Project: Brave New World

An Exploration of Autonomy vs Central Authority in Robotic Asteroid Mining

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UCLA Computer Science 263C Winter 2013
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Friday March 22, 2013

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Humans are utilizing the Earth's non-renewable resources at a rate which will deplete the Earth of all resources within one century (Swain, McCandless, Zagami, Quick, 2012). Mankind's expedited consumption of the Earth's resources has led to their testing other celestial bodies with the hope of finding similar resources (Nelson, Britt, Lebofsky, 1993). After extensive testing, researchers found C-Type asteroids containing Pyroxene and signs of water and S-Type asteroids containing Nickel-Iron and Pyroxene (Shaw, 2012). Scientists can produce several resources by combining or separating the elements found in these asteroids, thus increasing the possibility of mining both C-Type and S-Type asteroids (Deer, Howie, Zussman, 1992). As such, the need for efficient, automated resource harvesting tactics will be of interest in the near future.

Hypotheses

The current study seeks to explore two main hypotheses:

1. Robotic animats using learned environmental association cues to find resources of interest will perform better at exploratory tasks than those who do not (Experiment 1).
2. Robotic animats that act autonomously in a resource-mining scenario will outperform those that are directed by a central authority (Experiment 2).

Goals

The current study seeks to achieve the following goals:

1. Design robotic animats that use learned environmental association cues and memory to quickly find resources of interest.
2. Determine which, between autonomy and central control, is the better paradigm in a communication-inhibited environment.
3. Observe robotic animats' choices of roles in the mining operation to see if division of labor is learned.

Problems

The project encountered several setbacks:

1. Developing successful techniques for merging individual animats' experiences into a shared associative learning
2. Developing a method for the animats to realize how far they can go before they need fuel, while taking into account the distance they need to travel to reach the fuel
3. Developing an effective method for having animats update their cognitive maps
4. Some problems with proximity event handlers using the project's graphics engine

Methodology

The focuses of this study were twofold: to examine robotic exploration techniques and the factors that contribute to their success or failure, and to see how the organization of robots as individuals or part of a group can influence operation. As such, properties of the environment like the physical aspects of the animat were of less concern than the observation of animat learning and adaptation.

The approach was to create a rich environment filled with interactable objects whose diversity and randomized locations would sponsor a necessity for the animats to learn associations and adapt to the layout of a given trial, and by analogy, a given asteroid.

Environment

The scenario's environment contains a multi-level terrain map with various elements emulative of an asteroid surface; it is designed to test animat learning, and consists of the following.

1. Multi-level terrain map
   The multi-level terrain map serves to provide an environment that can test the robustness of each animats' pathfinding, creating obstacles that cannot be overcome by a straight-line path.
2. Central home base
   The central home base serves as a charging station in all developmental phases and a data storage unit in the phase in which animats are directed by a central authority. Animats interact with the central home base by charging when within a certain distance of the home base. In all toolset experiments, the animats may change their loadout at the home base.
3. Resources
   The resources serve as deposits from which animats can harvest minerals. Animats react with resources by noting their presence, updating associations, attaching beacons to the resources, and mining the resources. The current project contains 3 different types of resources, placed randomly throughout each map:
   a. Nickel-Iron resources
   b. Water resources
   c. Pyroxene resources
4. Resource cues
   Resource cues exist to test an animat's learning of environmental associations by helping to guide the animat towards a resource. Environmental resource cues are chosen to represent the signs of resources found in S-Type and C-Type asteroids, which can be detected by magnetic signatures and even values of surface albedo. Animats interact with resource cues by noting their presence and proximity to vital resources. The current project contains 3 different types of resource cues, placed within the general proximity of resource nodes:
   a. Nickel-Iron resource cues
   b. Water resource cues
   c. Pyroxene resource cues
5. Distractor Cues
   Distractor cues are not associated with any resources to test the suspected assertion that not all cues in an environment lead to resources. Animats interact with distractor cues by noting their presence and updating associations. The current project contains 2

different types of distractor cues, which are randomly placed on the map at slight distances away from resources:.
   a. Dead-end rock distractor cues
   b. Dead-end cliff distractor cues

Animats

The animats underwent iterative developmental stages, each adding more adaptive behaviors than the preceding model. Each stage of development is outlined below, starting with a description of the animat's basic properties. Abilities added to a particular stage are starred**.

