THE LAGR PROJECT
Integrating Learning into the 4D/RCS Control Hierarchy

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Abstract: The National Institute of Standards and Technology's (NIST) Intelligent Systems Division (ISD) is a participant the Defense Advanced Research Project Agency (DARPA) LAGR (Learning Applied to Ground Robots) Project. The NIST team's objective for the LAGR Project is to insert learning algorithms into the modules that make up the 4D/RCS (Four Dimensional/Real-Time Control System), the standard reference model architecture to which ISD has applied to many intelligent systems. This paper describes the 4D/RCS structure, its application to the LAGR project, and the learning and mobility control methods used by the NIST team's vehicle.

1 INTRODUCTION

The National Institute of Standards and Technology's (NIST) Intelligent Systems Division (ISD) has been developing the RCS (Albus-1, 2002; Albus-2, 2002) reference model architecture for over 30 years. 4D/RCS is the most recent version of RCS developed for the Army Research Lab Experimental Unmanned Ground Vehicle program. The 4D in 4D/RCS signifies adding time as another dimension to each level of the three dimensional (sensor processing, world modeling, behavior generation), hierarchical control structure. ISD has studied the use of 4D/RCS in defense mobility (Balakirsky, 2002), transportation (Albus, 1992), robot cranes (Bostelman, 1996), manufacturing (Shackleford, 2000; Michaloski, 1986) and several other applications.

In the past year, ISD has been applying 4D/RCS to the DARPA LAGR program (Jackel, 2005). The DARPA LAGR program aims to develop algorithms that enable a robotic vehicle to travel through complex terrain without having to rely on hand-tuned algorithms that only apply in limited environments. The goal is to enable the control system of the vehicle to learn which areas are traversable and how to avoid areas that are impassable or that limit the mobility of the vehicle. To accomplish this goal, the program provided small robotic vehicles to each of the participants (Figure 1). The vehicles are used by the teams to develop software and a separate DARPA team, with an identical vehicle, conducts tests of the software each month. Operators load the software onto an identical vehicle and command the vehicle to travel from a start waypoint to a goal waypoint through an obstacle-rich environment. They measure the performance of the system on multiple runs, under the expectation that improvements will be made through learning.

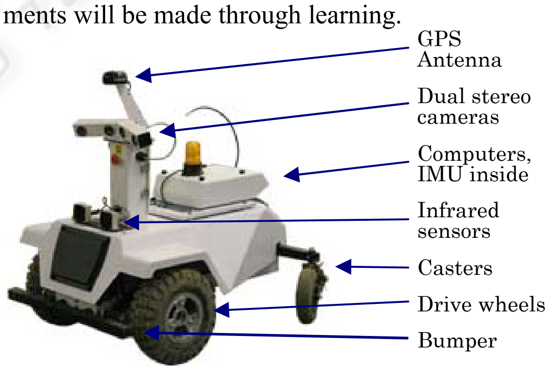

Figure 1: The DARPA LAGR vehicle.

The vehicles are equipped with four computer processors (right and left cameras, control, and the planner); wireless data and emergency stop radios; GPS receiver; inertial navigation unit; dual stereo cameras; infrared sensors; switch-sensed bumper; front wheel encoders; and other sensors listed later in the paper.

Section 2 of this paper describes the 4D/RCS Reference Model Architecture followed by a more

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specific description of the 4D/RCS application to the DARPA LAGR Program in Sections 3. Sections 4 include a summary and conclusion.

2 4D/RCS REFERENCE MODEL ARCHITECTURE

The 4D/RCS architecture is characterized by a generic control node at all the hierarchical control levels. The 4D/RCS hierarchical levels are scalable to facilitate systems of any degree of complexity. Each node within the hierarchy functions as a goal-driven, model-based, closed-loop controller. Each node is capable of accepting and decomposing task commands with goals into actions that accomplish task goals despite unexpected conditions and dynamic perturbations in the world.

At the heart of the control loop through each node is the world model, which provides the node with an internal model of the external world (**Figure 2**). The world model provides a site for data fusion, acts as a buffer between perception and behavior, and supports both sensory processing and behavior generation.

