A Simulation of Evolved Autotrophic Reproduction

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ABSTRACT
In this experiment we evolve reproductive behaviors for a simulated vehicle. Future work will employ the resulting behaviors to populate a simulated ecosystem.

Categories and Subject Descriptors
I.2.0 [**Artificial Intelligence**] General—*Cognitive simulation;*
I.2.6 [**Artificial Intelligence**] Learning—*Connectionism and neural nets*;
I.2.9 [**Artificial Intelligence**] Robotics—*Autonomous vehicles*;
I.2.11 [**Artificial Intelligence**] Distributed Artificial Intelligence —*Intelligent agents*;

General Terms
Algorithms, Experimentation

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Self-replication, Neuroevolution, Robotic Control

1. INTRODUCTION
Jon von Neumann proposed that self-replicating vehicles could be used as agents to explore the vast reaches of space [4]. Volume is proportional to the *cube* of distance and a single vehicle cutting a swath through space explores an area that is at best a *linear* function of the distance traveled and the *square* of the sensor range. Biological reproduction can approach exponential growth, so von Neumann's proposal seems like an appropriate reapplication of natural technology. A number of interesting control problems are presented by this hypothetical scenario. The possibility of centralized control is limited by the speed of light, so autonomy amongst the agents is probably necessary. Autotrophy is the capability of self-nourishment [4], which in von Neumann's space exploration scenario would be demonstrated by agents using local material and information for replication, fuel, navigation, etc. The novelty of exploration could tremendously compound the load on an agent's autotrophic behavioral capabilities. Perhaps in a scenario like deep space exploration, the demands of autotrophic reproduction are *so* severe that they will demand human levels of *intelligence* and *creativity*. This experiment is predicated on the hope that we will eventually be able to use the demands and process of autotrophic reproduction to select the characteristics *intelligence* and *creativity*.

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2. BACKGROUND AND MOTIVATION
Biological reproduction and the design and manufacture of artifacts share a useful, albeit abstract, similarity in that they are both fundamentally *creative domains*. By utilizing this similarity we will attempt to construct simulations that fuse useful aspects of both paradigms. In this effort we employ many of the techniques described in Valentino Braitenberg's *Vehicles: Experiments in Synthetic Psychology* [1]. *Vehicles* strongly expresses the possibility of transposing elements of biological and artificial phenomena. Frequently, similarities between vehicular and animal navigation are sufficient to utilize them as *compatible domains*. Countless examples exist for the transposition of aspects of vehicular and animal mobility. Simulated cars can be subjected to evolutionary pressures or controlled by artificial neural networks [8], and animals can be fitted with prosthetic wheels [11], or routed like traffic, etc. We propose that Braitenberg's vehicles can utilize a similar compatibility that exists between the domains of fabrication and reproduction. In the example of biological reproduction, most if not all evolved adaptations benefit the continuity of reproduction. In the example of the design and fabrication of artifacts, most if not all evolved adaptations benefit the continuity of production (including designed obsolescence).

Human intelligence and creativity, like all successful adaptations, resulted from selective pressure and results in enhanced reproductive fitness. From this we derive the two central premises of these experiments. First, it is likely to be easier and more effective to *generate* synthetic intelligence by reapplying the simple pressures that lead to human intelligence to evolving artifacts, than it would be to attempt *define and design* an embedded synthetic intelligence. Second, if we transpose the natural phenomena of autotrophic reproduction onto a simulated substrate where simple robotic agents can assemble and *modify* their offspring, it may be possible to detect signs of synthetic intelligence, experimentation, and even design using measures as simple as reproductive efficacy. In the history of our species, progress with fabrication techniques is often followed by increases in population. In the context of these experiments, synthetic fabrication and replication are unified so we can measure “technological” progress with reproductive rates.

