Intrinsic Evolution of Safe Control Strategies for Autonomous Spacecraft

GARRISON W. GREENWOOD, Senior Member, IEEE
Portland State University

Autonomous space vehicles need adaptive control strategies that can accommodate unanticipated environmental conditions. Although it is not difficult to construct alternative control strategies, a proper evaluation frequently can only be done by actually trying them out in the real physical environment. It therefore becomes imperative that any candidate control strategy be deemed safe—i.e., it won't damage any systems—prior to being tested online. How to do this has been a challenging problem.

We propose a solution to this problem. Our approach uses an evolutionary algorithm (EA) to intrinsically evolve new control strategies. All candidate strategies will be checked for safety using formal methods. More specifically, an EA will evolve a series of finite state machines (FSMs), each of which encodes a unique control strategy. Model checking will guarantee whether all safety properties are satisfied in the strategy. A numerical example is included to illustrate our approach.

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Author's address: Dept. of Electrical & Computer Engineering, EEN001, Portland State University, Portland, OR 97207, E-mail: (greenwood@ieee.org).

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I. INTRODUCTION

In October 1997 NASA launched the Cassini spacecraft to explore Saturn and its moons. Due to arrive at Saturn in 2004, the spacecraft will eventually establish an orbit around the moon Titan and then launch a probe, called Huygen, into the moon's atmosphere. Atmospheric data is relayed from Huygen to the Cassini spacecraft and then transmitted back to Earth. Engineers discovered last year that communications between the Huygen probe and the Cassini spacecraft would fail due to unanticipated Doppler effects, which could lead to a total loss of data on Titan's atmosphere. Fortunately, this problem was discovered in time and flight plan changes are being implemented to compensate for the Doppler effect [1].

But there is an even more important issue to consider: adaptive control strategies for autonomous spacecraft. Control strategies are critical ingredients of a space mission because they indicate what actions are to be taken by the spacecraft in response to environmental conditions. The Doppler problem on the Cassini spacecraft would only cause loss of data. Although such a loss is not to be taken lightly, it is inconsequential when compared with the loss of the spacecraft itself, which is entirely possible if the system is trying to adapt to an unanticipated environmental condition by switching to a new—and presently undefined—control strategy.

Reconfiguration was able to correct the Cassini spacecraft problem, and it may well prove to be the key to handling a whole host of such problems. More specifically, reconfigurable circuitry which can adopt different functionality can help to compensate for unanticipated environmental conditions. Reconfigurable circuitry or systems are also beneficial for fixing failures because it eliminates the need for redundant hardware (which consumes precious space and weight) by simply reconfiguring the existing hardware to compensate for the failure. But, despite the enormous advantages of reconfiguration, there remains a very important question:

Question 1. *If new reconfiguration information must originate from Earth, will it arrive in time to do any good?*

Communications between Earth and Mars takes around 10 min, which means the likelihood of receiving new configuration information for deep space missions—in a timely manner—is not good. Consequently, we must answer Question 1 in the negative.

The solution to the problem raised by Question 1 may lie with adaptive systems, i.e., systems capable of reconfiguring themselves in response to faults or a changing operational environment. Of particular interest is whether this adaption can be performed in-situ (in place), which removes any reliance upon Earth-bound resources for new configuration information. Stoica et al. [2] points out that much of the previous work on adaptive systems has been restricted to sensors and signal-conditioning circuitry because of the dire consequences of evolving an unsafe control strategy. Nevertheless, the ability to adaptively control spacecraft without requiring human intervention is still an area of enormous research interest [3].

Self-adaption suggests the system configuration evolves over time. Canham and Tyrell [4] demonstrated fault tolerance can be built into an evolutionary process, which can then accommodate real-world faults. We believe our approach, which incorporates an evolutionary process, is the first step towards solving the problem raised in Question 1. Specifically, we have developed a method for adapting control strategies in ways that are guaranteed to be disaster free during the reconfiguration process. This paper documents the key elements of our method.

II. OVERVIEW OF OUR APPROACH

Our basic approach is to evolve a series of deterministic finite state machines (FSMs), each which encodes a potentially new control strategy. The efficacy of each strategy will be assessed by actually trying it in the real physical environment. However, this will only be done with control strategies certified as being safe. The problem is formulated in such a way that the formal verification techniques can guarantee whether or not the safety properties are met in the control strategy.

A FSM is a digraph that completely describes a control strategy. Each state is a stable system condition and transitions between states occur based on new input information. The outputs associated with each state are command signals issued to the system being controlled. A hallmark of FSMs is the processing of inputs depends on the current state of the system. In other words, the same input applied at two different times may not illicit the same output response because the system may have been in different states at those two time periods.

FSM design requires completing several tasks: 1) define the number of states, 2) define the outputs in each state, and 3) define the transitions conditions between states. In many instances a design engineer could hand-code the FSM, but this can be tedious if the control strategy is complex. The solution space of all FSMs that apply to the problem of interest is often extremely large. This means a complete enumeration and evaluation of all solutions is impractical. Even deterministic searches through the solution space may simply take too long. Thus, in practice, only a stochastic search algorithm is likely to be successful in identifying an acceptable FSM.

