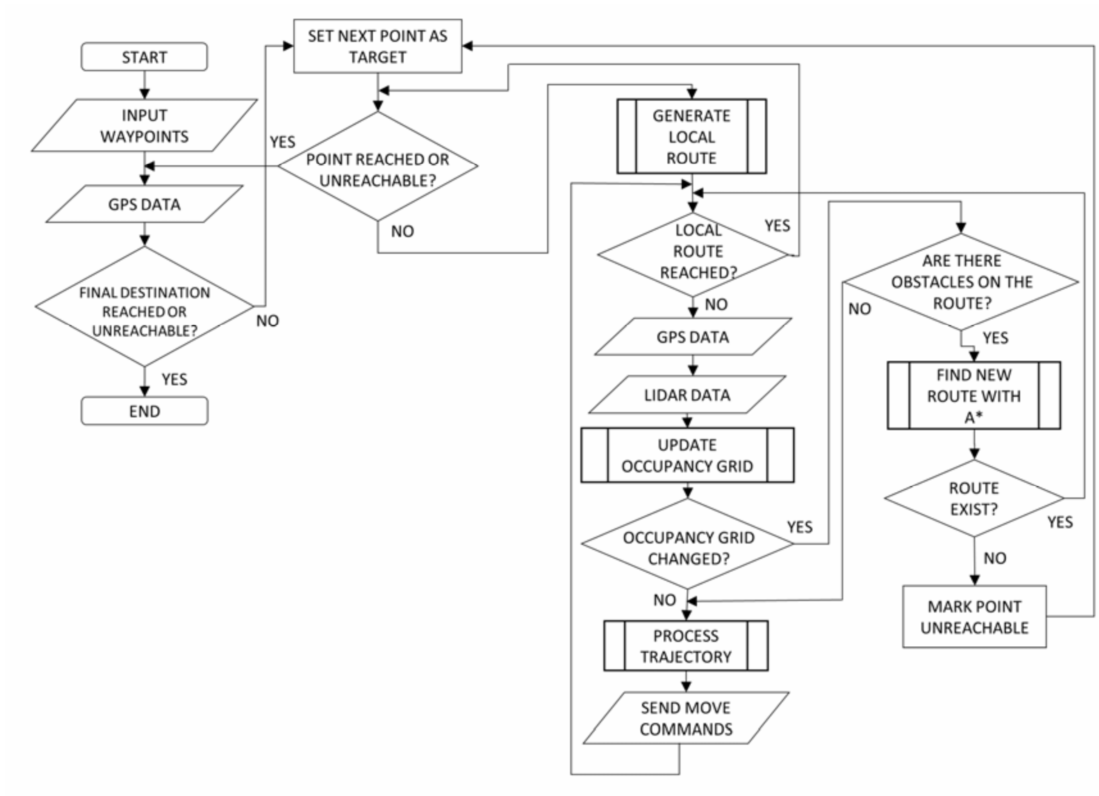


Figure 5. The unmanned movement algorithm diagram.

For the laboratory experiment, we developed a software simulating the operation of LIDAR device, Figure 6.

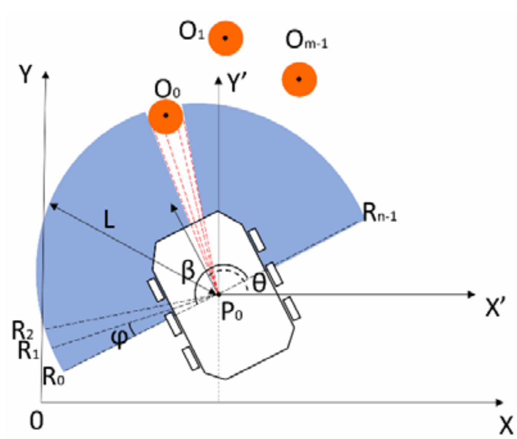


Figure 6. Representation of the virtual LIDAR.

