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IMPROVEMENT OF THE 3D MAP-BUILDING AND ITS FAST RENDERING USING COMPUTE UNIFIED DEVICE ARCHITECTURE (CUDA)

Key words

Mobile robotics, CUDA, 3D map.

Summary

The following paper shows an improvement of the 3D map-building algorithm and 3D map fast rendering using Compute Unified Device Architecture (CUDA). A computational intelligence algorithm has been applied to approximate 3D LRF data. The 3D data are acquired using 3D Laser Range Finder based on LRF SICK400 mounted onto rotated head of the robot chassis. The new idea of 3D map model is shown. The approximation is performed using the support vector machine (SVM) algorithm that allows to trade off between the model complexity and fitting accuracy. Hough Transform is implemented to obtain the approximation of the flat areas. The composition of the non-linear SVM function and linear function of the Hough algorithm result is implemented to obtain proper representation of the robot environment.

Introduction

The paper shows an improvement of the 3D map-building algorithm and 3D map fast rendering using Compute Unified Device Architecture (CUDA). The main goal is an implementation the robust algorithm of 3D map-building and its fast reconstruction during real time robot operation. The LMS 400, as a base of 3D LRF (Laser Range Finder), was chosen because of its rapid data capture, the long measurement range, high measurement accuracy, and real-time capability. The rotated head was designed for enabling 3D map data acquisition (Fig. 1). The 3D LRF system is the main perception of the cognitive model of the operator-supervisor of the robotic system [1–3] for crisis and disaster management [4].

The computational intelligence algorithm Multi-Kernel Support Vector Machine (MKSVM) and its usage in the 3D map building is shown. The advantage of the MK-SVM is used for non-flat 3D scene approximation. It is obvious that the INDOOR scenario, which has plenty of flat obstacles, such as, walls, floors and ceilings, has made the Hough Transform algorithm suitable to find lines.

The real time improvement of the 3D scene reconstruction, based on usage Common Unified Device Architecture (CUDA), makes the system operates in a real time. Furthermore, even robots without a 3D laser sensor can use this model to avoid obstacles. The experiments show an advantage of presented methods to increase the functionality of the robot perception.

1. 3D Laser Range Finder

The presented robot perception based on LMS SICK400 mounted onto a rotated head is shown in Fig. 1. The ATRVJr robot is used during the experiments. The localisation problem was solved using the odometry system of the robot. Therefore, the increased accuracy of the position of the robot is the main topic of future research, and it is not discussed in this paper.

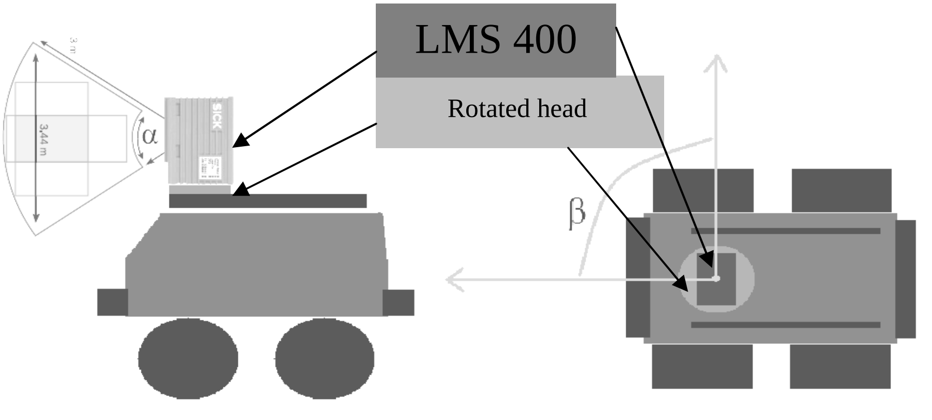

Fig. 1. The scheme of the ATRVJr chassis with mounted LMS SICK400 onto rotated head

The robot ATRVJr shown on Figure 1 is equipped with laser 2D (LMS SICK400). LMS reads data every vertical $\alpha = 0.25^0$ (55^0–135^0), and the horizontal rotating head rotates from

β = -30^0 to 45^0 every 1^0. The measurement set of points is compound by 280 * 75 = 21000 points.

2. SVM Support Vector Machine

The Support Vector Machine algorithm was chosen to approximate complex 3D objects. The idea is to imitate complex shapes by the composition of the Gaussian function. The support vector machine approximation is based on introducing the ε-insensitive loss-function:

$$|S_L - f(\mathbf{x})|_\varepsilon = \max\{0, |S_L - f(\mathbf{x})| - \varepsilon\} \tag{1}$$

where: S_L – represents the data of the 2D LMS400 measurement,
$f(\mathbf{x})$ – the smooth approximation function of S_L,
x – represents the index of the measured point.

