Cellular Neural Networks in 3D Laser Data Segmentation

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Abstract: - In this paper, we consider the problem of 3D maps building based on the laser 3D. The map of the environment is represented as a 2D array. Each cell represents rectangular region of the scene and consists of a list of objects. The main advantages of the system are real-time map building, low memory consumption and accuracy. We show that the system works properly in real indoor environment but it can be extended in order to built the map of unstructured environment.

Key-Words: - Map building, laser, cellular neural networks.

1 Introduction

Mobile robots work in a three dimensional real world, but usually they use two dimensional maps which is errors prone and has several limitations. 3D maps allow to move in a hilly surface and to recognize obstacles which are on a different height. Additionally it is impossible to search for certain objects in 2D maps. In robotics stereovision systems are used [1] but they consume a lot of computer resources and need stable light conditions.

In our algorithm we propose to build a 3D map based on 3D laser data. On account of large numbers of data the algorithm must be effective Aggregation and filtration time must be short. Scene representation must be so accurate that a robot must be able to move save and to localize itself. In the literature, there are many ways of scene representation [2, 5, 4, 3], for example creating 3D raster maps [6]. In each cell a value from 0 to 1 is kept and the value represents a probability that there is an obstacle in the cell. Another way of scene representing is to cover obstacles by a polygon network. Usually triangles are used because all vertexes lie on a plane. Sometimes other polygons are used, but first one must check if all vertexes lie on a plane. Scene can also be represented by calculating mathematical equations of obstacles.

All methods shown above consume a lot of computer memory and take a lot of time. Their main disadvantage is that they cannot be used directly in path planning.

Sometimes 2.5D representation is used [7,8], but it is not enough in localization process[9].

In the method presented in the article a hybrid raster-object representation is used. A map is represented as a two dimensional cells table but it differs from classical methods, that it keeps references to objects in each cell. The main idea of the system is using cellular neural networks which allow to do calculations parallel. The idea of the method is shown in fig.1.

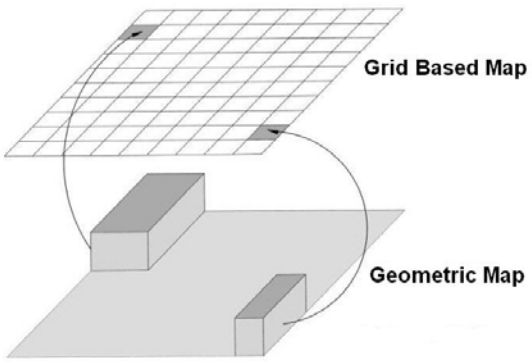


Fig. 1. Model of the environment

2 Cellular Neural Networks

The idea of Cellular Neural Networks (CNN) was introduced by Leon O. Chua and L. Young [10] in 1988. CNN is a single-layer network defined on regular lattices.

$$\frac{dx_{ij}(t)}{dt} = -x_{ij}(t) + \sum_{k,l \in N_{ij}} a_{kl}^{ij} f(x_{kl}(t)) + \sum_{k,l \in N_{ij}} b_{kl}^{ij} f(u_{kl}(t)) + I \qquad (1)$$

where x_{ij} denotes the state of a cell c_{ij} and $ij \in NxM$, where:

N_{ij} denotes the neighborhood of a cell c_{ij} , a_{kl}^{ij} is an interconnection weight between cells a_{kl} and a_{ij} , b_{kl}^{ij} is the feedforward template parameter, u_{ij} is an input signal, and I is bias term, f is a linear saturation function. A cell c_{kl} belongs to the neighborhood of the cell c_{ij} if the condition if fulfilled:

$$\max\{|i-k|,|j-l|\} \leq r, \qquad (2)$$

Where r is a neighborhood parameter.

The dynamic of discrete-time CNN is described by equation:

$$\begin{aligned} x_{ij}(t+1) &= \sum_{c_{kl} \in N_r^{ij}} a_{ij}^{kl} y_{kl}(t) + \sum_{c_{kl} \in N_r^{ij}} b_{ij}^{kl} u_{kl}(t) + I \\ y_{ij}(t+1) &= f_N x_{ij}(t+1) \end{aligned} \qquad (3)$$

Where f_N is output activation function.

