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INTELIGENCJA OBLICZENIOWA W ZASTOSOWANIU DO KOGNITYWNEGO NADZOROWANIA SYSTEMU WIELU ROBOTÓW PRACUJĄCYCH W SIECI

W niniejszym artykule zaprezentowano zastosowanie inteligencji obliczeniowej w do kongitywnego nadzorowania systemu wielu robotów pracujących w sieci. Został opisany kognitywny model człowieka nadzorcy. Koncepcja implementacji kognitywnego modelu człowieka-operatora została przedstawiona. Wykorzystanie algorytmów inteligencji obliczeniowej zostało opisane oraz implementacja metod klasyfikacji oraz regresji została przedstawiona. Zostało przedstawione opracowanie komponentów systemów z zastosowaniem zwiększającej wydajność architektury CUDA (Compute Unified Device Architecture).

COMPUTATIONAL INTELLIGENCE APPLIED IN COGNITIVE SUPERVISION OF THE WEB CONNECTED MULTI-ROBOTIC SYSTEM

Following paper is focused on the computational intelligence applied in cognitive supervision of the web connected multi-robotic system. The cognitive model of the human operator is described. The concept of the implementation of the cognitive model of human – operator is shown. The computational intelligence algorithms' usage in cognitive supervision is described, therefore the implementation of the classification and regression methods are presented. The development of the system components using Compute Unified Device Architecture (CUDA) is shown, therefore the increased performance is proven.

1. INTRODUCTION

This paper describes the Cognitive Theory – Based Approach of multi mobile robot control with focus on artificial intelligence application. The main goal of the approach lays on the implementation of the self reasoning which is provided by the model of human supervisor. The interfaces are implemented in server – client scheme, because the mobile platforms are prepared to cooperate in distributed control system. All the cooperation shown above requires a kind of complex architecture which can be derived from CORBA. This paper as well, has shown how the architecture is applied and in general inducing an idea of multi-robot supervision.

In managing the complexity of the attributes of the system as been described above, then the behavioral conceptual adoption should be applied. This application succeed it's intelligence system by perpetuating the decision selection system which grounding its operation by the fuzzyARTMAP algorithm system. This skill is a prominent achievement which leads into the perceptual associative memory, as another essential attribute of the systematic cognitive system that this research borrowed it's concept.

The perceptual associative memory in this system particularly rendered by an ability to interpret the incoming stimuli by recognizing individuals or objects, categorizing them and noting the relationships between the objects and categories. These attributes mentioned above are showing the pertinent robot action which are always consistent with the categories and their relations. So far, the study has able to provide the new approach of the robot's cooperation system

In the application, the autonomous mobile robot is accompanying the teleoperated one. Meanwhile, the main goal for the mobile robot itself is to acquire data from the environment and delivers into Command Operation Center through the wireless communication system. The concept of building geometrical map using MK-SVM Multi Kernel Support Vector Machine is presented. COC is functioned by the existing system of the cognitive modeled of human supervision which perceptually and behaviorally are able to recognize and execute the procedures needed in the case of some risky events, particularly the collision problems given by supervision of autonomous navigation module. Therefore the two substantial components from the perception and association actions by mapping and localizing tasks are achieved by the system.

2. WEB CONNECTED ROBOTICS SYSTEM

The industry standard CORBA has been chosen for the implementation of the distributed robotic control system. CORBA is language and platform independent. Using such a standard simplifies the development and improves the interoperability with existing software. CORBA is actually a specification of the Object Management Group and the TAO (The ACE ORB) implementation has been chosen among others because it is an open source, efficient and standards-compliant real-time implementation of CORBA. Each system component provides CORBA server with its functionality, therefore each sensor can be read by CORBA clients.

3. COGNITIVE SUPERVISION

Following scheme (fig. 1) shows an idea of cognitive model of human operator of the multi robotic system. Cognitive layer is a virtual space, where set of procedures is responsible for self reasoning based on input data given by robot sensors [2]. The 3D map arrow represents the geometrical map building using Hough transform and MK-SVM algorithm for convex figures. Cognitive map is solving supervision of autonomous navigation task.