Researchers have found much of the FSM design effort can be alleviated by using evolutionary algorithms (EAs). These are an extremely powerful class of stochastic search algorithms that use the principles of Darwinian evolution found in nature to conduct searches. More specifically, a population of solutions undergoes stochastic modification to create new candidate solutions. Each solution is assigned a fitness value that reflects the quality of the solution. A survival of the fittest criteria, i.e., those solutions with the highest fitness value, determines which solutions survive to reproduce in future generations. Done properly, the entire population evolves towards regions of the search space that contains optimal solutions. With respect to the problem of interest, each solution in the population is a FSM and its fitness measures the acceptability of its encoded control strategy, i.e., the better the control strategy performs, the higher its fitness value. New control strategies are created from existing strategies by any stochastic modification to a FSM. For instance, randomly adding or deleting a state, changing a state's output, or changing the position of an arc would create a new control strategy.

There are two ways of determining if an evolved control strategy is acceptable: an extrinsic evolution where the strategy is simulated first and only the one best strategy is actually implemented, or an intrinsic evolution where every candidate strategy is downloaded into the system and exercised in the real physical environment. EAs can work with either type, but the extrinsic evolution may be problematic. EAs typically have some closed-form objective function that assigns fitness values. Unfortunately, it may not always be possible to define an appropriate objective function for a needed control strategy, which means intrinsic evolution is the only option.

An example will help illustrate the need for intrinsic evolution. Sanchez-Peña et al. [5] studied the interaction of an orbital control maneuver with a spacecraft's attitude. Their idea was to use the thrusters that provide the force for orbit control as actuators for attitude control. They proved optimal control needs a minimum of 4 thrusters with no failures allowed or a minimum of 6 thrusters if one failure is tolerated. But they defined failure to mean the thruster force went to zero. This is not the only type of failure affecting the ability to maneuver and many of these other failures are not corrected easily. For instance, a solar panel stuck in a partially deployed position can shift the center of mass to an unexpected location. A collision with orbital debris could change a nozzle's geometry, which adversely affects thrust. Unforeseen failures like these are hard to represent accurately in a simulation, and even then only if the precise nature of the failure is known. Evolving a new control strategy with an incomplete or inaccurate simulation is futile. Indeed, the only way to truly evaluate a control strategy in the presence

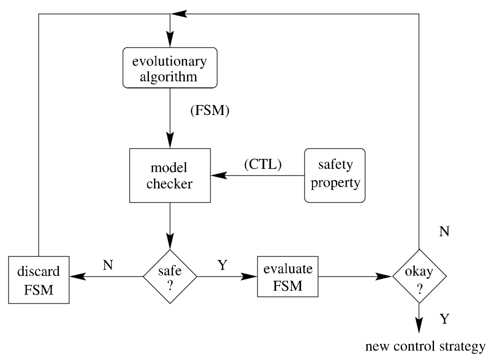

Fig. 1. Conceptual diagram showing how to evolve safe control strategies. Each candidate control strategy evolved by EA is described by FSM. All safety properties are stated as CTL expressions. MC uses formal verification techniques to determine if evolved control strategy is safe. Safe control strategies are evaluated in physical environment whereas unsafe strategies are immediately discarded and replacement strategy is evolved. Once an acceptable new control strategy is found, it replaces current control strategy.

of failures is to actually try it out in the physical environment and see what happens.

Whenever intrinsic evolution is used it is absolutely essential that the control strategy be safe, i.e., it does no harm to the controller itself nor to any other system, while it undergoes evaluation. This safety requirement presents what heretofore has been an open challenge:

Question 2. *Since an EA creates new FSMs randomly, is there some way to know if the encoded control strategy is safe before it is tested in the real physical environment?*

We believe our approach answers Question 2 in the affirmative. We will use an EA that searches for the optimal control strategy by creating candidate FSMs. However, only control strategies that pass a safety check will be downloaded for evaluation. We borrow automatic formal verification methods to assess this safety. These methods use mathematically provable techniques to characterize a system without conducting exhaustive simulation or testing. Specifically, we rely on model checking techniques [6] to verify the safety of candidate FSMs generated by the EA. Although model checking has been extensively used in hardware design and software verification, to the best of our knowledge no prior research effort in formal methods has attempted the problem we consider here. Fig. 1 shows the control strategy development environment.

III. BACKGROUND

A. Finite State Machines

A (deterministic) finite state machine $\mathcal{M}$ is defined by a 6-tuple

$$\mathcal{M} = (I, O, S, \delta, \gamma, S^o)$$

where
I is the set of inputs,
O is the set of outputs,
S is the set of states,
$\delta : I \times S \rightarrow S$ is the state transition function,
$\gamma : I \times S \rightarrow O$ is the output mapping function,
S^o is the initial state.

For a FSM that encodes a control strategy, the states are fixed conditions of the system under control, the inputs are measurements of the physical environment, the outputs are commands to the system, and δ defines the next system states based on the current input and the current state. We illustrate in Section IV how a control strategy is completely described by a FSM. We also show how its safety can be verified.

As a side comment, our method requires a data structure that satisfies two criteria: 1) it completely encodes all aspects of the control strategy, and 2) it is compatible with existing model checkers. We have chosen a FSM as the data structure. It is true that FSMs can be converted to logic circuits, but that does not mean we are solving a logic synthesis problem. We are not designing a digital circuit. We are trying to evolve a control strategy. In principle our method can use any data structure so long as it satisfies the above two criteria.