In the experiment setup, virtual lidar provides an ability to simulate obstacle detection based on a knowledge of obstacle positions and the robot position and therefore provides an ability to integrate autonomous movement algorithms to laboratory environment. It's model is described by the following algorithm:

Step 1. Get input data: P_0 - geometrical center of the vehicle, θ - turn angle of the vehicle, L - LIDAR ray length, β - angle of a scan, φ - angle between the rays (scan resolution), O - a set of m obstacles, where obstacle O_j, j = 0 … m-1 is defined as a polygon by a set of points D.

Step 2. Generate a set of rays

$$R = \{R_0, R_1, ..., R_{n-1}\}, \tag{1}$$

where

$$n = \frac{\beta}{\varphi} \tag{2}$$

$$R = \{R_{xi}, R_{yi}\}, \; i = 0...n-1 \tag{3}$$

and the components of R are defined by

$$\begin{cases} R_{xi} = P_{x0} + L\cos\left(\theta - \frac{\beta}{2} + i\varphi\right), \\ R_{yi} = P_{y0} + L\sin\left(\theta - \frac{\beta}{2} + i\varphi\right). \end{cases} \tag{4}$$

Step 3. For each ray line P_0R_i calculate intersect point K_i with obstacle $O = \{O_0, O_1, …, O_{m-1}\}$. If the intersect point K_i exists, then set $R_i = K_i$.

Step 4. Set output data: a set of points R.

For path simulation before experiment we used the simplified mathematical model of a robot motion, described by well-known equations:

$$\begin{cases} \dot{x} = v\cos(\theta), \\ \dot{y} = v\sin(\theta), \\ \dot{\theta} = \omega. \end{cases} \tag{5}$$

where x, y are the coordinates of the robot center, ω and ν are the linear and angular velocities, and θ is the rotation angle of the robot.

Operation of the above algorithm is presented on the flowchart shown in Figure 7.

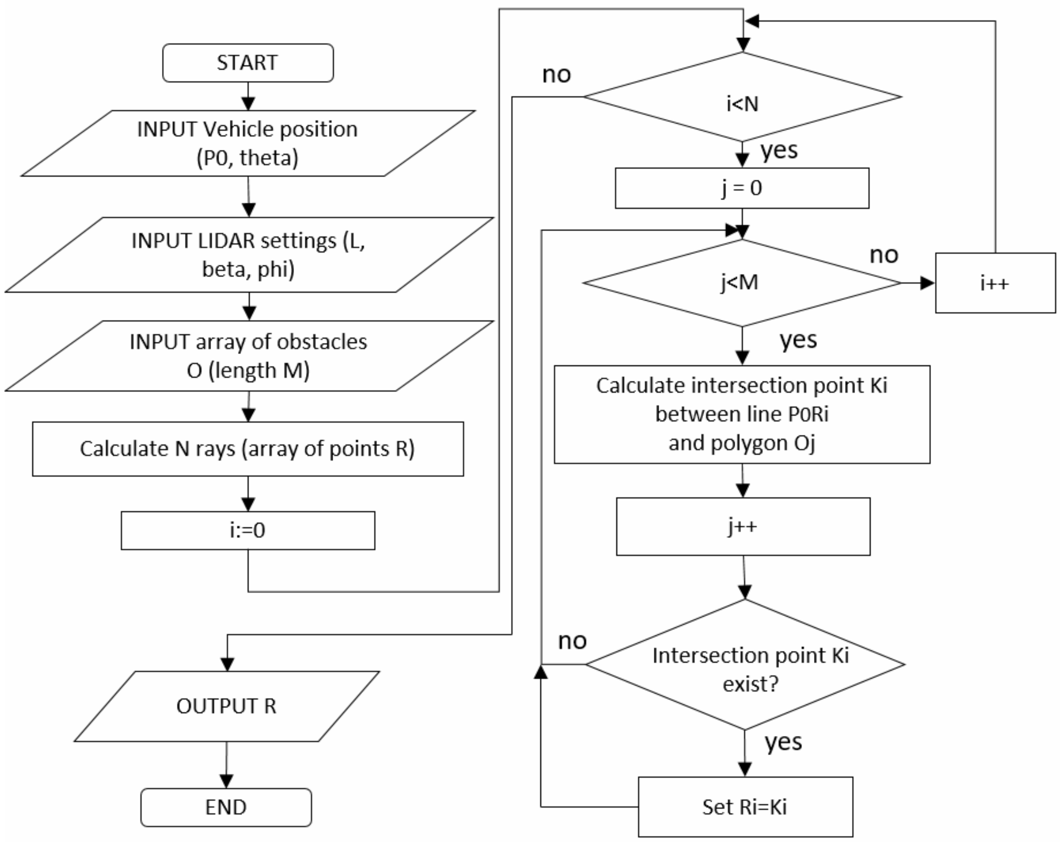


Figure 7. Virtual LIDAR operation flowchart.