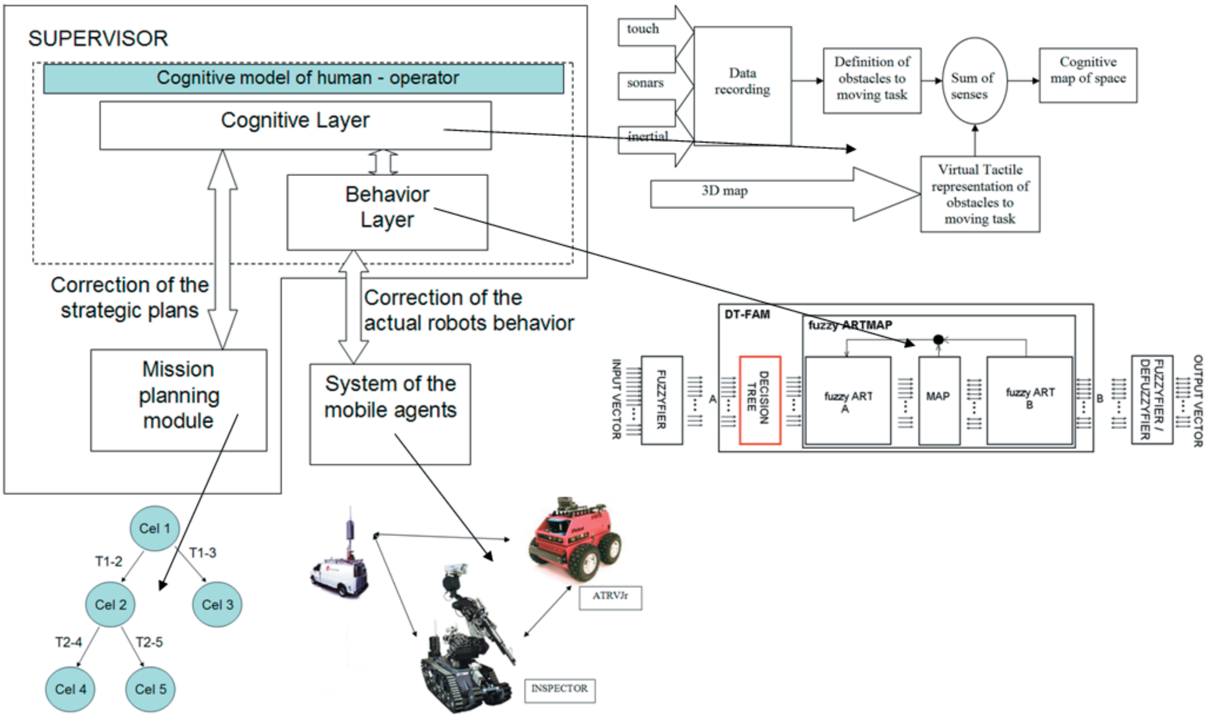

Fig. 1. Cognitive model of the human – operator

Behavior Layer solves the autonomous navigation task. We consider using VFH+ algorithm or alternatively fuzzyARTMAP neural network for obstacle avoidance. System of the mobile agents is built from mobile platforms connected by Ethernet operating in CORBA distributed control system. Mission planning module stores mission plans, therefore cognitive model can supervise the mission execution using graph similarity methods.

Cognitive model of human–operator is able to learn by developing geometrical map, set of mission plans, and learning fuzzyARTMAP.

4. HMI/CMMI (HUMAN MACHINE INTERFACE/COGNITIVE MODEL – MACHINE INTERFACE)

We introduce the new concept of Cognitive Model – Machine Interface (CMMI). Following fig. 2 shows the visualization of the Cognitive map of space. We assume that our approach provides useful mechanism for Cognitive map of space understanding, in the same time the visualization of the mentioned cognitive map can be used as the Human Machine Interface. Presented idea is showing cognitive nature of the cognitive model human – operator. We can assure that, model has imagination about robots position, it is visualized by robot models rendered on the global map. Model has imagination about mission and its execution, therefore the mission is represented by set of flags correspond to local goals. The model has knowledge about geometrical representation of the environment, therefore it can execute supervision if the autonomous navigation task. The geometrical map is given by rendered triangles, supervision of the autonomous navigation corresponds to the color of the rectangular prism surrounding mobile robot. If red color occurs, it denotes a problem.