B. Evolutionary Algorithms

EAs are a class of search, learning, and optimization methods based on analogies to Darwin's theory of natural selection. The genetic algorithm (GA) [7, 8] is the most widely known form of EA and they have been applied to a number of scientific and technical problems. Fogel et al. [9] independently developed an EA called evolutionary programming (EP) that evolves FSMs to induce sequential patterns and make predictions. Still another EA called an evolutionary strategy (ES) was independently developed by Rechenberg [10]. All EAs share the same basic organization: iterations of competitive selection and random variation. Unlike traditional methods, every EA processes a population of potential solutions in parallel rather than just a single solution. However, it has been shown that no one type of EA—or for that matter any other kind of non-EA algorithm—performs optimally over all problem classes [11].

The GA is arguably the most widely known EA, and it is almost exclusively used by the evolvable hardware community (e.g., see [12]). However, we have decided not to use a GA but to instead adopt a variant of the EP algorithm. The most compelling reason for not using GAs is that they are not well suited for evolving structures—which is precisely what we want our EA to do! (See [13] for a discussion on generating structures with GAs.)

1. randomly create an initial population of μ FSMs
2. evaluate all FSMs (see Section IV(B))
3. create μ new FSMs by repeating the following two steps:
   (*i*) conduct a binary tournament to select a parent FSM from the current population
   (*ii*) randomly mutate the parent FSM to create a new offspring FSM
4. evaluate the combined population of μ parent FSMs and μ offspring FSMs. rank them according to fitness.
5. save the μ best ranked FSMs and discard the others.
6. exit if termination criteria is met. otherwise, go to step 3.

Fig. 2. EA for creating FSMs. Note that algorithm as shown does not make any safety checks. See Section IV(C) for details on modifying algorithm to add necessary safety checks.

Conversely, EP is ideally suited for such applications. In fact, its very first application was designing FSMs [9]. It is for these reasons we have decided to use an EA similar to an EP to evolve our FSM structure. Our EA differs from the pure EP in two ways: tournament selection is not used to rank the entire population, and adaptive mutation strengths are not used. Our EA is described in Fig. 2.

Offspring are randomly generated on-the-fly and extensive testing to verify safety takes too long to be practical. We use symbolic model checking techniques to verify the control strategy safety. This is a well-established formal verification technique that quickly verifies if a proposed control strategy satisfies the necessary safety properties. In the next section we discuss the safety checking in depth. Specific details for implementing the EA are presented in Section IV.

C. Model Checking

Our goal is to check that the control strategy satisfies critical behavioral properties to ensure reliable and correct functioning. Model checking (MC) is an advanced formal method which has potential to help us achieve that goal [14].

There are three methods of functional verification: simulation, emulation, and formal verification [15]. Simulation and emulation are widely used, but they do have one inherent problem: they are good at proving the presence of unsafe conditions, but they are not so good at proving the absence of unsafe conditions.

Formal verification methods do not rely on running test inputs through a system to determine its behavior. Rather, these methods use mathematical techniques to examine the entire solution space for a specified design property [15]. There is no need to construct test vectors or patterns. Moreover, the results are guaranteed, i.e., if formal verification says a property is verified, then it exists under all conditions. What makes this possible is formal verification methods employ mathematical logic and can theoretically account for every possible situation.

MC is a formal method that verifies if a system, modeled as a FSM, adheres to a specified property. The properties of interest are encoded as temporal logic expressions. Temporal logic is just a formal way of expressing properties that change over time [16]. There are many different kinds of temporal logic but computation tree logic (CTL) is the most widely used with model checkers. The basic idea is that we start with ordinary Boolean logic, and then add special temporal operators for describing future events. For example, in CTL, the operator **AX** means "for all possible input observations, in the next state,...," the operator **EX** means "there exists an input such that in the next state,...," the operator **AG** means "for all possible input observations, it will always be true that,...," the operator **EF** means "there exists a sequence of input observations such that eventually...," and so forth. The temporal operators can nest, so for example, **AGEF** (reset) says that it is always possible to find a path back to reset, and **AG** (req) $\Rightarrow$ **AF** (ack) says that every request is always eventually followed by an acknowledgment. It is also possible to express properties using propositional connectives. For example, if f and g are CTL formulas, so are $\neg f$, $f \wedge g$, and $f \vee \neg g$.

The FSM states are labeled with the safety properties that hold in that state. We can now transform the FSM into a Kripke structure $M(S,I,R,L)$ where

S is the set of states,
I is the set of initial states,
$R \subseteq S \times S$ is the set of transitions,
$L : S \to 2^{AP}$ is a labeling function,
AP is the set of atomic propositions (i.e., safety properties).

A path $\pi = s_0, s_1, s_2, \ldots$ through the control strategy (where s_0 is the initial state and $R(s_i, s_{i+1})$ holds for all i), describes the sequence of actions to be taken by a system in response to a sequence of observed inputs. The MC problem can then be described as follows.

Given a Kripke structure $M(S,I,R,L)$ representing a control strategy, and a safety property f to be verified, find the set of states that satisfy

$$\{s \in S \mid M, s \models f\}.$$

A graphical representation of the MC algorithm is shown in Fig. 3. This algorithm can be executed in $O(|S| + |R|)$ time.