In support of behavior generation, the world model provides knowledge of the environment with a range and resolution in space and time that is appropriate to task decomposition and control decisions that are the responsibility of that node.

A world modeling process maintains the knowledge database and uses information stored in it to generate predictions for sensory processing and simulations for behavior generation. Predictions are compared with observations and errors are used to generate updates for the knowledge database. Simulations of tentative plans are evaluated by value judgment to select the "best" plan for execution. Predictions can be matched with observations for recursive estimation and Kalman filtering. The world model also provides hypotheses for gestalt grouping and segmentation. Thus, each node in the 4D/RCS hierarchy is an intelligent system that accepts goals from above and generates commands for subordinates so as to achieve those goals.

The centrality of the world model to each control loop is a principal distinguishing feature between 4D/RCS and behaviorist architectures. Behaviorist architectures rely solely on sensory feedback from the world. All behavior is a reaction to immediate sensory feedback. In contrast, the 4D/RCS world model integrates all available knowledge into an internal representation that is far richer and more complete than is available from immediate sensory feedback alone. This enables more sophisticated behavior than can be achieved from purely reactive systems.

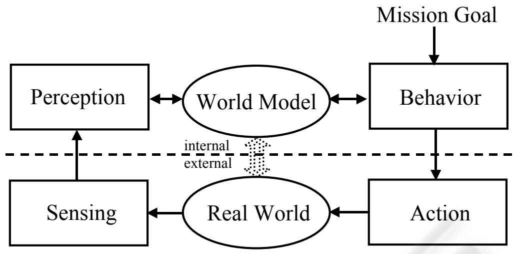


Figure 2: The fundamental structure of a 4D/RCS control loop.

The nature of the world model distinguishes 4D/RCS from conventional artificial intelligence (AI) architectures. Most AI world models are purely symbolic. In 4D/RCS, the world model is a combination of instantaneous signal values from sensors, state variables, images, and maps that are linked to symbolic representations of entities, events, objects, classes, situations, and relationships in a composite of immediate experience, short-term memory, and long-term memory. Real-time performance in modeling and planning is achieved by restricting the range and resolution of maps and data structures to what is required by the behavior generation module at each level. Short range and high resolution maps are implemented in the lowest level, with longer range and lower resolution maps at the higher level.

A high level diagram of the internal structure of the world model and value judgment system is shown in Figure 3. Within the knowledge database, iconic information (images and maps) are linked to each other and to symbolic information (entities and events). Situations and relationships between entities, events, images, and maps are represented by pointers. Pointers that link symbolic data structures to each other form syntactic, semantic, causal, and situational networks. Pointers that link symbolic data structures to regions in images and maps provide symbol grounding and enable the world model to project its understanding of reality onto the physical world.

3 4D/RCS APPLIED TO LAGR

The 4D/RCS architecture for LAGR (Figure 4) consists of only two levels requiring plans at each low and high level out to approximately 10 m and 100 m, respectively, in front of the vehicle. This is because the size of the LAGR test areas is small (typically about 100 m on a side, and the test missions are short in duration (typically less than 4 minutes.) For controlling an entire battalion of autonomous vehicles, there may be as many as five or more 4D/RCS hierarchical levels.

The following sub-sections describe the type of algorithms implemented in sensor processing, world modeling, and behavior generation, as well as a section that describes the learning algorithms that have been implemented.

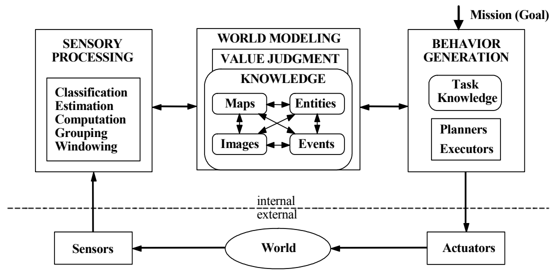


Figure 3: The basic internal structure of a 4D/RCS control loop.