There are two different approaches to design the robot controller logic. It can be developed with complex mathematical models based on dynamic systems (Besancon-Voda, 1998; Ginter et al., 2011) or fuzzy logic methods (Precup et al., 2013). But since the weight and the velocity of the laboratory robot is rather low, we do not consider complex mathematical methods. These methods will be considered in further studies with application to the full scale robot. Within the current investigation, the developed controller design is based on a simple finite state machine model, see Figure 8.

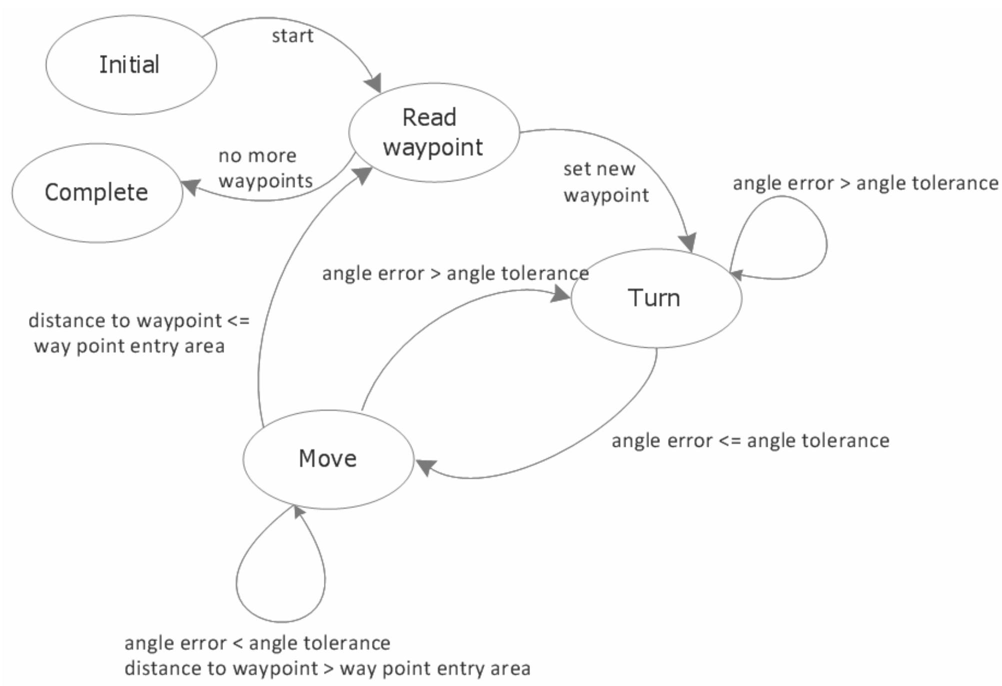


Figure 8. The robot controller model.