We are concerned with sets of states rather than a single state. These sets can be represented by their characteristic functions

$$f_A(u) = \begin{cases} 1 & u \in A \\ 0 & u \notin A \end{cases}. \tag{1}$$

A Boolean encoding of the states in a Kripke structure makes $f_A(\cdot)$ a Boolean function and any set operations now become Boolean operations.

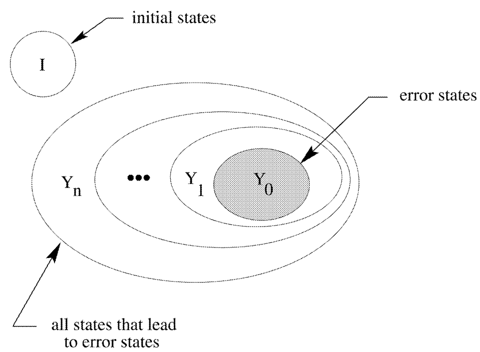

Fig. 3. Graphical depiction of MC algorithm. I is set of all initial states and Y_0 is the set of states that violates a safety property. Algorithm recursively computes $Y_{i+1} = \mathrm{Pre}(Y_i) \cup Y_i$ for $i = 0,1,2,\ldots n-1$ where $\mathrm{Pre}(Y_i)$ is preimage of set Y_i. Y_n then represents set of all states that can reach an error state. System is safe if $Y_n \cap I = \emptyset$. Check can be done in linear time.

That is, set intersection becomes conjunction and set union becomes disjunction. Binary decision diagrams (BDDs) are efficient data structures for Boolean functions. Representing transition relations such as $R(x,x')$ makes it possible for MC to verify properties in systems with over 10^{100} states—far, far more states then what is found in realizable control strategies.

Several important issues concerning our use of MC to check safeness of control strategies are worth highlighting.

1) MC has been widely used to verify hardware and software systems. However, the large number of states often forces one to use a reduced FSM model, created via model reduction techniques, in which some details are abstracted out. This has important consequences: MC may verify that the reduced model is safe with respect to the operational environment, but this does not necessarily guarantee the original system is safe.

However, in our approach the EA renders FSMs which are complete in the sense that every aspect of the control strategy is explicitly described in the FSM structure. In other words, no details are abstracted out or reduced. Consequently, in our application MC will guarantee whether or not the candidate control strategy fully satisfies the safety properties.

2) Model checkers typically provide trace information to help pinpoint where the safety property failed.

We do not use this feature. Indeed, we treat the entire safety issue as a decision problem, i.e., either the strategy is safe or it is not. Unsafe control strategies are immediately discarded, so there is no need to know why it is unsafe.

3) Model checkers are used to verify functional specifications and other properties, e.g., liveness.

In our approach MC only verifies safety, which is simpler than trying to verify liveness. Any other performance criteria will be assessed by trying out the control strategy in its operational environment. This has an important consequence: $\mathbf{AG}(\cdot)$ is the only form of CTL operator we will ever need.

4) In practice, control strategies tend to have orders of magnitude less states than what has been described above. Since MC algorithm complexity is linear in the size of the FSM and in the length of the CTL expression [14], the safety of a control strategy can be quickly verified.

There are several very good model checkers available free from universities. Among these are SMV from Carnegie-Mellon University [17] and VIS [18, 19] from the University of California at Berkeley.

D. Creating Safe Initial Populations

MC assures safe parent FSMs always produce safe offspring FSMs. This assurance does presume the initial population (which is randomly generated) only contains safe FSMs. Fortunately it is always possible to create such a population in a very straightforward manner. Safety property violations are identified by the 3-tuple (s,i,α) where s is the current system state, i is an input, and α is an action. The interpretation is as follows. If the system is in state s, and input i is observed from the operational environment, then the system responds by performing action α, which violates a safety property. Every 3-tuple is manifested in the FSM as an arc, labeled with i, with its tail at state s and its head at a state which performs action α. The set of all possible unsafe 3-tuples is known a priori because the safety properties are already known. Hence, it is easy to randomly create a safe FSM by just assigning the head of the arc (associated with input i) with a uniform probability to any state in the FSM so long as that target state does not perform action α. (This same method could be used as an intelligent reproduction operator for use in subsequent generations, but MC would still be needed because moving arcs is not the only form of reproduction.)

IV. IMPLEMENTATION DETAILS

This section provides detailed guidance on how to implement our method for evolving safe control strategies. An example problem is included to illustrate our approach.

A. Test Problem

The easiest way to understand how to implement our approach is to explain it within the context of a problem. Our method is widely applicable throughout the aerospace field. However, the aerospace field is incredibly diverse, which makes it very important to choose the test problem with care. Specifically, the problem of choice has to have two main properties:

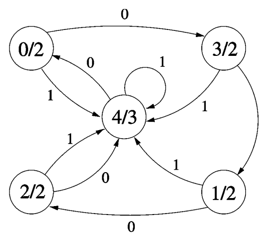

Fig. 4. Example of evolved FSM that encodes control strategy for Santa Fe Trail Problem. Input to FSM is observation of food or no food and output is command for ant to make some movement. Any state may be chosen to be initial state. Numbers on arcs represent observed input (0: no food, 1: food). Within bubbles are indicated state/output action (0: NOP, 1: turn left, 2: turn right, 3: step forward). Every aspect of control strategy is completely encoded within FSM structure. For instance, if current state is state 3, and no food is observed directly ahead, then strategy transitions to state 1 and ant is directed to turn to the right. However, if food is observed directly ahead, strategy transitions to state 4 and ant is directed to step forward to consume food pellet. This control strategy is taken from [21]. FSM for Hazardous Santa Fe Trail Problem is similar in structure, but labeling of arcs is different (see text).