The function $f(\mathbf{x})$ can be obtained with precision ε by solving the constraint optimisation problem [5]:

$$\max\left[-\frac{1}{2}\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(\mathbf{x}_i,\mathbf{x}_j)-\varepsilon\sum_{i=1}^{l}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{l}S_{Li}(\alpha_i-\alpha_i^*)\right] \tag{2}$$

subject to

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \qquad \alpha_i,\alpha_i^*\in[0,C] \tag{3}$$

Where: α, α^* – the Lagrange multipliers of each data point,
l – the total number of data points,
C – the maximum value of Lagrange multipliers for points lying outside of the tube,
$k(\mathbf{x}_i, \mathbf{x}_j)$ – the kernel function satisfying Mercer's theorem.

The support vector approximation is equal:

$$f(\mathbf{x})=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)k(\mathbf{x}_i,\mathbf{x})+b \tag{4}$$

The kernel function is given:

$$k(x_i,x)=e^{-\frac{(x_i-x)^2}{2\cdot c^2}} \tag{5}$$

The support vector machine approximation can be solved by using decomposition methods. We applied the Sequential Minimal Optimization (SMO) - extreme decomposition of the QP problem that involves two Lagrange multipliers at one step, the smallest possible optimisation problem, because they must obey a linear equality constraint. The basic operations at every step of the SMO procedure are the heuristic choice of two Lagrange multipliers to jointly optimise, an analytical method to optimise values for these multipliers, and a method for computing b, which updates the SVM to reflect the new optimal values.

The SMO procedure is computationally efficient. It solves two Lagrange multipliers, which can be done analytically with no requirement for large matrix storage. The support vector approximation has some advantageous properties. The points inside the insensitive tube have Lagrange multipliers α, α^*=0; hence, they have no influence on the function approximation. The support vectors are points lying on the border of the tube (their Lagrange multipliers α, $\alpha^* > 0$) and the points lying out of the tube (their Lagrange multipliers α, $\alpha^* = C$).

The quality of SVM approximation strongly depends on the proper choice of the parameters ε and C and on the kernel function and its parameters. The best selection gives the sparse function approximation of high accuracy represented by the least number of support vectors giving rise to the simplest function representation. In our approach, the number of support vectors varies from 12% to 55% of the total number of points of the dataset.

3. MK - Multi Kernel Support Vector Machine

The multi kernel support vector approximation is equal:

$$f(\mathbf{x}) = \sum_{j=1}^{m} \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) k_j(\mathbf{x}_i, \mathbf{x}) + \sum_{j=1}^{m} b \tag{6}$$

The algorithm of the multi-kernel support vector machine training is given:

```
for j = 1:m
        set k(j) //set different kernel for each SVM
        setSVMparams(j) //set proper input parameters
                                    //for each SVM
end

trainingset = inputdata   //input data are given by
                                         //laser system measurement
oldresult = trainSVM(j=1)
newresult = inputdata;
```

```
for j = 2:m
        tempresult = resultSVM(j-1)
        trainingset = newresult – tempresult
        newresult = trainSVM(j)
end
```

The crucial point of the MK-SVM algorithm is the selection of the parameter's value input. After some experiments for MK-SVM, the following values of the parameters were taken into the consideration: C = 3m, ε = 0.02m, j = 2, c1 = 16, c2 = 8. The following Fig. 2 shows 2 kernel functions (c = 8, c = 16). SVM (c = 16) approximates the 2D LRF function with lower accuracy; therefore, the next step of MK-SVM (with kernel c = 8) increases the accuracy of the approximation.

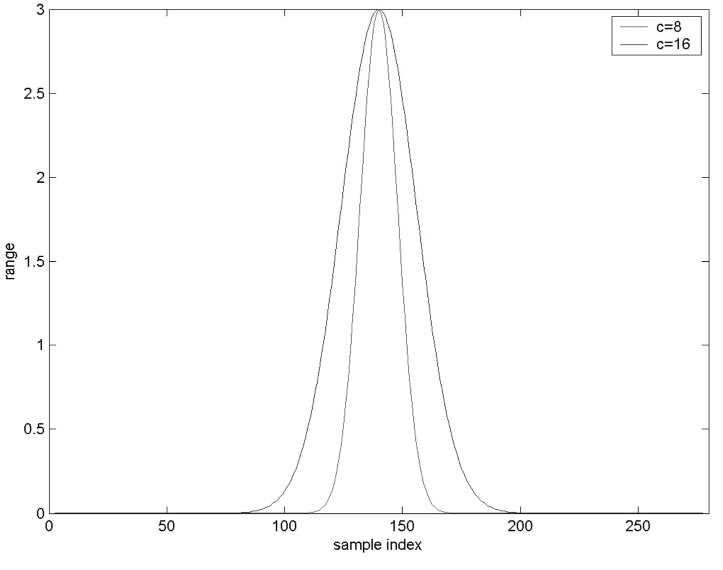

Fig. 2. An example of the Gaussian kernel functions (c = 16, c = 8)

4. Hough transform

The Hough Transform algorithm solves the common problem of fitting a set of line segments to a set of discrete image points (in our case given by 2D LRF measurement).