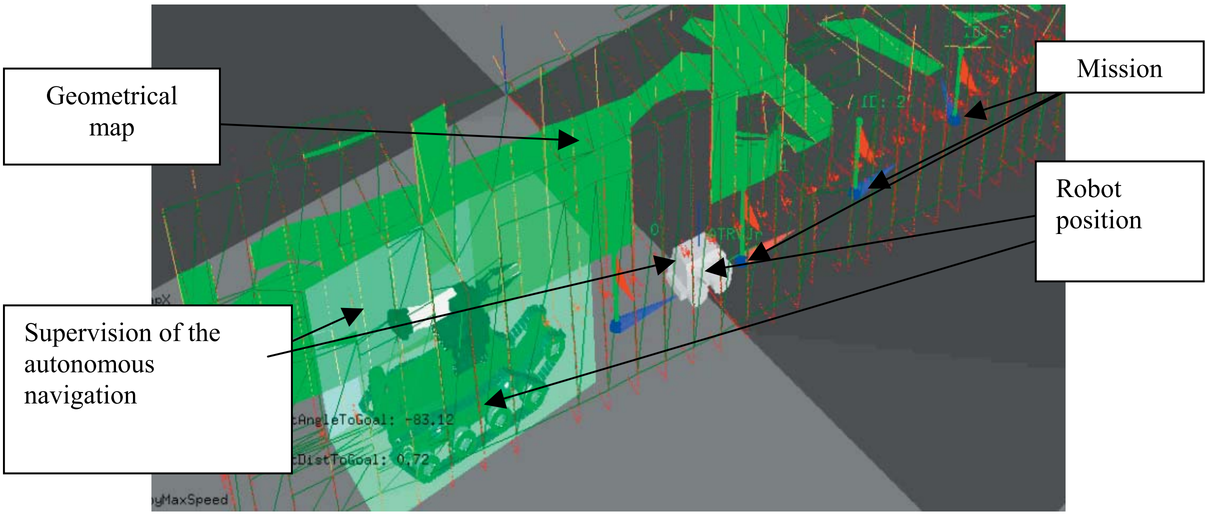

Fig. 2. Visualization of the Cognitive map of space

5. GEOMETRICAL MAP

We assume that at least one mobile robot is equipped with sensor available to build geometrical 3D map. For the experimental purpose we equipped mobile platform with 3D Laser Range Finder. Therefore the 3D range data can be acquired during the robot executing task. Fig. 3 shows a scheme for 3D map representation on the flat area as the set of nodes stores local 3D maps.

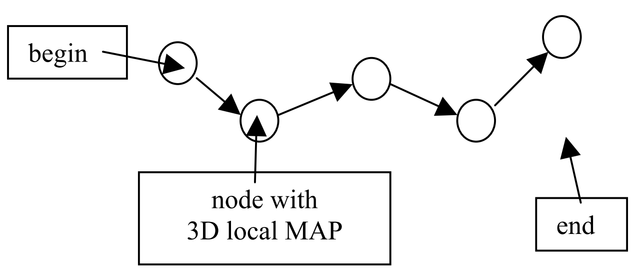

Fig. 3. The robot path with nodes stored 3d local MAP

The geometrical map is a basic input for the supervision of the autonomous navigation. 3D local map is built from triangles. To compute the set of triangle we are using Hough transform for line extraction and for rest points the SVM – Support Vector Machine for convex figure approximation. 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 RLF measurement, $f(\mathbf{x})$ is the smooth approximation function of S_L and the vector $\mathbf{x}$ represents the index of the measured point.

The function $f(\mathbf{x})$ can be obtained with precision ε by solving the constraint optimization problem [4]

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

subject to

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

where α, α^* are the Lagrange multipliers of each data point, l is the total number of datum points, C is the maximum value of Lagrange multipliers for points lying outside of the tube and $k(\mathbf{x}_i, \mathbf{x}_j)$ is 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 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 optimization problem, because they must obey a linear equality constraint. The basic operations at every step of the SMO procedure are: heuristic choice two Lagrange multipliers to jointly optimize, analytical method to optimize values for these multipliers, a method for computing b, 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 $\alpha, \alpha^*=0$, hence they have no influence on the function approximation. The support vectors are points lying on the border of the tube (their Lagrange multipliers $\alpha, \alpha^* > 0$) and the points lying out of the tube (their Lagrange multipliers $\alpha, \alpha^* = C$).

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.

We introduce an imprudent of the SVM algorithm [1] – MK-SVM. The multi kernel support vector (MK-SVM) approximation is given:

$$f(\mathbf{x}) = \sum_{j=1}^{m}\sum_{i=1}^{l}(\alpha_i - \alpha_i^*)k_j(\mathbf{x}_i, \mathbf{x}) + \sum_{j=1}^{m} b \tag{5}$$

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 for our cognitive decision computation is the 3d map reconstruction. To obtain the virtual laser beam measurement the reconstruction of the local 3d map of the node (fig. 3) has to be done in real time mode to keep the safety of the mobile platform movement. It is important to realize, that presented idea allows to operate the platform without sensors in 3d space. The 3d map and localization problem have to be solved to achieve the manipulation safety of the "blind" robot. We applied the Common Unified Device Architecture (CUDA) to solve the highly computational complexity of the problem.

The following fig. 4 shows the idea of the 3d map reconstruction for convex figures.