1. Animat Model 1: The General Issue
   a. Movement
      i. Directions - Animats can move in any direction
      ii. Mechanism - (abstracted) Two thrusters situated under the animat allow it to move around the asteroid
   b. Sensors
      i. Vision
         1. 360° camera system designed to detect environmental features in an 8m area around the animat
         2. Used to detect resources, resource cues, distractor cues, home base, and other objects in the environment
            a. Mark discovered resources with indicator beacon
      ii. Energy
         1. Bot breaks down if energy reaches 0
2. Animat Model 2: Neural Net with Associative Learning
   a. Movement
      i. Directions
         1. Animats can move in any direction
         2. ** Modified by learned environmental cues; the animat trends towards cues with high resource association, and away from those with low resource association
      ii. Mechanism - (abstracted) Two thrusters situated under the animat allow it to move around the asteroid
   b. Sensors
      i. Vision
         1. 360° camera system designed to detect environmental features in a 8m area around the animat
         2. Used to detect resources, resource cues, distractor cues, home base, and other objects in the environment
            a. Mark discovered resources with indicator beacon
      ii. Energy
         1. ** Determines whether or not the animat will return to home base to recharge; bot breaks down if energy reaches 0
   c. Brain Structure

            i. ** Neural network with pre-learned set of actions deemed applicable to the animat's assigned tasks
            ii. ** Learned environmental cues affect movement direction
                1. Long Term Memory - Positive or negative associations between cue type and resource proximity
                2. Short Term Memory - Indicator per cue type of recently seen cues

3. Animat Model 3: Neural Net and Cognitive Map
    a. Movement
        i. Directions
            1. Animats can move in any direction
            2. Modified by learned environmental cues; the animat trends towards cues with high resource association, and away from those with low resource association
            3. ** Markable locations on cognitive map that can be returned to after recharging instead of exploring more
        ii. Mechanism - (abstracted) Two thrusters situated under the animat allow it to move around the asteroid
    b. Sensors
        i. Vision
            1. 360° camera system designed to detect environmental features in an 8m area around the animat
            2. Used to detect resources, resource cues, distractor cues, home base, and other objects in the environment
                a. Mark resources with indicator beacon
        ii. Energy
            1. Determines whether or not the animat will return to home base to recharge; bot breaks down if energy reaches 0
    c. Brain Structure
        i. Neural network with pre-learned set of actions deemed applicable to the animat's assigned tasks
        ii. Learned environmental cues affect movement direction
            1. Long Term Memory - Positive or negative associations between cue type and resource proximity
            2. Short Term Memory - Indicator per cue type of recently seen cues
        iii. Cognitive Map
            1. Location memory (remember location, recharge, return to last location)
4. Animat Model 4: Fully Autonomous Toolset Selection
    a. Movement
        i. Directions
            1. Animats can move in any direction on the ground
            2. Modified by learned environmental cues
            3. ** Markable locations on improved cognitive map that can be

returned to after recharging instead of exploring more; “priorities” such as a broken down bot or unmined resource can be revisited
    - ii. Mechanism - (abstracted) Two thrusters situated under the animat allow it to move around the asteroid
- b. Sensors
    - i. Vision
        1. ** This bot can choose to remove or equip the omnidirectional camera to save energy in lieu of just the bot’s range finder (4m “vision” radius). The 360° camera system is designed to detect environmental features in an 8m area around the animat (see toolset description)
        2. Used to detect resources, resource cues, distractor cues, home base, and other objects in the environment
            - a. Mark discovered resources with indicator beacon
    - ii. Energy
        1. ** Determines whether or not the animat will return to home base to recharge; bot breaks down if energy reaches 0, but can be jumped by a nearby bot with a repair kit
- c. Brain Structure
    - i. Neural network with pre-learned set of actions deemed applicable to the animat’s assigned tasks
    - ii. Learned environmental cues affect movement direction
        1. Long Term Memory - Positive or negative associations between cue type and resource proximity
        2. Short Term Memory - Indicator per cue type of recently seen cues
    - iii. ** Cognitive Map
        1. Location memory (remember location, recharge, return to last location)
        2. ** Energy-depleted animat memory (remember location of any energy-depleted animats)
        3. ** Resource memory (remember location of resources to mine later)
        4. ** Shared cognitive map with Home Base (in central control condition)
- d. ** Tools: in the autonomous bot condition, bots will select the tools that they desire most based on their recent field work; in the central authority condition, toolsets are assigned to each bot
    - i. Omnidirectional Camera (Increased Vision)
        1. Increases rate at which energy is consumed when equipped
        2. Double vision radius field of view to 8m (Scouting)
    - ii. ** Additional Thrusters (Increased Velocity)
        1. Increases rate at which energy is consumed when equipped
        2. Increases speed by a factor of 1.5 (from 3m/s to 4.5m/s)

iii. ** Drill (Ability to Mine)
    1. Increases rate at which energy is consumed when equipped
    2. Adds ability to mine resources

iv. Repair Kit (Ability to Fix)
    1. Increases rate at which energy is consumed when equipped
    2. Adds ability to repair nearby energy-depleted animats