Many complex aspects of human behavioral and physical capabilities have clear causes in relatively simple pressures born by our ancestors. At some point in our phylogenetic past, a few simian species transitioned from a diet of vegetables to a diet of fruit. The window of opportunity for obtaining ripened fruit is much smaller than that of vegetables. It is likely that the pressure of this simple constraint and the opportunity for novel adaptations to ameliorate it, lead to the amazingly complex adaptation of navigational planning. Similarly, the radical adaptation of tool usage was predicated on the freeing up of the forelimbs by a series of minor adaptations gained by transitioning niches, first to arboreal, and eventually to savanna. The simple constraint presented by the physical structure of trees favored a semi-erect posture, and that in turn allowed the defensive adaptation of throwing, which in turn lead to an offensive reapplication of throwing; hunting on a savanna. In this case, a series of niche transitions and the adaptations they caused served to increase the likelihood of a successful transition to a subsequent niche. Similarly, in the artificial domain, it has been shown that the generalization capabilities of an evolved learning rule are improved by exposure to a series of problems [2]. It is likely that the robust noise handling capabilities of the human brain are the result of the rich complexity of natural ecosystems. Artificial ecosystems can generate an "unfolding fitness landscape" by producing an unending stream of pressure variations [12]. Can the variation produced by an artificial ecosystem produce desirable noise handling and generalization capabilities? Tom Ray "inoculated" a computational substrate with a hand coded assembly program to create the artificial ecosystem *Tierra*. In contrast, we are attempting to evolve the seed population of a simple four dimensional simulated ecosystem using a more conventional steady state genetic algorithm.

The experimental simulations described in this paper rely on hindsight to subtend aspects of the evolutionary path that brought about human intelligence and creativity. Bipedal ambulation is costly and difficult, but the demand for navigational planning may be sufficient to create a general behavioral tendency and capability for *prediction*; So why not start an agent with wheels instead of feet? Ten independent digits with four degrees of freedom apiece is likely sufficient manipulatory capability to allow tool usage, but is it *necessary*? Unfortunately, the cost of simulating or synthesizing and maintaining a pair of hands and feet is prohibitive. It is likely that there is trade off between degrees of freedom and cost, for all manipulators, and unlikely that we have to pay the whole cost upfront. In the way of Braitenberg's elegantly simple vehicles, we believe we can approximate the key aspects of manipulation with far less expense.

3. SIMULATING THE AUTOTROPHIC WORLD

In this experiment, we characterized the vehicles as autotrophic to reflect the fact that they are supplied with boundless amounts of energy and the "raw" elements in the world are not "live."

3.1 Reproduction vs. Replication

3.1.1 Semantic Separation from Replication

Reproduction differs from replication in that replication produces an *exact* copy while reproduction produces a *similar* copy. Strictly speaking, reproduction is a superset of replication, affording both exact duplication *and* variation [8].

3.1.2 An Assembly Scenario as an Approximation of a Natural Genetic Algorithm

Biological evolution is the product of tiny variations produced in a reproductive process. Design evolution can be the product of serendipitous, experimental, or insightful variation. The simulations used for the experiments in this paper allowed the possibility of a trial or parent vehicle resizing a component before or after the component is integrated into a second, or offspring, vehicle. The degrees of freedom this provides are critical for future experiments using the behaviors produced in this initial phase. First, we hope to use an evolved population to "jump start" an artificial ecosystem where physical variations have a bearing on reproductive fitness. Second, it may be possible to detect the capability for creative design by looking for super-linear performance in a scenario where the parent brain is directly transferred to the child upon completion. For the sake of reproductive repeatability in future applications, we explicitly rewarded the minimization of the difference between the dimensions of the parent and offspring vehicles.

In humans, the ability of a parent to alter or select a child's attributes can be viewed as an example of intelligently managed epigenetic variation. Agricultural practices are examples of intelligently managed genetic variation. Humans also select attributes in artifacts by means of artificial genetic algorithms. This work is an effort to evolve behaviors like recovery, resizing, and assembly in simulated agents capable of motility, manipulation, and variation of components. By allowing the variation of components found in the environment, the simulation gives a parent vehicle degrees of *creative* freedom. Here we define creative freedom as a variation of one of the three major dimensions of a rectangular prism representing a component. These experiments are meant to be the first stage in a series of progressively higher fidelity simulations of macro-scale automated reproduction. Tom Ray's *Tierra* system simulates an ecosystem by using a limited amount of memory and process cycles as a competitive substrate for the self-replication of assembly code lifeforms. In contrast, this experiment attempts to simulate a physical substrate in which reproduction can be achieved through kinematic manipulations.

3.2 Assembly Scenario

Specifically, the target behavior in this experiment is the resizing and assembly of seven components into a vehicle of the dimensions of the trial vehicle (See Figure 1). The components represent the stock or *raw* material from which a second manipulator must be constructed. The joining of the components is handled by the simulation and is triggered by collision of the components that are or become eligible for joining based on simple rules (See Figure 2).

