

IMA Workshop Highlights Opportunities For Women in Industry

By Barry A Cipra

Cooperating robots, nonlinear viral dynamics, and asynchronous parallel optimization algorithms—a typical range of topics for a workshop at the Institute for Mathematics and its Applications at the University of Minnesota. But the meeting that featured them, held the weekend of September 8–10, was atypical in one important respect: All the participants were women.

The workshop, Connecting Women in Mathematical Sciences to Industry, drew nearly six dozen participants from around the country. Mostly graduate students, they came to learn about opportunities in industrial mathematics and to get career advice from women already working in or with industry. Co-sponsored by the Association for Women in Mathematics, the meeting was organized by Rosemary Chang of Coastcom, Suzanne Lenhart of the University of Tennessee, and Margaret Wright of Bell Laboratories, Lucent Technologies.

The number of women working in industrial careers is small enough that “we still have the need to interact with each other as a community and give some advice to people,” Lenhart says. “The idea was to let students know there are lots of possibilities.”

Parallel Paths

The scientific part of the program featured a variety of applications of mathematics. Lynne Parker of Oak Ridge National Laboratory led off with a talk on distributed control approaches to multirobot cooperation. The notion that a gang of small robots can accomplish things a single large automaton cannot—think about cleaning up a hazardous waste site, or doing military reconnaissance—is hardly new, but good algorithms for coordinating the actions of a robotic gang have emerged only recently. The numerous areas of research, Parker says, range from task allocation to multirobot learning. Evaluation metrics is another area in which a lot of work is being done.

Parker described a software architecture, called Alliance, that she and colleagues at Oak Ridge have developed for robust, fault-tolerant control of multirobot teams. Under Alliance, each robot is given a set of behaviors—the physical actions it can perform—and a set of “motivations” that select among behaviors. The robots, more insect- than people-like, communicate but don’t negotiate with one another. This simplifies the scale-up problem, Parker explains. Controlling the motivational behaviors are thresholds of “impatience” and “acquiescence.” If a robot senses that its co-workers are stuck or not making suitable progress, it may decide to jump in; alternatively, if it senses that its own efforts aren’t accomplishing anything, it may drop out and let others take over.

Videos (viewable at Parker’s ORNL Web site) show actual robots in action, including three R2D2-like “janitors” cleaning up a spill of hockey pucks. One of the robots sat around reporting on the progress of the others until one of them was disabled (the video shows a person surrounding the robot with blocks— “sometimes we’re mean to the robots,” Parker says jokingly of the various ways her group interferes with them, which includes disrupting their communication or removing a robot altogether); at that point, the inactive robot grew impatient and jumped into the fray. That’s one of the main advantages of self-motivated robots, Parker says: They can cope with unexpected change. There could be a lesson here for people as well.

Coordinated computing is important even when no moving parts are involved. Tamara Kolda of Sandia National Laboratories in Livermore, California, presented a new strategy for farming out pieces of an optimization problem to a cluster of computers that differ in both processor speed and reliability. The approach, asynchronous parallel pattern search (APPS), is geared for problems with complicated functions—problems in which it’s not only impossible to compute a gradient, but in which the function evaluations themselves are time-consuming calculations, often requiring days of computation.

Pattern search is, conceptually, a simple technique. It assumes that the function to be optimized, say F , has been evaluated at an initial point, x_0 . It then evaluates F at a small set of nearby points, $x_0 + u_1, x_0 + u_2, \dots, x_0 + u_n$, where the direction vectors u_1, u_2, \dots, u_n form a “positive spanning set” for the underlying vector space. This simply means that every vector is expressible in terms of u_k ’s with *positive* coefficients. In two dimensions, for example, three u_k ’s suffice (see Figure 1).

If one of the nearby points gives a better solution, the pattern search algorithm shifts to it and iterates. If no better point is found,



Suzanne Lenhart, president of the Association for Women in Mathematics and an organizer of the IMA workshop, pointed out that the number of women working in industry is still small enough that they “need to interact with each other as a community.” For the many graduate students in attendance, Lenhart had an optimistic message: “There are lots of possibilities.”

the algorithm stays put at x_0 , divides the direction vectors by 2, and *then* repeats. Under reasonably general conditions, the algorithm is guaranteed to converge to the optimal solution.

Pattern search lends itself to parallelization: At each step, the function evaluations at the nearby points can be done by separate processors. But a straightforward, synchronized parallel approach is inefficient—if one evaluation takes a particularly long time (because, say, one of the processors is a bit slow—or fails altogether), the rest of the processors will spend a lot of time waiting. APPS does away with the waiting. In effect, as soon as a processor is done at a point, it looks for the current best solution, heads there, and keeps going. A processor may even abandon a function evaluation in mid-computation if its counterparts report better prospects elsewhere.