Design

System Architecture

The current project uses the StarCraft® II gaming engine to accomplish the following goals:

1. Handles object physicality and relations of objects in an allocentric reference frame
2. Provides a compelling illustration of asteroid mining potential
3. Allows a shift in focus from graphics implementation to adaptive animat behavior

Consult Figure 4 for a description of the project structure

Algorithms

1. Neural Net Resource Cue Interpretation: The Short Term Memory / Long Term Memory resource cue associations were formed using a neural net with the STM neurons as axo-axonal weight modifiers of LTM neurons, which in turn influenced movement direction given a cue in the environment
2. Decision Tree Task Choice: Each animat in the 3rd and 4th Models performed tasks according to a given priority; these were assessed by a binary decision tree with descending priority: Need to recharge, need to drop off cargo, need to return to mine, need to return to last explored location, and finally, need for peripersonal exploration. Some conditions required the bot to lend aid to unpowered animats as well
3. Neural Net Toolset Selection: Model 4 animats could autonomously select the tools that they thought were best for the current situation; this was accomplished via neural net through accounting for historical reinforcement while using a given tool and by assessing the needs of the current environment for a particular tool

Representational Constructs

Long Term Memory and Short Term Memory

Animats beginning with Model 2 use Long Term Memory (LTM) and Short Term Memory (STM), which represent the associations between resources and resource cues. Both Long Term Memory and Short Term Memory are implemented using arrays of registers to store associations between cues and resources. The following pseudocode describes the registers' functions:

```
if (cue within vision radius)
  STM_cue += 1 / (STM_cue + 1)   // Diminishing returns for cue STM
```

```
if (resource within vision radius)
  for (each cue c in STM)
    LTM_cue += STM_c * STM_c_weight   // Where weight is a function of the axon

while (pacemaker_neuron.tick())
  for (each cue c in STM)
    LTM_cue -= STM_c * attrophyMultiplier   // LTM atrophying if STM cue seen but no resource
```

Note: LTM associations were seeded with a “curiosity” factor to encourage bots to initially, slightly trend towards cues, even if they were distractors, as a real asteroid mining bot would likely be more exploratory before any associations had been made

Cognitive Map

Animats beginning with Model 2 use Cognitive Maps, which keep track of locations the animat wants to return to after recharging. With Model 3, the Cognitive Map was expanded to include the locations of unmined resources for later mining and unpowered bots to repair. The Cognitive Maps are implemented using arrays of points to store resource locations.

Phases

The current project consists of 3 phases:

Phase 1

The initial project phase consists of animats with associative learning for environmental cues - Short Term Memory and Long Term Memory - and cognitive maps for remembering their last location before returning to charge.

Phase 2

This project’s second phase consists of animats with associative learning for environmental cues - Short Term Memory and Long Term Memory. Each animat will have a cognitive map which will keep track of the resources that the animat has found and the locations at which the animat has found each resource. Additionally, this phase will contain 4 various types of tools. Each tool, when equipped, will make the animat use fuel at a quicker rate. Animats will start off with a random number of tools, with the probability of each tool being equally likely. Animats get increased probabilities for using the tools that they have equipped, which also aids in their probability for choosing certain tools. Additionally, each time an animat goes back to Home Base, it will determine whether or not to remove tools, equip tools, or keep the tools it has. As the animat uses its tools (for what they’re intended), the animat gets positive feedback (in the form of an increased probability) for using those tools. The positive feedback associated with a tool will serve to modify the animat’s probability of choosing that specific tool.

Phase 3

This project’s third phase consists of animats with associative learning for environmental cues - Short Term Memory and Long Term Memory. Each animat will have a cognitive map which will keep track of the resources that the animat has found and the locations at which the animat has found each resource. Additionally, this phase will contain 4 various types of tools. Each tool, when equipped, will make the animat use fuel at a quicker rate. Animats will start off with sets of tools assigned to them by the home base. Each time an animat passes by within a certain proximity of the home base, it will share its cognitive map with the home base and the home base will then update its internal cognitive map and share a revised version back with the animat. Additionally, each time the animat goes back to the home base, the home base will issue a command telling the animat what it should do. All animats, when not equipped with a repair kit, will keep track of any broken down animats that they have discovered, and will report them to the home base once they need to charge.