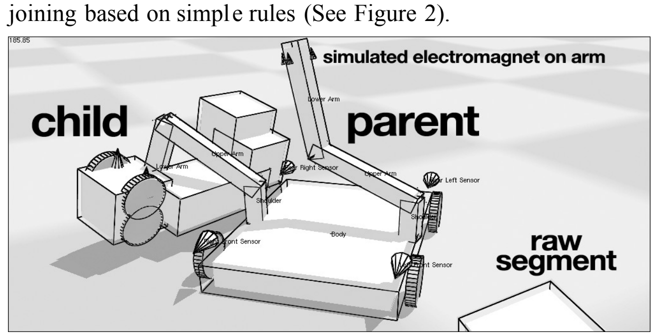

Figure 1: Trial vehicle with partially assembled child.

1. The first time the right arm of the trial vehicle collides with a raw (non-integrated) component while attempting to lift, the component automatically becomes the chassis element of a second or offspring vehicle.
2. If the chassis block of the offspring collides with an unused block prior to having its two shoulder sockets filled, then the colliding block is integrated into the offspring and joined at the shoulder, becoming the base element in an arm.
3. If any raw block collides with the most distal element in an arm of the offspring, then it is joined to that arm, becoming the new most distal element.

Figure 2: Assembly Rules.

If the trial vehicle integrates a block into its offspring, then the trial vehicle is given a ten second extension in that trial phase. This trial phase time reward is used to eliminate protracted simulation of non-viable vehicles, while extending sufficient time for a successful vehicle to recover and integrate several elements.

3.3 Vehicle, Control, and Engine

3.3.1 Braitenberg Manipulator

Braitenberg [1] describes a series of simple vehicles that powerfully illustrate the behavioral diversity of simple circuits interacting with an environment. Braitenberg boldly suggests there is sufficient similarity between the domains of vehicle and animal navigation that biological and artificial examples of phenomena like improvement models, and control models, can be readily interchanged. This experiment employs Braitenberg's technique by using a four wheeled cart to represent a simple mobile agent, and employs evolution and learning to improve its artificial neural network controller. The trial scenario used in these experiments involves the introduction of a trial vehicle onto a plane with a spiraling distribution of 40 components that can be integrated into an offspring vehicle. Simple eyes and limited output channels reduce the minimum size of the neural network needed to control the agent.

It is hoped that the vehicle simulated in these experiments is in some sense representative of an autonomous robot that could convey “raw” stock, load and assemble machines, and maintain, and otherwise expedite, the duplication of a system composed of a conventional machine shop and the mobile robot *itself*. Related experiments by Hod Lipson and company have demonstrated evolved self-assembly behaviors for physical multi-bodies consisting of motorized hinged cubes that selectively attach to one another by means of magnets [14]. Similarly, in this experiment we use simulated electromagnets as a simple mechanism to allow an agent to manipulate objects in its environment. (See Figures 3, 4, and 5.)

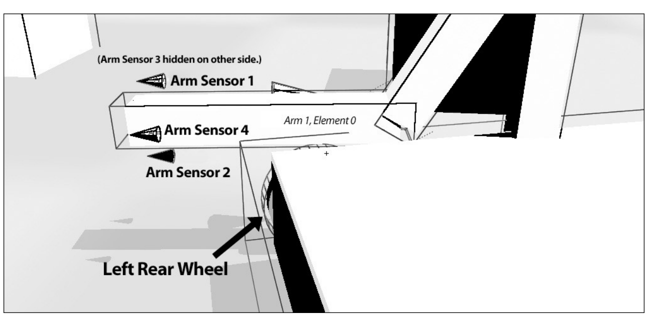

Figure 3: Side view of tool tip.

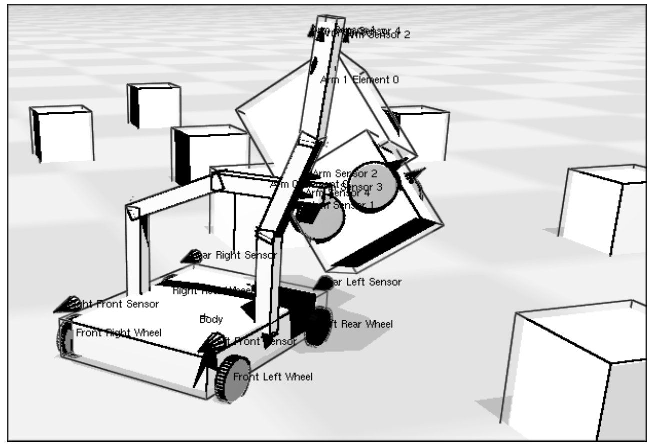

Figure 4: Parent lifting child.