Kolda and colleagues have tested APPS on several benchmark problems. In one, a circuit simulation run on 50 processors, APPS took half the time required for a straightforward parallel pattern search (PPS), and got a significantly better result. The asynchronous algorithm did more function evaluations, but with far less idle time—the 50 processors in the PPS computation spent more than half their time twiddling their binary thumbs.

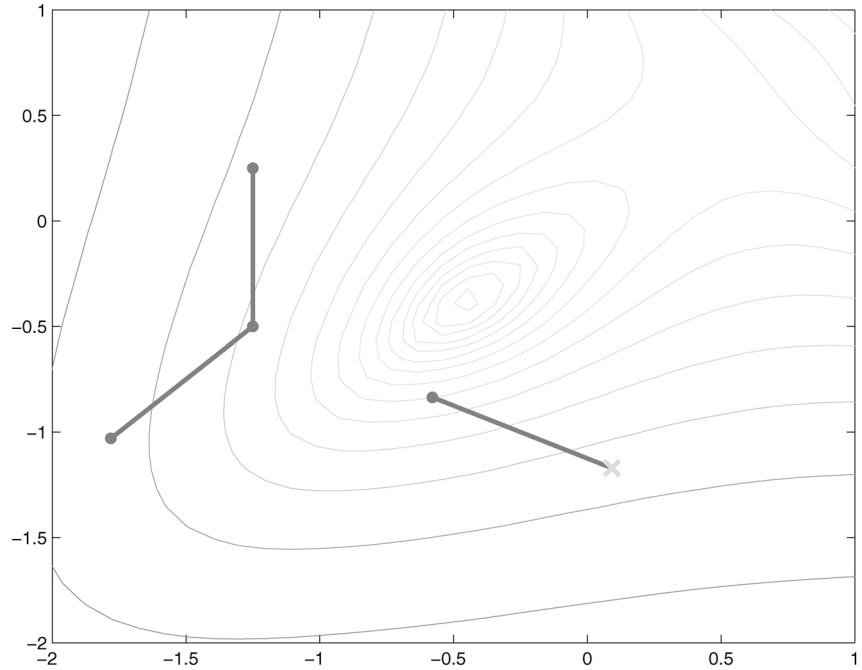


Figure 1. Three vectors form a positive spanning set in two dimensions. The APPS (asynchronous parallel algorithm pattern search) quickly homes in on an optimal solution.

Nonlinear Effects

Sarah Holte, a mathematician at the Fred Hutchinson Cancer Research Center in Seattle, described some new mathematical models of HIV infection dynamics. She and colleagues have concluded that a linear model first studied by Alan Perelson and others (see *SIAM News*, March 1999) gives a better fit to experimental data when modified with a nonlinear, density-dependent term. Their results, Holte says, have significant implications for long-term treatment strategies.

The basic model studies what happens to a patient’s viral load V (measurable from blood samples) when the virus is being produced in infected cells of two types—short-lived T-cells and long-lived (but still un-identified) cells—but because of aggressive therapy is not able to infect new cells. If X and Y denote the numbers of short- and long-lived cells, respectively, the change in viral load is described by $dV/dt = pX + qY - cV$. In the original (linear) model, the infected cells are cleared at constant rates: $dX/dt = -rX$ and $dY/dt = -sY$ (with $r \gg s$). In the nonlinear model, the clearance rates become $dX/dt = -(rX^{k-1})X$ and $dY/dt = -(sY^{k-1})Y$, for some parameter k .

A statistical analysis of experimental data indicates that k lies between 1.396 and 1.479, with $k = 1.435$ as the best fit. As yet, there’s no known biological mechanism for a density-dependent nonlinearity, Holte says. But if the nonlinear model is indeed correct, patients may need to continue therapy for years instead of months: The nonlinear model predicts much slower long-term decay for the infected cell populations than Perelson’s linear model (see Figure 2).

Nonlinearity was a key feature of another talk, by Kathleen Hoffman of the University of Maryland Baltimore County. Hoffman, whose PhD thesis in applied mathematics was on the supercoiling of DNA, had tackled a problem for an automobile manufacturer: The automaker’s