Chua extended the definition of CNN in 1997 [11]. It is assumed that it consists of cells that interact locally. This type of CNN can be view as a generalization of cellular automata. The neurons can be modeled as locally connected finite states machines. The state of a cell depends on the states of the neighboring cells, values of input signals, and values of templates. The neurons are usually arranged in rectangular network. Each neuron communicates with nearest neighbors. CNNs are widely used for image processing and patterns recognition but it can be also used for path planning.

2 Hardware

The experiments have been done on a mobile robot "Elektron" which has been design and build at Institute of Automatic Control and Robotics of Warsaw University of Technology.

The basic sensor is a head module comprising a 3-dimentional scanning laser rangefinder used for navigation and creating 3-dimensional representation of the environment. The module consists of a SICK LMS 200 scanning laser rangefinder installed on a rotating head. The head can rotate the scanner around the horizontal axis within the angular range from -15° to +90°.

The scanning laser enables to measure the distance from to the obstacle within 180° with resolution of 0.5°. The data is subsequently transmitted to the control unit by means of an RS 422 bus.

The module is powered by a DC planetary gear motor. The power is then transferred by means of a toothed belt transmission. Two rotational encoders measure the scanning velocity and angle. The first encoder installed on the motor shaft is used for regulating the position whereas the other is responsible for measuring the rotation angle directly on the rotation axis of the scanner. The two measuring systems allow precise steering and positioning of the sensor. The unit controlling the head enables both continuous as well as step-by-step modes of the head. PID control algorithms were used for positioning and controlling the drive unit. Communication with the main control unit is achieved by means of an RS 422 bus.

The robot is presented on the fig. 2.

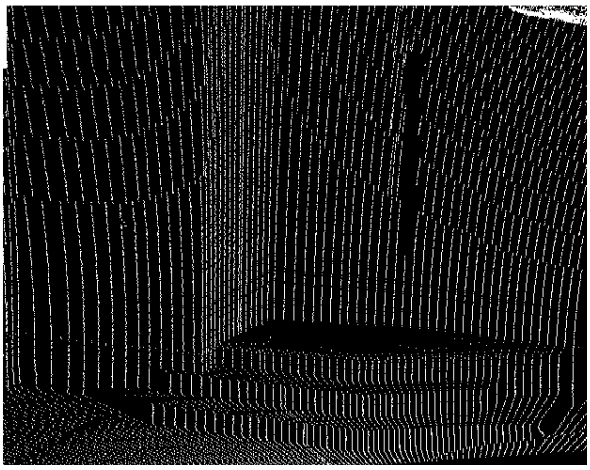
Fig. 2. Robot "Elektron" with 3D laser on a rotating head.

A laser gives data in polar coordinate system $(r_i, \varphi_i, \theta_i)$, where θ_i is vertical angle of rotating support, φ_i is a horizontal scan angle and r_i is the distance to an obstacle. If we assume a robot moves in a flat surface and its position is in the beginning of a Cartesian coordinate system along the OX axis, the position of an obstacle is as follows:

$$x_i = r_i \sin\theta_i \sin\varphi_i$$
$$y_i = r_i \sin\varphi_i \qquad (4)$$
$$z_i = r_i \cos\theta_i \sin\varphi_i$$

Figure 3 shows the real photo and data given from 3D laser.

(a)



(b)

Fig 3. A place where the data was taken (a) and the data from 3D laser (b).

3 System. Architecture

The classical multilayered CNN was used, shown in figure 4. Neurons are positioned on a regular network. Input value u_{ij} to a cell c_{ij} is the value indicated by the laser properly to the horizontal angle $i\Delta\varphi$ and vertical angle θ_j. Based on u_{ij}, horizontal angle φ_i, and vertical angle θ_j it is possible to figure out the position (x,y,z) according to (4). For every point *p*=(x,y,z) a normal vector to the surface is calculated. In our algorithm the normal vector is a product of vectors *p1* and *p2*, where *p1* and *p2* are figured out from the neighborhood points to the analyzed point. Data obtained from a laser is noised and if the distance between points is small (less than laser error) than the vector product error may be high.

In the algorithm *p1* and *p2* are figured out not from the closest points to the explored point *p*, but from such points (x_i, y_i, z_i), where the inequality (5) is fulfilled:

$$\varepsilon_1 \geq \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} \geq \varepsilon_2, \quad (5)$$

where ε, and ε_2 are fixed threshold. The normal vectors are output signal of one layer and input signals to the next one.