Phase 3 Commands (Home Base to Animat)

Scouting:

"Equip Omnidirectional Camera [and Additional Thrusters if the location is distant]. Proceed to this location." [Implied: Once you run out of battery, come back and report what you have added to your cognitive map. We will exchange information. You will recharge. I will assign another task to you.]

Mining:

"Equip Drill [and Additional Thrusters if the location is distant]. Proceed to this location and mine the resource." [Implied: Once you have run out of battery, come back and deliver the resource you have mined. We will exchange cognitive map information. Let me know if resource is depleted. You will recharge. I will assign another task to you.]

Repairing:

"Equip Repair Kit [and Additional Thrusters if you need to repair several bots or the bots you need to repair are in distant locations]. Proceed to these locations (in this order) and repair the animats at these locations." [Implied: Once are done or you have run out of battery (whichever comes first), come back. We will exchange cognitive map information. You will tell me which animats you have repaired. I will assign another task to you.]

Experiments

Two experiments were conducted to assess the study's hypotheses; the first examines the refinement of robotic scouting techniques for discovering resources while the second investigates the organizational tactics and modular tool choices that bots may make to achieve optimal resource gathering. Both experiments involved 12 animats begun at the home base in the center of a 256m x 256m map. At the beginning of each trial, 30 resources, each with 5 cues, were randomly seeded throughout the map; 75 distractor cues were placed in areas slightly away from resources.

Experiment 1

Three conditions were examined in experiment 1, with each condition consisting of 10 trials lasting 5 minutes a piece. The dependent measure in each condition was the number of resources that the scouts discovered (moved within visual range of) before the 5 minutes elapsed. Each condition corresponded to a new development in the scouting capabilities of the robotic animats, and consisted of the following:

1. Condition 1 - Completely Random Movement: The baseline control for experiment 1 in which robots wandered aimlessly, rarely explored a wide area of the map, and generally ran out of battery before a trial ended.
2. Condition 2 - Neural Net Associative Learning: Animats now use environmental cues and their associations to resources to guide their movement.
3. Condition 3 - Neural Net + Location Memory: The same as condition 2, except with the added capacity for simple cognitive maps noting the location that a bot stopped exploring in order to return to base to recharge; they would then return to this location after recharging to resume exploration.

Experiment 2

Two conditions were examined in experiment 2, with each condition consisting of 10 trials lasting 10 minutes a piece. There were several dependent measures recorded for each trial, including: amount of resources mined (100 resources to be mined per node at a harvest rate of 30), amount of resources discovered, and the retention rates for toolsets. In these trials, a bot could choose to switch out its toolset for any combination of those listed in the Model 4 description; the retention rate is equal to the number of times that a bot chose to keep a tool after being given the option to unequip it. The conditions included:

1. Condition 1 - Random Toolset Requests: The baseline control for experiment 2 in which robots randomly start with and then randomly choose different tools.
2. Condition 2 - Autonomous Toolset Choice: The bots use their history of effectiveness with a given tool to choose it more often in the future. Additionally, they will use aspects of their cognitive maps to influence their tool choices; e.g., if a bot sees a number of resource nodes while scouting, but doesn't have a drill to harvest them, it will be much more likely to choose a drill the next chance it's given.

Analysis

Experiment 1

Results from a 2 X 2 ANOVA suggest a significant main effect of neural net, F (1,27) = 8.05, p = .009 and of location memory, F (1,27) = 6.98, p = .014. A significant interaction could not be calculated due to the incomplete design of the experiment. Further, results from an independent samples t-test suggest that within animate groups with no neural net, animate groups without location memory (M = 8.80, SD = 2.04) discovered fewer resources than animate groups with location memory (M = 11.50, SD = 2.50), t (18) = 2.64, p = .017. Similarly, within animate groups with no location memory, groups without neural nets (M = 5.90, SD = 2.28) discovered significantly fewer resources than groups with neural nets (M = 8.80, SD = 2.04), t (18) = 2.99, p = .008 (see Figure 1).