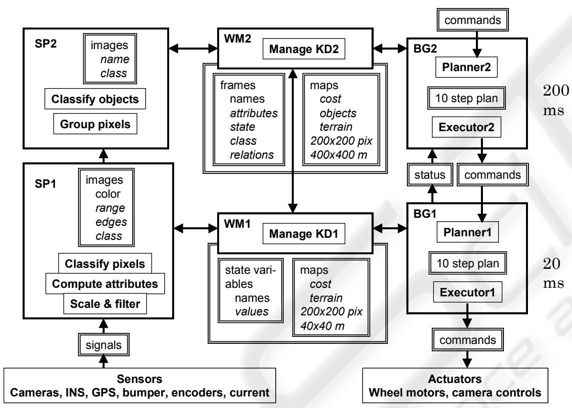


Figure 4: Two-level instantition of the 4D/RCS hierarchy for LAGR.

3.1 Sensory Processing

The sensor processing column in the 4D/RCS hierarchy for LAGR (Figure 4) starts with the sensors on board the LAGR vehicle. Sensors used in the sensory processing module include the two pairs of stereo color cameras, the physical bumper and infra-red bumper sensors, the motor current sensor (for terrain resistance), and the navigation sensors (GPS, wheel encoder, and INS). Sensory processing modules include a stereo obstacle detection module, a bumper obstacle detection module, an infrared obstacle detection module, an image classification module, and a terrain slipperyness detection module.

3.2 Stereo Vision

Stereo vision is primarily used for detecting obstacles. We use the SRI Stereo Vision Engine (Konolige, 2005) to process the pairs of images from the two stereo camera pairs. For each newly acquired stereo image pair, the obstacle detection algorithm processes each vertical scan line in the reference image independently and classifies each pixel as GROUND, OBSTACLE, SHORT_OBSTACLE, COVER or INVALID. Figure 5 illustrates the basic obstacle detection algorithm (Chang, 1999).

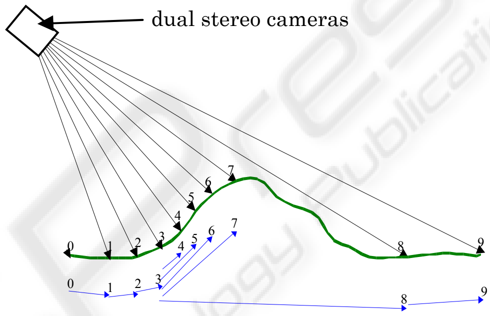


Figure 5: A single vertical scanline detecting the ground. *Pixel 0 is altered to correspond to the bottom of the vehicle wheel. Pixels 1, 2, 3, 8 and 9 are ground pixels due to shallow slopes. Pixel 4, 5, 6 and 7 are obstacles due to steeper slopes. The slopes are shown by the direction vectors on the bottom of the figure.*

Pixels that are not in the 3D point cloud are marked INVALID. Pixels corresponding to obstacles that are shorter than 5 cm high are marked as SHORT_OBSTACLE. The obstacle height threshold value of 5cm was chosen such that the LAGR vehicle can ignore and drive over small pebbles and rocks. Similarly, COVER corresponds to obstacles that are taller than 1.5 m, a safe clearance height for the LAGR vehicle.

Within each reference image, the corresponding 3D points are accumulated onto a 2D cost map of 20 cm by 20 cm cell resolution. Each cell has a cost value representing the percentage of OBSTACLE pixels in the cell. In addition to cost value, color and elevation statistics are also kept and updated in each cell. This map is sent the world model at the current level and to the sensory processing module at the level above in the 4D/RCS hierarchy.

Figure 6 shows a view of obstacle detection from the operator control unit (OCU). The vehicle is shown driving on a dirt road lined with trees with an orange fence in the background.

3.3 Learning Classification in Color Vision

A color-based image classification (Tan, 2006) module runs independently from the obstacle detection module in the lower-level sensory processing module. It learns to classify objects in the scene by their color and appearance. This enables it to provide information about obstacles and ground points even when stereo is not available. A flat world assumption is used when determining the 3D location of a pixel in the image. This assumption is valid for points close to the vehicle providing that the vehicle does not get too close to an obstacle.