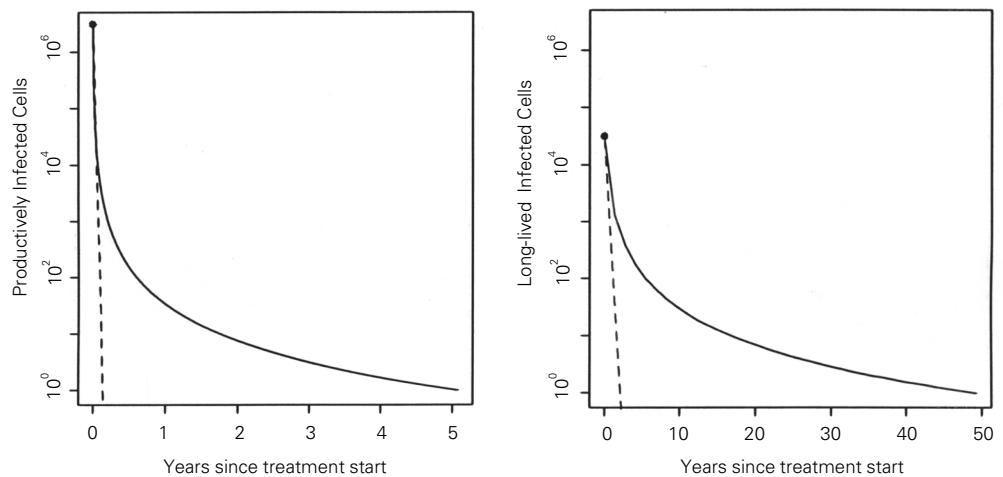


Figure 2. The nonlinear, density-dependent model of HIV (solid curves) predicts much slower decay—5.1 versus 0.1 years for short-lived T-cells and 49.1 versus 2.1 years for long-lived cells—than the original linear model (dashed lines).

engineers knew that the order in which spot welds are made in the assembly of sheet metal affects the final shape—indeed, their numerical models of the clamping and welding process could accurately predict the result—but they didn’t know why. By simplifying things to a pair of one-dimensional beams spot-welded at a handful of points, Hoffman and Fadi Santosa, associate director for industrial programs at IMA (and also associate director of the Minnesota Center for Industrial Mathematics), found an intuitive explanation.

The crucial insight, Hoffman says, came from conversations with engineers about what actually happens when pieces are clamped together for welding. When a clamp is applied, the metal is allowed to slide slightly along the clamp. But what seems to be an insignificant change can have enormous effects: Just lay a strip of paper on a table, push the two ends toward each other a quarter inch or so, and look at the arc that results. (The classic version is to calculate the height of the arc formed when the ends of a one-mile length of train track are pushed toward each other by one inch. The calculation is trickier than it sounds.) Hoffman’s analysis for the pair of one-dimensional beams showed that small slips create large displacements.

Hoffman also found that the order in which welds are made affects the consistency of the end result. In statistical simulations, the standard deviation of the displacement at the far end of the beams (see Figure 3) was less when the spot welds were made from “inside out” than when they were made in the opposite order. Being able to get consistent results is obviously important to manufacturers, she points out.

Networks

Workshop participants also spent time in breakout groups discussing practical issues of beginning a career in industry. While some topics were gender-specific (Anna Gilbert of AT&T Labs Research, for example, described hunting for company policy on maternity leave, and finally finding it under “short-term anticipated disability leave”), most were gender-good as well. Go to meetings and workshops. Practice the talks you give—and *don’t talk past the time limit!* Be ready to learn new fields. (Holte’s PhD was in point set topology; Kathryn Brenan of Aerospace Corporation switched five years ago from numerical techniques for space shuttle trajectory planning to signal and image processing; Chang’s new job at Coastcom has her learning not only about multiplexers, but also about budget planning.) Find a good mentor. (A mentor need not be of the same sex, but should have similar attitudes toward balancing work and family.) Apply for internships. And above all, the women stressed, network, network, network.

“I want to see more women out there,” Chang says. “I want to see women who can be successful without changing their personalities. I want to see women who are happy, who have balanced lives, have family, have outside interests—just being very successful, and well rewarded. I want to see women contributing to companies, I want to see women who are valued for their work, and judged for their work.”

Having more women working in industry will have a snowball effect, Chang says. “Once we have more women out there to be models of success, it’s going to be easier for women going through school to say ‘I can do that.’”

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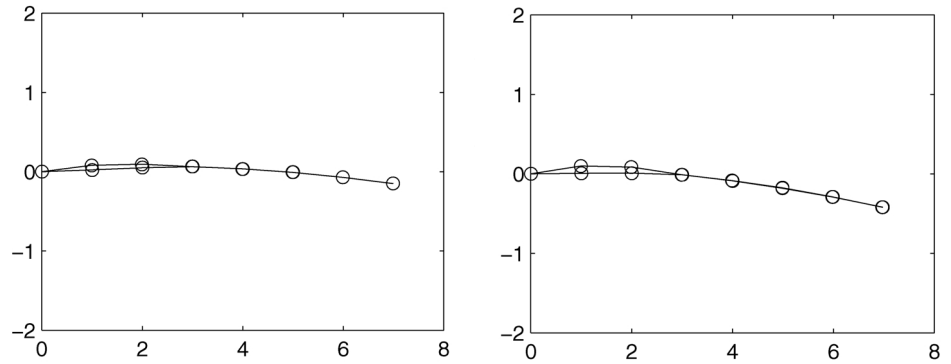


Figure 3. When two beams are clamped together, tiny amounts of slippage always produce displacement in the far (right-hand) end; as shown here (after the second weld in both cases), an inside-out welding sequence (left) does better than an outside-in sequence (right).