Experiment 2

An independent samples t-test revealed did not find a significant difference between the baseline (*M* = 807, *SD* = 173.78) and the autonomous group (*M* = 907, *SD* = 190.97) in the number of resources mined, t (18) = 1.23, p = .236, but the result trended in the predicted direction. However, results suggest the ratio of the number of resources mined and resources discovered between baseline (*M* = 0.57, *SD* = 0.11), and the autonomous group (*M* = 0.70, *SD* = 0.17), was marginally significant, t (18) = 1.97, p = .065 (see Figure 2).

Further investigation into the toolsets used and chosen by the animates revealed significant differences between the two groups. A MANOVA revealed a significant difference on the retention rates of tool sets between the baseline and autonomous groups, F (4,15) = 11.92, p < .001 (see Figure 3). While MANOVA tests for the simultaneous effect of group on toolset retention rates, when analyzed individually using ANOVA, only a significant difference in sprinter tool retention rates was found between the two groups, F (1,18) = 17.07, p = .001.

Discussion

1. The significant results of the first experiment, condition two, make a compelling argument for the validity of using associative learning of resource cues for the efficient detection of vital resources.
2. The results of the first experiment, condition three, are not surprising because the ability for a scout to resume exploring where it left off interrupts deviation toward the mean that might be witnessed without this capacity; it would be expected that bots without this skill would tread a predictable standard deviation around the home base as a function of their stride length.
3. One of the more surprising findings is that the autonomous group of experiment 2 did not gather significantly more resources than the random toolset condition, although the trend was in the predicted direction; this may be due to the low power afforded by small sample sizes in experiment 2.
4. There may be something to say about the marginal significance of the ratio of found to harvested resources between the two conditions in experiment 2: although it is again possible that this effect is due to chance spawn locations of the resources on the map, it is also worth considering that autonomously adapting bots are better at addressing current needs (many un-mined resources require shift from exploration) than are randomly toolset-swapping ones (which may be equipped for exploration despite the currently discovered resource amount).
5. Perhaps the most interesting finding of experiment 2 is the specialization of labor represented in Figure 3. In the autonomously adapting condition, the relatively low need for bot repairs appears to be reflected by the low repair tool retention rate. The desire for more mining tool retention can be rationalized due to scouts (without the mining tool) seeing unmined resources and logging the locations in their cognitive maps. The spike in sprinter retention is curious, and may not be immediately rationalized.

Current Status and Future Directions

The current project contains fully implemented, and tested, phases 1 and 2, with the cognitive maps in place for phase 3. That said, the central authority's command power has not yet been programmed, and so an analysis between autonomous scouts and directed ones cannot be gleaned at this time. Additionally, the authors hoped to implement a stigmergy behavior with resources marked with a beacon such that the beacon would attract mining bots in the surrounding area. Unfortunately, due to recent conception of these ideas, the final phase was not met.

Project Contributions

Work on Project: Brave New World was performed equally by both members of the group and was accomplished almost entirely at frequent group meetings. A special thank-you to Dr. Dyer for guidance on the developmental stages of the project and to Chela Willey for consultatory statistics.