1) it describes a system that needs a safe control strategy, and 2) it has to be easily understood by the widest possible audience. The second property is particularly important because it allows readers to concentrate on the details of our proposed method instead of getting lost in the details of some test problem for which they may have little or no technical background. We used the Santa Fe Trail Problem as a starting point because that problem has those desirable properties. This problem has been studied by the evolutionary computation community for a number of years.

The original Santa Fe Trail Problem, which is fully described in [20], involves placing an artificial ant on a 32×32 grid. The ant starts out facing east. At each time step the ant can turn left, turn right, walk one step forward, or do nothing. Food pellets have been randomly scattered on the grid points and the objective is to have the ant consume as much food as possible within a given number of time steps. The grid is the operational environment for the ant and a control strategy tells the ant how to navigate around the grid. Fig. 4 shows how a control strategy is encoded in a FSM. Sanchez et al. [21] have recently shown that EAs can evolve FSMs that encode high performance control strategies for this problem.

As previously stated, the objective of our research effort is to see if our approach can quickly evolve safe control strategies. Consequently, we need a modified version of the Santa Fe Trail Problem that adds a safety component. We call this new version the *Hazardous Santa Fe Trail Problem* because it introduces hazards, i.e., unsafe conditions, that the control strategy must avoid. These hazards are "black holes," which are randomly placed at vacant grid locations. If the ant steps into a black hole, it dies. The FSMs we evolve will be similar in structure to that shown in Fig. 4, except now each arc is labeled with two observed inputs: one indicates the presence of food and the other indicates the presence of a black hole.[1]

The Hazardous Santa Fe Trail Problem is an ideal forum for evaluating not just our approach, but any method for designing safe adaptive control strategies. Observe that the currently implemented control strategy may be optimal for the existing placement of food pellets or black holes, but any changes in those locations can make the strategy ineffective (or even unsafe), thereby forcing an adaption. It is therefore easy to construct scenarios requiring adaption of an existing control strategy. Moreover, the problem is easy to simulate with accuracy.[2]

B. Implementing the Evolutionary Algorithm

We intend to use random mutations as the reproduction operator in our EA. A number of mutation varieties are possible: adding or deleting states; changing the location of an arc; changing the action taken in a state; and changing the machine's initial state. The general rule for mutations is that they preserve some degree of similarity with the original structure, which leads to producing new structures with a similar fitness. This prevents the mutation process from degenerating into a simple random search (e.g., as done by simulated annealing).

The EA steps are shown in Fig. 2. (There is one additional step, which is given in Section IV(C).) The algorithm begins with an initial population of μ randomly generated FSM structures, each encoding a control strategy. All μ FSMs are then evaluated for fitness by placing an ant on the grid at location (0,0) and then executing the encoded control strategy for 200 time steps to see how many food pellets are consumed. The fitness value equals the number of food pellets consumed.

Subsequent iterations of the EA select μ parents, copy them, and then mutate the copies to produce new offspring FSMs. Only one of the above mutation operators is used to produce an individual offspring. (Mutation operators are chosen with equal probability.) The μ parents and μ offspring are collected into a temporary population. All of the individuals are ranked by fitness and the top μ survive while the rest are discarded. Notice that parent FSMs and children FSMs compete equally for survival. This iterative procedure, called processing a generation, is repeated until a defined termination criteria is met.

[1] We also dropped the NOP action.

[2] The results here were obtained via extrinsic evolution because the author did not have access to robot ants. Nevertheless, hardware robot ants specifically designed for Santa Fe Trail Problem investigations are available [22]. Our results can therefore be duplicated via intrinsic evolution.

Randomly chose two parents α and β from the current population

If fitness(α) > fitness(β), then return α
If fitness(β) > fitness(α), then return β
If α has more states with action == 3, then return α
If β has more states with action == 3, then return β
If none of the above are satisfied, then return return α or β with equal probability

Fig. 5. Binary tournament algorithm. Each if-then statement is evaluated in order shown.

Usually this criteria is either that an acceptable FSM has been found or a fixed number of generations have been processed. In the latter case the best fit FSM from the final generation is used.

The μ parents selected for reproduction are picked from the survivors of the previous generation. The highest fit individual from the previous population is copied unchanged to the next generation. This elitist policy ensures the fitness monotonically increases throughout the evolutionary process. The remaining $\mu - 1$ parents used during a generation are selected by conducting a binary tournament, which helps to choose the better fit parents for reproduction. Two randomly chosen parents compete in this tournament and there are two criteria used to determine the winner: first is best fitness and second is the best exploration capability.[3] If neither parent is a clear winner, then one of them is chosen at random. The binary tournament algorithm for the Santa Fe Trail Problem is described in Fig. 5. The selection criteria, along with their priority, can be tailored for the problem at hand.

