Landscape characterization can be viewed as an attempt to invert the forward mapping of the simulator and recover the inputs that produce a particular output.

Given that a single simulation run can take days or weeks to complete even on a large computing cluster, SimLearn attempts to reduce costs by reducing the number of simulations needed to effect discoveries. Unlike conventional data-mining methods that are applied to static predefined datasets, SimLearn involves an iterative process in which a "most informative" dataset is constructed dynamically by using the simulator as an oracle. On each iteration, the algorithm models the knowledge it has gained through previous simulation trials and then chooses which simulation trials to run next. Running these trials through the simulator produces new data in the form of input-output pairs.

The overall process is embodied in an algorithm that combines support vector machines (SVMs) with active learning. SVMs use learning from examples (the examples are the input-output pairs generated by running the simulator) and a principle called maximum margin to derive predictors that generalize well to new inputs. In SimLearn, the SVM plays the role of modeling the knowledge that has been gained through previous simulation trials. Active learning is used to determine which new input points would be most informative if their output were known. The selected input points are run through the simulator to generate new information that can be used to refine the SVM. The process is then repeated. SimLearn carefully balances exploration (semi-randomly searching around the input space) versus exploitation (using the current state of knowledge to conduct a tightly focused search).

During each iteration, SimLearn uses not one, but an ensemble of SVMs. Each SVM in the ensemble is characterized by different hyperparameters that control various aspects of the learned predictor — for example, whether the predictor is constrained to be very smooth (nearby points in input space lead to similar output predictions) or whether the predictor is allowed to be "bumpy." The various SVMs will have different preferences about which input points they would like to run through the simulator next. SimLearn includes a formal mechanism for balancing the ensemble SVM preferences so that a single choice can be made for the next set of trials.

Initial tests with two real-world scientific simulators have shown that SimLearn is effective in reducing the number of trials needed to accurately identify the regions of input space leading to particular output behaviors. In the first application involving simulations of collisions between asteroids and the gravitational interactions between the resulting fragments, parameters of the two colliding asteroids that lead to binary pairs (gravitationally bound fragments in orbit around a common center of mass) were identified using only half the simulation trials needed to obtain equivalent knowledge from a grid-based sampling approach. In the second application involving simulations of the Earth's magnetosphere, there was a corresponding reduction by a factor of six in the number of simulation trials required.

This work was performed by Michael Burl, Dennis DeCoste, Dominic Mazzoni, and Lucas Scharenbroich of Caltech and Brian Enke and William Merline of the Southwest Research Institute for NASA's Jet Propulsion Laboratory. Further information is contained in a TSP (see page 1).

The software used in this innovation is available for commercial licensing. Please contact Karina Edmonds of the California Institute of Technology at (626) 395-2322. Refer to NPO-43399.

Electro-Optical Modulator Bias Control Using Bipolar Pulses

Bias is automatically adjusted to maintain maximum extinction during "off" periods.

NASA's Jet Propulsion Laboratory, Pasadena, California

An improved method has been devised for controlling the DC bias applied to an electro-optical crystal that is part of a Mach-Zehnder modulator that generates low-duty-cycle optical pulses for a pulse-position modulation (PPM) optical data-communication system. In such a system, it is desirable to minimize the transmission of light during the intervals between pulses, and for this purpose, it is necessary to maximize the extinction ratio of the modulator (the ratio between the power transmitted during an "on" period and the power transmitted during an "off" period). The present method is related to prior dither error feedback methods, but unlike in those methods, there is no need for an auxiliary modulation subsystem to generate a dithering signal. Instead, as described below, dither is effected through alternation of the polarity of the modulation signal.

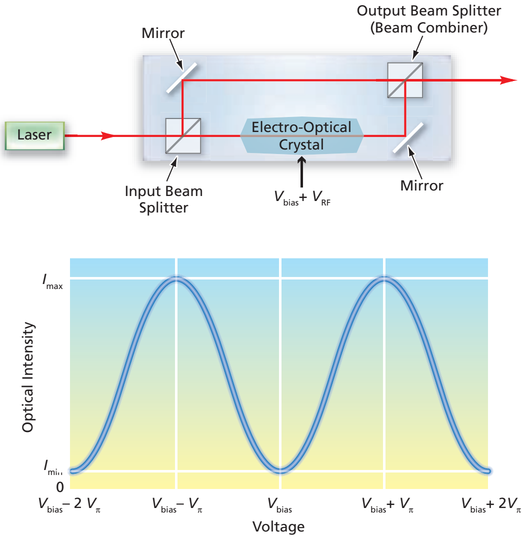


Figure 1. A **Mach-Zehnder Modulator** is a Mach-Zehnder interferometer that includes an electro-optical crystal for varying the difference between the lengths of its two optical paths. If V_{bias} is set at the optimum value, then the output optical power varies as a symmetrical function of V_{RF}.