References

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Appendix

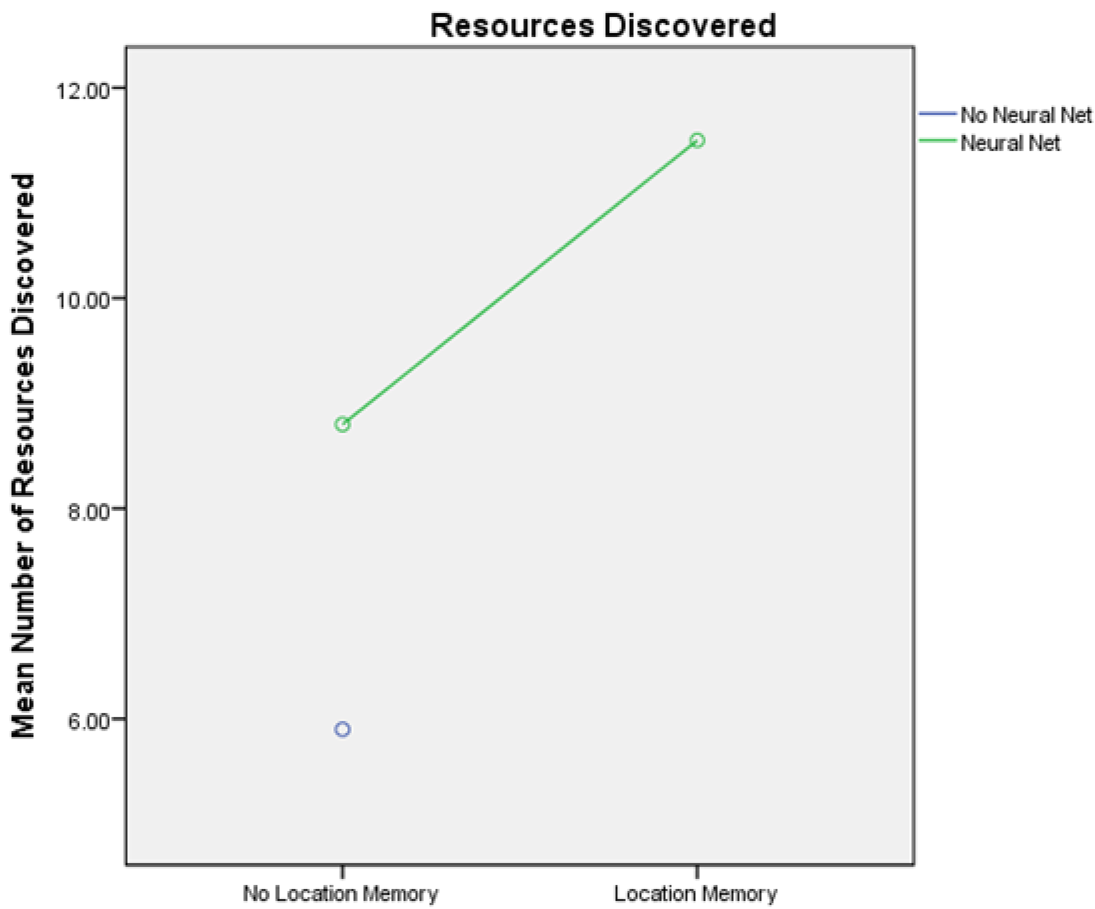

Figure 1: Results from Experiment 1. Number of resources discovered increased with the presence of location memory and neural net