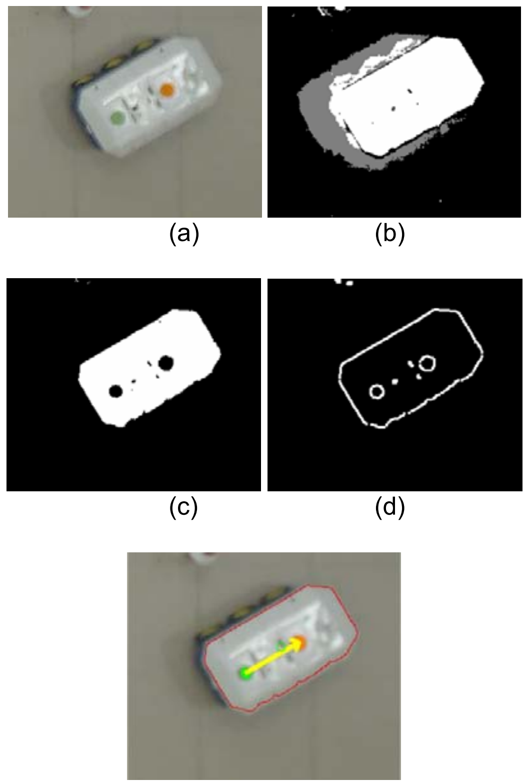
Figure 8 represents low level logic below the high-level logic of autonomous algorithms. The high-level logic defines the coordinates of the way points. The controller waits for start command at the initial state. When the start command is received, it begins to read first way point coordinates and makes a transition to the turn state. In this state, the controller performs rotation until the error (difference between target angle and current angle) reaches minimal acceptable value (angle tolerance). Robot position and angle are defined by feedback system based on video camera data (in real environment mode) or vehicle coordinates in simulation mode. After that the controller performs transition to the move state. In this state, the robot moves along the direct line to target way point. If the angle error exceeds the error tolerance then controller performs transition back to the turn state. Otherwise, if the target way point is reached, then controller returns to the state of reading the next waypoint. In case of the last waypoint, the controller moves to the complete state.

Due to the model simplification and performance limitation of the feedback system, the parameters of the controller (the turn and move velocities, the angle tolerance and the distance between the current state and the waypoint tolerance) are obtained during the experimental runs. The turn and move velocities of the robot depend on the overall feedback system performance. Running on the 4-th generation of Intel Corei7 processor and using 2 FullHD cameras we have got about 15 frames per second processed. This frequency is similar to an average frequency of GPS receiver (of around 10Hz).

To determine the coordinates of the position and the angle of the robot turn, the method of image recognition on a video stream was applied. We have developed a software module that imitates a GPS receiver. To do this, we installed 2 web cameras Logitech C920 on the ceiling, each provides a video stream of 30 frames per second at Full HD resolution. To recognize the robot object, we used the widely known OpenCV framework version 3.1.

The following sequence of filters was applied: subtraction of the background matrix from the current frame for object highlighting, pixel filtering based on the color values, the Canny filter for extracting object outlines, searching for contours, filtering by the size of the found objects, analyzing the object and determining its center and the angle of turn.

Figure 9(a) shows the initial view of the image area with the object placed on it. To filter the background, an image obtained without objects is used.



(a) (b)

(c) (d)

(e)

Figure 9. Stages of image processing: original image (a), background substraction (b), noise filtering (c), contours detection (d), position and orientation detection (e).

After removing the background, as shown in Figure 9(b), there is a distinct trail of objects, denoted by white color, and some noise associated with the inconsistency of illumination around the object, as well as with the appearance of the side faces of the object. Such appearance is caused by camera view angle.

To remove the noise, only color filtering is used for pixels that are marked as the background difference.

The robot is mostly white on the top side. So, if the pixel marked as the background difference on the processed image also has a white pixel in the original image (determined by the threshold), then this pixel is considered as an object pixel, otherwise the pixel is filtered out, Figure 9(c). As a result, the contour filter determines the precise contour of the object, Figure 9(d), regardless of the view angle of the camera.

At the last stage, the analysis of color marks is performed, Figure 9(e). The robot object has two marks (orange and green). To extract an information about the position of marks, color analysis is used in the area bounding the dimensions of the object. If no marks are found, then this object is not the robot object.

If they are found, then the absolute rotation angle is determined. It is defined as the angle between the vector of the X coordinate axis and the vector defined by the marks.

The coordinates of the position of the object are calculated as the geometric center of the rectangle described around it, rotated to the same angle as the object itself.

3.2. Application of the algorithm

To create a small-scale laboratory robot, we used full-scale robot design with replaceable movers (Figure 10).

Figure 10. The model design and the laboratory robot.

The robot was implemented using 3D printing technology. It's structure completely repeats the original design of the full-scale robot. The robot movement performed by six servo drives, controlled in such a way as to simulate the transmission of a full-scale sample. The turn is performed by slowing the rotation of three servo drives on one side. To control the robot, a single-board Raspberry Pi 2 computer is used.