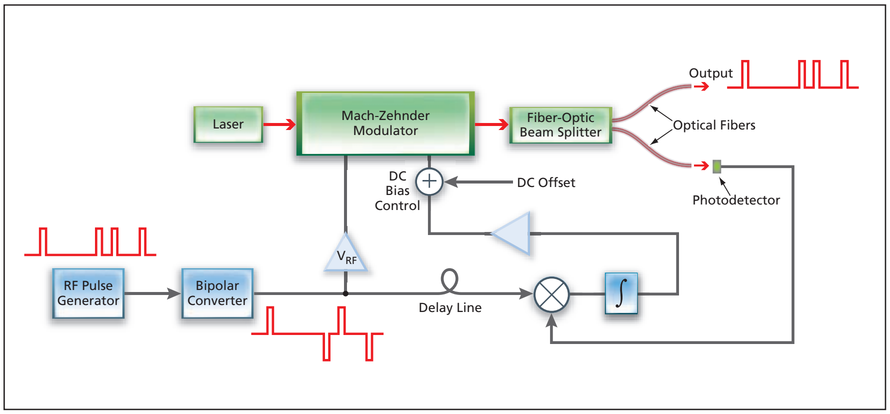


Figure 2. This **Modulation System** for PPM optical communication includes a bias control loop that corrects for electrical and thermal drifts to maintain a maximum extinction ratio.

The upper part of Figure 1 schematically depicts a Mach-Zehnder modulator. The signal applied to the electro-optical crystal consists of a radio-frequency modulating pulse signal, V_{RF}, superimposed on a DC bias V_{bias}. Maximum extinction occurs during the "off" ($V_{RF} = 0$) period if V_{bias} is set at a value that makes the two optical paths differ by an odd integer multiple of a half wavelength so that the beams traveling along the two paths interfere destructively at the output beam splitter. Assuming that the modulating pulse signal V_{RF} has a rectangular waveform, maximum transmission occurs during the "on" period if the amplitude of V_{RF} is set to a value, V_π, that shifts the length of the affected optical path by a half wavelength so that now the two beams interfere constructively at the output beam splitter.

The modulating pulse signal is AC-coupled from an amplifier to the electro-optical crystal. Sometimes, two successive pulses occur so close in time that the operating point of the amplifier drifts, one result being that there is not enough time for the signal level to return to ground between pulses. Also, the difference between the optical-path lengths can drift with changes in temperature and other spurious effects. The effects of both types of drift are suppressed in the present method, in which one takes advantage of the fact that when V_{bias} is set at the value for maximum extinction, equal-magnitude positive and negative pulses applied to the electro-optical crystal produce equal output light pulses.

In a modulation system designed and operated according to this method (see Figure 2), the modulating pulses are converted to alternating polarity, a small portion of optical output power is sampled by a photodetector, the photodetector output is multiplied by a sample of the alternating-polarity modulating signal, and the product is integrated over time to obtain an error signal. When V_{bias} is not at the optimum, maximum-extinction value, there is either an overshoot or an undershoot in the output light pulse, such that the integral signal amounts to an error signal that is proportional, in both magnitude and sign, to the difference between the actual and optimum values of V_{bias}. The integral signal is amplified and added to a DC offset voltage, and the sum fed to a bias control input terminal to drive the modulator toward optimum bias. Normally, the DC offset voltage would be set initially at a maximum-extinction point.

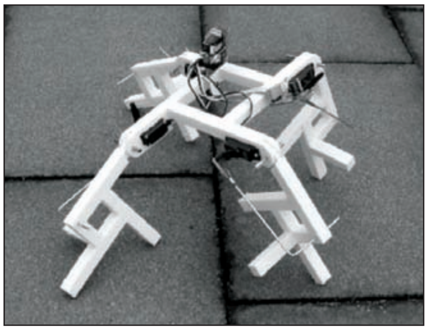
This work was done by William Farr and Joseph Kovalik of Caltech for NASA's Jet Propulsion Laboratory. Further information is contained in a TSP (see page 1).
NPO-41301

Generative Representations for Automated Design of Robots

Compact representations circumvent the computational obstacle to complexity.

Ames Research Center, Moffett Field, California

A method of automated design of complex, modular robots involves an evolutionary process in which generative representations of designs are used. The term "generative representations" as used here signifies, loosely, representations that consist of or include algorithms, computer programs, and the like, wherein encoded designs can reuse elements of their encoding and thereby evolve toward greater complexity.



The **"Quatrobot" Is a Walking Robot** that was designed by automated evolutionary synthesis, using a generative representation. The robot was built after 13 iterations.

Automated design of robots through synthetic evolutionary processes has already been demonstrated, but it is not clear whether genetically inspired search algorithms can yield designs that are sufficiently complex for practical engineering. The ultimate success of such algorithms as tools for automation of design depends on the scaling properties of representations of designs. A non-generative representation (one in which each element of the encoded design is used at most once in translating to the design) scales linearly with the number of elements. Search algorithms that use non-generative representations quickly become intractable (search times vary approximately exponentially with numbers of design elements), and thus are not amenable to scaling to complex designs.

Generative representations are compact representations and were devised as means to circumvent the above-mentioned fundamental restriction on scalability. In the present method, a robot is defined by a compact programmatic form (its generative representation) and the evolutionary variation takes place on this form. The evolutionary process is an iterative one, wherein each cycle consists of the following steps:

1. Generative representations are generated in an evolutionary subprocess.
2. Each generative representation is a program that, when compiled, produces an assembly procedure.
3. In a computational simulation, a constructor executes an assembly procedure to generate a robot.
4. A physical-simulation program tests