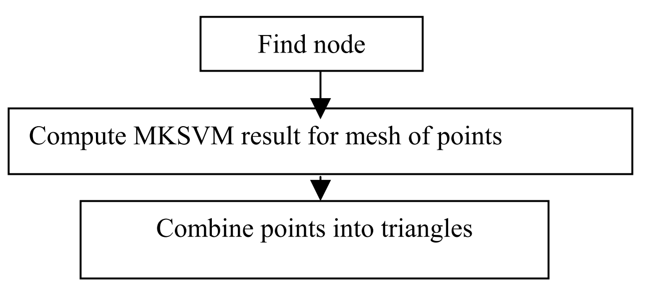

Fig. 4. Algorithm for 3D map reconstruction

The *Find node* block represents the algorithm of robot path searching (the robot paths is shown on fig. 3) to obtain the node which stores the 3d local MAP. The *Compute MKSVM result for mesh of points* block represents the algorithm of the 3d local map points computation using equation 5 (MKSVM approximation). The input is defined as matrix of points I[i, j] (x, y, α_i ,β_j) , where x, y are the node positions in global map, α_i and β_j are the vertical and horizontal angles of the laser beam. The *Combine points into triangles* block represents the algorithm of the obtaining the set of rendered triangles from mesh of computed 3d points.

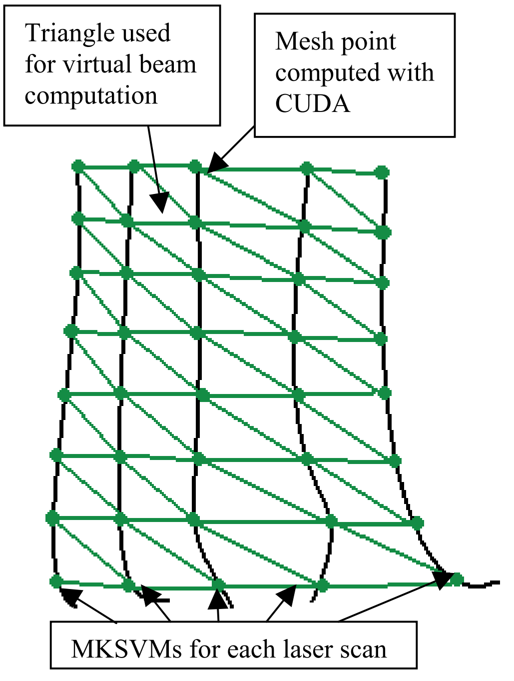

Fig. 5. The idea of 3d map reconstruction.

To compute mesh of points of the 3D map we are using Compute Unified Architecture (NVIDIA CUDA). Therefore the computation is executed in highly parallel way. The result of the map 3D reconstruction algorithm is the set of the vertexes of the 3D robot environment. The reconstruction algorithm is based on the kernel execution in the Grid of Thread Blocks. There is a limited maximum number of threads that a block can contain. The implementation uses 256 threads (16 x 16). Blocks of the same dimensionality and size that execute the same kernel are batched together into a grid of blocks, therefore the number of threads that can be launched in a single kernel invocation is much larger:

$$NTh = Dx\_Th * Dy\_Th * Dx\_B * Dy\_B \tag{6}$$

where:

NTh – number of threads, Dx_Th – number of rows in thread table, Dy_Th – number of columns in thread table, Dx_B – number of rows in grid table, Dy_B – number of columns in grid table.

Each thread is identified by its thread ID, which is the thread number within the block ID_Th(x, y) = x+y*Dx_Th. Each block is identified by it's block ID, which is the block number within the grid ID_B(x, y) = x+y*Dx_B [9]. Each thread executes the kernel function for one triangle of the scene, therefore the maximum number of triangles are limited by number of threads - NTh. The following picture shows the thread organization as a grid of thread blocks.