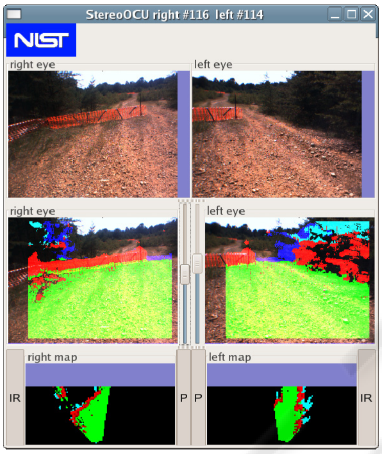


Figure 6: OCU display showing original images (top), results of obstacle detection (middle), and cost maps (bottom). *Red represents obstacles, green is ground, and blue represents obstacles too far away to classify.*

Pixels near the vehicle, as defined by a 1 m wide by 2 m long rectangular area in front of the vehicle, are used to construct and update the GROUND color histogram. Similarly, the BACKGROUND color histogram is constructed and updated from pixel locations that were previously believed to be background.

The construction of the background model initially randomly samples the area above the horizon. Once the algorithm is running, the algorithm randomly samples pixels in the current frame that the previous result identified as background. These samples are used to update the background color model using temporal fusion

In order to remember multiple color distributions, multiple GROUND color histograms are maintained. However, only one BACKGROUND color histogram is used.

The cost for each pixel is determined by a color voting method and the degree of belief that a point is a background is calculated from the two histograms as

$$\frac{N_{BACKGROUND}}{N_{BACKGROUND} + N_{GROUND}}$$

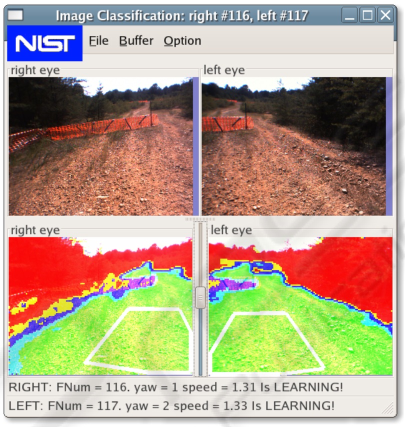


Figure 7: OCU display showing original images (top) and cost images (bottom). The 1 m wide by 2 m long rectangular areas assumed to be ground (white boxes) are overlaid on the cost images.

Where $N_{BACKGROUND}$ and N_{GROUND} are the number of hits in the corresponding histogram bin. In the case of multiple GROUND color histograms, the minimum cost is used. The cost image is sent to the world model. Figure 7 illustrates color classification on the same image as shown in Figure 6

3.4 World Modeling

The world model is the system's internal representation of the external world. It acts as a bridge between sensory processing and behavior generation in the 4D/RCS hierarchy by providing a central repository for storing sensory data in a unified representation. It decouples the real-time sensory updates from the rest of the system. The world model process has two primary functions: To create a knowledge database and keep it current and consistent, and to generate predictions of expected sensory input.

For the LAGR project, two world model levels have been built (WM1 and WM2). Each world model process builds a two dimensional (200 x 200 cells) map, but at different resolutions. These are used to temporally fuse information from sensory processing. Currently the lower level (SP1) is fused into both WM1 and WM2 as the learning module in

SP2 does not yet send its models to WM. Figure 8 shows the WM1 and WM2 maps constructed from the stereo obstacle detection module in SP1. The maps contain traversal costs for each cell in the map. The position of the vehicle is shown as an overlay on the map. The red, yellow, blue, light blue, and green are cost values ranging from high to low cost, and black represents unknown areas. Each map cell represents an area on the ground of a fixed size and is marked with the time it was last updated. The total length and width of the map is 40 m for WM1 and 120 m for WM2. The information stored in each cell includes the average ground and obstacle elevation height, the variance, minimum and maximum height, and a confidence measure reflecting the "goodness" of the elevation data. In addition, a data structure describing the terrain traversability cost and the cost confidence as updated by the stereo obstacle detection module, image classification module, bumper module, infrared sensor module, etc. The map updating algorithm is based on confidence-based mapping as described in (Oskard, 1990). The costs and the confidences are combined to determine the relative safety of traversing the grid with the following equation:

$$Cost_{cell} = W_s \times Cost_{stereo} + W_l \times Cost_{lagrLearn} + W_c \times Cost_{classification}$$

where $Cost_{cell}$ is the cost to traverse each grid cell. $Cost_{lagrLearn}$, $Cost_{classification}$, and $Cost_{stereo}$ are the fused costs in the world model based on the learning module, classification module, stereo obstacle detection module. W_s, W_l, and W_c are weighting constants for each cost. However, $Cost_{cell}$ is a bumper cost if there is a bumper hit.

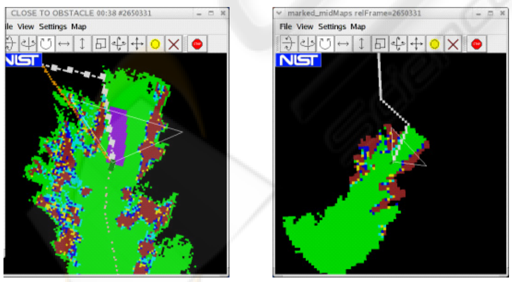


Figure 8: OCU display of the World Model cost maps built from sensor processing data. *WM1 builds a 0.2 m resolution cost map (left) and WM2 builds a 0.6 m resolution cost map (right).*

The final cost placed in each map cell represents the best estimate of terrain traversability in the region represented by that cell, based on information fused over time. Each cost has a confidence associated with it and the map grid selects the label with the highest confidence. The final cost maps are constructed by taking the fused cost from all the sensory processing modules.

Efficient functions have been developed to scroll the maps as the vehicle moves, to update map data, and to fuse data from the sensory processing modules. A map is updated with new sensor data and scrolled to keep the vehicle centered. This minimizes grid relocation. No copying, only updating, of data is done. When the vehicle moves out of the center grid cell of the map, the scrolling function is enabled. The map is vehicle-centered, so only the borders need to be initialized. Initialization information may be obtained from remembered maps saved from previous test runs as shown in Figure 9. Remembering maps is a very effective way of learning about terrain, and has proved important in optimizing successive runs over the same terrain.

The cost and elevation confidence of each grid cell is updated every sensor cycle: 5 Hz for the stereo obstacle detection module, 3 Hz for the learning module, 5 Hz for the classification module, and 10-20 Hz for the bumper module. The confidence values are used as a cost factor in determining the traversability of a cell.

We plan additional research to implement modeling of moving objects (cars, targets, etc.) and to broaden the system's terrain and object classification capabilities. The ability to recognize and label water, rocky roads, buildings, fences, etc. would enhance the vehicle's performance.

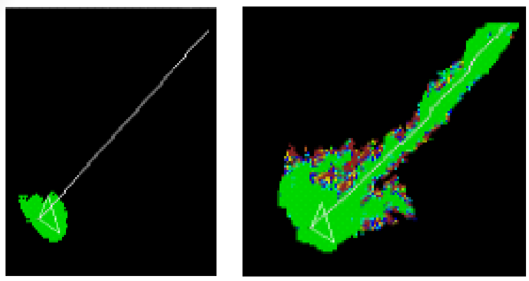


Figure 9: Initial (left) and remembered (right) cost maps as the system starts without and with saved maps, respectively.

3.5 Behavior Generation

Top level input to Behavior Generation (BG) (Figure 10) is a file containing the final goal point in UTM (Universal Transverse Mercator) coordinates. At the bottom level in the 4D/RCS hierarchy, BG produces a speed for each of the two drive wheels updated every 20 ms, which is input to the low-level controller included with the government-provided vehicle. The low-level system returns status to BG, including motor currents, position estimate, physical bumper switch state, raw GPS and encoder feedback, etc These are used directly by BG rather than passing them through sensor processing and world modeling since they are time-critical and relatively simple to process.