The computer is powered by a 10000 mAh battery pack, which ensures a continuous work of the robot for up to 4 hours. Servo drives are connected to a separate battery, since they require a voltage of 6V, in addition, separate power circuits for the computer and drives provide better robot stability as the batteries are discharged and the voltage drops. The WiFi module is used to transmit the turn and move commands. The robot also has two cameras for video streaming (Figure 11).

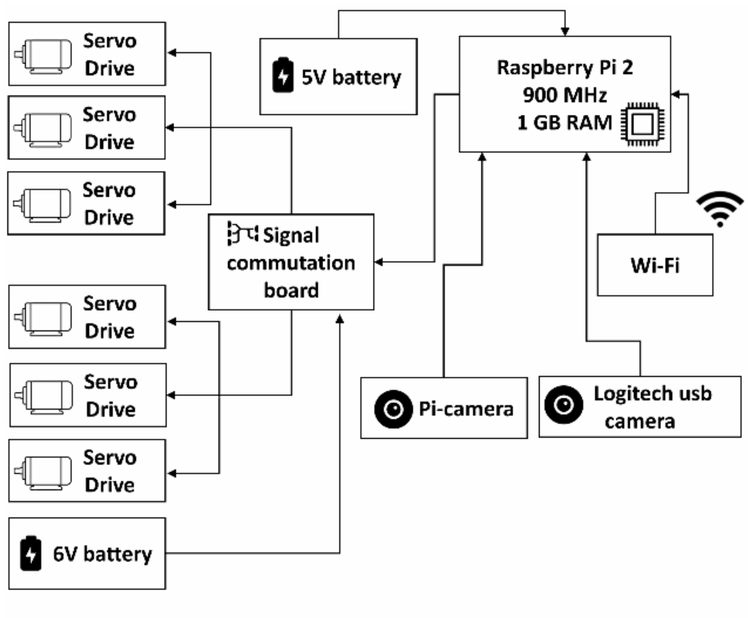


Figure 11. The small-scale robot scheme.

The location of the modules and the general view of the internal design of the robot are shown in (Figure 12).

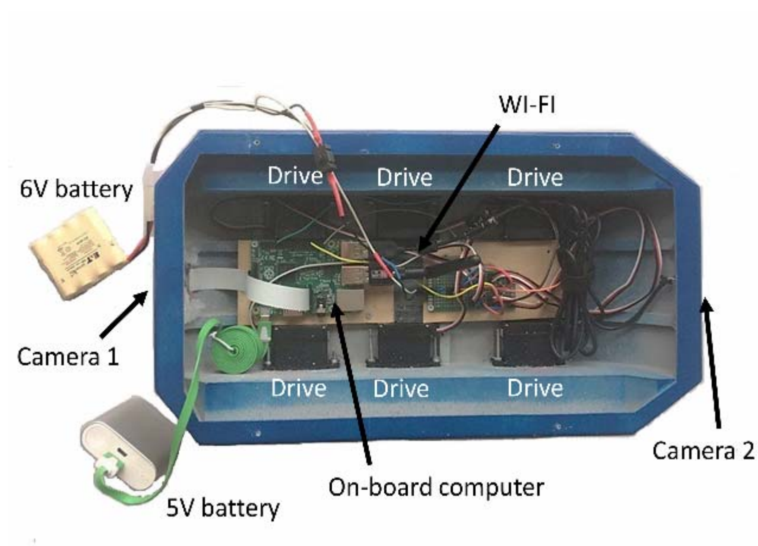


Figure 12. The robot modules structure.

To create a laboratory environment, with various types of road surface (grass, stones, sand), a special track was developed. It consists of square cells forming a single path. Separation into cells makes it possible to use a different filling to reproduce the real off-road conditions of coastal zones and to change the configuration of the track. Figure 13 shows a cell of the track with sand fill.