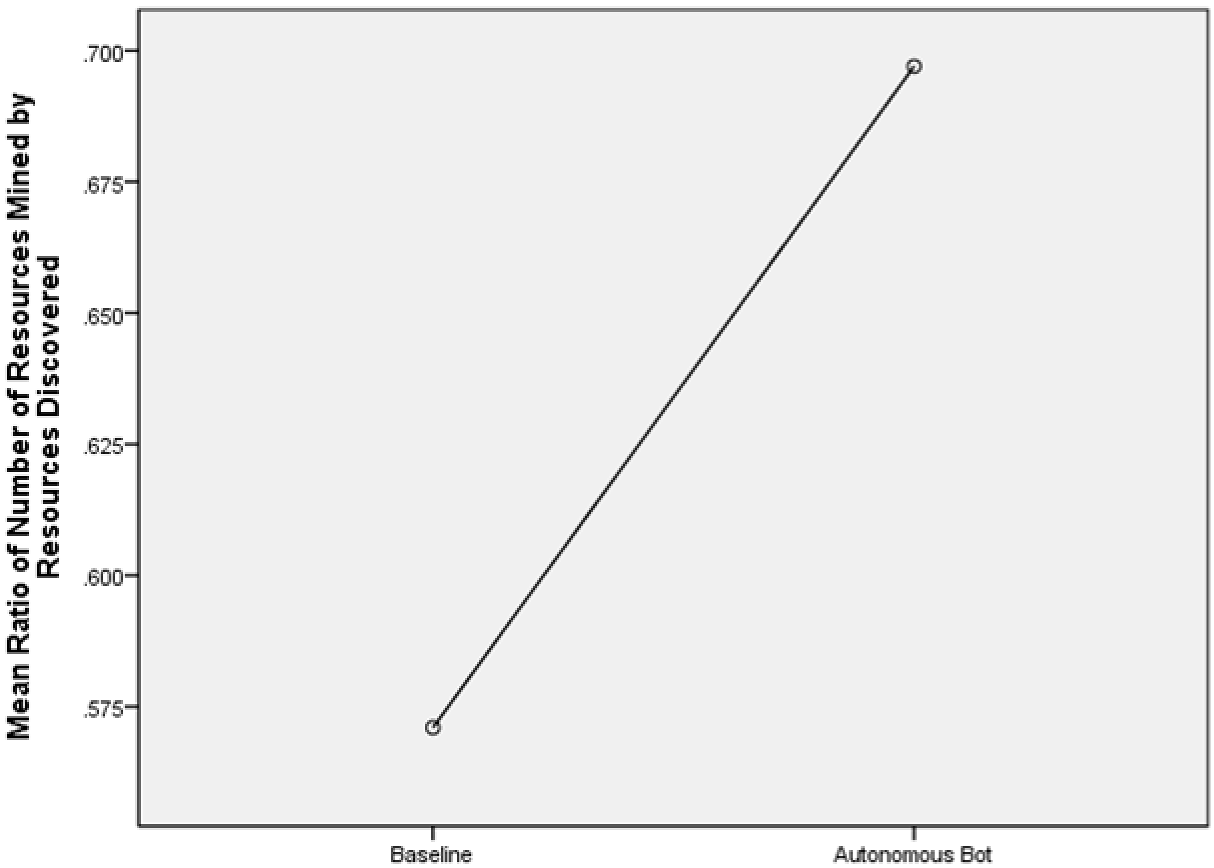

Figure 2: Ratio of number of resources mined and resources discovered between the baseline and autonomous groups, i.e., the proportion of found resources to mined resources

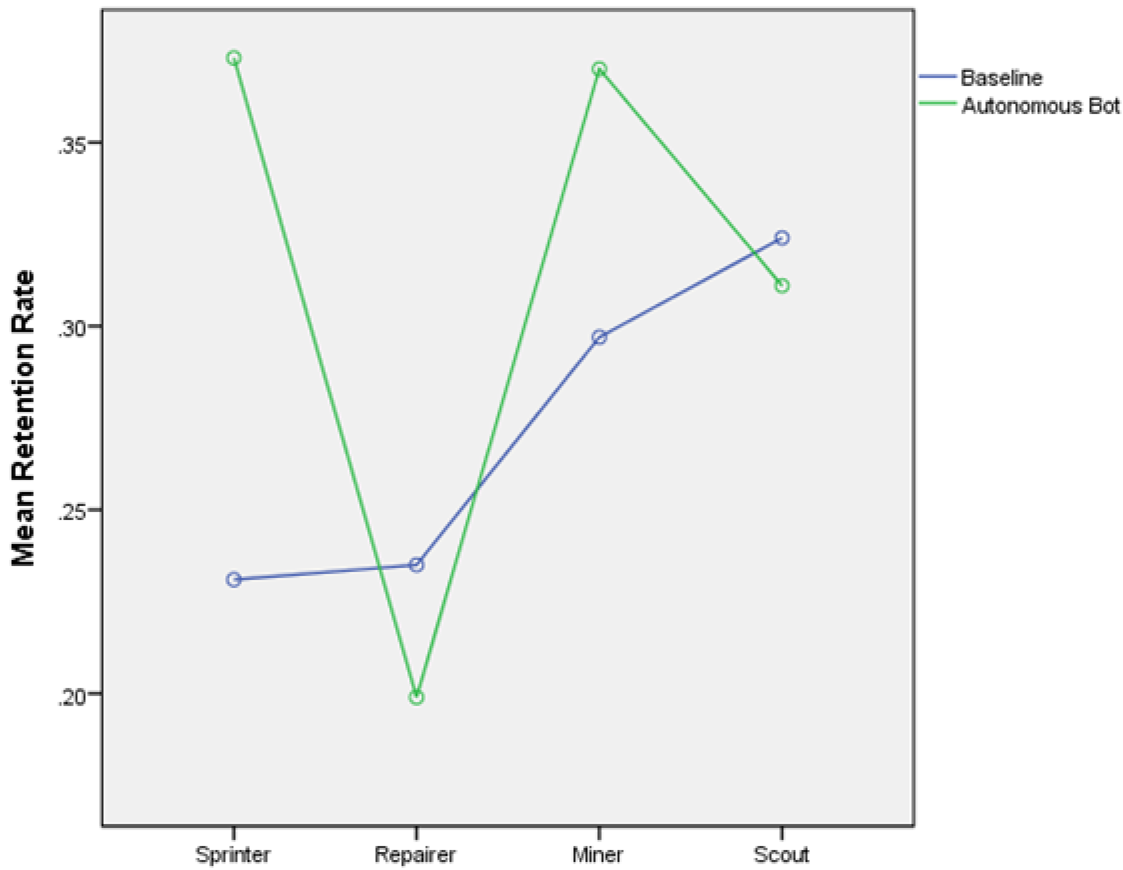

Figure 3: Mean toolset retention rates between the baseline and autonomous conditions of experiment 2