Two position estimates are used in the system. Global position is strongly affected by the GPS antenna output and is more accurate over long ranges, but can be noisy. Local position uses only the wheel encoders and inertial measurement unit (IMU). It is less noisy than GPS but drifts significantly as the vehicle moves, and even more if the wheels slip.

The system consists of five separate executables. Each sleeps until the beginning of its cycle, reads its inputs, does some planning, writes its outputs and starts the cycle again. Processes communicate using the Neutral Message Language (NML) in a non-blocking mode, which wraps the shared-memory interface (Shackleford, 1990). Each module also posts a status message that can be used by both the supervising process and by developers via a diagnostics tool to monitor the process.

The LAGR Supervisor is the highest level BG module. It is responsible for starting and stopping the system. It reads the final goal and sends it to the waypoint generator. The waypoint generator chooses a series of waypoints for the lowest-cost traversable path to the goal using global position and translates the points into local coordinates. It generates a list of waypoints using either the output of the A* Planner (Heyes-Jones, 2005) or a previously recorded known route to the goal.

The planner takes a 201 X 201 terrain grid from WM, classifies the grid, and translates it into a grid of costs of the same size. In most cases the cost is simply looked up in a small table from the corresponding element of the input grid. However, since costs also depend on neighboring costs, they are automatically adjusted to allow the vehicle to continue motion.

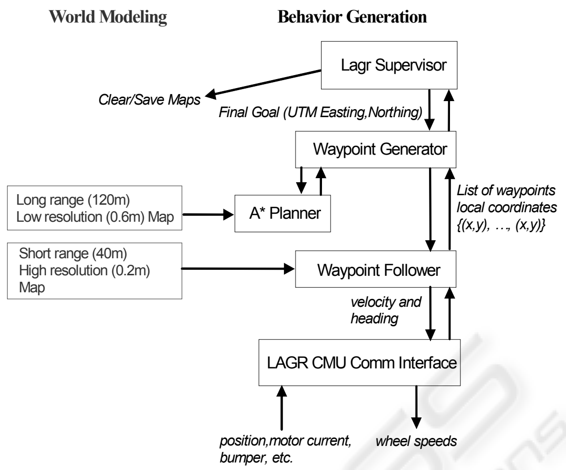


Figure 10: Behavior Generation High Level Data Flow Diagram.

The waypoint follower receives a series of waypoints, spaced approximately 0.6 m apart that could be used to drive blindly without a map. However, there are some features of the path that make this less than optimal. When the path contains a turn, it is either at a 0.8 rad (45 degree) or 1.6 rad (90 degree) angle with respect to the previous heading. The waypoint follower could smooth the path, but it would at least partially, enter cells that were not covered by the path chosen at the higher level. The A* planner might also plan through a cell that was partially blocked by an obstacle. The waypoint follower is then responsible for avoiding the obstacle. The first step in creating a short range plan is to choose a goal point from the list provided by the A* Planner. One option would be to use the point where the path intersects the edge of the 40m map. However, due to the differences between local and global positioning, this point might be on one side of an obstacle in the long range map and on the other side in the short range map. To avoid this, the first major turning point is selected. The waypoint follower searches a preset list of possible paths starting at the current position and chooses the one with the best score. The score represents a compromise between getting close to the turning point, staying far away from obstacles and higher cost areas, and keeping the speed up by avoiding turns.

The waypoint follower also implements a number of custom behaviors selected from a state table. These include:

- AGGRESSIVE MODE—Ignore obstacles except those detected with the bumper and drive in the direction of the final goal. Terrain such as tall grass causes the vehicle to wander. Short bursts of aggressive mode help to get out of these situations.

- HILL CLIMB—Wheel motor currents and roll and pitch angle sensors are used to sense a hill. The vehicle attempts to drive up hills without stopping to avoid momentum loss and slipping.
- NARROW CORRIDOR/CLOSE TO OBSTACLE—In tight spaces the system slows down, builds a detailed world model, and considers a larger number of alternative paths to get around tight corners than in open areas.
- HIGH MOTOR AMPS/SLIPPING—When the motor currents are high or the system thinks the wheels are slipping it tries to reverse direction and then tries a random series of speeds and directions, searching for a path where the wheels are able to move without slipping.
- REVERSE FROM BUMPER HIT—Immediately after a bumper hit the vehicle backs up and rotates to avoid the obstacle.