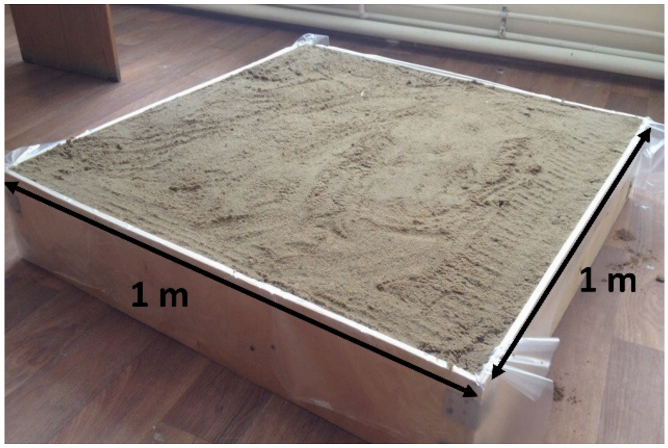


Figure 13. A cell with sand.

To determine the coordinates of the robot and obstacles, two Logitech C920 web cameras installed to the ceiling are used (Figure 14).

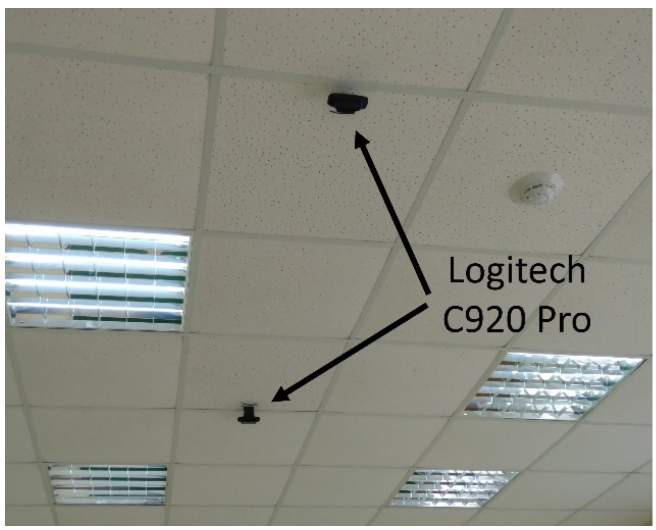


Figure 14. Video registration system.

The track consists of 16 cells and has a total area of 16 m^2. The structure of the track is shown in (Figure 15).

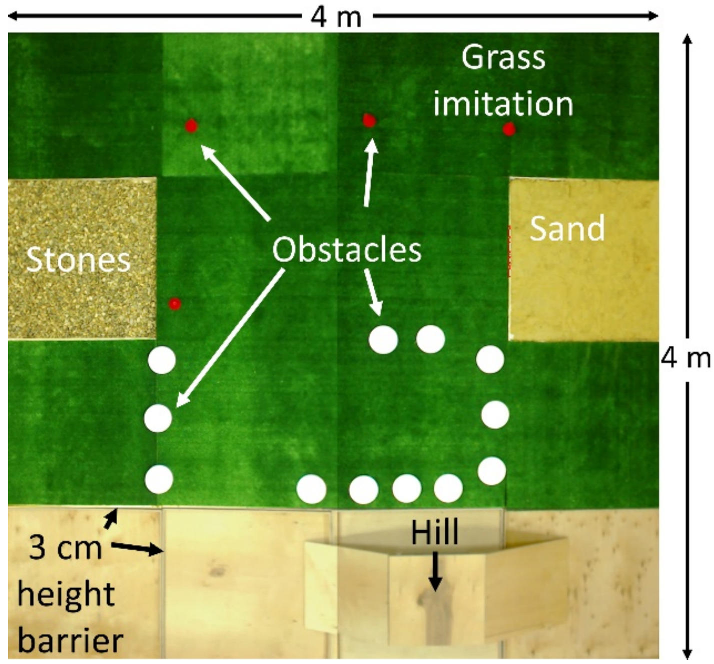


Figure 15. The laboratory environment for simulation of unmanned movement in coastal zones conditions

Figure 16 shows the results of the experiment on autonomous movement using virtual devices for locating the robot position and detecting obstacles, based on a simulation and a real execution in laboratory environment.