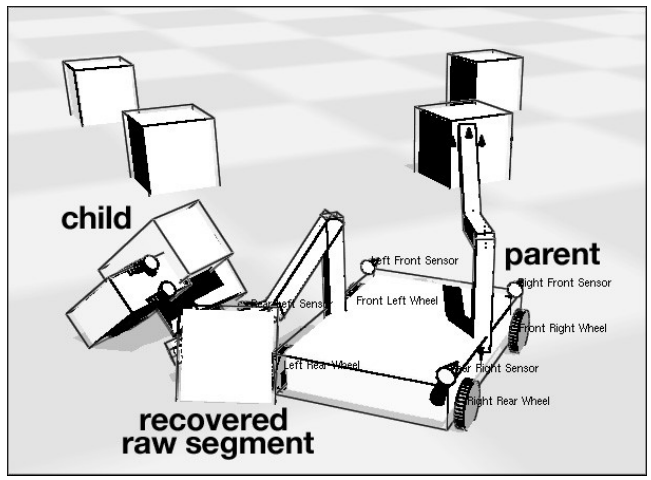

Figure 5: Parent delivering (or “feeding”) a recovered segment to child.

3.3.2 Artificial Neural Network

In this experiment we utilized 376 node fully connected artificial neural networks as a primary control apparatus for the trial vehicles. The primary network's genome is encoded as a square matrix composed of 5,625 double-precision floating point inter-weight values with 376 values in the diagonal entries serving as autapses. Sensors deliver signals to 41 of the nodes, and 16 are tied to effectors, leaving 319 nodes without dedicated functional roles. (See Table 1.) Sensations "perturb" the activation states of the input vector by the rule, "old activation + sensation = new activation." This technique was designed to preserve recurrent signal, which is left over after the application of a decay step that replaces the refresh step of a feed-forward neural network (at rate 0.07).

3.3.3 Breve Engine and Computation

This experiment was conducted using Jon Klein's *breve,* an a-life engine built on top of the the Open Dynamics Engine and the Open Graphics Library. The code for these experiments was written in *steve,* the *breve* development environment's native object-oriented language. Computation was carried out on an eight node cluster computer. Migration of individuals between various machines was achieved by a fixed schedule of replacing members of the local population with members of a population from a shared network folder containing elite individuals from every node in the cluster.

3.4 Genetic Algorithm & Fitness Function

Substantial work has already been done in the domain of evolving both processes and mechanisms for self-replication [3, 9, 10]. Our experiment assumes that the physical morphology of the trial vehicle can be left static and only the behavior generating neural network is subject to the genetic algorithm.

3.4.1 Genetic Algorithm

The method of improvement used in this experiment is a variation of the steady-state tournament style genetic algorithm used in Jon Klein's SuperWalker.tz demo, which comes with the *breve* simulation environment. A tournament consists of randomly selecting four neural networks from a population, running trials of all four, and finally replacing the two lowest scoring individuals with new neural networks that are produced by two-point crossover from the two highest scoring individuals in that tournament with 10% of the weights replaced by novel mutations. Following a short pilot experiment (1,500 trials), we found no immediate benefit from using uniform crossover, however, future experiments will attempt to confirm if this holds for longer runs.

3.4.2 Fitness Function

Fitness of the trial vehicle is assessed by a composition of several measures. The measure used to enforce morphological fidelity is determined by summing the absolute values of the difference of the dimensions from corresponding edges on the trial and offspring vehicles to generate an evaluation of total dimensional difference. A complete vehicle consists of a set of seven rectangular prisms or blocks with three major dimensions apiece; so 21 points of difference are measured. If an offspring vehicle lacks a component, the difference with the corresponding component on the trial vehicle is not evaluated.

$$\boldsymbol{F = C_0^{1000} + \sum A_{n0}^{333} - \sum \left| E_{ntv} - E_{nov} \right| - D} \text{ where,}$$

F = Fitness,

C_0^{1000} = Bonus for offspring chassis, either 1000 if it exists, or 0,

A_{n0}^{333} = Bonus for the n^{th} arm segment in the offspring, either 333 if it exists, or 0,

E_{ntv} = Length of n^{th} edge of the trial vehicle,

E_{nov} = Length of n^{th} edge of the offspring vehicle,

D = Distance between the tip of the closest arm of the trial vehicle and the chassis of the offspring vehicle.