The steps of algorithm are given as follows:

1. Compute all lines indicated by each pair of points.
2. For each point in the original space, consider all the lines that go through that point. For each line, calculate the distance to the line through the point, and,

if the computed distance is less than its tolerance, the parameter increases the proper Hough accumulator.

3. After considering all the lines through all the points, a Hough accumulator with a highest value will correspond to an expected line of points.

The idea of the set of lines computation for 2D LRF measurement is given: put all points to a set called set_of_points

```
while (number_of_points > tol)
    find line with Hough Transform
    find line interval
    s = size_set_of_points
    clear set_of_points
    for i=1:s
    d = distance point(i) to plane
    if(d<d_tol)
    put point(i) to set_of_points
            end
    end
end
```

The result is the set of line intervals.

5. 3D map model

The following, Fig. 3, shows an example of the robot path with nodes stored in 3D local maps. The robot has to stop the movement to start building the local 3D map. Once the 3D local map is computed, the node is added to list of nodes; therefore, the 3D model is developed.

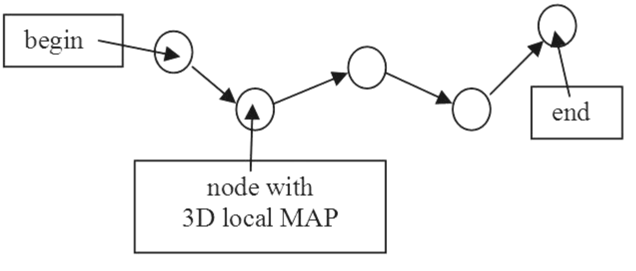

Fig. 3. The robot path with nodes stored on 3D local map

The complexity of the 3D map model determines the CUDA (Common Unified Device Architecture) usage for real time rendering. Figure 4 shows the idea of the 3D map reconstruction.

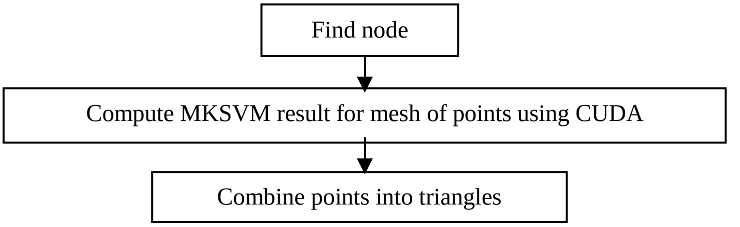

Fig. 4. Algorithm for 3D map reconstruction

The idea of using CUDA for local 3D map reconstruction given by MK-SVM is based on the usage of multi-parallel GPU architecture for computing the mesh of points in separate threads. Each thread executes the computation of Equation 6; therefore, the set of points is obtained in the time needed to compute a single point.

For the model obtained by Hough Transform to reconstruct the 3D scene, the neighbouring line intervals are connected as triangles. The biggest problem to solve is to compound the model obtained by MK-SVM with model obtained by the Hough Transform. The model based on line intervals is computed as first; therefore, the subset of points not satisfying distance to line interval constraint gives an input for the MK-SVM mesh of points reconstruction procedure. In this way, flat areas are approximated by a compound of triangles from line intervals, non-flat areas are approximated by non-linear function MK-SVM.

6. Experiments

The experiments show the approximation of the LRF range function. The input set of points consists of 280 measurement points. The maximum range is determined by the LMS SICK400 capacity (less than 3m). The results are obtained using SMO Sequential Minimal Optimization algorithm [4] for MK-SVM Multi-Kernel Support Vector Machine. Figs. 5 and 6 show the approximation of the LRF range function.