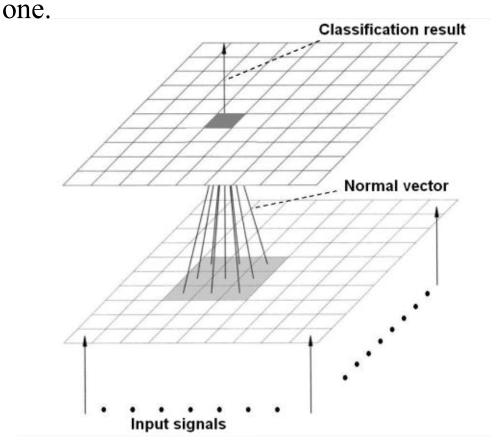


Fig. 4. Network structure

The dimension of layers is the same. Normal vectors neighborhood analyzing allows to do surface classification. The idea behind the method is presented at figure 5.

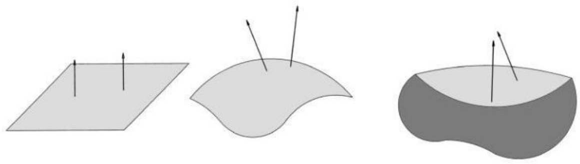


Fig. 5. Normal vectors to flat, convex and concave surfaces.

If a point belongs to a surface, than the neighborhood cells normal vectors are parallel. Figures 6a and 6b present results of data classification where the normal vector is figured out based on respectively the closest and adaptive neighborhood. On figure 6a different colors on the bottom represent negative influence of error in taking measurements to classification.

If a set of points $\{x_i, y_i, z_i\}_{i=1..N}$ lies on a surface:

$$n_x x + n_y y + n_z z + 1 = 0, \qquad (6)$$

than using the regression method [12], we are looking for such parameters n_x, n_y, n_z, that the function *S* (7) has a minimum.

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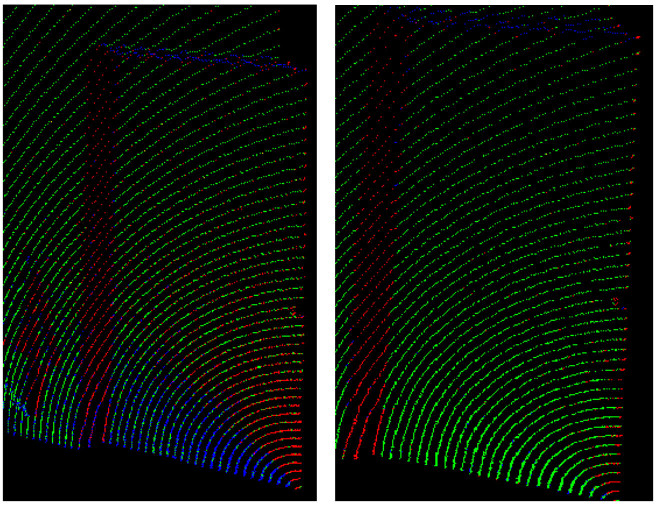
$$S(n_x, n_y, n_z) = \sum_{i=0}^{N} (n_x x_i + n_y y_i + n_z z_i + 1)^2 \qquad (7)$$

Values n_x, n_y, n_z fulfill the equations:

$$\begin{aligned} \frac{\partial S}{\partial n_x} &= 2\sum_{i=1}^{N} (n_x x_i + n_y y_i + n_z z_i + 1) x_i = 0 \\ \frac{\partial S}{\partial n_y} &= 2\sum_{i=1}^{N} (n_x x_i + n_y y_i + n_z z_i + 1) y_i = 0 \\ \frac{\partial S}{\partial n_z} &= 2\sum_{i=1}^{N} (n_x x_i + n_y y_i + n_z z_i + 1) z_i = 0 \end{aligned} \qquad (8)$$

Equitation (8) may be written as (9).

$$\begin{bmatrix} \sum x_i^2 & \sum x_i y_i & \sum x_i z_i \\ \sum x_i y_i & \sum y_i^2 & \sum y_i z_i \\ \sum x_i z_i & \sum y_i z_i & \sum z_i^2 \end{bmatrix} \begin{bmatrix} n_x \\ n_y \\ n_z \end{bmatrix} = \begin{bmatrix} -\sum x_i \\ -\sum y_i \\ -\sum z_i \end{bmatrix} \qquad (9)$$