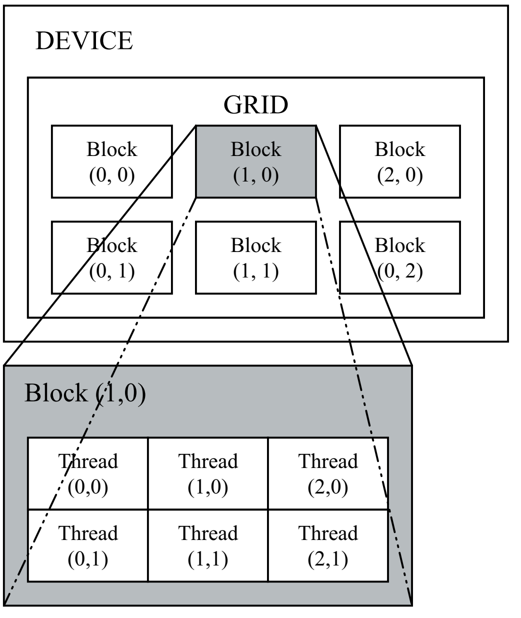

Fig. 6. The thread organization as a grid of thread blocks

The thread realizes the kernel function for the input data assign by its block id. For the 3D reconstruction kernel's function realizes the equation (5). Further, the reconstructed map is used for virtual laser beam computation for cognitive supervision. Therefore the collision detection between robot chassis and the complex environment is obtained. The virtual laser beam measurement is coded into the tactile representation of the 3D scene as an input of the classifier.

6. SUPERVISION OF AUTONOMOUS NAVIGATION

Robot navigation means its ability to determine its own position in its frame of reference and then to plan a path towards some goal location. In order to navigate, the mobile robot requires representation of its environment i.e. a map of the environment and the ability to interpret that representation. The art of navigation consists of smaller robot competences like:

-ability to self-localizing in the environment, which requires

-map-Building and Map-Interpretation

-ability to path plan

-local obstacle avoidance

Localization denotes the robot's ability to establish its own position and orientation within the frame of reference. Path planning is effectively an extension of localization, in that it requires the determination of the robot's current position and a position of a goal location, both within the same frame of reference or coordinates. Map building can be in the shape of a metric map or any notation describing locations in the robot frame of reference. In this study we will present the most popular approaches to global path planning using A* and Dijkstra's algorithms and two approaches to local obstacle avoidance using VFH (Vector Field Histogram) and Fuzzy ARTMAP. It is worth to mention main advantages of two algorithms to global path planning. A* algorithm is preferred when searching the shortest path from the position point of the robot to the target point. It is experimentally proved to get the shortest path in reasonably short time using this algorithm. On the other hand Dijkstra's algorithm is preferred when the robot needs to search shortest paths to many targets and choose one on this basis.

The idea of robot navigation in 3D virtual world built from 3D LRF data is based on the verification of the hypothesis of the motion without collision. Multi hypothesis verification is high computational task, therefore CUDA capabilities are used for solving real time navigation. The basic object of the algorithm is the rectangular prism. Scene is represented as set of triangles and cloud of points. The fundamental procedure of 3D navigation is based on verification if there is an intersection of the triangle from the scene with current rectangular prism. If intersection appears the probability of safety navigation in current direction is low and decreases when another intersection is detected.

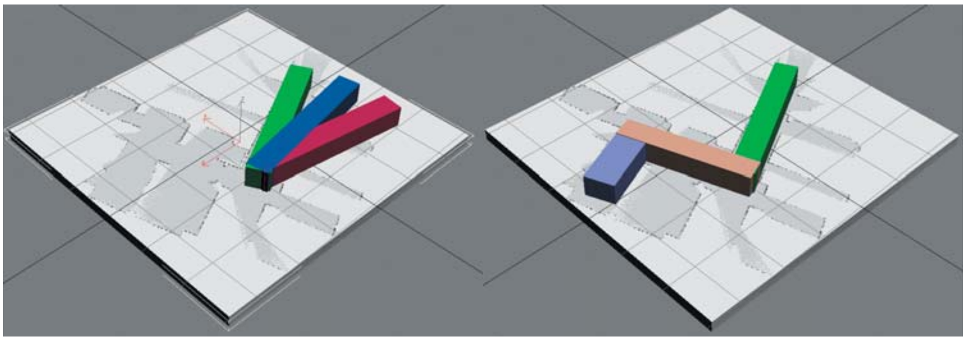

Fig. 7. Supervision of the autonomous navigation.

7. CONCLUSION

The following paper has described the Cognitive Theory – Based Approach of multi mobile robot control. The main goal of the approach lays on the implementation of the computational intelligence applied to decision selection which is provided by the model of human supervisor. The usage of the Multi Kernel Support Vector Machine in the robotic system with cognitive supervision is investigated. The goal is achieved. Multi Kernel Support Vector Machine solves the problem of approximation efficiently. The concept of Cognitive Model – Machine Interface (CMMI) is presented, therefore useful mechanism for Cognitive map of space understanding, in the same time the visualization of the mentioned cognitive map can be used as the Human Machine Interface. The idea of robot navigation in 3D virtual world built from 3D LRF data based on the verification of the hypothesis of the motion without collision is shown. The advantage of Compute Unified Device Architecture usage in cognitive supervision is shown.

8. REFERENCES

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