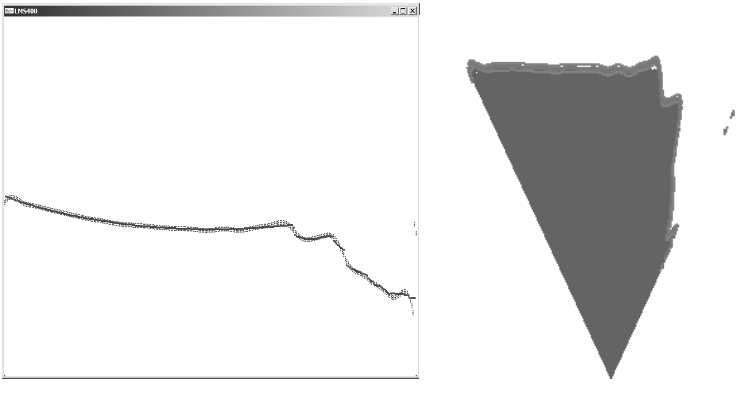

Fig. 5. LRF approximation using MK-SVM algorithm

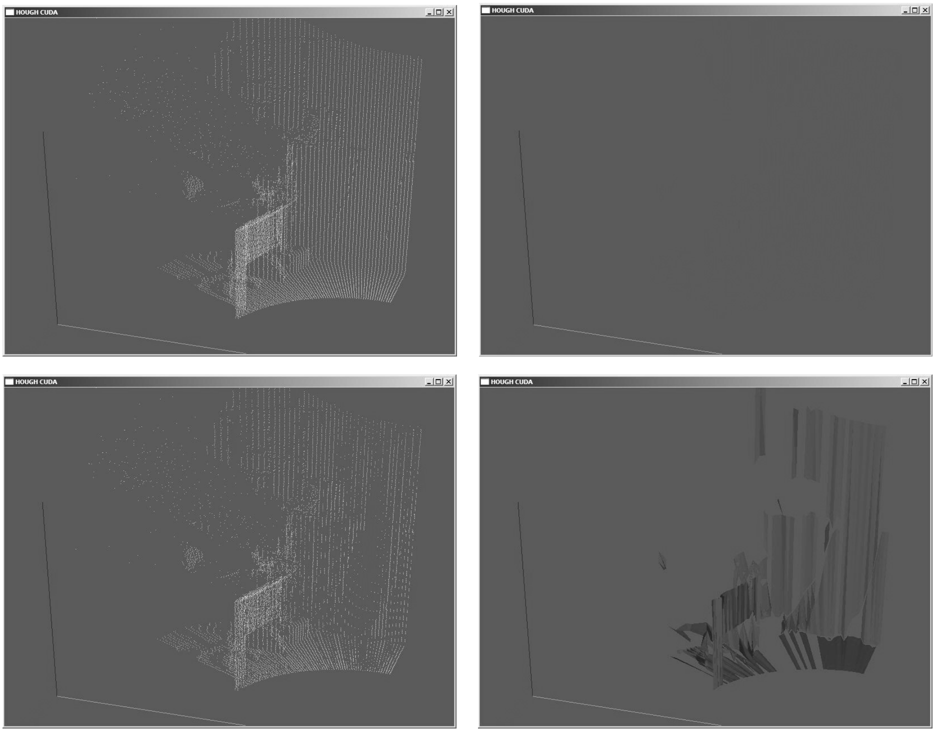

Fig. 6. An example of the Hough Transform approach for the detection of line intervals. Top left – 3D points of the local map, top right – line intervals, bottom left – combined lines with points, bottom right – reconstructed 3D scene

Conclusions

The usage of the Multi-Kernel Support Vector Machine in the 3D map building is investigated. The goal is achieved. The Multi-Kernel Support Vector Machine solves the problem of approximation efficiently. Therefore, the model of LRF measurement function is obtained. Furthermore, the model is used for 3D scene reconstruction. The 3D map building efficiency is increased by the CUDA - based implementation. The idea of the approximation of flat regions, using the Hough Transform is shown. The advantage of compounding Hough Transform and MK-SVM with a non-linear kernel is introduced.

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Reviewer:
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Usprawnienie budowy i szybkiego odtwarzania sceny 3D z wykorzystaniem technologii obliczeń równoległych (CUDA)

Słowa kluczowe

Robotyka mobilna, CUDA, mapa 3D.

Streszczenie

W niniejszym artykule przedstawiono algorytm budowy trójwymiarowej sceny 3D oraz możliwość jej szybkiego odtwarzania z wykorzystaniem architektury obliczeń równoległych CUDA (Compute Unified Device Architecture). Algorytm sztucznej inteligencji zastał zastosowany do aproksymacji danych 3D zebranych z laserowego czujnika odległości. Dane do eksperymentu zostały zebrane z laserowego czujnika odległości LRF SICK 400 zamontowanego na obrotowej głowicy umieszczonej na robocie mobilnym. W artykule zaprezentowano nowe podejście do budowy trójwymiarowej mapy otoczenia. Aproksymacja została zrealizowana przy użyciu algorytmu maszyny wektorów wspierających SVM (Support Vector Machine) pozwalającego na zapewnienie równowagi pomiędzy złożonością modelu a dokładnością obliczeń. Transformata Hough-a została zaimplementowana w celu aproksymacji płaskich powierzchni. Połączenie nieliniowej funkcji SVM oraz liniowej funkcji transformaty Hough-a pozwala na otrzymanie poprawnej reprezentacji otoczenia robota.