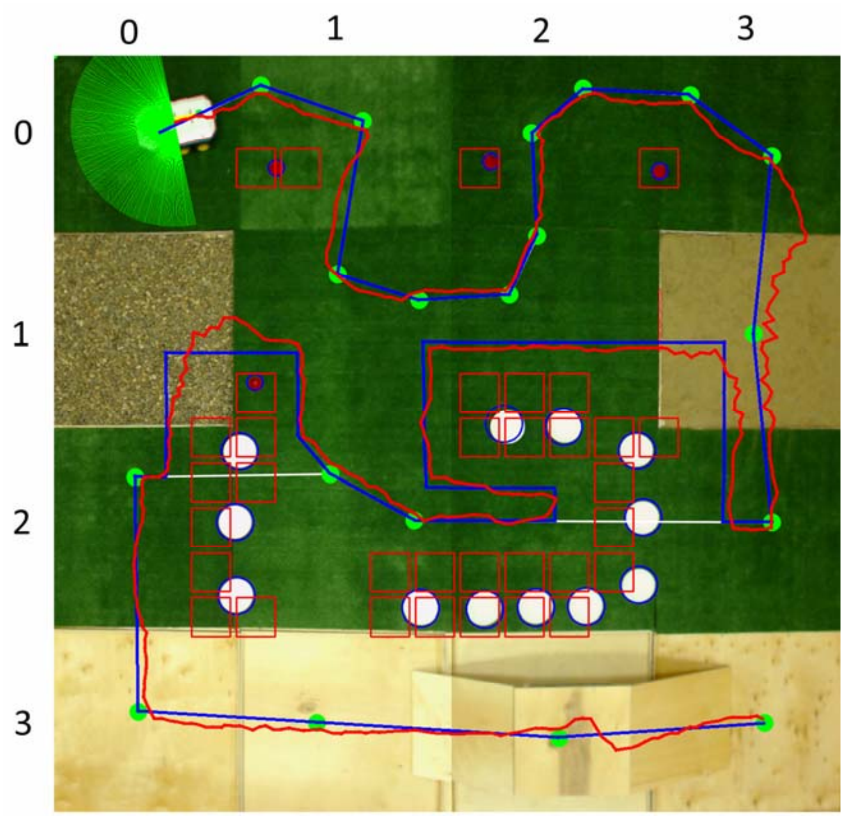


Figure 16. Planned (blue line) and passed (red line) ways of the robot during real execution.

The target route (white line and green points) was planned in such a way to move the robot through every track surface and collide with most of the obstacles. Blue line represents a path obtained during simulation and used as a reference path for error estimation. Red line represents position of the robot during the execution. Square red cells represent the occupancy grid obtained during the experiment.

The experiment started from the cell (3,3). The robot passed the hill of 35-degree slope, and there is a significant error found between reference and obtained paths. Such an error appears at the stage of maximal wheels hanging while moving from sloped surface to horizontal. Next part of the route up to the stones cell (1,0) was mostly optimal.

The cell of the stones also introduces significant error. While passing this cell the robot moved with slipping and roll. Movement in such conditions requires adaptive correction. Next problematic cell is (1,3). It introduces the most significant error due to slipping. The lower half of the cell (as shown in Figure 16) was filled with 35% wet sand and shows lower error in comparison to the upper half that was dry and soft.

Comparison of planned and obtained paths is illustrated by Figure 17.

The results show, that the variability of wheels' friction on different coverage types of the track can essentially influence a trajectory of the movement. Passage of the zones of hill (1), stones (2), wet sand (3) and dry sand (4), given in Figure 18, cause a slip, roll and changes in the parameters of the motion and introduces significant positioning errors.