It is important to start out with a safe initial population. This is easily accomplished even though that population is randomly generated. For example, in the Hazardous Santa Fe Trail Problem, randomly assign the arcs between states, but do this in a way that ensures the arcs traversed whenever a hole is present do not point to a state with action = 3 (i.e., take a step forward).

Each control strategy is evaluated by trying it out in the real physical environment; the better the strategy performs, the higher its fitness value. However, each strategy is first checked for safety and any unsafe strategy is immediately discarded and a new candidate strategy is evolved by mutating the same parent FSM again.

C. Adding MC to an EA

The model checker makes successive sweeps through the FSM states, labeling states in which the safety property holds. For example, consider the safety property $\mathcal{S} \Rightarrow$ did not step into a black hole. The CTL formula $\mathbf{AG}(\mathcal{S})$ says it is not possible to get to a state where $\mathcal{S}$ no longer holds, because this is unsafe condition for the ant. All states are checked and labeled to indicate whether $\mathcal{S}$ holds. It is then possible to verify if the CTL formula is true or false in linear time. For the Hazardous Santa Fe Trail Problem the formula for $\mathcal{S}$ is quite simple: never take a step forward if a hole is in front of you. That is,

$$\mathcal{S} \Rightarrow \neg(\text{step forward} \wedge \text{hole present}). \tag{2}$$

The safety of a control strategy for the Hazardous Santa Fe Trail Problem can be checked in a straightforward manner. First, we note that each state has three incident arcs: one traversed if there is no food or no hole present; one if food is present but no hole is present; and one if no food is present but a hole is present. The MC process begins by initially labeling all states as safe. Next, check all states with action = 3 to see if they have an arc pointing to it that is traversed because a hole is present. All states incident to the tail of those arcs have their labels changed to unsafe. Following the procedure outlined in Fig. 3, all states that transition to these unsafe states also have their labels changed to unsafe. This process continues until all states are visited and labeled as safe or unsafe. Finally, let $f_I(\cdot)$ be the characteristic function for the set of all initial states, and let $f_U(\cdot)$ be the characteristic function for the set of all states labeled as unsafe. $\mathbf{AG}(\mathcal{S})$ holds if $f_I(u) \wedge f_U(u) = 0\ \forall u$.

In the general case several safety properties will have to be satisfied. Similar sweeps must be conducted for all other CTL formulas describing safety properties, because all safety properties must hold before the control strategy can be deemed safe. This means the safety check for any control strategy is expressed in compact form as

$$\mathbf{AG}\left(\bigwedge_{j=1}^{K} \mathcal{S}_j\right) = 1 \tag{3}$$

where $\mathcal{S}_j$ is the jth safety property and $\mathcal{S}_j = 1$ means that property holds. Equation (3) must hold from any initial state in the Kripke structure.

Any control strategy that fails the safety check is immediately discarded and the parent FSM is mutated again. This process usually will not have to be repeated too many times before a safe offspring is produced. Once the control strategy has been safety certified, it can then be evaluated in the operational environment. Hence, step 3 in Fig. 2 should be changed to the following form:

3) create μ new FSMs by repeating the following two steps:
i) conduct a binary tournament to select a parent FSM from the current population
ii) randomly mutate the parent FSM to create a new offspring FSM

[3] For the Hazardous Santa Fe Trail Problem this latter characteristic is measured by the number of states where the action is to take a step forward.

TABLE I
70 Food Pellet and 15 Hole Grid Locations used in Section V Example

Item	Location
food pellets	(2, 1) (2, 23) (3, 10) (3, 15) (3, 20) (3, 23) (3, 29) (4, 4) (5, 15) (5, 31) (6, 7) (6, 14) (6, 19) (7, 7) (8, 20) (8, 22) (8, 28) (8, 30) (9, 8) (9, 10) (9, 17) (10, 12) (10, 13) (10, 20) (11, 20) (11, 28) (12, 25) (13, 2) (13, 4) (13, 10) (13, 27) (14, 30) (15, 22) (16, 6) (16, 20) (17, 26) (19, 1) (19, 2) (20, 25) (20, 30) (21, 4) (21, 7) (21, 10) (21, 13) (21, 26) (21, 30) (22, 1) (22, 4) (22, 16) (22, 25) (23, 12) (24, 7) (24, 8) (24, 9) (24, 21) (24, 24) (24, 29) (25, 3) (25, 9) (25, 11) (25, 31) (26, 22) (28, 5) (28, 20) (28, 28) (29, 25) (30, 12) (30, 13) (30, 19) (31, 5)
holes	(5, 2) (6, 2) (7, 31) (8, 13) (9, 14) (17, 17) (18, 21) (18, 27) (20, 1) (23, 21) (24, 16) (25, 24) (26, 12) (27, 23) (28, 25)

iii) use MC to verify offspring safety. if unsafe, go to step 3(ii).

V. NUMERICAL EXAMPLE

The numerical example of the Hazardous Santa Fe Trail Problem was conducted on a 32×32 grid. Seventy food pellets and fifteen black holes were randomly assigned to grid locations (see Tables I–III for the exact locations).