The lowest level module, the LAGR Comms Interface, takes a desired heading and direction from the waypoint follower and controls the velocity and acceleration, determines a vehicle-specific set of wheel speeds, and handles all communications between the controller and vehicle hardware.

3.6 Learning Algorithms

Learning is a basic part of the LAGR program. Several kinds of learning have to be addressed. There is learning by example, learning from experience, and learning of maps and paths. Most learning relies on sensed information to provide both the learning stimulus and the ground truth for evaluation. In the LAGR program, learning from sensor data has mainly focused on learning the traversability of terrain. This includes learning by seeing examples of the terrain and learning from the experience of driving over (or attempting to drive over) the terrain. One example of learning by example was discussed in Section 0.

Another model-based learning process occurs in the SP2 module of the 4D/RCS architecture, taking input from SP1 in the form of labeled pixels with associated *(x, y, z)* positions. Classification is an SP1 process that uses the models to label the traversability of image regions based only on color camera data.

An assumption is made that terrain regions that look similar will have similar traversability. The learning works as follows (Shneier, 2006). The system constructs a map of the terrain surrounding the vehicle, with map cells 0.2 m by 0.2 m. Each pixel passed up from SP1 has an associated red (R), green (G), and blue (B) color value in addition to its (x, y, z) position and label (obstacle or ground). Points are projected into the map using the (x, y, z) position. Each map cell accumulates descriptions of the color, texture, intensity, and contrast of the points that project into it.

Color is represented by 8-bin histograms of ratios *R/G*, *R/B*, and *G/*B. This provides some protection from the color of ambient illumination. Texture and contrast are computed using Local Binary Patterns (LBP) (Ojala, 1996). The texture measure is represented by a histogram with 8 bins. Intensity is represented by an 8-bin histogram, while contrast is a single number ranging from 0 to 1.

When a cell accumulates enough point, it is ready to be considered as a model. To build a model we require that 95% of the points projected into a cell have the same label (obstacle or ground). If a cell is the first to accumulate enough points, its values are used to create the first model. If other models already exist, the cell is matched to these models to see if it can be merged or if a new model must be created. Matching is done by computing a weighted sum of the elements of the model and the cell. Each model has an associated traversability, computed from the number of obstacle and ground points that were used to create the model. These models correspond to regions learned by example. Learning by experience is used to modify the models. As the vehicle travels, it moves from cell to cell in the map. If it is able to traverse a cell that has an associated model, the traversability of that model is increased. If it hits an obstacle in a cell, the traversability is decreased.

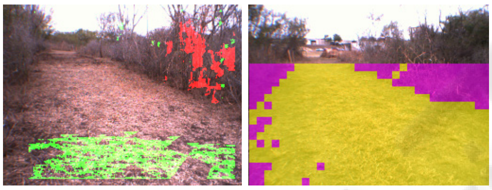
To classify a scene, only the color image is needed. A window is passed over the image and color, texture, and intensity histograms, and a contrast value are computed as in model building. A comparison is made with the set of models, and the window is classified with the best matching model, if a sufficiently good match value is found. Regions that do not find good matches are left unclassified.

Figure 9a shows an image taken during learning. The pixels contributing to the learning are shown in red for obstacle points and green for ground points. Figure 9b shows a scene labeled with traversability values computed from the models built from previous data.

4 SUMMARY AND CONCLUSIONS

The NIST 4D/RCS reference model architecture was implemented on the DARPA LAGR vehicle, which was used to prove that 4D/RCS can learn. Sensor processing, world modeling, and behavior generation processes have been described in this paper. Outputs from sensor processing of vehicle sensors are fused with models in WM to update them with external vehicle information. World modeling acts as a bridge between multiple sensory inputs and a behavior generation (path planning) subsystem. Behavior generation plan vehicle paths through the world based on cost maps provided from world modeling. Learning, as used on the LAGR vehicle includes learning by example, learning from experience, and learning of behaviors that are more likely to lead to success.