Figure 6: Fitness Algorithm.

In Figure 6, the terms C and A are positive values with a maximum possible total of 2,998 which gives us the upper bound of the possible fitness values. The minimum possible value of the negative terms is achieved when the dimensions of the offspring are identical to the trial vehicle and one of the trial vehicles' arms is resting on the offspring. Roughly speaking, the positive terms are coarse resolution (integers) and the negative terms are fine resolution (double-precision floats), serving as a means to differentiate the members of the classes defined by the discrete bonus schedule of the positive terms.

4. RESULTS

We confirm the possibility of evolving reproductive behaviors for this scenario using a *t*-test of two samples of fitness values consisting of the first 100 trials (x1) and the last 100 trials (x2) of a run of 16,400 trials. (See Figures 7 and 8.)

Sample	N	Mean	St. Dev.	S.E. Mean
x1	100	932	301	30
x2	100	1787	729	73

Difference = mu (x1) – mu (x2)
Estimate for difference: -855.398
90% lower bound for difference: -957.020
T-Test of difference = 0 (vs >):
T-Value = -10.84, P-Value = 1.000, DF = 131

Figure 7: Result of one-tailed *t*-test for difference of two samples.

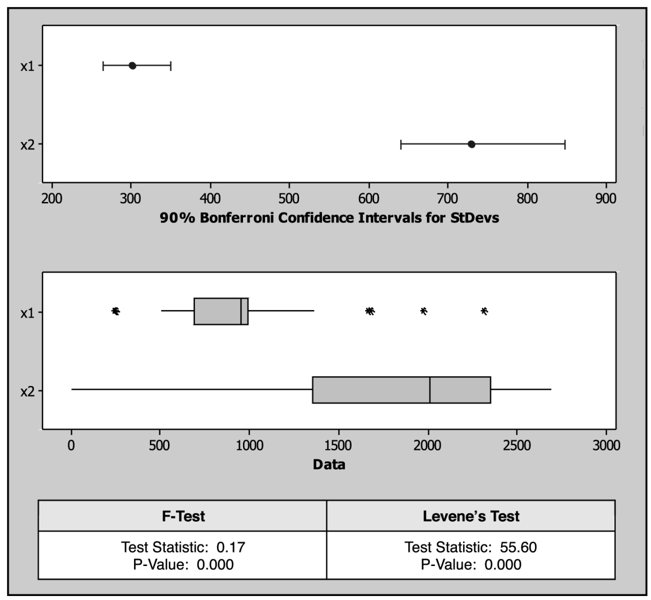

Figure 8: Test for equal variances for x1 and x2.

5. FUTURE WORK

Future work will be centered around verifying that individuals, evolved in an explicitly defined genetic algorithm (where reproduction is simplified to the transcription of a genome), can be migrated to the more demanding scenario of an artificial ecosystem where reproduction is solely the result of an agent's behavior. Because the individuals evolved in this experiment are exposed, during their trial phase, to an evaluation of their own fitness (Table 1, Node 39), it may be possible to seamlessly replace this input with a measurement of fitness customized to *explicitly* approximate the *implicit* reproductive fitness criteria of an artificial ecosystem. A good replacement might be a normalized recursively generated measure of an individual's reproductive fitness encoded as an *n*-ary number, where *n* is the maximum number of offspring of any one generation of its descendants and each successive generation's total offspring count is represented in a more significant digit. Note that this evaluation is skewed toward *repeatability* by crediting each successive generation with a higher order of magnitude than the previous. By presenting evaluations of fitness as stimuli during the trial phase, it is possible to provide detailed performance feedback to the agent. This feedback, combined with an epigenetic capability to alter behavior provided by a meta-network [6, 7], should allow the possibility of *informed* systematic variation of parental behaviors and offspring configuration. A version of the code used in this experiment has been prepared to study the emergence of language and mimetic crossover by evolving pairs of vehicles with two channels for simulating communication. Several forms of variation (genetic, epigenetic, ontogenetic, and mimetic) [13] are available in the code base used for this experiment; future experiments will include more extensive tests of the interaction of these variational modes.