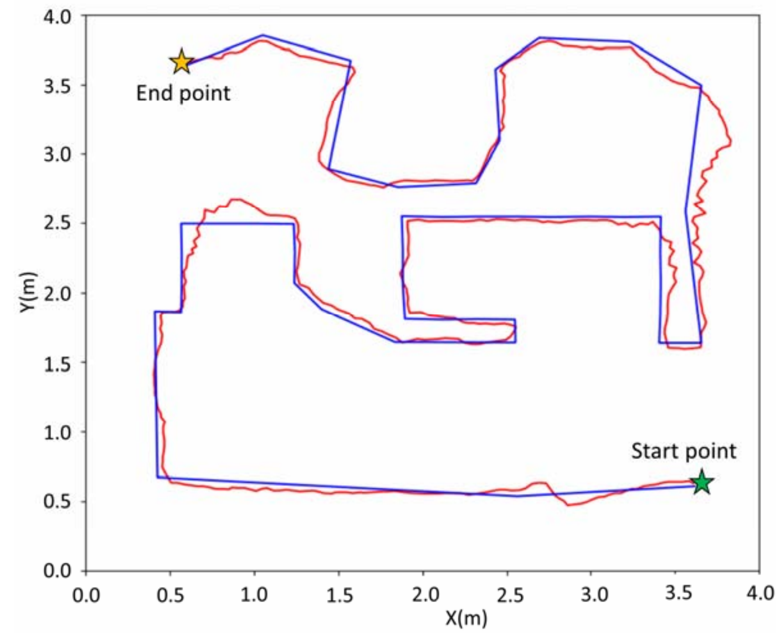


Figure 17. The passed ways during the experiment (blue line – planned path during simulation, red line - real execution)

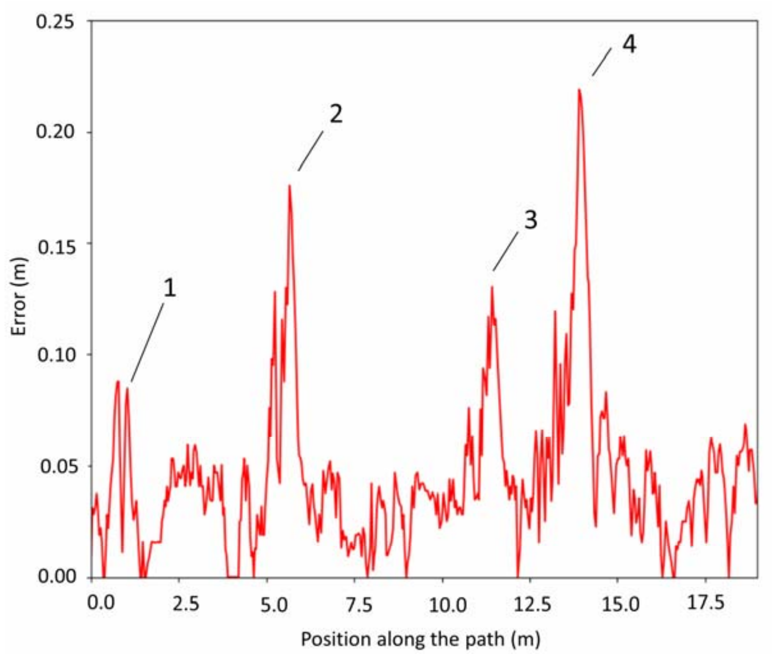


Figure 18. Error estimation between reference and obtained paths

Thus, for the movement of the robot in coastal zones conditions, it is necessary to detect and consider additional parameters. To determine the angle of the robot slope, an electronic gyroscope can be used, to extract vibration parameters, an accelerometer is necessary (Elsts et al., 2014), to detect the slipping, an encoder for each wheel can be applied.

Based on additional data, the basic control algorithm can be supplemented with machine learning algorithms for selecting the optimal speed, depending on the characteristics of the surface.

4. CONCLUSIONS

In the article, we considered the novel approach for exploration of movement characteristics of research autonomous robot in coastal zone conditions with various types of coverage. The conditions for the movement of mobile robotic platforms for a coastal zone are described. They are characterized by different types of road surfaces and complex movement characteristics that cause a robot position error between obtained and reference paths.

The experiments were carried out under laboratory conditions that showed the working capability of the developed approach. Movement characteristics of mobile robot and error estimation for each type of surface are discussed and compared.

New methods and approaches are proposed that can be used in laboratory research, which consist in the creation of algorithms and software based on image processing methods, which allow creating virtual devices - GPS and LIDAR, free of limitations when working in the laboratory, but with characteristics equivalent to real devices.

Further work involves the improvement of motion control algorithms that consider the nature of the road surface, and implement adaptive mobility. The final stage of the project will be the adaptation of algorithms for the full-scale robot and the organization of an expedition for testing it in real coastal zones conditions to determine the various difficulties during the movement.

The discussed software and source code available at http://lmnad.nntu.ru/en/pages/unmanned_lab_robot.

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