Future research will include completion of the sensory processing upper level (SP2) and developing even more robust control algorithms than those described in this paper.



(a) (b)

Figure 9: Learning by example images. *(a) is an image taken during learning and overlaid with (red) obstacles and (green) ground, (b) is the same image overlaid with traversability information as obstacles (magenta) and ground (yellow).*

REFERENCES

Albus, J.S., Juberts, M., Szabo, S., *RCS: A Reference Model Architecture for Intelligent Vehicle and Highway Systems*, Proceedings of the 25th Silver Jubilee International Symposium on Automotive Technology and Automation, Florence, Italy, June 1-5, 1992.

Albus, J.S., Huang, H.M., Messina, E., Murphy, K.N., Juberts, M., Lacaze, A., Balakirsky, S.B., Shneier, M.O., Hong, T.H., Scott, H.A., Proctor, F.M., Shackleford, W., Michaloski, J.L., Wavering, A.J., Kramer, Tom , Dagalakis, N.G., Rippey, W.G., Stouffer, K.A., *4D/RCS Version 2.0: A Reference Model Architecture for Unmanned Vehicle Systems*, NISTIR, 2002.

Albus, J.S., Balakirsky, S.B., Messina, E., *Architecting A Simulation and Development Environment for Multi-Robot Teams*, *Proceedings of the International Workshop on Multi Robot Systems, Washington, DC, March 18 – 20*, 2002

Balakirsky, S.B., Chang, T., Hong, T.H., Messina, E., Shneier, M.O., *A Hierarchical World Model for an Autonomous Scout Vehicle*, Proceedings of the SPIE 16th Annual International Symposium on Aerospace/Defense Sensing, Simulation, and Controls, Orlando, FL, April 1-5, 2002.

Bostelman, R.V., Jacoff, A., Dagalakis, N.G., Albus, J.S., *RCS-Based RoboCrane Integration*, Proceedings of the International Conference on Intelligent Systems: A Semiotic Perspective, Gaithersburg, MD, October 20-23, 1996.

Chang, T., Hong, T., Legowik, S., Abrams, M., *Concealment and Obstacle Detection for Autonomous* Driving, Proceedings of the Robotics & Applications Conference, Santa Barbara, CA, October, 1999.

Heyes-Jones, J., *A* algorithm tutorial,* 2005 http://us.geocities.com/jheyesjones/astar.html.

Shneier, M., Chang, T., Hong, T., and Shackleford, W., *Learning Traversability Models for Autonomous Mobile Vehicles*, Autonomous Robots (submitted), 2006.

Jackel, Larry, LAGR Mission, http://www.darpa.mil/ipto/programs/lagr/index.htm, DARPA Information Processing Technology Office, 2005

Konolige, K., *SRI Stereo Engine*, 2005 http://www.ai.sri.com/~konolige/svs/.

Michaloski, J.L., Warsaw, B.A., *Robot Control System Based on Forth*, Robotics Engineering, Vol. 8, No. 5, pgs 22-26, May, 1896.

Ojala, T., Pietikäinen, M., and Harwood, D., *A Comparative Study of Texture Measures with Classification Based on Feature Distributions,* Pattern Recognition, 29: 51-59, 1996.

Oskard, D., Hong, T., Shaffer, C., Real-time Algorithms and Data Structures for Underwater Mapping, National Institute of Standards and Technology, 1990.

Shackleford, W., The NML Programmer's Guide (C++ Version), 1990. http://www.isd.mel.nist.gov/projects/rcslib/NMLcpp.html.

Shackleford, W., Stouffer, K.A., *Implementation of VRML/Java Web-based Animation and Communications for the Next Generation Inspection System (NGIS) Real-time Controller*, Proceedings of the ASME International 20th Computers and Information in Engineering (CIE) Conference, Baltimore, MD, September 10 – 13, 2000.

Tan, C., Hong, T., Shneier, M., and Chang, T., "Color Model-Based Real-Time Learning for Road Following," in Proc. of the IEEE Intelligent Transportation Systems Conference (Submitted) Toronto, Canada, 2006