5.1 Heterotrophic Reproduction

Two future experiments will replace the "raw" block elements of the current simulation with a descendant class of objects that behave by rules similar to those of Conway's game of "Life."[5] The first will utilize non-motile blocks; the second will utilize both motile and non-motile blocks. By giving the blocks their own crude reproductive algorithm, we can construct scenarios where behaviors similar to agriculture and husbandry are beneficial to evolving vehicles.

Table 1: Neural network nodes and their association with the trial vehicle.

Node	Association	Formula	Notes
0	Carrying with arm 1.	$a_j = 0 \vee 1$	Boolean 1 indicates carrying an object is being lifted.
1	Carrying with arm 2.	*Same as above.*	*Same as above.*
2	*x* dimension of object carried by arm 1.	$a_j = D_i$	Where is D_i the dimensional measure and a_j is the activation value of this node
3	*y* dimension of object carried by arm 1.	*Same as above.*	*Same as above.*
4	*z* dimension of object carried by arm 1.	*Same as above.*	*Same as above.*
5	*x* dimension of object carried by arm 2.	*Same as above.*	*Same as above.*
6	*y* dimension of object carried by arm 2.	*Same as above.*	*Same as above.*
7	*z* dimension of object carried by arm 2.	*Same as above.*	*Same as above.*
8	Left front chassis sensor channel 1.	$a_j = \sum \frac{1}{D_n} \lvert (A_p - A_n) \rvert$	Where D_n is the distance to n^{th} resolved object, $A_p = 1.6\, radians$ and is the pan or maximum angle of separation from the centerline of the sensor that an object can be resolved, and A_n is the angular distance from the centerline to the n^{th} resolved object.
9	Left front channel 2.	*Same as above.*	*Same as above.*
10	Right front chassis sensor channel 1.	*Same as above.*	*Same as above.*
11	Right front chassis sensor channel 2.	*Same as above.*	*Same as above*
12	Left rear channel 1.	*Same as above.*	*Same as above.*
13	Left rear channel 2.	*Same as above.*	*Same as above.*
...	...	...	...
17	Arm 1 Sensor 1 channel 1.	*Same as above.*	*Same as above.*
18	Arm 1 Sensor 1 channel 2.	*Same as above.*	*Same as above.*
19	Arm *x* Sensor *y* channel *z*.	*Same as above.*	*Same as above.*
20-30	...	...	...
31	Arm 1 Joint 1 angle.	$a_j = A_j$	A_j is the flex angle in radians of the joint *j*.
32-38	Arm *x* Joint *y* angle.	*Same as above.*	*Same as above.*
39	Fitness.	$a_j = \frac{F_t}{3000}$	F_t is the fitness assessed at time *t*. The constant approximately normalizes the fitness scale which spans from 0 to 2998.
40-357	Unassigned.	$a_j = \sum a_i * w_{ij}$	Where a_i is the activation at node i and w_{ij} is the weight between i and j, and j is this node.
358	Magnet tool arm 1.	If $a_j > 0$ then $M_i = 1$; else $M_i = 0$	Lift and set, where $M_i = 0$ is set and $M_i = 1$ is lift.
359	Magnet tool arm 2.	*Same as above.*	*Same as above.*

Node	Association	Formula	Notes
360	Perturb *x* dimension of object carried by arm 1.	$D_i^{t=0}+a_j=D_i^{t=1}$	Where $D_i^{t=0}$ is the initial dimension, a_j is the activation of this node, and $D_i^{t=1}$ is the resulting dimension.
361	Perturb *y* dimension of object carried by arm 1.	*Same as above.*	*Same as above.*
362-366	...	...	...
367	Arm 1 shoulder joint.	$V_i^{t=0}+a_j=V_i^{t=1}$	Where $V_i^{t=n}$ is the rotational velocity of the i^{th} joint at time n and a_j is the activation at this node.
368	Arm 1 elbow.	*Same as above.*	*Same as above.*
369	Arm 1 wrist.	*Same as above.*	*Same as above.*
370	Arm 2 shoulder.	*Same as above.*	*Same as above.*
371	Arm 2 shoulder	*Same as above.*	*Same as above.*
372	Arm 2 elbow.	*Same as above.*	*Same as above.*
373	Arm 2 wrist.	*Same as above.*	*Same as above.*
374	Left side wheels.	*Same as above.*	*Same as above.*
375	Right side wheels.	*Same as above.*	*Same as above.*

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