Our EA used a population size of $\mu = 25$ FSMs that evolved over 150 generations. The initial population was randomly created with each FSM having between 10 and 15 states. Parents in subsequent generations were selected using a binary tournament. The mutation operators, defined in Section IV(B), were applied with equal probability but only one operator could be used to produce a given offspring. Each offspring was safety checked using an MC algorithm before being evaluated for fitness. About 10%–15% of the created offspring were found to be unsafe. Recall FSMs that fail the safety check are immediately discarded and the same parent FSM is mutated again. This procedure must continue until a safe offspring is produced. Usually one or two tries were sufficient to achieve this.

Each safe FSM was evaluated by placing the ant at grid location (0,0) and executing the encoded control strategy. The number of food pellets the ant consumed within 200 time steps was recorded and this became the fitness value of the FSM. The simulation was written in C++ and run on a SPARC ULTRA-10 workstation. Each run took less than 20 s to complete. Fig. 6 shows the results of a typical run. Notice that the fitness monotonically increases. (See Tables I–III for the state table describing this FSM.)

TABLE II
State Table for Best Evolved Control Strategy Found During Single EA Run

	Next State			
Present State	F H 0 0	F H 0 1	F H 1 0	Action
0	12	5	1	1
1	18	5	8	3
2	19	9	1	1
3	10	2	1	1
4	16	5	1	1
5	1	13	1	1
6	2	7	1	2
7	4	4	23	2
8	9	6	8	3
9	12	5	10	2
10	8	4	1	3
11	6	22	8	1
12†	3	7	14	3
13	11	5	8	2
14	17	2	12	3
15	3	5	21	1
16	20	11	8	3
17	10	6	12	2
18	16	3	8	3
19	17	17	1	3
20	7	0	18	3
21	12	6	14	3
22	7	6	12	2
23	0	13	1	3

Note: The next state is shown for the three possible food/hole conditions visible to the ant ("0" implies absence, "1" implies presence). Actions 1, 2, and 3 are turn left, turn right, and step forward, respectively. '†' indicates the initial state. The control strategy is safe because F = 0 and H = 1 never causes a transition to a state with action = 3. This control strategy consumed 22 food pellets in 200 time steps.

TABLE III
State Table for One of the Unsafe Control Strategies

	Next State			
Present State	F H 0 0	F H 0 1	F H 1 0	Action
0†	6	5	1	2
1	7	5	8	3
2	1	9	10	1
3	7	2	1	1
4	1	5	1	1
5	1	9	1	1
6	2	7	1	3
7	4	4	1	2
8	2	6	11	3
9	6	2	8	2
10	4	5	10	3
11	1	0	10	3

Note: The next state is shown for the three possible food/hole conditions visible to the ant ("0" implies absence, "1" implies presence). Actions 1, 2, and 3 are turn left, turn right, and step forward, respectively. '†' indicates the initial state. Notice that state 8 is unsafe because F = 0, H = 1 causes a transition to state 6, which has action = 3. This control strategy caused the ant to fall into a hole at time step 55.

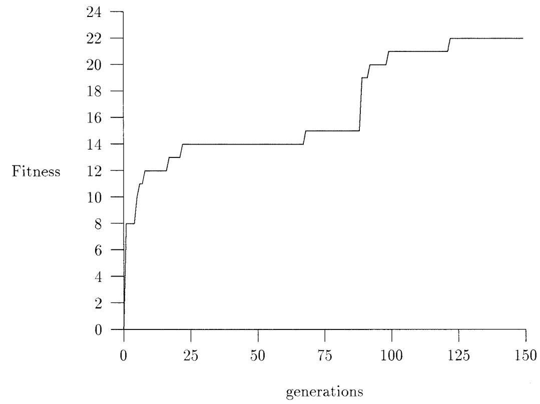

Fig. 6. Fitness versus generations for typical run.

It is important to realize that unsafe control strategies do not necessarily always produce unsafe results. We took one of the unsafe FSMs and executed it. (See Table III for this FSM's state table). The ant only consumed two food pellets before it died, which makes it a relatively poor control strategy. However, the ant did not fall into a hole until time step 55, which means it was completely safe for 54 time steps. It is likely that this unsafe action would occur at some different time step with a different placement of food pellets and holes. But, the key point here is unsafe actions take place only if the FSM is in a specific subset of states and, even then, only if a specific set of inputs are present. A FSM could, in principle, undergo thousands of state transitions without ever producing unsafe actions. This means unsafe actions are eventuality events, something difficult to find using simulation or emulation methods. The MC algorithm checks for these unsafe eventuality events by identifying paths that terminate at unsafe states.

VI. DISCUSSION

The evolved control strategy is only good for a specific operational environment. Put another way, an evolved control strategy that is good for one operational environment may not be any good in a second environment because it's efficacy was tied to the first operational environment. The operational environment for an instance of the Hazardous Santa Fe Trail Problem is defined by the food pellet and hole placements. While it is true that a safe control strategy for one placement of food pellets and holes will certainly be safe for any other placement, its ability to consume food pellets in different environments may vary considerably. So, how useful is it to evolve such a restricted control strategy?

We believe restricted control strategies are the norm for real-world applications. Electronic systems installed in space vehicles are designed to optimally perform over specified environmental ranges. Any deviation from these range boundaries at a minimum degrades the system's performance or, in the worst case, leads to system failure. The control strategy should start to evolve so that a system can recover most (if not all) of its previous functionality. For instance, suppose a deep-space probe suddenly encounters a high radiation environment, which causes degraded performance in a gyro system. The gyro system's control strategy should begin to adapt, but this adaption is to a known environmental change. The control strategy does not have to make the gyro system work in say a high temperature or high pressure environment because nothing indicates such an environment exists. In other words, a changed operational environment invokes the evolutionary process, and the scope of that change is known. If this was not the case, then the environmental change goes undetected and there is no reason to suspect the existing control strategy is inadequate. In either case the control strategy is restricted to work under a defined operational environment.