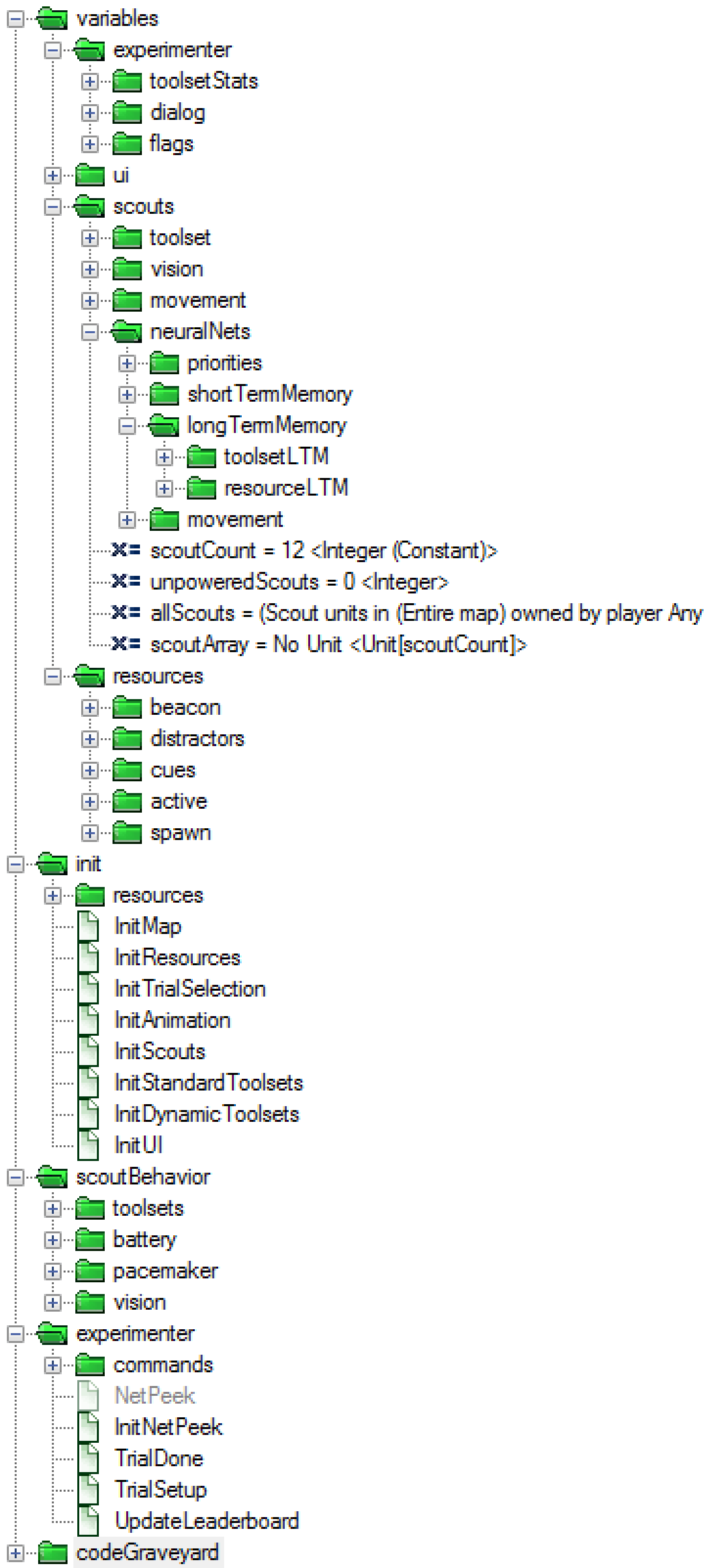

Figure 4: Tree diagram of the project structure in the Starcraft® II Map Editor.

Table 1: List of links regarding the project, its data, data analysis, and demo

Link Item	**URL**
GitHub Project	https://github.com/Forns/project-brave-new-world
Experimental Data and Analysis	https://github.com/Forns/project-brave-new-world/tree/master/doc/data
Video Demo	https://docs.google.com/folder/d/0B5VVQmeWeaSwZjh3V0JPbXNkTms/edit?docId=0B5VVQmeWeaSwQkJWcFBIT0NEZWM
Map Editor File, all inclusive (NOTE: may require at least a demo version of Starcraft® II in order to actively run)	https://github.com/Forns/project-brave-new-world/blob/master/src/main/maps/ProjectBraveNewWorld.SC2Map