(a) (b)

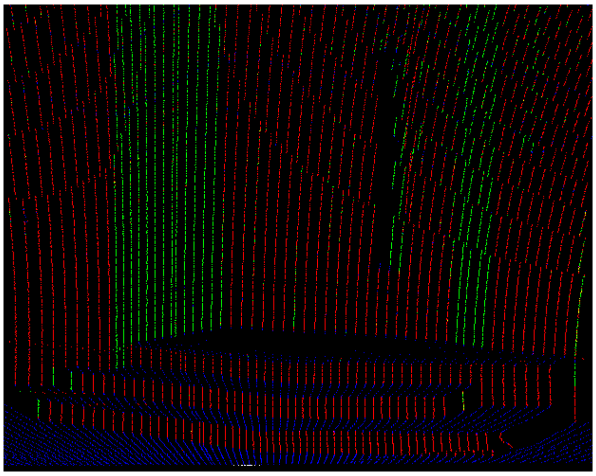
Fig. 6. Points classification a) neighborhood=1, b) adaptive neighborhood.

Uncertainty of the surface position defines the equitation (10):

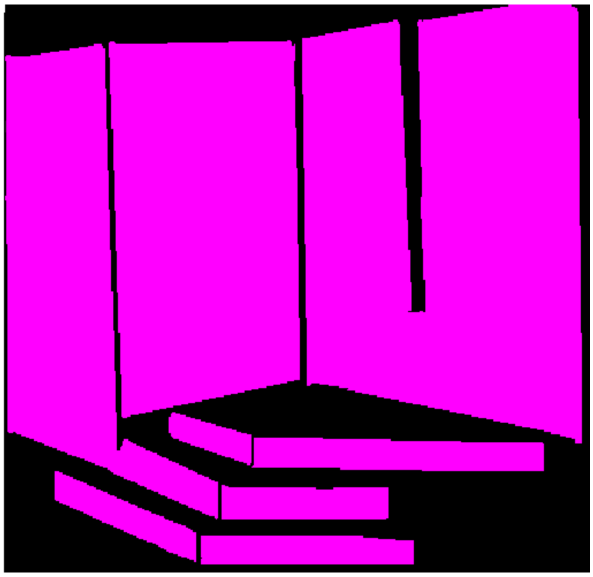
$$\sigma = \frac{1}{N} \sum_{i=1}^{N} \frac{|n_x x_i + n_y y_i + n_z z_i + 1|}{\sqrt{n_x^2 + n_y^2 + n_z^2}} \qquad (10)$$

Figure 7 presents the results of an experiment:

Other kinds of detection may be done, in the similar way, e.g. a point belongs to an edge if neighborhood normal vectors describe such two planes, that crossing the planes describes the edge.



(a)



(b)

Fig. 7. Planes detection. a) Points classification, b) Detected planes.

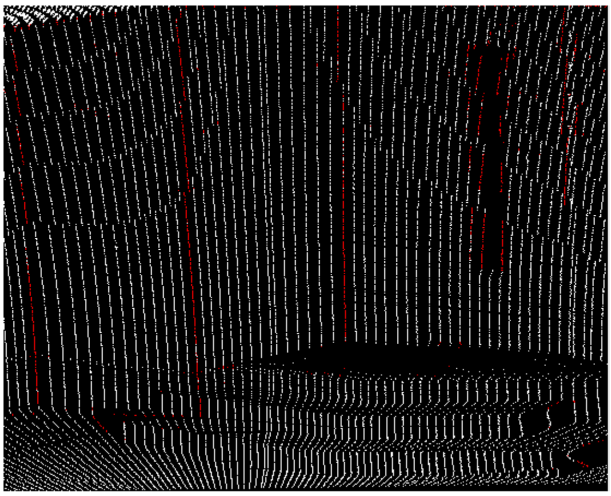


Fig. 8. Vertical edge detection (red lines)

Figure 8 presents the result of vertical edges detection. The same mechanism can be used to detect concave and convex surfaces.

4 Conclusion

In the article a method of using Cellular Neural Networks (CNN) in segmentation data from 3D laser was presented. Our research is a base of a bigger topological system to describe robots environment. Such description will allow to robot to understand human commands given in a natural way, e.g. go the door.

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