No attempt was made to use implication tables or other reduction techniques to check for equivalent states in the evolved FSMs. These techniques may be appropriate for extrinsic evolution, but they are probably too computationally expensive for intrinsic evolution, which is the intended application area for our approach.

A system is deemed unsafe if it continues to operate under current conditions, and that continued operation can cause harm to itself or some other system. Harm, however, is merely a matter of degree and it cannot be considered independent of the system. For instance, in some systems harm can mean imminent total destruction, while in other systems it may only mean a minor corruption of data. Nevertheless, our objective is to render control strategies that are completely safe, without regard for the effects of safety violations—i.e., the control strategy is either completely safe or it is classified unsafe. Any safety violation is undesirable because there is always a real potential for a minor safety violation, left untreated, to cause even more harm in the future. For this reason we chose not to differentiate between safety violations because we believe all safety violations are intolerable.

Changing operational environments do not really affect our method because safety properties are associated with systems and not the environments in which these systems must operate. Safety properties follow naturally from a systems design limitations and are therefore minimally affected by changes in the operational environment. Indeed, such changes may affect attribute levels, but the fundamental definitions remain intact. For instance, suppose a robotic arm was designed to lift objects weighing not more than 100 kg. Extreme cold may reduce this upper limit to say 80 kg, but the safety property itself still holds. That is, do not attempt to lift an object heavier than the upper limit or the arm could be damaged. Attribute level changes are easily accommodated by the EA. In other cases the safety properties are completely time invariant. For example, in the hazardous Santa Fe Trail Problem the safety property which says the ant should not step into a black hole or it will die holds regardless of where the black holes are actually located. In other words, the hole locations define the operational environment, but they do not define the safety property for the ant.

The only real effect of a changing operational environment is it may invalidate the current control strategy, which means a new one must be created. However, because the safety properties themselves undergo little or no change, and safe FSMs are always evolved in the same way, our method can be used whenever necessary regardless of how often the operational environment changes.

In this initial effort we only concentrated on the efficacy of the approach without worrying about computational effort. Clearly time to evolve cannot be ignored because an autonomous space vehicle cannot survive for an indefinite period of time without a viable control strategy. There is no way to accurately predict how many generations it takes before an EA can evolve a new control strategy, but there are circumstances where an upper bound is definable. One issue of enormous concern for NASA is aging effects in long-life spacecraft. These aging effects can lead to degraded performance or even system failures. One method of compensating for aging effects is to have spacecraft systems taken off line at regular intervals for preventive maintenance activities [23]. This is an ideal time to evaluate a current control strategy and, if necessary, evolve a new one. The duration of the preventive maintenance period will dictate the maximum running time of the EA. However, in other cases a changed operational environment or system fault makes the current control strategy suddenly unreliable, and failure is not an option. There is no choice under these circumstances but to immediately conduct corrective maintenance during which the EA is allowed to run as long as it takes until a replacement control strategy is found. That does not, however, mean the EA must be allowed to run forever. One possible approach would be to quickly evolve a control strategy that, while suboptimal, will suffice until enough time is available to conduct a more thorough search. This latter approach conducts corrective maintenance in stages rather than one long extended time period. Which approach should be used depends on how crucial it is to bring a new control strategy online.

VII. FINAL REMARK

Hardware-only implementations of EAs have been developed [24], and we find this to be an appealing method of implementation for deep-space probes because it is timely and fully supports in-situ intrinsic evolution. Our future efforts will focus on that very approach for evolving control strategies under real-time constraints.

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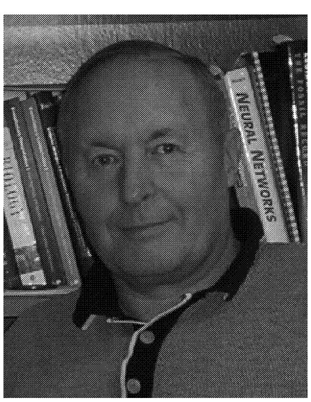

Garrison Greenwood (SM'00) received the Ph.D. degree in electrical engineering from the University of Washington, Seattle.

After spending more than a decade in industry designing multiprocessor embedded system hardware, he entered academia where he is now an associate professor in the Department of Electrical and Computer Engineering at Portland State University. In 1999 and 2000 he was a National Science Foundation Scholar-in-Residence at the National Institutes of Health. His research interests are evolvable hardware, adaptive systems, and operator methods in quantum computing.

Dr. Greenwood has served as a program committee member on many international conferences and is the general chair of the 2004 Congress on Evolutionary Computation. In 1999 he was an associate editor of the *IEEE Transactions on Neural Networks*, and since 2000 has been an associate editor of the *IEEE Transactions on Evolutionary Computation*. He is currently serving as chair of the IEEE Neural Network Society technical committee on evolutionary computation. He is a member of Tau Beta Pi and Eta Kappa Nu, and is a registered professional engineer.